International Institute for Applied Systems Analysis
IIASA www.iiasa.ac.at

Address: IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria
Email: reiter@iiasa.ac.at **Department:** World Population | POP

Working paper

The Demography of Skills-Adjusted Human Capital

Claudia Reiter (reiter@iiasa.ac.at)
Caner Özdemir (caner.oezdemir@oeaw.ac.at)
Dilek Yildiz (yildiz@iiasa.ac.at)
Anne Goujon (anne.goujon@oeaw.ac.at)
Raquel Guimaraes (guimaraes@iiasa.ac.at)
Wolfgang Lutz (lutz@iiasa.ac.at)

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Approved by:

Name Albert van Jaarsveld
Program: Director General and Chief Executive Officer
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Table of contents

1 Introduction ... 9

1.1 Quantity vs. quality of education: a new policy focus ... 10
1.2 Human capital data: from attainment to skills ... 11
1.2.1 Global educational attainment data ... 11
1.2.2 Global skills data ... 13

1.3 Closing the gap: The need for skills-adjusted human capital data ... 14

2 Data Sources ... 18

2.1 Wittgenstein Centre (WIC) Human Capital Data Explorer ... 18
2.2 International Adult Literacy Survey (IALS) ... 19
2.3 International Adult Literacy and Life Skills Survey (ALL) ... 19
2.4 Programme for the International Assessment of Adult Competencies (PIAAC) ... 20
2.5 Skills toward Employment and Productivity Survey (STEP) ... 23
2.6 Demographic and Health Survey (DHS) ... 23
2.7 UNESCO Institute for Statistics (UIS) literacy data ... 24
2.8 Global Data Set on Education Quality (1965-2015) ... 24

3 Methodology ... 26

3.1 Assumptions ... 26
3.1.1 Tested literacy as proxy for general adult skills ... 26
3.1.2 Population representativeness within countries ... 27
3.1.3 Reference time of assessment for the base year estimates ... 27

3.2 Calculation of SAMYS based on empirical data ... 28
3.2.1 Computations for the base year (2015) ... 28
3.2.2 Reconstruction of SAMYS along cohort lines (1970-2015) ... 29
3.2.3 Adjustments for calculating SAMYS using DHS data ... 34

3.3 Calculation of SAMYS based on prediction regression models ... 35
3.3.1 Base year predictions (2015) ... 35
3.3.2 Reconstructions to 1970 ... 38

4 Results ... 40
5 Conclusions ... 52
References ... 53

List of Figures

Figure 1: Comparison of quantitative (a) and qualitative (b) measures of education, Chile, Hong Kong, and Iran 15

Figure 2: Correlation between PIAAC mean literacy and numeracy scores by age, sex, and country, all PIAAC countries 27

Figure 3: Changes in literacy skills over time from a cohort and period perspective, Denmark and Poland, 1998 and 2011 32

Figure 4: Estimated standard age effect, cohort perspective, 16 countries, both sexes, IALS 1994-98 and PIAAC 2011-17 33

Figure 5: Estimated percent change of literacy skills due to age effect (reverse direction used for reconstruction) 34

Figure 6: Correlation between empirical and fitted Skills-adjusted Mean Years of Schooling (SAMYS), 2015, Model 1 36

Figure 7 : Correlation between empirical and fitted Skills-adjusted Mean Years of Schooling (SAMYS), 2015, Model 2 37

Figure 8: Correlation between empirical and fitted Skills-adjusted Mean Years of Schooling (SAMYS), 1970-2015, Model 3 39

Figure 9: Estimated skills-adjustment factor by country, age 20-64, 2015 40

Figure 10: Relationship between skills adjustment factor and mean years of schooling by country and year 41

Figure 11: Population-weighted Mean Years of Schooling (MYS) and Skills-Adjusted Mean Years of Schooling (SAMYS) by region and continent, age 20-64, 2015 42

Figure 12: Population-weighted Mean Years of Schooling (left) and Skills-Adjusted Mean Years of Schooling (right) by continent, age 20-64, 1970-2015 42

Figure 13: Mean Years of Schooling (left) and Skills Adjusted Mean Years of Schooling (right), selected OECD countries, age 20-64, 1970-2015 43

Figure 14: Mean Years of Schooling (left) and Skills-Adjusted Mean Years of Schooling (right), selected developing countries, age 20-64, 1970-2015 44

Figure 15: Skills-adjusted Mean Years of Schooling (bars) and Mean Years of Schooling (dots), 30-34 and 60-64 year-olds, PIAAC and STEP countries, 2015 51

List of Tables

Table 1: PIAAC countries that have participated in IALS and/or ALL by year and assessment....................... 21

Table 2: Average PIAAC literacy and numeracy score by country... 22

Table 3: 2015 population-weighted OECD mean in PIAAC literacy scores by age, sex, and educational attainment 29

Table 4: Ordinary Least Squares model summary and coefficient estimates for Eq. 3. Model 1. [Dependent variable is logarithm of adjustment factor] 36

Table 5: Ordinary Least Squares model summary and coefficient estimates for Eq. 4. Model 2. [Dependent variable is logarithm of adjustment factor] 37

Table 6: Time-series model summary and coefficient estimates for Eq. 5. Model 3. [Dependent variable is logarithm of adjustment factor]... 39

Table 7: Mean Years of Schooling (MYS) and Skills-adjusted Mean Years of Schooling (SAMYS) by country, age 20-64, 1970 and 2015 (continues in the next pages) 45

Abstract

The human capital of the working age population has in the past shown to be a key driver not only of economic growth and poverty reduction but also of health, quality of institutions, and adaptive capacity to environmental change. Human capital has mostly been measured in terms of mean years of schooling of the population or the highest educational attainment distribution. But in recent years the attention has shifted to trying to also measure the quality of education in terms of the skills acquired. While much empirical information already exists on the tests of skills of school age children, the situation is not as good with respect to globally comparable data on adult skills. However, what matters for the multiple benefits of human capital is the skill level of adults of working age rather than the skill level of school age children. While the skills of the school-age population are sometimes used as a proxy for that of the adult population, the two can differ widely, particularly in countries that have seen recent expansions of schooling or changes in the educational system. Hence, for many purposes ranging from economic growth regressions to projections of future productivity, or demographic behaviours that reflect the heterogeneity of adults by their skills, there has not yet been an available dataset on skills adjusted human capital for adults on a global scale.

This paper presents the first such global data set for the period 1970-2015 for a new summary measure of adult human capital called Skills-Adjusted Mean Years of Schooling (SAMYS). Additionally, for 44 countries we present SAMYS by age and sex. The new measure combines the tested level of skills with the quantity of schooling measured by the average years spent in school. Several features of SAMYS advance the state of the art in the field of human capital measurement. Firstly, it combines tests on adult skills with conventional educational and demographic indicators to gain a fuller understanding of the level of human capital in a country. Second, SAMYS have been estimated for a very large number of countries (201 countries for the year 2015 and 185 countries for the period 1970-2015) to present the broadest possible picture of trends in global human capital. Finally, through using the demographic method of back projection along cohort lines, this new measure gives consistent and comparable data for skills adjusted human capital for all adult age groups and both sexes over a 45-year period. The results show that SAMYS have been improving over time in virtually all countries but that the differences between countries are much greater for SAMYS than for mean years of schooling.

About the authors

Claudia Reiter is a Research Assistant at the World Population Program at IIASA, Wittgenstein Centre for Demography and Global Human Capital (Univ. Vienna, IIASA, VID/ÖAW), Laxenburg, Austria. She is also a Ph.D. student and research assistant at the Department of Demography at the University of Vienna. (Contact: claudia.reiter@univie.ac.at)

Caner Özdemir is a Post-Doctoral Researcher at the Vienna Institute of Demography of the Austrian Academy of Science, Wittgenstein Centre for Demography and Global Human Capital (Univ. Vienna, IIASA, VID/ÖAW), Vienna, Austria. He is also an assistant professor at Zonguldak Bülent Ecevit University (Turkey), Department of Labour Economics and Industrial Relations. (Contact: caner.oezdemir@oeaw.ac.at)

Dilek Yildiz is a Post-Doctoral Research Scholar at the World Population Program at IIASA, Wittgenstein Centre for Demography and Global Human Capital (Univ. Vienna, IIASA, VID/ÖAW), Laxenburg, Austria, and a Post-Doctoral Research Scholar at the Vienna Institute of Demography of the Austrian Academy of Science, Vienna, Austria. (Contact: yildiz@iiasa.ac.at)

Anne Goujon is a Contract Agent in the European Commission's Knowledge Centre on Migration and Demography (KCMD) at the Joint Research Centre in Ispra, Italy. Until 2020 she was a Research Scholar at the World Population Program at IIASA and at the Vienna Institute of Demography of the Austrian Academy of Sciences, Wittgenstein Centre for Demography and Global Human Capital (Univ. Vienna, IIASA, VID/ÖAW), where she was leading the "Human Capital Data Lab". (Contact: anne.goujon@oeaw.ac.at)

Raquel Guimaraes is a Post-Doctoral Research Scholar at the World Population Program at IIASA with support from the Brazilian Coordination for the Improvement of Higher Education Personnel (CAPES). She is also an Assistant Professor at the Federal University of Parana (Brazil), Department of Economics. (Contact: guimaraes@iiasa.ac.at)

Wolfgang Lutz is Founding Director of the Wittgenstein Centre for Demography and Global Human Capital, a cooperation between the University of Vienna (where he is Professor at the Department of Demography), IIASA (where he is Director of the World Population Program), and the Austrian Academy of Sciences (where he is Scientific Director of the Vienna Institute of Demography). (Contact: lutz@iiasa.ac.at)

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1 Introduction

Human capital is widely acknowledged to be a key driver not only of economic growth and poverty reduction but also of health, quality of institutions, and adaptive capacity to environmental change. But the notion of human capital as used in this paper requires some clarification because it is used with quite different meanings by different research communities. While human capital is sometimes narrowly defined as the benefit of education that results in higher market income, this economic interpretation neither reflects the linguistic roots of the term nor its broader usage. Linguistically the word capital derives from the Latin *caput* (genitive *capitis*) which means head. Hence, human capital literally means "human heads" which is exactly the meaning that we will use in this paper, with heads not only referring to the number of heads but also to the brain power inside the heads. This usage of the term is very much in line with today's demographic usage of human capital formation and depletion through fertility, mortality and migration. Both the narrow and broad uses of human capital are in use today and here we will consistently use the latter one.

In empirical terms, human capital has mostly been measured in terms of mean years of schooling of the population aged 15 and above or the distribution of the population by highest educational attainment level. The full distribution by educational attainment already gives a much richer representation of human capital than the average number of years that people have spent in school, because it also shows the heterogeneity of the population with respect to education and allows to study e.g. the effects of a different education mix on economic growth. Also, differentiating the human capital distribution by age cohorts provides much more relevant information for assessing the impacts of education than simply taking the average education across all age groups, particularly in countries that have recently gone through strong education expansions, with younger cohorts being much better educated than older ones. For instance, Lutz et al (2008) have shown that economic growth was boosted with the access of better educated young cohorts to the workforce in the Asian tiger states during their period of rapid economic growth. This study also indicated that universal primary education is not enough to bring low income country populations out of poverty, but that it also requires high proportions of the population with at least completed junior secondary education. While the Millennium Development Goals (MDGs) defined in 2000 still focussed primarily on universal primary education, the Sustainable Development Goal for education (SDG4) now also targets universal high-quality primary and secondary education, in line with the findings mentioned above.

The focus on educational attainment distributions already includes some elements of quality control since in many countries successful completion of schooling levels is validated by a test, e.g. high school graduation. But data on skills tests also show clearly that there are marked differences between countries in the average skills of people that formally have the same level of educational attainment. Therefore, in recent years the attention has shifted to trying to also measure the quality of education in terms of the skills acquired. Several attempts have been made to adjust the conventional measures of mean years of schooling in a way that also reflects differences in the quality of education. Because of lack of data on adult skills, most of these studies used data from student test scores as proxies for the skills of the adult population in the respective countries (Hanushek and Woessmann 2012). But for countries with rapid education expansions or changes in the education system over time this is a very crude if not misleading approximation and it would would be much more desirable to measure and estimate the adult skills directly for the different age cohorts. This is what the current paper attempts to do.

Here we present the first global data set for the period 1970-2015 for a new summary measure of adult human capital called Skills-Adjusted Mean Years of Schooling (SAMYS). Additionally, for 44 countries we present SAMYS by age and sex. The new measure combines the tested level of skills with the quantity of schooling. Several features of SAMYS advance the state of the art in the field of human capital measurement. Firstly, it combines tests on adult skills with conventional educational and demographic indicators to gain a fuller understanding of the level of human capital in a country. Second, SAMYS have been estimated for a very large number of countries (201 countries for 2015 and 185 countries for the period 1970-2015), at present the broadest possible picture of trends in global human capital. Finally, using the demographic method of back-projections along cohort lines, this new measure gives consistent and comparable data for skills-adjusted human capital for all adult age groups and both sexes over a 45-year period.

This paper is structured as follows: after the introduction we present the data sources used for the estimates in Chapter 2, in Chapter 3 we present a summary of methods and assumptions utilized in the calculation of SAMYS, as well as explain the models used to predict SAMYS for countries that have not conducted adult skills tests. Finally, Chapter 4 presents and discusses the results, followed by some conclusions in Chapter 5. In the rest of the introductory chapter, we provide an overview on how the education policy focus expanded to quality of education in addition to length of education (section 1.1). Next, we present an overview of the available human capital data sets (section 1.2) and stress the need for skills-adjusted human capital data and present how SAMYS help to close this data gap. Finally, we highlight to what extent our indicator differs from other recent attempts to incorporate both quantity and quality dimensions into one indicator (section 1.3).

1.1 Quantity vs. quality of education: a new policy focus

The quest for quality education for all, regardless of age, sex, and ethnicity, is not new in the international community. Already in 1968, René Maheu, Director-General of UNESCO, delivered a speech at the United Nations International Conference on Human Rights, entitled "One must be able to read" (UNESCO 1968), demonstrating that the international policy community was aware of learning differentials and recognized the need for interventions to achieve universal literacy levels. In fact, nowadays, a growing number of research suggests that it is not only formal education that plays a crucial role in a country's development, but also the quality of education, i.e. relevant cognitive skills, that has an important impact on socio-economic outcomes – whether it is about earnings (Mateos-Romero et al. 2017) or health (Kakarmath et al. 2018) on the individual level, or about economic growth (Hanushek and Woessmann 2012, 2020) and employment rates (Li et al. 2016) on a macro-economic level.

Over the last decades, policymakers have been focusing primarily on universalizing access to education. Only recently, there has been an emergence of a new policy focus, from increasing the quantity of schooling to the quality of these schooling years. As an example, while Goal 2 of the Millennium Development Goals (MDGs) targeted in 2000 to "achieve universal primary education", Goal 4 of the successional 2015 Sustainable Development Goals (SDGs) envisaged to "ensure inclusive and equitable quality education and promote life-long learning opportunities for all". In fact, education access and attendance are currently no longer the main issues for many countries, as many young cohorts increasingly complete primary and attend some years of secondary school. With the average educational attainment increasing for younger cohorts, the attention shifts towards how successfully people can acquire skills during and beyond school, and why populations in some countries are learning more than others. In addition, economists, demographers, and sociologists have increasingly recognized not only the intrinsic value of skills, but also provided evidence of their social and economic benefits (Becker 1993; Crespo Cuaresma et al. 2014; Das Gupta 1990; Lutz 2012; Mincer 1974; Muttarak and Lutz 2014; Schultz 1961).

This new policy focus, however, calls for information on the level of skills of a population. Traditionally, researchers and policymakers around the world have explored population data on adults' educational attainment as an approximate measure of their skills (Barro and Lee 1993, 2001, 2013). However, as international and national assessments of education quality point out, the achievement of basic cognitive skills is not without heterogeneity among individuals, even when considering those who reached advanced schooling levels (Lindberg and Silvennoinen 2018). One important reason for the disconnection between indicators of educational attainment and learning outcomes of education is, paradoxically, the world-wide expansion of education. For many years, scholars have demonstrated the existence of a quantity-quality trade-off, in which the quality of education system is expected to decline when the educational system expands, at least in the initial stage (Mare 1979, 1981; Raftery and Hout 1993; Shavit and Blossfeld 1993). This is a result of the inability of the education system to cope with the increase in the number of students, also from less advantaged social backgrounds in the education system. In addition to the increase in attendance rates, the insufficiency of school inputs and the low government spending in education in low-income settings also affect education achievement[1].

In sum, it is now widely recognized that formal education itself does not guarantee the acquisition of cognitive skills (Hanushek and Woessmann 2012; Pritchett 2013), but at the same time, a comprehensive acquisition of cognitive skills by those in school clearly does not necessarily translate in universal access to education. These potential discrepancies of rising educational attainment without a likewise increase in skills, on the one hand, and measuring learning outcomes which might exclude substantial parts of the population who do not have access to school, on the other, pose a challenge for adequately estimating human capital in a population.

1.2 Human capital data: from attainment to skills

1.2.1 Global educational attainment data

The pioneers in constructing global education data were Robert Barro and Jong-Wha Lee (Barro and Lee 1993, 2001, 2013, 2015)[2], henceforth Barro-Lee. In their latest dataset (2015), the authors estimate the educational attainment of the population aged 15 or more for 146 countries in 5-year time intervals between 1950 and 2010. Barro-Lee indicators are further disaggregated by sex and quinquennial age intervals. Educational attainment in their dataset is measured along the following levels of schooling: no education,

[1]This statement should be relativized, as there are opportunities to learn outside the school setting. Formal learning opportunities take place in a variety of contexts and situations: adults may acquire reading skills from family members, social networks, community engagement or in-the job learning (Barton et al. 2012).

[2] The datasets are available at the website http://www.barrolee.com/.

incomplete primary, completed primary, incomplete secondary, completed secondary, incomplete tertiary, and completed tertiary. The authors also compute mean years of schooling for each country and world region.

While previous datasets by Barro-Lee (1993;2001) were largely constructed based on enrolment data applying the perpetual inventory method to estimate past educational attainment, the authors have updated their methodology in their latest revision (Barro and Lee 2015). Based on the collection of empirical data points, mainly from the UNESCO Institute for Statistics (UIS), Barro and Lee now use observations in 5-year age intervals for the previous or subsequent 5-year periods. Further, they assume differential mortality by education for the population aged 65 or older, broadly distinguishing between groups of OECD and non-OECD countries as well as between two broad educational groups: a less educated population, having attained primary education at most, and a more educated population, with at least secondary schooling. Based on enrolment data, aggregated and overlapping education categories from censuses are split up into four education classes, which are then further disaggregated into the seven categories mentioned above by means of age- and sex-specific completion ratios (Barro and Lee 2013).

Other initiatives to obtain global estimates for educational attainment were developed thereafter. To compile global and harmonized census data, the Minnesota Population Center released in 1999 the Integrated Public Use Microdata Series (IPUMS). The dataset contains several educational attainment indicators, such a school attendance[3], years of schooling, and highest level of education attained (Minnesota Population Center 2020). In addition, in 1999, the UNESCO established its statistical programme UIS (UNESCO Institute for Statistics) to provide education statistics that could be compared across countries, including share of the population by educational attainment and average years of schooling.

More recently, the Wittgenstein Centre for Demography and Global Human Capital (henceforth WIC) developed a dataset containing a global reconstruction of the population by age, sex, and six levels of educational attainment (no education, incomplete primary, completed primary, lower secondary, upper secondary, and post-secondary education). While their first dataset included 120 countries from 1970 to 2000 (Lutz et al. 2005), it was further updated to cover 171 countries from 1970 to 2010 (Goujon et al. 2016) and reconstruction was recently updated (Speringer et al. 2019) expanding both the period covered (1950-2015) and the number of countries included (185 countries). For estimating past educational attainment, WIC used four main input types for each country: (1) the most recent and reliable education structure by age and sex, (2) any reliable historical education data by age and sex to use as marker points in the reconstruction to increase output accuracy, (3) a set of age- and sex-specific mortality differentials and education transition rates by education, and (4) population estimates by age and sex. Multi-state back-projection techniques were used to estimate the population in 5-year time intervals from the base year 2015 to 1950 (Speringer et al. 2019).[4]

[3] Available for 270 editions (country-time) and 186 countries.

[4] The dataset (including projections) is available at http://dataexplorer.wittgensteincentre.org/

1.2.2 Global skills data

As argued in section 1.1, there has been a worldwide shift of focus from increasing the quantity of schooling to improving its quality. One consequence of the current emphasis on education achievement was a major increase in student evaluations, including the development of national and international assessments. Such tests aim primarily at tracking students' achievement between schools, countries, and over time. However, these tests have limited spatial and temporal coverage and predominantly take place in high-income countries in the Global North. Only recently, some low-income countries have been included as well (Kamens and McNeely 2010; Sellar and Lingard 2014).

The first efforts to measure skills were targeted at the population attending school. Starting from the 1960s, the International Association for the Evaluation of Educational Achievement (IEA) pioneered in developing the following international assessments: the 'First International Mathematics Study' (FIMS) and the 'First International Science Study' (FISS), both conducted to compare the educational achievement of different school systems. Thereafter, IEA conducted follow-up studies such as SIMS (Second International Mathematics Study) and SISS (Second International Science Study) in the 1970s and 1980s. Since 1995, IEA has conducted every four years the 'Trends in Mathematics and Science Study' (TIMSS), measuring both mathematics and science skills of pupils in 4th and 8th grades. IEA has also been conducting an international reading comprehension survey called 'Progress in International Reading Literacy Study' (PIRLS) since 2001. PIRLS tests reading skills of 4th graders and is conducted every 5 years. Since its start, IEA's test coverage around the globe has increased considerably. The latest 2016 PIRLS survey tested pupils in 50 countries and 11 regions, whilst the most recent 2015 TIMSS covered 57 countries and 7 regions.

In addition to IEA, in 2000, the Organisation for Economic Co-operation and Development (OECD) also started to collect skill data through the 'Programme for International Students Assessment' (PISA). It has been measuring skills of 15-year-old students in reading, mathematics, and science every three years in many countries and is today's the most widespread large-scale international students' assessment. In the 2018 PISA wave, a total of around 600,000 pupils were tested in 79 countries.

In addition to the above-mentioned international student skills assessments targeted at young population groups, there have also been initiatives to test the skills of adults. OECD collected data on adult skills via the 'International Adult Literacy Survey' (IALS) between 1994 and 1998 and the 'International Adult Literacy and Life Skills Survey' (ALL) between 2003 and 2008 for a limited number of countries. Then, in 2011, OECD implemented the 'Programme for the International Assessment of Adult Competencies' (PIAAC). Two additional rounds of PIAAC were conducted in 2014 and 2017 to include more countries. Skills of numeracy, literacy, and problem-solving in technologically rich environments of adults aged between 16 and 65 were tested so far in a total of 37 countries, most of which are OECD members. For developing countries, World Bank has developed a similar test, named the 'Skills toward Employment and Productivity Survey' (STEP). Further information about these adult skills tests will be presented in chapter 2.

1.3 Closing the gap: The need for skills-adjusted human capital data

Despite this rising awareness for measuring skills, research and development initiatives too often assess the quantitative (i.e. educational attainment) and qualitative (i.e. skills) dimension of education separately. As already pointed out previously, this disintegrated approach proves problematic for two main reasons:

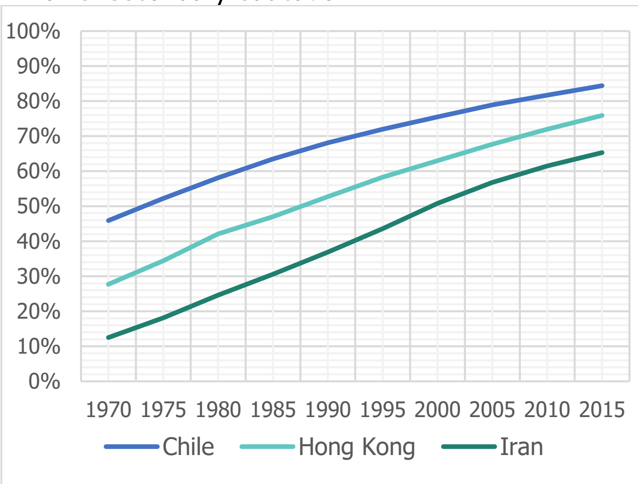
1. Focusing merely on the quantitative dimension by measuring attainment and enrolment rates clouds the analysis, primarily because enrolment/attainment does not necessarily guarantee learning.
2. Analysing educational outcomes without regard of enrolment and completion rates of the respective countries may result in biased conclusions, largely due to selection effects in which only the more advantaged students are able to progress to more advanced stages of the school trajectory (Spaull & Taylor, 2015).

Consequently, while both quantitative and qualitative measures are important complementary indicators to evaluate human capital in a population, they might lead to biased assessments when looked at separately. The graphs below exemplify the relevance of a composite approach. Figure 1a compares the share of the population aged 15 years or older, having attained at least lower secondary education, from 1970 to 2015 in Chile, Hong Kong (China SAR), and Iran. Figure 1b depicts the share of students who were assessed to have at least intermediate skills[5] according to harmonized learning outcomes as calculated by Altinok and colleagues for the same countries and over the same period (Altinok et al. 2018). The two education indicators (quantity and quality, respectively) lead to different conclusions: while the indicator on educational attainment suggests all countries are rapidly increasing their human capital, with Hong Kong and Iran further catching up with Chile, the qualitative education indicator reveals a different and less optimistic picture: with the exception of Hong Kong, only a fraction of students in the two other countries possesses an intermediate level of knowledge and skills in line with their level of education. Also, the development over time reveals to be less favourable, as only in recent years some improvements in learning outcomes are observable in Chile and Iran. While country-specific explanations for this divergence between quality and quantity of education would require further investigation, the aim of these graphs is to accentuate the relevance of a holistic assessment of human capital.

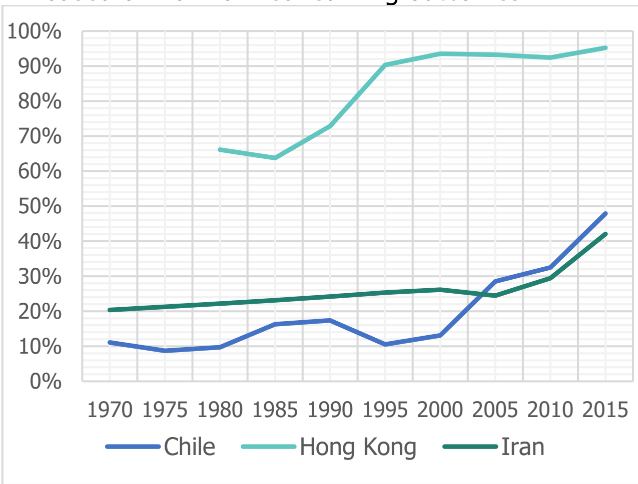
[5] The thresholds of low, intermediate, and advanced skills as defined by Altinok et al. make use of benchmarks determined by PIRLS, TIMSS, and PISA. A thorough description of expected competences at each threshold and level of education can be found in Altinok, Angrist, and Patrinos (2018).

Figure 1: Comparison of quantitative (a) and qualitative (b) measures of education, Chile, Hong Kong, and Iran, 1970-2015

(a) Share of population aged 15 or more with at least lower secondary education



(b) Share of students with at least intermediate skills based on harmonized learning outcomes



Source: WIC Human Capital Data Explorer; Altinok, Angrist & Patrinos, 2018

As a response to this data gap in measures that combine both education quality and quantity dimensions, some studies have explored this issue, although most of them only cover a limited number of countries. Michaelowa (2001), for example, conducted a study using PASEC (Programme of Analysis of Education System) data and net enrolment rates to measure educational success for Francophone Sub-Saharan Africa (Michaelowa 2001). Filmer et al. (2006) estimated the proportion of 15-year-olds who achieve basic learning standards for a small number of developed and developing countries (Filmer et al. 2006). Hanushek and Woessmann (2008) combined educational attainment and student achievement test outcomes to provide a holistic depiction of the educational system for 14 developing countries (Hanushek and Woessmann 2008). Spaull and Taylor (2015) formalised a method for combining school access and learning indicators and applied their so-called 'Access to Learning' indicator to 11 Sub-Saharan African countries (Spaull and Taylor 2015). Most recently, Filmer, Rogers, Angrist and Sabarwal (2020) constructed a dataset named 'Learning Adjusted Years of Schooling' (LAYS) by combining TIMSS 2015 8th grade mathematics assessment data with mean years of schooling by country. Singapore, the best performer in TIMSS 2015, was set to have an index value of 1. Based on that, learning adjusted years of schooling by gender for a total of 157 countries were calculated (Filmer et al. 2020).

In addition, it is worth mentioning, that data on population by educational attainment (as presented in 1.2.1) may already bring some element of quality control in the analysis. Albeit many studies on the implications of changing levels of educational attainment use just one average indicator of human capital (e.g. mean years of schooling), using the full distribution across educational attainment categories can be of additional benefit, when, for example, graduating from high school involves a standardized national exam. However, this comparable feature of students in terms of their skills at the end of a cycle is given only for some countries and some educational attainment categories, whereas the level of skills may be substantially different for others. For instance, the completion of primary education in some African countries does not necessarily entail the achievement of full literacy skills (Lutz et al. 2008), demonstrating once again the need for incorporating educational quality and skills assessed into existing data on educational attainment.

Furthermore, the World Bank has recently started a new initiative, the Human Capital Index (HCI), which combines education and health outcomes (Kraay 2018; The World Bank 2018). The components of the HCI are expressed as contributions to productivity relative to the benchmark of complete high-quality education and full health. The benchmark of complete high-quality education corresponds to 14 years of schooling and a harmonized learning outcome (HLO) test score of 625, which equals the advanced level international benchmark in TIMSS. The benchmark of full health corresponds to 100 percent child and adult survival and a stunting rate of 0 percent. HCI estimates the number of years of schooling a new-born is expected to achieve by the time she/he is 18 years old based on harmonized learning outcomes as in HLO, adjusted expected years of schooling as in LAYS, and returns to education and improvements in productivity associated with an improvement in health, using adult survival and stunting as proxies for health[6].

A very recent contribution to the list of global datasets for education attainment indicators was published by Friedman and colleagues to track the achievements of countries in reaching the SDG goals by 2030 (Friedman et al. 2020). By combining 3,180 nationally representative censuses and surveys from 195 nations and territories, the authors derive education attainment estimates by age, sex, country, and single years from 1970 to 2018. As compared to the previous datasets, the authors claim that their methodology advances by incorporating uncertainty in the back-projected estimates through simulation analysis and relying on regional trends to provide information on educational outcomes for those countries with sparse data. The educational attainment indicators modelled were the mean years of schooling and the proportion of the population without any formal schooling. Their study, nevertheless, is limited to the population aged 25-29 years.

In sum, the above-mentioned attempts mostly concentrate on the school-age population, except from the work of Friedman et. al, that focus on a small parcel of the adult population (25-29 years). However, quantitative and qualitative dimensions of education are crucial also for the measurement of human capital for the total adult productive population, as they are of substantive interest for a large array of social, economic, and health-related issues. Accordingly, changes toward higher skill levels of the working-age population may directly impact its productivity levels, the health status of its population and, by consequence, its economic growth (Barro and Lee 2001, 1994; Crespo Cuaresma et al. 2014; Krueger and Lindahl 2001; Lutz et al. 2008; Muttarak and Lutz 2014).

That is the gap this research is trying to fill, by proposing a new indicator, the 'Skills-Adjusted Mean Years of Schooling' (SAMYS), that brings at least four distinctive properties:

1. **Reliance on adult-skills data:** Albeit it is mostly the skills of the working-age population that have an important impact on socio-economic outcomes, existing skills-adjusted indicators are heavily based on school tests, i.e. information on skills for cohorts that do not yet participate in the labour force. This proves problematic for two main reasons. First, although there might be some correlation, the test scores of 15-year-olds currently in school are most likely not the same as the cognitive skills of today's working-age population, thus requiring additional transposing methods of some kind to also consider skills of adults. Second, school assessments do not inform on changes of skills over the life course (also beyond

[6] The returns to an additional year of school are considered as 8% per year. Parameters for adult survival rate (0.65) and rate of stunting for children under the age of five (0.35) are used to measure the improvements in the health component of HCI.

the age when formal education is usually attained). Therefore, by using student assessments, it is neither possible to account for increases of skills over the life course (e.g. life-long learning), nor for potential depreciation of skills with age. SAMYS is the first indicator measuring skills-adjusted human capital based on international, large-scale adult skills assessments as well as student skills assessments.

2. **Cohort analysis:** While most of the research in this field is conducted through the lenses of the economic production function of education and based on aggregate cross-sectional indicators, we take advantage of the demographic tool of cohort analyses, in which we follow cohorts, i.e. a group of people, born in a similar time period and thus exposed to similar circumstances over a specified period, by reconstructing skill levels along cohort lines. In addition, we rely on population estimates by gender, age-groups, and educational attainment, thus considering how the changing composition of population influences the development of skills and human capital.

3. **Global coverage**: Except for LAYS, which is currently available for 157 countries, existing attempts to merge qualitative and quantitative aspects of human capital are mostly limited to a specific set of countries. However, skills-adjusted data for as many countries as possible are desired, given the evidence that people who have completed the same number of years of schooling often vastly differ in their level of skills. A global perspective allows for the comparative analysis of countries with completely distinct education systems as well as different cultural and socio-economic characteristics. Our current dataset on SAMYS provides estimates for 201 countries, which makes it – to the best of our knowledge – the largest cross-sectional dataset on skills-adjusted human capital.

4. **Temporal evolution**: The availability of time-series data for SAMYS for the period 1970-2015 in 5-year steps allows to follow some main trends at global level. First, and as already mentioned previously, it was observed that quality of education tends to decline with the expansion of the educational system, at least on its initial stages. Second, recurring educational policy reforms may affect the quality of schooling and hence the level of skills in a population. Finally, job requirements and skills used in daily life are considerably changing over time. Therefore, we expect that adults with post-secondary educational attainment a few decades ago most likely showed different skills than today's adults with a university degree in the same country.

On grounds of the points highlighted above, we believe that SAMYS will be able to provide a valid and holistic assessment of human capital enabling the study of a full range of human capital-related effects on economic growth, sustainable development, and demographic changes.

2 Data Sources

To estimate SAMYS globally and over time, we rely on a variety of data sources. The quantitative dimension of our indicator, i.e. mean years of schooling, comes from the WIC Human Capital Data Explorer (2.1). The qualitative dimension, on the other hand, rests on different skills assessments, including the OECD's adult skills assessments IALS, ALL, and PIAAC (2.2, 2.3, 2.4 respectively), the World Bank's STEP Measurement Program (2.5), and the Demographic and Health Survey (DHS) (2.6). To expand our estimates to a global scale, we apply prediction regression models by using variables from additional data sources: the UNESCO Institute for Statistics (UIS) (2.7) and the Global Data Set on Education Quality of the World Bank (2.8).

In this chapter we present a summary of all the above-mentioned data sources. When describing the data, we point out the population surveyed, the countries investigated, the age-groups of reference, and what competencies are measured.

2.1 Wittgenstein Centre (WIC) Human Capital Data Explorer

The WIC Data Explorer (Wittgenstein Centre for Demography and Global Human Capital 2018) presents the reconstruction of population by levels of educational attainment from 1950 to 2015, and a set of different scenarios of future population and human capital trends in 201 countries of the world to 2100. The projections provide an update (scope, coverage and quality) of those presented in 2014 (Lutz et al. 2014) and are built on the so-called 'Shared Socioeconomic Pathways' (SSPs)[7]. These scenarios also serve policy considerations in many other fields ranging from the economic consequences of population ageing to development priorities in Africa, global population, or environmental interaction. The reconstruction of population by levels of educational attainment from 1950 to 2015, which was used within this paper, is published in Speringer et al. (2019).

The databank contains detailed data by 5-year age groups, sex and educational attainment (6 categories for 201 countries, 8 categories for 60 countries) for a large set of indicators:

- Population and Human Capital Stocks: Population size, median age, sex ratio, dependency ratio, educational attainment distribution, mean years of schooling, gender gap in educational attainment.
- Demographic Change: Growth rate, natural increase, fertility rate, birth rate, mean age at childbearing, life expectancy, survival ratio, death rate, net migration.

[7] The SSPs (Shared Socioeconomic Pathways) are widely used in the global change research community. They consist of narratives or storylines describing alternative socioeconomic developments and the corresponding challenges for mitigation and adaptation (Hynes et al. 2020; Lanzi et al. 2020; Lutz and Muttarak 2017; O'Neill et al. 2014). The demographic assumptions for the three main scenarios are the following: The Medium scenario (SSP2) foresees that fertility and mortality follow a medium pathway that is most likely from today's perspective. The scenario of Rapid Development (SSP1) assumes rapid increases in life expectancy, a faster fertility decline in high fertility countries and an education expansion path that follows the education goals as given by the Sustainable Development Goals (SDGs). The Stalled Development scenario (SSP3) presents a divided world foreseeing a stall in educational expansion in developing countries as well as continued high fertility and high mortality.

- New ageing indicators: Age when remaining life expectancy is below 15 years, proportion of population with a remaining life expectancy below 15 years.

Besides providing data for the main quantitative dimension of the SAMYS indicator, i.e. mean years of schooling, we are additionally making use of the following indicators from the WIC Data Explorer: population size, proportion of the population having more than lower secondary education, and old-age dependency ratio.

2.2 International Adult Literacy Survey (IALS)

As mentioned in Chapter 1, compared to school tests, international adult skills tests have a relatively short history. The first attempt to measure adult skills across countries was the 'International Adult Literacy Survey' (IALS) coordinated by the OECD. The IALS was conducted between 1994 and 1998. Eight countries, namely Canada, Germany, Ireland, Netherlands, Poland, Sweden, Switzerland, and the United States took part in the first round of IALS in 1994. In 1996, Australia, Belgium (Flanders only), England, New Zealand, and Northern Ireland conducted the test. Finally, Chile, Czech Republic, Denmark, Finland, Hungary, Italy, Norway, Slovenia, and Switzerland (Italian speaking region only) completed IALS in 1998.

IALS' main objective was to develop an assessment instrument that would permit the comparison of literacy performance across languages and cultures. The measurement method was based on the 1992 US National Adult Literacy Survey. It aimed to measure three types of skills: prose literacy, document literacy, and quantitative literacy. Literacy was defined as: "using printed and written information to function in society, to achieve one's goals, and to develop one's knowledge and potential" (Murray et al., 1998, p. 17). A score of literacy skills from 0 to 500 has been calculated for each of the three domains. In addition to the literacy exam, a background questionnaire was also administered. Nationally representative samples for the adult population between the ages of 16 to 65 have been selected and sample sizes were around 3,000 for each country.

2.3 International Adult Literacy and Life Skills Survey (ALL)

The 'International Adult Literacy and Life Skills Survey' (ALL) was designed as a successor to IALS (Statistics Canada and OECD, 2005). Italy, Norway, Switzerland, Bermuda, Canada, Nuevo Leon (Northern Mexico), and the United States joined the first phase of ALL in 2003. Between 2006 and 2008 Hungary, Netherlands, Australia, and New Zealand additionally participated in the survey.

ALL measured literacy and numeracy. Literacy skills consisted of both prose and document literacy (as in IALS), and numeracy was designed to replace quantitative literacy in IALS. In addition, a problem-solving domain was also included in some countries. In line with IALS, the scoring scale ranges from 0 to 500. As it also includes trend items which can be linked to IALS, it is claimed that a comparison over time is possible for countries that participated both in IALS and ALL.

The data collection consisted of a 45 minutes background questionnaire, that collected information about demographic and socio-economic characteristics of the respondent, and of a roughly one-hour-long skills assessment part. In addition to 16 to 65-year-old adults, some of the participating countries also collected data for older individuals. Sample sizes differ across participating countries. While Bermuda had a sample size of 2,696 respondents, Canada had a sample size of over 20,000.

2.4 Programme for the International Assessment of Adult Competencies (PIAAC)

The 'Programme for the International Assessment of Adult Competencies' (PIAAC) is conducted by OECD with the aim of collecting data on "key information processing competencies" that are thought to be needed to fully participate in contemporary society (OECD, 2019). The first round of the survey collected data from around 166,000 adults aged 16 to 65 in 24 countries or regions in 2011 and 2012. In 2014, the second round of the survey was conducted, and data was collected in 9 additional countries. Finally, in 2017-2018 five new countries participated in the survey and the US conducted the survey for a second time. In total, 37 countries participated in PIAAC so far. It is planned to repeat the survey every ten years, with preparations for the second wave of data collection having already started.

PIAAC scores are calculated for the following skills: literacy, numeracy, and problem-solving in technology rich environments. The measurement index is scaled between 0 and 500 in line with IALS and ALL. As in the other adult skills programs, PIAAC also includes a detailed background questionnaire that collects information about demographic and socio-economic characteristics, use of skills in daily life, and characteristics of working life additional to the module on the direct assessment of skills. A nationally representative sample of around 5,000 respondents were selected in every participating country/economy.

Building on knowledge and experiences gained from previous international adult assessments, items from IALS and ALL were also included in PIAAC, allowing data from previous surveys to be linked to trend data from participating countries in PIAAC. Table 1 provides an overview about which PIAAC countries have also participated in IALS and/or ALL.

Table 1: PIAAC countries that have participated in IALS and/or ALL by year and assessment

Country	IALS			ALL		PIAAC		
	1994	1996	1998	2003	2006-08	2011-12	2014	2017-18
Australia		✓			✓	✓		
Belgium		✓				✓		
Canada	✓			✓		✓		
Chile			✓				✓	
Czech Republic			✓			✓		
Denmark			✓			✓		
Finland			✓			✓		
Germany	✓					✓		
Hungary			✓		✓			✓
Ireland	✓					✓		
Italy			✓	✓		✓		
Netherlands	✓				✓	✓		
New Zealand		✓			✓		✓	
Norway				✓		✓		
Poland	✓					✓		
Slovenia			✓				✓	
Sweden	✓					✓		
UK		✓				✓		

Source: Authors' elaboration

For the analyses throughout this paper, public use files including microdata from 36 countries are used. The only exception is Australia for which microdata are not publicly available[8]. Table 2 highlights the average literacy and numeracy scores in PIAAC for all participating countries. In both literacy and numeracy Japan was ranked as top country, followed by Finland and the Netherlands. Peru brings up the rear, having an average score of roughly 60% of the best-performing country, both in literacy and numeracy.

[8] Authors are currently in the process of purchasing Australian PIAAC data. Unfortunately, the approval process for providing overseas access can take 4 to 6 months, which is why results presented in this paper exclude Australian performance in PIAAC.

Table 2: Average PIAAC literacy and numeracy score by country

Country	Literacy	Numeracy	PIAAC round
Australia	280	268	2011-12
Austria	269	275	2011-12
Canada	273	265	2011-12
Chile	220	206	2014
Cyprus	269	265	2011-12
Czech Republic	274	276	2011-12
Denmark	271	278	2011-12
Ecuador	220	206	2017-18
England (UK)	273	262	2011-12
Estonia	276	273	2011-12
Finland	288	282	2011-12
Flanders (Belgium)	275	280	2011-12
France	262	254	2011-12
Germany	270	272	2011-12
Greece	254	252	2014
Hungary	264	272	2017-18
Ireland	267	256	2011-12
Italy	250	247	2011-12
Israel	255	251	2014
Japan	296	288	2011-12
Kazakhstan	249	247	2017-18
Korea	273	263	2011-12
Lithuania	267	267	2014
Mexico	222	210	2017-18
Netherlands	284	280	2011-12
New Zealand	281	271	2014
Northern Ireland (UK)	269	259	2011-12
Norway	278	278	2011-12
Peru	196	178	2017-18
Poland	267	260	2011-12
Russian Federation	275	270	2011-12
Singapore	258	257	2014
Slovak Republic	274	276	2011-12
Slovenia	256	258	2014
Spain	252	246	2011-12
Sweden	279	279	2011-12
Turkey	227	219	2014
United States	272	257	2011-12 & 2017-18
OECD average	266	262	

Source: Adapted from OECD (2019)

2.5 Skills toward Employment and Productivity Survey (STEP)

The 'Skills toward Employment and Productivity Survey' (STEP) was developed by the World Bank in order to measure skills relevant to the labour market in low and middle-income countries (Pierre et al., 2014). Data were collected between 2012 and 2017 in Albania, Armenia, Azerbaijan, Bolivia, Bosnia & Herzegovina, Colombia, Georgia, Ghana, Kenya, Kosovo, Lao PDR, Macedonia, Serbia, Sri Lanka, Ukraine, Vietnam, and the Yunnan Province in China.

Cognitive skills measured in STEP include a direct assessment of reading proficiency and related competencies scored on the same scale at the OECD's PIAAC. However, only eight countries, namely Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine, and Vietnam, have implemented the full cognitive assessment including both the paper-based literacy assessment as in PIAAC and a short reading test. The remaining countries conducted only the reading core test, consisting of 8 short items and thus not relatable to IALS, ALL, and PIAAC literacy scores. For this reason, only data from the above mentioned eight countries are included in the analyses used throughout this paper.

In addition to the cognitive assessment, the STEP survey also includes a questionnaire gathering information about respondents' personality, behaviour, use of job-relevant skills, etc. Some countries additionally conducted an employer survey, collecting data on the structure of the labour force, skills sought in the hiring processes, and the satisfaction of employers about their employees' skills. The sample size for each country is around 3,000 and the sample is representative of the urban adult population between the ages of 16 and 65.

2.6 Demographic and Health Survey (DHS)

The Demographic and Health Survey (DHS) is an international household survey program designed to provide current and reliable information on a given population's demographic and health status. Since 1984, DHS Program has provided technical assistance to more than 400 surveys in over 90 countries, advancing the global understanding of health and population trends in developing countries (Croft et al. 2018; Rutstein and Rojas 2006).

In addition to providing representative data on fertility, family planning, maternal and child health, gender, HIV/AIDS, malaria, and nutrition, DHS is also an important source for education statistics. Besides collecting data on educational attainment and years of schooling of all interviewees, since 2000, the standard DHS questionnaire also includes a short literacy test (results of which are used in SAMYS estimates, as further elaborated in Chapter 3.2.3). Each respondent with low education[9] is asked to read a sentence of a cue card aloud in their preferred language. The cards consist, in general, of short and simple sentences related to the countries' daily life. Also, cards are prepared for every language in which the respondents are likely to be literate. Interviewers categorized respondents as having no reading skills (did not read any of the words),

[9] For earlier rounds, DHS assumed that all individuals with secondary education were literate. For the more recent waves (DHS VII and subsequent), the survey conducted the literacy test also for individuals with secondary education level or below.

some reading skills (read some of the words), or full reading skills (read every word). Respondents who are blind or visually impaired, and whose literacy skills could not be assessed can be identified in the sample.

Many DHS countries have conducted multiple surveys at five-year intervals. Sample size varies across surveys, with a huge effort to obtain representativeness also on subnational levels. The DHS sample design is based on a stratified random sampling approach, where within each selected cluster, the DHS randomly samples households. Eligible to participate are women aged 15 to 49 and, in some cases, men aged 15 or more.

2.7 UNESCO Institute for Statistics (UIS) literacy data

UNESCO Institute for Statistics (UIS) is publishing global data to track progress of countries in terms of the Sustainable Development Goal 4 on education (UIS, 2019). Among other educational indicators, adult literacy rates for males and females above the age of 15 are estimated/calculated at the country level. In this dataset, literacy is defined as "the ability to read and write a simple statement about everyday life" (UIS, 2019, p. 66). The data is collected from national data sources such as censuses or household surveys. Literacy estimates are based on the self- or household-declaration of respondents (instead of any proficiency assessments) and are reported on a binary scale: literate and illiterate. While exact calculations are available for some countries, for others, national estimates or UIS estimations are used. Because in many of the high-income countries literacy rates converged to 100% a few decades ago, there are many missing data points for those countries, especially for recent years.

For the purpose of this paper, the latest adult illiteracy estimates are taken from UIS Statistics[10] between 1970 and 2015. Then, 5-year averages are calculated from 1970-75 to 2010-15 using the available data points. After averaging, the missing values are replaced by earlier estimates of UIS whenever available. The remaining missing points are replaced by average illiteracy rates in the respective region (based on UN regional definitions) for the given time period. After these imputations, there are still some missing values for high-income countries. For these cases, an imputation is made using a linear model estimating a value between 0.2 and 2 percent[11].

2.8 Global Data Set on Education Quality (1965-2015)

Given the relevance of quality education to development and to obtain a global dataset with common testing assessments of skills, the World Bank recently launched the Human Capital Project (HCP). One important part of this project is the measurement of actual learning outcomes (Filmer et al., 2020).

Within the Human Capital Project, the World Bank developed a global data set called 'Global Data Set on Education Quality (1965-2015)', currently covering a total of 163 countries. The authors merged various regional and international student assessment data through methods of mean and percentile linking. Using

[10] Data can be retrieved from http://data.uis.unesco.org/.

[11] These imputations are based on already available illiteracy rates of Poland (since most of the missing countries are neighbouring European countries), the age and sex structure of the countries in the given time periods, and the level of educational attainment.

‘National Assessment of Educational Progress’ (NAEP) data of the United States – the country that attended all international student assessment tests – and ‘Programme of Analysis of Education System’ (PASEC) data of Burkina Faso as anchors, they linked various datasets and constructed a single index for learning outcomes (Altinok, Angrist, & Patrinos, 2018a and 2018b). Also, they developed methodologies to estimate learning indicators for some countries in the developing world, to which no national or scholastic assessment was available. As this global data set is still work in progress, we are using a preliminary, incomplete version of it for our estimation of SAMYS (“Global Data Set on Education Quality (1965-2015)” 2018). More detailed information on the methodology can be found elsewhere (Altinok et al. 2018; Patrinos and Angrist 2018).

3 Methodology

In this chapter, we provide a detailed explanation of the estimation and reconstruction of SAMYS. Before providing methodological details, we highlight the main assumptions of our estimates (section 3.1). We then continue with the formal presentation of SAMYS and detail the calculation (section 3.2). The development of the global dataset was conducted in three steps: first, for 44 countries we compute baseline estimates of SAMYS using PIAAC and STEP results (section 3.2.1) and conduct a cohort analysis to obtain past estimates (section 3.2.2). Second, to increase coverage among developing countries, we used DHS data to provide skills adjustments for 59 additional countries, as further elaborated in section 3.2.3. Finally, to obtain results on a global scale, we used prediction regression models, as further explained in section 3.3, both for the base year (2015, 201 countries) as well as for the time-series (1970-2015, 185 countries).

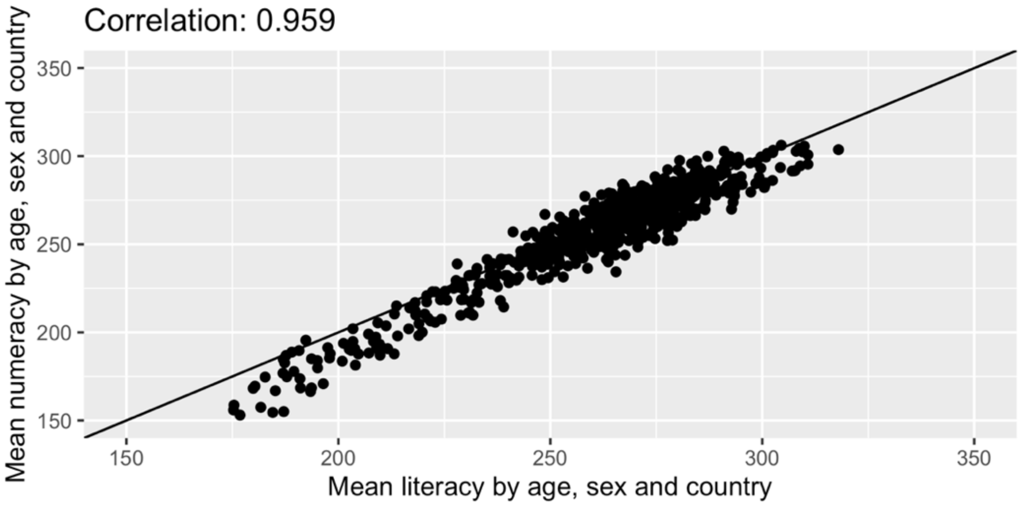
3.1 Assumptions

3.1.1 Tested literacy as proxy for general adult skills

As mentioned previously, literacy represents only one domain of a variety of skills considered essential for the formation of human capital. However, due to limited availability of longitudinal assessment data of other domains (e.g. numeracy, problem-solving, etc.)[12], results for SAMYS in this paper exclusively rest upon literacy assessments. Despite this limitation, sensitivity analyses have revealed that literacy and numeracy test results are highly correlated. Figure 2 displays the correlation between the mean score in literacy and the mean score in numeracy by age-sex-education groups for all countries participating in the 1st round of PIAAC. The Pearson correlation coefficient of 0.96 and the high statistical significance (p-value < 0.001) points out that the level of literacy skills is a good proxy for the overall skill level in the population - particularly when considering them at the aggregate level.

[12] Literacy is the only domain assessed in all three large-scale international adult skills assessments (IALS, ALL, PIAAC). In addition, we can resort to tested literacy data from DHS, literacy assessment data from STEP, and UIS literacy estimates – all of them not available for numeracy or other skill domains.

Figure 2: Correlation between PIAAC mean literacy and numeracy scores by age, sex, and country, all PIAAC countries



Source: Authors' elaboration

3.1.2 Population representativeness within countries

As opposed to IALS, ALL, and PIAAC, which are surveys designed to be representative of the total civilian, non-institutionalized population aged 16-65 in each country, the STEP Skills Measurement Program targets *urban* adults aged 15 to 64. Due to the lack of available country-wide data on literacy skills measured in STEP, these data are still used to estimate SAMYS for the total (urban and rural) population. This is indeed a strong assumption as previous studies have shown that there are substantial urban-rural differences in skills (Cartwright and Allen 2002; Lounkaew 2013). We intend to develop further research to adjust urban STEP scores to make them representative for the entire country in the next version of SAMYS. Thus, as for now, for the following countries results presented in this paper are based on literacy tests only conducted in urban areas: Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine, and Vietnam.

Similarly, in some countries, tests were only conducted in selected regions. More specifically, the PIAAC assessment for Belgium took only place in Flanders and those for the United Kingdom only in England and Northern Ireland. Again, for this version of the results, the regional data are used to estimate SAMYS for the whole countries.

3.1.3 Reference time of assessment for the base year estimates

PIAAC has been envisaged by OECD as a decennial survey. The PIAAC cycle 1 assessment was conducted between 2011 and 2017, with three rounds of data collection in a total of 37 countries. PIAAC cycle 2 will be administered in 2021-22, with currently 33 countries taking part in the sample[13]. As our data output is aimed to provide time-series data for quinquennial time-periods and is partly based on WIC data on population and

[13] Ecuador, Kazakhstan, Mexico, and Peru, who participated in PIAAC Cycle 1, are currently not planning to participate in Cycle 2. Instead, the assessment will take place in four additional countries: Croatia, Latvia, Portugal, and Switzerland.

human capital, we decided to use 2015 as base year[14]. The reader should note, however, that what is reported in this study as "2015 empirical PIAAC literacy test results", could originate from any round of data collection of PIAAC cycle 1 (2011-2017). Ideally, data could be interpolated in single-year intervals to obtain 2015 values. However, interpolation is not feasible due to the non-availability of more than one data points over time for most countries. Hence, to calculate the population-weighted OECD average test score, survey results from different years (2011-2017) were weighted with the Wittgenstein Centre's 2015 population data.

Similarly, STEP data collection took place at different times in different countries. For the eight countries that are thus included in our empirical dataset, four countries (Bolivia, Colombia, Ukraine, and Vietnam) were tested in 2012, three countries (Armenia, Georgia, Ghana) in 2013, and one country (Kenya) in 2016. All of them provide the unmodified basis for our 2015 estimates.

3.2 Calculation of SAMYS based on empirical data

3.2.1 Computations for the base year (2015)

When adding a skills dimension to educational attainment, a standard of comparison needs to be established, whether it is a perfect (unattainable) score (e.g. 500 in PIAAC; 1,000 in PISA, etc.), a benchmark result of the top-performer, or the performance of any group of individuals. Since our estimates are based on the average performance of populations, we decided to use the mean proficiency of the OECD population, disaggregated by age-sex-education groups, as standard of comparison. More specifically, our standard equals the 2015 population-weighted[15] OECD mean PIAAC literacy test score, calculated separately for each education group as presented in Table 3. As quality of education changes in a country, the effects on skills are different for different age cohorts. Moreover, a change in the level of skills in a country may also be the consequence of a changing composition of the population (i.e. younger cohorts with different educational attainment distribution slowly replacing older ones). Therefore, disaggregating the standard of comparison by age, sex, and educational attainment is essential. Since PIAAC literacy test results are only available for 30 of the 36 OECD countries, the following six OECD countries had to be excluded in the calculation of the benchmark: Australia, Iceland, Latvia, Luxembourg, Portugal, and Switzerland.

[14] Data on past reconstructions and future projections of the global population by age, sex and education from the Wittgenstein Centre Data Explorer are also based on collected census and survey data around 2015, which was hence defined as the base year. More information can be found in Speringer et al. (2019).

[15] Population estimates by age, sex, and educational attainment come from the Wittgenstein Centre Data Explorer.

Table 3: 2015 population-weighted OECD mean in PIAAC literacy scores by age, sex, and educational attainment

Age	FEMALES				MALES			
	Primary or less	Lower secondary	Upper secondary	Post-secondary	Primary or less	Lower secondary	Upper secondary	Post-secondary
15-19	180.0	259.2	273.0		217.4	257.4	275.8	
20-24	168.4	237.1	273.9	289.9	170.3	231.1	277.7	291.7
25-29	196.9	229.6	262.9	295.1	198.2	232.1	267.3	299.8
30-34	196.6	232.4	262.2	293.7	190.1	231.8	262.6	297.8
35-39	198.4	227.6	262.4	291.9	203.9	230.2	264.6	300.9
40-44	197.9	231.2	264.1	291.0	193.4	236.8	263.6	297.2
45-49	190.4	230.6	263.4	287.3	199.0	232.6	258.3	293.4
50-54	190.0	233.1	260.0	282.3	194.9	231.1	258.7	288.7
55-59	191.8	232.3	254.6	280.8	191.4	231.5	257.8	282.9
60-64	189.6	234.8	255.8	276.5	195.2	231.0	254.2	279.5

Source: Authors' calculations based on OECD's PIAAC data and WIC Data Explorer.

Having decided upon the benchmark, the skills adjustment was designed in such a way that, for our standard of comparison, the mean years of schooling (MYS) is set to be equal to the SAMYS. As a consequence, taking the benchmark, for any population of a country's age-sex-education group that performed worse than the population-weighted OECD mean, its SAMYS will be lower than its MYS; accordingly, for any country-specific age-sex-education group which scores better than the OECD mean, the opposite holds.

Formally, consider $SAMYS_{c,a,s,e}$ as the skills-adjusted mean years of schooling for country c, age a, sex s and education level e in the base year, 2015. Also, let $MYS_{c,a,s,e}$ represent the respective mean years of schooling and $MP_{c,a,s,e}$ the mean literacy performance. Finally, consider $MP^*_{a,c,e}$ the mean performance of the benchmark age-sex-education group. The skill-adjusted measures can be derived as per equation 1.

$$SAMYS_{c,a,s,e} = MYS_{c,a,s,e} \times \frac{MP_{c,a,s,e}}{MP^*_{a,c,e}} \quad \textit{(Eq. 1)}$$

In this way, we were able to estimate SAMYS for 44 countries for the base year 2015, disaggregated by 5-year age groups, sex, and four levels of educational attainment (primary or less, lower secondary, upper secondary, and post-secondary education[16]). Estimated SAMYS for 36 countries are based on PIAAC data; for 8 countries we relied on STEP literacy test results. Data for MYS by country, age, and sex come from the WIC Data Explorer.

3.2.2 Reconstruction of SAMYS along cohort lines (1970-2015)

The estimation of SAMYS for quinquennial years between 1970 and 2015 is based on the same rationale as provided by Eq. 1, but now including the time dimension t. It should be noted that the 2015 population-weighted OECD mean proficiency is held constant as the standard of comparison.

[16] We refrained from a more detailed disaggregation of education categories as test sample sizes would otherwise become too small. Referring to the International Standard Classification of Education (ISCED), 'primary or less' corresponds to ISCED 0 or 1, 'lower secondary' corresponds to ISCED 2, 'upper secondary' corresponds to ISCED 3, and 'post-secondary' corresponds to ISCED 4, 5, 6, 7, or 8.

$$SAMYS_{c,a,s,e,t} = MYS_{c,a,s,e,t} \times \frac{MP_{c,a,s,e,t}}{MP^{*}_{a,c,e}} \qquad \textit{(Eq. 2)}$$

However, since large-scale assessment tests of adult literacy were only introduced in the 1990s for a handful of countries, we had to follow a different approach to estimate SAMYS for several decades. Therefore, time-series estimates for SAMYS rest on the reconstruction of $MP_{c,a,s,e,t}$ along cohort lines, based on observed age effects from countries where $MP_{c,a,s,e}$ exist for more than one point in time.

Age effects have been identified as key drivers of skills change over the life course. Several studies have found a tendency for cognitive skills to rise in the early years and then eventually decline as adults age. However, ageing and skills is not a straightforward relationship, with many individual, contextual, and social factors influencing the development. Nevertheless, there are attempts in the literature to define a "normal age effect" related to skill development. Herzog et al. (2009), for example, suggest that skill decline for an individual under 'typical' circumstances can begin as early as age 20 and continue into old age, accelerating particularly after the age of 50. However, especially for young adults, individual trajectories may vary considerably, depending on biological, behavioural, environmental, and social influences. Similarly, Desjardins & Warnke (2012) highlight that until about the age of 18 to 20, cognitive skills of all kinds are expected to increase, but thereafter, development patterns are expected to diverge. For some people and type of skills, this would mean a decline already in early adulthood, while others may experience a continuous rise of skills, followed by a stagnation, and only eventually a decline. Factors found to influence skill gain and skill loss over the lifespan and over time include education and training, behavioural and practice factors, and social factors (see Desjardins & Warnke (2012) for an extensive literature overview of the evidence on the factors causing skill gain and skill loss).

In addition to pure age effects, cohort effects, i.e. being born in a different time period and thus being exposed to different circumstances (e.g. the nature and quality of schooling), may influence the development of skills over time. Similarly, period effects (e.g. wars, famines, economic crises, etc.), which impact everyone at the time of assessment – regardless of age and generation – can play an important role, when assessing skills over time. Unfortunately, the scarcity of data hampers the undertaking of country-specific age-period-cohort analysis on a global scale. Surveys measuring adult skills have been traditionally cross-sectional, hence only reflecting combinations of age and cohort effects. Only recently, internationally comparable large-scale assessments at different points of time representing the same population became available, allowing for a separation of these effects and a better understanding of skill development across generations.

For the reconstruction of SAMYS along cohort lines, from 1970 to 2015, we rely on data from three international, large-scale assessments: (1) the 1994-1998 IALS, (2) the 2003-2008 ALL, and (3) the 1st cycle (2011-2017) PIAAC. This is possible because trend items from IALS and ALL were included in PIAAC, allowing data from previous surveys to be linked to trend data from participating countries in PIAAC (National Center for Education Statistics, 2019). Countries for which tested adult literacy data are available for at least two points in time include Belgium, Canada, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden, Switzerland, United Kingdom, and the United States.

Our empirical analyses are based on a pooled dataset of IALS, ALL and PIAAC, from which we build cohorts[17] to investigate the skill development of different age groups over a period of roughly 20 years. Ideally and when available, we used single year age groups, which were then aggregated to 5-year age groups, depending on the year the surveys took place and the time lag between different surveys in each country. For example, in the United States surveys took place in 1996 (IALS), 2007 (ALL), and 2014 (PIAAC); hence, our analysis follows a synthetic cohort, which was e.g. 25-29 years old in IALS, 36-40 years old in ALL, and 43-47 years old in PIAAC.

Based on a review of the relevant literature, one would expect to find the following patterns (as summarized in Box 1) in the empirical demographic analysis of skills.

Box 1: Summary of hypotheses based on the literature on skill-age-patterns

Expectation 1	Within cohorts, there is an age-skill decay, consistent with the literature on age effects on cognitive skills (Herzog et al. 2009).
Expectation 2	For each cohort, the development of skills (decrease/stagnation/increase), particularly at young ages, depends partly on educational attainment levels (Desjardins and Warnke 2012).
Expectation 3	Between cohorts and for same age groups, populations may gain or lose skills as time passes due to generational and environmental changes (Flisi et al. 2019).

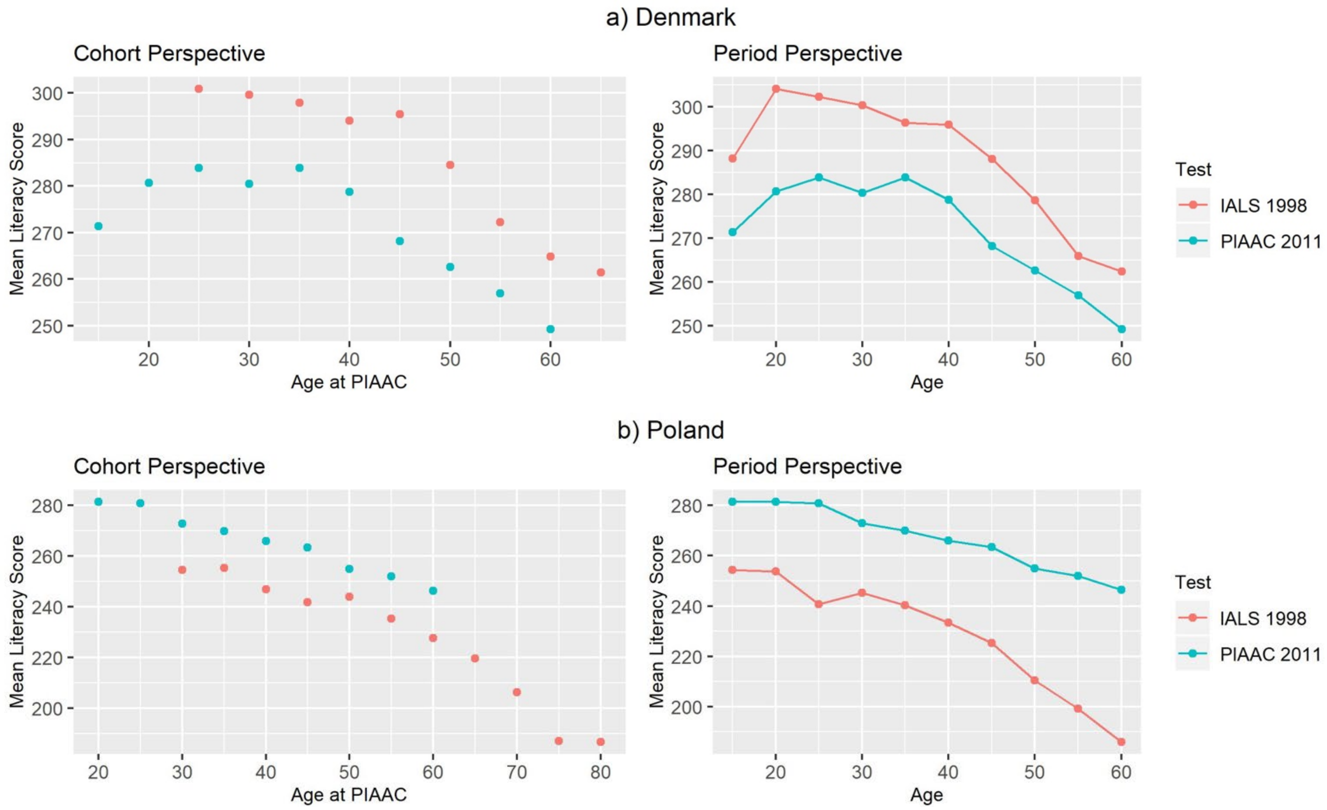
Source: Authors' elaboration

In line with these hypotheses, our empirical cohort analysis results suggest indeed that deterioration in the level of skills is happening because of age effects (Expectation 1), with the beginning and extent of the decrease strongly depending on educational attainment (Expectation 2). Also, changes in the level of skills are observable across generations, with more recent birth cohorts tend to have lower levels of literacy than previous ones (Expectation 3). However, these results could not be found to be consistent between all countries.

Figure 3 exemplifies this, showing two countries, a) Denmark and b) Poland, with a) experiencing skill loss, and b) experiencing skill gain between 1998 and 2011. In both countries, this development holds among all age groups, both from a cohort perspective (left panel: cohorts are represented vertically; x-axis represents the age at PIAAC, participants in IALS are accordingly younger) and from a period perspective (right panel: x-axis represents the age at the time of the test).

[17] Ideally, we would be able to follow the same individuals over their life course. However, as no true panel data are available, we take advantage of the fact that although we cannot observe the same people at different points in time, we are able to observe representative samples of the population at different points in time.

Figure 3: Changes in literacy skills over time from a cohort and period perspective, Denmark and Poland, 1998 and 2011



Source: Authors' calculations based on OECD's IALS and PIAAC test results

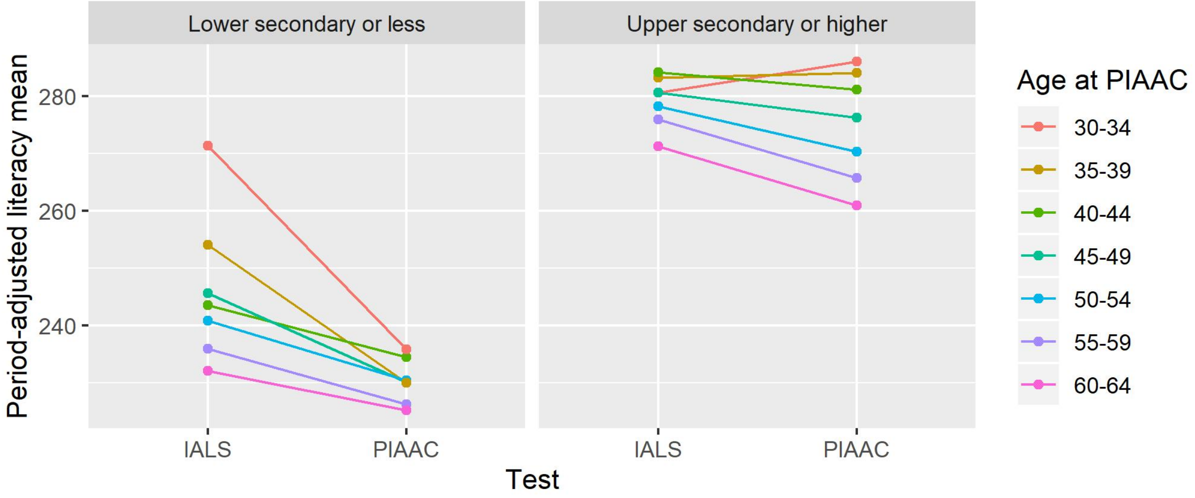
These findings certainly give us important insights on cohort effects and shifts in the level of skills between generations for a specific time and country. At the same time, they prove that cohort effects can reveal very different trends for relatively similar countries. Given the fact that, at present, there are not enough data available to expand these analyses to a global scale and a longer period, we thus needed to establish assumptions for the reconstruction of SAMYS.

First, we assumed a standard skill-age decay pattern by pooling all countries that participated in both IALS and PIAAC[18]. For this analysis, we did not consider sex differentials. Next, we adjusted for the mean score difference observable for the same age group in different years. In this way, we were able to separate the pure age effect (literature finding 1) – which is assumed to be more stable across countries and time – from the more context-sensitive between-cohorts-effect (literature finding 2). These calculations were done for two broad education categories ('lower secondary or less' and 'upper secondary or higher') separately to account for potential differences in skill loss/gain due to attainment of formal education. Figure 4 depicts the resulting standard age effect which was used to reconstruct SAMYS until 1970. Sensitivity analyses of conducting the

[18] As the number of countries participating in ALL is much smaller than for IALS and PIAAC, ALL test results were excluded from the estimation of a standard age effect. To additionally integrate ALL results, we either would have had to further reduce the country coverage, or we would have made comparisons between non-comparable (i.e. differently composed) populations, both potentially distorting the results.

same kind of analysis for different countries separately confirmed that the age effect tends to be largely constant for different populations.

Figure 4: Estimated standard age effect, cohort perspective, 16 countries[19], both sexes, IALS 1994-98 and PIAAC 2011-17



Source: Authors' calculations based on OECD's IALS and PIAAC test results

As shown in the figure above, the pattern implies that the skill loss due to age effects significantly differs by educational attainment levels and age. Those with lower education tend to lose the highest share of their skills rather soon after leaving school. Without having clear empirical evidence for this, a plausible explanation could be that less educated people enter jobs in which they need fewer of the cognitive skills that are tested and thus not practise some of those skills they had learned in school. On the other hand, parts of the PIAAC 30-34-years-old cohort may have been still in education at time of IALS, thus potentially moving to the higher education group when participating in PIAAC. On the contrary, higher-educated people are still able to moderately gain skills up to the age of 35. After that, skills remain largely constant until the age of approximately 45 when cognitive skills eventually start decreasing.

Based on these period-adjusted trends of cohorts over time, we further estimated an age- and education-level specific skill growth function over the life course, which – for this preliminary set of results – is assumed to be constant for all countries and over time. Figure 5 presents the skill pattern over the life course for the two broad education categories, which is essential for the reconstruction of literacy test scores over time along cohort lines. More specifically, we take the scores of 60-64-year-olds tested in 2015 as the basis for the estimated score of 55-59-year-olds in 2010, adjusted by the percentage change due to the assumed reverse age pattern[20]. In this way and based on the country-, age-, sex-, and education-specific literacy scores from PIAAC and STEP, we were able to obtain estimated mean scores by 5-year age groups, sex, and four

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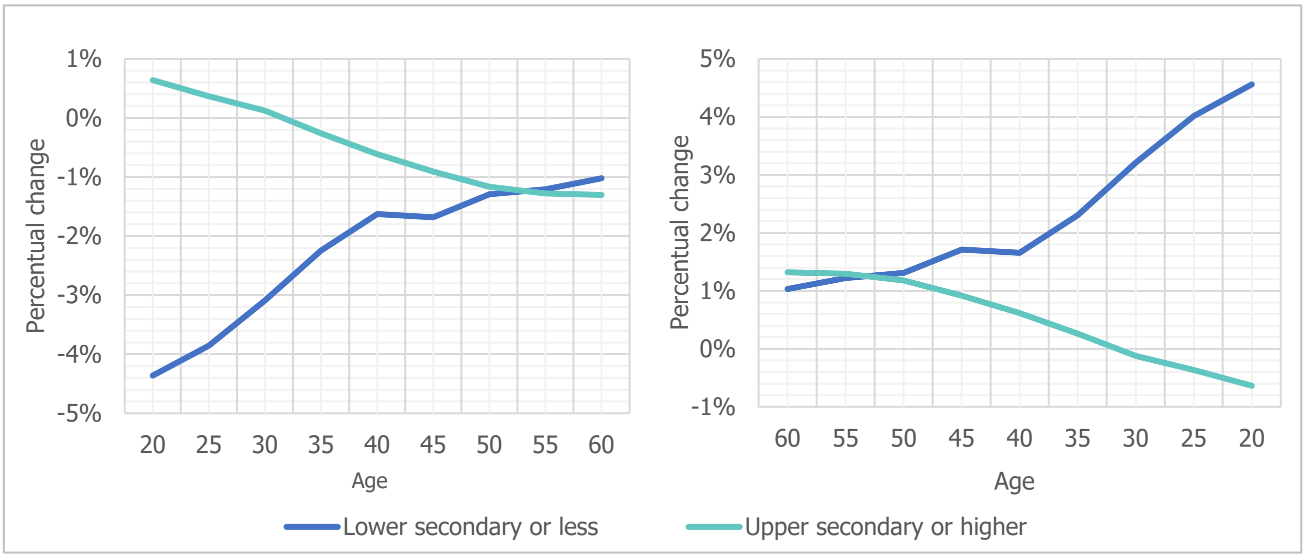
[19] The following 16 countries were merged to develop the standard age effect: Belgium, Canada, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden.

[20] For age groups for which we were not able to build synthetic cohorts for the whole or part of the reconstruction period (e.g. 60-64-year-olds in 2010 who were too old to be tested in 2015), we assumed the scores to be constant over time.

education categories from 1970-2015 for all 44 countries with empirical data available[21]. SAMYS were then calculated based on the formula explained above, with the 2015 OECD average used as standard of comparison in all years. In order to aggregate quality-adjusted MYS only by country and year (or by country-year-age-sex / country-year-age / country-year-sex), we weighted the scores based on population size by age, sex, and educational attainment for each country and year, as retrieved from the WIC Data Explorer.

Figure 5: Estimated percent change of literacy skills due to age effect (reverse direction used for reconstruction)



Source: Authors' calculations based on OECD's IALS and PIAAC test results

3.2.3 Adjustments for calculating SAMYS using DHS data

As noted above, adult skills assessments provide valuable information about the level of human capital disaggregated by age, sex, and educational attainment. However, there are only 44 countries that participated in PIAAC or STEP and for which microdata are available. Furthermore, most of these countries are highly developed OECD members, thus unrepresentative of the world population. To include more observations to our dataset, we decided to additionally include tested literacy data from DHS. DHS tested literacy data are available for 63 countries which are more diverse in terms of social and economic development than the high-income OECD countries. Moreover, among them, Bolivia, Ghana, Kenya, and Peru, have participated in both PIAAC/STEP and DHS. As a result, PIAAC/STEP literacy proficiencies and consequently SAMYS could be additionally estimated for those 59 countries that have DHS data for tested literacy using an equating procedure.

For these countries, considering the proportion of the population that have full tested literacy in DHS, adjustment scores were calculated to find concordance between PIAAC/STEP literacy proficiency and DHS full

[21] While the empirical scores of the base year are disaggregated by age, sex, and four levels of educational attainment, the estimated standard age effect as well as the estimated skill growth function over the life course are only defined for two education categories. This crude disaggregation was found to be most consistent between countries. Given the different scores in the base year, reconstruction results, however, still differ between gender and are available for four education categories.

literacy. As a result, PIAAC/STEP literacy proficiencies and consequently SAMYS could be additionally estimated for those 63 countries that have DHS data for tested literacy. In order to further validate our results, the ratios between the SAMYS calculated using PIAAC/STEP results and SAMYS estimated by DHS tested literacy data were checked for Bolivia, Ghana, Kenya, and Peru which are the countries that have both sources of information. The results showed that due to conducting an easier literacy test than PIAAC and STEP DHS-SAMYS estimates were consistently 20% higher than the estimates calculated by empirical PIAAC/STEP scores. For this reason, we made a further adjustment by multiplying the SAMYS estimates derived from DHS tested literacy data by a factor of 0.8.

3.3 Calculation of SAMYS based on prediction regression models

3.3.1 Base year predictions (2015)

After calculating SAMYS for 103 countries based on empirical data, results for the remaining countries are estimated using regression models. The goal is to predict SAMYS for countries which do not have information on adult skills data. Again, 2015 is selected as the base year for the estimation.

The prediction of the SAMYS for countries with missing observations is conducted in two steps. First, skills-adjustment factors are estimated for every country c (SAF_c) and then these adjustment factors are multiplied with MYS_c for the same country to get $SAMYS_c$. This strategy avoids multicollinearity issues between MYS and other estimators. To estimate SAF_c several educational and demographic indicators, for which data are available for most countries, are selected from various data sources. Adult illiteracy rates (AIR_c) from the UIS dataset are taken in order to capture the most basic skill of literacy. Albeit most of the adult population have been literate in many developed countries for decades, this indicator might be useful to detect differences in less developed countries. The percentage of adult population having at least upper secondary educational attainment ($aboveLS_c$) is also included in the model to see the effect of schooling beyond basic education. Lastly, country-specific old-age dependency ratios (ODR_c), which can be considered as a proxy for the state of demographic transition in a country, are also included in the models. ODR_c and $aboveLS_c$ are both taken from WIC Data Explorer. To decide which of the above-mentioned independent variables remain in the final model, the stepwise-regression function from R MASS package was used.[22]

The resulting first regression model (Model 1) is as follows:

$$log(SAF_c) = \beta_0 + \beta_1 ODR_c + \beta_2 AIR_c + \varepsilon_C \qquad \textit{(Eq. 3)}$$

[22] StepAIC command in the MASS package of R software is an OLS selection method, which is a combination of forward and backward selection methods. In this method, the main criteria for variable selection is Akaike information criterion (AIC) instead of p-values. For this reason, some variables in the final model may have p values bigger that 0.05 (see https://www.rdocumentation.org/packages/MASS/versions/7.3-51.5/topics/stepAIC for further information).

Equation 3 was estimated via ordinary least squares based on the sample of 103 countries for which $SAMYS_c$ and thus SAF_c scores are available. As can be seen in the model summary and the estimated coefficients (Table 4), the model works well in predicting the skills adjustment for calculating SAMYS for our sample.

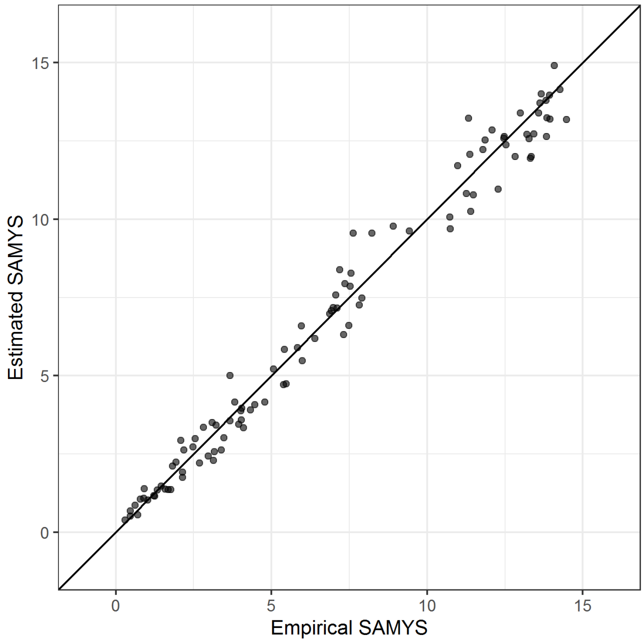
Table 4: Ordinary Least Squares model summary and coefficient estimates for Eq. 3. Model 1. [Dependent variable is logarithm of adjustment factor]

Model Summary						
Residual std. error	**Multiple R^2**	**Adjusted R^2**	**F**	**df**	**p**	**n**
0.143	0.912	0.910	518.5	2; 100	0.000	103

Coefficients				
Variables	**Estimate**	**Std. Error**	**t-statistic**	**p-value**
Intercept	-0.259	0.039	-6.608	0.000
ODR	1.078	0.190	5.684	0.000
AIR	-1.941	0.091	-21.328	0.000

As depicted in Figure 6, the actual SAMYS (displayed on the X-axis) are highly correlated (correlation coefficient = 0.990, p-value <0.001) with the predicted SAMYS (Y-axis), using Eq. 3. Therefore, this model provides a good benchmark for estimating SAMYS for those countries for which no empirical data on skills are available.

Figure 6: Correlation between empirical and fitted Skills-adjusted Mean Years of Schooling (SAMYS), 2015, Model 1



Source: Authors' calculations

Alternatively, we use another specification for the skills-adjustment factor using the most recent score of the 'Global Data Set on Education Quality' (GDSEQ) between 2000 and 2015 for each available country as an additional explanatory variable which might be a good proxy for quality of education despite not being available for all countries. Again, we use stepwise-regression models to choose the dependent variables.

The second regression model (Model 2) is as follows:

$$log(SAF_c) = \beta_0 + \beta_1 ODR_c + \beta_2 AIR_c + \beta_3 \text{GDSEQ}_c + \varepsilon_c \quad \textit{(Eq. 4)}$$

As shown by the model summary and the estimated coefficients (Table 5), the new model has a slightly better fit to the SAMYS in our sample (as measured by the adjusted R-squared). Also, the model has the same number of statistically insignificant independent variables.

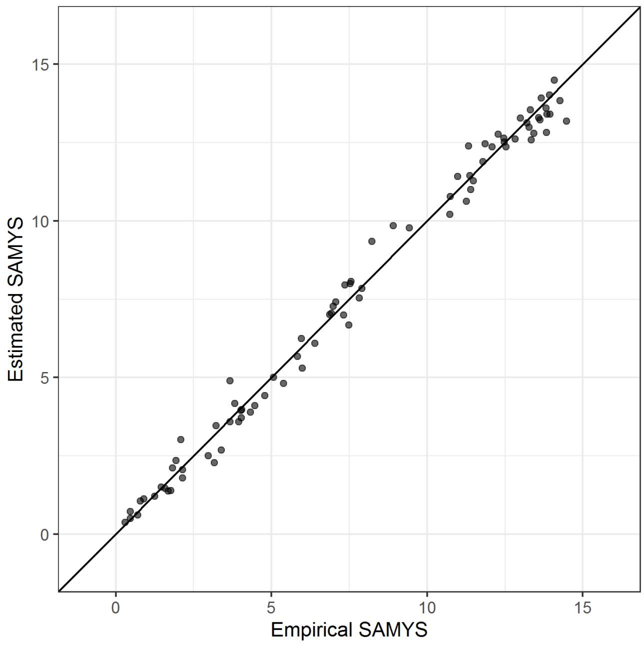
Table 5: Ordinary Least Squares model summary and coefficient estimates for Eq. 4. Model 2. [Dependent variable is logarithm of adjustment factor]

Model Summary						
Residual std. error	**Multiple R^2**	**Adjusted R^2**	**F**	**df**	**p**	**n**
0.122	0.934	0.932	379.6	3; 80	0.000	84

Coefficients				
Variables	**Estimate**	**Std. Error**	**t-statistic**	**p-value**
Intercept	-0.569	0.117	-4.879	0.000
ODR	0.509	0.229	2.219	0.029
AIR	-1.707	0.118	-14.496	0.000
GDSEQ	0.001	0.000	-3.066	0.003

As depicted on Figure 7, empirical SAMYS based on PIAAC, STEP, and DHS data (displayed on the X-axis) are highly correlated (correlation coefficient = 0.995, p-value < 0.001) with the predicted SAMYS (Y-axis) using Eq. 4. Therefore, this model also provides a good benchmark for estimating SAMYS for those countries for which no empirical data on skills are available.

Figure 7 : Correlation between empirical and fitted Skills-adjusted Mean Years of Schooling (SAMYS), 2015, Model 2



Source: Authors' calculations

In summary, both Model 1 and Model 2 (with GDSEQ) predict skills-adjustment factors with a high adjusted coefficient of determination. The inclusion of GDSEQ results in an about 2% increase in adjusted R^2. However, there are only 134 countries covered in the GDSEQ since 2000, while Model 1 allows calculating SAMYS for a total of 201 countries. For this reason, we opted for equation 3 as a benchmark model for the computation of the SAMYS for 201 countries for 2015.

3.3.2 Reconstructions to 1970

As explained in Section 3.2.2, SAMYS scores are reconstructed along cohort lines for the countries that participated in PIAAC or STEP. Using these estimates as the sample, SAMYS is estimated retrospectively for all countries for every five years between 1970 and 2015. As it is done for the base year of 2015, the skills adjustment factor is estimated through regression models and SAMYS are then calculated by multiplying this adjustment factor with mean years of schooling for each respective year. The percentage of adult population with higher education than lower secondary level ($aboveLS_{c,t}$), old-age dependency ratios ($ODR_{c,t}$) (both from WIC Data Explorer, 2018), and adult illiteracy rates ($AIR_{c,t}$) (from UIS datasets) for each country c and each time t (5-year intervals between 1970 and 2015) are used as independent variables. Additionally, dummy variables for the respective year are added as further independent variables.

Furthermore, another independent variable to capture quality of education differences is also added to the model. As shown in the previous section, using GDSEQ improved the estimations. However, GDSEQ data are missing for most countries and years especially before 1990. For this reason, a new independent variable as a 'Quality of Education Indicator' ($\mathrm{QEI}_{c,t}$) is constructed using available GDSEQ scores[23] (see Eq. 5). Model summary and coefficient estimates are presented below (Table 6).

$$log(SAF_c) = \beta_0 + \beta_1 aboveLS_{c,t} + \beta_1 ODR_{c,t} + \beta_2 \mathrm{AIR}_{c,t} + \beta_2 \mathrm{QEI}_{c,t} + \sum_{i=1970}^{1990} \delta_t + \varepsilon_c \qquad \textit{(Eq. 5)}$$

[23] To estimate QEI, several imputation methods were tested. Based on available GDSEQ scores, a missing data imputation is made by replacing the missing data points with the closest time period to the future for the given country, then replacing the remaining missing data with UN detailed geographical region averages and finally replacing the remaining missing data with UN broader geographical region averages. Furthermore, several linear models are constructed to estimate missing data using variables like educational expenditure, pupil-teacher ratio, geographical region and year. As all methods produce quite similar estimates, the first method mentioned above, i.e. neighbouring time periods and regional averages is used. Appendix A.4 gives detailed information on these imputations and comparisons between them.

Table 6: Time-series model summary and coefficient estimates for Eq. 5. Model 3. [Dependent variable is logarithm of adjustment factor]

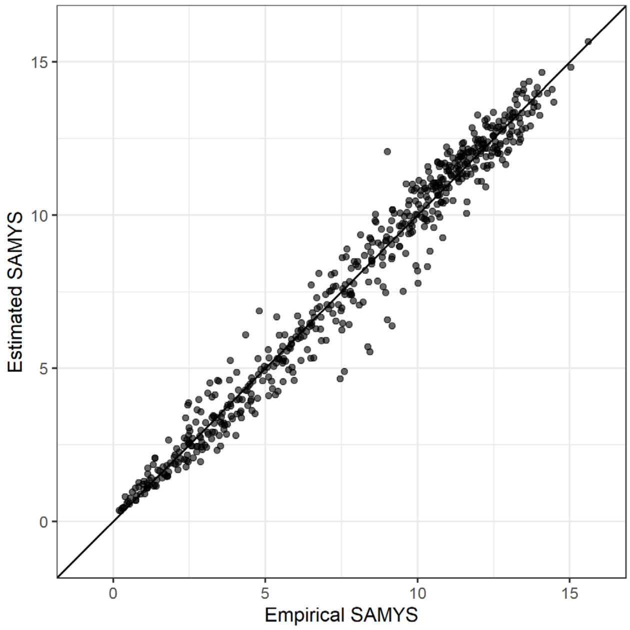
Model Summary						
Residual std. error	**Multiple R^2**	**Adjusted R^2**	**F**	**df**	**p**	**n**
0.1353	0.858	0.856	379,8	9; 567	0.000	577

Coefficients				
Variables	**Estimate**	**Std. Error**	**t-statistic**	**p-value**
Intercept	-0.563	0.049	-11.418	0.000
aboveLS	0.258	0.036	7.080	0.000
ODR	0.246	0.119	2.058	0.040
AIR	-1.196	0.051	-23.642	0.000
QEI	0.001	0.000	2.058	0.000
Year(1970-74)	0.157	0.023	6.884	0.000
Year(1975-79)	0.129	0.022	5.736	0.000
Year(1980-84)	0.097	0.022	4.309	0.000
Year(1985-89)	0.061	0.022	2.762	0.006
Year(1990-94)	0.050	0.022	2.300	0.022

Note: Base period for year dummies is Year(2015-19).

Using the estimated coefficients from the model presented above, skills-adjustment factors could be estimated for 185 countries (adjustment factors could not be calculated for 16 countries included in the base year estimates due to the fact that for these countries WIC MYS data are not available) in 5-year time steps between 1970 and 2015. Then, through multiplying these estimated skills adjustment factors with MYS for the given country and time period, SAMYS were estimated. Figure 8 shows the fit between estimated and empirical SAMYS, which is high with a correlation coefficient of 0.986 and a p-value <0.001.

Figure 8: Correlation between empirical and fitted Skills-adjusted Mean Years of Schooling (SAMYS), 1970-2015, Model 3



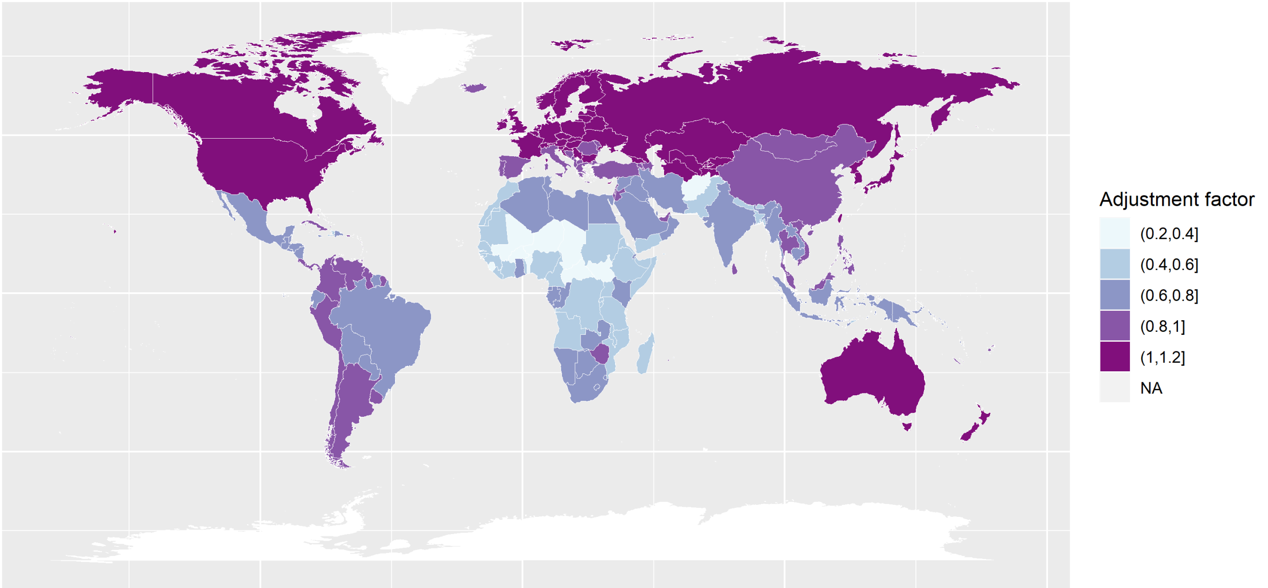
Source: Authors' calculations

4 Results

Based on the methodology described in Chapter 3, we were able to estimate the new summary measure of adult human capital called Skills-Adjusted Mean Years of Schooling (SAMYS) for 185 countries between 1970 and 2015 (in 5-year steps) and for 201 countries for the base year 2015. SAMYS combines the tested level of skills with the quantity of schooling measured by the average years spent in school.

Results[24] reveal that, for most countries, estimated skills-adjustment factors (SAFs) are between 0.2 and 1, i.e. lower than the population-weighted OECD average. This implies that, considering the average of OECD as a benchmark, countries have a lower performance on adult skills assessments, and, therefore, their SAMYS are lower than their MYS. Estimated SAFs for 201 countries for 2015 are presented in Figure 9. The SAF map shows a division like Global South – Global North countries with some exceptions. For example, SAFs of Latin American countries are, on average, closer to Global North values.

Figure 9: Estimated skills-adjustment factor by country, age 20-64, 2015

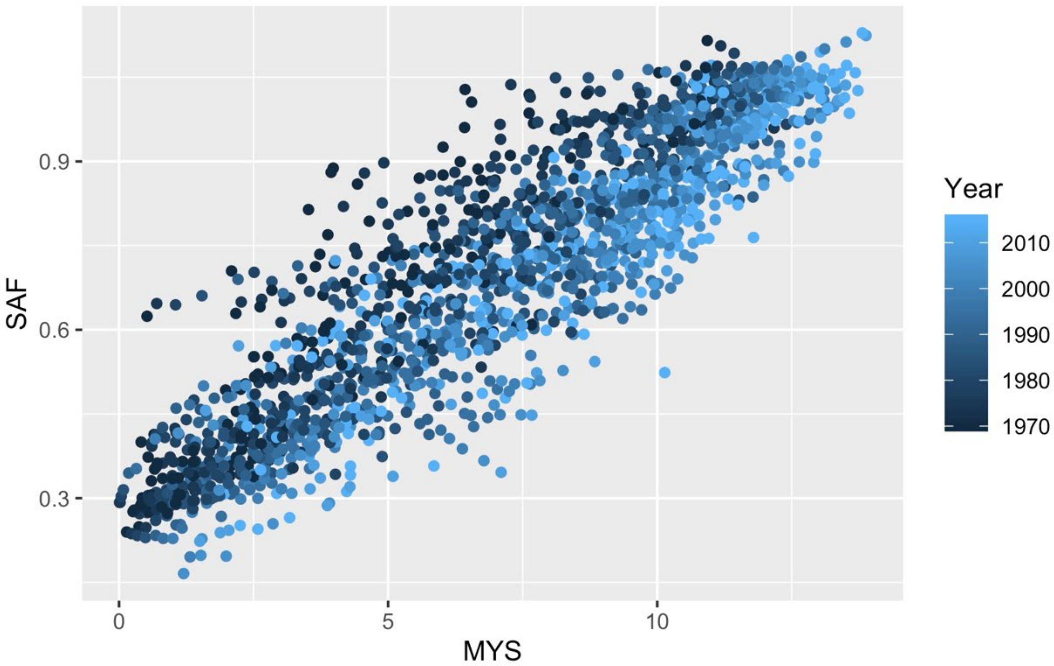


Source: Authors' calculations

When plotting MYS against SAF as depicted in Figure 10, the following general pattern is observable: the lower the MYS in a country, the lower the skills adjustment factor, reflecting the expected correlation between quantitative and qualitative measures of human capital. In addition, for a given number of MYS, the skills adjustment factor tends to decrease with time. This skill loss over time may be explained by massive education expansions in recent times, particularly in developing countries which are rapidly catching up with more developed countries in quantitative terms, but less so as regards the quality of education.

[24] Figures and tables in the results section are based on empirical values (estimated from PIAAC, STEP, and DHS) whenever possible, and on predicted values if no empirical data are available.

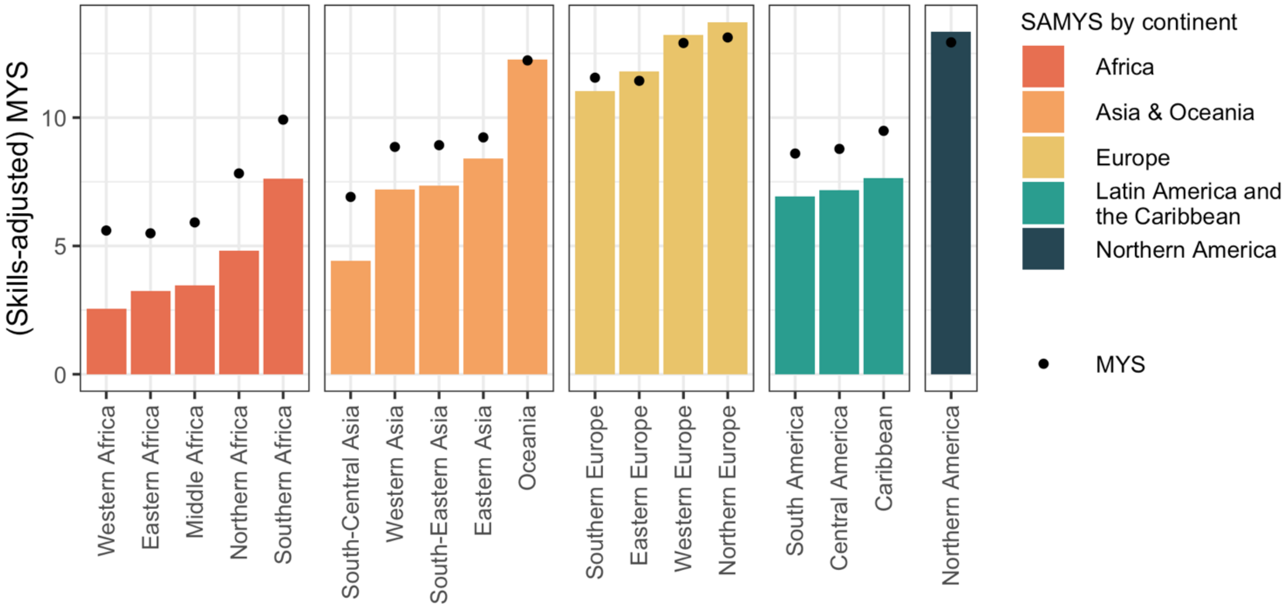
Figure 10: Relationship between skills adjustment factor and mean years of schooling by country and year



Source: Authors' calculations

Figure 11 shows population-weighted SAMYS and MYS by continent for the base year 2015. Bars represent SAMYS, whereas dots represent MYS by region and continent. As can be seen on the chart, Northern America and Europe are the only two continents where SAMYS for 2015 are – for the most part – slightly higher than MYS. In Oceania, SAMYS roughly equal MYS, indicating a skills adjustment factor of about 1. All other regions in the world have considerably lower SAMYS than MYS, suggesting that expected skills acquired in formal education are less assured, taken the OECD average as benchmark. SAMYS are lowest in Western Africa, whereas MYS are lowest in Eastern Africa. The region with the highest value in both SAMYS and MYS is Northern Europe.

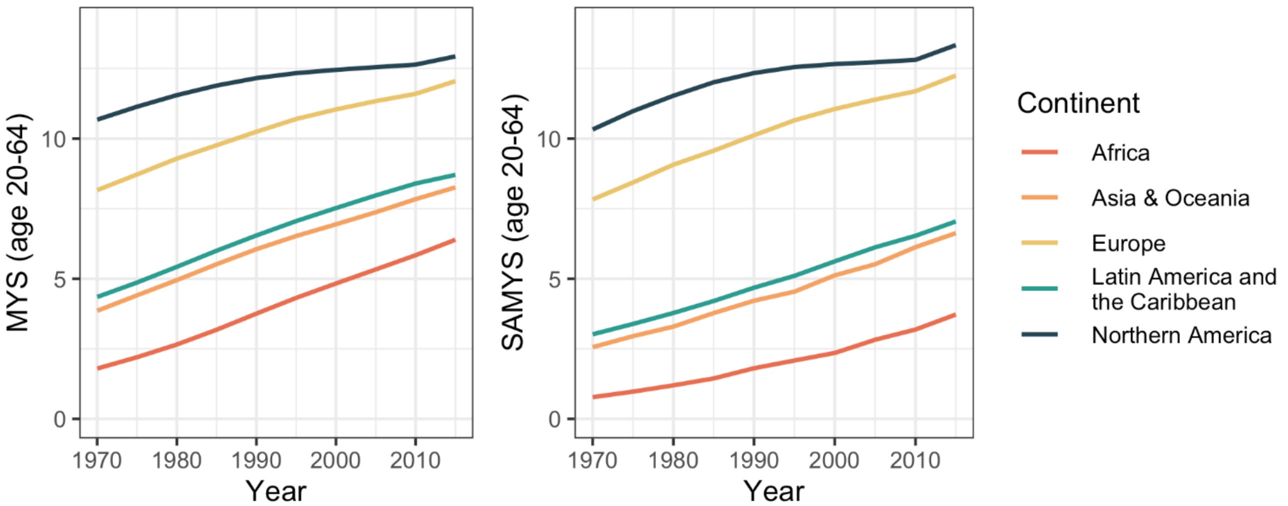
Figure 11: Population-weighted Mean Years of Schooling (MYS) and Skills-Adjusted Mean Years of Schooling (SAMYS) by region and continent, age 20-64, 2015



Source: Authors' calculations

Very similar results can be found when looking at the estimated time-series from 1970 to 2015 (Figure 12). While both MYS and SAMYS constantly increase during the whole period of reconstruction, increments in SAMYS have been slower in Africa in the beginning. A more rapid growth in SAMYS can be observed after 1990. In Northern America and Europe, on the other hand, a minor damping in the increase of both MYS and QAMYS is noticeable starting from 2000 which is clearly more pronounced in North America. Latin America depicts an almost linear growth rate of MYS and – on a lower level – of SAMYS over the last four decades. Given that SAMYS are calculated by multiplying MYS and SAF the correlation is not surprising.

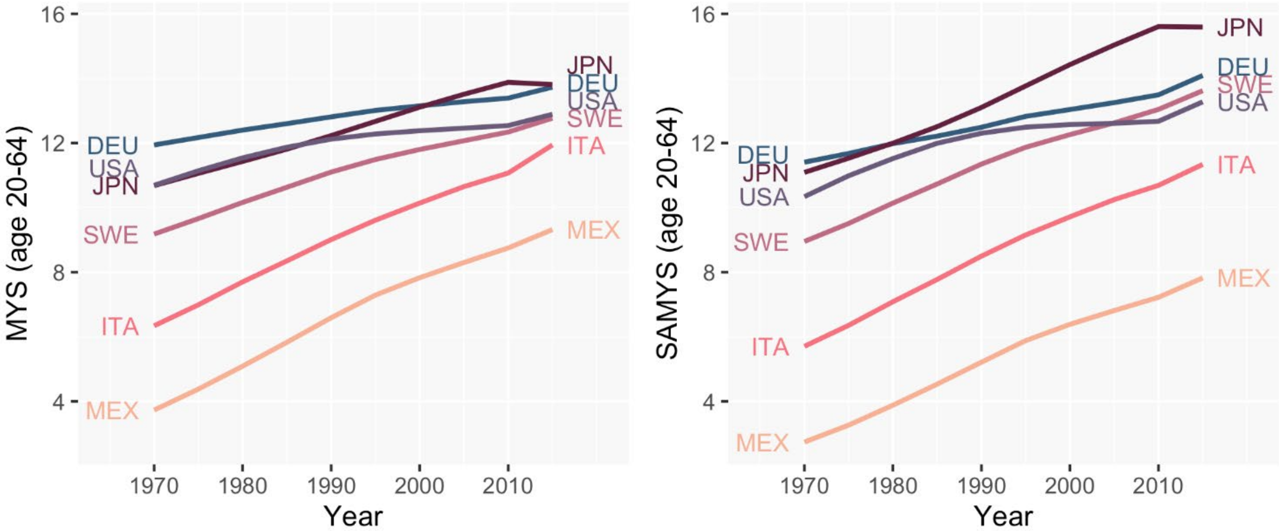
Figure 12: Population-weighted Mean Years of Schooling (left) and Skills-Adjusted Mean Years of Schooling (right) by continent, age 20-64, 1970-2015



Source: Authors' calculations

Figure 13 shows the time-series results of both MYS and SAMYS for selected OECD countries (Germany, Italy, Japan, Mexico, Sweden, United States). A particularly interesting case is Japan. The country has experienced significant increases in MYS during the last decades with the population aged 20-64 having attended, on average, the greatest number of schooling-years in the world. Even more outstanding, however, was Japan' development in terms of SAMYS. Already by 1980, the country outperformed other rich countries such as Germany, Sweden, or the United States, with the gap further increasing ever since. Generally, differences between OECD countries are more pronounced when looking at skills-adjusted human capital as compared to purely quantitative measures. The weaker performance of Italy and Mexico is consistent with regional trends of SAMYS as shown before.

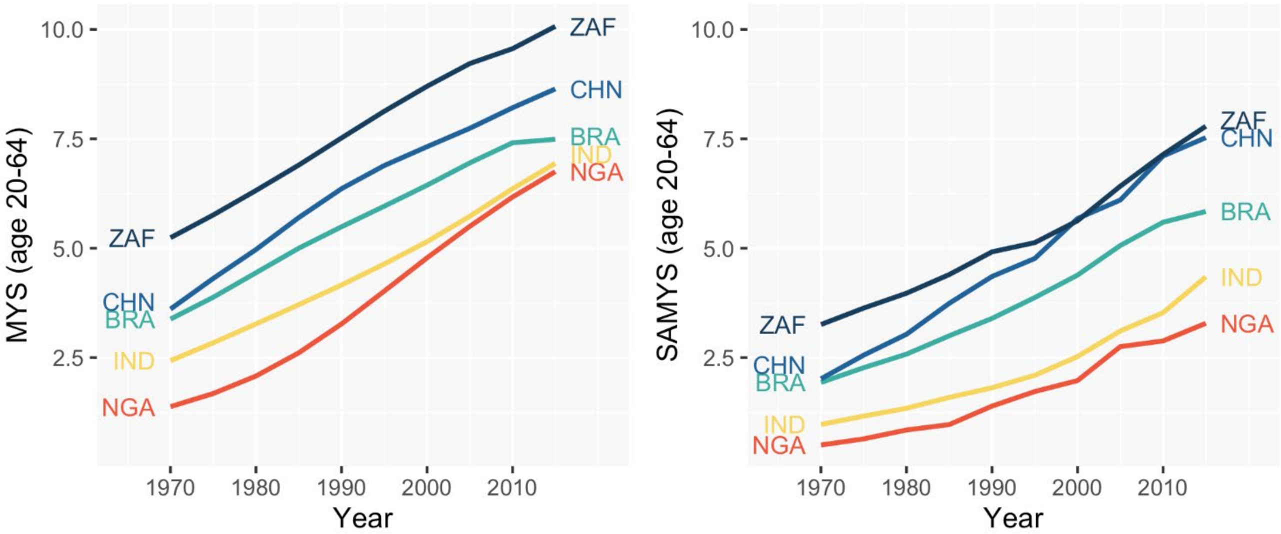
Figure 13: Mean Years of Schooling (left) and Skills Adjusted Mean Years of Schooling (right), selected OECD countries, age 20-64, 1970-2015



Source: Authors' calculations

Time-series results for selected developing countries (Brazil, China, India, Nigeria, South Africa) are depicted in Figure 14. As opposed to more developed economies, SAMYS, for this group of countries, reveal to be consistently lower than MYS at all points of time. Nevertheless, differences between countries are striking. Whereas China is rapidly improving in term of skills-adjusted human capital (with a slightly more moderate growth in MYS), other countries, such as India or particularly Nigeria, seem to struggle to complement their substantial increase in the number of average years spent in school with a likewise rise in the level of skills of the population.

Figure 14: Mean Years of Schooling (left) and Skills-Adjusted Mean Years of Schooling (right), selected developing countries, age 20-64, 1970-2015



Source: Authors' calculations

In addition to the selected and aggregated results presented above, Table 7 displays MYS and SAMYS for all countries for 1970 and 2015. For more detailed and country-specific analyses, the appendix contains the full account of mapping SAMYS and MYS for 201 countries in the base year (A.1) and for 185 countries for the time-series (A.2)[25].

[25] Results presented in Appendix A.1 and A.2 are solely based on predictions; empirical results are shown in Appendix A.3.

Table 7: Mean Years of Schooling (MYS) and Skills-adjusted Mean Years of Schooling (SAMYS) by country, age 20-64, 1970 and 2015 (continues in the next pages)

Country	1970		2015	
	MYS	SAMYS	MYS	SAMYS
Afghanistan	0.56	0.16	3.17	0.84
Albania	5.52	2.95	10.57	8.44
Algeria	1.86	0.68	9.7	6.47
Angola	0.66	0.23	2.91	1.66
Antigua and Barbuda	NA	NA	10.8	9.11
Argentina	6.75	5.64	10.31	9.10
Armenia	7.7	7.45	11.03	10.73
Aruba	4.97	3.64	9.46	7.78
Australia	10.03	10.61	13.68	14.47
Austria	8.63	8.13	12.16	12.48
Azerbaijan	6.95	4.15	11	10.61
Bahamas	8.5	7.44	12.94	11.82
Bahrain	2.58	1.34	9.39	7.80
Bangladesh	2.06	0.70	5.66	3.04
Barbados	NA	NA	10.24	8.21
Belarus	7.62	7.77	11.56	12.14
Belgium	8.3	7.97	11.95	12.53
Belize	4.98	3.32	8.73	6.93
Benin	0.85	0.24	4.3	1.54
Bhutan	0.41	0.16	5.12	2.71
Bolivia (Plurinational State of)	4.33	2.08	9.53	7.11
Bosnia and Herzegovina	4.65	3.69	11.24	10.85
Botswana	2.44	1.13	9.74	7.01
Brazil	3.38	1.93	7.49	5.84
Brunei Darussalam	NA	NA	9.77	8.24
Bulgaria	8.29	8.03	11.7	11.90
Burkina Faso	0.26	0.07	2.58	0.63
Burundi	0.81	0.27	3.95	2.34
Cambodia	2.26	1.12	5.28	3.42
Cameroon	2.28	0.88	7.49	4.42
Canada	10.53	10.18	13.29	13.85
Cape Verde	1.77	0.70	6.61	4.31
Central African Republic	0.6	0.18	5.85	2.09
Chad	0.28	0.08	2.93	0.90
Channel Islands	NA	NA	12.06	12.25
Chile	7.12	5.09	11.32	9.43
China	3.61	2.02	8.64	7.53
Colombia	3.79	2.51	8.51	7.49

Country	1970		2015	
	MYS	SAMYS	MYS	SAMYS
Comoros	0.65	0.27	7.18	3.44
Congo	2.49	0.92	8.43	5.16
Costa Rica	5.36	4.35	9.14	7.61
Cote d'Ivoire	0.87	0.26	4.64	1.87
Croatia	7.91	7.16	12.03	12.37
Cuba	6.99	6.06	11.25	9.87
Curaçao	7.29	5.70	10.55	9.19
Cyprus	6.55	6.59	13.01	13.35
Czech Republic	10.52	10.66	13.02	13.59
Democratic People's Republic of Korea	7.33	5.79	11.01	11.80
Democratic Republic of the Congo	2.4	0.86	6.74	4.14
Denmark	10.49	10.04	12.6	13.00
Djibouti	NA	NA	4.08	2.48
Dominican Republic	3.31	1.94	8.79	6.52
Ecuador	4.2	2.87	9.4	6.98
Egypt	2.49	1.00	8.64	5.12
El Salvador	2.88	1.53	8.04	5.75
Equatorial Guinea	2.18	0.99	7.44	5.31
Eritrea	NA	NA	3.78	2.19
Estonia	9.98	9.80	13.27	13.93
Ethiopia	0.43	0.13	3.18	1.43
Fiji	6.04	4.13	11.52	10.32
Finland	8.85	8.71	13.03	14.27
France	7.97	7.31	12.14	12.09
French Guiana	5.49	3.89	8.54	6.91
French Polynesia	5.67	4.23	10.91	9.71
Gabon	2.1	0.75	8.76	5.71
Gambia	0.56	0.15	4.38	2.02
Georgia	8.39	7.60	12.65	11.79
Germany	11.94	11.41	13.73	14.09
Ghana	3.13	1.33	7.58	3.83
Greece	6.42	6.17	11.78	11.37
Grenada	NA	NA	10.62	8.45
Guadeloupe	5.01	3.70	10.14	8.44
Guam	NA	NA	10.28	9.01
Guatemala	2.5	1.13	6.2	4.42
Guinea	0.6	0.18	4.23	1.32
Guinea-Bissau	0.4	0.11	4.07	1.89
Guyana	7.02	5.65	10.06	8.69

Country	1970		2015	
	MYS	SAMYS	MYS	SAMYS
Haiti	1.25	0.45	5.71	3.72
Honduras	1.98	0.98	5.91	3.99
Hong Kong Special Administrative Region of China	5.15	3.76	12.54	12.65
Hungary	8.15	6.76	12.41	12.47
Iceland	10.91	10.51	13.57	13.38
India	2.43	0.97	6.94	4.35
Indonesia	3.63	1.96	9.06	7.03
Iran (Islamic Republic of)	2.14	0.87	9.19	6.65
Iraq	2.18	0.81	7.82	5.30
Ireland	8.11	7.77	12.63	12.82
Israel	7.08	5.46	11.86	11.48
Italy	6.34	5.70	11.94	11.34
Jamaica	5.57	3.54	10.39	7.78
Japan	10.68	11.09	13.81	15.59
Jordan	4.56	2.35	9.97	7.82
Kazakhstan	7.62	7.51	11.31	10.74
Kenya	2.51	0.85	8.28	5.39
Kiribati	3.94	3.47	9.43	8.03
Kuwait	3.9	2.12	8.05	6.05
Kyrgyzstan	6.56	4.78	10.86	10.98
Lao People's Democratic Republic	2.17	1.37	6.48	4.54
Latvia	10.65	9.39	12.59	13.25
Lebanon	3.84	2.33	10.39	8.61
Lesotho	3.34	1.78	7.61	5.59
Liberia	1.04	0.32	4.87	2.22
Libyan Arab Jamahiriya	NA	NA	8.17	5.97
Lithuania	8.69	8.87	13.48	13.67
Luxembourg	9.37	8.62	13.17	13.10
Macao Special Administrative Region of China	4	2.87	11.34	10.57
Madagascar	2.02	0.87	4.48	2.56
Malawi	2.19	0.90	6.16	3.64
Malaysia	3.8	2.27	11.61	10.02
Maldives	2.09	1.47	7.4	5.83
Mali	0.37	0.09	2.25	0.57
Malta	6.85	5.16	11.17	9.86
Martinique	6.5	5.29	10.97	9.94
Mauritania	NA	NA	4.22	1.83
Mauritius	3.92	2.40	9.34	7.11

Country	1970		2015	
	MYS	SAMYS	MYS	SAMYS
Mayotte	NA	NA	10.14	5.31
Mexico	3.73	2.74	9.32	7.82
Micronesia (Federated States of)	3.98	3.53	9.72	8.44
Mongolia	5.8	3.96	10.48	10.39
Montenegro	7.48	6.27	11.97	11.58
Morocco	0.6	0.20	5.66	3.25
Mozambique	0.42	0.12	2.93	1.20
Myanmar	2.62	1.68	6.36	4.52
Namibia	3.01	1.57	8.43	6.27
Nepal	0.79	0.22	5.62	3.57
Netherlands	9.36	9.29	12.42	13.42
New Caledonia	5.65	3.25	11.5	9.46
New Zealand	9.75	9.10	13.52	14.48
Nicaragua	2.52	1.30	6.78	4.33
Niger	0.14	0.03	1.95	0.60
Nigeria	1.38	0.50	6.75	3.28
Norway	10.8	10.89	13.1	13.95
Occupied Palestinian Territory	3.9	1.95	10.74	8.92
Oman	1.1	0.37	9.21	7.21
Pakistan	1.38	0.47	5.08	2.48
Panama	5.45	3.81	10.2	8.20
Papua New Guinea	NA	NA	6.94	4.12
Paraguay	4.58	3.16	8.79	6.63
Peru	5.24	3.56	10.22	7.52
Philippines	5.88	4.39	9.42	8.64
Poland	9.84	9.23	13.04	13.20
Portugal	2.84	1.90	9.35	8.60
Puerto Rico	7.69	6.41	12.44	10.87
Qatar	4.88	2.65	9.32	7.22
Republic of Korea	6.02	5.57	12.9	13.31
Republic of Moldova	4.43	3.81	11.06	10.36
Reunion	3.59	2.08	9.91	7.99
Romania	7.27	6.62	11.65	11.31
Russian Federation	6.43	6.61	10.87	11.40
Rwanda	1.18	0.43	4.56	3.02
Saint Lucia	5.3	3.89	10.58	8.39
Saint Vincent and the Grenadines	6.73	5.83	10.82	8.24
Samoa	7.39	4.49	10.74	9.21
Sao Tome and Principe	0.69	0.25	4.68	3.23

Country	1970		2015	
	MYS	SAMYS	MYS	SAMYS
Saudi Arabia	2.27	0.92	10.2	8.08
Senegal	1.05	0.31	4.26	1.77
Serbia	6.9	5.96	12.06	12.18
Seychelles	NA	NA	10.65	8.69
Sierra Leone	1.14	0.35	4.3	1.47
Singapore	4.9	3.58	12.64	12.28
Slovakia	10.35	10.80	13.25	13.83
Slovenia	10.3	9.62	12.2	11.87
Solomon Islands	2.51	1.39	6.69	4.79
Somalia	0.9	0.25	3.31	1.89
South Africa	5.24	3.26	10.07	7.79
South Sudan	0.54	0.20	2.63	0.92
Spain	5.58	4.86	11.47	10.98
Sri Lanka	5.08	3.47	10.77	8.67
Sudan	0.71	0.26	4.98	2.87
Suriname	6.79	4.65	10.19	7.80
Swaziland	2.77	1.43	9.5	6.76
Sweden	9.18	8.95	12.77	13.62
Switzerland	10.93	12.19	13.4	14.16
Syrian Arab Republic	2.53	1.11	7.29	5.00
Taiwan Province of China	5.83	4.59	12.39	12.66
Tajikistan	6.67	5.91	11.79	9.01
Thailand	6.15	4.58	10.22	8.25
The former Yugoslav Republic of Macedonia	3.88	2.98	10.64	9.33
Timor-Leste	0.52	0.32	6.72	4.25
Togo	0.99	0.33	5.25	2.51
Tonga	7.66	4.66	11.03	9.61
Trinidad and Tobago	6.78	5.69	11.63	10.35
Tunisia	1.38	0.53	8.99	6.08
Turkey	3.52	2.87	9.21	7.91
Turkmenistan	7.99	6.11	10.73	11.07
Uganda	2.64	1.05	6.68	3.77
Ukraine	6.66	5.38	10.98	11.26
United Arab Emirates	5.19	2.82	10.24	8.25
United Kingdom of Great Britain and Northern Ireland	10.9	11.63	13.26	13.81
United Republic of Tanzania	2.27	0.94	7.22	4.54
United States of America	10.69	10.34	12.89	13.27
United States Virgin Islands	NA	NA	9.99	8.10
Uruguay	6.02	5.27	9.55	8.22

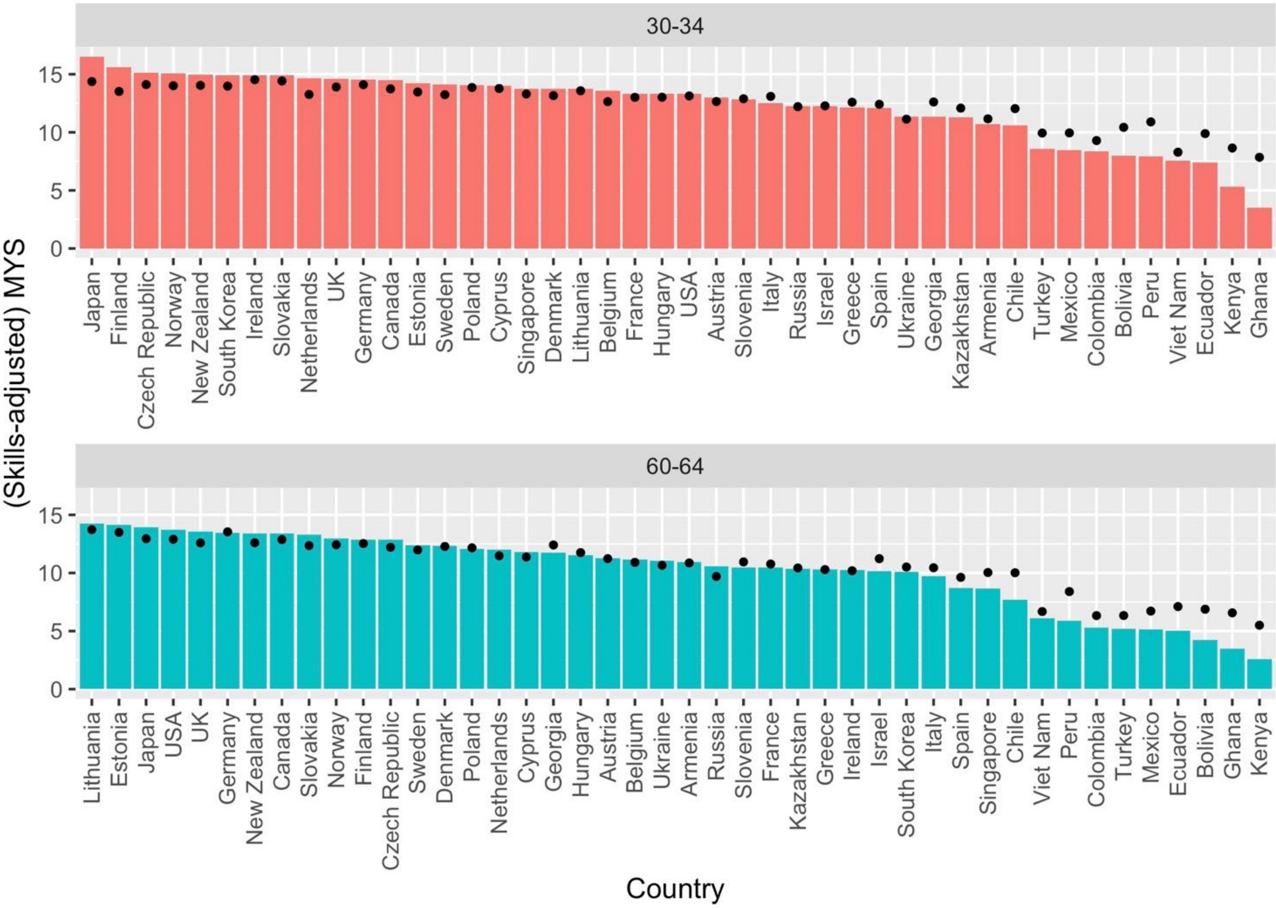
Country	1970		2015	
	MYS	**SAMYS**	**MYS**	**SAMYS**
Uzbekistan	NA	NA	11.23	11.48
Vanuatu	2.77	1.53	7.2	5.17
Venezuela (Bolivarian Republic of)	5.37	3.58	10.11	8.52
Viet Nam	3.65	2.60	8.08	7.33
Western Sahara	NA	NA	3.58	1.97
Yemen	0.01	0.00	2.38	1.02
Zambia	3.59	1.71	7.94	4.76
Zimbabwe	4.14	2.23	10.96	8.36

Source: Authors' calculations

Finally, as mentioned earlier, for 44 countries we were able to further disaggregate results by 5-year age groups, sex, and educational attainment. Figure 15 compares SAMYS of 30-34 year-olds and 60-64 year-olds in 2015 in these 44 countries. Results reveal that, on average, the younger age group tends to show slightly higher SAMYS than the older one. In addition, the country ranking differs considerably for different age groups. Whereas for 30-34 year-olds Japan, Finland, and Czech Republic are the leading countries, for the older population SAMYS are highest in Lithuania, Estonia, and Japan. The relationship between MYS and SAMYS seems to be rather similar over age.

Complete results for sub-populations, i.e. SAMYS disaggregated by age and sex for all 44 countries can be found in Appendix A.3.

Figure 15: Skills-adjusted Mean Years of Schooling (bars) and Mean Years of Schooling (dots), 30-34 and 60-64 year-olds, PIAAC and STEP countries, 2015



Source: Authors' calculations

5 Conclusions

Education and the resulting human capital are becoming ever more important as our societies transform into knowledge societies and sophisticated comprehension and advanced skills of all kinds become essential for success – not only on the labour market but also in other spheres of life. Given this all-encompassing importance of knowledge and skills it is indeed a shortcoming of the statistical analysis of human capital so far that it almost exclusively focussed on the quantity of education while it is so evident that quality and levels of skills that people maintain throughout their lives also matter. One reason often given for leaving out this obvious importance of skills in the statistical analysis of the effects of education is the lack of consistent data across countries and over time.

The current paper tried to improve this situation by estimating a global data set of skills adjusted human capital by age and sex for the past 45 years. This is the first attempt to produce such a comprehensive dataset. In the methodological sections, we have pointed out the existing shortcomings in the available data and the assumptions that had to be made in order arrive at the estimates presented, which will need to be addressed in the future as more empirical information on tested adult skills become available. Our main data source of adult skills PIAAC is only covering a limited number of countries, most of which are high-income OECD countries, and it has been conducted only once so far. The scope of countries included could be significantly enlarged by incorporating other sources of tested adult skill data such as STEP and DHS and finally by estimating data for the remaining countries through regression analysis. Once an empirical base for skills adjusted mean years of schooling for 5-year age groups of men and women has been established for 2015, we used the methods of demographic back-projection along cohort lines to estimate the data in 5-year steps back to 1970. For this we also applied certain patterns of loss of skills with age which we assumed to differ by level of education based on empirical evidence from some countries. As with any such ambitious estimation efforts there are many assumptions involved.

Finally, at the end of such a methodological paper focussing on the measurement and estimation of skills adjusted human capital data, it is also worth asking, what does education do to us that makes it so important for our lives. Different scientific disciplines have quite different views on this. Social scientists often view education as one dimension of social stratification that is a consequence of the class structure of society. Economists tend to see education primarily as an investment that make individuals more productive and employable, and benefit from higher wages on the labour market. While educationists have long conceptualized education as an independent force that changes the way we perceive the world and behave, outside of the field, this view has rarely taken hold in the quantitative social sciences. But there is no doubt that education effects the cognitive functioning of humans, affects their behaviours and at the same time equips them with better social and economic opportunities. All of these empower humans to better manage their lives and help to build better communities. Hence, improving our measures of human capital as we have attempted in this paper will also help societies to better monitor progress and advance policies that help to improve the skills that empower people around the world to improve their lives.

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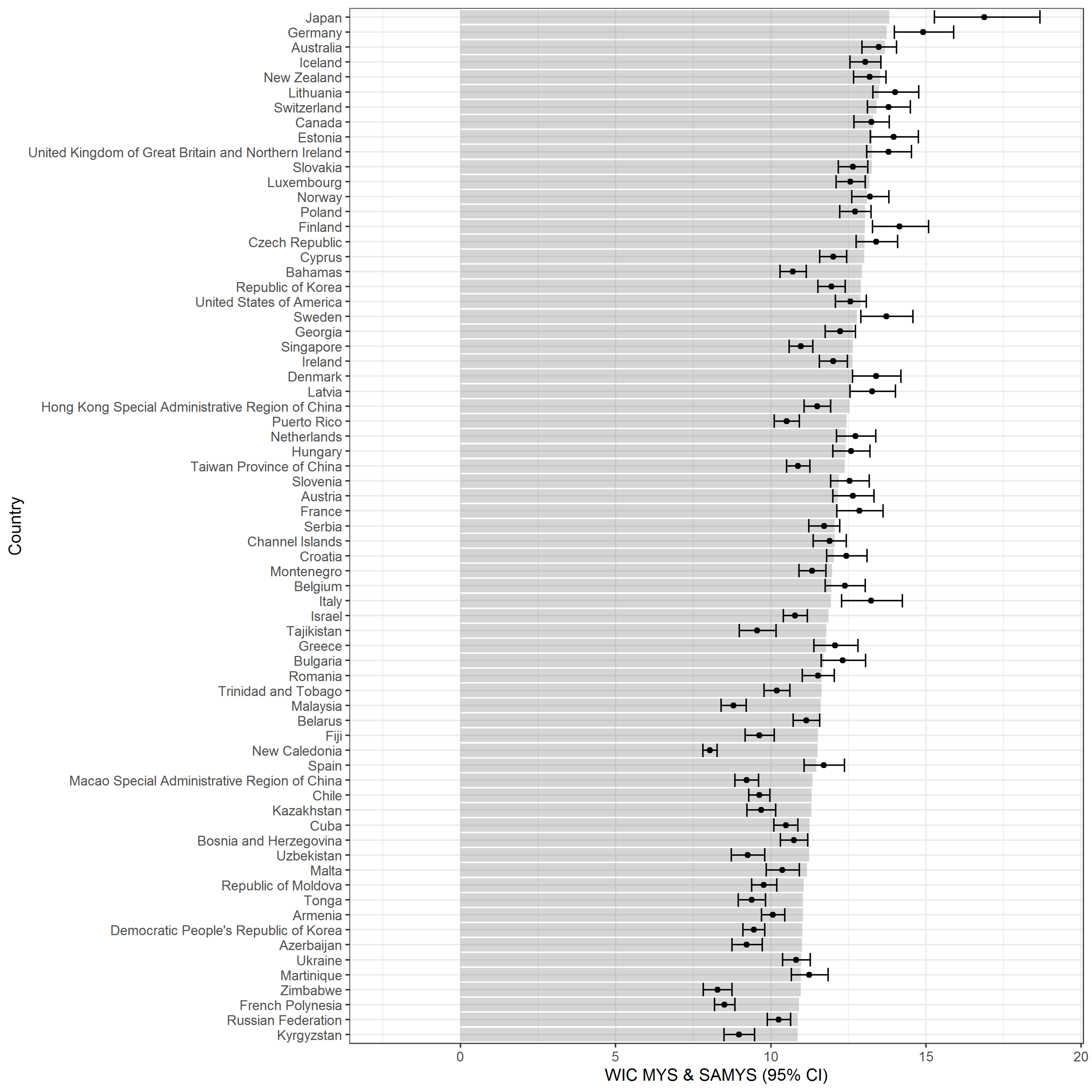
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Czech Republic
Cyprus
Bahamas
Republic of Korea
United States of America
Sweden
Georgia
Singapore
Ireland
Denmark
Latvia
Hong Kong Special Administrative Region of China
Puerto Rico
Netherlands
Hungary
Taiwan Province of China
Slovenia
Austria
France
Serbia
Channel Islands
Croatia
Montenegro
Belgium
Italy
Israel
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Greece
Bulgaria
Romania
Trinidad and Tobago
Malaysia
Belarus
Fiji
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Spain
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Kazakhstan
Cuba
Bosnia and Herzegovina
Uzbekistan
Malta
Republic of Moldova
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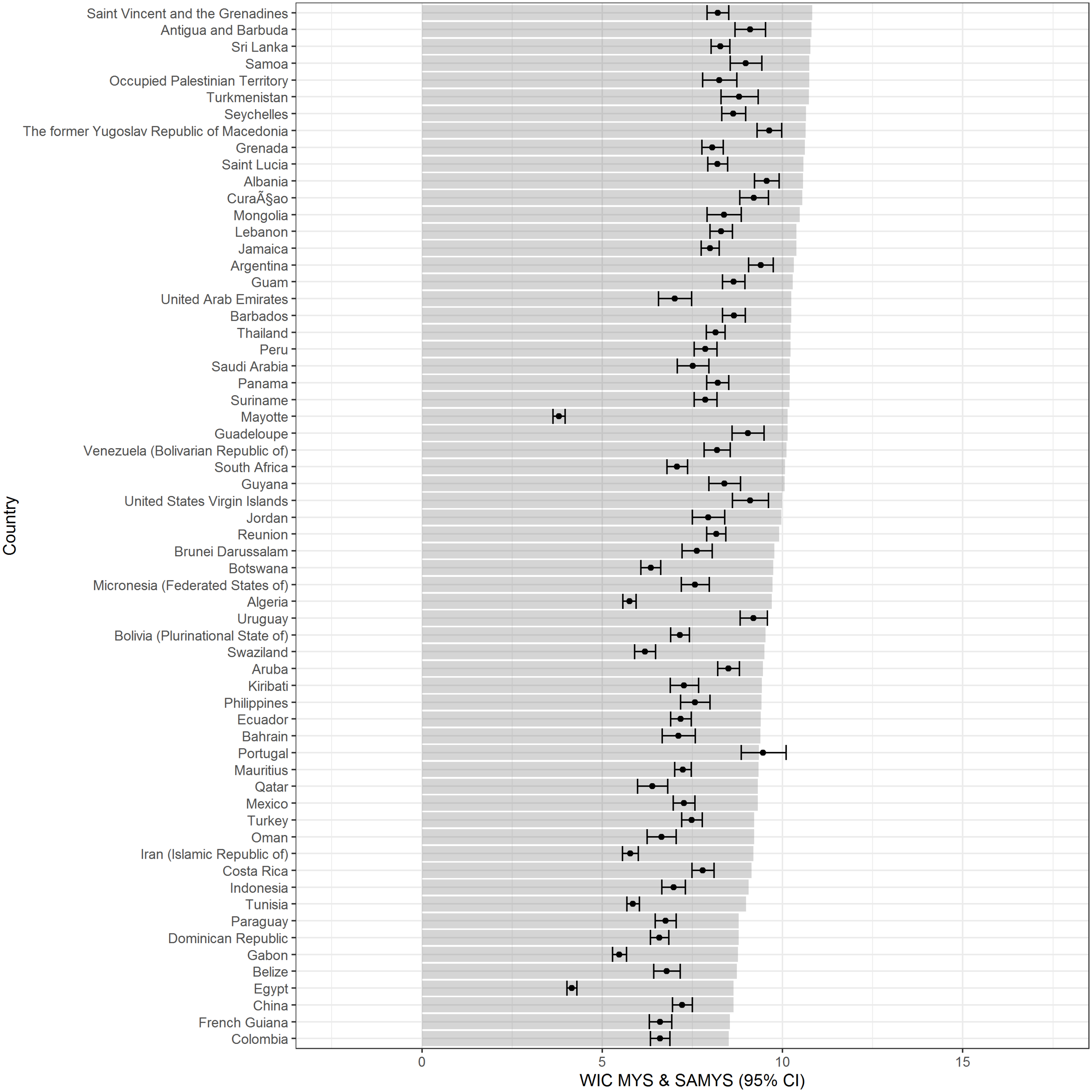
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Thailand
Peru
Saudi Arabia
Panama
Suriname
Mayotte
Guadeloupe
Venezuela (Bolivarian Republic of)
South Africa
Guyana
United States Virgin Islands
Jordan
Reunion
Brunei Darussalam
Botswana
Micronesia (Federated States of)
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Uruguay
Bolivia (Plurinational State of)
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Aruba
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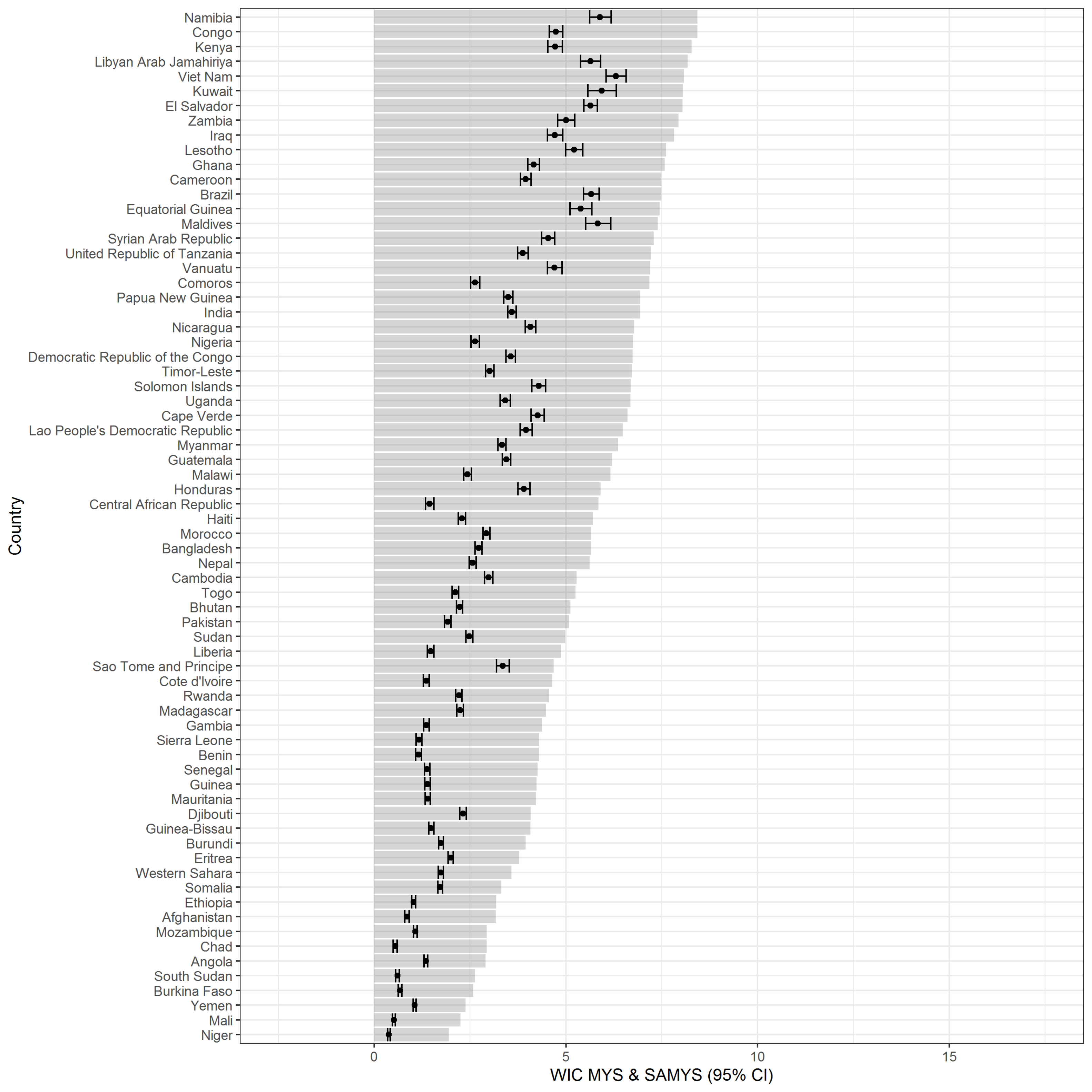
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Democratic Republic of the Congo
Timor-Leste
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Lao People's Democratic Republic
Myanmar
Guatemala
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Pakistan
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Cote d'Ivoire
Rwanda
Madagascar
Gambia
Sierra Leone
Benin
Senegal
Guinea
Mauritania
Djibouti
Guinea-Bissau
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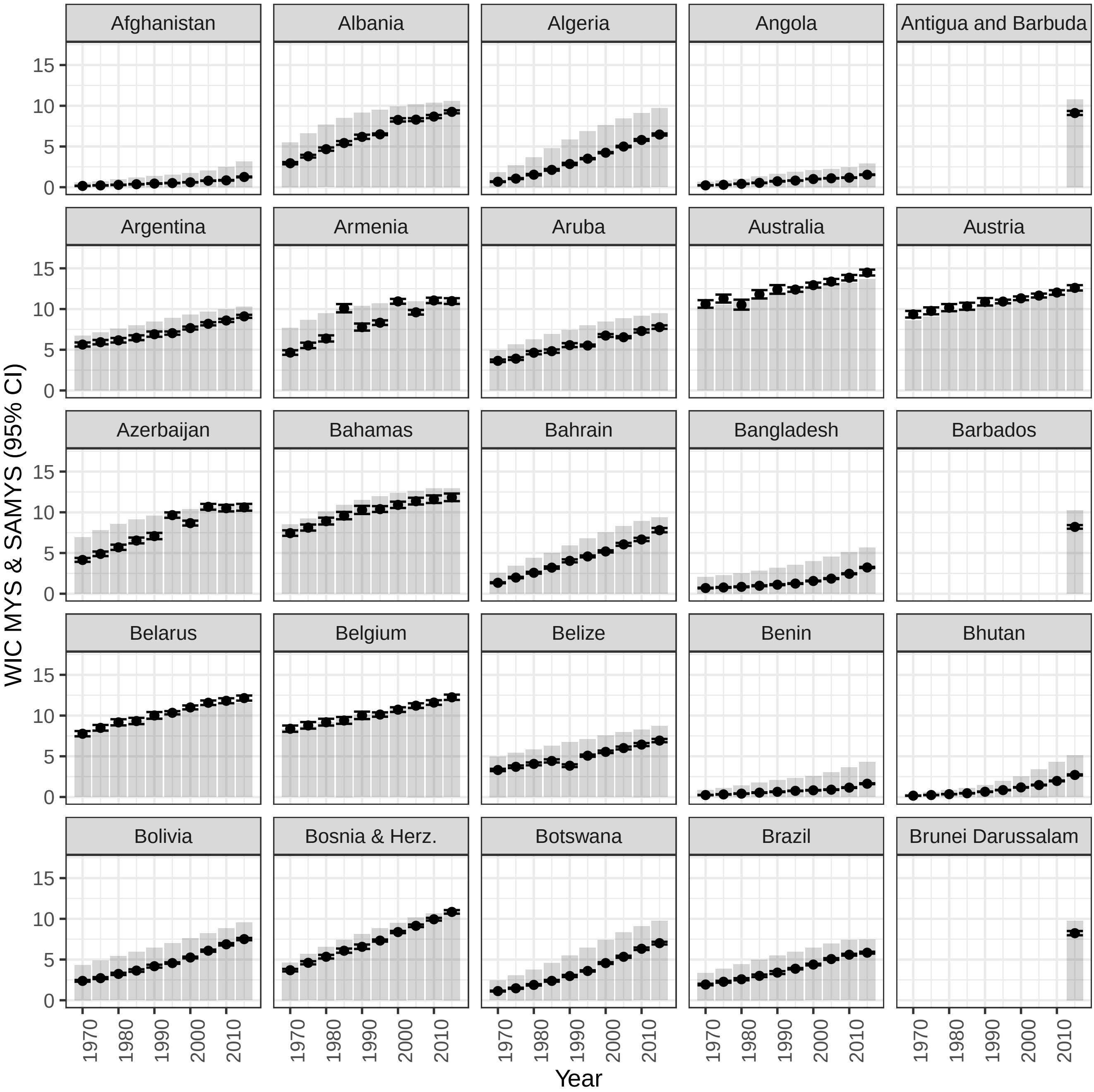

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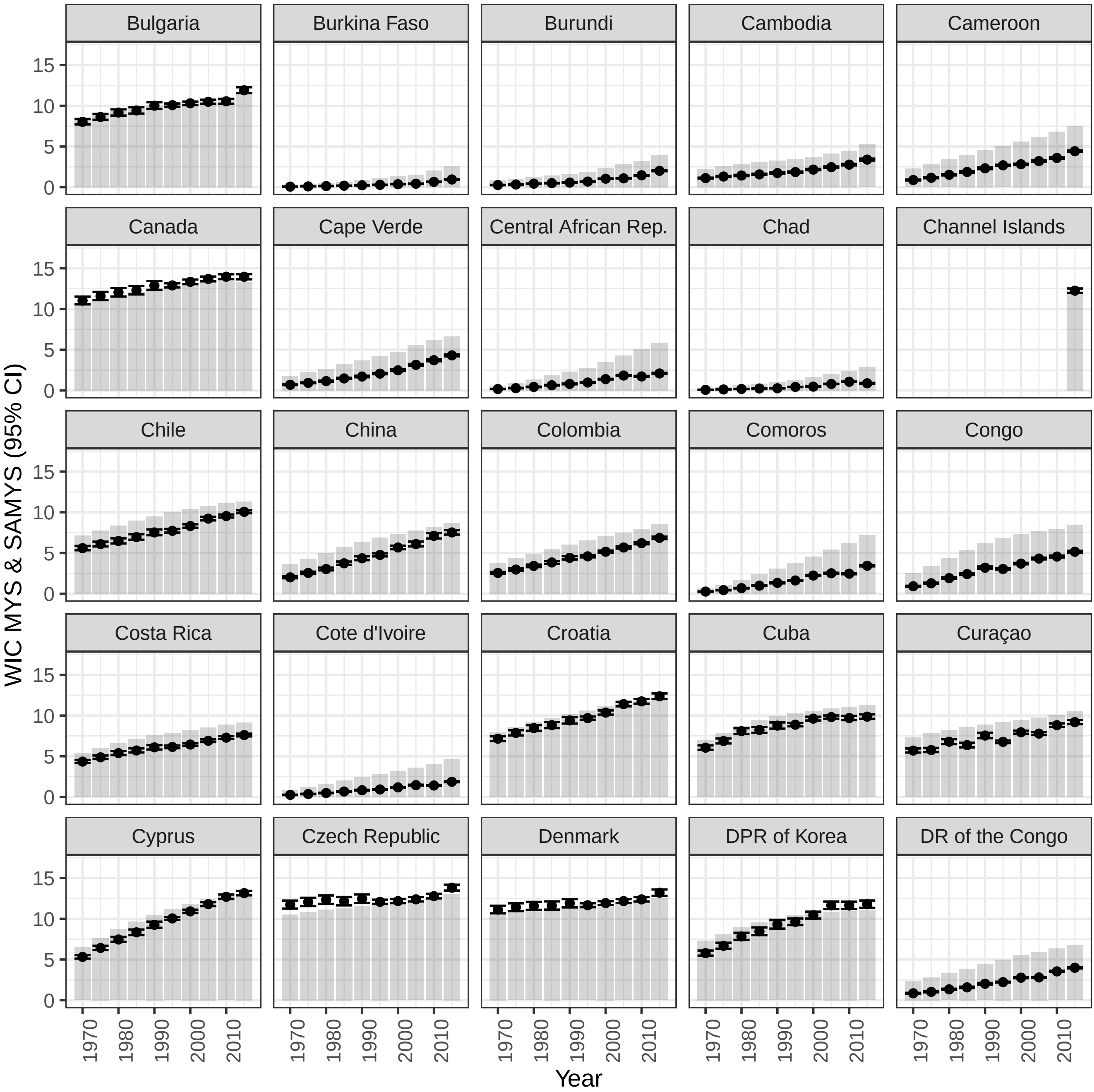
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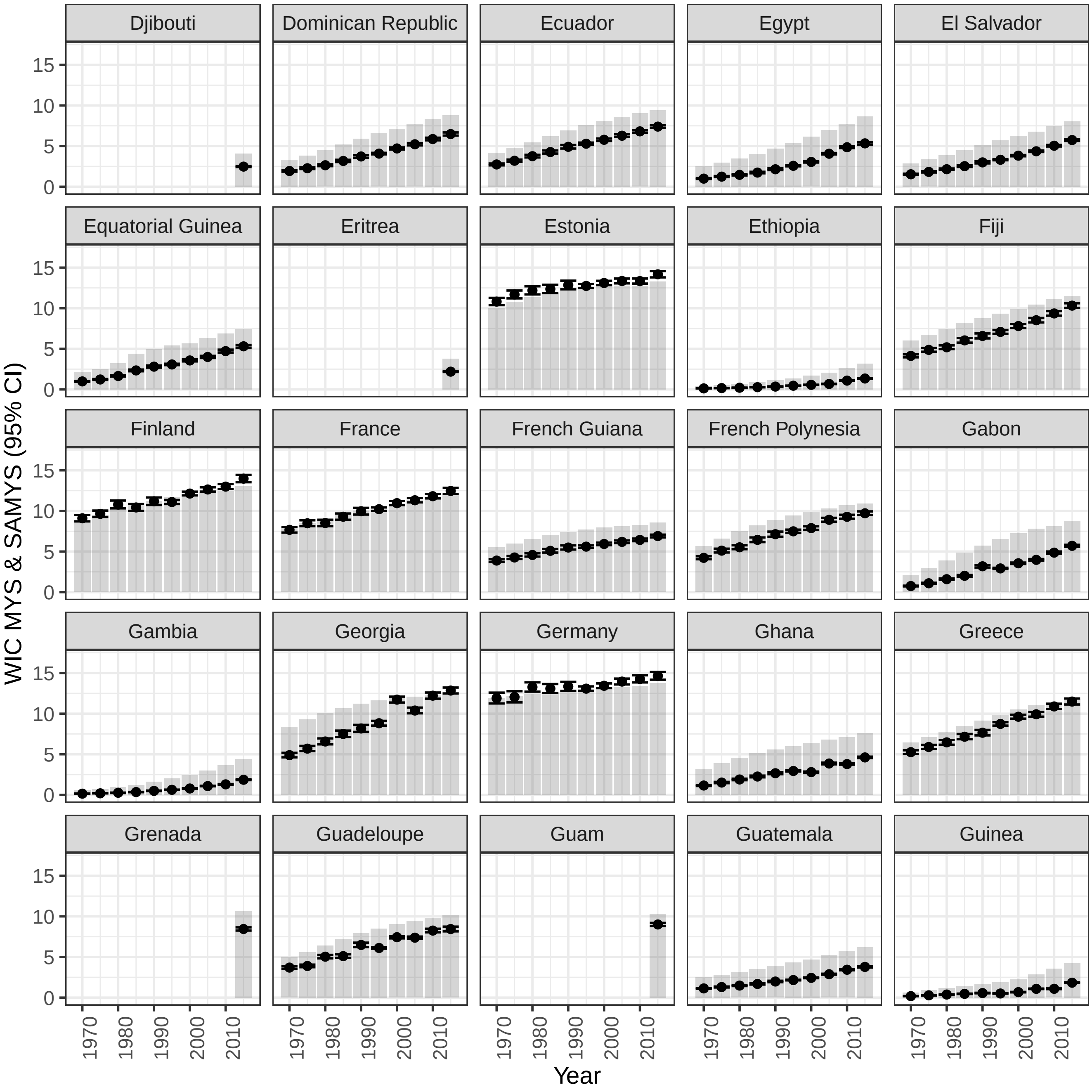

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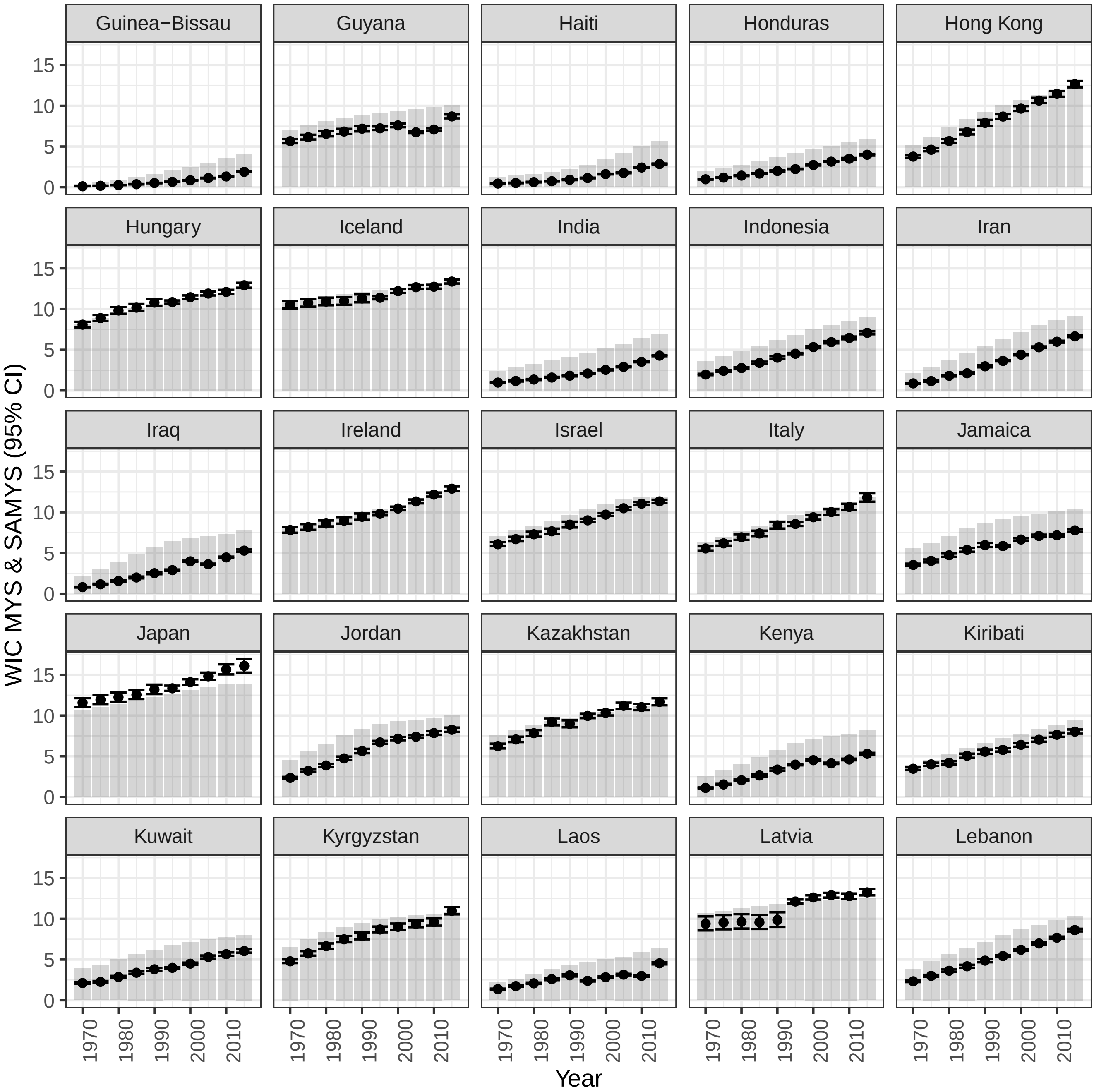
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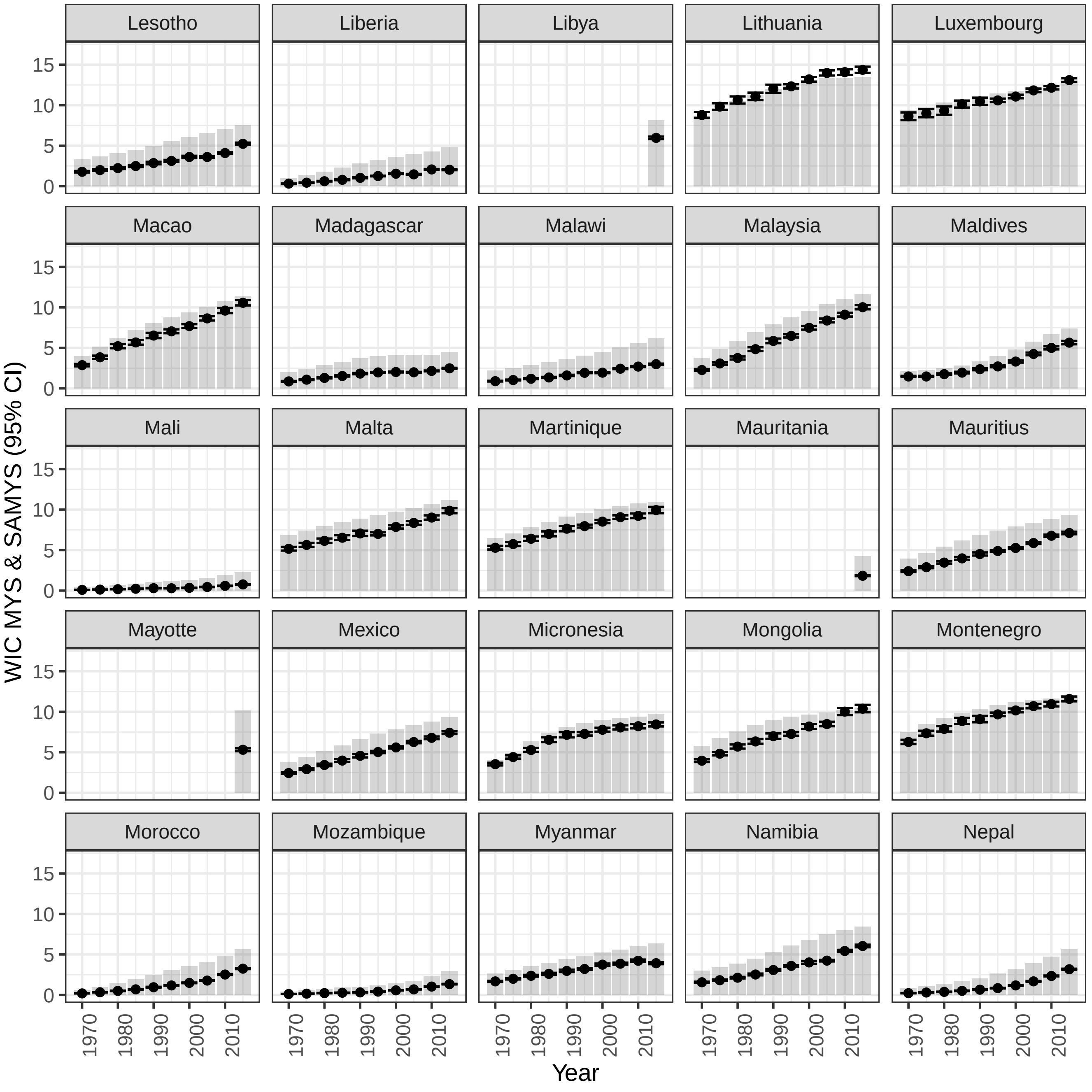
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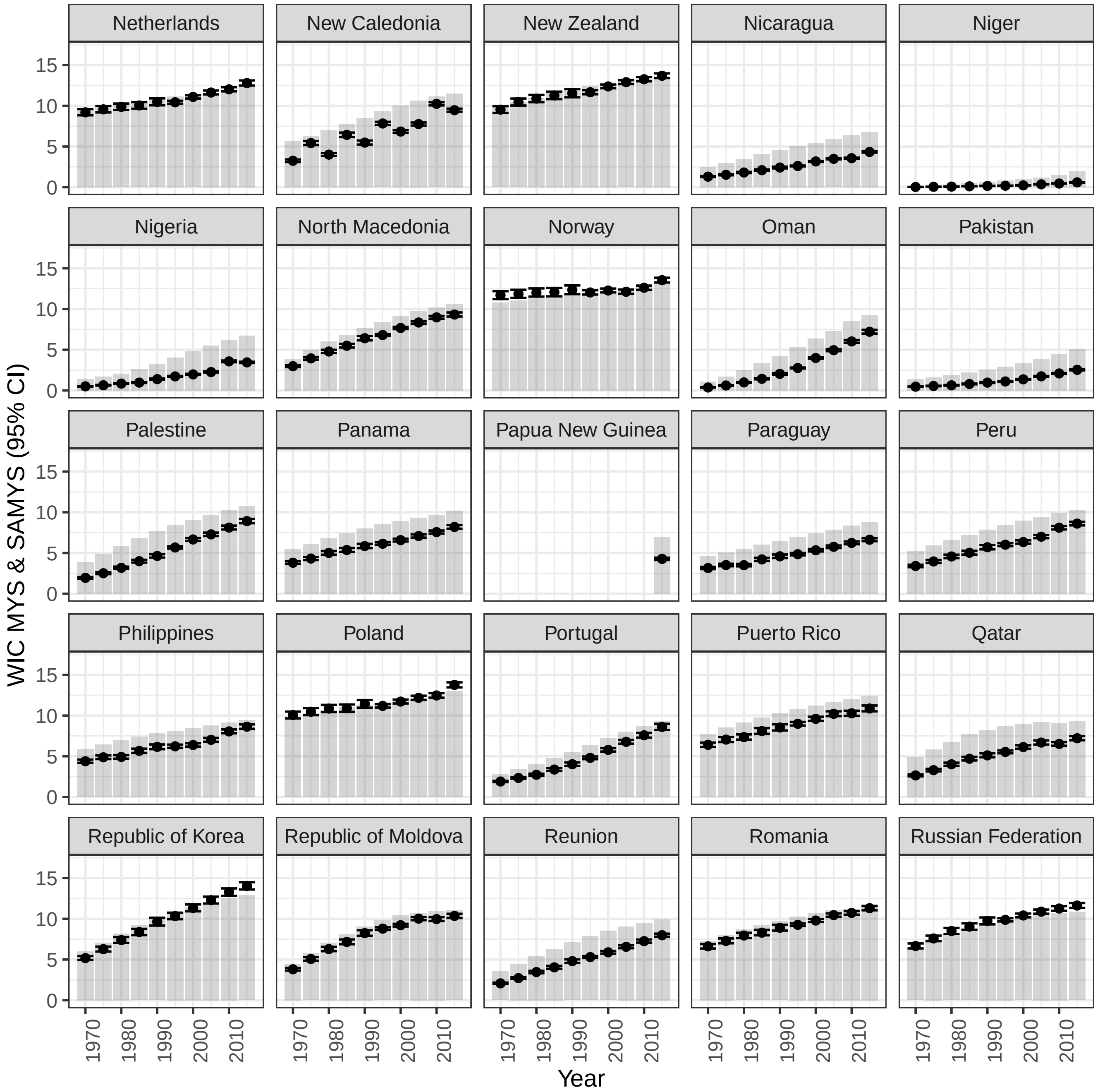
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Peru
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Republic of Korea
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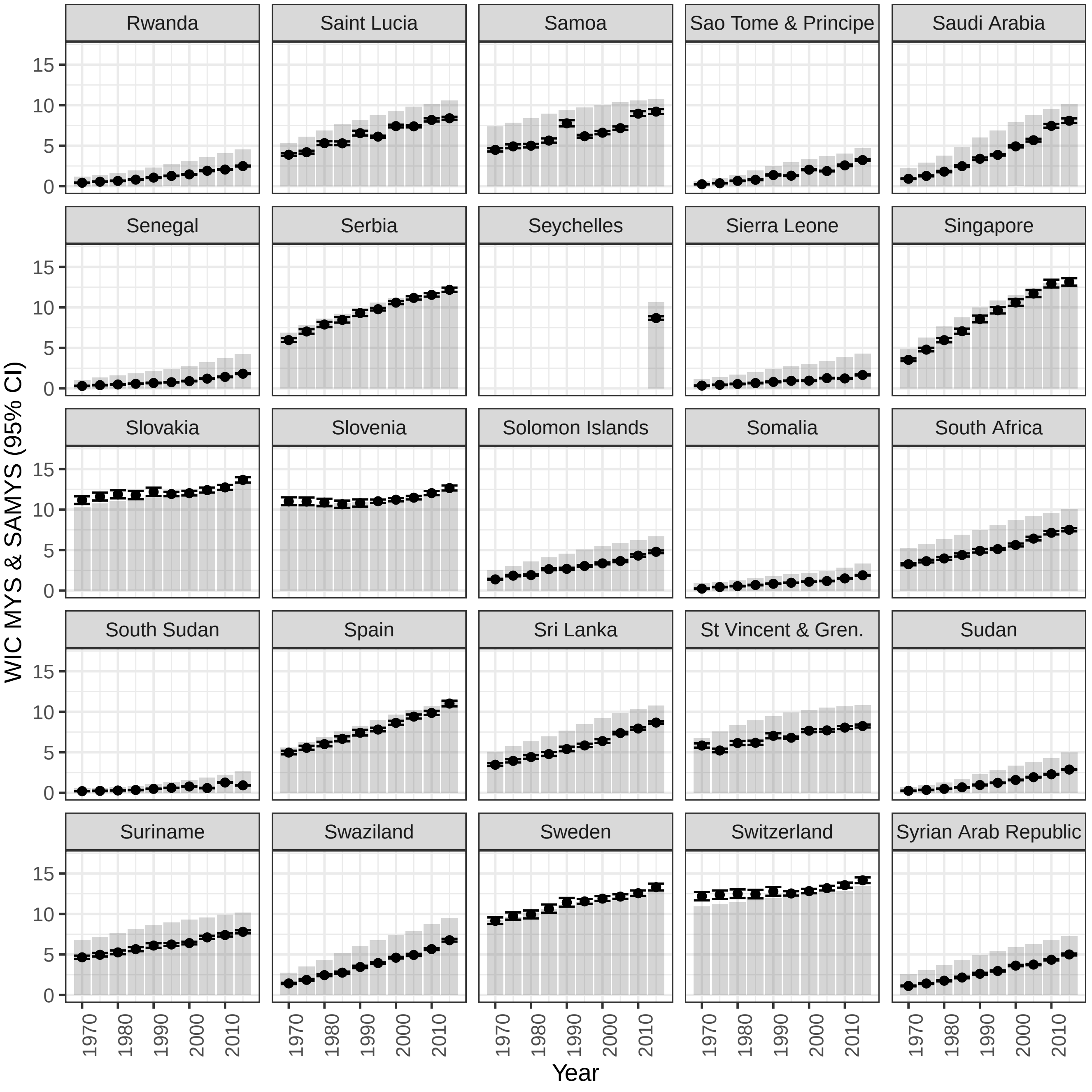
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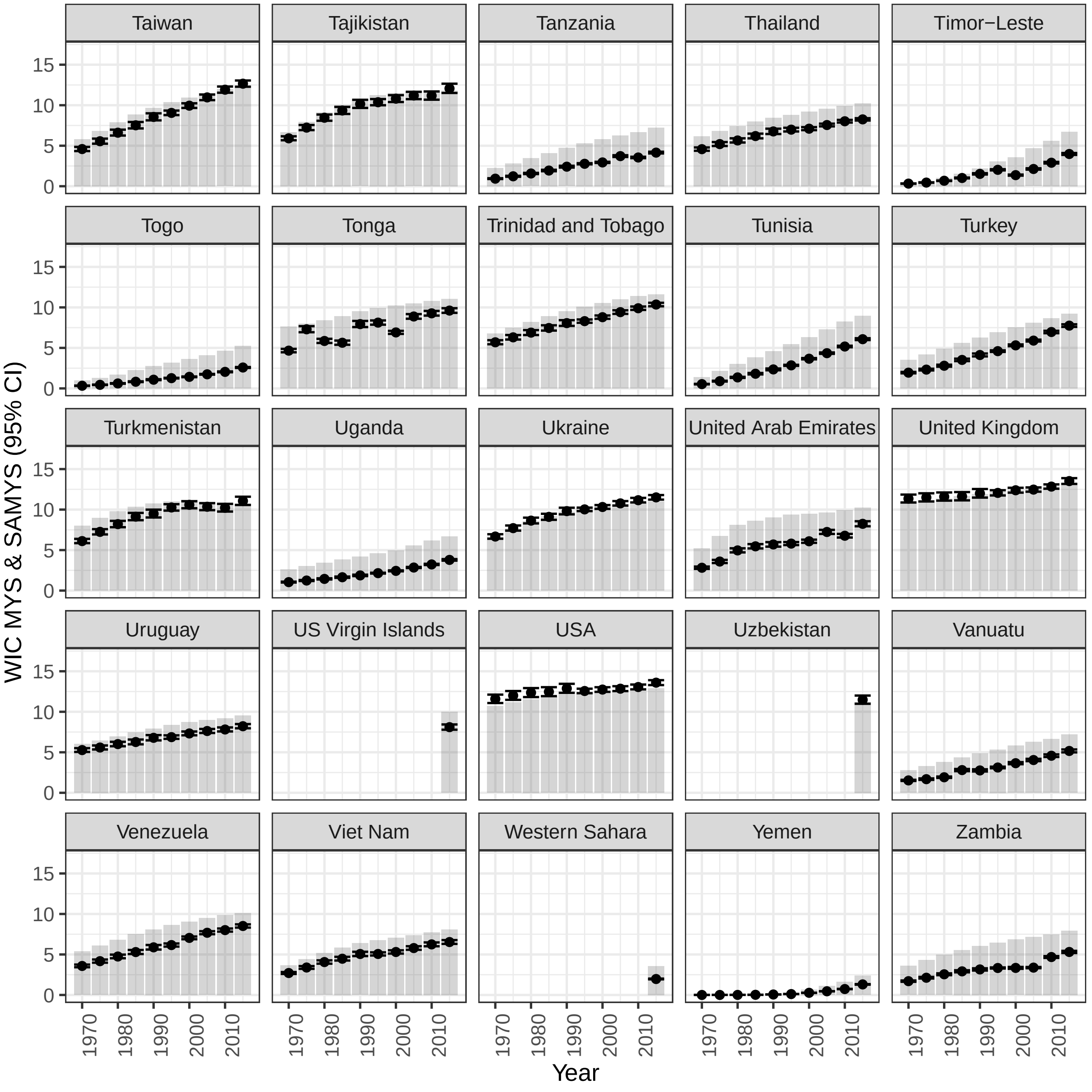

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United Arab Emirates
United Kingdom
Uruguay
US Virgin Islands
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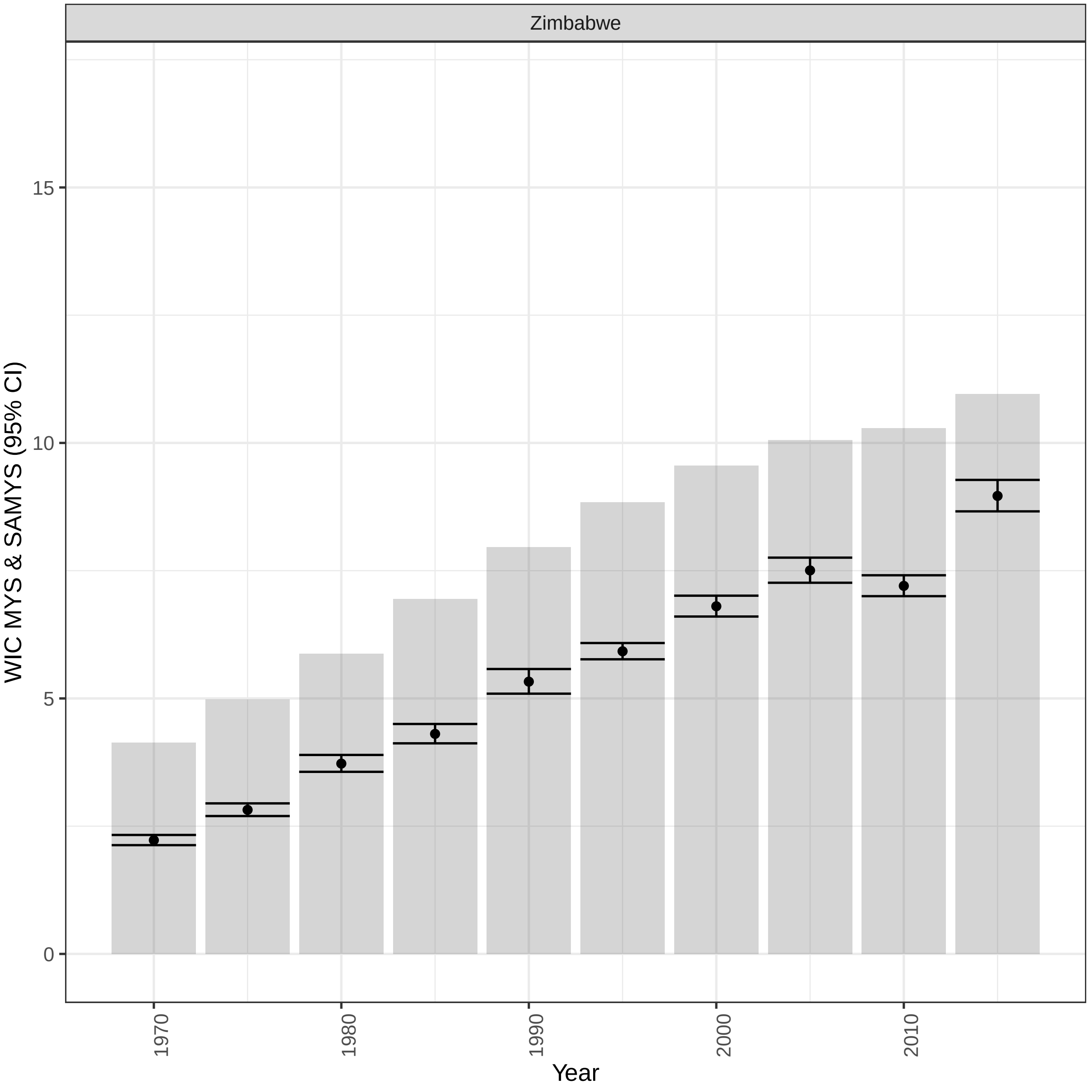
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Table A.4. Model comparisons with different estimates of QEI

DV:log(adj_factor)	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**	
Predictors	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	-0.34 (0.03)	**<0.001**	-0.59 (0.05)	**<0.001**	-0.62 (0.07)	**<0.001**	-0.63 (0.06)	**<0.001**	-0.47 (0.07)	**<0.001**	-0.60 (0.06)	**<0.001**	-0.59 (0.05)	**<0.001**
highLS	0.32 (0.04)	**<0.001**	0.28 (0.03)	**<0.001**	0.29 (0.04)	**<0.001**	0.34 (0.04)	**<0.001**	0.35 (0.04)	**<0.001**	0.34 (0.04)	**<0.001**	0.26 (0.04)	**<0.001**
illiterate_prop	-1.27 (0.05)	**<0.001**	-1.21 (0.05)	**<0.001**	-1.15 (0.06)	**<0.001**	-1.10 (0.06)	**<0.001**	-1.26 (0.06)	**<0.001**	-1.13 (0.06)	**<0.001**	-1.18 (0.05)	**<0.001**
year_1970	0.19 (0.03)	**<0.001**	0.18 (0.03)	**<0.001**	0.19 (0.03)	**<0.001**	0.19 (0.03)	**<0.001**	0.19 (0.03)	**<0.001**	0.18 (0.03)	**<0.001**	0.18 (0.03)	**<0.001**
year_1975	0.16 (0.03)	**<0.001**	0.15 (0.03)	**<0.001**	0.16 (0.03)	**<0.001**	0.16 (0.03)	**<0.001**	0.16 (0.03)	**<0.001**	0.15 (0.03)	**<0.001**	0.15 (0.03)	**<0.001**
year_1980	0.12 (0.03)	**<0.001**	0.12 (0.03)	**<0.001**	0.13 (0.03)	**<0.001**	0.14 (0.03)	**<0.001**	0.13 (0.03)	**<0.001**	0.11 (0.03)	**<0.001**	0.12 (0.03)	**<0.001**
year_1985	0.08 (0.03)	**0.002**	0.08 (0.03)	**0.002**	0.08 (0.03)	**0.004**	0.09 (0.03)	**0.003**	0.07 (0.03)	**0.013**	0.07 (0.03)	**0.020**	0.08 (0.03)	**0.002**
year_1990	0.07 (0.03)	**0.010**	0.07 (0.03)	**0.007**	0.09 (0.03)	**0.002**	0.09 (0.03)	**0.002**	0.08 (0.03)	**0.010**	0.06 (0.03)	0.055	0.07 (0.03)	**0.006**
year_1995	0.04 (0.03)	0.138	0.04 (0.03)	0.087	0.04 (0.03)	0.199	0.04 (0.03)	0.202	0.04 (0.03)	0.172	0.03 (0.03)	0.293	0.04 (0.03)	0.083
year_2000	0.02 (0.02)	0.425	0.03 (0.02)	0.146	0.03 (0.03)	0.248	0.02 (0.03)	0.423	0.03 (0.03)	0.278	0.01 (0.03)	0.594	0.03 (0.02)	0.147
year_2005	0.00 (0.02)	0.894	0.02 (0.02)	0.404	0.01 (0.02)	0.662	-0.00 (0.02)	0.885	0.01 (0.02)	0.579	-0.00 (0.02)	0.843	0.02 (0.02)	0.436

year_2010	0.01 (0.02)	0.806	0.02 (0.02)	0.331	0.01 (0.02)	0.712	-0.01 (0.02)	0.815	0.01 (0.02)	0.632	-0.01 (0.02)	0.713	0.02 (0.02)	0.350
old_dep	0.41 (0.12)	**0.001**											0.25 (0.12)	**0.039**
hlo			0.00 (0.00)	**<0.001**									0.00 (0.00)	**<0.001**
hlo1					0.00 (0.00)	**<0.001**								
hlo2							0.00 (0.00)	**<0.001**						
hlo3									0.00 (0.00)	**0.025**				
hlo4											0.00 (0.00)	**<0.001**		
Observations	577		577		486		451		486		451		577	
R^2 / R^2 adjusted	0.851 / 0.848		0.858 / 0.855		0.855 / 0.852		0.853 / 0.849		0.851 / 0.848		0.852 / 0.848		0.859 / 0.855	

NOTES:

QEI1 is imputed using closest year values and regional averages.

QEI2, QEI3, QEI4 and QEI5 are imputed using linear models where empirical data from World Bank's Global Data Set on Education Quality (1965-2015) is dependent variable;

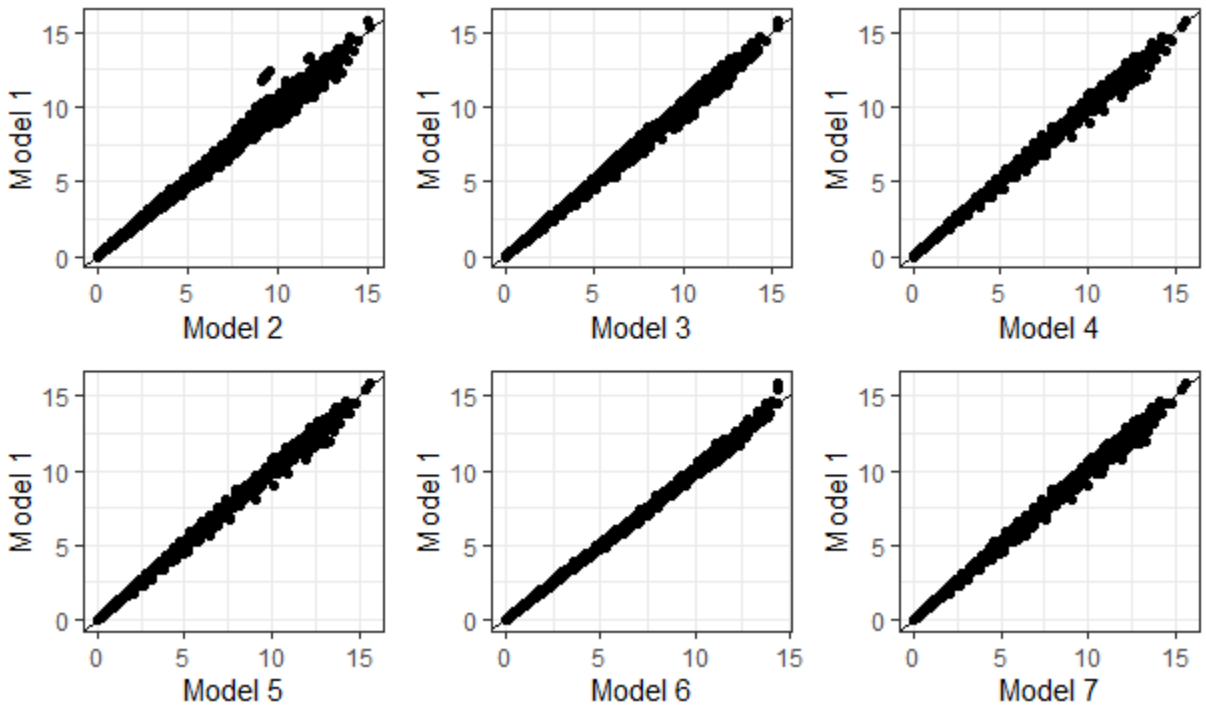
Estimators for QEI2: region (UN detailed geographical regions), pupil-teacher ratio (UIS, pupil-teacher ratio in primary education), educational expenditure (UIS, government expenditure on education as a percentage of GDP), year periods

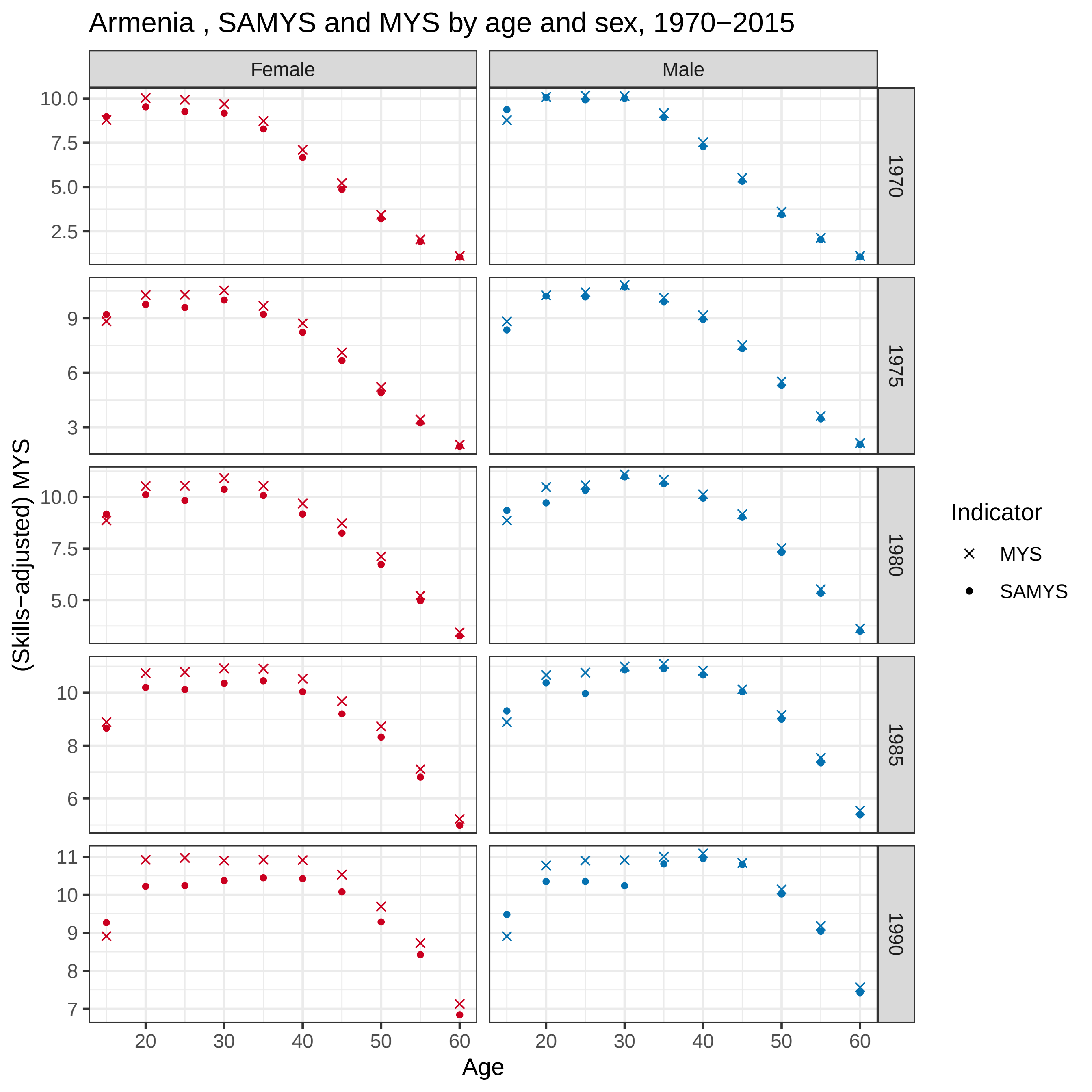
Estimators for QEI3: country, pupil-teacher ratio (UIS, pupil-teacher ratio in primary education), educational expenditure (UIS, government expenditure on education as a percentage of GDP), year periods

Estimators for QEI4: pupil-teacher ratio (UIS, pupil-teacher ratio in primary education), educational expenditure (UIS, government expenditure on education as a percentage of GDP), year periods

Estimators for QEI1: country, pupil-teacher ratio (UIS, pupil-teacher ratio in primary education), educational expenditure (UIS, government expenditure on education as a percentage of GDP)

Figure A.4. Comparison of SAMYS estimates of the models summarized in Table A.4.




Armenia , SAMYS and MYS by age and sex, 1970−2015
Female
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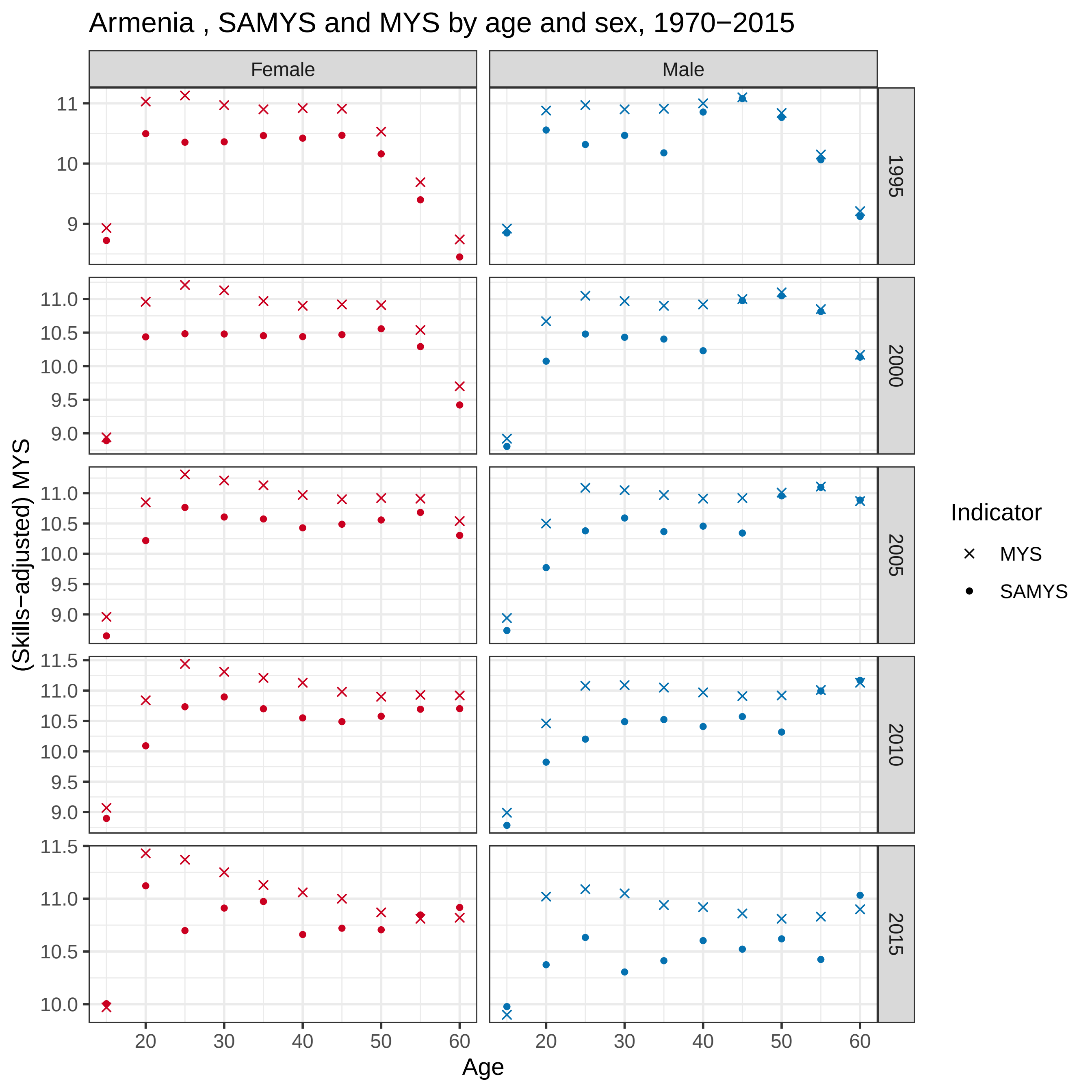
Armenia , SAMYS and MYS by age and sex, 1970−2015
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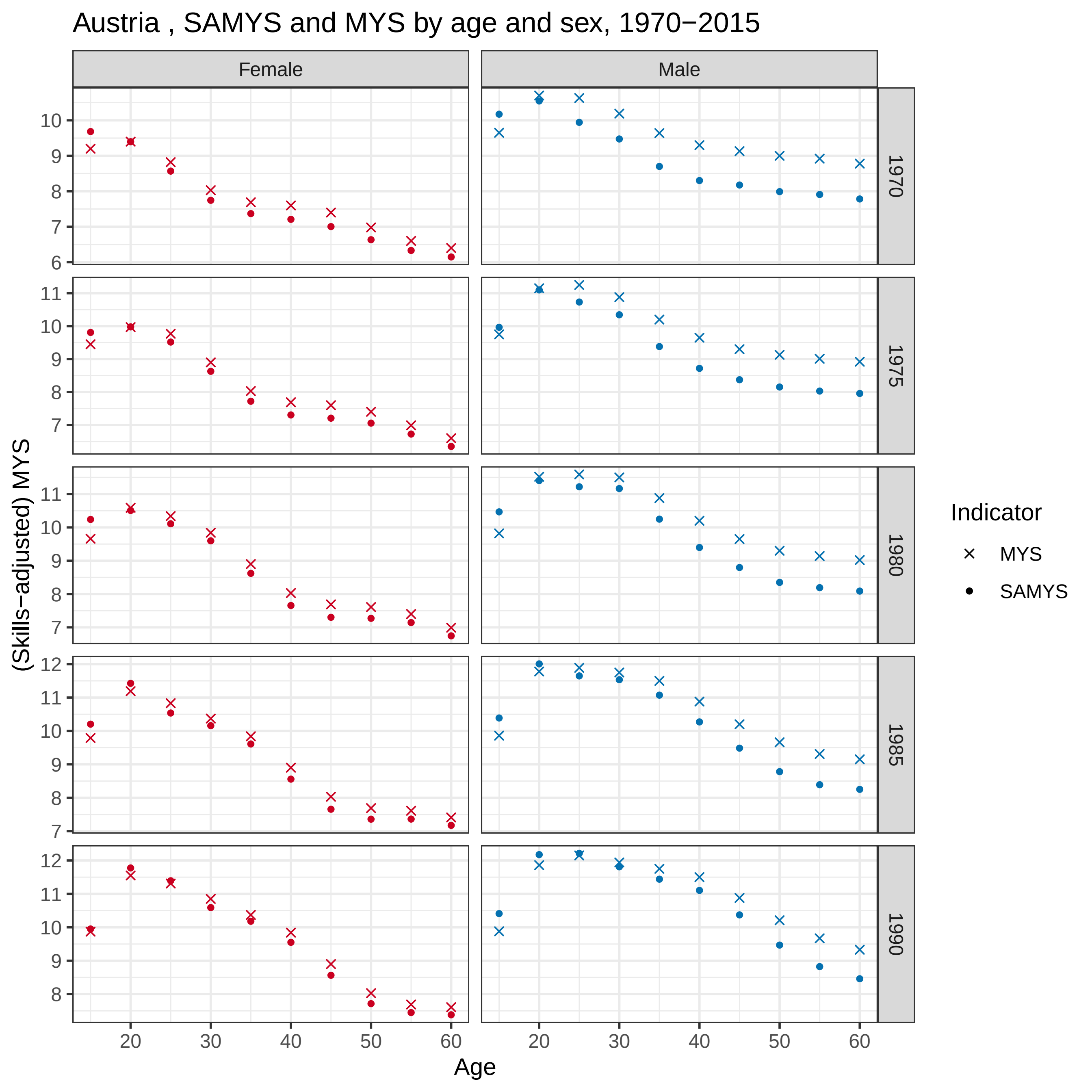

Austria , SAMYS and MYS by age and sex, 1970−2015
Female
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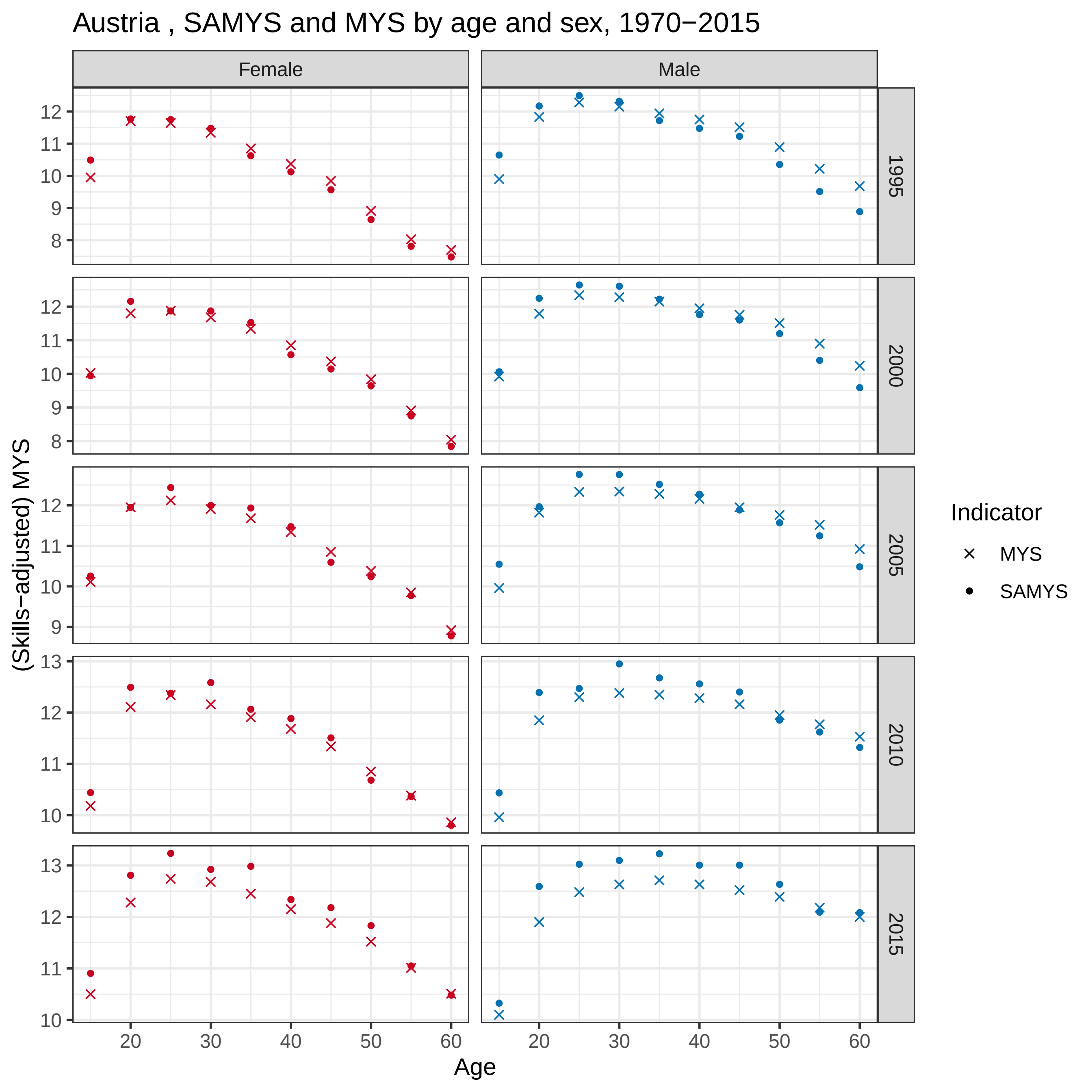
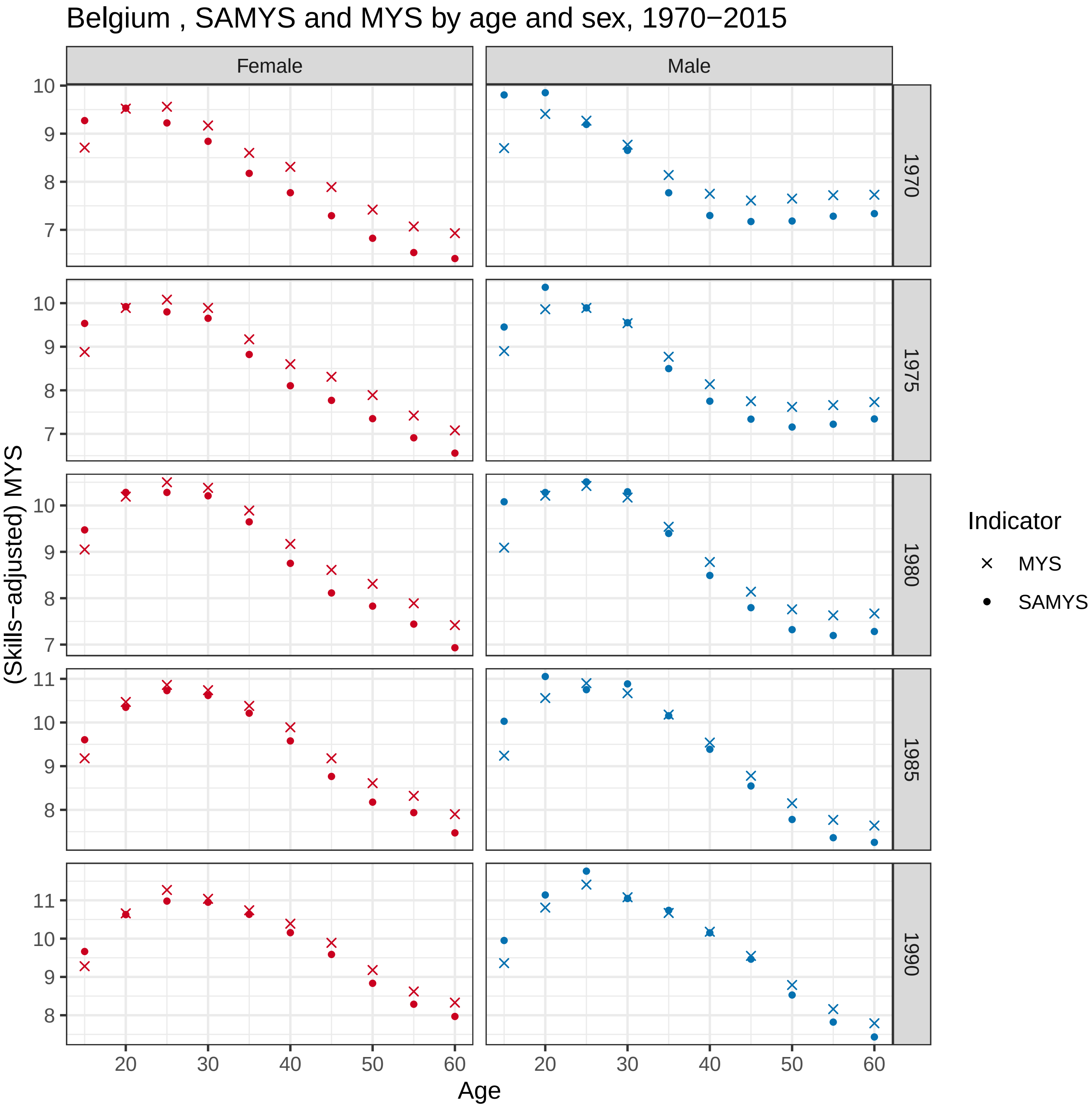
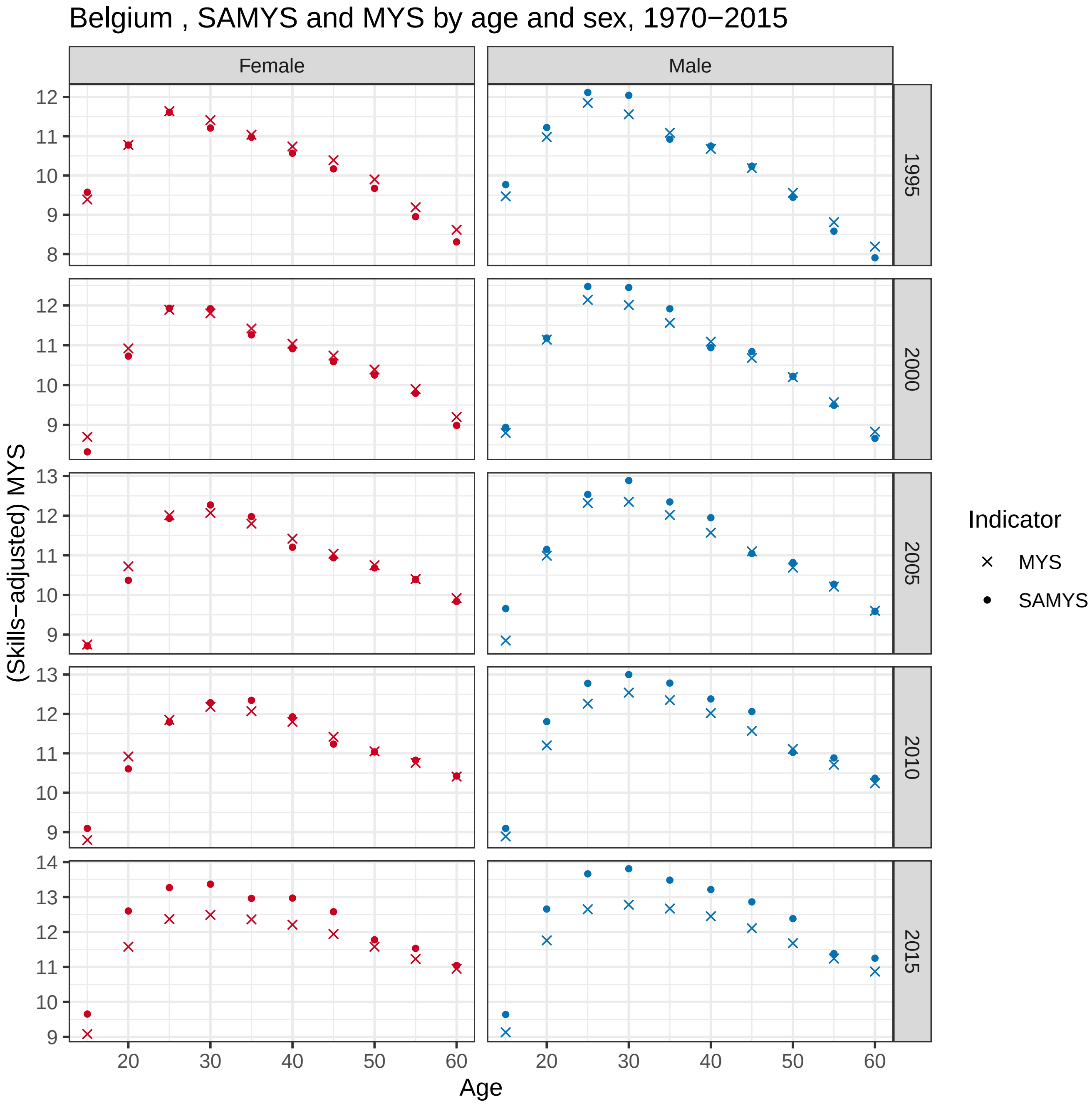
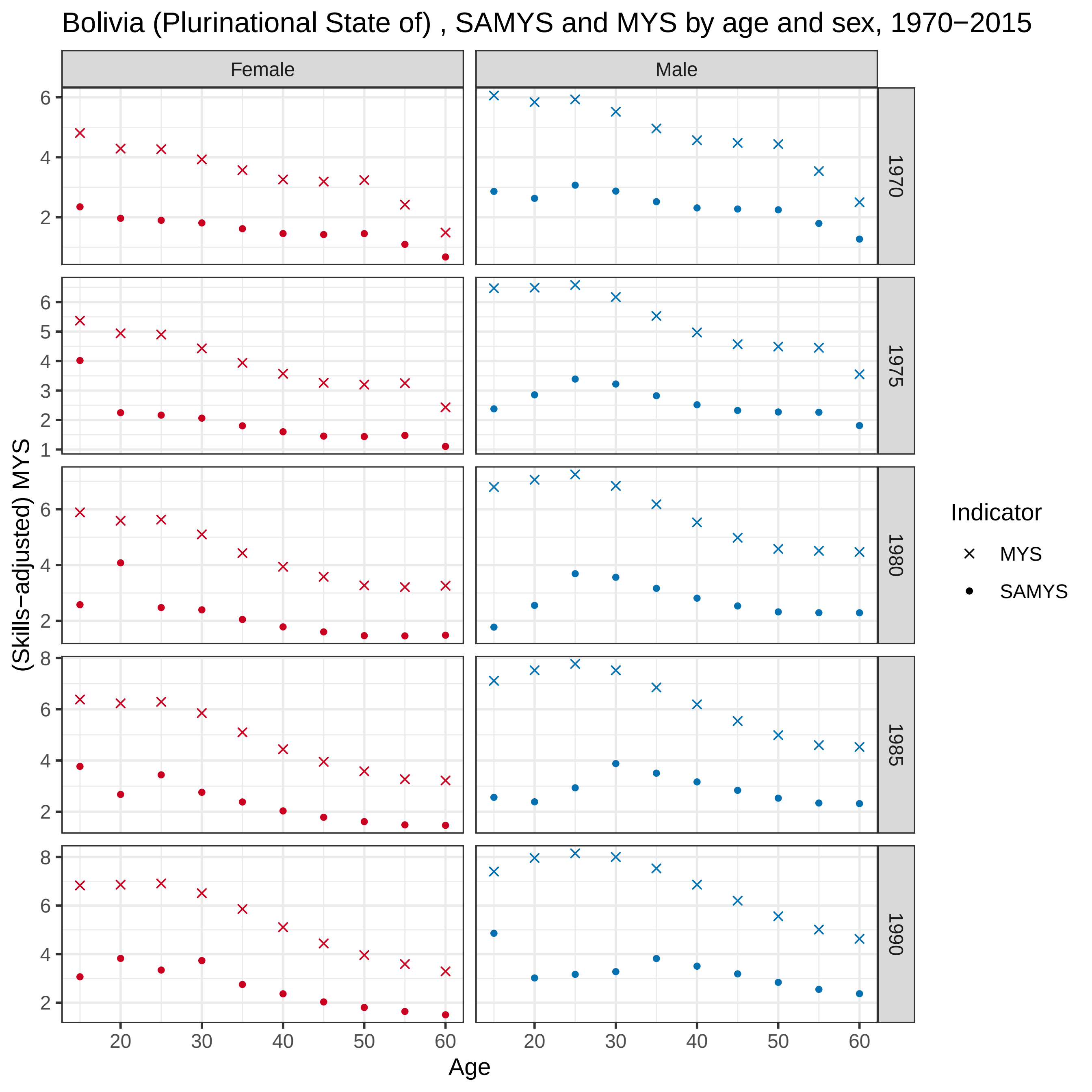
MYS
SAMYS


Austria , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

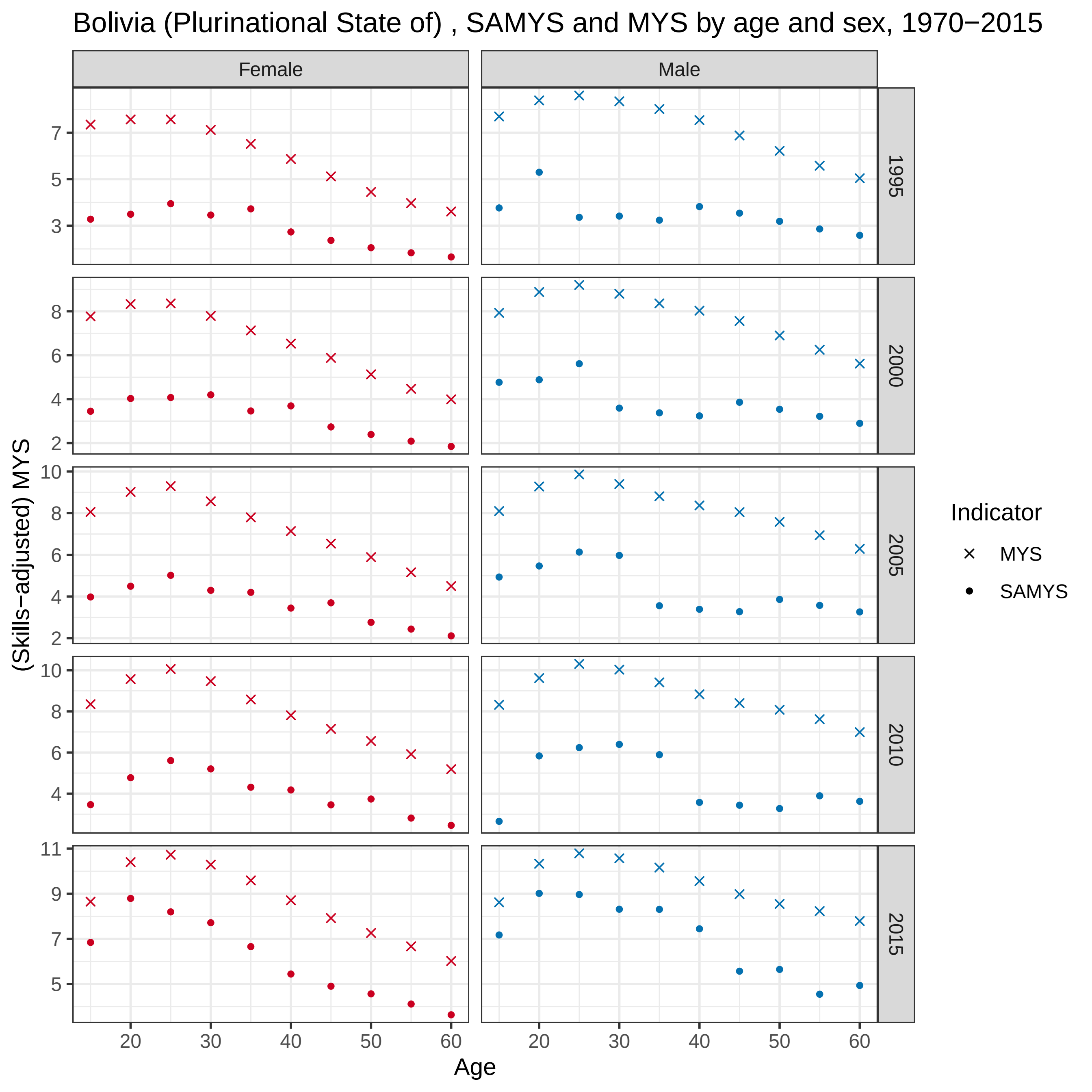


Belgium , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

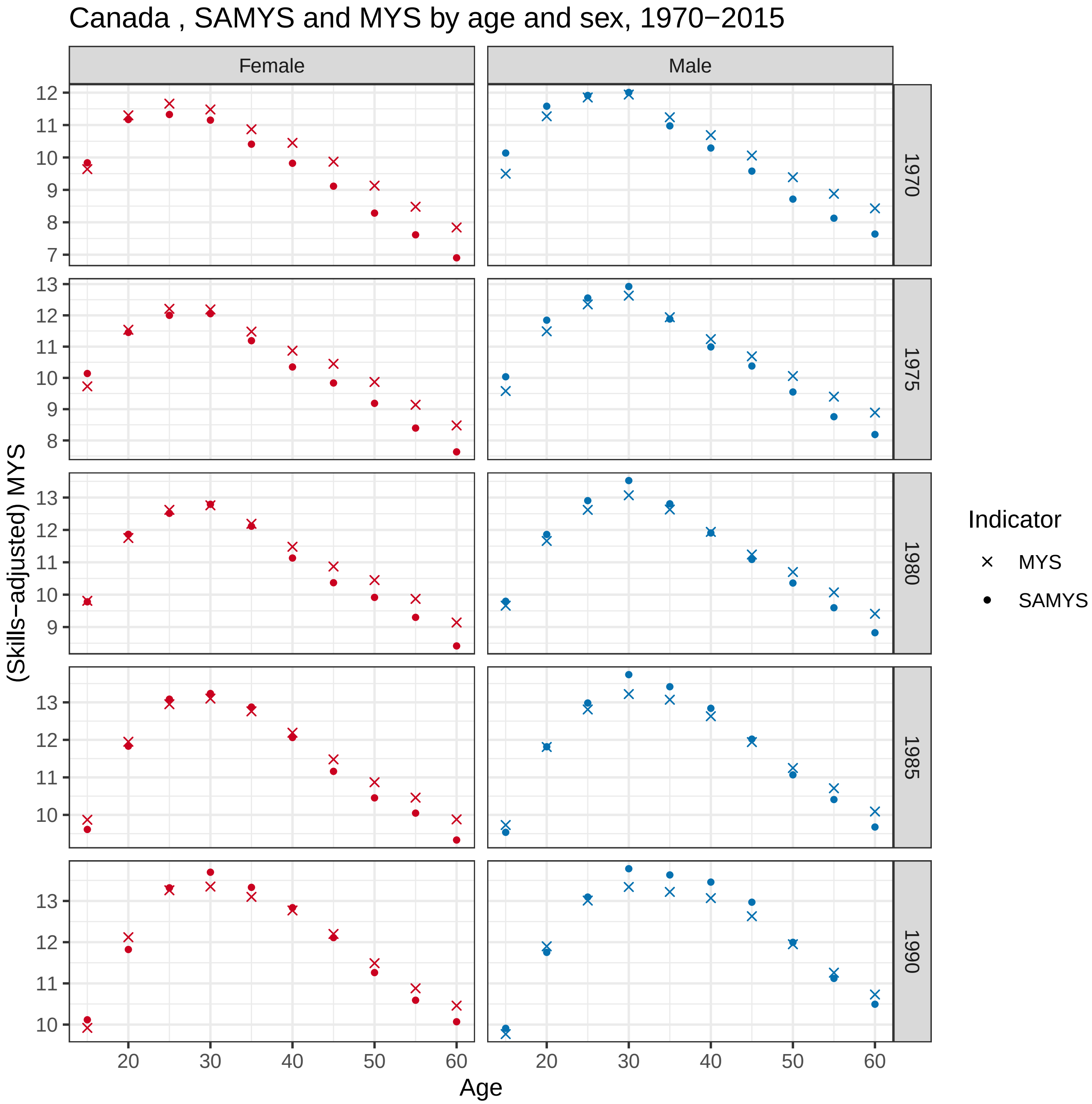

Belgium , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

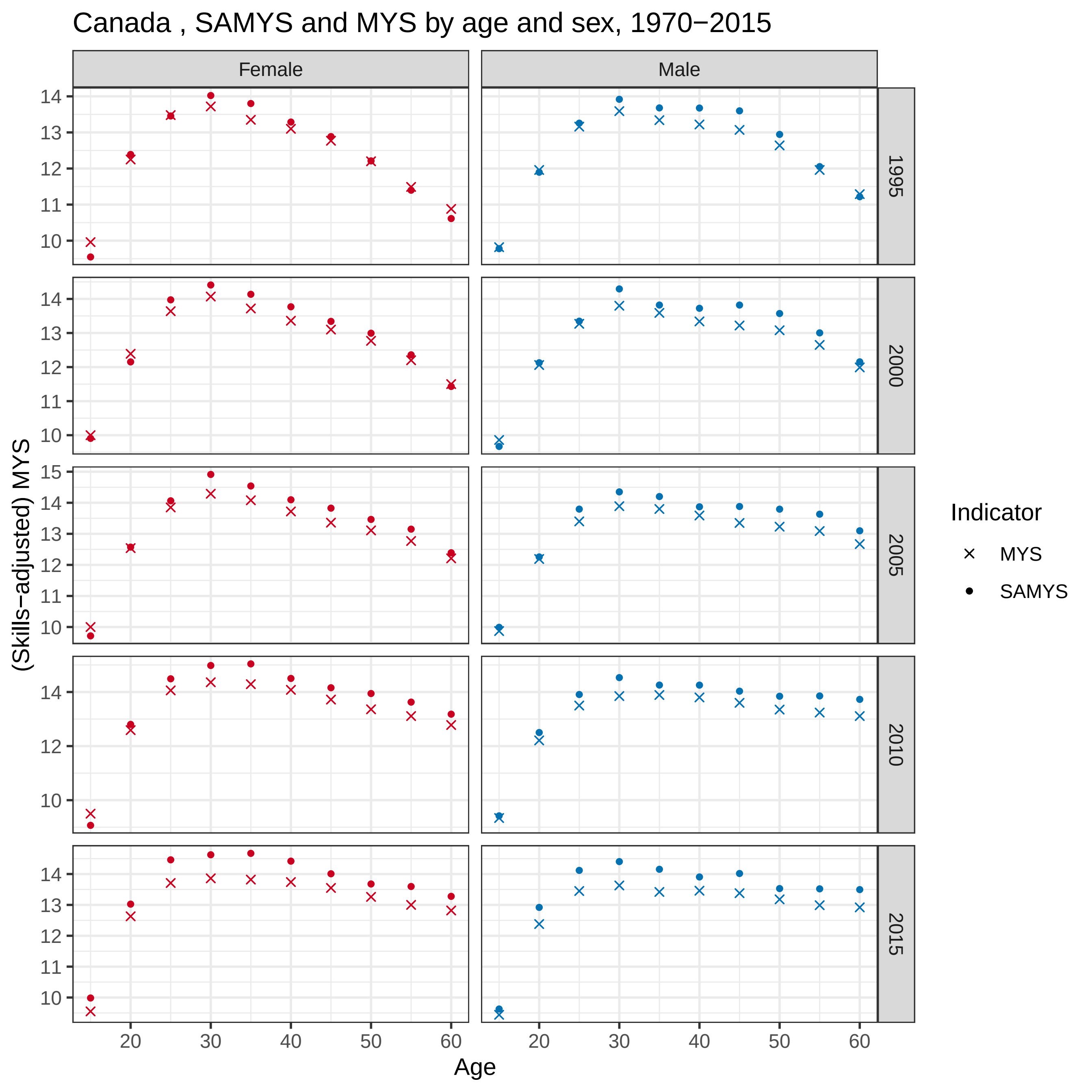


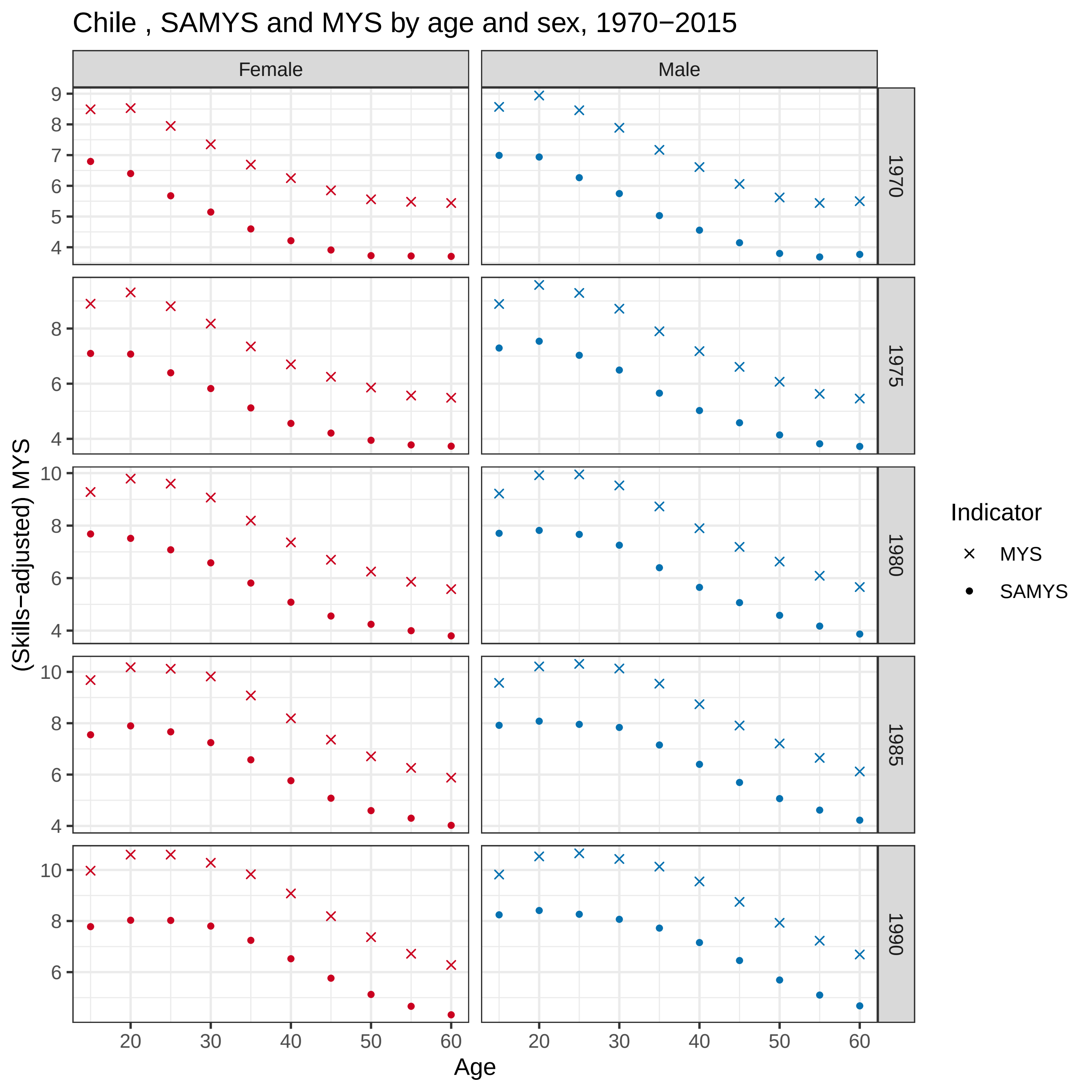
Bolivia (Plurinational State of) , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

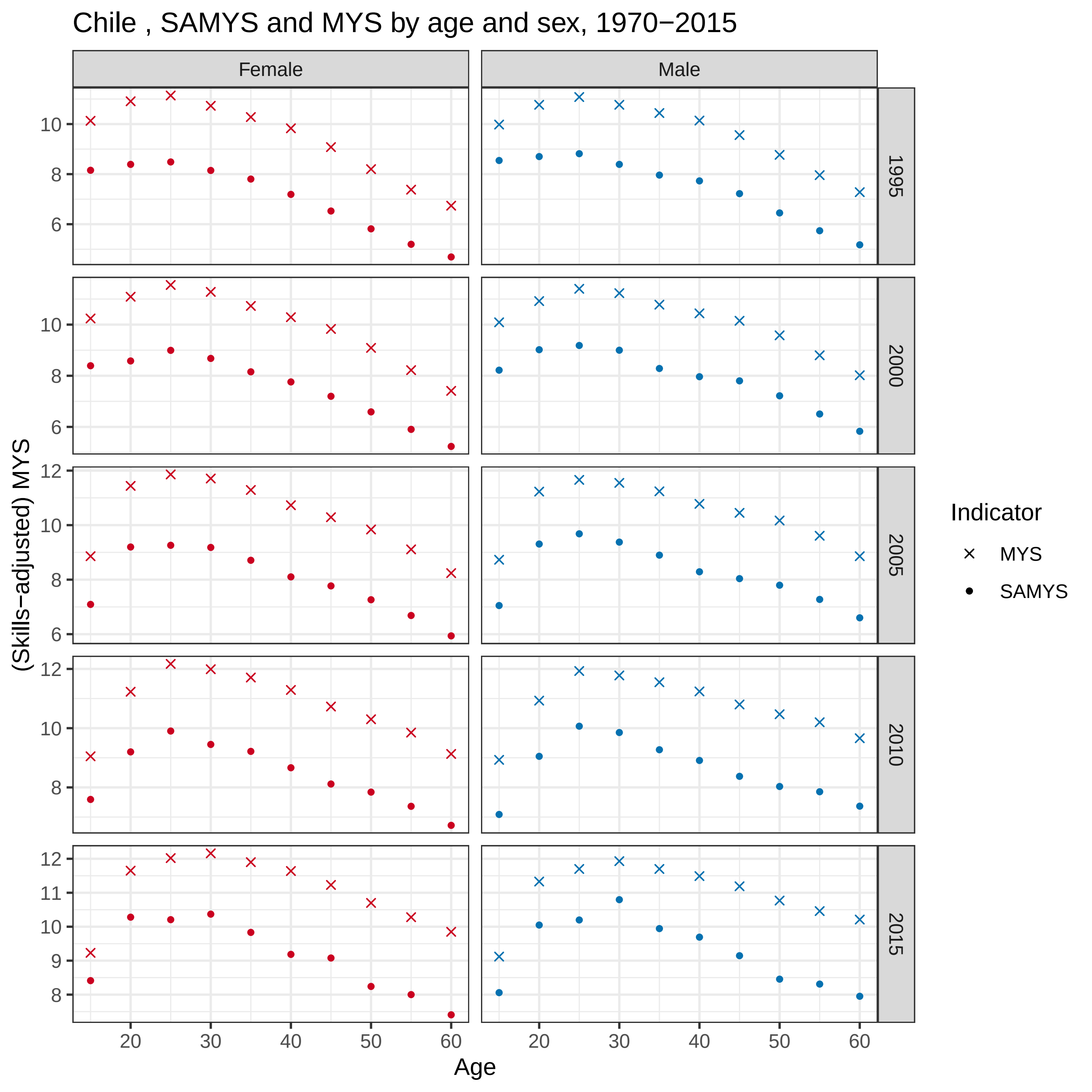


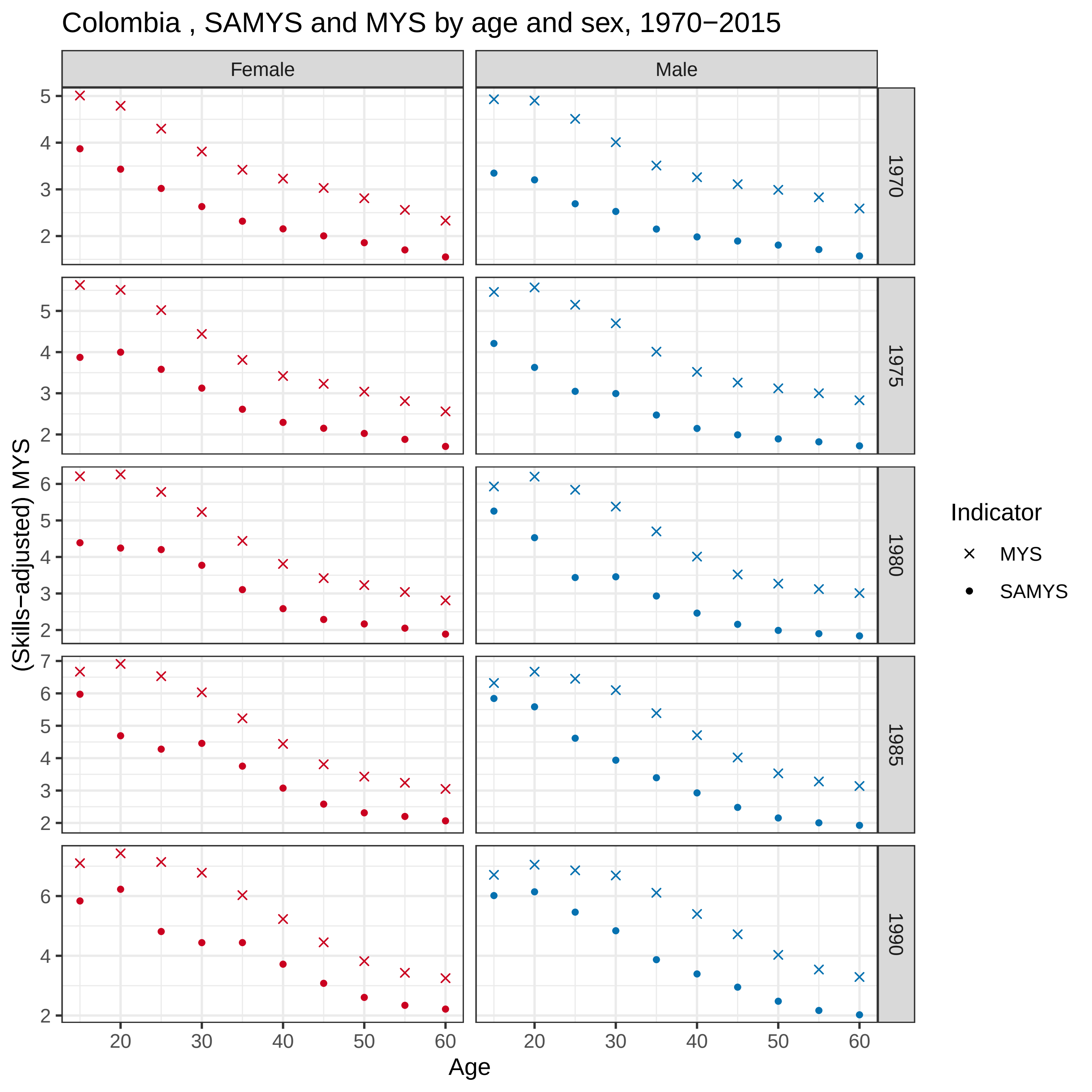
Bolivia (Plurinational State of) , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

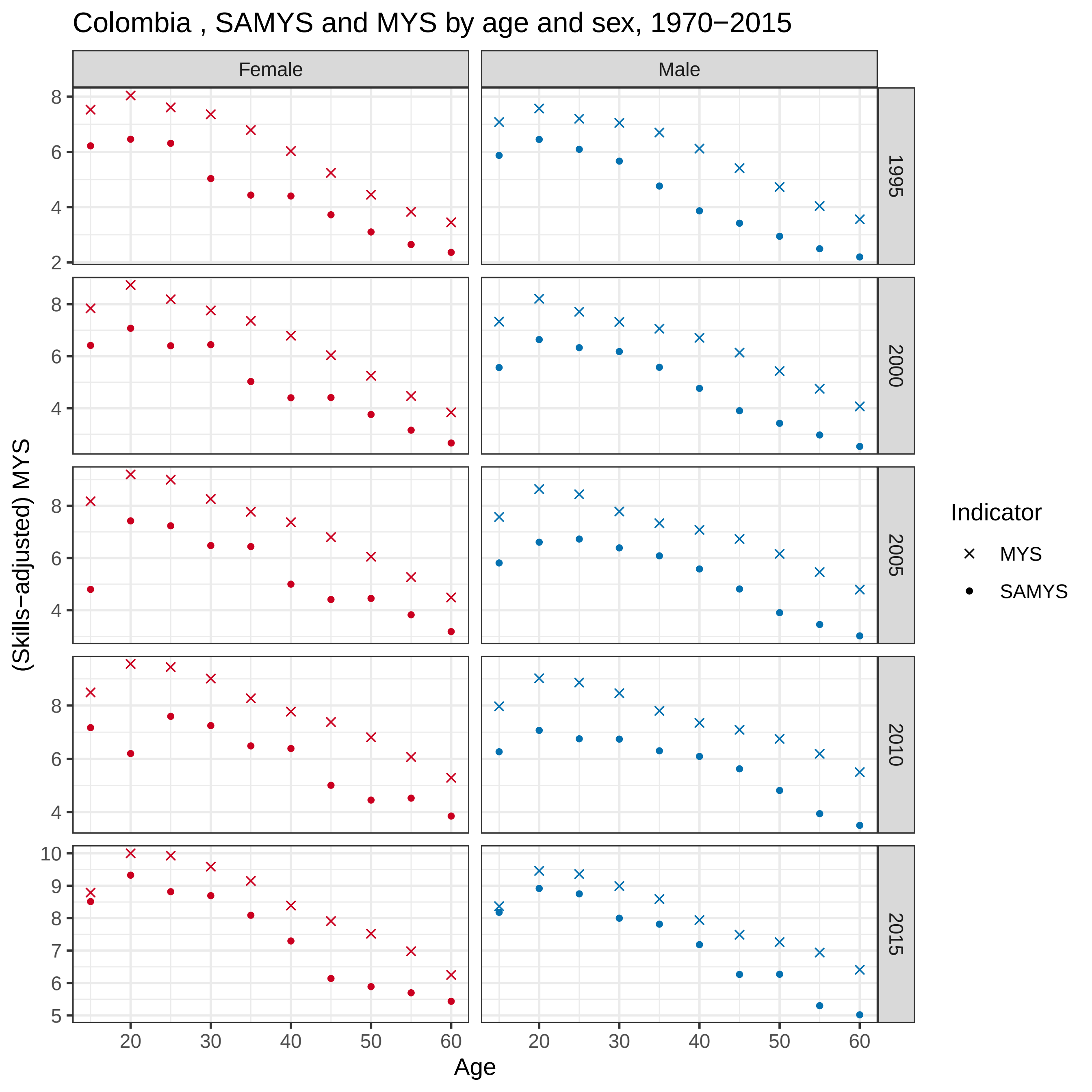

Canada , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Canada , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

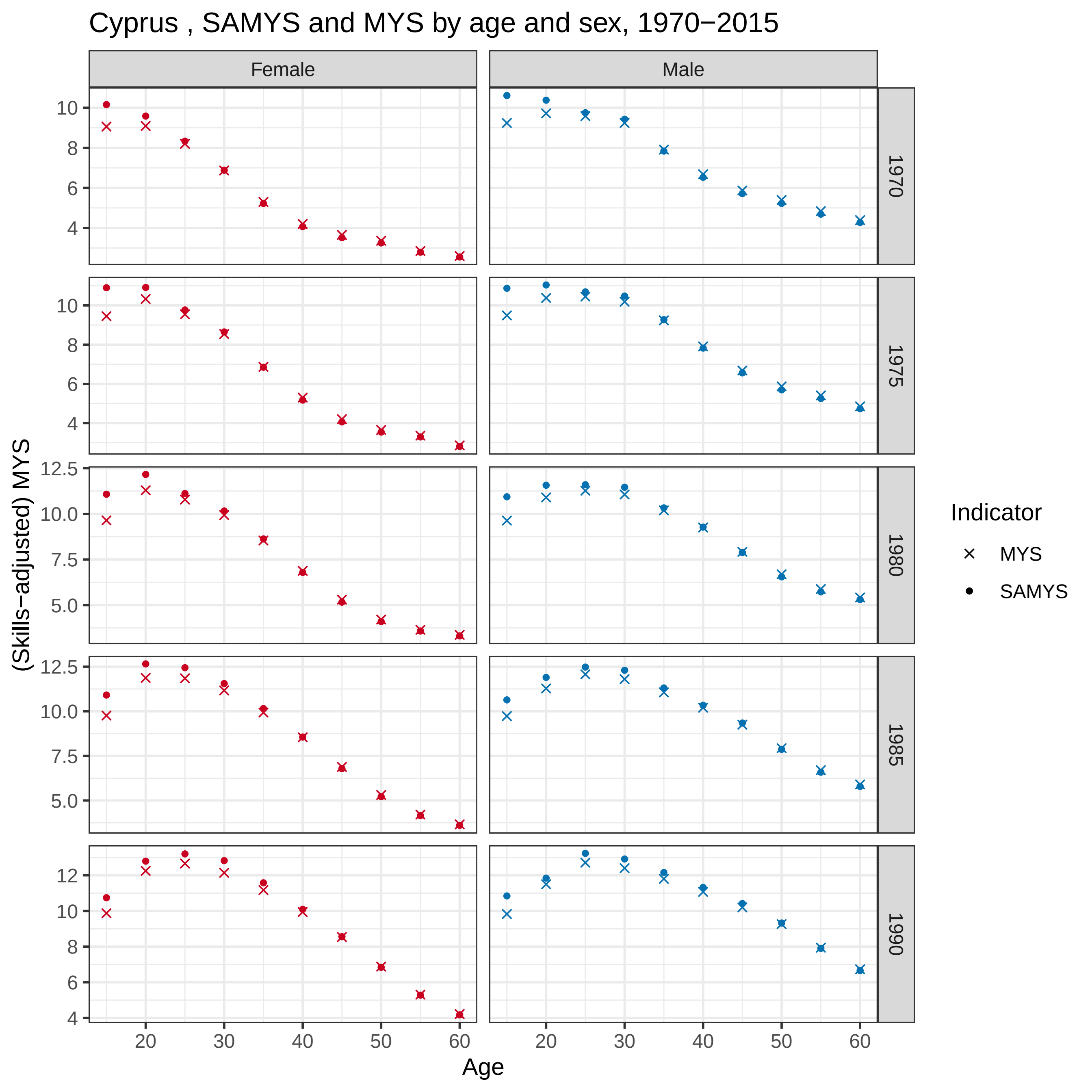

Chile , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Chile , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

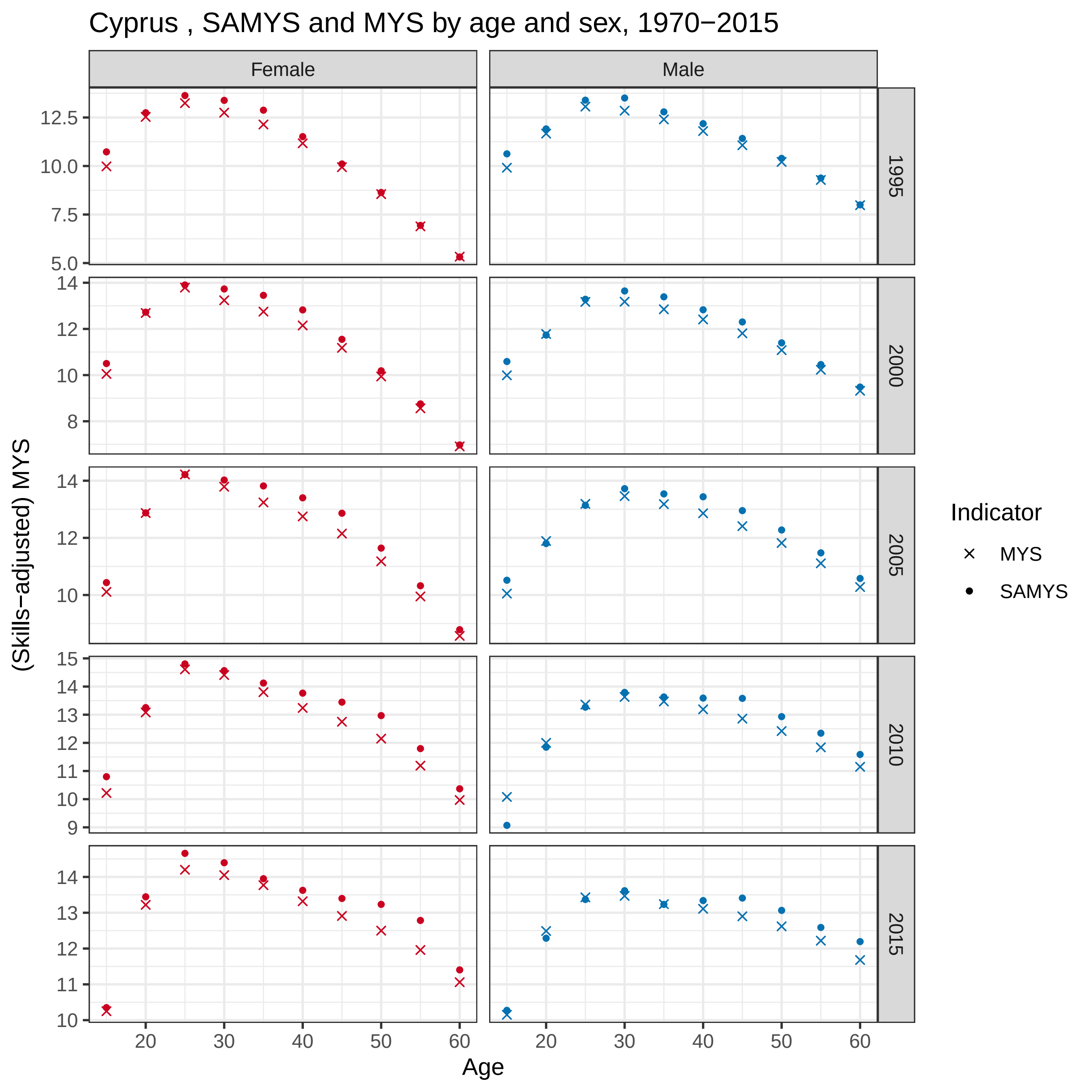

Colombia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



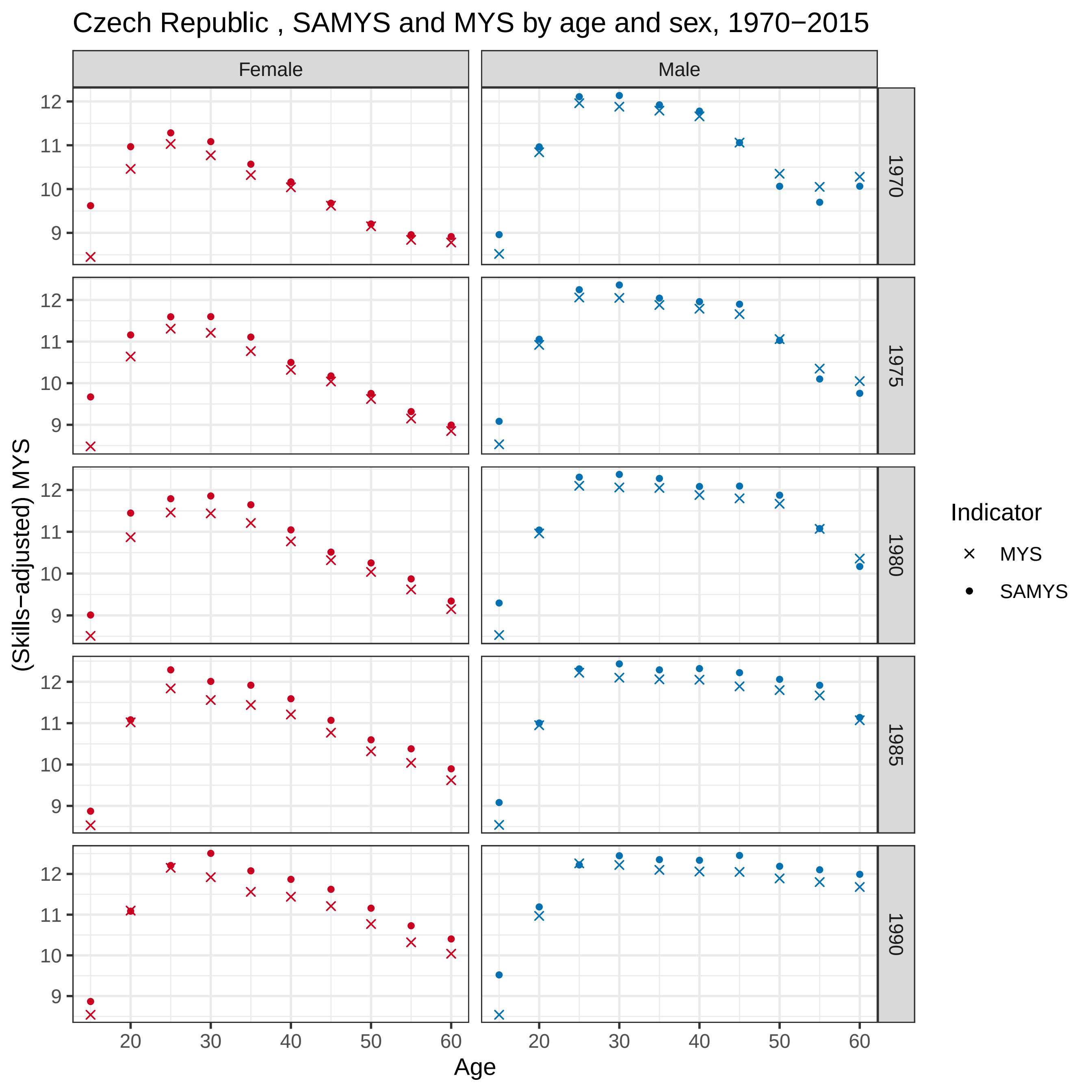
Colombia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



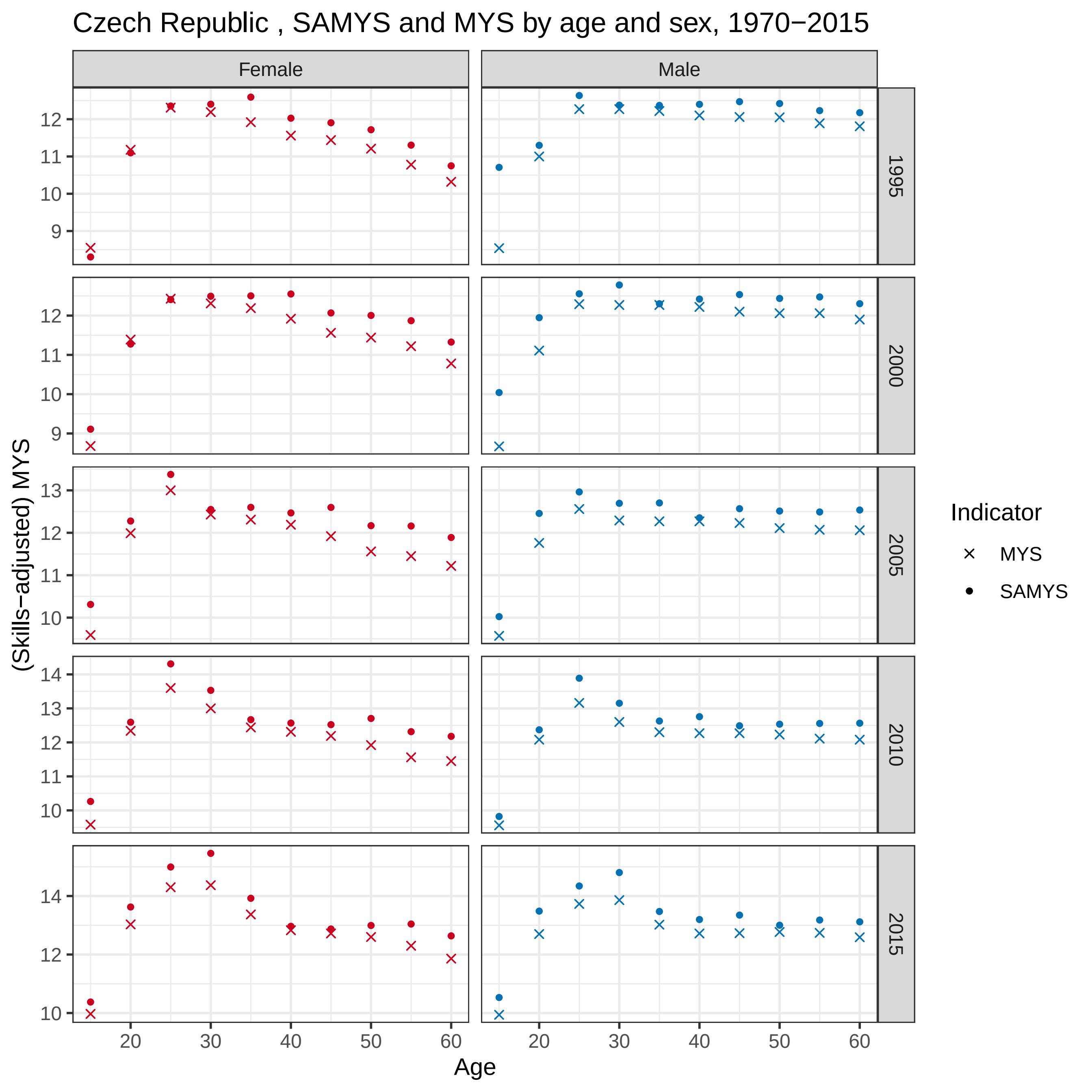
Cyprus , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

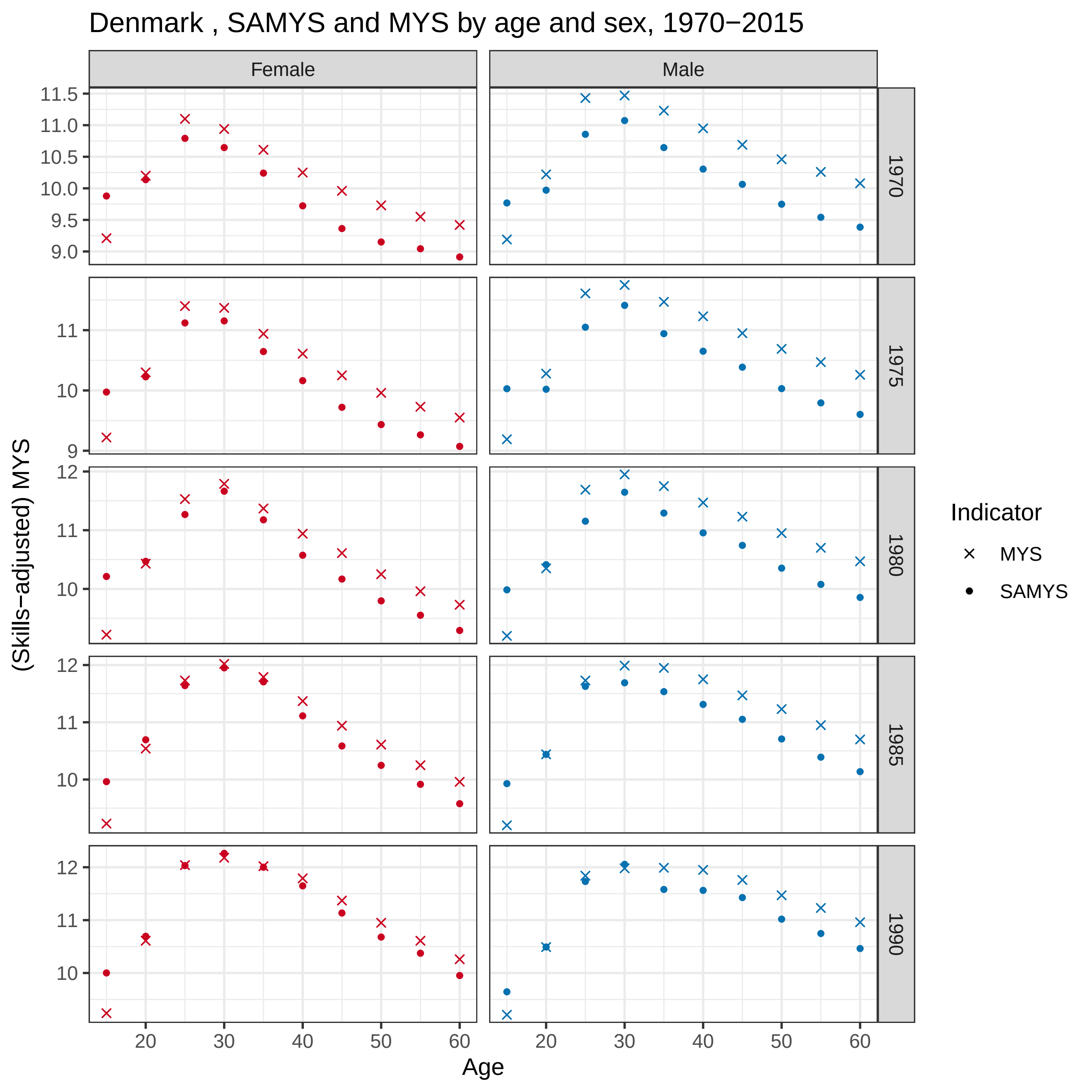


Cyprus , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

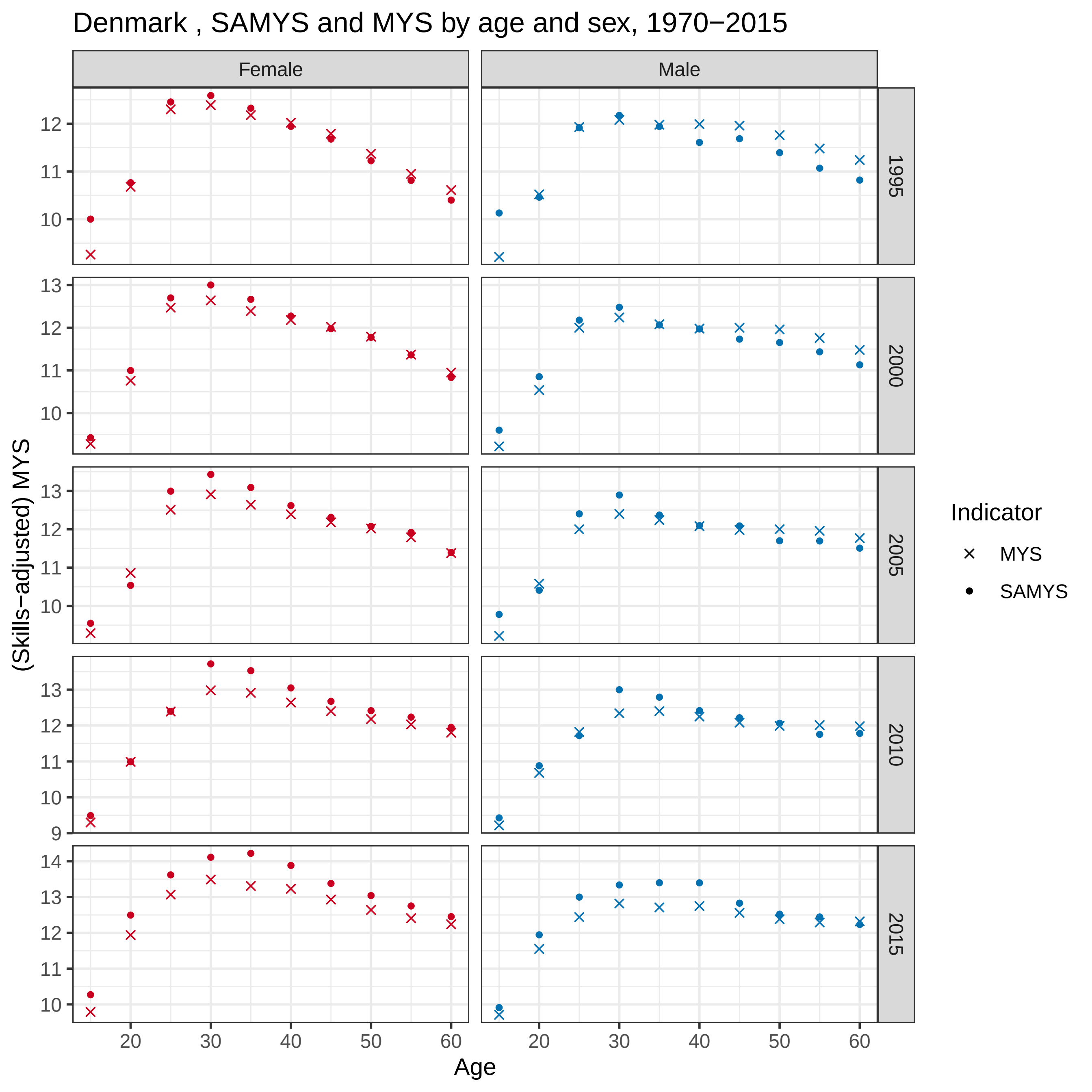


Czech Republic , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

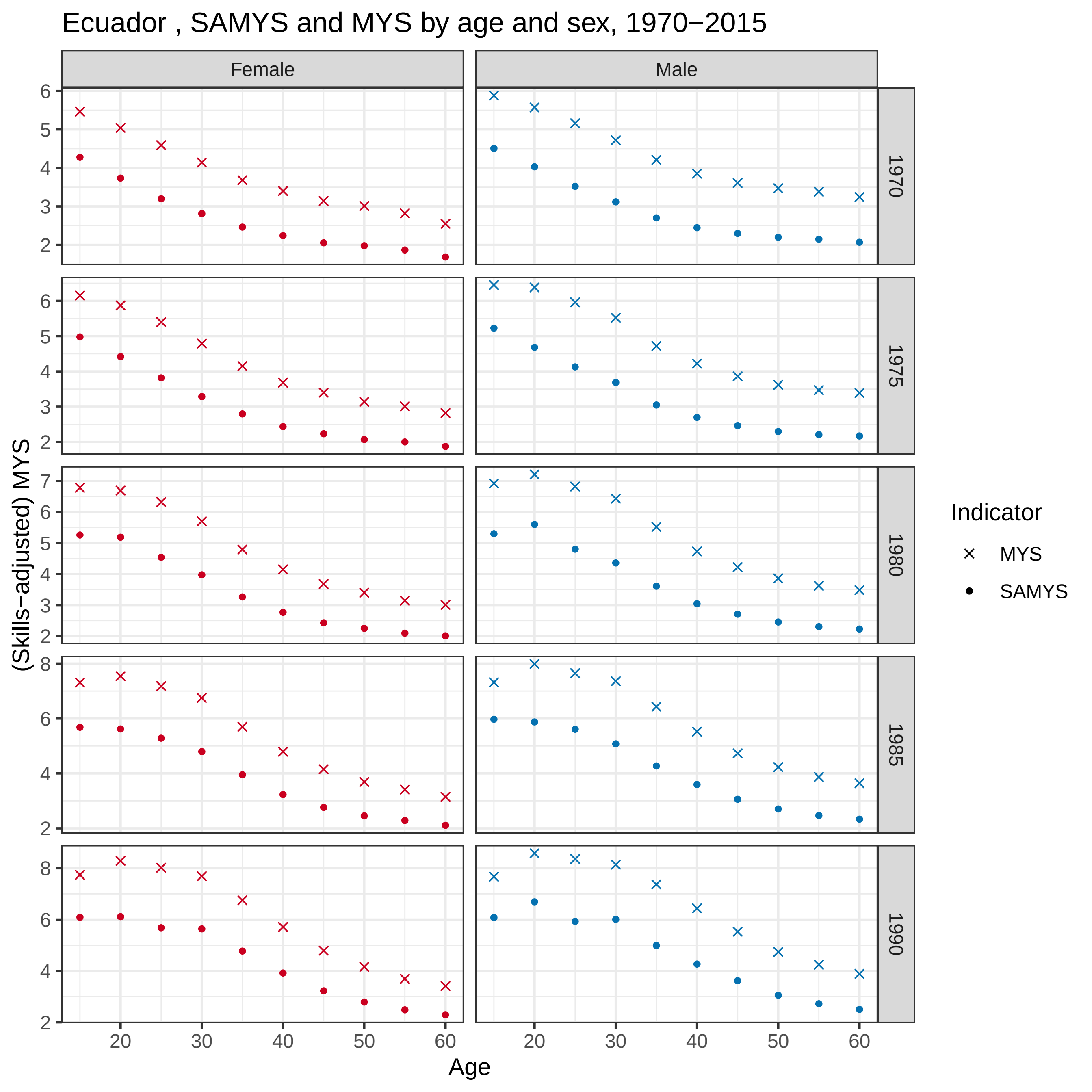

Czech Republic , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



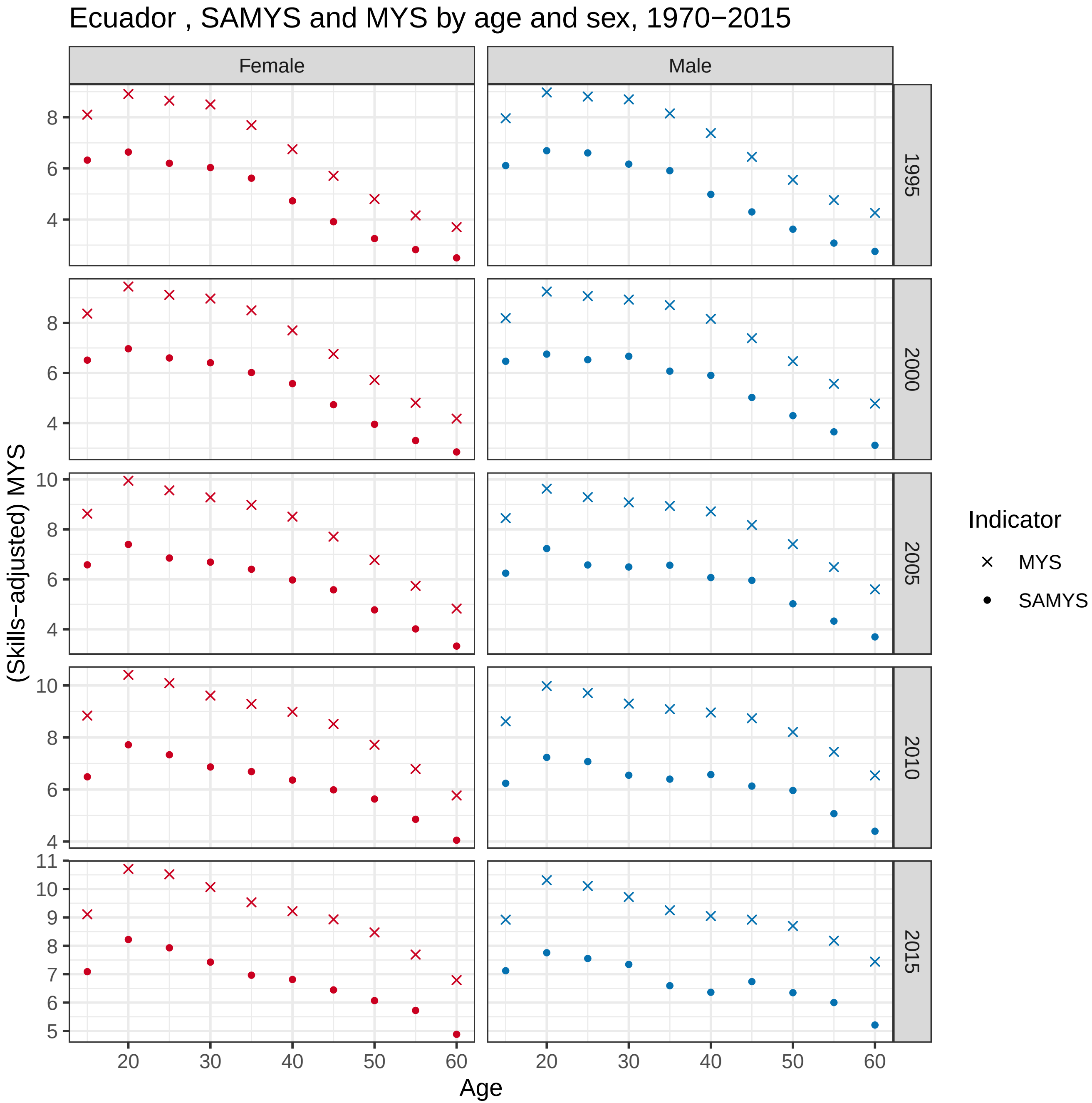
Denmark , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

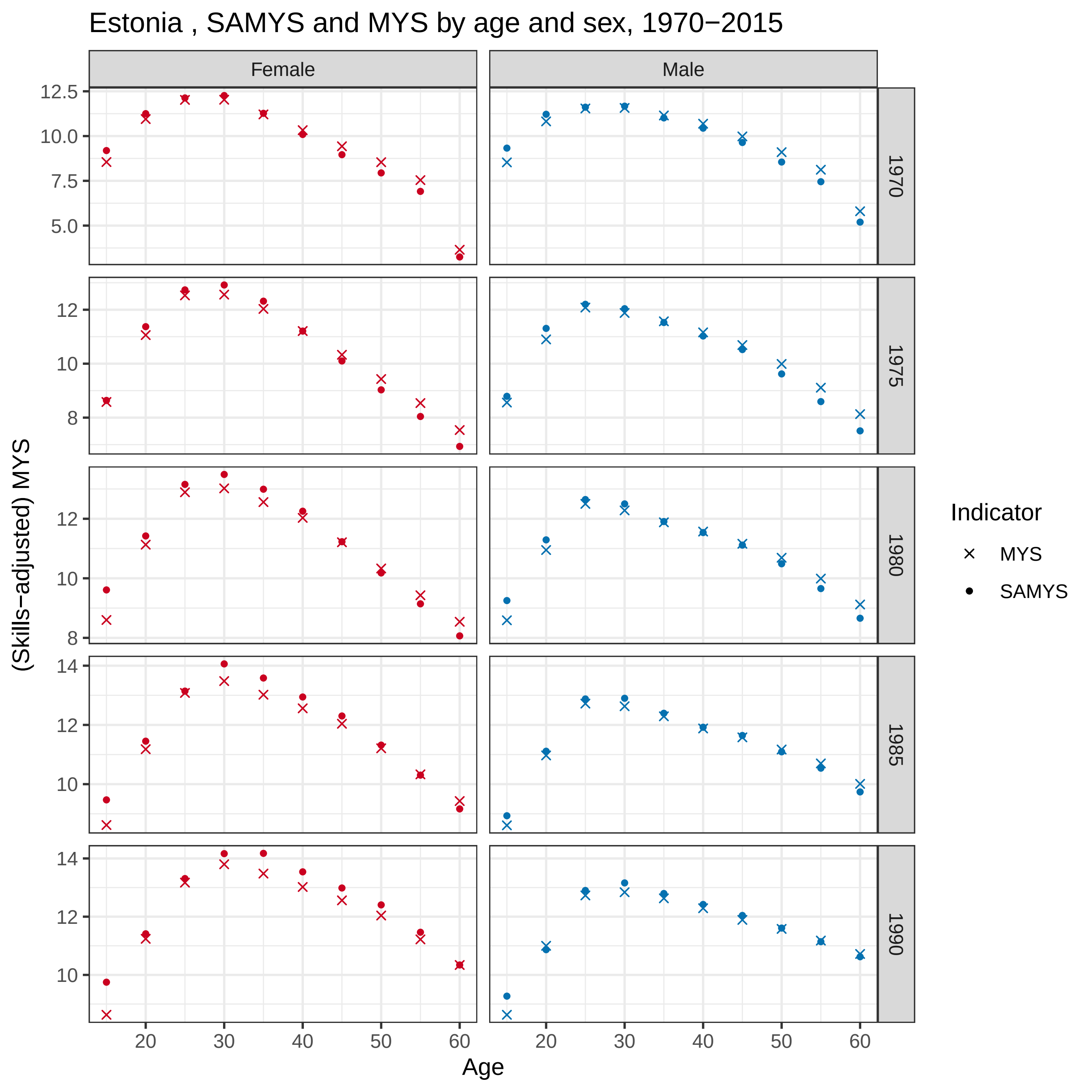


Denmark , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

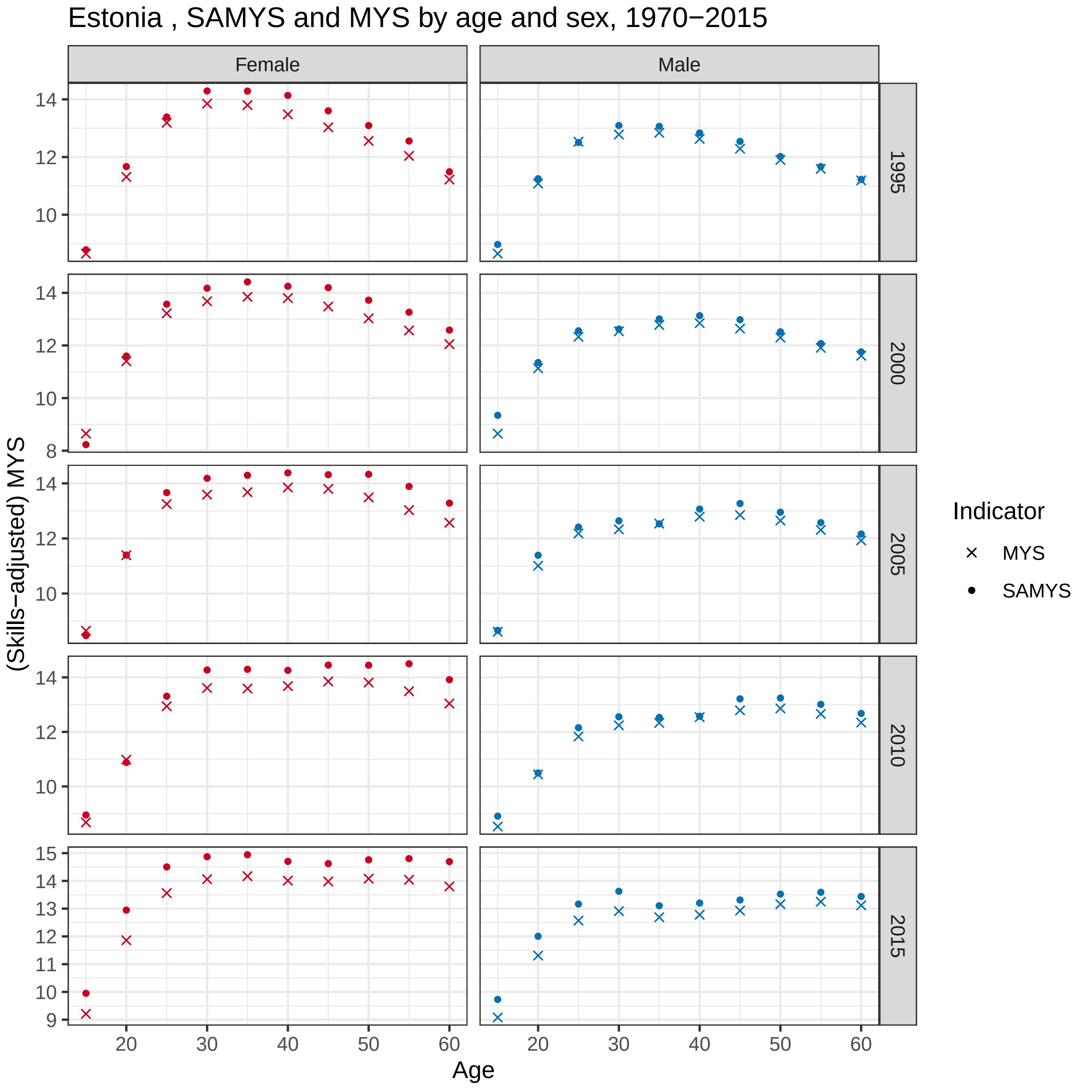


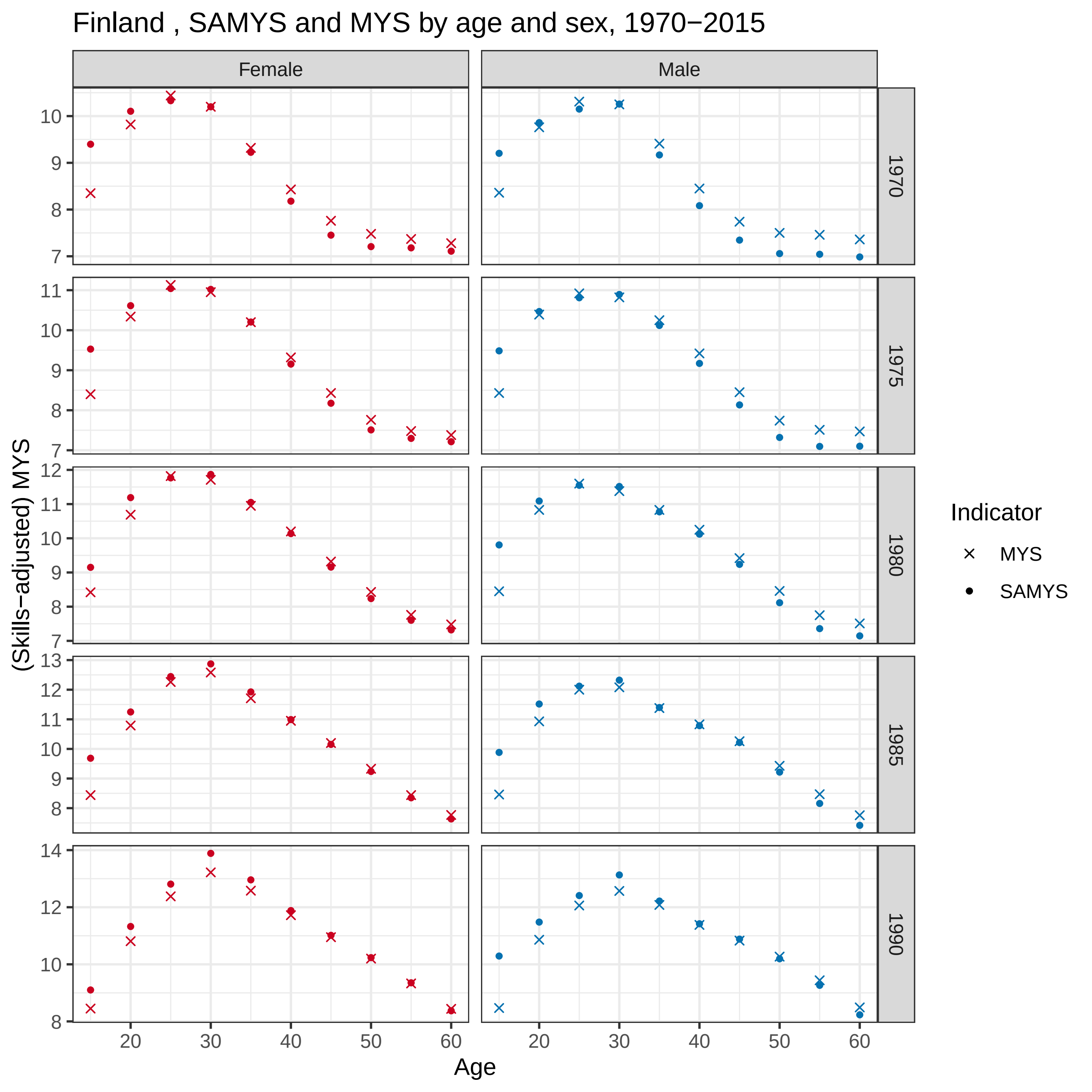
Ecuador , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Ecuador , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

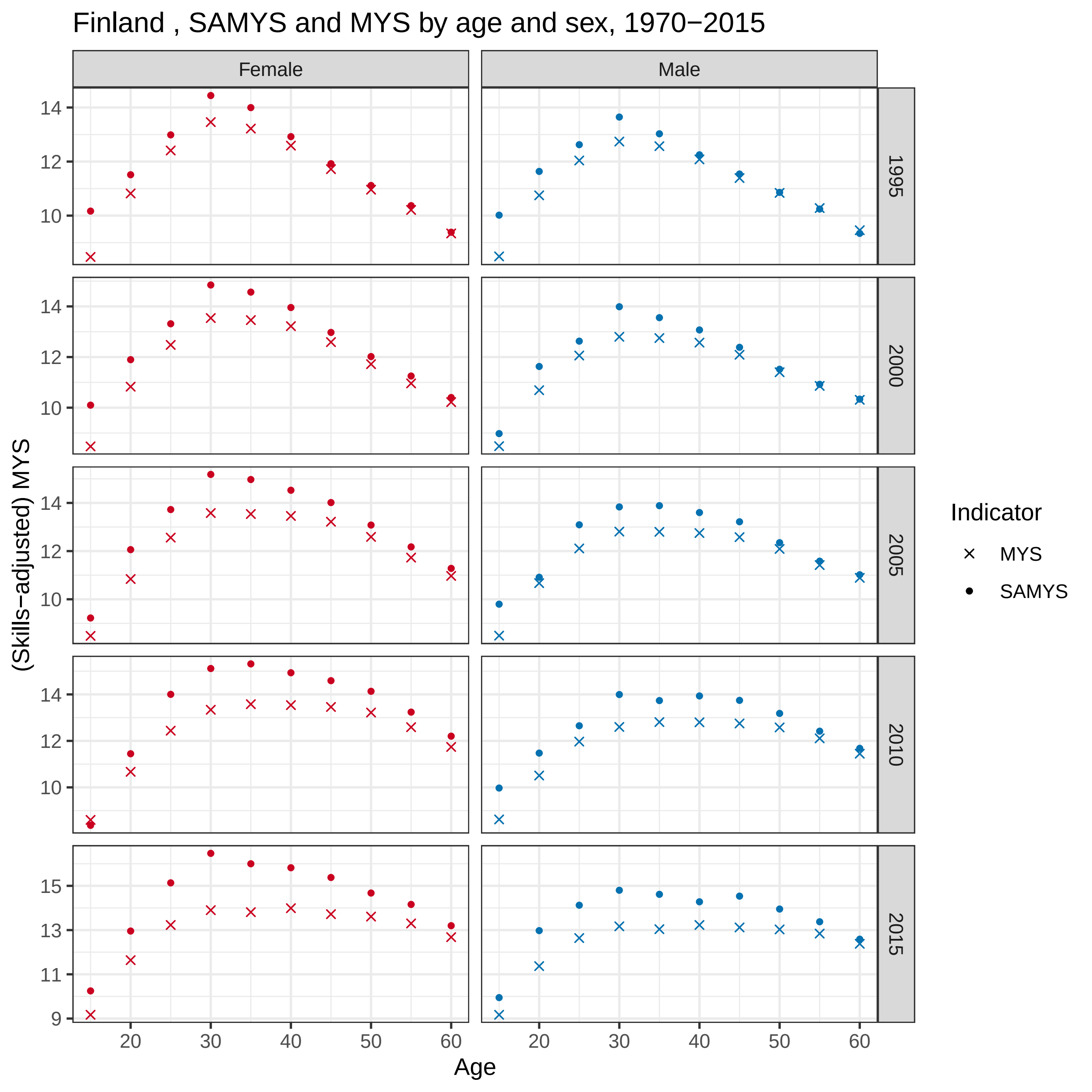


Estonia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

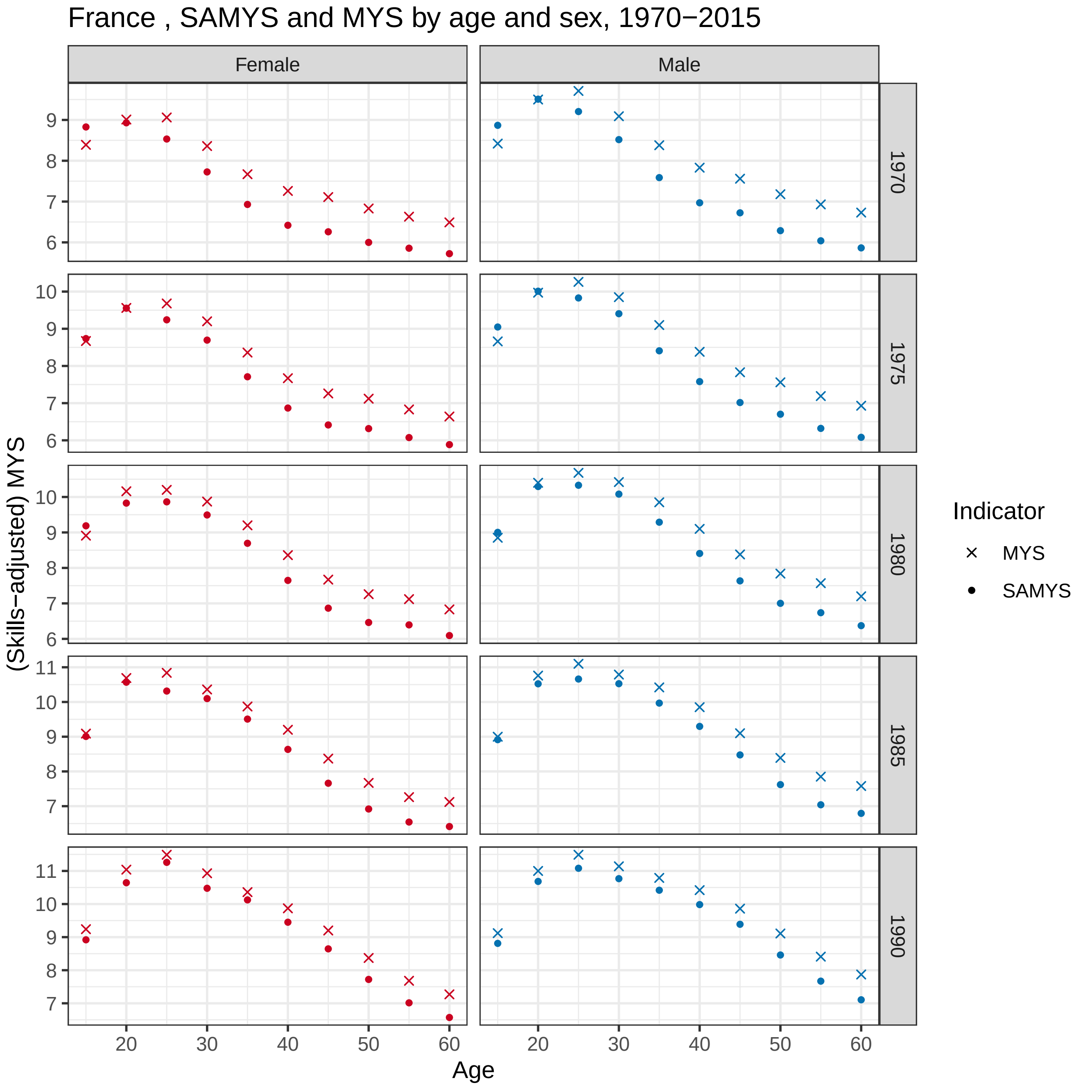

Estonia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



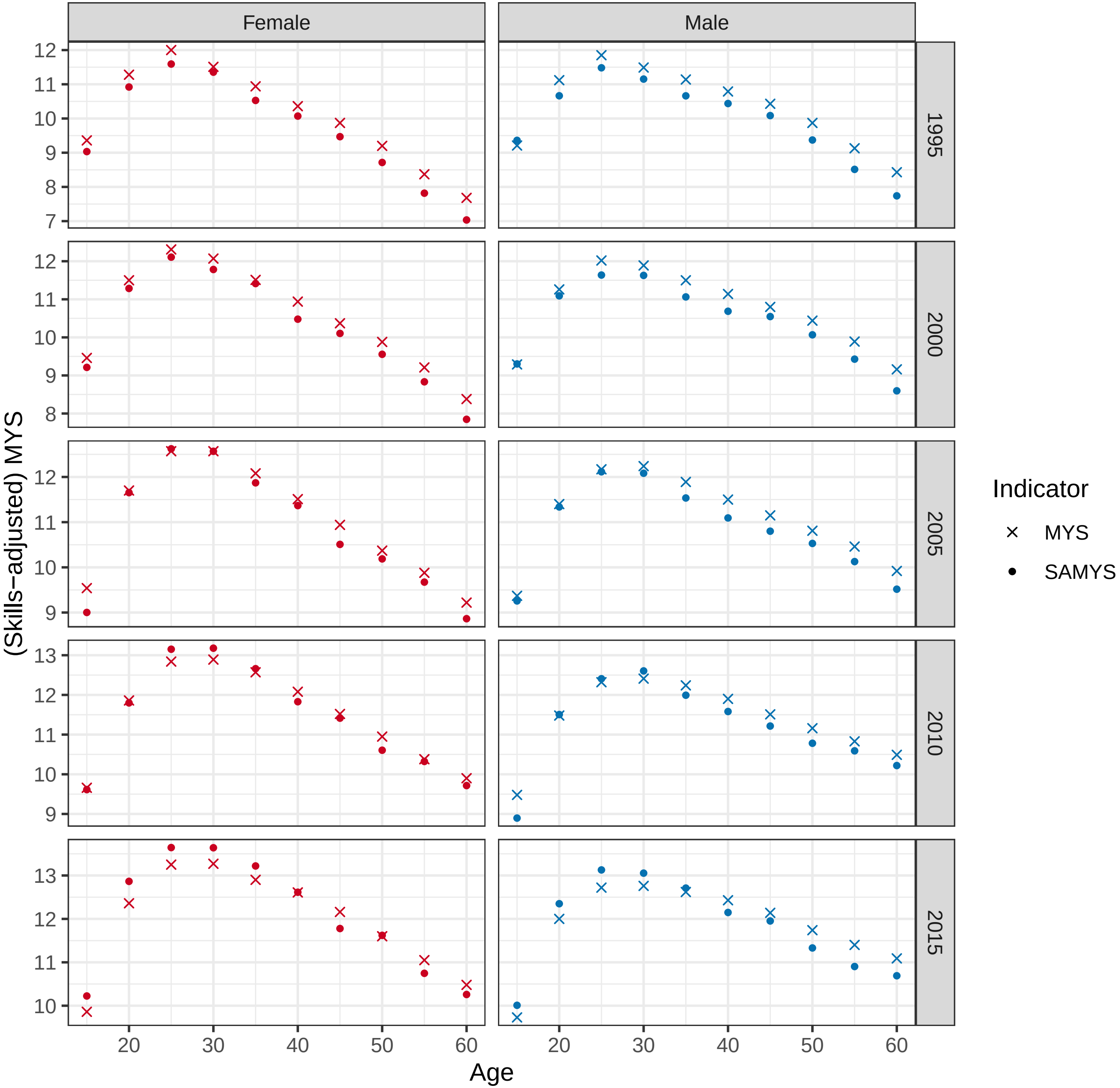
Finland , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

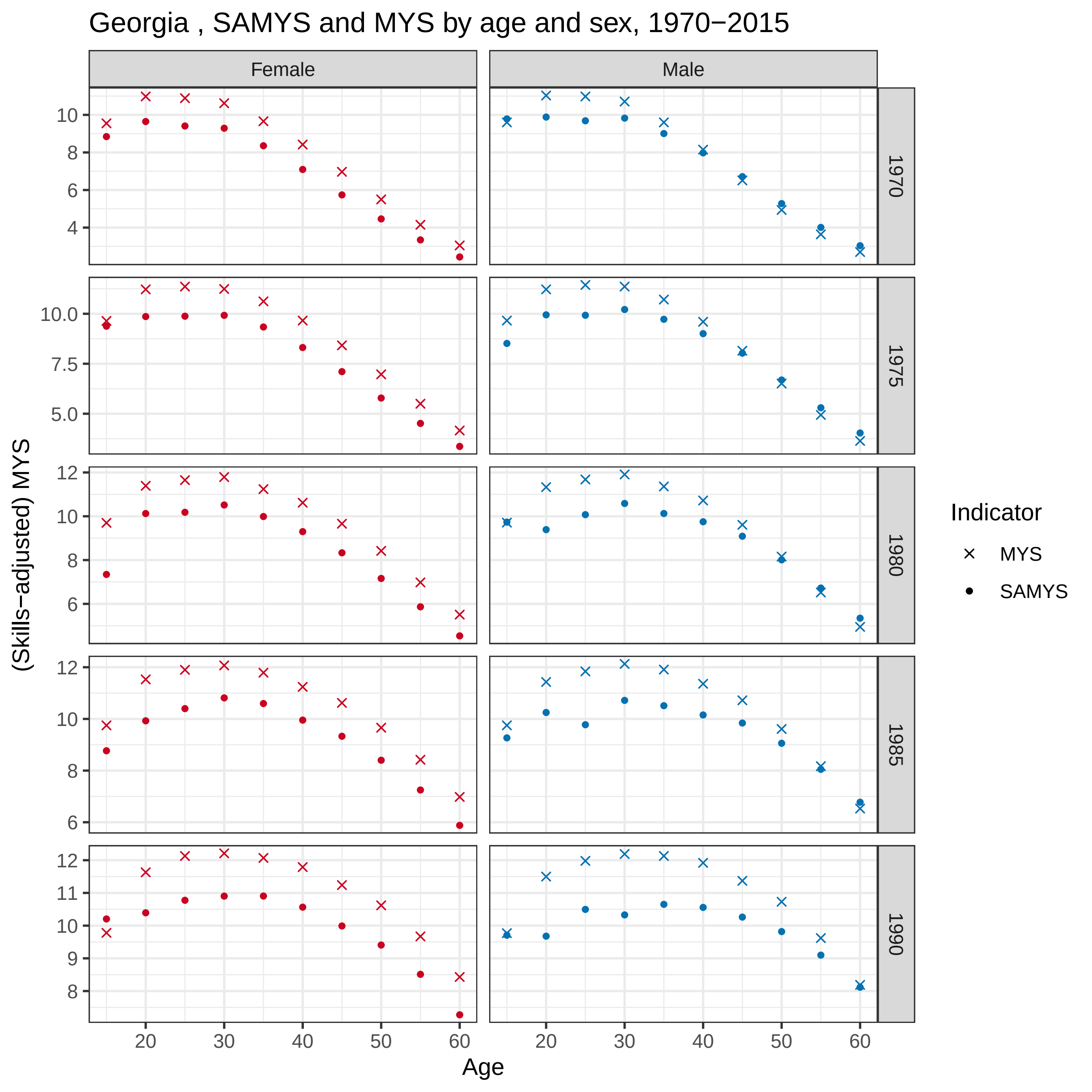


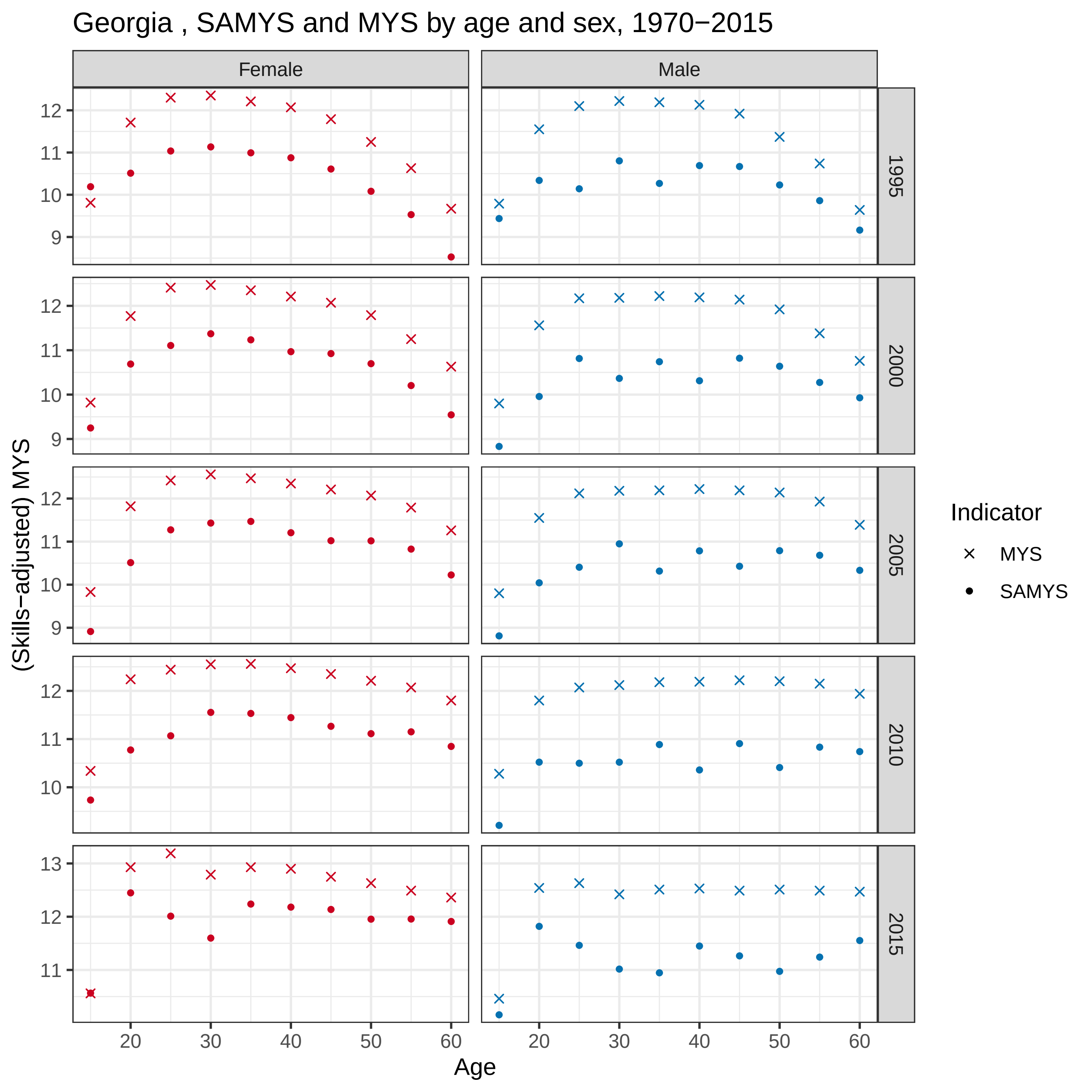
Finland , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


France , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

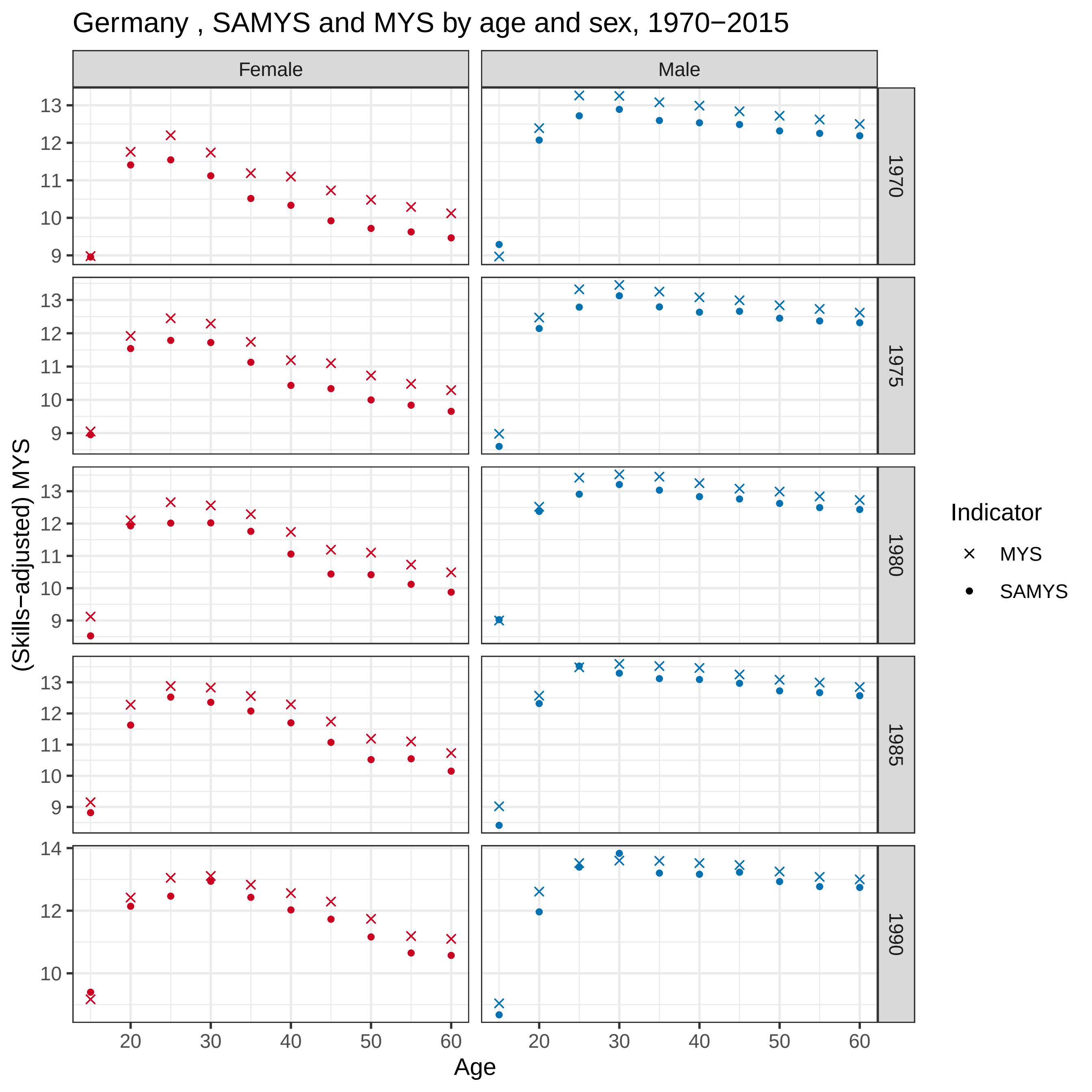
France , SAMYS and MYS by age and sex, 1970−2015



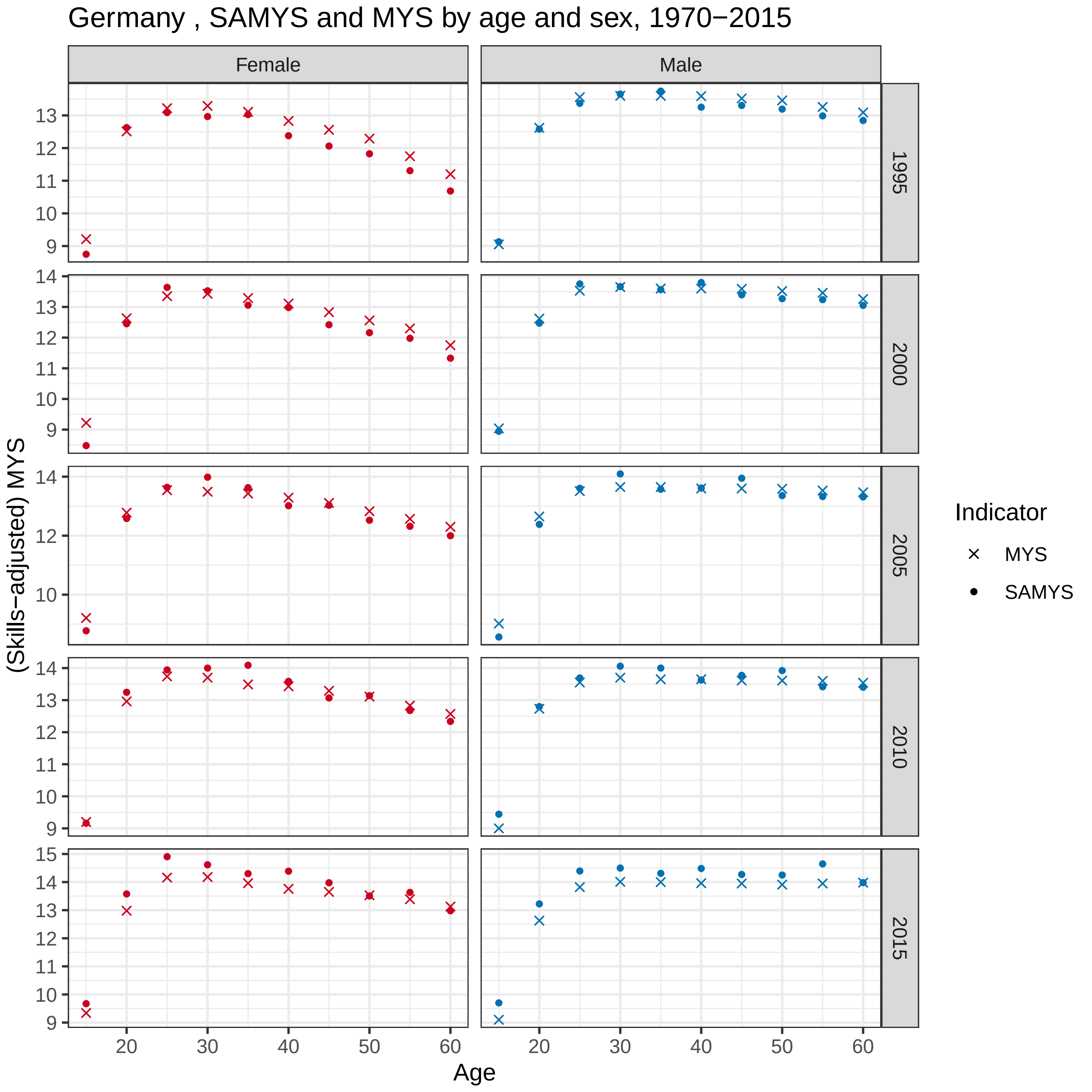

Georgia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



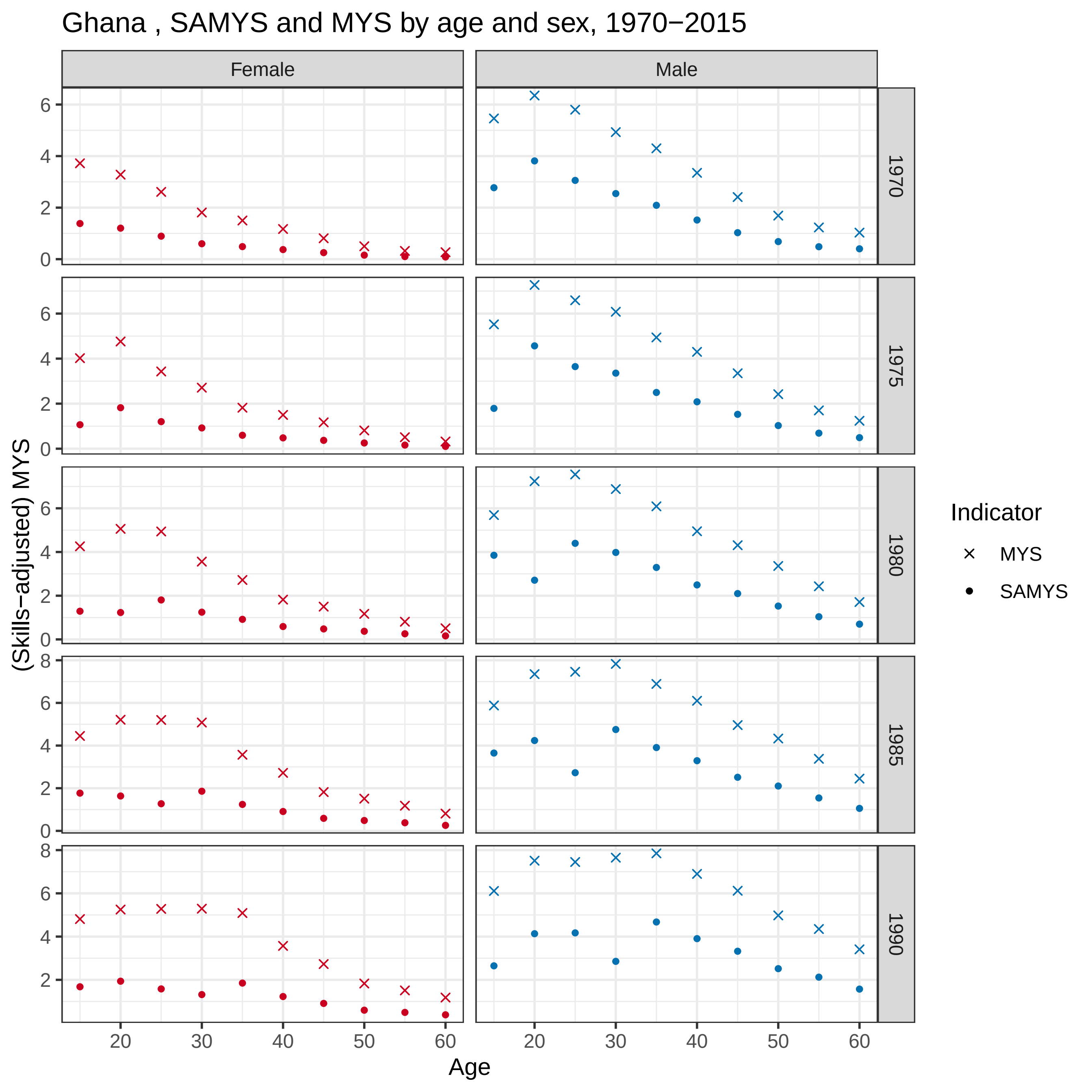
Georgia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



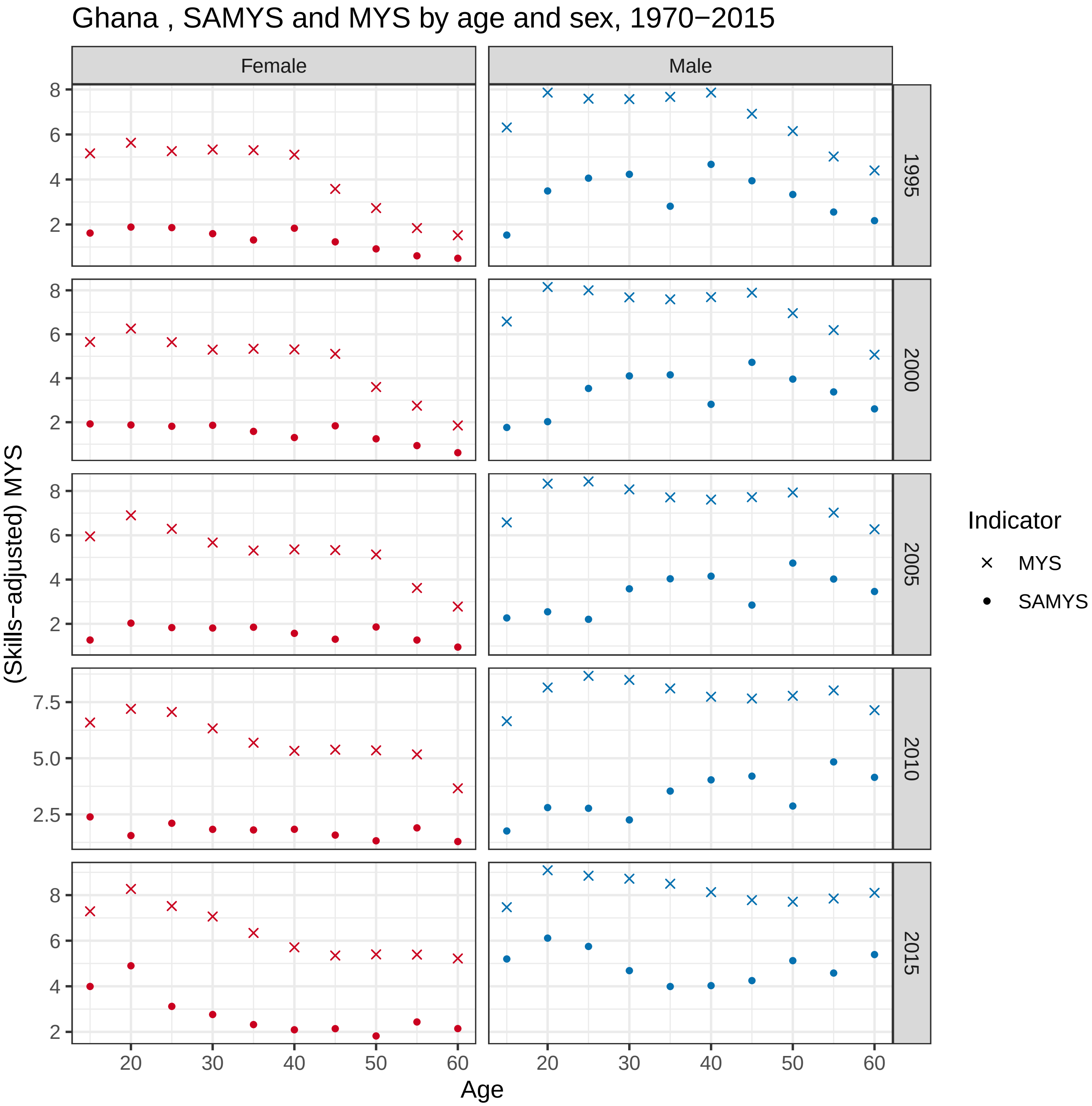
Germany , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



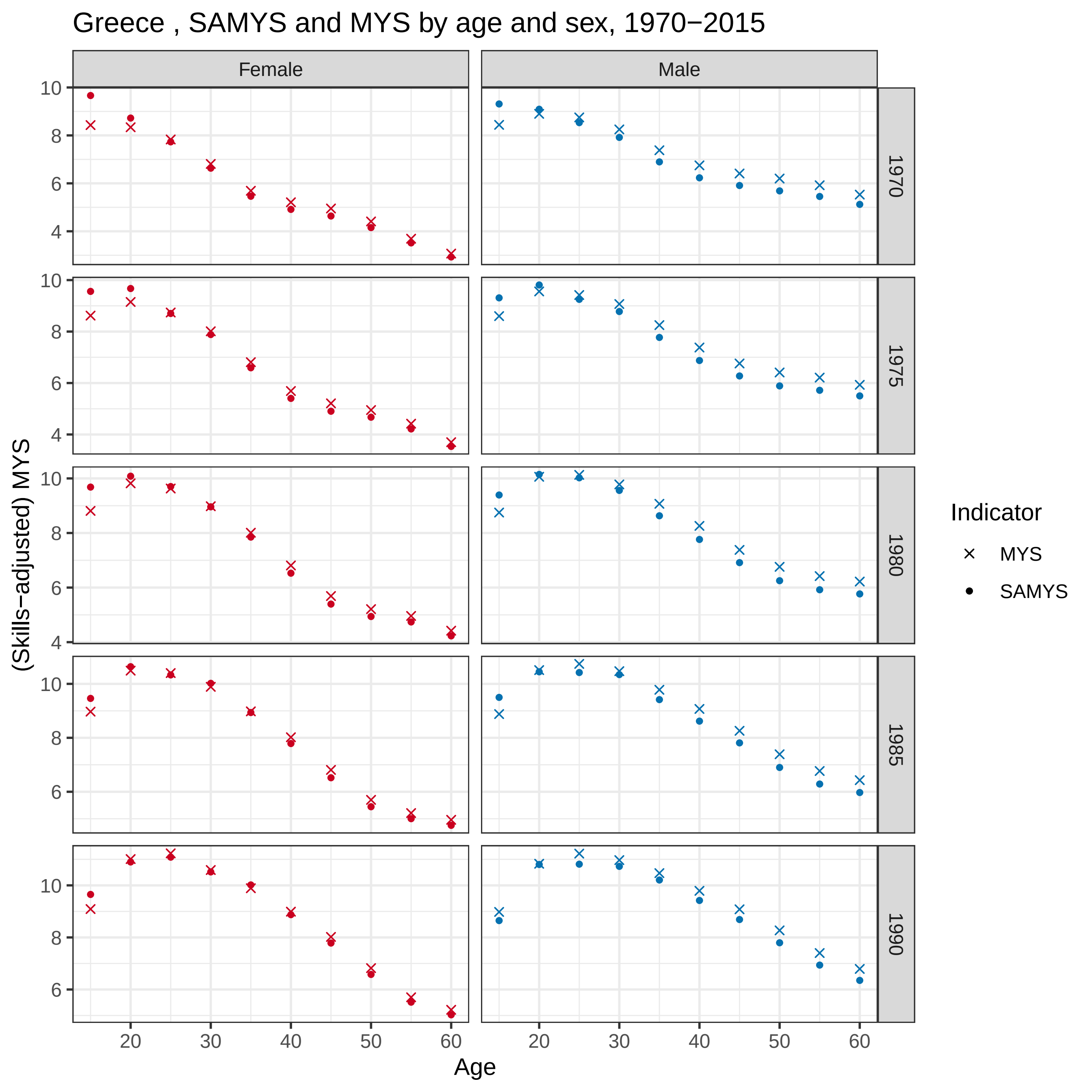
Germany , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

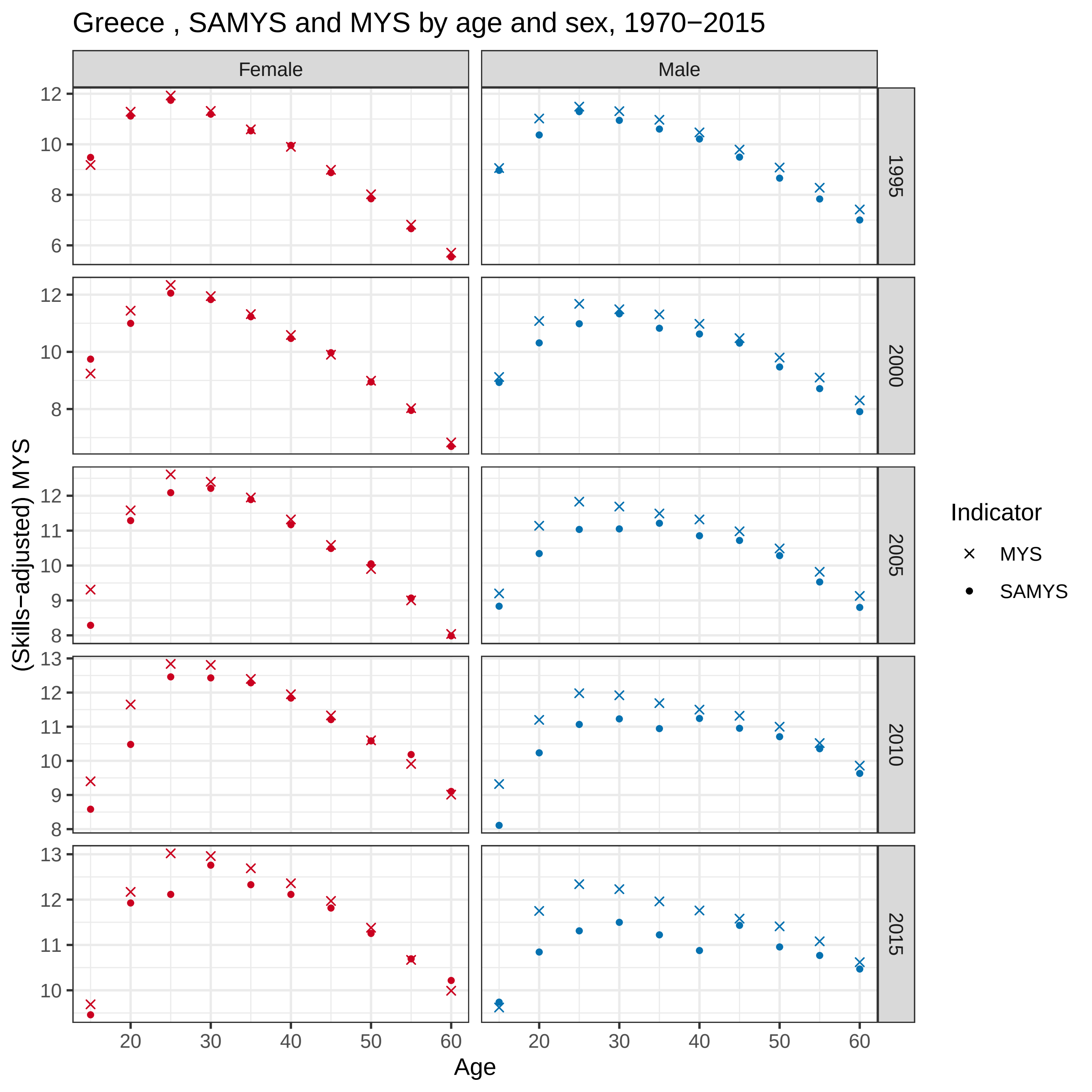


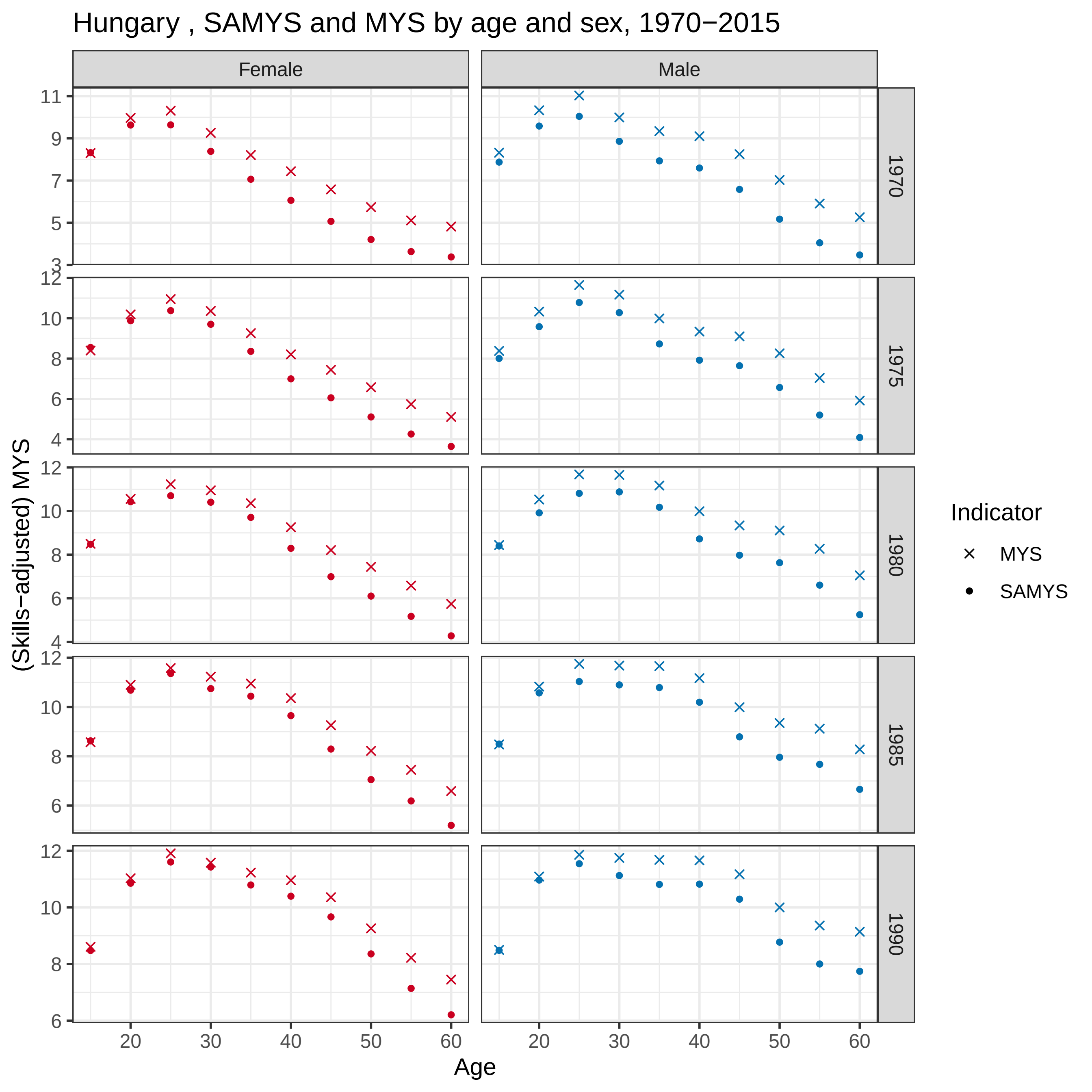
Ghana , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



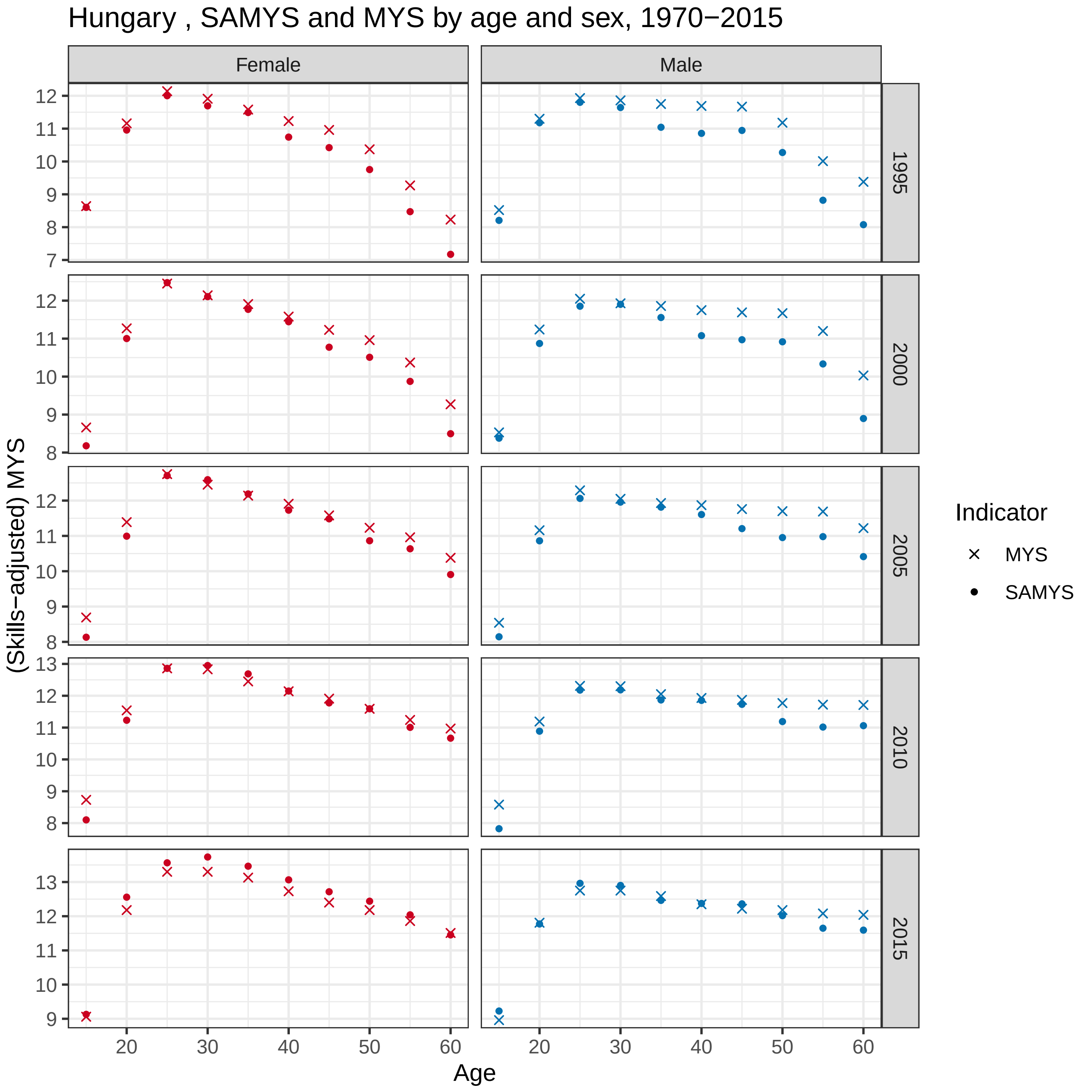
Ghana , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

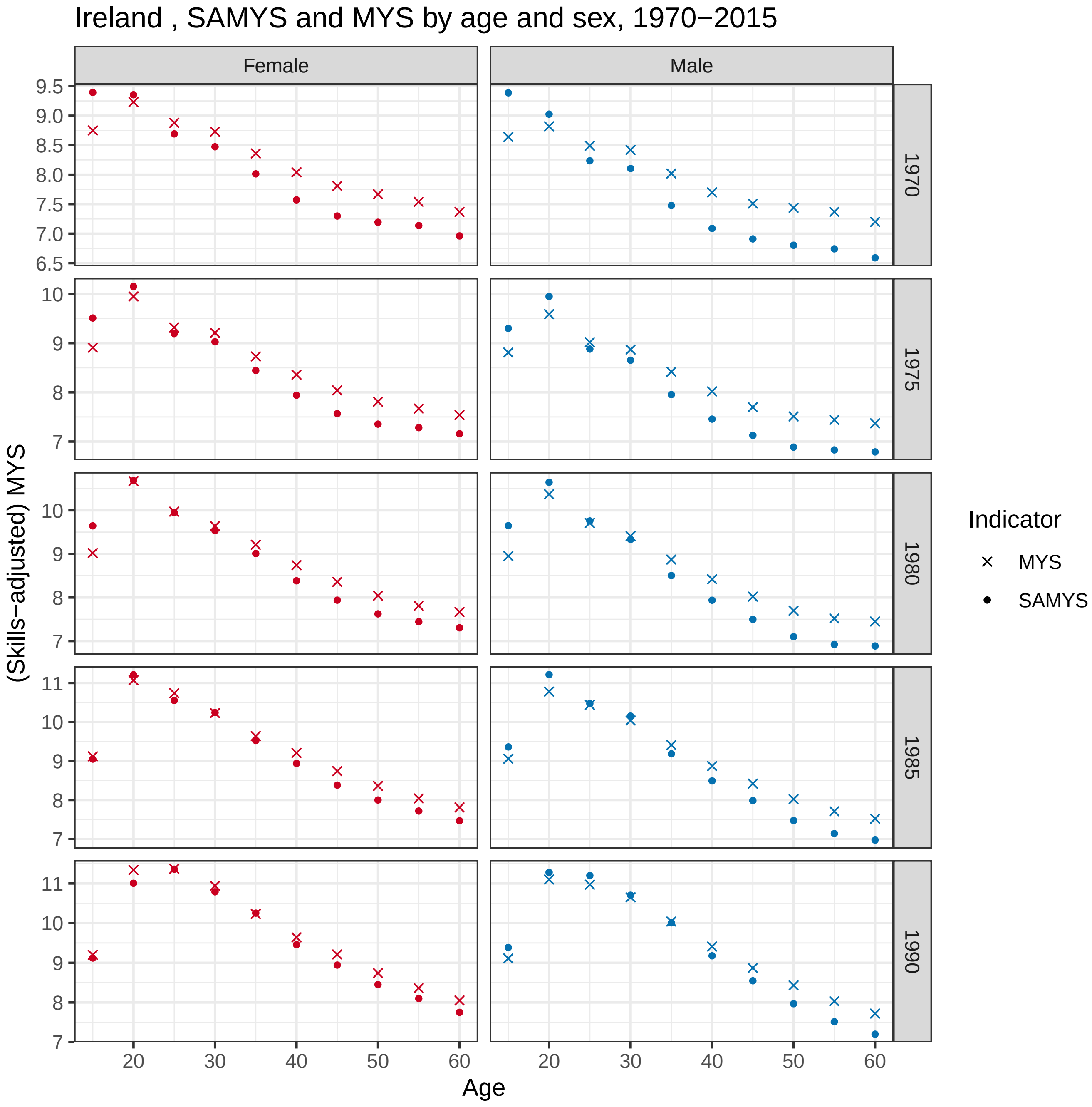

Greece , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS
10
8
6
4
20
30
40
50
60


Greece , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

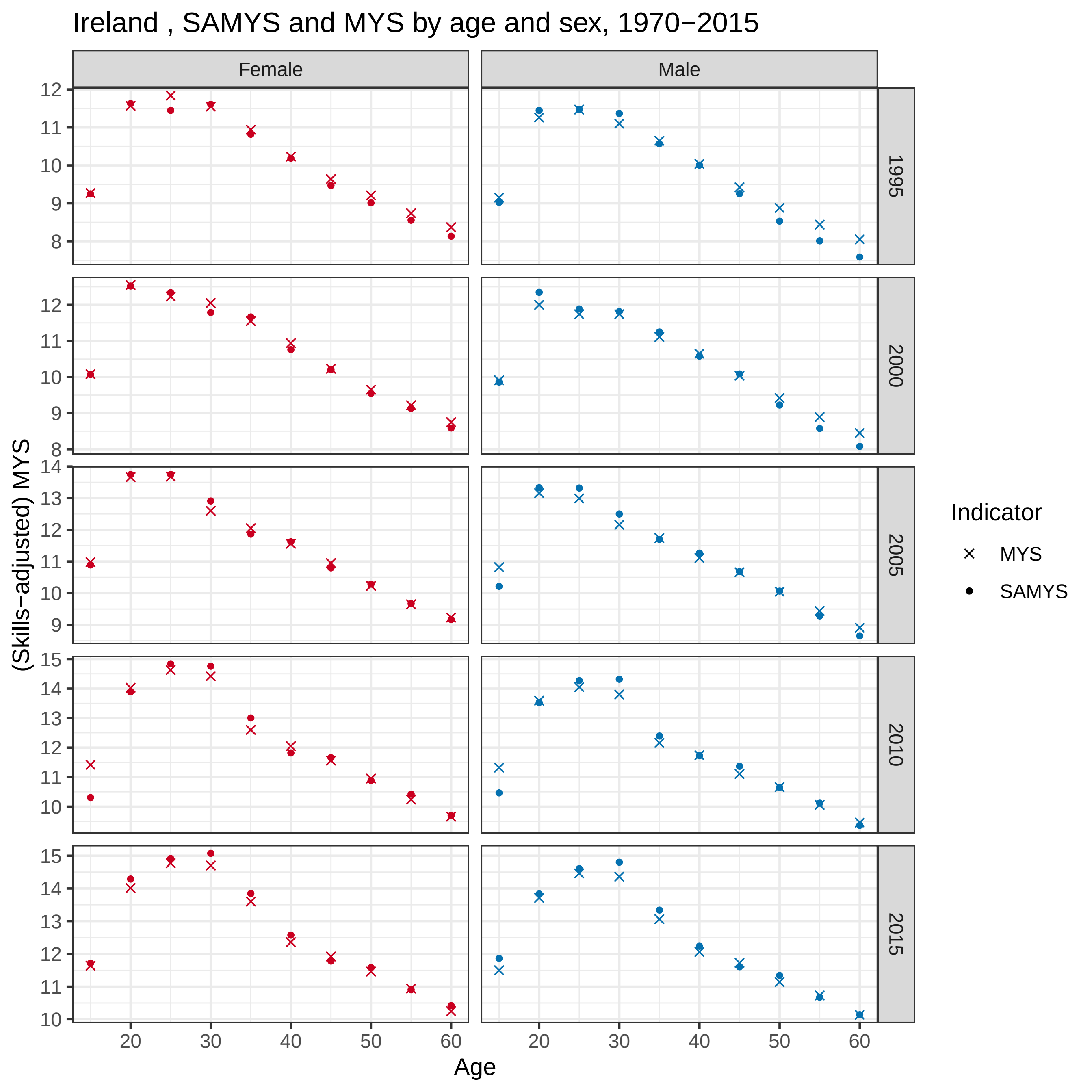


Hungary , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

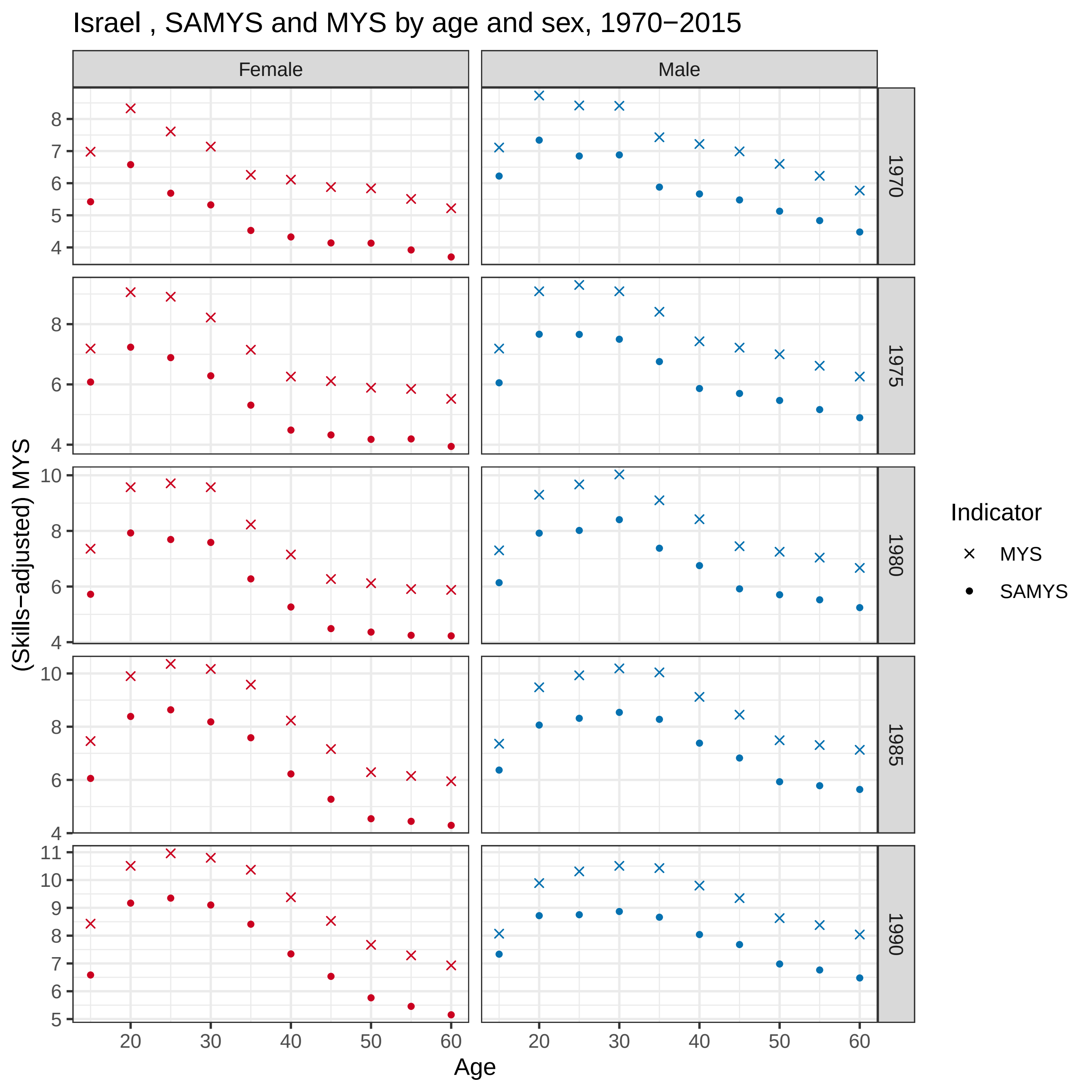

Hungary , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



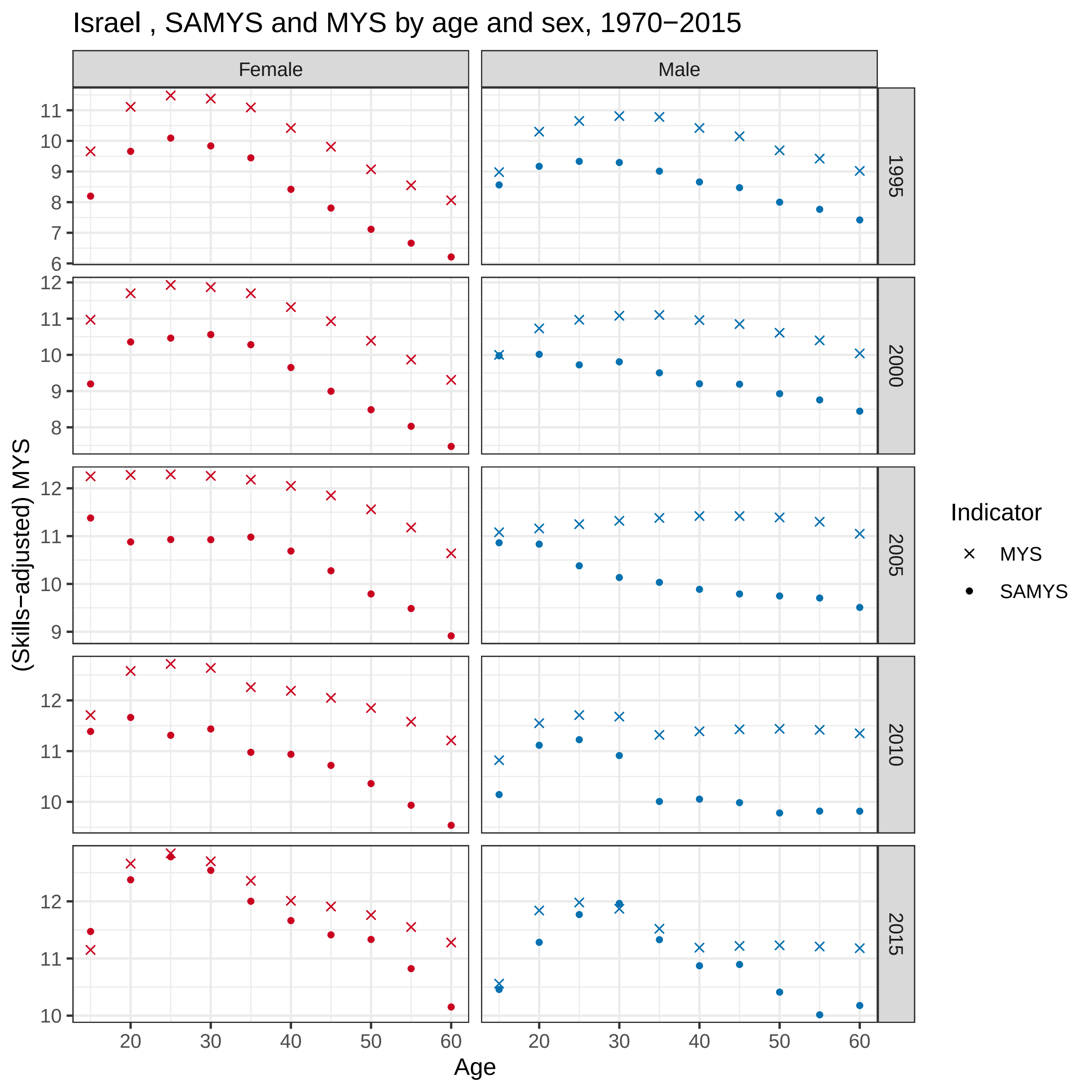
Ireland , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



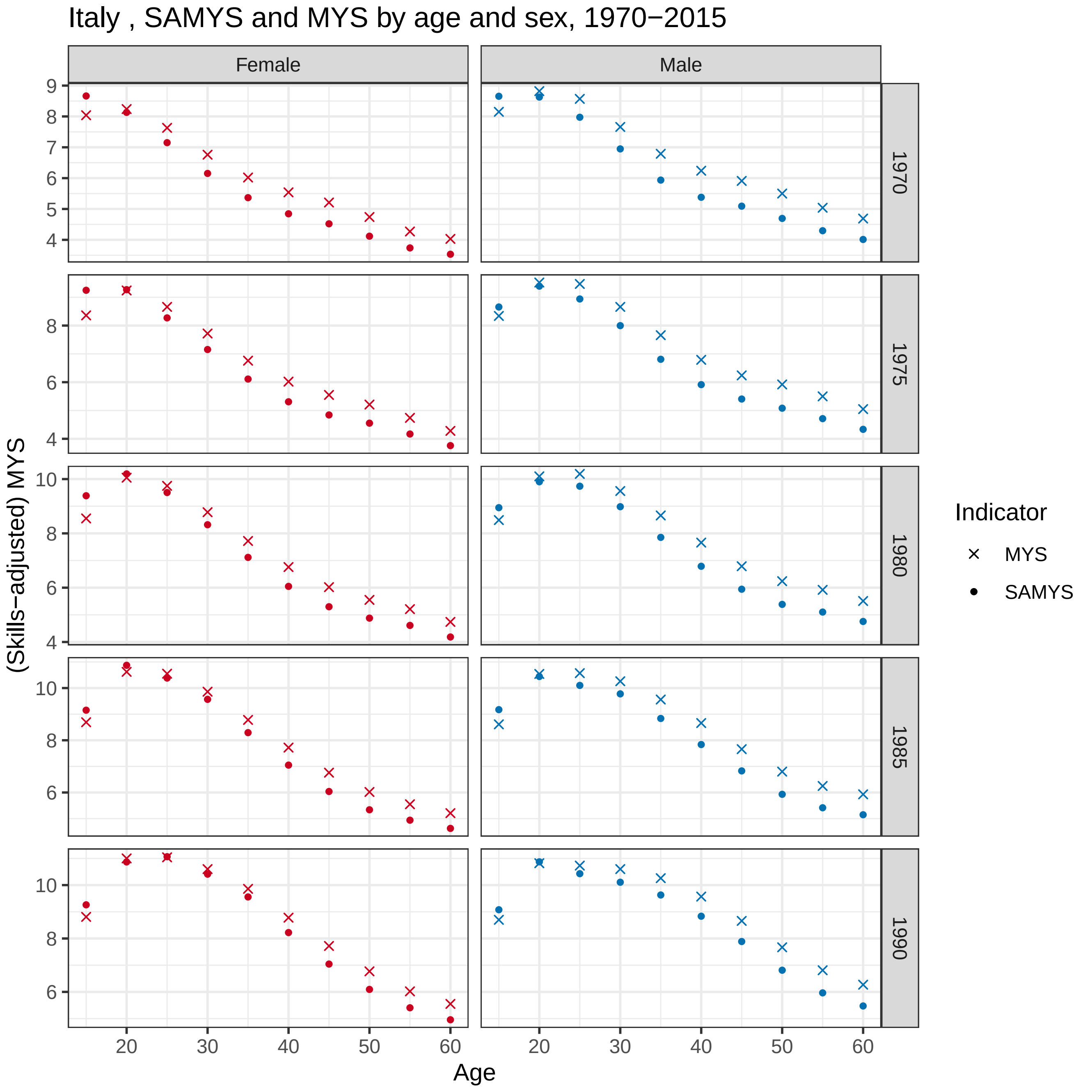
Ireland , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

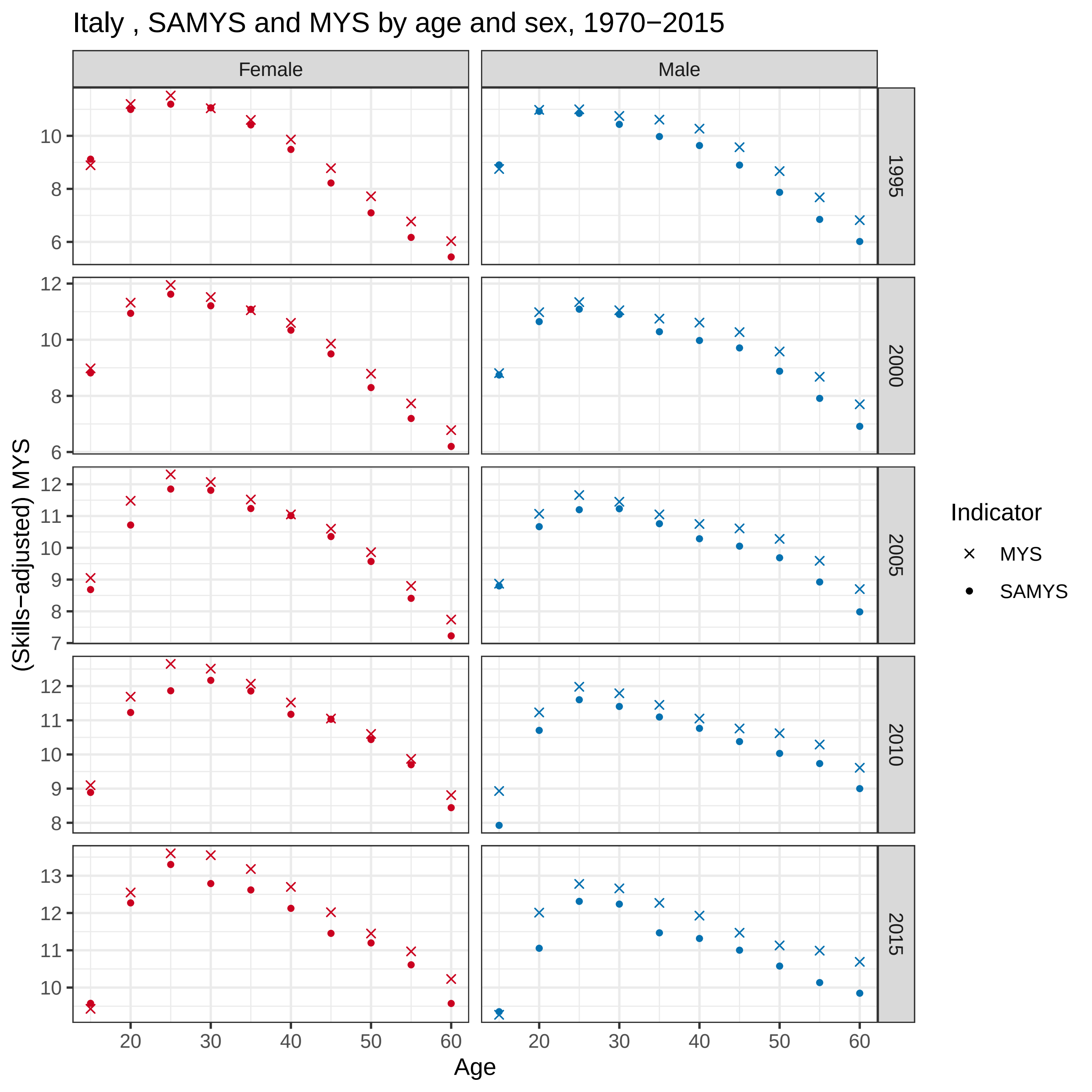


Israel , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

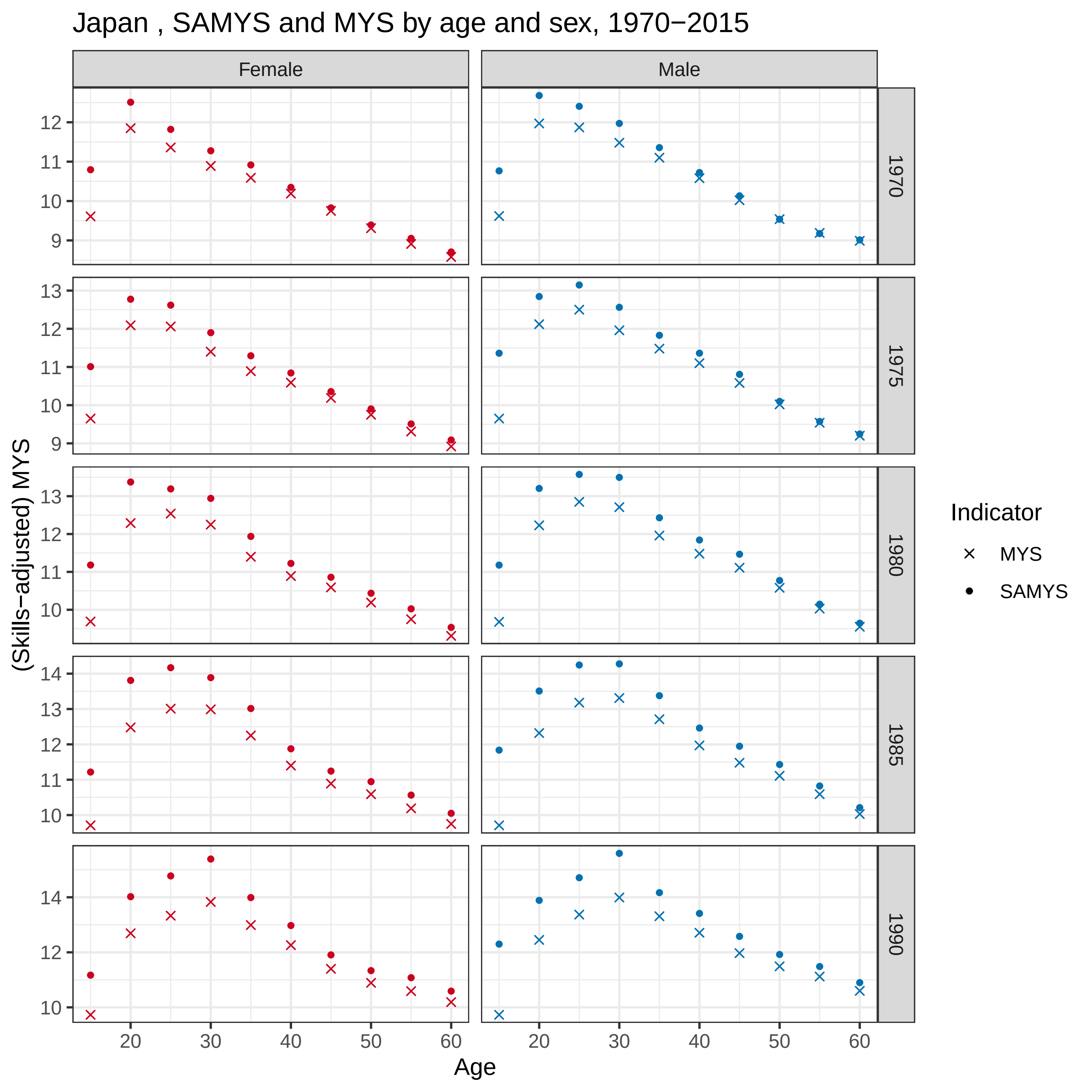


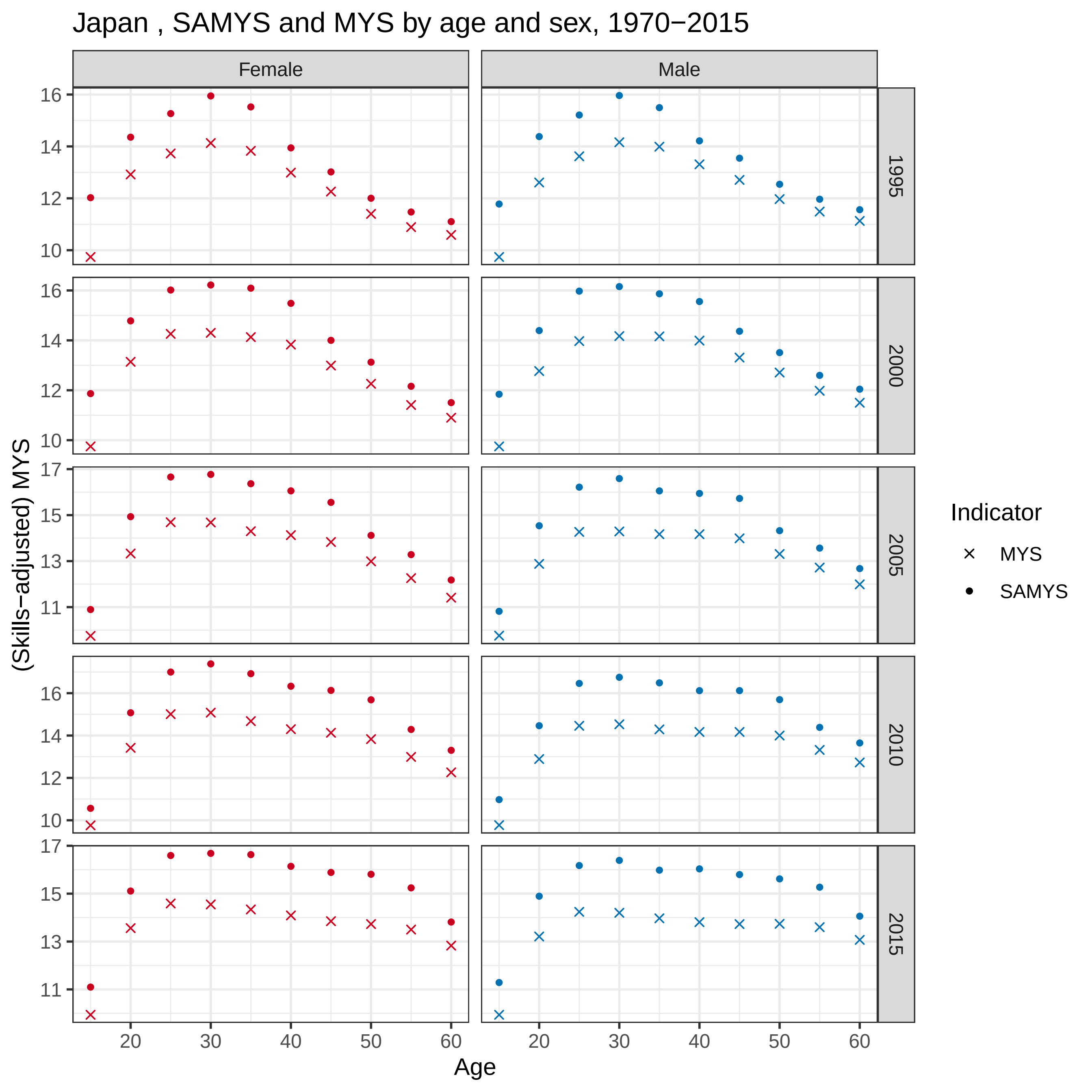
Israel , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

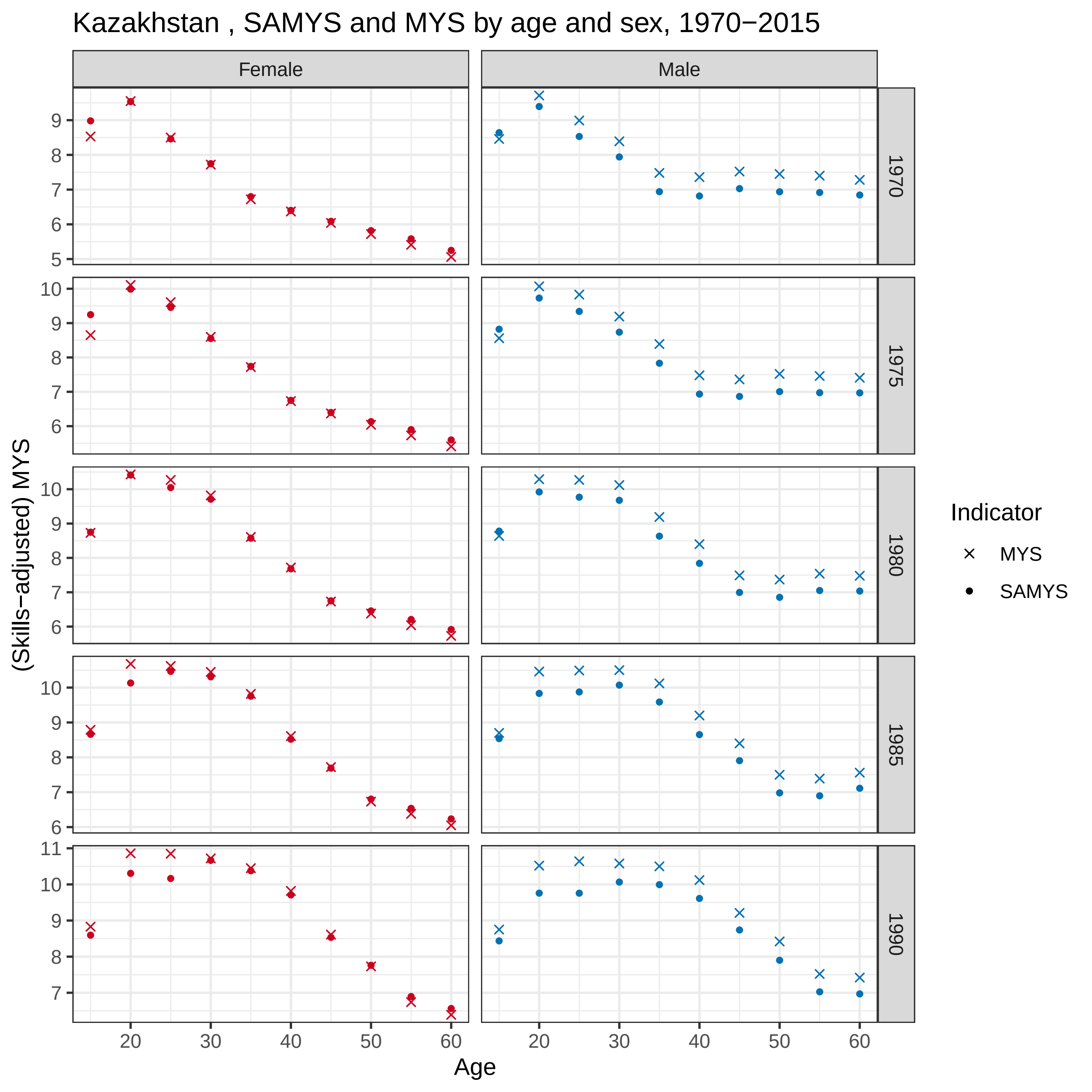

Italy , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



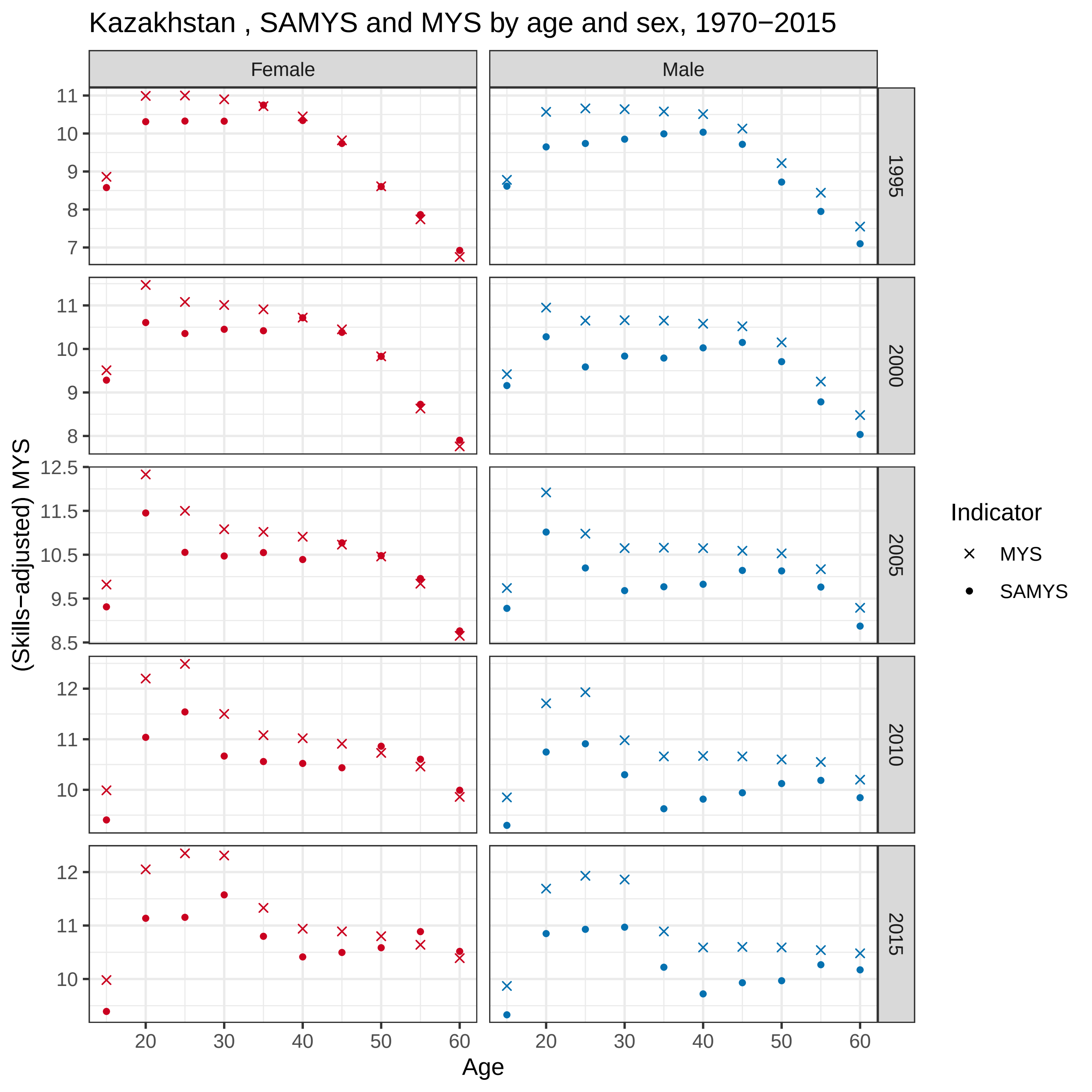
Italy , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Japan , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

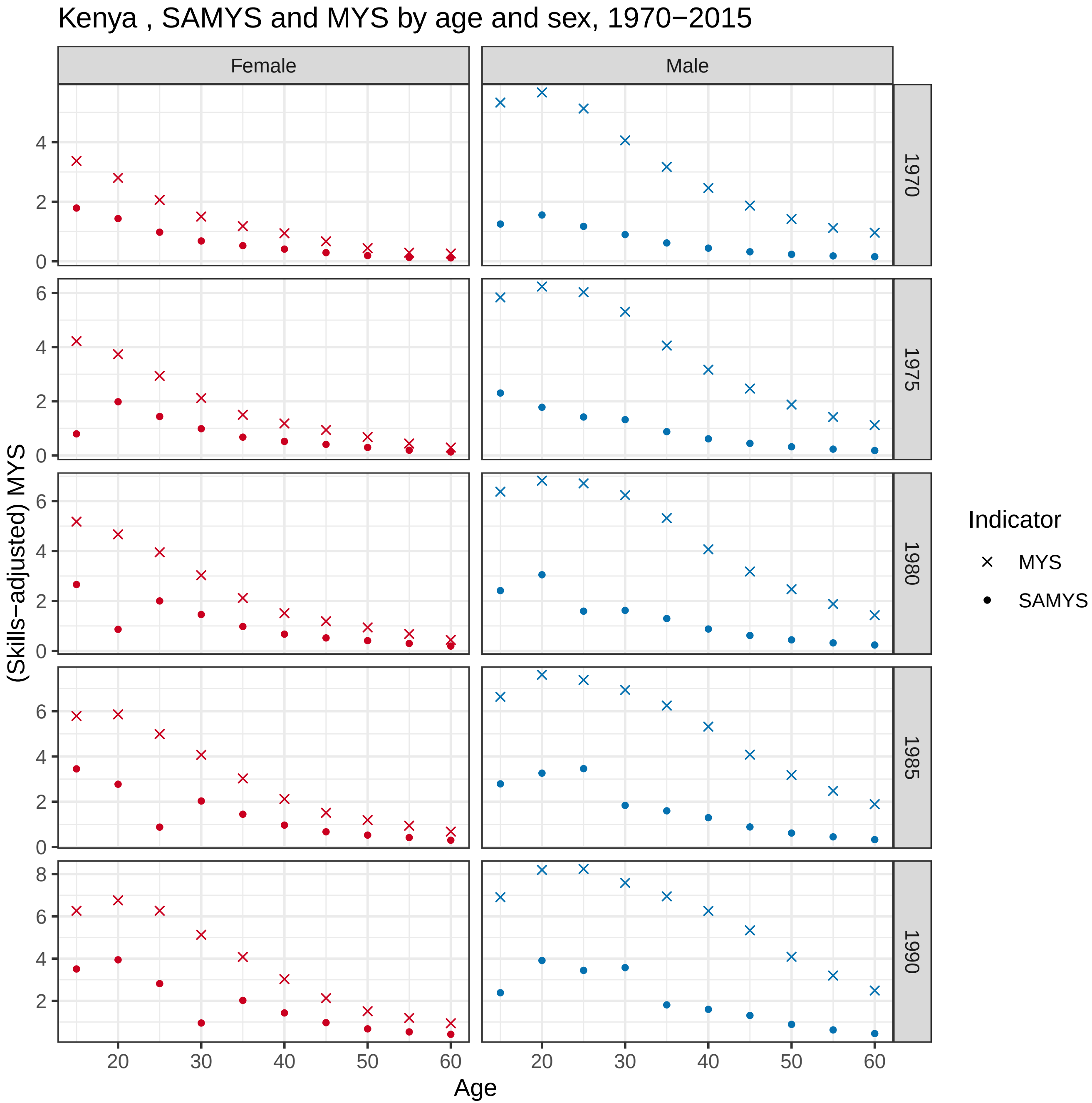

Japan , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

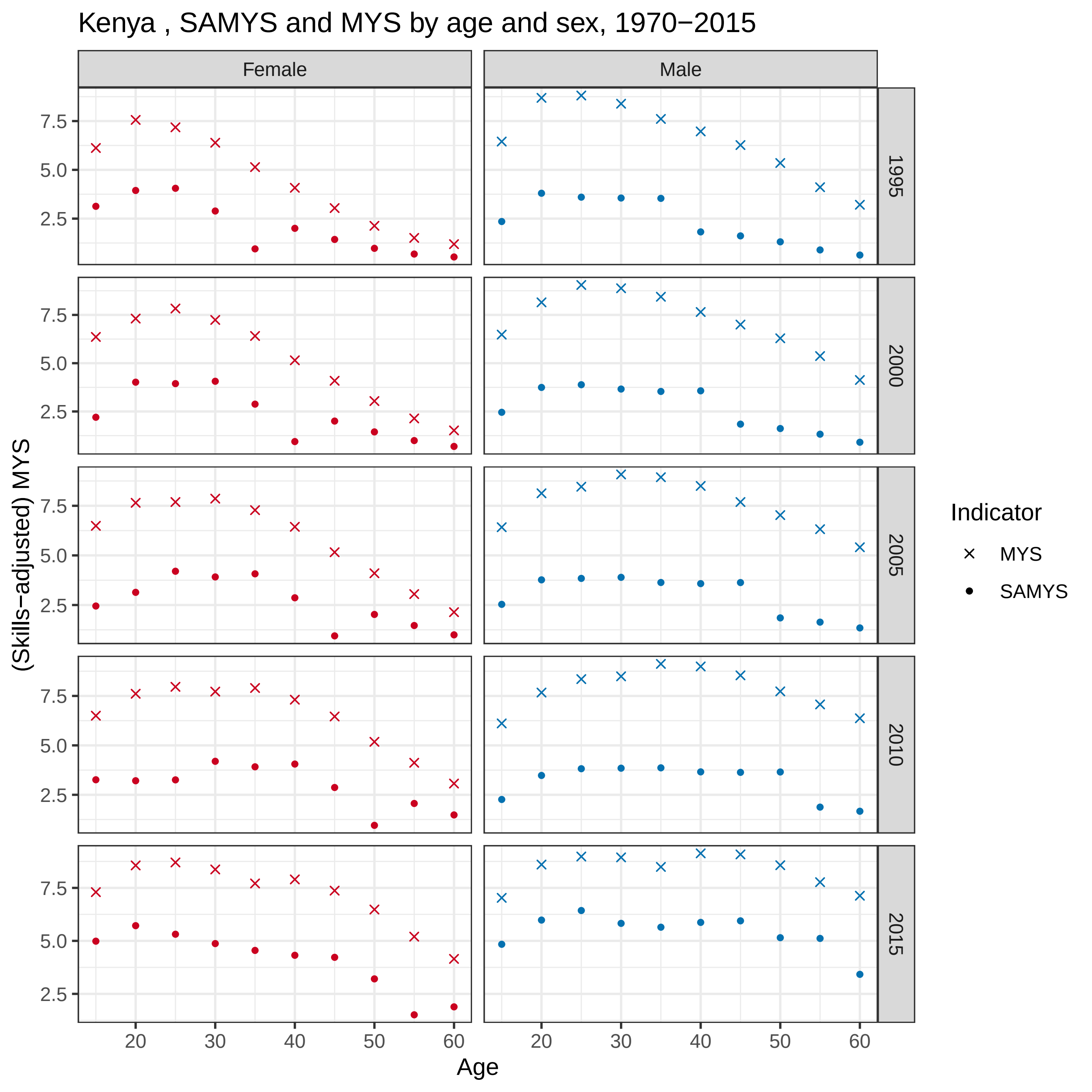


Kazakhstan , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

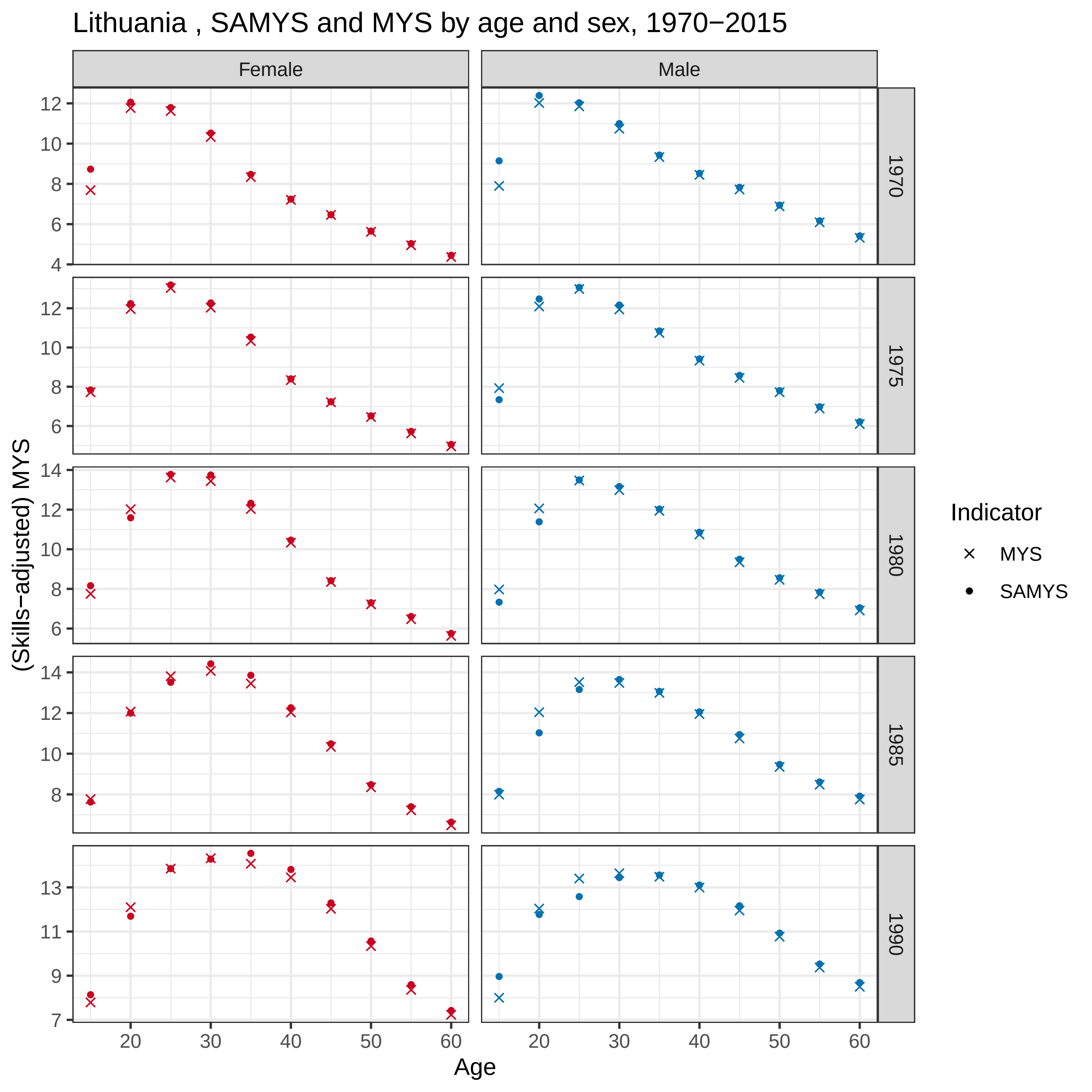


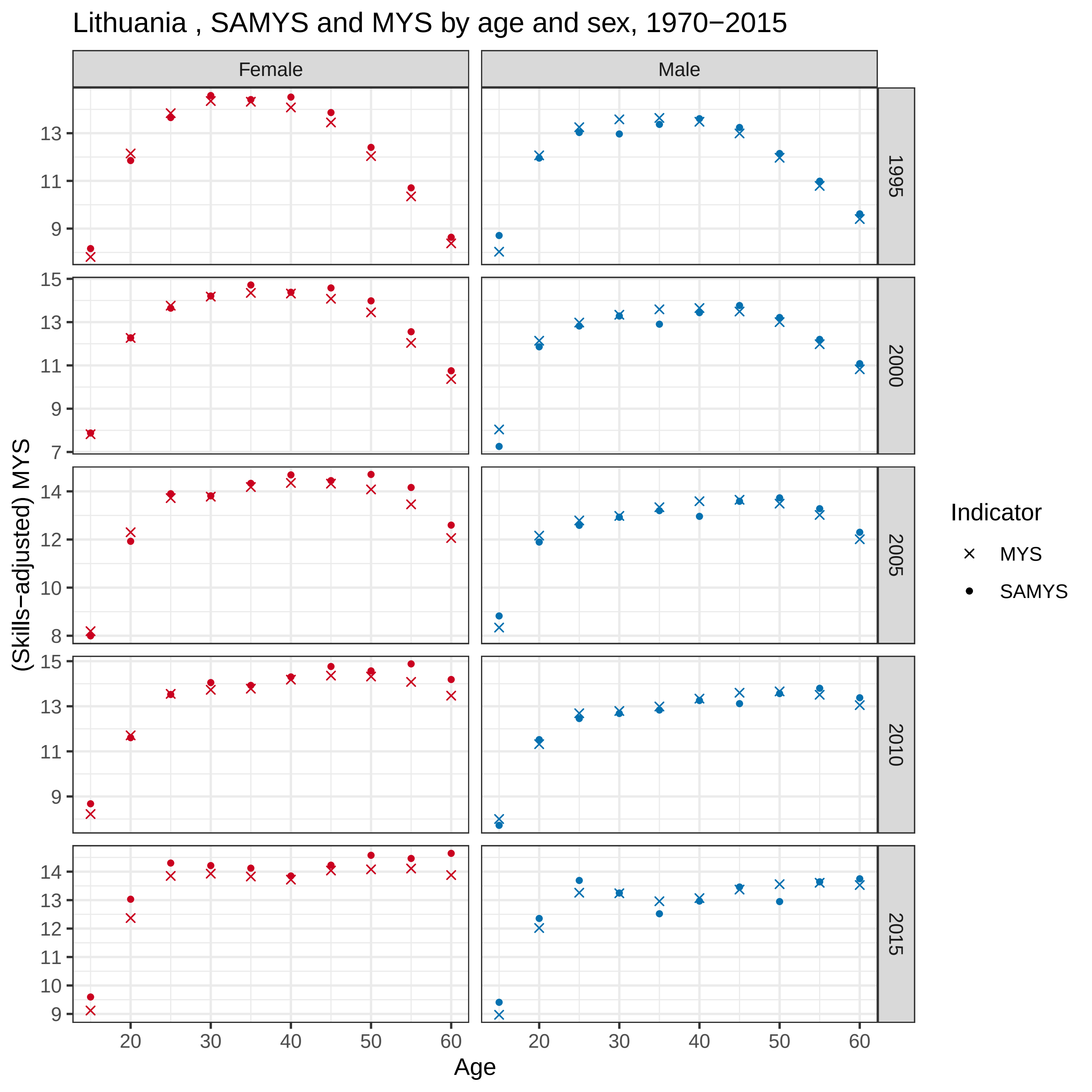
Kazakhstan , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Kenya , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

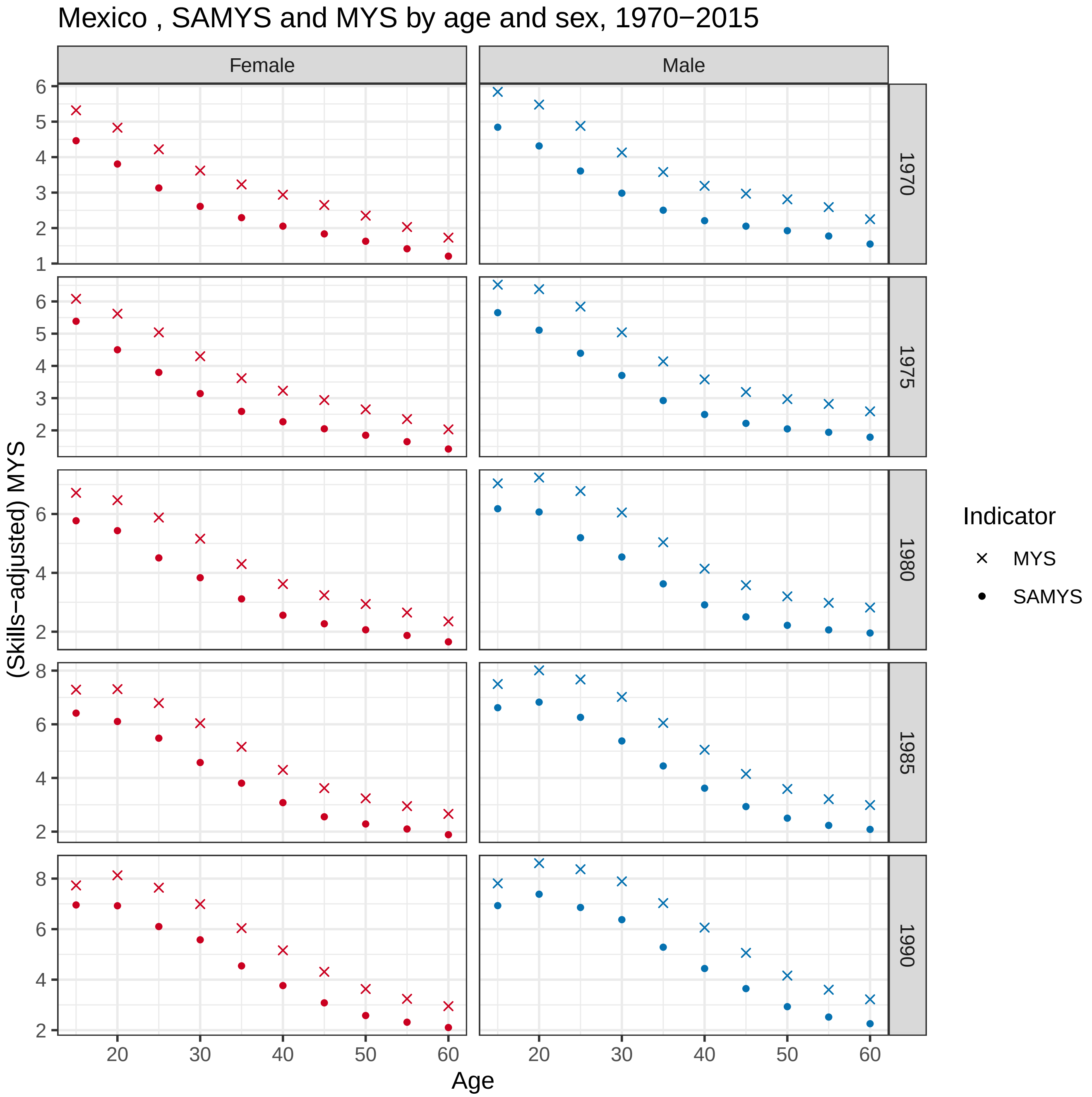


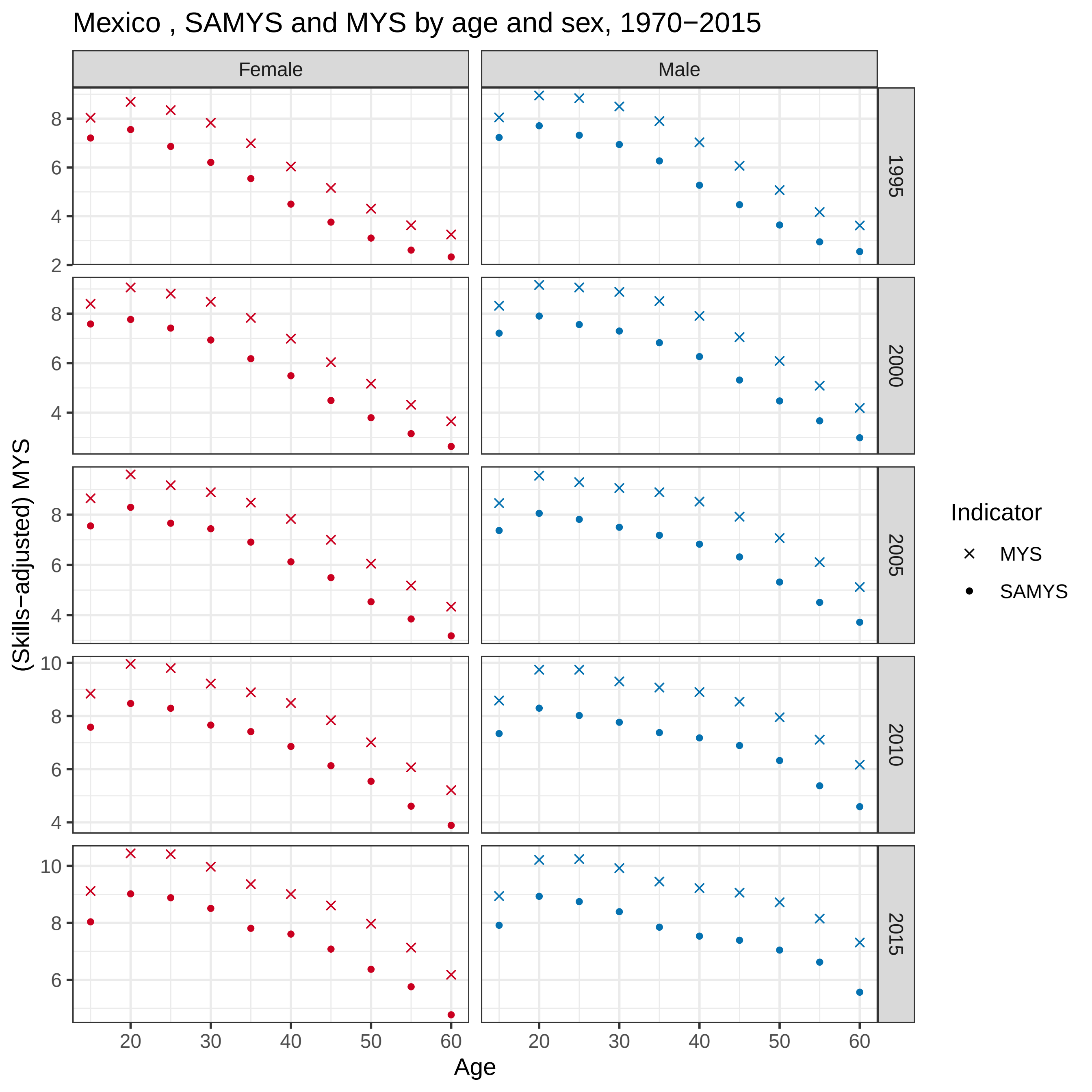
Kenya , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

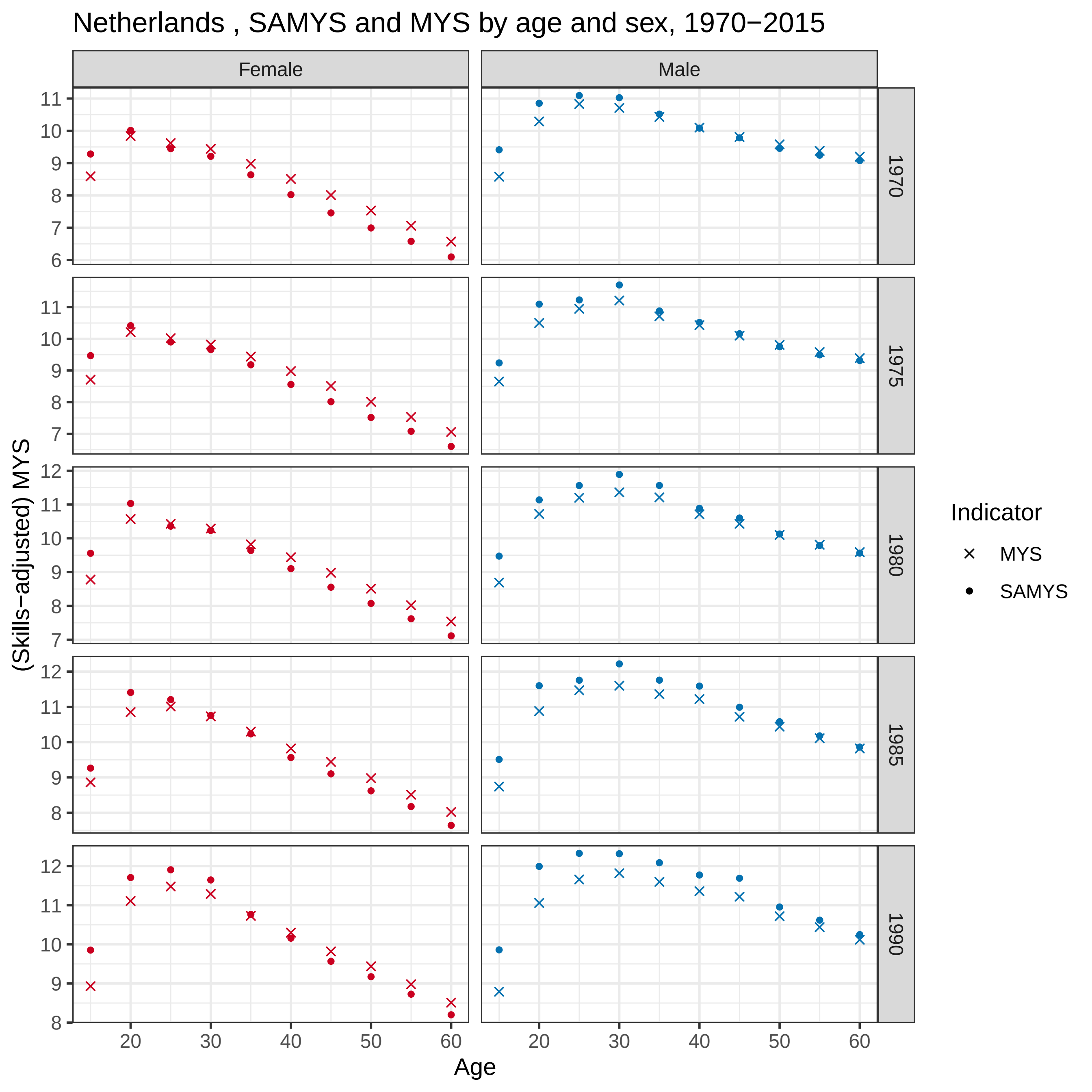

Lithuania , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

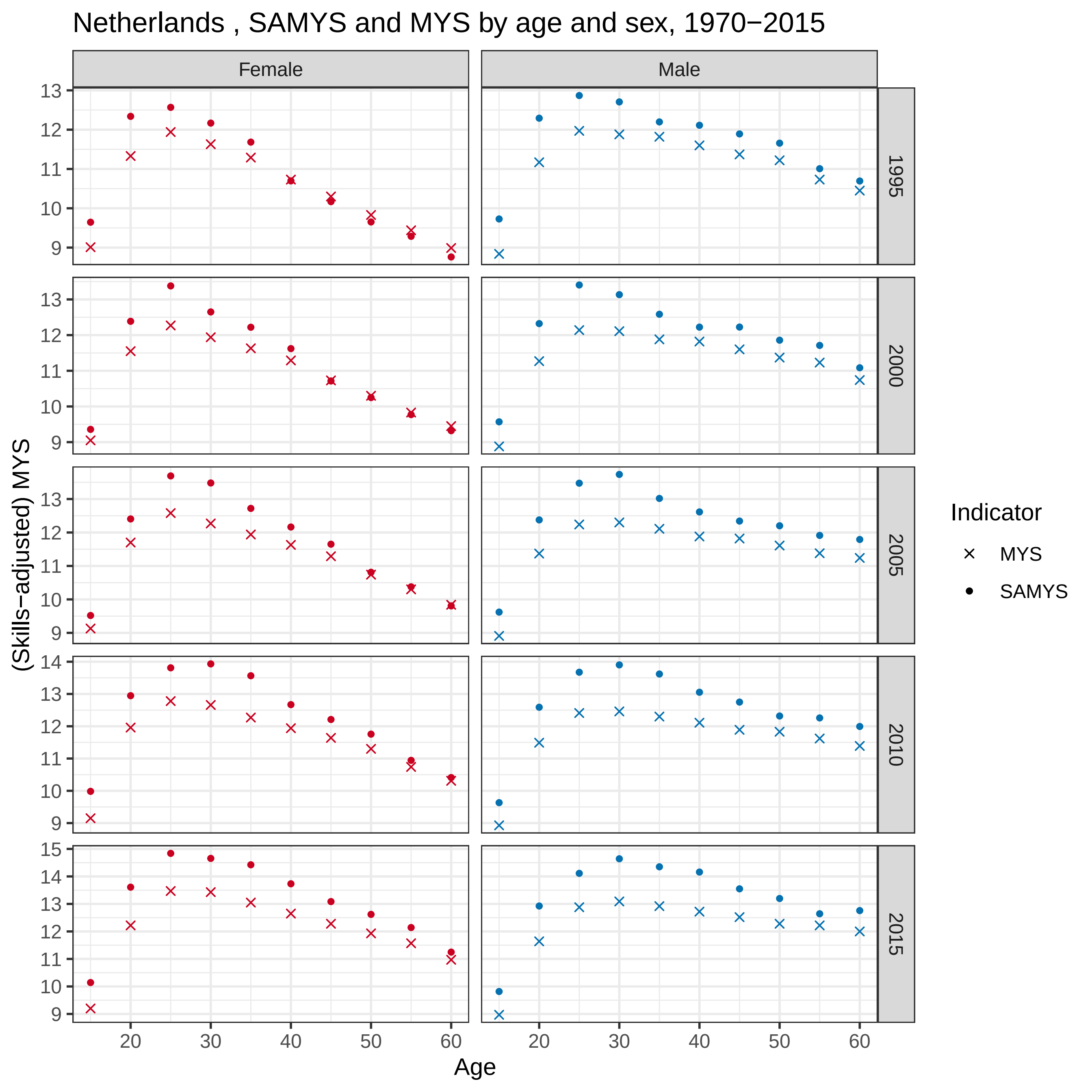


Lithuania , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

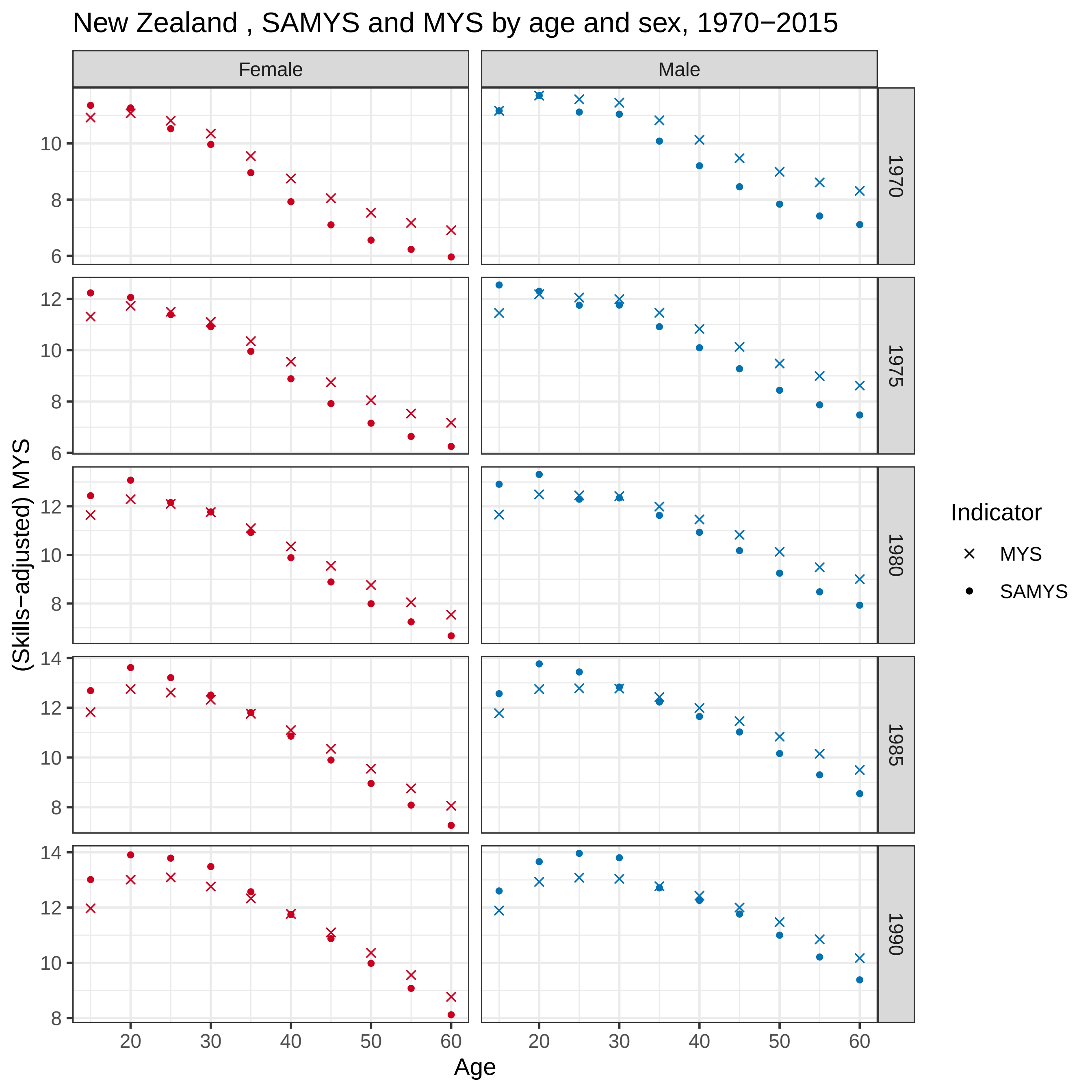

Mexico , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

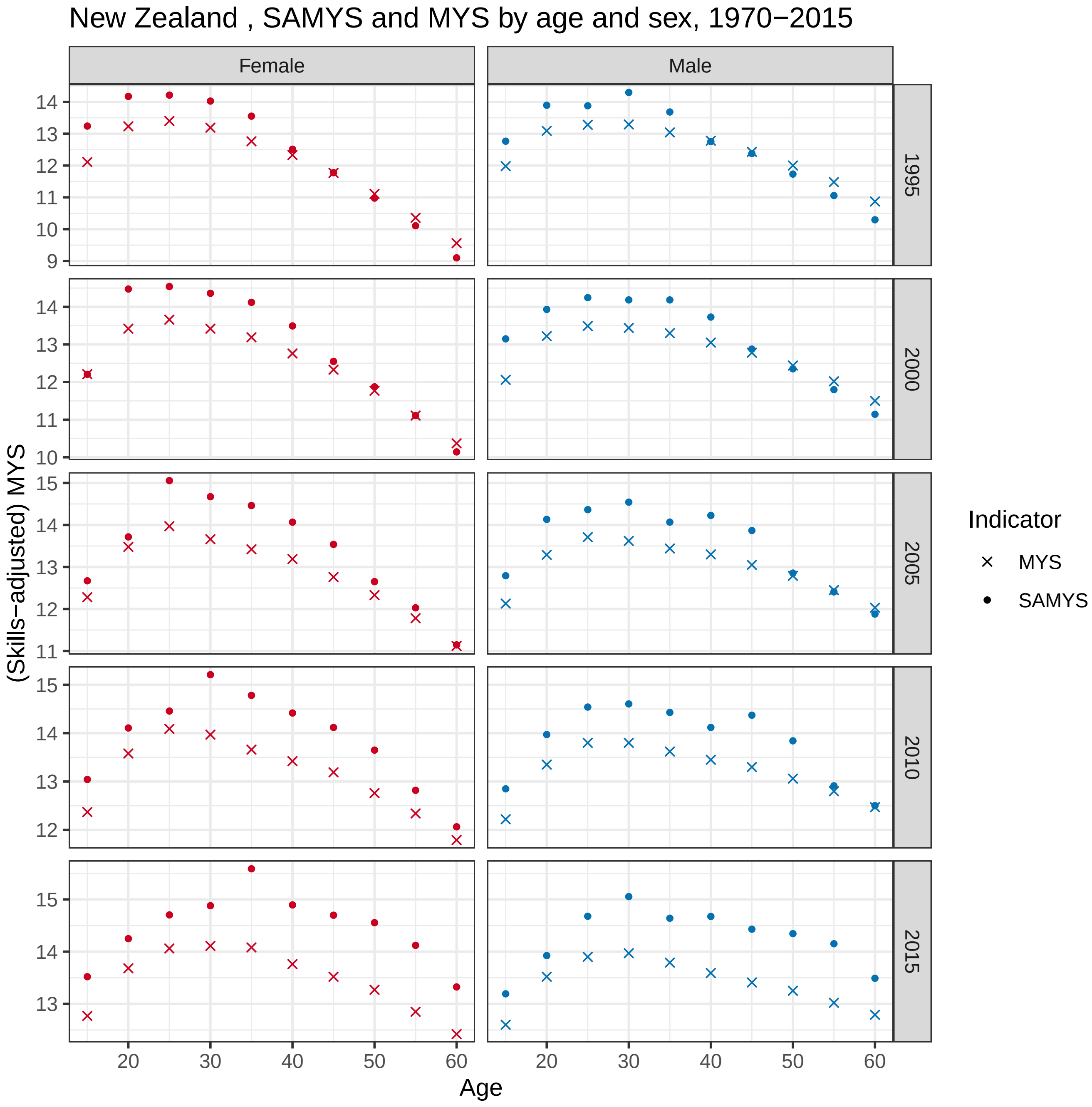

Mexico , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

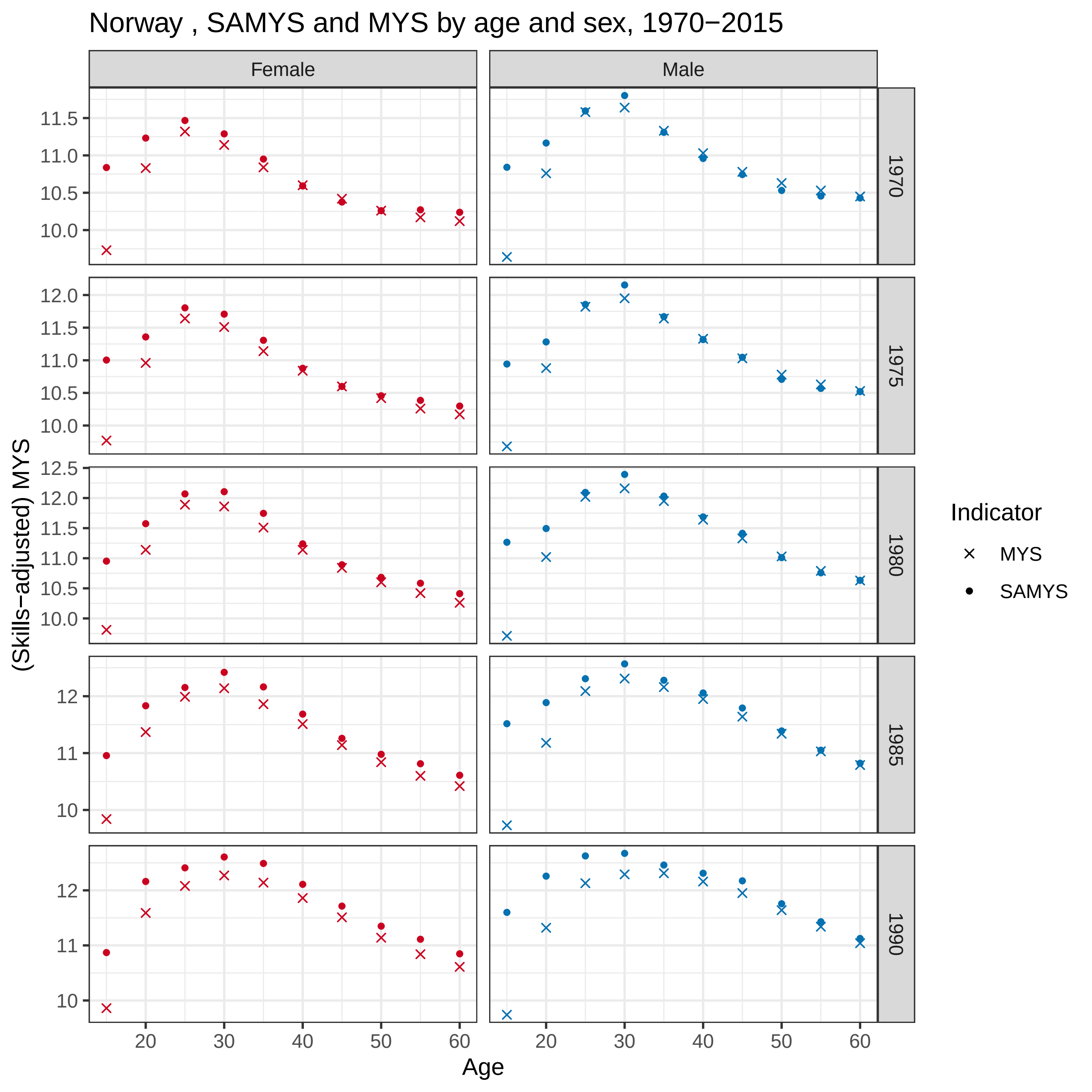

Netherlands , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

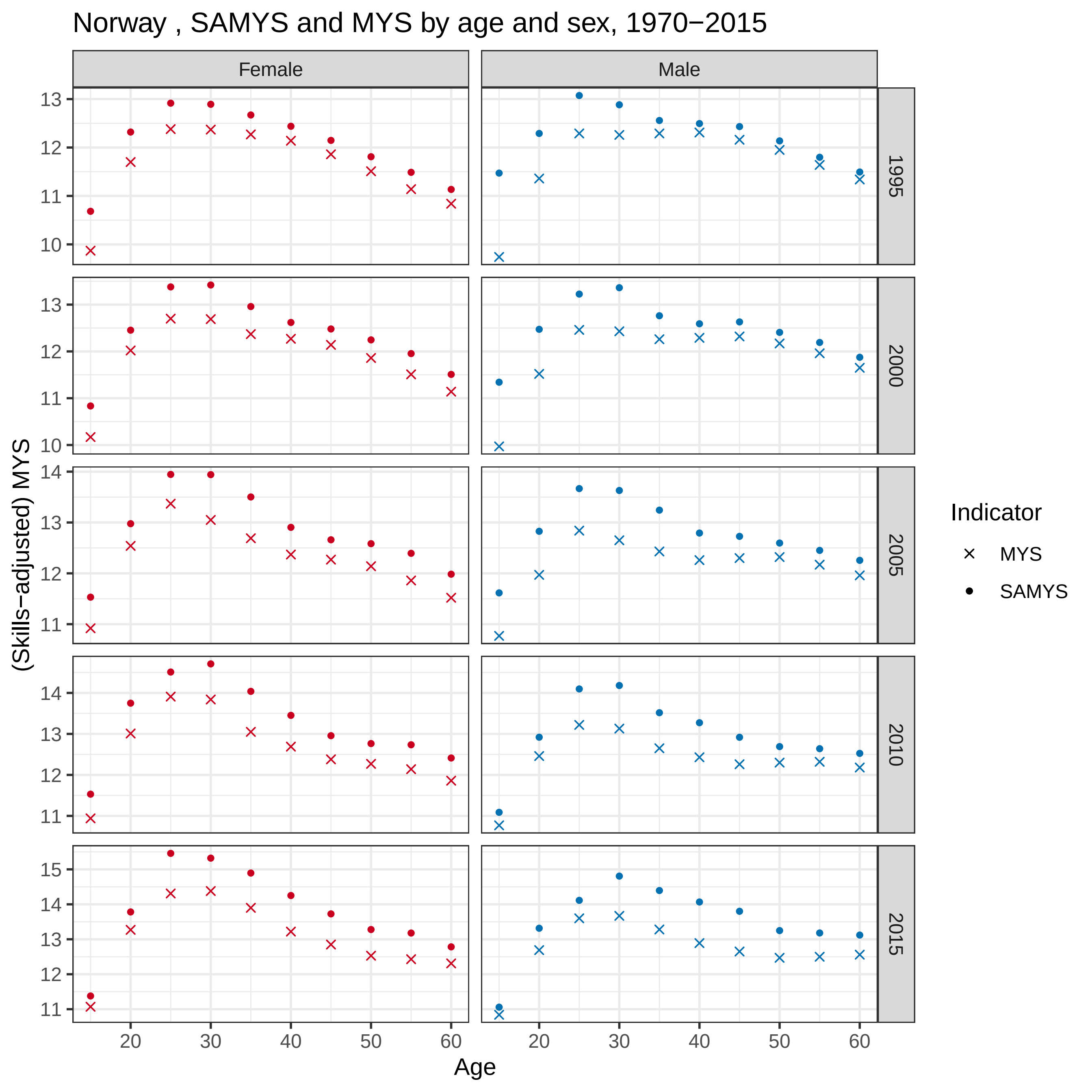


Netherlands , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

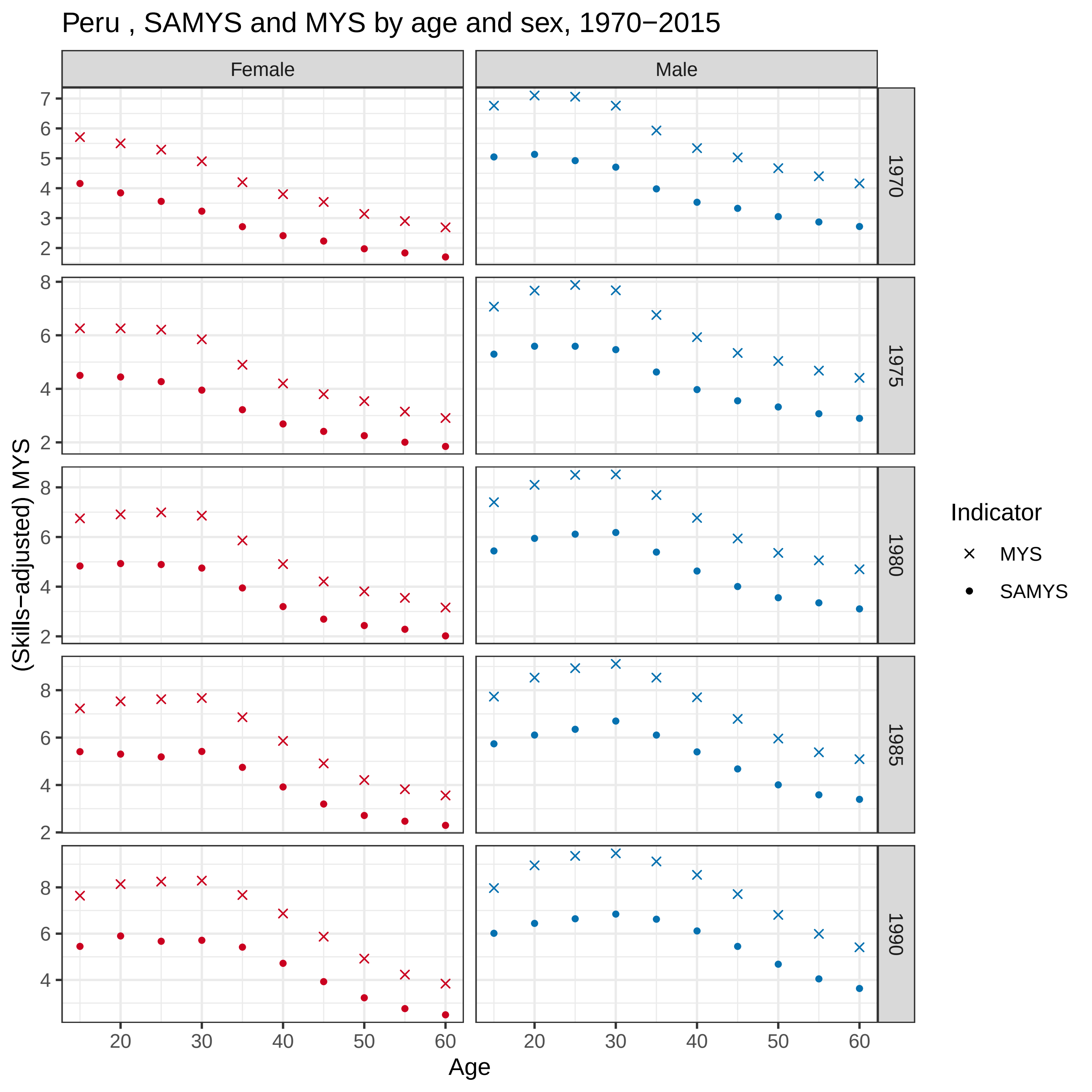

New Zealand , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

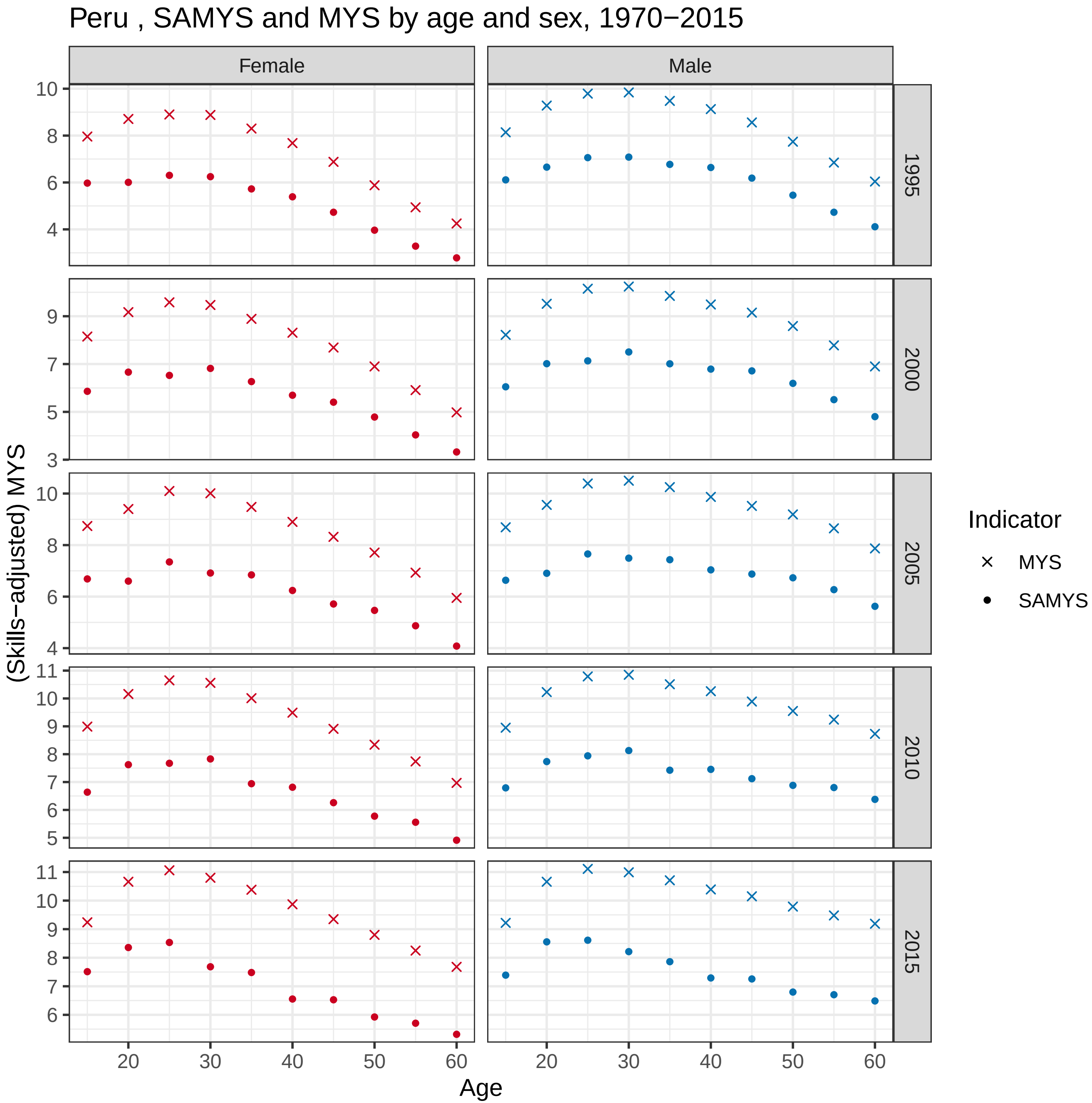

New Zealand , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Norway , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

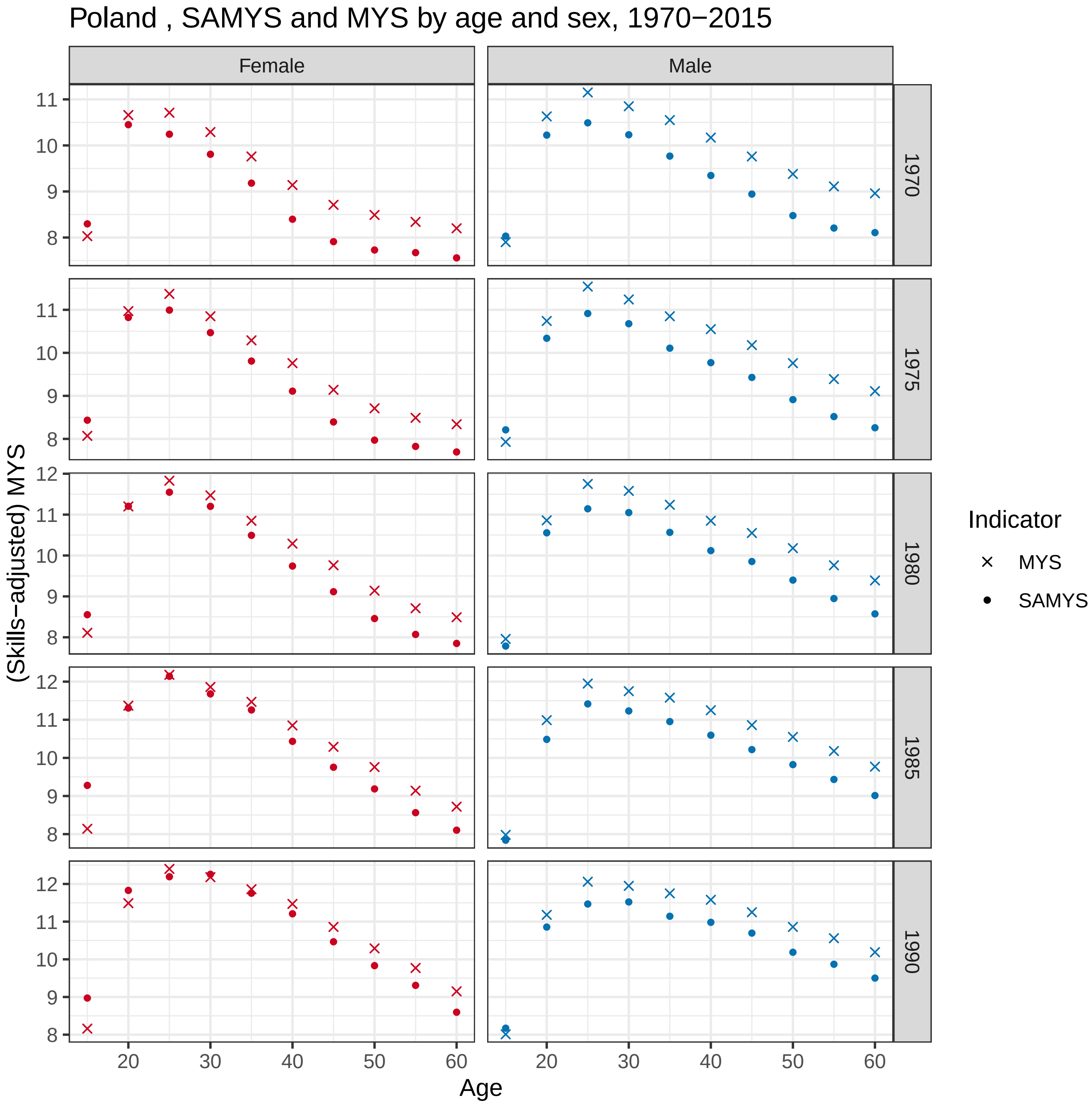


Norway , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

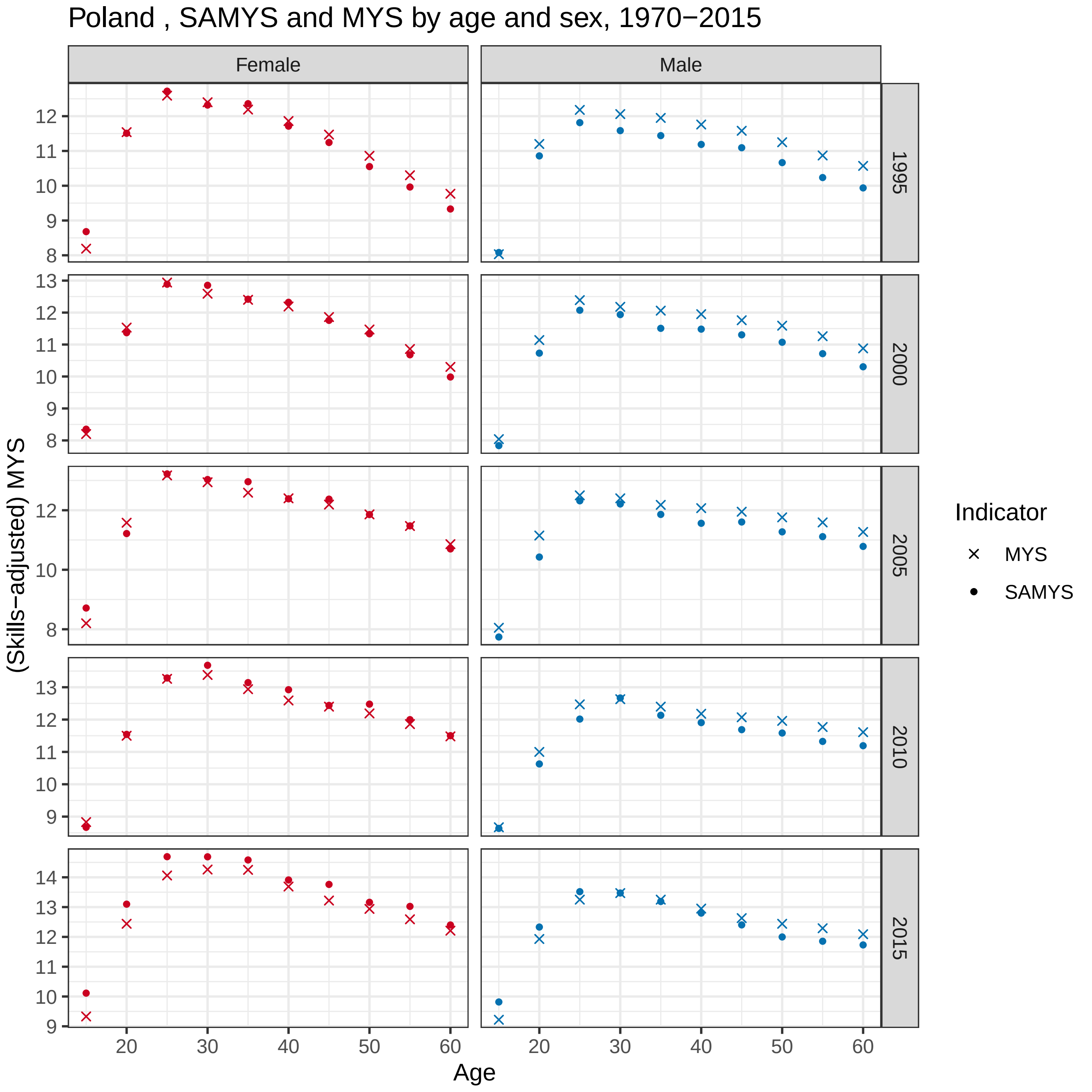

Peru , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



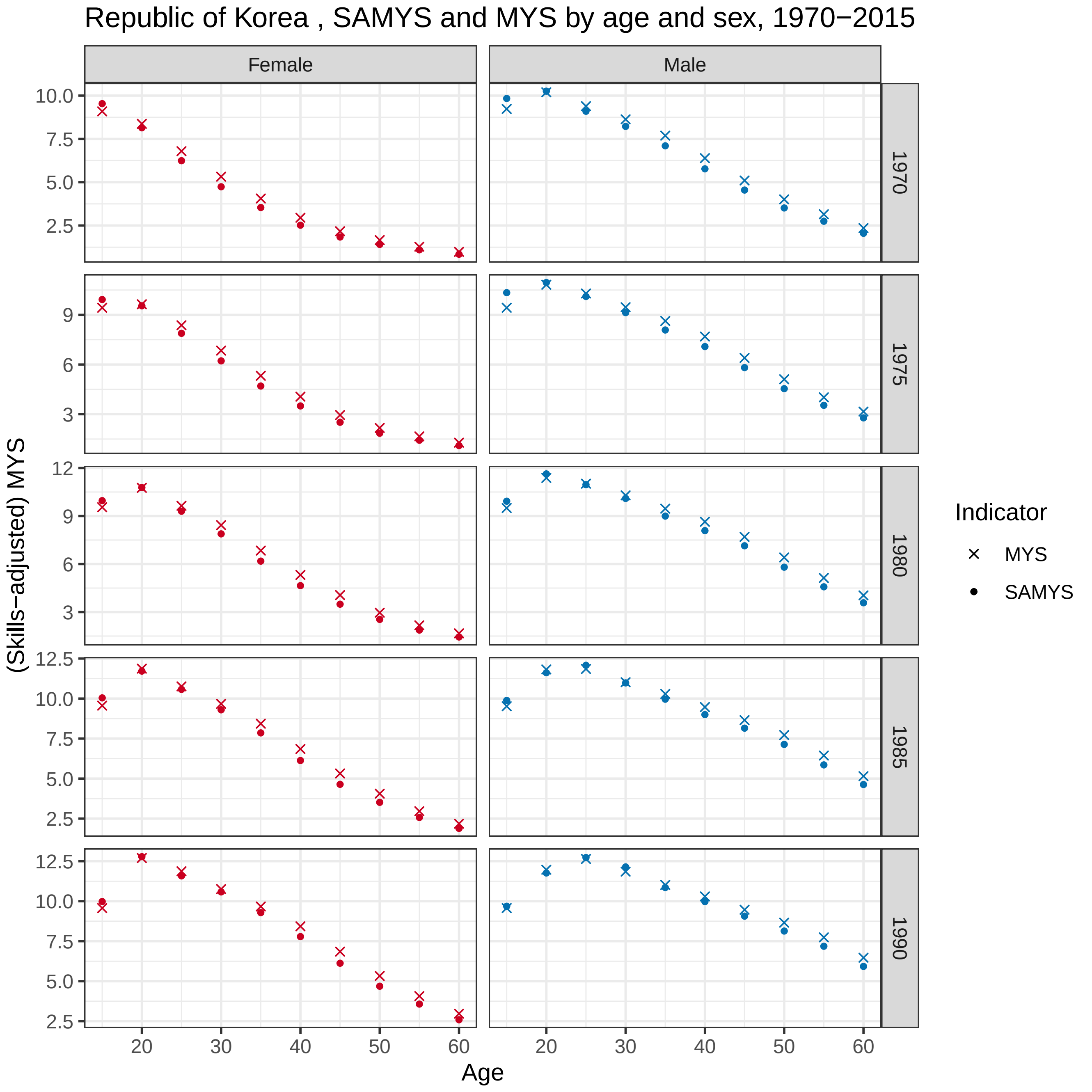
Peru , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

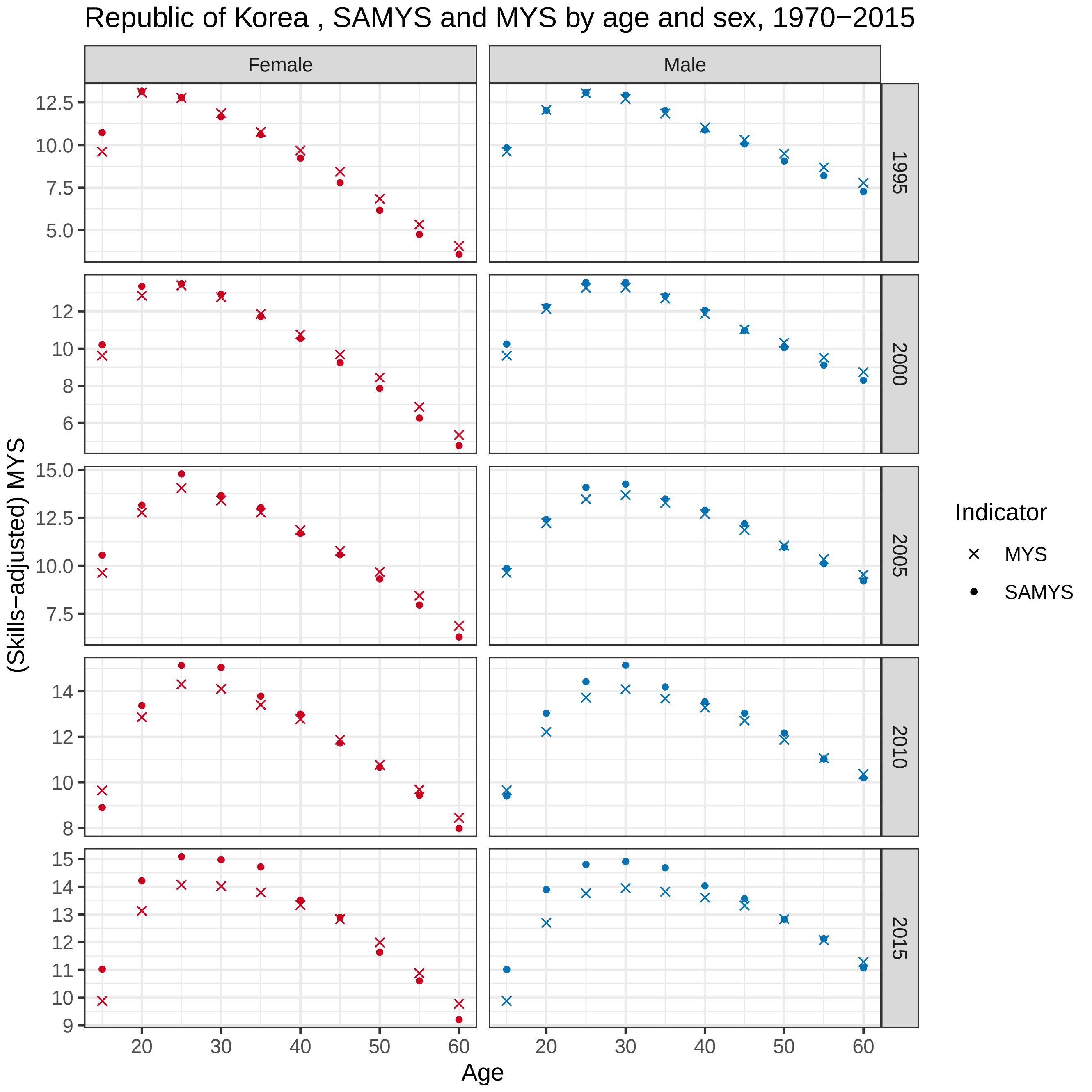


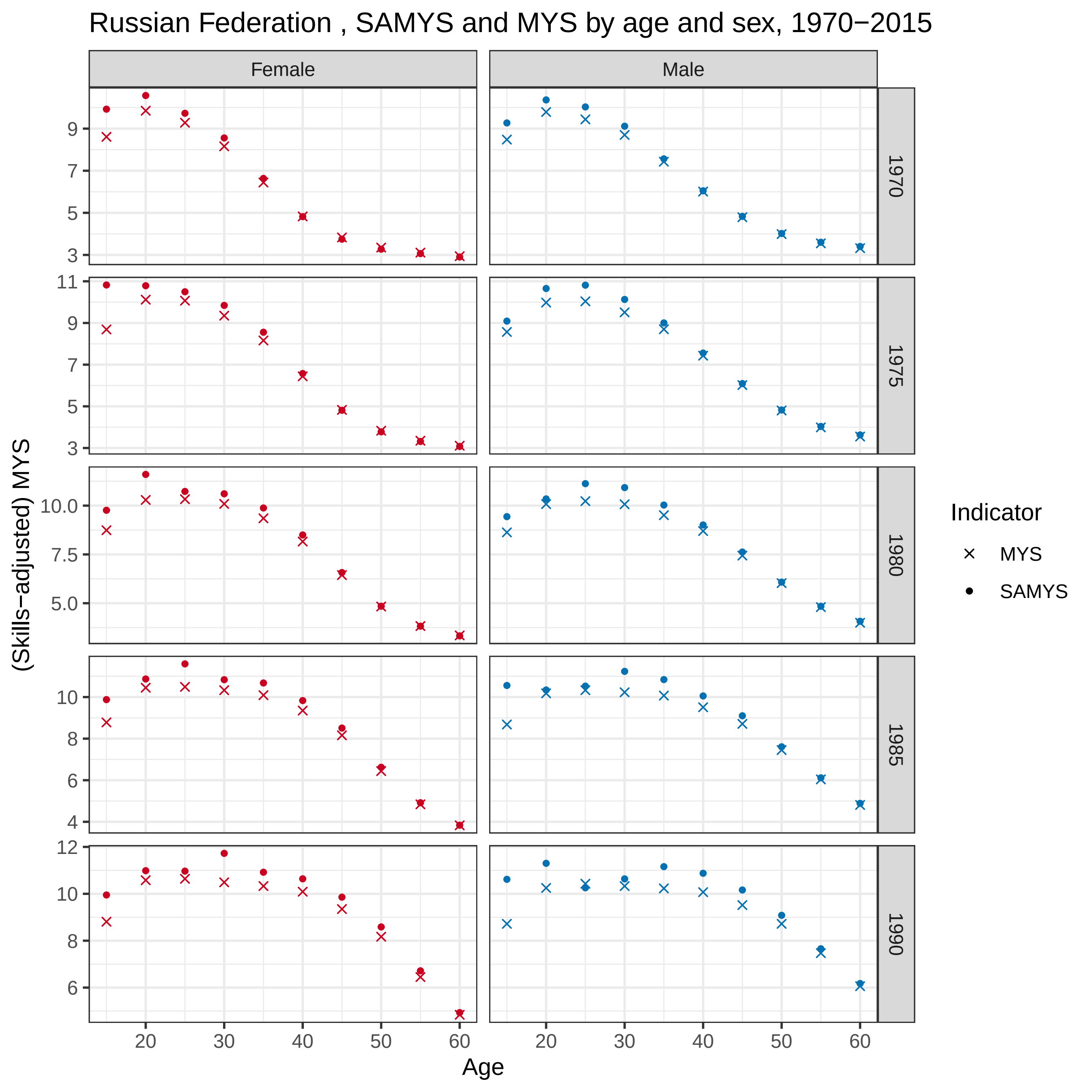
Poland , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



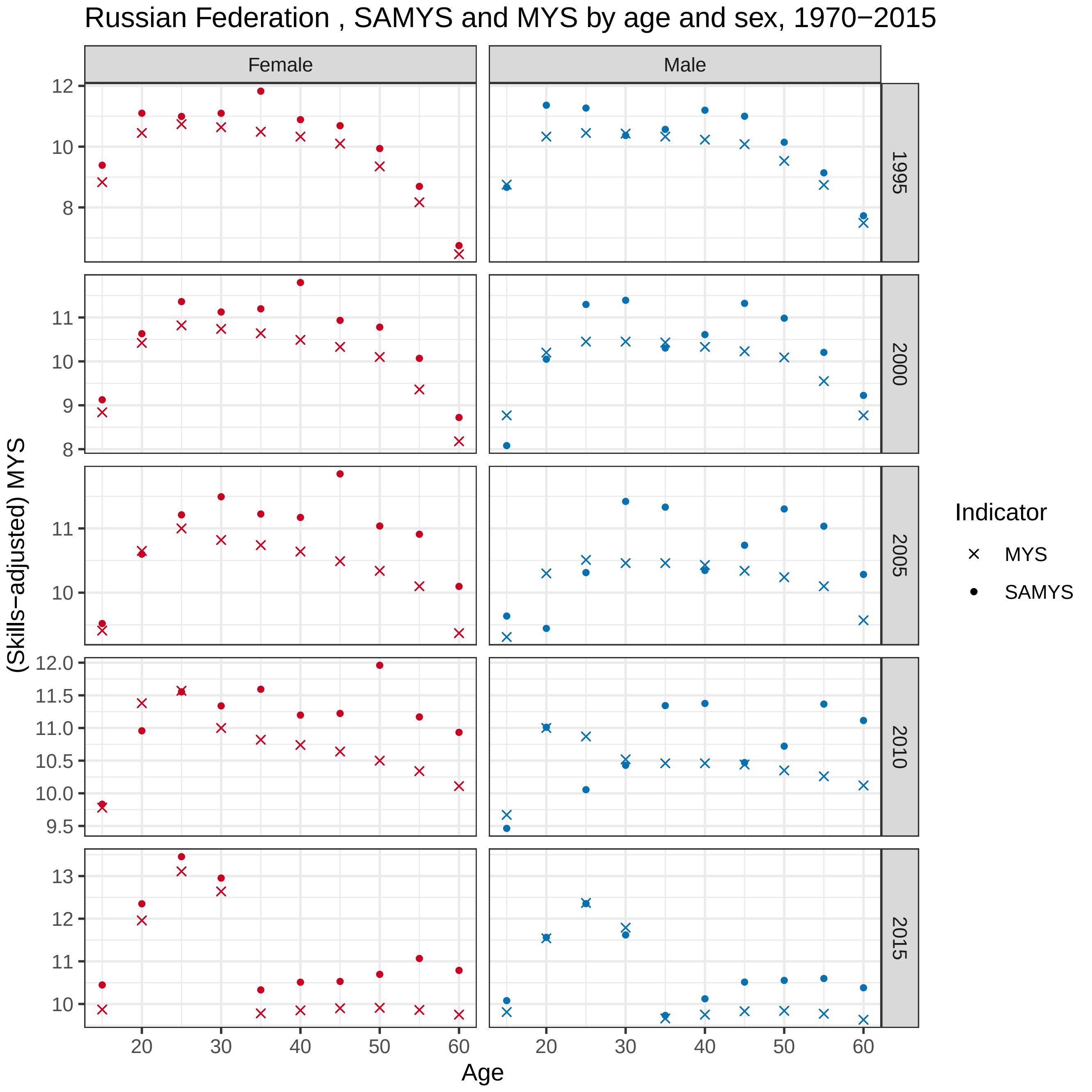
Poland , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

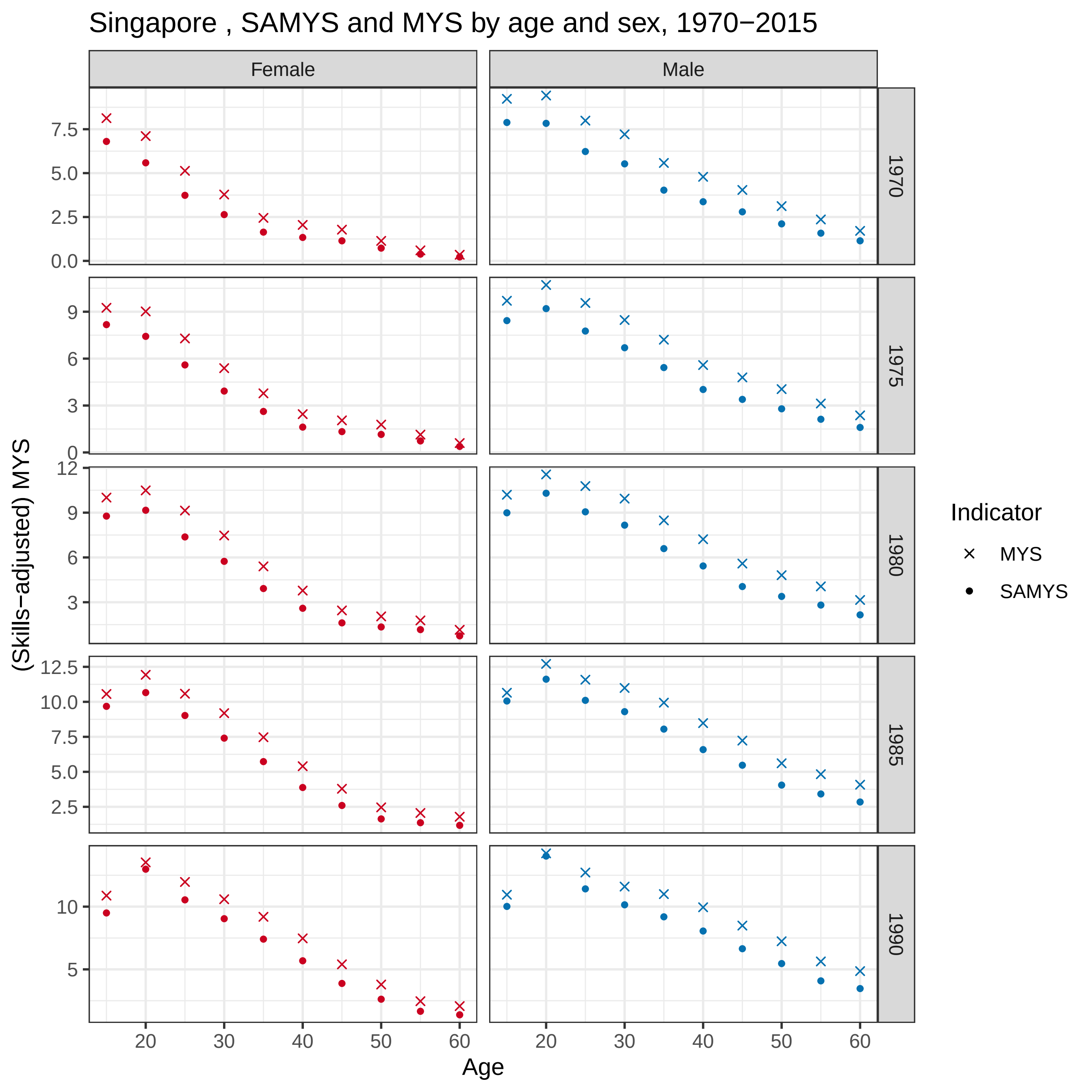

Republic of Korea , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

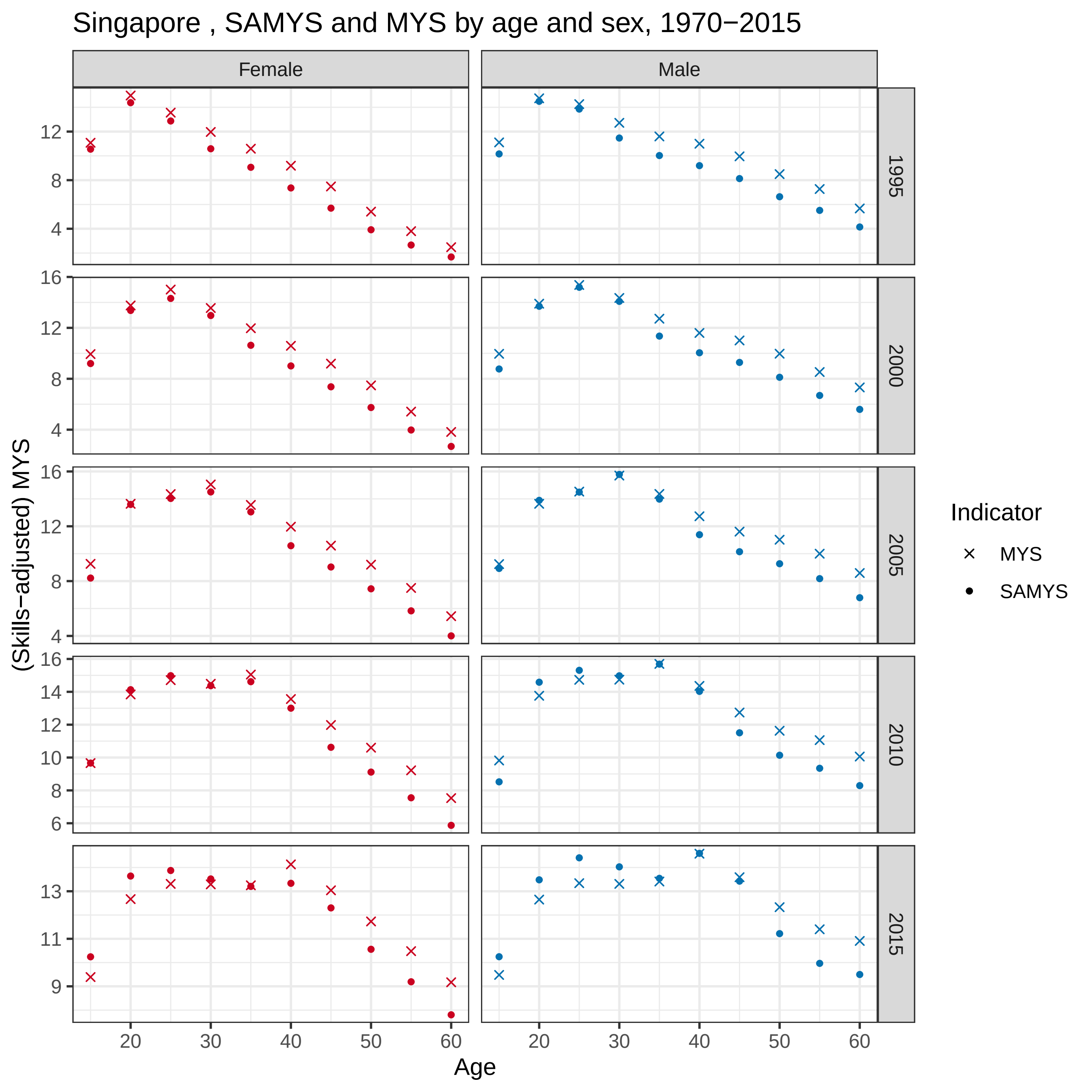

Republic of Korea , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



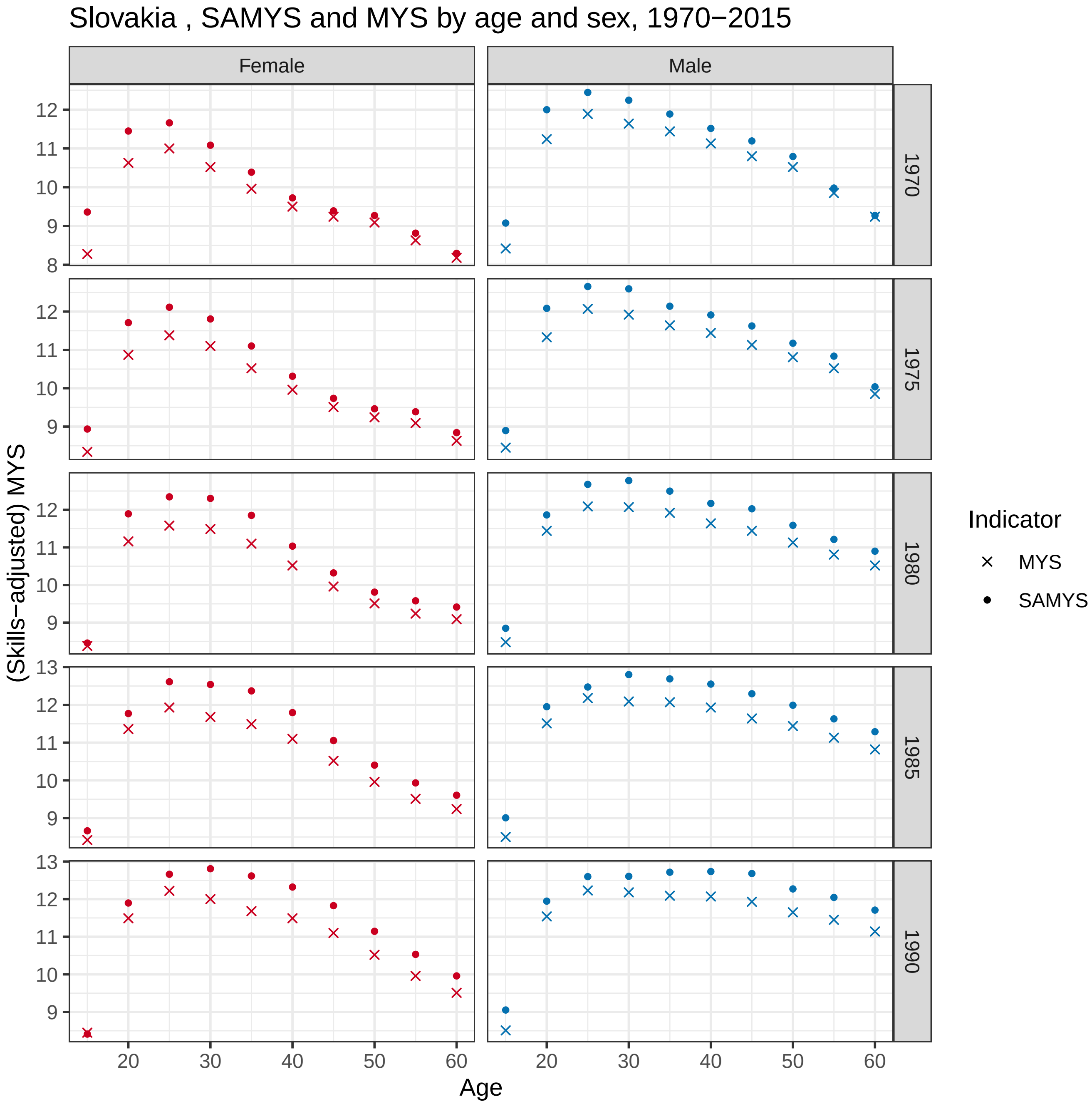
Russian Federation , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

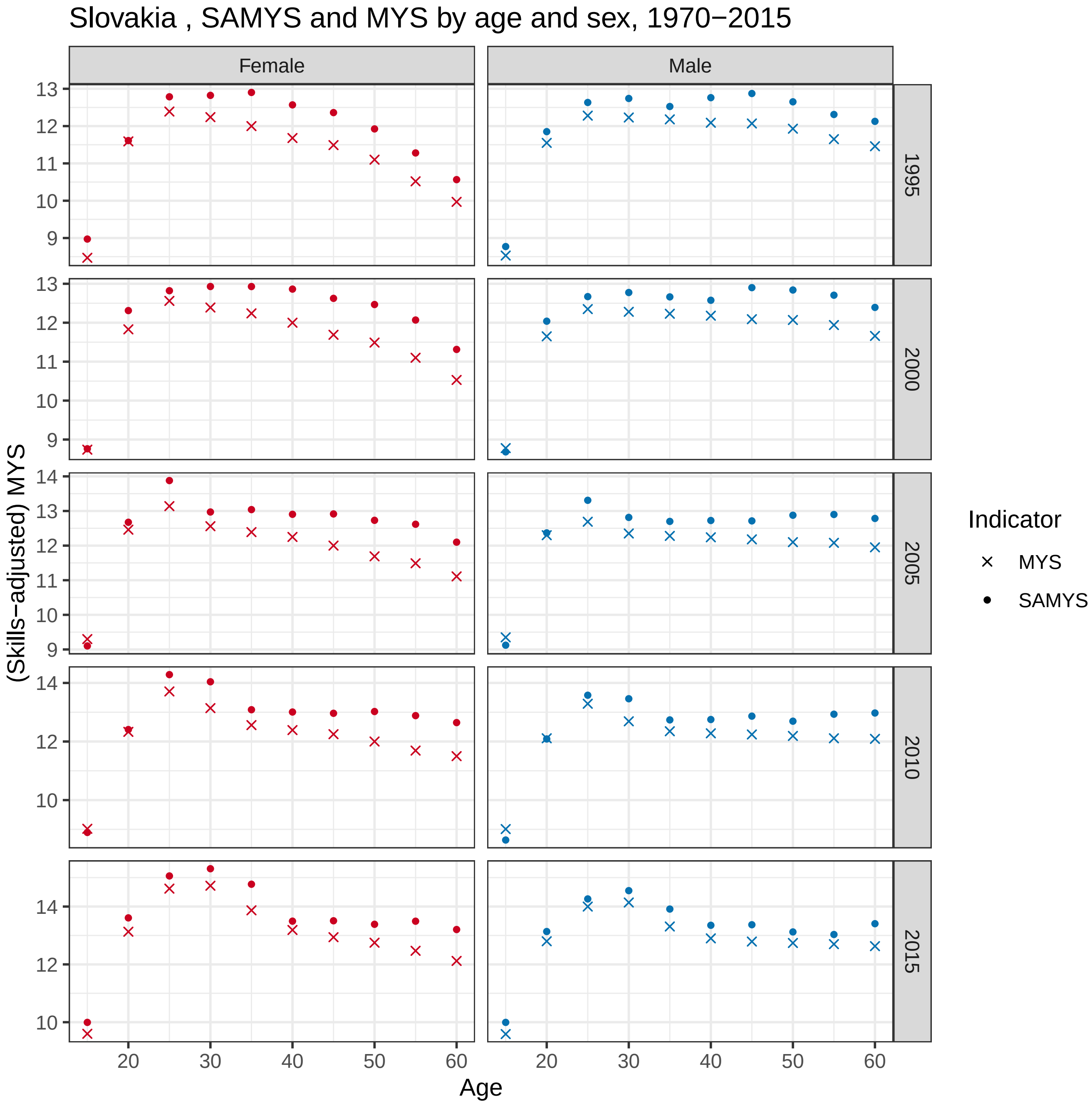

Russian Federation , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Singapore , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS
0.0
2.5
5.0
7.5
0
3
6
9
12
10.0
12.5
10
5
20
30
40
50
60

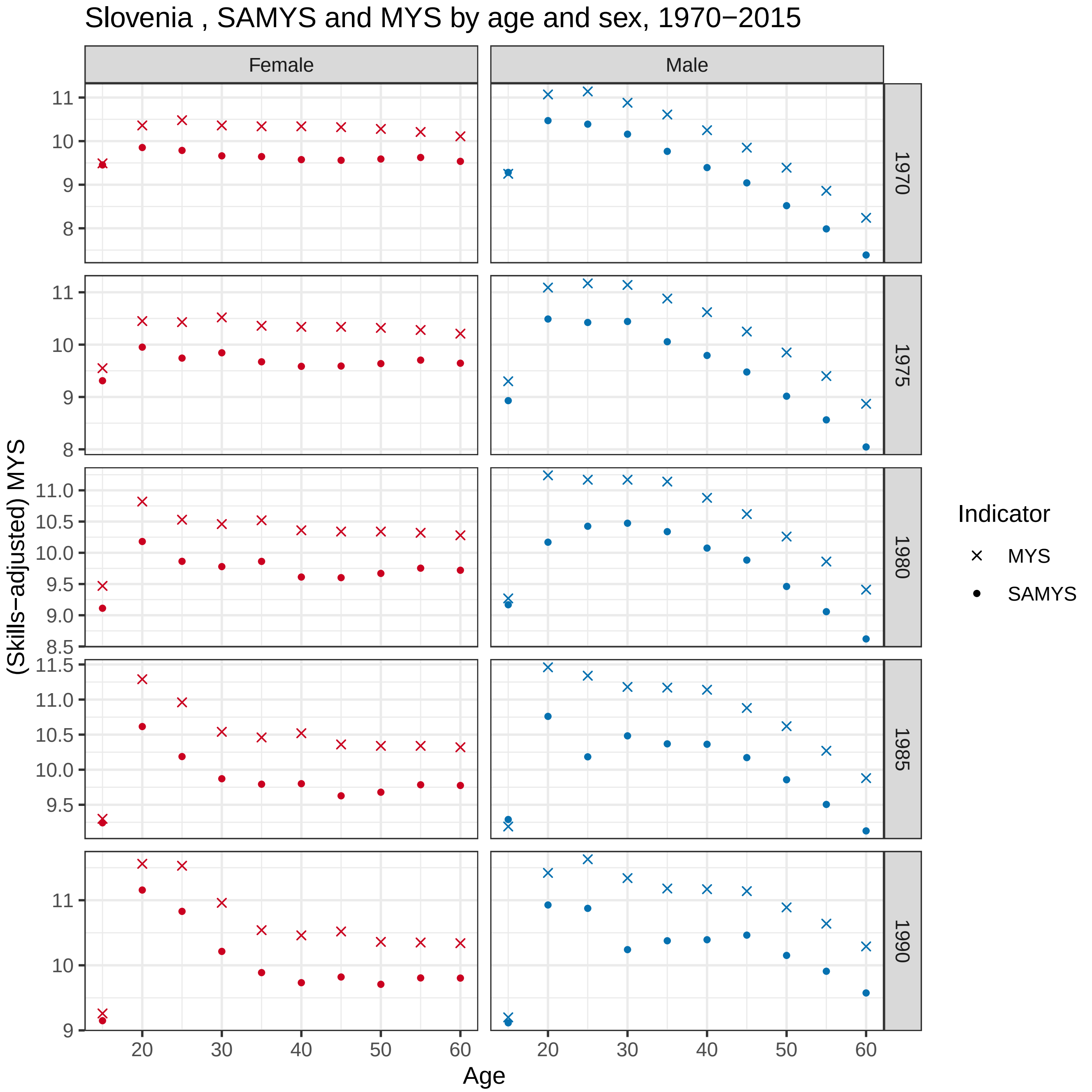


Singapore , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

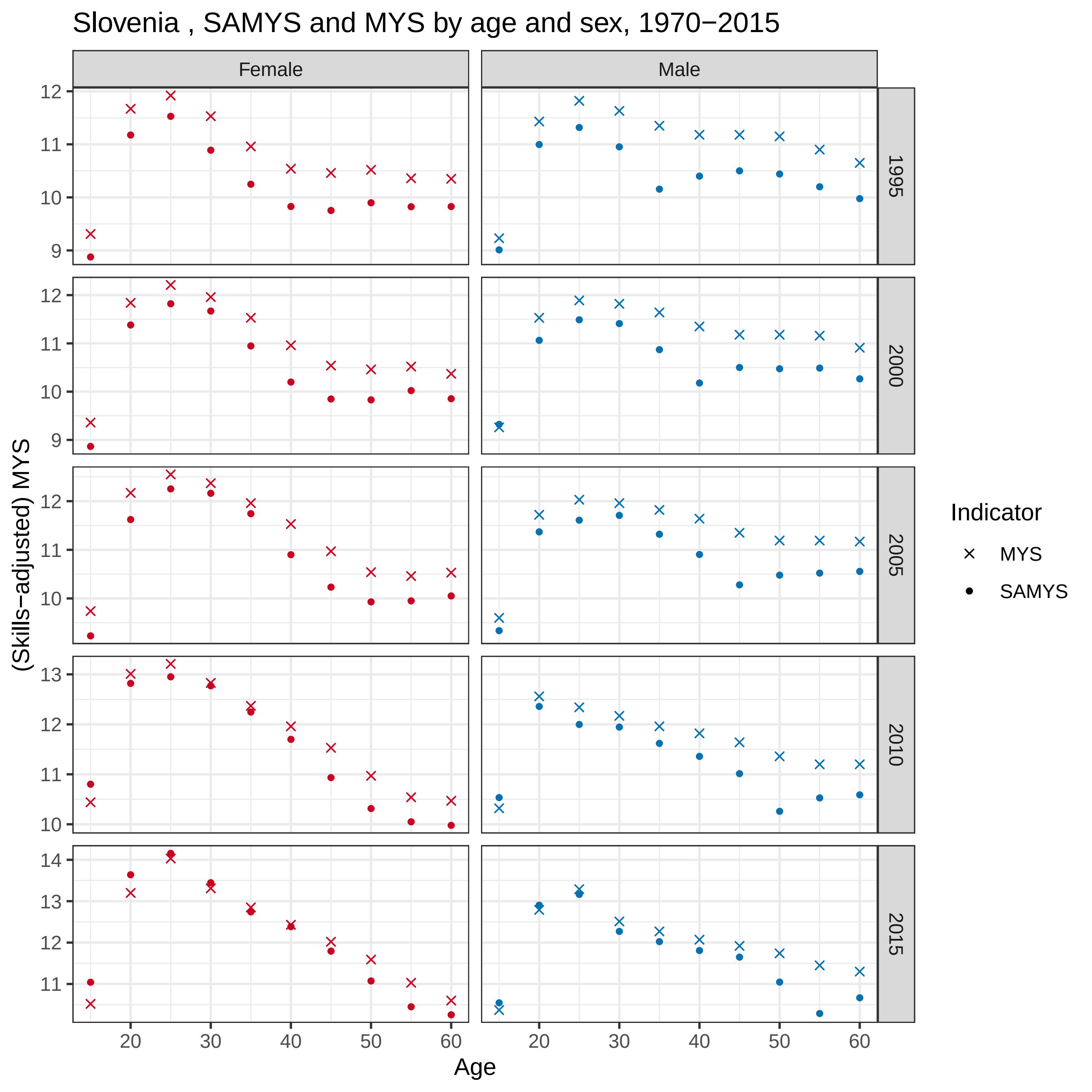

Slovakia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



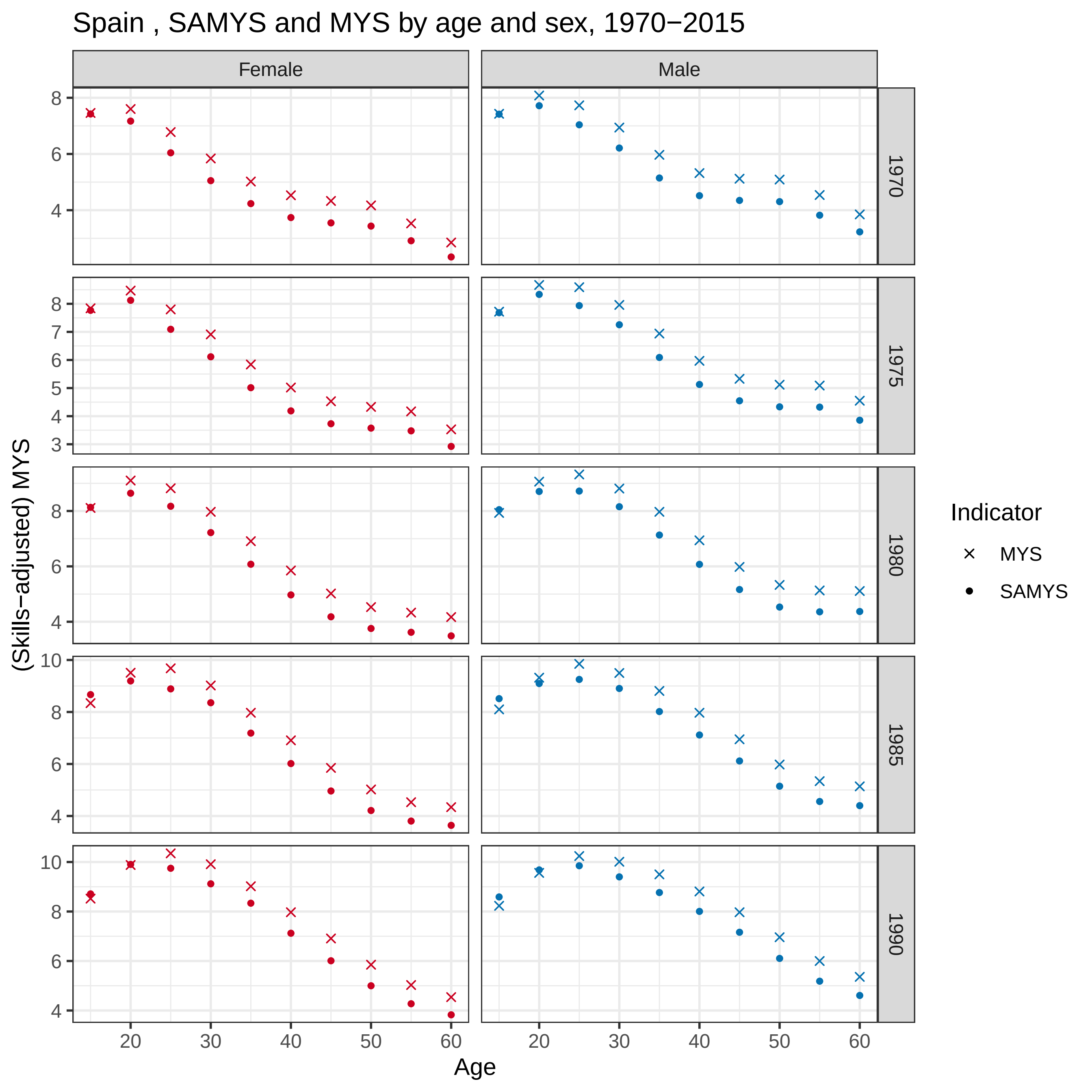
Slovakia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

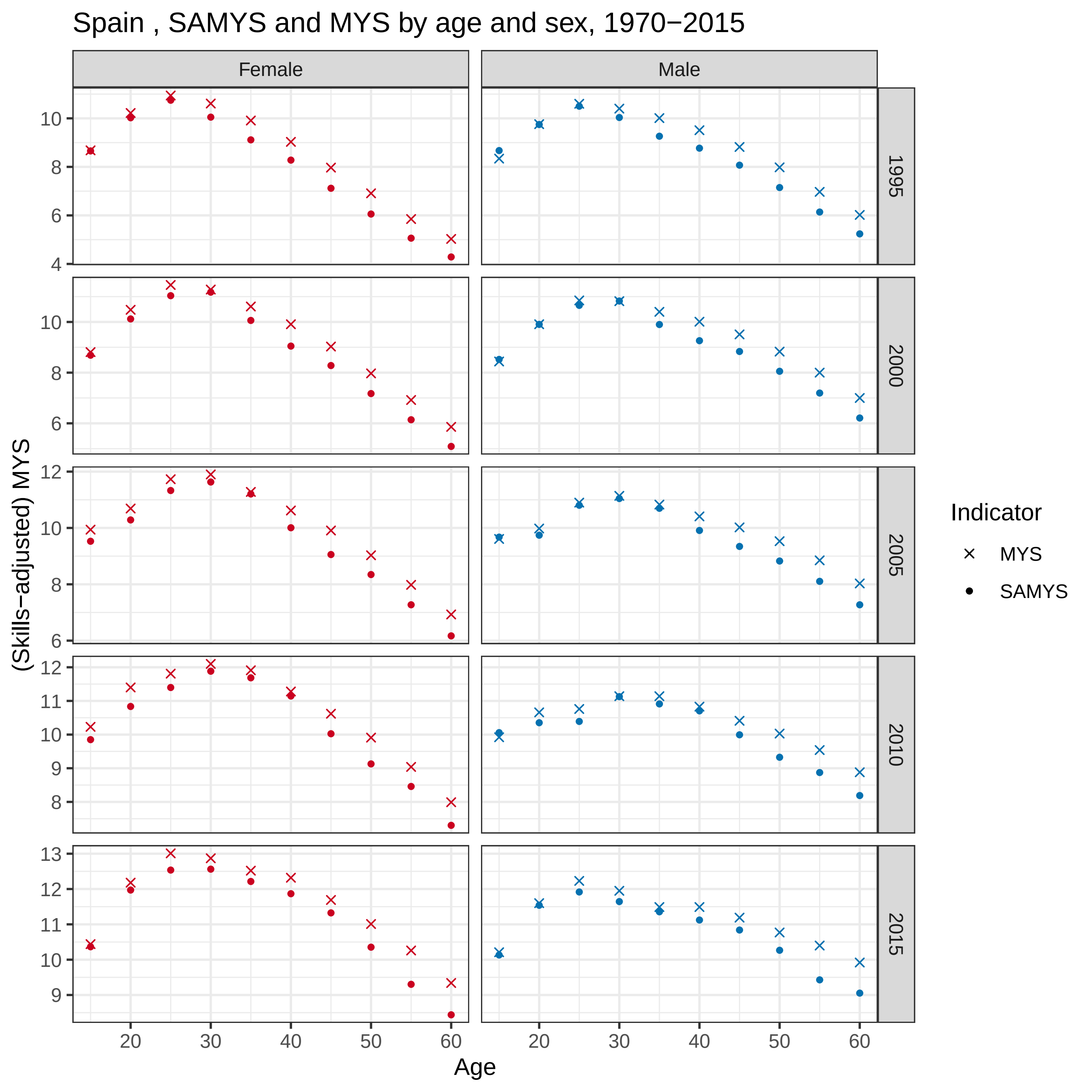


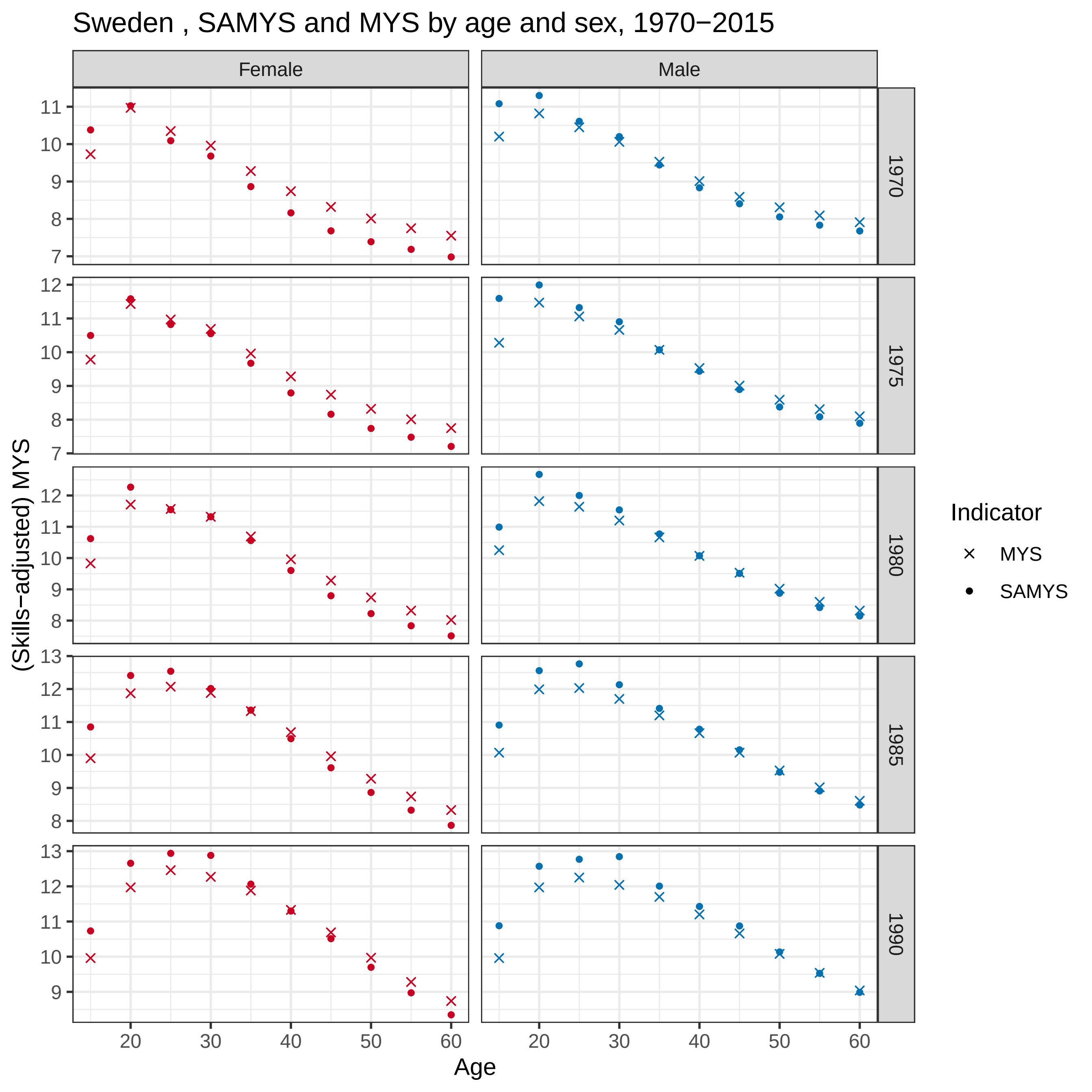
Slovenia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

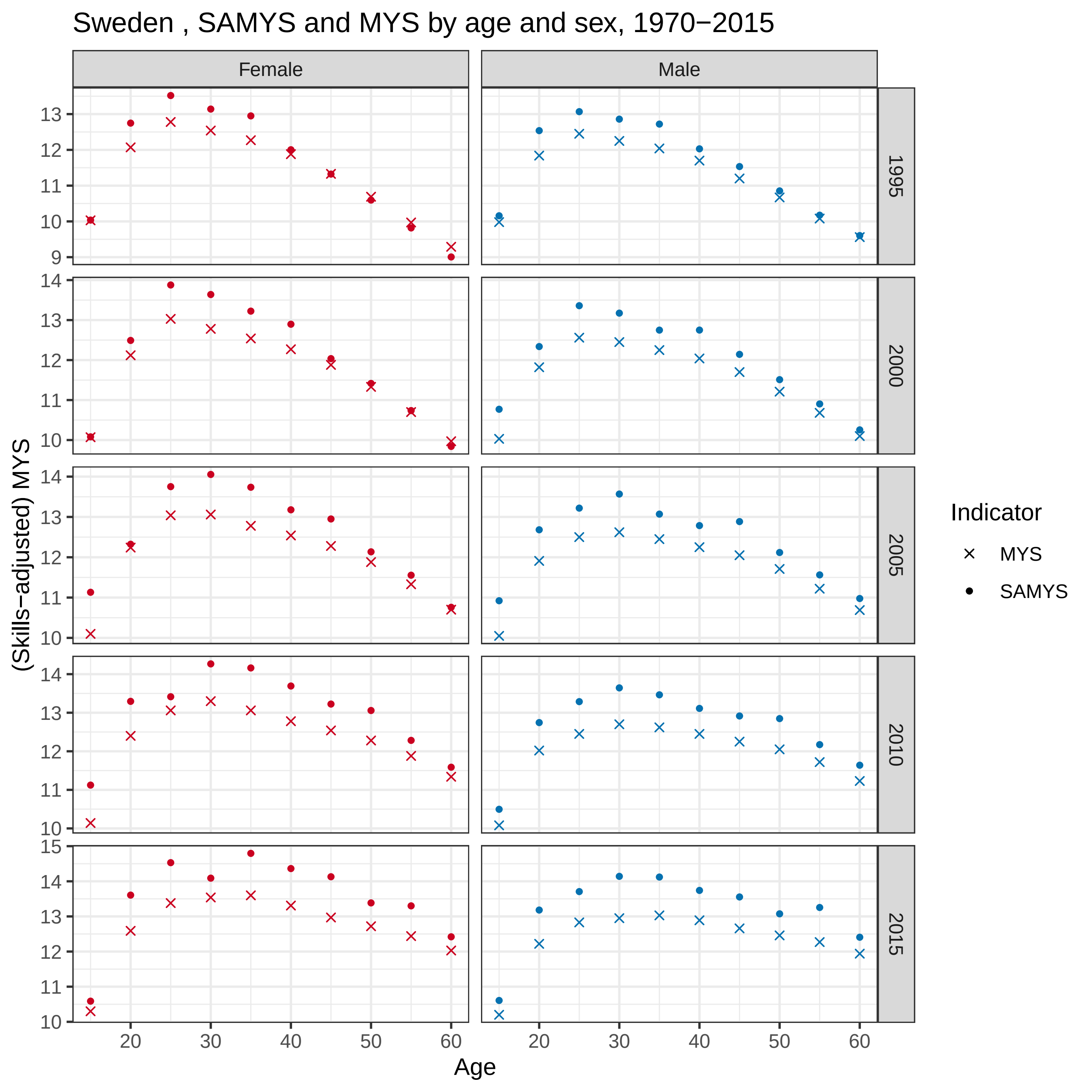


Slovenia , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

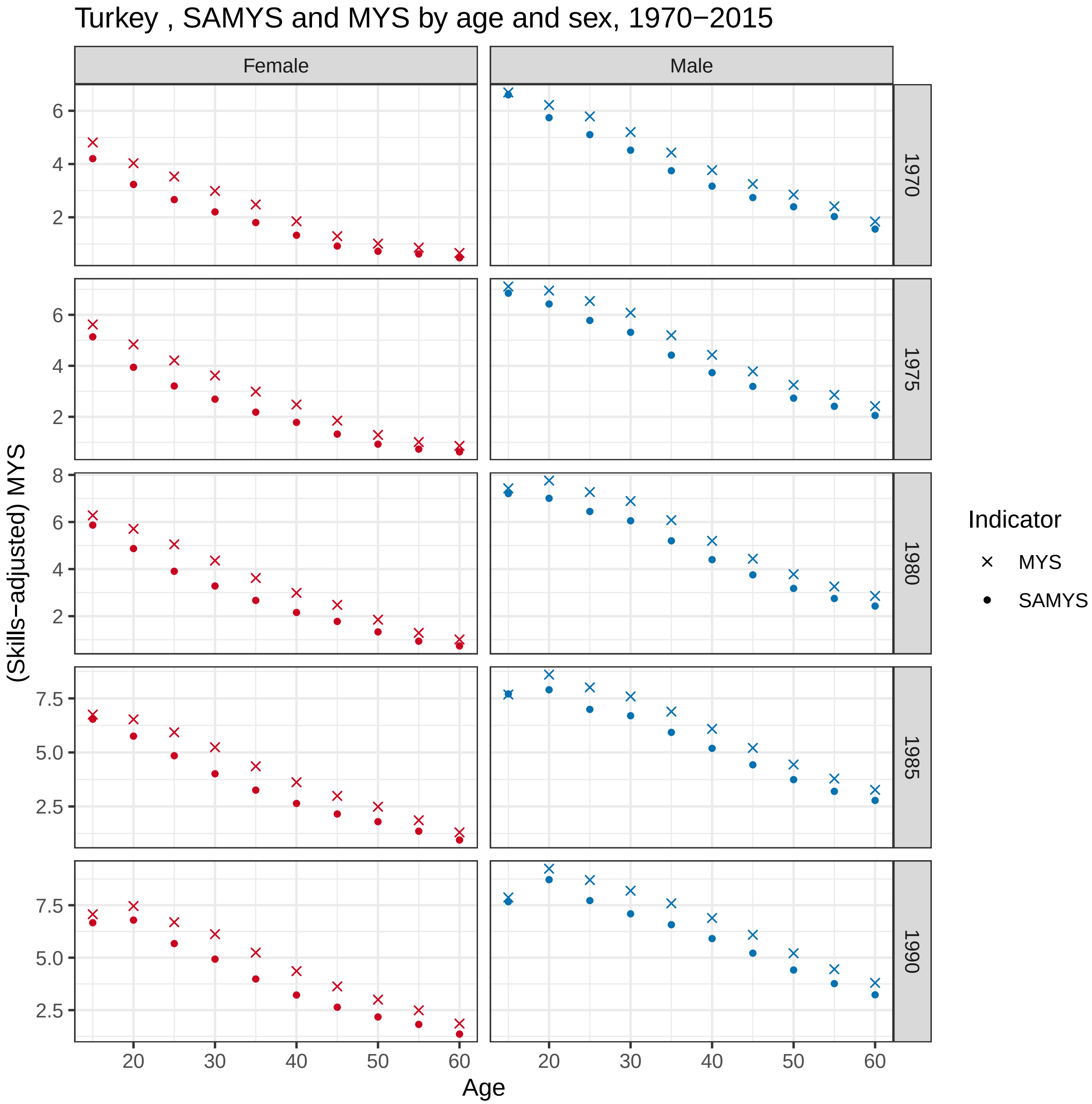

Spain , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

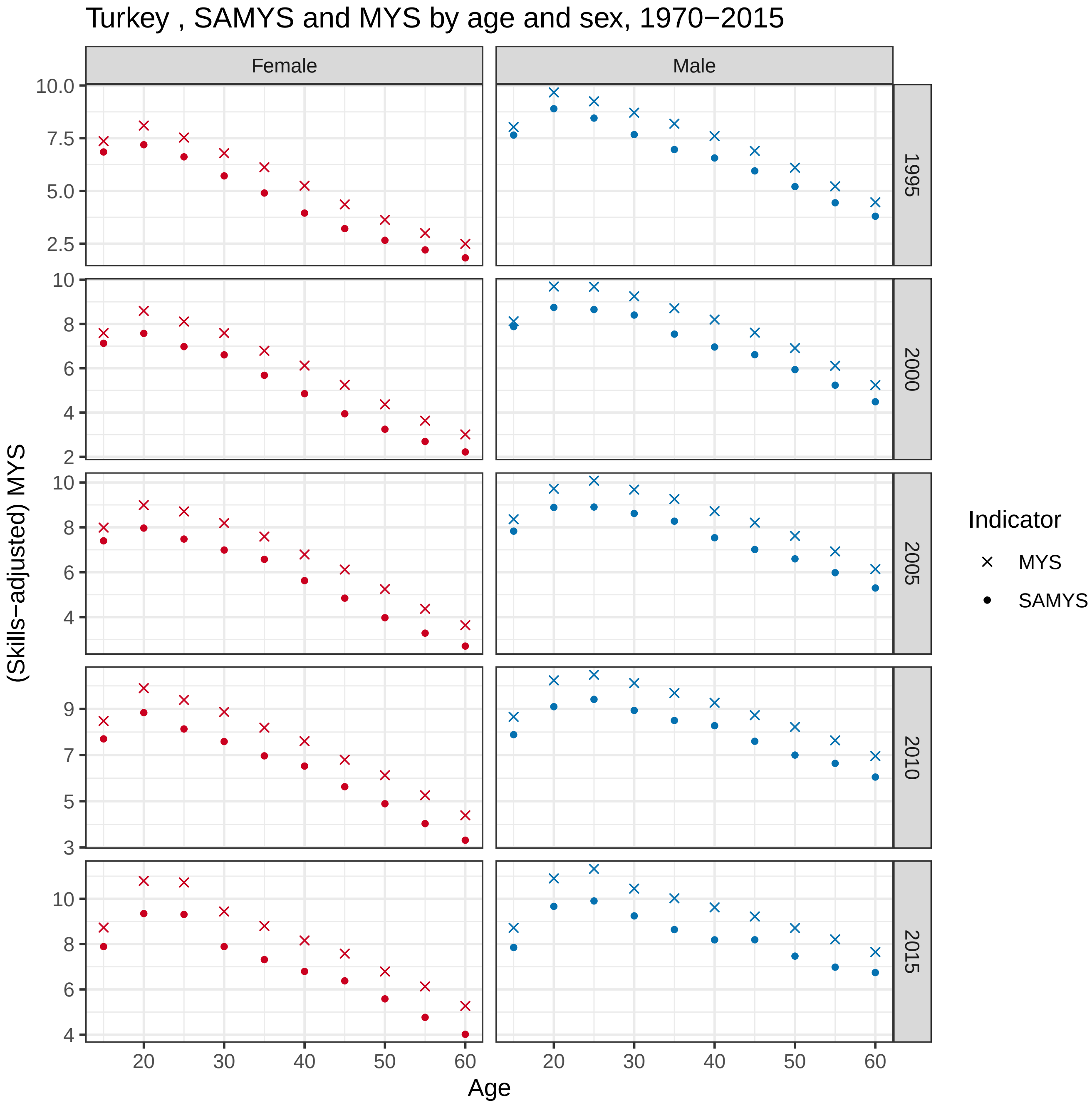

Spain , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Sweden , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

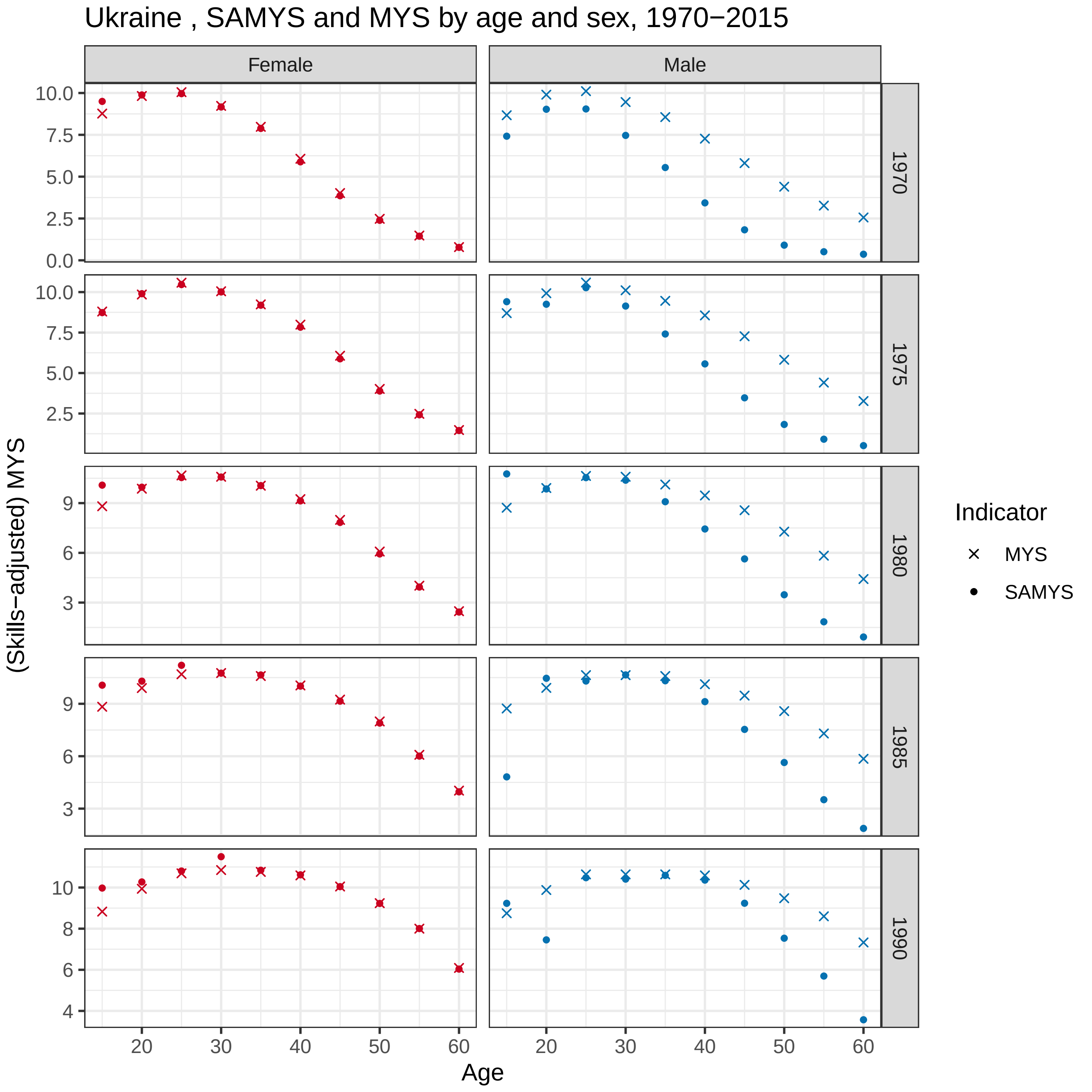


Sweden , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

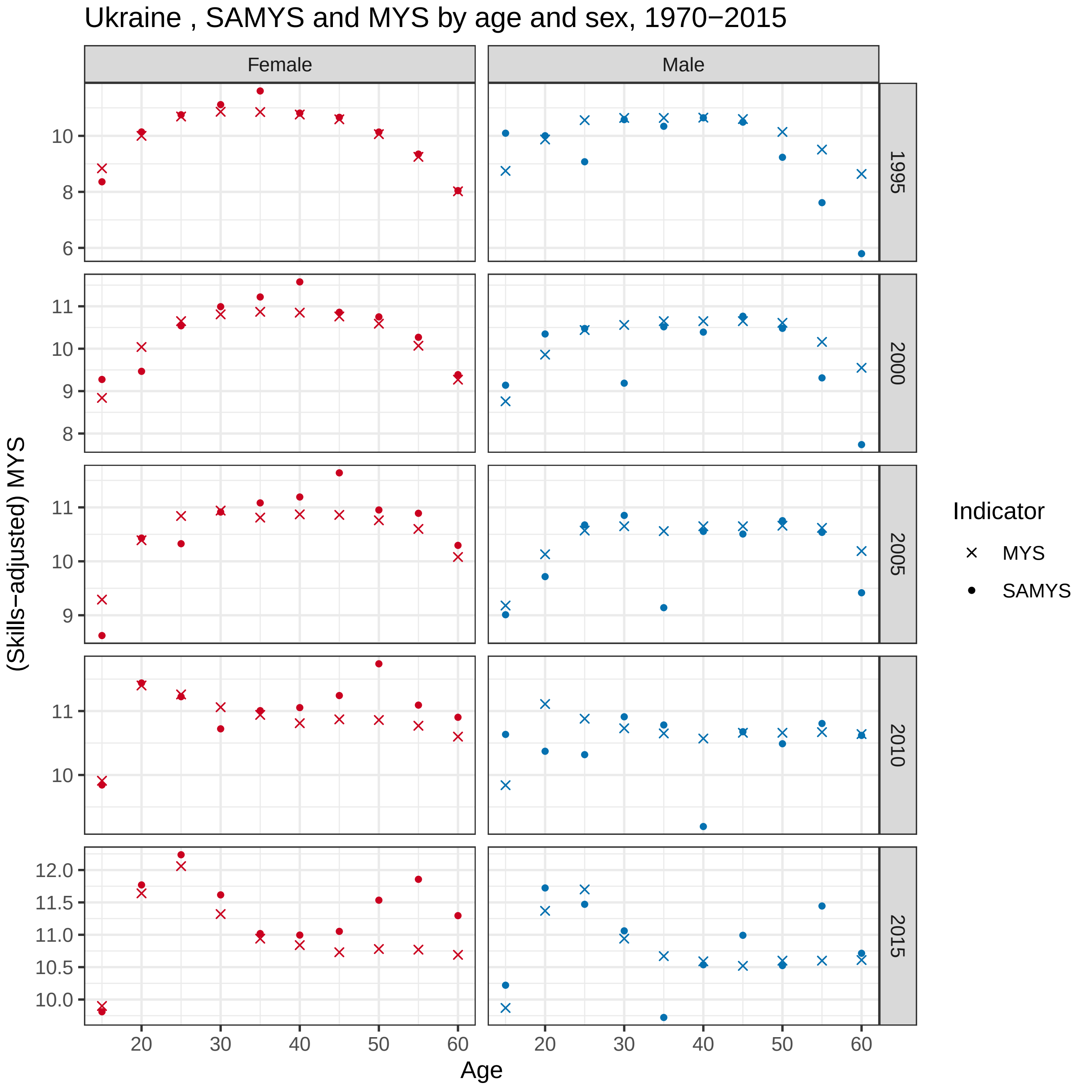

Turkey , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



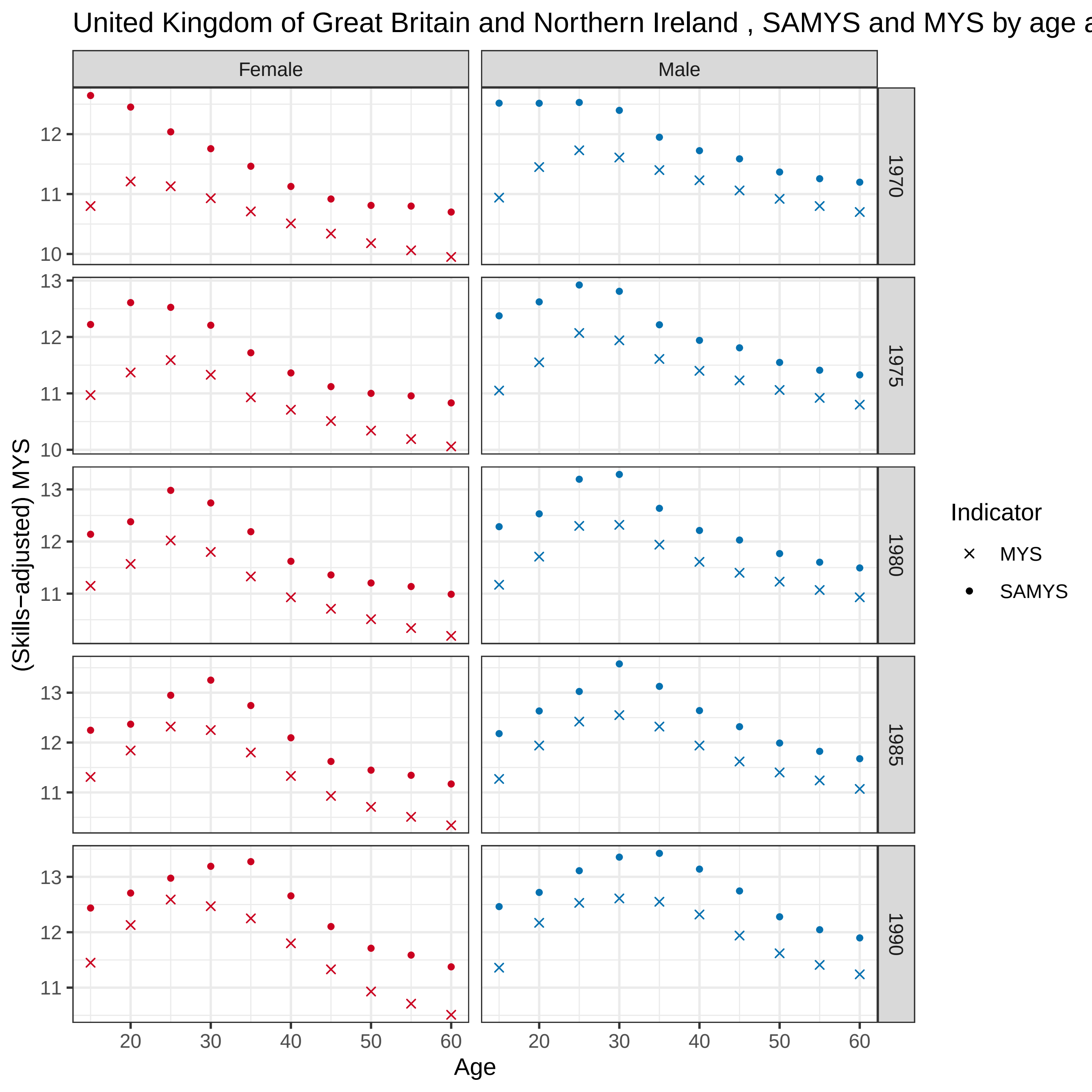
Turkey , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

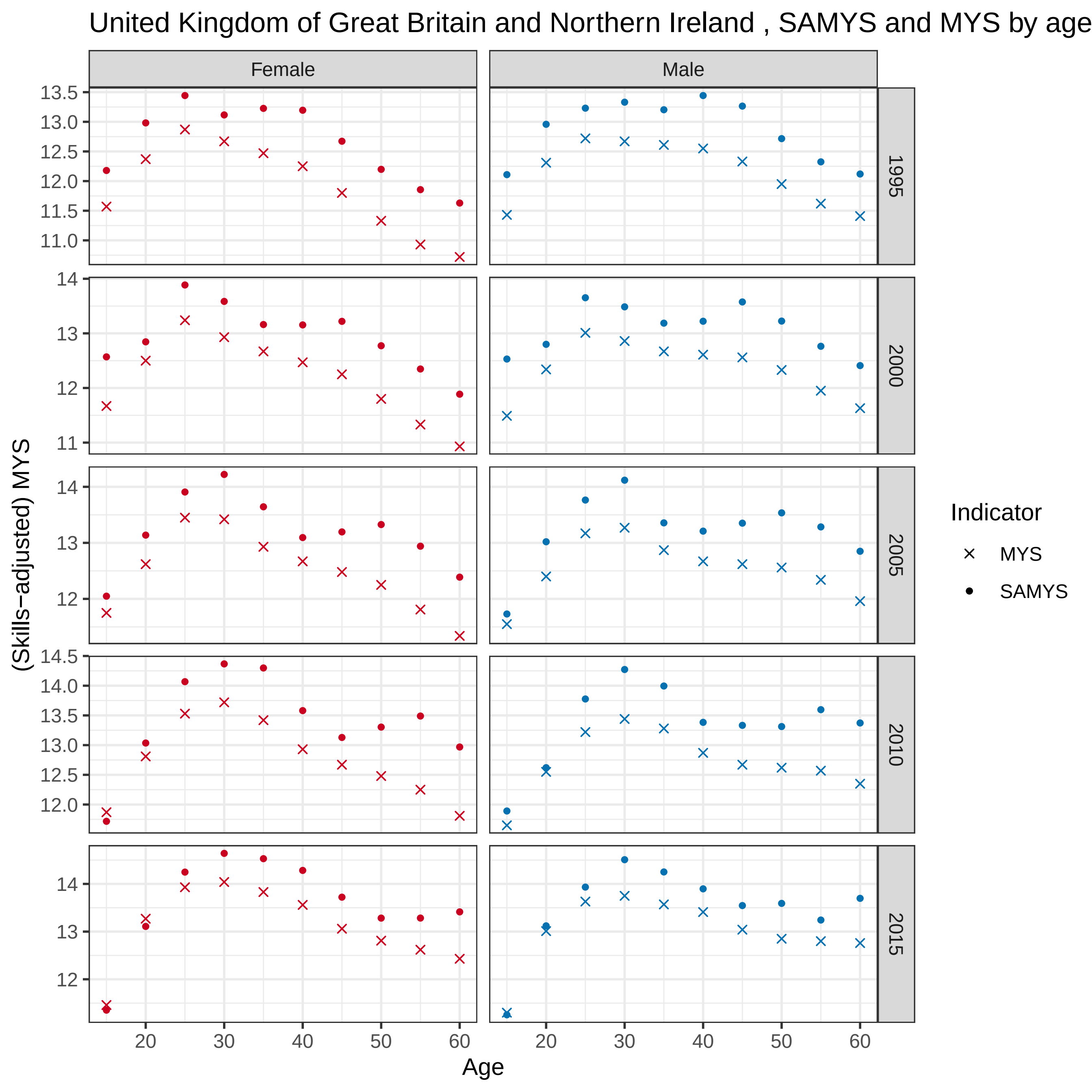


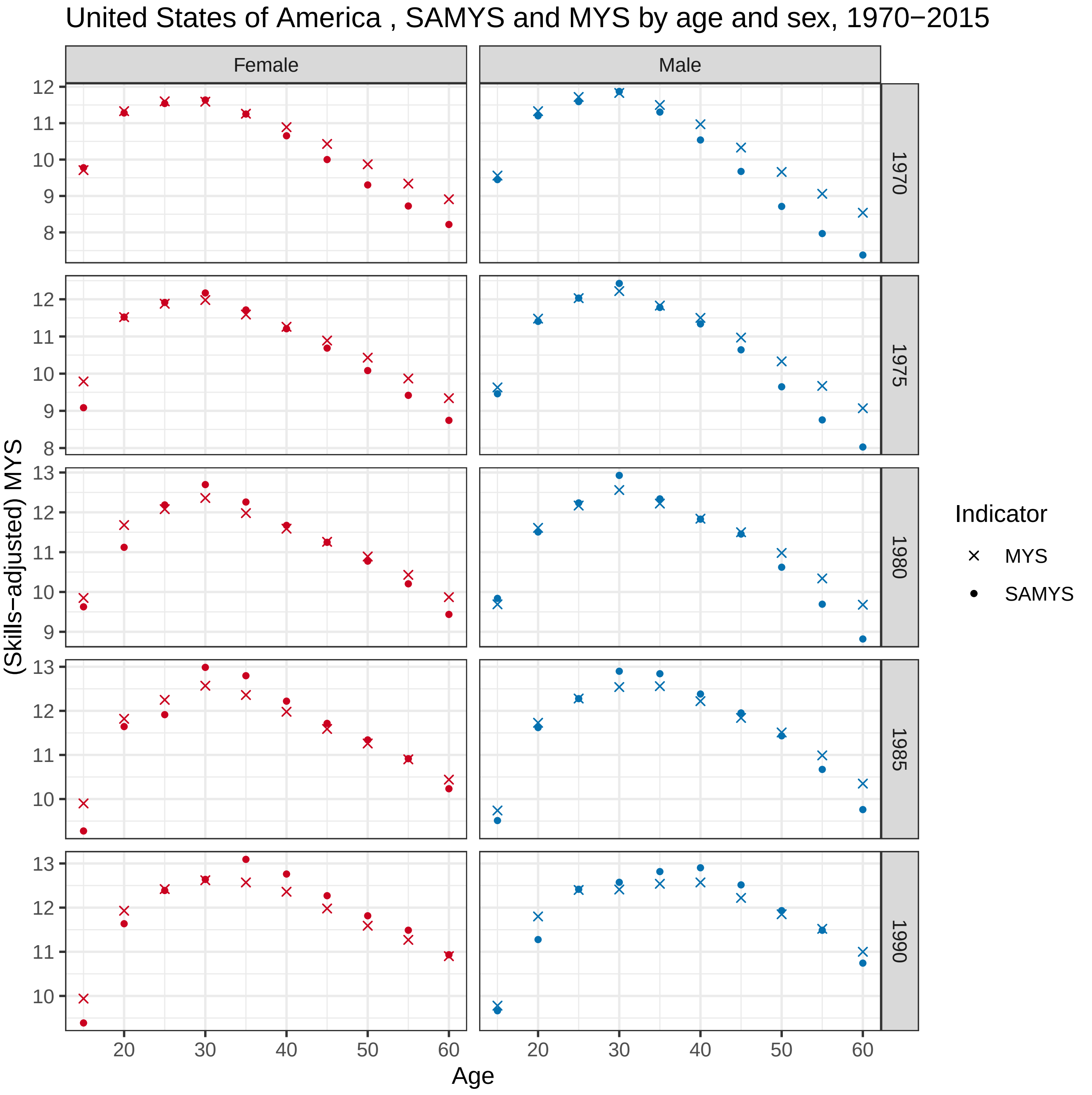
Ukraine , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

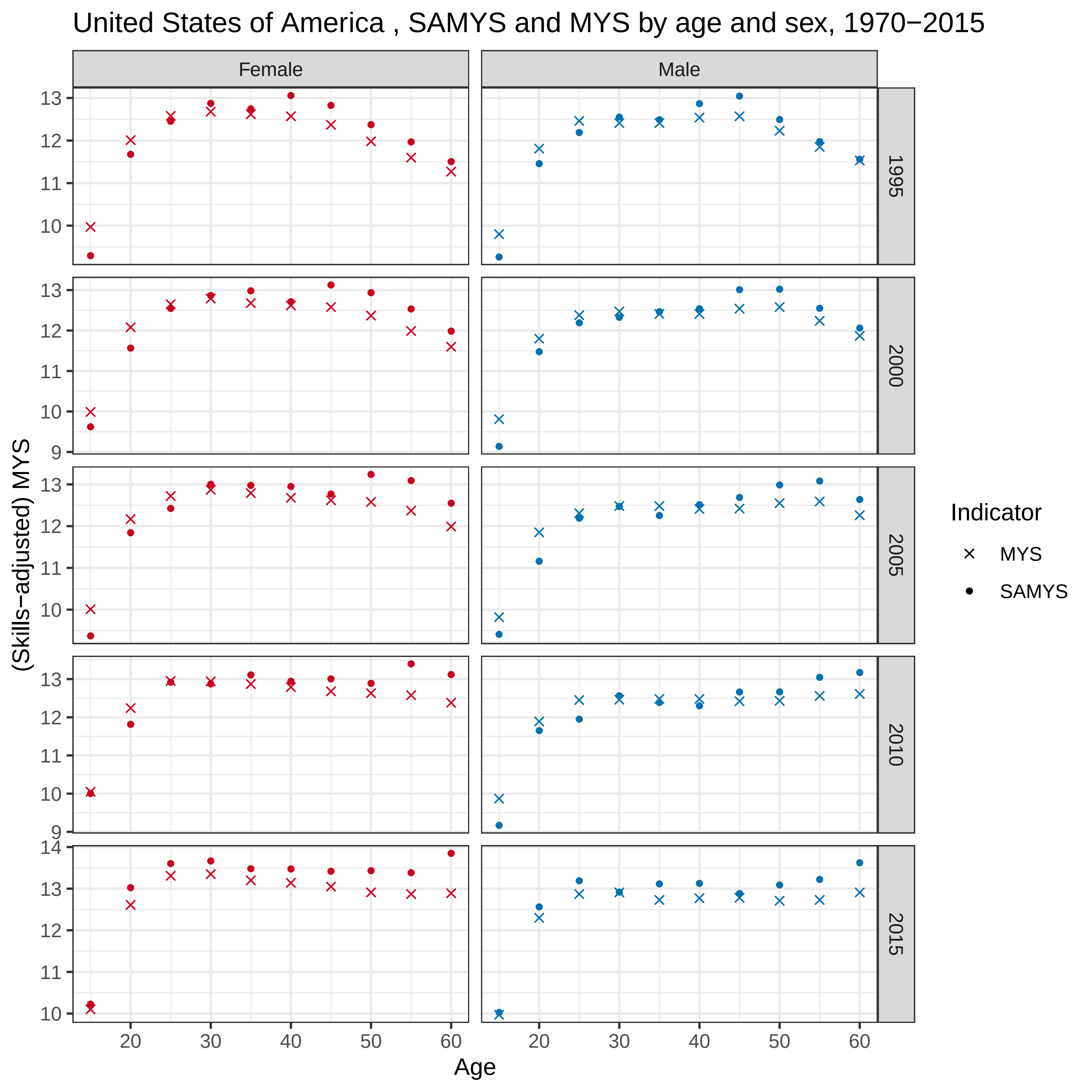


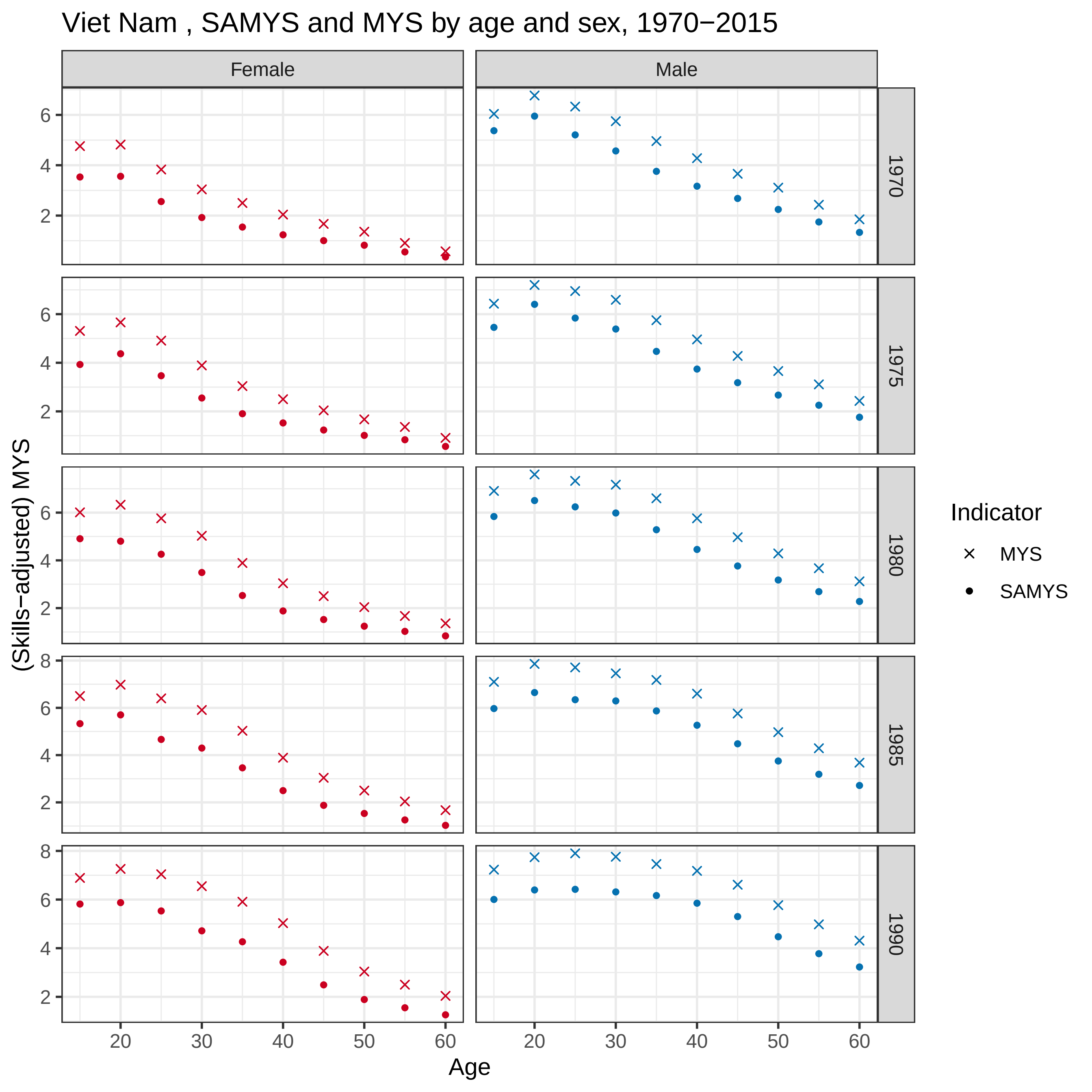
Ukraine , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


United Kingdom of Great Britain and Northern Ireland , SAMYS and MYS by age a
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS

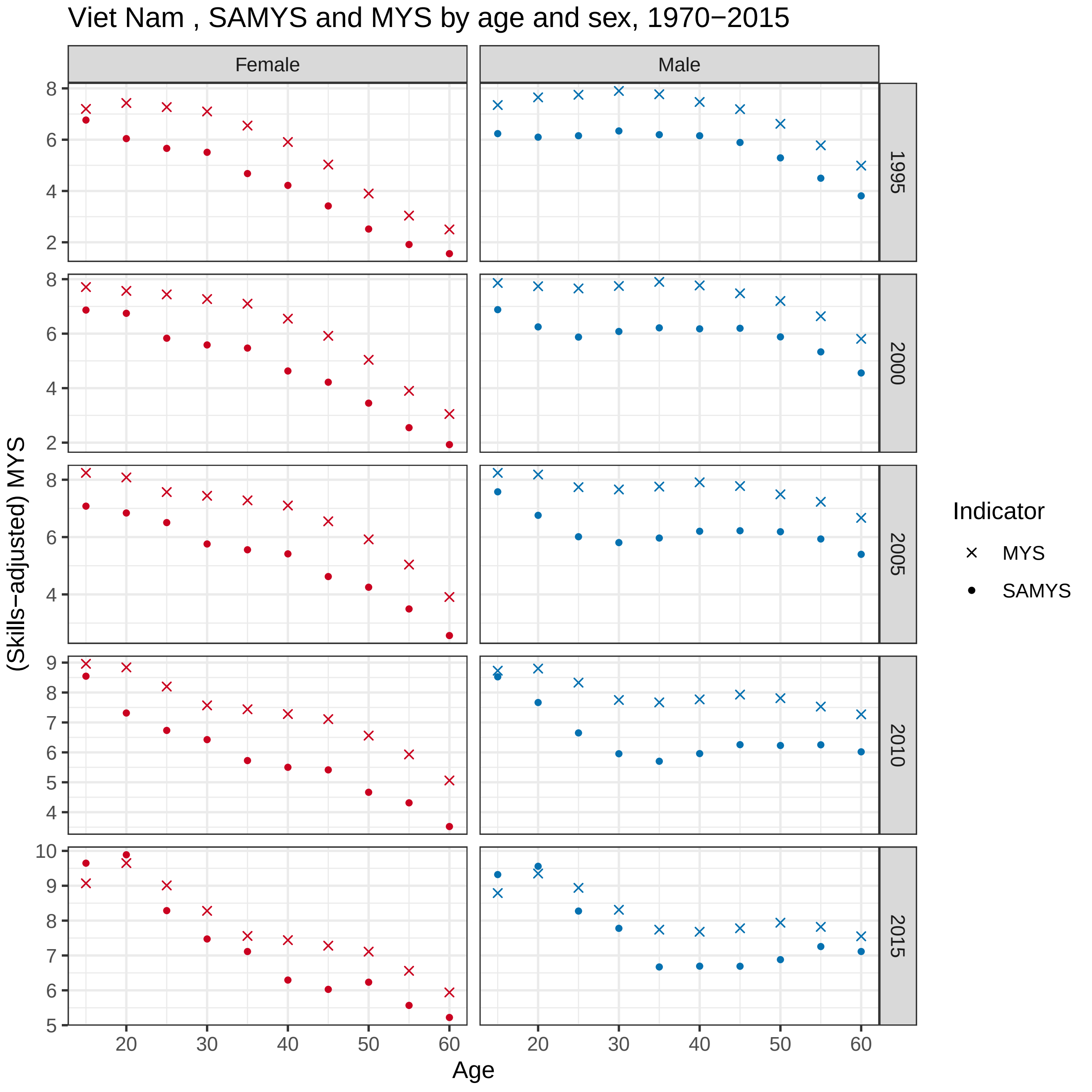

United Kingdom of Great Britain and Northern Ireland , SAMYS and MYS by age
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS
13.5
13.0
12.5
12.0
11.5
11.0
14
13
12
11
14.5
20
30
40
50
60


United States of America , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


United States of America , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS



Viet Nam , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1970
1975
1980
1985
1990
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS


Viet Nam , SAMYS and MYS by age and sex, 1970−2015
Female
Male
1995
2000
2005
2010
2015
(Skills−adjusted) MYS
Age
Indicator
MYS
SAMYS