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Global Wealth Dynamics: Understanding the Determinants

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Global Wealth Dynamics: Understanding the Determinants

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Abstract

This paper studies the dynamics of global wealth and its determinants across the five continents. We do so by building the first Global Wealth Accounts using official balance sheets combined with other external sources such as surveys or censuses. Our new database includes assets, liabilities and investment flows by sector (i.e., households, government, corporations, rest of the world) and asset class (i.e., housing, business assets, financial assets, etc.) for most countries in the world between 1995 until the present. We find substantial heterogeneities in both the level and trajectory of wealth across world regions. In particular, the level of private wealth relative to income has been much larger in Europe, North America, Oceania and South East Asia since the 1990s than in the rest of world regions and it has also risen more. Using standard wealth accumulation decompositions and counterfactual simulations, we show that both differences in volume effects and capital gains are behind the steeper rise in private wealth to income ratios in these regions.

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Contents

A Wealth Concepts

This section defines the various concepts of wealth and assets categories that we use in this paper. Our wealth concepts are defined using the 2008 System of National Accounts (United-Nations, 2010). We only deviate from these concepts in the treatment of unfunded employers' pensions. This is the same treatment of wealth concepts adopted in the Distributional National Accounts Guidelines (Alvaredo et al., 2020) of the World Inequality Database, to which our project adheres.

For a given country, the SNA-2008 defines 6 basic institutional sectors: 5 resident sectors and the foreign sector. The five resident sectors are households (S.14), non-profit institutions serving households (S.15), non-financial corporations (S.11), financial corporations (S.12), and the general government (S.13). We re-group the five sectors into three: (i) the private sector (the sum of households and non-profit institutions serving households), (ii) the corporate sector (financial plus non-financial corporations), and (iii) the general government.

For a given resident sector i (i.e., private, corporate, or government sectors), wealth (or net worth) is the sum of non-financial assets plus financial assets, less liabilities: $W_i = A_i^{NF} + A_i^F - L_i$. At the country level, we follow the two definitions of national wealth used by Piketty and Zucman (2014). The first one, called the book value of wealth, basically follows the SNA standards by computing, for each resident sector i, their non-financial assets (A_i^{NF}), and adding the net foreign wealth (NFW).[1] Grouping households and non-profit institutions into the private sector and financial and non-financial corporations into the corporate sector, book-value of national wealth (W_N^B) can be expressed as follows: $W_N^B = A_P^{NF} + A_C^{NF} + A_G^{NF} + NFW$. The other definition of national wealth, named market-value of wealth (W_N^M), is the sum of private wealth (W_P) and public sector wealth (W_G): $W_N^M = W_P + W_G$.

The link between these two definitions can be traced to the corporate sector. To see this, start with a closed economy, where financial assets cancel out with liabilities, and national wealth equals the national stock of non-financial assets. Given that in an open economy net foreign wealth equals the sum of financial assets A_i^F minus liabilities L_i of resident sectors: $NFW = A_P^F - L_P + A_C^F - L_C + A_G^F - L_G$, then the book-value of national wealth equals the market-value definition plus the wealth of the corporate sector: $W_N^B = W_N^M + W_C$. In our paper we favor the market-value definition of national wealth, but we also present results for book-value national wealth.

As a rule, all financial assets and liabilities of resident sectors are unconsolidated.[2] For the rest of the world, series are consolidated.

Decomposition of the stock of wealth

In what follows, we explain the decomposition of wealth into the assets and liabilities of a given sector. We use as an example the household sector in France. The details of the computations are given in Table 1, where we also provide a number of decompositions into different classes of assets.

Our basic decomposition includes four classes of assets and liabilities: housing assets, business assets (and other non-financial assets), financial assets, and liabilities. Housing assets are defined as the sum of the market value of dwellings and land underlying dwellings: in practice, it is generally easier to measure the sum (as in observed real estate transactions) than the two components separately. Business assets (and other non-financial assets) are the difference between total non-financial assets and housing

[1] In the SNA, the rest of the world sector only holds financial positions, with non-financial assets holdings being accounted as financial. In ESA-2010, non-financial assets of non-residents are classified in AF.519.

[2] The SNA-2008 guidelines indicate that "the accounting entries in the System are not consolidated. Therefore, the financial balance sheet of a resident sector or subsector is to be presented on a non-consolidated basis" United-Nations (2010).

	Gross personal wealth	4689
AN, S14	Non-financial assets owned by households	1429
	Housing assets of households	*1174*
AN111, S14	*Dwelings owned by households*	*681*
AN21111, S14	*Land underlying dwellings owned by households*	*493*
	Business and other non-financial assets of households	*255*
AN2112, S14	*Agricultural land of households*	*23*
	Other domestic capital of households	*232*
AF, S14	Financial assets owned by households	3260
AF2+AF3+AF4+AF7+AF8, S14	*Currency, deposits, bonds and loans of households*	*1120*
AF5, S14	*Equity and investment fund shares of households*	*1749*
AF6, S14	*Life insurance and pension funds of households*	*391*
AF, S14	Minus: Liabilities of households	189
	Equals: Net personal wealth	**4500**

Adapted from the SNA-2008 "Sequence of accounts" (United-Nations, 2010) and the French Table of Integrated Economic Accounts (INSEE, 2018).

Table 1: Net Personal Wealth

assets.

Note that existing national balance sheets do not always provide separate estimates for the different uses of land. The most recent international system of national accounts (SNA-2008) does not provide a decomposition of land into different components. This is in contrast with the previous international guidelines (SNA-1993) which did provide a disaggregation of land. The adaptation of the SNA-2008 in Europe by the European Commission (ESA-2010) has, however, retained a basic decomposition of land into four categories: Land underlying buildings and structures (AN.2111), Land under cultivation (AN.2112), Recreational land and associated surface water (AN.2113), Other land and associated surface water (AN.2119). The latter two categories (AN.2113 and AN.2119) are generally very small and sometimes are not even estimated in official balance sheets.

Moreover, the SNA-2008 recommends following the disaggregation of land proposed by the System of Environmental-Economic Accounting (United-Nations (2014)) whenever national statistical offices want to decompose land. This land disaggregation is consistent with that of ESA-2010, but adds a more detailed decomposition of Land underlying buildings and structures (AN.2111) and Land under cultivation (Land under cultivation (AN.2112). The former is decomposed into Land underlying dwellings (AN.21111) and Land underlying other buildings and structures (AN.21112). The latter is decomposed into Agricultural land (AN.21121), Forestry land (AN.21122), and Surface water used for aquaculture (AN.21123). Many national statistical agencies follow this break down.

In this project, we aim at using the more detailed decomposition suggested by System of Environmental-Economic Accounting whenever possible. In particular, we aim at capturing housing (including its underlying land) and agricultural land, as these have been the two most important assets owned by households over their path of development (e.g., Piketty and Zucman, 2014). Moreover, we also break down 'Other domestic capital' into natural resources other than land and business assets. Natural resources such as mineral and energy reserves can be very substantial in certain countries, in particular in developing ones.

A special mention on how agricultural land is defined. The Eurostat-OECD manual on land estimation (Eurostat-OECD, 2015) defines agricultural land as "Land primarily used for agricultural purposes. The total of land under temporary or permanent crops, meadows and pastures as well as land with temporary fallow; this category includes tilled and fallow land, and naturally grown permanent meadows and pastures used for grazing, animal feeding or agricultural purpose. Excludes land underlying farm dwellings, farm buildings or other corresponding structures". While statistical offices not always report data on the value of agricultural land, many compile statistics on agricultural land area, classifying this land into three basic types: arable land, permanent grassland, and permanent crops.[3] These statistics have a long history, both in rich and developing countries. The Food and Agriculture Organization has fostered their collection over more than half a century, within the framework of the decennial World Census of Agriculture (e.g., Deininger and Squire, 1998; Frankema, 2010). As we explain in the data sources section (section B), in some countries, we will use these statistics to provide our own estimates of agricultural land values.

We split financial assets into three categories: currency, deposits, bonds and loans (the sum of AF1, AF2, AF3, AF4, AF7 and AF8), equity and investment fund shares (AF5), and life insurance and pension funds (AF6). For all sectors, we report total liabilities, except for corporations, where we distinguish between equity and non-equity liabilities.

Finally, we consider that one aspect of the current SNA's definition of financial assets is problematic: the range of pensions that are included within asset category AF6. While the SNA-1993 only included funded pension assets, the most recent SNA-2008 also includes unfunded employers' pensions. In our view, and that of the DINA project, the SNA-2008 treatment is not satisfactory, since unfunded pensions are promises of future transfers that are not backed by actual wealth. In the United States, Saez and Zucman (2016) remove unfunded pensions from wealth. In other countries, we have been unable to remove this component at the moment, but hope to make progress in the future. For some countries,

[3] In most countries, arable land and permanent grassland are the most important types of agricultural land, followed by permanent crops (Eurostat-OECD, 2015, pg. 126). Some countries do also include a forth category: kitchen gardens. This type of land is almost irrelevant when compared to other land categories and should be included within land underlying buildings and structures (AN.2111) for national accounts purposes (Eurostat-OECD, 2015, chapter 8). As we explain below, we have made use of statistics on agricultural land area to estimate agricultural land values, and have excluded kitchen garden, when possible.

we already know that unfunded pensions are either not part of official balance sheets (France and the UK) or have a very low value (Germany).

B Data Sources

B.1 Authors' estimates

The are some countries for which balance sheets were already reconstructed using official balance sheets and/or other official sources. Piketty (2014) reconstruct the balance sheets of Australia (1970-2010), Canada (1970-2010), France (1700-2010), Germany (1870-2010), Japan (1960-2010), Italy (1965-2010), United Kingdom (1700-2010) and United States (1770-2010). We update the series up to 2020 using official balance sheets or extrapolating when not available, and follow the previous update of the series made by Bauluz (2019) and Bauluz and Brassac (2020). Blanco, Bauluz, and Martínez-Toledano (2021) reconstruct the balance sheet of Spain from 1900 to 2017 and have updated their series up to 2018.[4] We extrapolate the series forward up to 2020. Baselgia and Martínez (2020) reconstruct the balance sheet of Switzerland since 1900 and we rely on their series for the time frame and asset categories that are not available in official online data sources. In particular, we use the series of net private wealth (1900-1999), public non-financial assets (1990-2018), public financial assets, public financial liabilities and net public wealth (1990-1998), and net foreign assets (1995-1998). Waldenström (2017), Moatsos, Toussaint, and Vicq de Cumptich (2021) and Daly and Morgan (2021) build the balance sheets for Sweden (1810-2014), the Netherlands (1853-2019) and Ireland (1995-2019), respectively. We update the series up to 2020 for both countries using official balance sheets or extrapolating when not available.

Novokmet, Piketty, and Zucman (2018), Kumar (2019), Piketty, Yang, and Zucman (2019) and Chatterjee, Czajka, and Gethin (2020) have also reconstructed the balance sheet of Russia (1905-2016), India (1860-2012), China (1978-2015) and South Africa (1975-2018), respectively. We update the series up to 2020 for all four countries using official balance sheets or extrapolating when not available. For the case of China, we specifically update the balance sheet of the household sector using data from Li, Zhang, and Chang (2020). For India, in addition to the series of national wealth from Kumar (2019), we provide data for the household sector covering the period since 2012. For financial assets and liabilities, we use Financial Accounts from OECD. For non-financial assets, we estimate the value of housing, agricultural land, and other non-financial assets from All-India Debt and Investment Survey. We extend the housing series using the All-India House Price Index from the Reserve Bank of India, combined with series of population growth (a

[4] See `https://sites.google.com/view/spainwealthdatabase/`.

proxy for new residential investment). For agricultural land and other non-financial assets we assume they have remained constant as a percentage of national income. The same procedure is followed to extend the Russian series of household non-financial assets since 2015. In this case, we use average dwelling price series from BIS.

Finally, Bauluz, Flores, and Morgan (2021) have built the financial balance sheet for Brazil (2004-2018), Chile (2003-2020), Colombia (1996-2019) and Mexico (2003-2019), together with data on the non-financial balance sheet of Mexico (2003-2019), and household non-financial assets of Brazil (1999-2019). We also extrapolate these series up to 2020.

B.2 Financial Assets and Liabilities

To reconstruct the balance sheet of financial assets and liabilities, we rely when possible on official balance sheets, which are usually published by National Central Banks or National Statistical Offices. When official balance sheets are not available, we rely on other official sources. If no data source is available, then we proceed with the imputation methods as explained in Section C. In what follows, we detail the availability of sources and the methods used for countries for which partial or complete data are available.

B.2.1 Official Financial Accounts

We have collected official financial balance sheets by institutional sector and asset type for the following countries: Albania (2013-2019), Austria (1995-2019), Belgium (1995-2020), Bulgaria (1995-2019), Croatia (1995-2019), Cyprus (1995-2019), Czech Republic (1993-2020), Denmark (1994-2020), Estonia (1995-2019), Finland (1995-2020), Greece (1995-2020), Hungary (1989-2020), Iceland (2003-2019), Israel (2010-2019), Latvia (1995-2019), Lithuania (1995-2019), Luxembourg (1995-2020), Malta (1995-2020), New Zealand (2007-2019), Norway (1995-2020), Poland (1995-2020), Portugal (1994-2020), Romania (1995-2020), Singapore (1995-2019), Slovakia (1995-2020), Slovenia (1995-2020), South Korea (2008-2020), Switzerland (1999-2020), Taiwan (2000-2019) and Turkey (2010-2020). The countries for which we rely on authors' estimates do also have official financial accounts for the recent period. This is the case of Australia (1989-2019), Brazil (2005-2018), Canada (1990-2020), Chile (2003-2020), China (2000-2017), Colombia (1996-2019), France (1978-2020), Germany (1999-2019), Italy (1995-2020), India (2011-2018), Ireland (2001-2018), Japan (1994-2019), Mexico (2004-2019), Netherlands (1995-2020), Russia (2011-2020), South Africa (1975-2019), Spain (1970-2019), Sweden (1995-2020), United Kingdom (1987-2020), and United States.

B.2.2 International Monetary Fund (IMF)

For countries for which official financial balance sheets are not available, we need to rely on other sources. The International Monetary Fund (IMF) publishes rich financial statistics for a much larger set of countries than those available in official financial balance sheets. In particular, we rely on four main data sources: the *Monetary and Financial Statistics*, which provide the balance sheets of the financial corporations sector and its counterparts, *Government Finance Statistics*, which include the financial balance sheets of the government sector, the *Global Debt Database*, which provides information for financial liabilities, and the *Public Sector Balance Sheet Database*, which also includes the balance sheets of the government sector.[5]

Monetary and Financial Statistics (MFS)

The Monetary and Financial Statistics (MFS) database contains macroeconomic aggregates for the financial corporations (FCs). The Monetary and Financial Statistics Manual and Compilation Guide summarizes the methodological and practical aspects of the compilation process for MFS. Important for our analysis, the series conform with the System of National Accounts (SNA). The presentation of the data is done by decomposing the financial corporations sector into three subsectors: i) Central Bank, ii) Other Depository Corporations (ODCs) and iii) Other Financial Corporations (OFCs). By using these series we can ensure consistency with SNA and its institutional sectors, as the MFS financial corporations sector perfectly maps to the SNA financial corporations sector. First, the MFS central bank subsector perfectly maps to the SNA central bank subsector. Second, the MFS ODCs subsector map to the sum of the deposit-taking corporations except the central banks and the money market funds (MMFs) subsectors. Finally, the OFCs subsector maps to the sum of non-MMF investment funds, other financial intermediaries except insurance corporations and pension funds, financial auxiliaries, captive financial institutions and money lenders, insurance corporations, and pension funds.

The majority of countries use the standardized report forms (SRFs) to report monetary data to the IMF and are presented under SRF Countries. The SRFs were introduced by the IMF in 2004 to ensure methodological soundness, facilitate cross-country comparability, provide a uniform way for presenting monetary data for reporting to the IMF and also be used as a platform for the monetary statistics disseminated through national sources. The SRFs for the central bank, ODCs, and OFCs use a harmonized accounting presentation of assets and liabilities (stocks only) of the FCs. The key advantage of the database for our purpose is that the statistics are presented in a balance-sheet-like structure according to the instrument, currency of denomination (domestic and foreign) and the sector of

[5]We only use the MFS for the government sector whenever direct statistics on the government sector from the Government Finance Statistics, Global Debt Database or the Public Sector Balance Sheet (see subsections below) are not available.

counterpart (corresponding to the main sectors of the 2008-SNA), making it possible to infer the assets and liabilities owned by other sectors in financial corporations.

Countries that do not use the SRFs for reporting Monetary data are presented under Non-SRF Countries. The IMF changes the presentation of these countries whenever they implement the reporting of SRF-based data. We only focus on SRF countries for now, as for non-SRF countries the information provided is very limited. There are two set of SRF countries, those that report very detailed monetary and financial data and those that report less detailed information. In what follows, we detail the availability of data for the two groups of SRF countries, specifying the sector of counterpart and the financial instruments we can infer.

- Detailed monetary and financial data based on standardized report forms (SRFs)

The detailed monetary and financial data based on SRFs provide information on the assets and liabilities by financial instrument for the central bank, ODCs and OFCs. Given that information of the sector of counterpart is provided, we can not only infer the assets and liabilities for the FCs, but also those of the households and NPISH, the non-financial corporations and the general government sectors.

We do so by mapping each of the SRFs financial instruments for every sector to the SNA financial instruments as follows: Monetary gold and special drawing rights (SDRs) correspond to AF.1 Monetary gold and SDRs; Holdings of national and local currency and Currency in circulation correspond to AF.21 Currency; Transferable deposits, Other deposits, Required reserves and clearing balances, Required reserves (other deposits), Excess reserves, Counterpart funds and Government lending funds correspond to AF.2 Deposits; Securities other than shares and Required reserves securities other than shares correspond to AF.3 Debt Securities; Loans correspond to AF.4 Loans; Shares and other equity correspond to AF.5 Equity and investment fund shares; Net equity of households in life insurance reserves and Prepaid premiums/reserves against outstanding claims correspond to AF.6 Insurance, pension and standardized guarantee schemes; Financial derivatives correspond to AF.7 Financial derivatives and Trade credit/advances, Settlement accounts, Dividends receivable, Dividends payable, Items in the process of collection, Miscellaneous asset items and Miscellaneous liability items correspond to AF.8 Other accounts receivable/payable.

The equity and fund shares category is not available by sector of counterpart, so that we only count on the series for the financial corporations sectors and rely on the imputations methods explained in Section C to allocate them to the rest of sectors.

Among the set of SRF countries that provide detailed monetary and financial statistics, not all of them report information for all three subsectors (central bank, ODCs and OFCs).

The countries for which information for the central bank and ODCs is provided and we rely on are the following: Afghanistan (2006-2019), Bangladesh (2001-2020), Bolivia (2001-2019), Cameroon (2001-2019), Central African Republic (2001-2018), Chad (2001-2018), Congo (2001-2019), Costa Rica (2001-2019), El Salvador (2001-2019), Equatorial Guinea (2001-2018), Gabon (2001-2019), Jordan (2014-2019), Kazakhstan (2006-2019), Kosovo (2001-2019), Kuwait (2001-2019), Lesotho (2001-2019), Mauritania (2012-2019), Mauritius (2001-2019), Morocco (2001-2020), Myanmar (2001-2019), Nepal (2004-2019), Nicaragua (2001-2019), Nigeria (2001-2019), Pakistan (2001-2019), Paraguay (2001-2019), Samoa (2001-2019), Sao Tomé and Principe (2001-2019), Seychelles (2001-2019), Sierra Leone (2001-2019), Sri Lanka (2001-2019), Suriname (2001-2019), Swaziland (2001-2019), Tajikistan (2001-2019), Tunisia (2001-2019), United Arab Emirates (2001-2019) and Vanuatu (2001-2019).

The countries for which information for OFCs is also provided and we rely on are the following: Bolivia (2005-2019), Costa Rica (2008-2019), El Salvador (2001-2019), Kazakhstan (2015-2019), Kosovo (2004-2019), Kuwait (2001-2019), Nicaragua (2001-2019), Nigeria (2017-2019), Samoa (2007-2019), Seychelles (2001-2019), Tajikistan (2008-2019) and United Arab Emirates (2017-2019).

- Surveys based on standardized report forms (SRFs)

The non-detailed monetary and financial data based on SRFs also provide information on the assets and liabilities for the central bank, ODCs and OFCs, but the sector of counterpart information and decomposition by financial instrument is much more limited. We map each of the SRFs financial instruments to the SNA financial instruments in the same way as we did for the detailed monetary and financial statistics based on SRFs. In this case, the assets are not decomposed by financial instrument nor sector of counterpart, so that we only count on aggregate information on the financial assets for the financial corporations sector. In the case of liabilities, we have aggregate information for the households & NPISH, non-financial corporations, other financial corporations and state and local government on the following financial instruments: deposits, securities, loans, financial derivatives and equity. The liabilities to the central government, central bank, other depositary corporations and to non-residents are included separately and not decomposed by financial instrument.

Among the set of SRF countries that provide non-detailed monetary and financial statistics, not all of them report information for all three subsectors (central bank, ODCs and OFCs).

The countries for which information for the central bank and ODCs is provided and we rely on are the following: Anguilla (2001-2020), Antigua and Barbuda (2001-2019), Armenia (2001-2019), Azerbaijan (2001-2019), Bahamas (2010-2020), Barbados (2001-2019), Belarus (2001-2019), Belize (2001-2020), Benin (2001-2019), Bhutan (2001-2019), Bosnia and Herzegovina (2001-2019), Botswana (2001-2019), Brunei (2001-2019), Burkina Faso (2001-2019), Burundi (2001-2019), Cabo Verde (2001-2019), Cambodia (2001-2019), Comoros (2001-2019), Cote d'Ivoire (2001-2019), Democratic Republic of Congo (2001-2019), Dominica (2001-2019), Dominican Republic (2001-2019), Ecuador (2001-2019), Egypt (2001-2019), Eritrea (2001-2014), Fiji (2001-2020), Gambia (2001-2018), Georgia (2001-2019), Ghana (2001-2019), Grenada (2001-2020), Guatemala (2001-2020), Guinea Bissau (2001-2019), Guyana (2001-2019), Haiti (2001-2019), Honduras (2001-2019), Honk Hong (2008-2019), Indonesia (2009-2019), Iraq (2004-2019), Jamaica (2001-2020), Kenya (2001-2019), Kyrgyzstan (2002-2019), Madagascar (2006-2019), Malaysia (2001-2019), Maldives (2001-2019), Mali (2001-2019), Moldova (2001-2019), Mongolia (2001-2020), Montserrat (2001-2020), Mozambique (2001-2019), Namibia (2001-2019), Niger (2001-2019), Oman (2001-2019), Panama (2002-2020), Papua New Guinea (2001-2020), Peru (2006-2019), Philippines (2001-2019), Qatar (2001-2020), Rwanda (2001-2019), Senegal (2001-2019), Solomon Islands (2001-2020), South Sudan (2011-2020), Saint Kitts and Nevis (2001-2020), Saint Lucia (2001-2020), Saint Vincent and the Grenadines (2001-2020), Serbia (2001-2020), Sudan (2001-2020), Syria (2001-2011), Tanzania (2001-2019), Thailand (2001-2020), Timor-Leste (2002-2019), Togo (2001-2020), Tonga (2001-2020), Trinidad and Tobago (2001-2020), Uganda (2001-2019), Ukraine (2001-2020), Uruguay (2001-2019), Uzbekistan (2013-2020), Venezuela (2001-2016), Zambia (2001-2020) and Zimbabwe (2009-2019).

The countries for which information for OFCs is also provided and we rely on are the following: Armenia (2009-2019), Azerbaijan (2006-2019), Bahamas (2016-2020), Belarus (2007-2019), Bosnia and Herzegovina (2006-2019), Bhutan (2003-2019), Brunei (2006-2019), Burundi (2001-2019), Cambodia (2013-2019), Comoros (2001-2010), Dominican Republic (2004-2019), Ecuador (2001-2019), Georgia (2008-2019), Guatemala (2001-2020), Guyana (2001-2019), Honduras (2010-2019), Indonesia (2015-2019), Kyrgyzstan (2016-2019), Maldives (2004-2019), Moldova (2010-2019), Namibia (2015-2019), Panama (2010-2020), Papua New Guinea (2009-2020), Philippines (2017-2019), Solomon Islands (2001-2020), Thailand (2007-2020), Trinidad and Tobago (2010-2020), Uganda (2011-2019), Ukraine (2008-2019), Uruguay (2001-2019) and Zambia (2011-2018).

Government Finance Statistics (GFS)

The Government Finance Statistics (GFS) database contains detailed government data on revenues, expenditures, transactions in financial assets and liabilities, and balance sheet data for all reporting countries in the framework of the Government Finance Statistics Manual 2014 (GFSM 2014). The database includes data for the general government sector and its subsectors (i.e., central government (budgetary/extra-budgetary central government and social security funds), local government and state government). GFS data are compiled by country authorities and reported to the IMF Statistics Department annually.

We rely on these statistics for countries for which official data balance sheets are not available. We prefer this database over the MFS database for the government sector, as it contains information for the full balance sheet by financial instrument. Among the set of countries for which we use GFS not all of them report information for the general government, so that we rely instead on the available subsectors and impute the missing government assets and/or liabilities using the techniques explained in Section C.

The countries for which information for the general government is available and we rely on are the following: Belarus (Assets: 2014-2019, Liabilities: 2005-2019), El Salvador (2005-2019), Indonesia (2008-2019), Kazakhstan (Assets: 2013-2019, Liabilities: 2010-2019), Kyrgyzstan (2014-2018), Moldova (Assets: 2005-2019, Liabilities: 2002-2019), Mongolia (2014-2018), Morocco (Liabilities: 2006-2011), Seychelles (2008-2015), Thailand (2012-2019), Uganda (Assets: 2004-2019, Liabilities: 1998-2019), Ukraine (2008-2019), United Arab Emirates (Assets: 2013) and Uruguay (2001-2019).

The countries for which information only for the budgetary central government is available and we rely on are the following: Anguilla (Liabilities: 2005-2014), Armenia (Assets: 2019, Liabilities: 2003-2019), Bahamas (Liabilities: 1990-2000; 2006-2019), Barbados (Assets: 2005-2015, Liabilities: 2004-2015), Bolivia (Assets: 2003-2007, Liabilities: 1998-2007), Bosnia and Herzegovina (2011-2019), Burkina Faso (2018-2019), Costa Rica (Assets: 2008-2019, Liabilities: 1998-2001, 2008-2018), Dominican Republic (2006, 2018-2019), Ethiopia (2013-2019), Iraq (2015-2019), Jamaica (Liabilities: 1990-2019), Jordan (Assets: 2008-2019, Liabilities: 1995-2019), Montserrat (Liabilities: 2000-2014), Mozambique (2016-2019), Oman (Assets: 2010-2013, Liabilities: 2003-2013), Republic of Congo (2009-2010) and Serbia (2007-2012).

Finally, the countries for which only information for the state government is available and we rely on are Micronesia (2008-2019) and Peru (Assets: 2006-2019, Liabilities: 2009-2019).

Global Debt Database

The Global Debt Database (GDD) comprises total gross debt of the private and public nonfinancial sector for a large set of advanced, emerging and low-income countries. The GDD is more limited in scope for our purpose than GFS, as it does not contain any information on assets, it only includes partial information for liabilities (i.e., loans and debt securities) and gross private debt is not decomposed between Households & NPISH and Non-financial corporations.[6] Hence, we rely on it for countries for which GFS data is inexistent or incomplete. We split the gross debt of the private sector between Households

[6]For more details on the methodology and definitions, please see Mbaye, Badia, and Chae (2018).

& NPISH and Non-financial corporations using the imputation techniques explained in Section C.

The countries for which information on private debt is available and we rely on are the following: Algeria (1995-2019), Argentina (1950-2019), Azerbaijan (1992-2019), Bahrain (1965-2015), Barbados (2012-2019), Benin (1960-2019), Bhutan (1983-2019), Botswana (1972-2019), Burkina Faso (1960-2019), Burundi (1964-2019), Cabo Verde (1976-2019), Cambodia (1993-2019), Comoros (1982-2017), Cote d'Ivoire (1960-2019), Democratic Republic of Congo (1963-2019), Djibouti (1983-2018), Dominica (1975-2019), Dominican Republic (1991-2010), Ecuador (1950-2019), Egypt (1950-2019), Eritrea (1995-2014), Ethiopia (1960-2008), Gambia (1964-2019), Georgia (1995-2019), Ghana (1955-2019), Grenada (1970-2019), Guatemala (1950-2019), Guinea-Bissau (1990-2019), Guyana (1960-2019), Haiti (1955-2019), Honduras (1950-2019), Hong Kong (1978-2019), Indonesia (1980-2019), Iran (1955-2016), Iraq (2004-2018), Jamaica (1953-2019), Kenya (1961-2019), Kyrgyzstan (1995-2019), Laos (1989-2010), Lebanon (1964-2017), Liberia (2000-2018), Madagascar (1962-2019), Maldives (1976-2019), Mali (1960-2019), Micronesia (1995-2019), Moldova (1991-2019), Mongolia (1991-2019), Mozambique (1988-2019), Niger (1960-2019), Oman (1972-2019), Papua New Guinea (1973-2019), Peru (1950-2019), Philippines (1950-2019), Qatar (1966-2019), Rwanda (1964-2019), Saint Vincent and the Grenadines (1975-2019), Senegal (1960-2019), Serbia (1997-2019), Solomon Islands (1978-2018), South Sudan (2011-2019), Saint Lucia (1975-2019), Sudan (1960-2019), Tanzania (1961-2019), Thailand (1950-2013), Timor-Leste (2002-2019), Togo (1960-2019), Tonga (1974-2019), Trinidad and Tobago (1951-2019), Uganda (1960-2019), Ukraine (1995-2019) Uruguay (1950-2019), Venezuela (1950-2016), Vietnam (1992-2019), Yemen (1990-2013), Zambia (1965-2019), Zimbabwe (1979-2019).

The countries for which information on debt of the general government is available and we rely on are the following: Cambodia (1995-2019), China (2016-2019), Egypt (1970-2019), Georgia (1995-2011, 2017-2019), Honduras (1990-2019), Kosovo (2009-2019), Kyrgyzstan (1994-2013), Mauritius (1970-2019), Nicaragua (1997-2019), Nigeria (2011-2019), Panama (1950-2019), Philippines (1950-2019), Saint Vincent and the Grenadines (1990-2019), Saint Kitts and Nevis (1996-2019), Tajikistan (1998-2019), Tanzania (1970-2019), Thailand, United Arab Emirates (1973-2019), Uzbekistan (1998-2019), Venezuela (1998-2017), Vietnam (2000-2018), Yemen (1990-2019).

The countries for which information on debt of the general government is not available, but instead debt of the central government is available and we rely on are the following: Afghanistan (2002-2019), Algeria (1970-2019), Angola (1995-2019), Antigua and Barbuda (1990-2014), Argentina (1950-2019), Azerbaijan (1994-2019), Bangladesh (1973-2019), Bahrain (1974-2019), Belize (1976-2019), Benin (1970-2019), Botswana (1972-2019), Brunei Darussalam (2001-2019), Burundi (1964-2019), Cabo Verde (1981-2019), Cameroon (1970-

2018), Central African Republic (1970-2018), Chad (1970-2018), Comoros (1984-2019), Cote d'Ivoire (1970-2019), Democratic Republic of Congo (1971-2019), Djibouti (1995-2019), Dominica (1975-2019), Ecuador (1990-2019), Equatorial Guinea (1980-2019), Eritrea (1995-2019), Fiji (1970-2019), Gabon (1970-2019), Gambia (1973-2019), Ghana (1962-2019), Grenada (1970-2019), Guatemala (1950-2019), Guinea-Bissau (1986-2019), Guyana (1963-2019), Haiti (1970-2019), Hong Kong (2001-2019), Iran (1970-2019), Kenya (1963-2019), Kuwait (1987-2019), Laos (1976-2019), Lebanon (1970-2019), Lesotho (1970-2019), Liberia (2000-2019), Libya (1973-2017), Madagascar (1970-2019), Maldives (1976-2019), Mali (1970-2019), Mauritania (1970-2019), Myanmar (1998-2019), Namibia (1989-2019), Nepal (1970-2019), Niger (1970-2019), Pakistan (1951-2019), Papua New Guinea (1970-2019), Paraguay (1970-2019), Qatar (1990-2019), Rwanda (1970-2019), Samoa (1970-2019), Sao Tomé and Principe (1977-2019), Senegal (1970-2019), Sierra Leone (1970-2019), Solomon Islands (1978-2019), South Sudan (2012-2019), Sri Lanka (1951-2019), Saint Lucia (1981-2019), Sudan (1992-2019), Suriname (1994-2019), Swaziland (1970-2019), Syria (1970-2010), Timor-Leste (2013-2019), Togo (1970-2019), Tonga (1985-2019), Trinidad and Tobago (1963-2019), Tunisia (1970-2019), Vanuatu (1981-2019), Zambia (1970-2019), Zimbabwe (1964-2019).

Public Sector Balance Sheet (PSBS)

The Public Sector Balance Sheet (PSBS) Database is an alternative source on public wealth statistics by financial instrument, which was developed in the context of the October 2018 Fiscal Monitor. The dataset is compiled using the conceptual framework of the IMF's Government Finance Statistics Manual 2014 (GFSM 2014), so that it is also fully consistent with SNA. The two government sectors covered are the general and the central government. The set of countries covered is smaller and the time frame shorter, so that we only rely on these statistics when not available in GFS.

The only two countries for which information on public wealth in available in PSBS and we rely on are thus Bhutan (2000-2016) and Georgia (2012-2016).

B.2.3 Locational Banking Statistics (BIS)

The Bank of International Settlements (BIS) published the *Locational Banking Statistics*, which provide quarterly data on the outstanding claims and liabilities of internationally active banks located in reporting countries. The statistics thus provide information for the other depositary corporations sector and for the following financial instruments: total assets, deposits and loans, debt securities and total liabilities.[7] The database also provides counterpart information on total assets and liabilities for Banks (Central Banks

[7]The total assets category consists of the sum of deposits, loans, debt securities, derivatives and other instruments, but only disaggregated information is provided for deposits and loans on the one hand and debt securities on the other.

& Other Depository Corporations) and Non-Banks (Non-bank financial corporations & Non-financial sectors). The information provided is thus more limited for our purpose than the one provided in the MFS. We only use it for countries for which no other information is available. We split of non-banks between Households & NPISH and Non-financial corporations using the imputation techniques explained in Section C.

The only countries for which these statistics are available and we rely on are Bahrain (1995-2019), Bermuda (2002-2019), Cayman Islands (1995-2019), Guernsey (2001-2019), Isle of Man (2013-2019) and Jersey (2001-2019). For Bermuda (2014-2019), Cayman Islands (1995-2019), Guernsey (2014-2019) and Isle of Man (2014-2019) the category of Non-banks is further decomposed into Non-Banks Non-Financial (sum of Household & NPISH, Non-Financial Corporations, General Government).

B.2.4 Pension Wealth (OECD)

In addition to estimates of pension assets available from official balance sheets, we rely on the OECD Global Pension Statistics. This database compiles estimates of pensions for over 80 countries covering the period 2009-2019. The definition, concept and valuation of pension assets used in OECD follows the standards of the SNA-2008. The countries for which we use OECD data are the following: Angola (2018-2019), Armenia (2014-2019), Bolivia (2009-2010), Botswana (2013, 2017-2018), Costa Rica (2009-2019), Dominican Republic (2009-2019), Egypt (2013-2019), El Salvador (2009-2019), Georgia (2019), Ghana (2014-2019), Guyana (2009-2019), Hong Kong (2009-2019), Indonesia (2009-2019), Isle of Man (2016-2018), Jamaica (2009-2019), Kazakhstan (2018-2019), Kenya (2009-2019), Kosovo (2012-2019), Lesotho (2011-2012), Malawi (2013-2019), Malaysia (2011-2019), Maldives (2011-2019), Mauritius (2012-2017), Mozambique (2018), Namibia (2010-2019), Nigeria (2009-2019), Pakistan (2009-2019), Panama (2010-2011, 2013-2019), Papua New Guinea (2013, 2017-2018), Peru (2009-2019), Serbia (2009-2019), Suriname (2016-2019), Tanzania (2013-2017), Thailand (2009-2019), Trinidad and Tobago (2009-2012), Uganda (2016), Ukraine (2010-2011, 2017-2019), Uruguay (2009-2019), and Zambia (2009-2019).

B.2.5 Foreign Assets and Liabilities

To reconstruct the balance sheet of the foreign sector, we rely when possible on official balance sheets, which are usually published by National Central Banks or National Statistical Offices. When official balance sheets are not available, we rely on other authors' estimates or on other official sources. If no data source is available, then we proceed with the imputation methods as explained in Section C. In what follows, we detail the availability of sources and the methods used for countries for which partial or complete data are available.

The countries for which official balance sheets for the foreign sector are available and we rely on are the following: Albania (2013-2019), Austria (1995-2019), Belgium (1995-2020), Bulgaria (1995-2019), Croatia (1995-2019), Cyprus (1995-2019), Czech Republic (1993-2020), Denmark (1994-2020), Estonia (1995-2019), Finland (1995-2020), Greece (1995-2020), Hungary (1989-2020), Iceland (2003-2019), Israel (2010-2019), Latvia (1995-2019), Lithuania (1995-2019), Luxembourg (1995-2020), Malta (1995-2020), New Zealand (2007-2019), Norway (1995-2020), Poland (1995-2020), Portugal (1994-2020), Romania (1995-2020), Slovakia (1995-2020), Slovenia (1995-2020), South Korea (2008-2020), Switzerland (1999-2020), Taiwan (2000-2019) and Turkey (2010-2020). The countries for which we rely on authors' estimates do also have official financial accounts for the recent period. This is the case of Australia (1989-2019), Brazil (2005-2018), Canada (1990-2020), Chile (2003-2020), China (2000-2015), Colombia (1996-2019), France (1978-2020), Germany (1999-2019), Italy (1995-2020), India (2011-2018), Ireland (2001-2018), Japan (1994-2019), Mexico (2004-2019), Netherlands (1995-2020), Russia (2011-2020), South Africa (1975-2019), Spain (1970-2019), Sweden (1995-2020), United Kingdom (1987-2020), and United States.

When official balance sheets are not available, we rely on the estimates of external assets and liabilities——the so-called International Investment Position (IIP)—from M. P. R. Lane and M. G. M. Milesi-Ferretti (2017).The dataset follows the standard decomposition of assets and liabilities according to the Balance of Payments Statistics Manual 6. Specifically, assets and liabilities are divided in the following categories: foreign direct investment; portfolio equity; portfolio debt; other investment; and financial derivatives; plus foreign exchange reserves on the asset side. They exclude gold holdings from foreign exchange reserves, which are included in official IIP statistics, as these are not financial claims on another economy. When international investment position data are not available, estimates are constructed from a variety of sources, as discussed in detail in P. R. Lane and G. M. Milesi-Ferretti (2007) and G.-M. Milesi-Ferretti and Tille (2011).

The countries for which official balance sheets for the foreign sector are not available and we rely on M. P. R. Lane and M. G. M. Milesi-Ferretti (2017) are the following: Afghanistan (2002-2015), Algeria (1970-2015), Angola (1980-2002), Anguilla (1990-2015), Antigua and Barbuda (1977-2015), Argentina (1970-2015), Armenia (1996-2015), Azerbaijan (1995-2015), Bahrain (1970-2015), Bangladesh (1973-2015), Barbados (1970-2015), Belarus (1994-2015), Belize (1976-2019), Benin (1970-2015), Bhutan (1983-2015), Bolivia (1970-2015), Bosnia and Herzegovina (1998-2015), Botswana (1974-2015), Brunei Darussalam (1985-2015), Burkina Faso (1974-2015), Burundi (1970-2015), Cabo Verde (1981-2015), Cambodia (1993-2009), Cameroon (1970-2015), Central African Republic (1970-2015), Chad (1970-2017), Comoros (1979-2015), Congo (1970-2015), Costa Rica (1970-2015), Cote d'Ivoire (1970-2015), Democratic Republic of Congo (1970-2015), Djibouti (1977-

2015), Dominica (1977-2015), Dominican Republic (1970-2015), Ecuador (1970-2015), Egypt (1970-2015), El Salvador (1970-2015), Equatorial Guinea (1980-2015), Eritrea (1995-2015), Ethiopia (1970-2015), Fiji (1977-2015), Gabon (1970-2015), Gambia (1970-2015), Georgia (1995-2015), Ghana (1970-2015), Grenada (1971-2015), Guatemala (1970-2015), Guinea-Bissau (1980-2000), Guyana (1970-2015), Haiti (1970-2015), Honduras (1970-2015), Hong Kong (1979-2015), Indonesia (1970-2015), Iran (1970-2015), Iraq (2005-2015), Jamaica (1970-2015), Jordan (1970-2015), Kazakhstan (1994-2015), Kenya (1970-2015), Kosovo (2004-2015), Kuwait (1974-2015), Kyrgyzstan (1993-2015), Laos (1977-2015), Lebanon (1970-2015), Lesotho (1975-1999), Liberia (1970-2015), Libya (1972-2015), Madagascar (1970-2006), Maldives (1978-2015), Mali (1970-2015), Moldova (1994-2001), Mauritania (1970-2015), Mauritius (1970-2015), Micronesia (1995-2015), Mongolia (1992-2015), Montserrat (1983-2015), Morocco (1970-2015), Mozambique (1980-2015), Myanmar (1970-2015), Namibia (1989-2006), Nepal (1970-2015), Nicaragua (1970-2015), Niger (1970-2015), Nigeria (1970-2015), Oman (1973-2015), Pakistan (1970-2015), Panama (1970-2015), Papua New Guinea (1973-2015), Paraguay (1970-2015), Peru (1970-2015), Philippines (1970-2015), Qatar (1970-2015), Rwanda (1970-2015), Saint Kitts and Nevis (1981-2015), Saint Lucia (1976-2015), Saint Vincent and the Grenadines (1976-2015), Samoa (1970-2012), Sao Tomé and Principe (1987-2015), Senegal (1970-2015), Serbia (1999-2015), Seychelles (1977-2015), Sierra Leone (1970-2009), Singapore (1970-2015), Solomon Islands (1977-2015), South Sudan (2011-2015), Sri Lanka (1970-2015), Sudan (1970-2008), Suriname (1976-2015), Swaziland (1970-2013), Syria (1970-2015), Tajikistan (1997-2015), Tanzania (1970-2013), Thailand (1970-2015), Timor-Leste (2005-2015), Togo (1970-2015), Tonga (1980-2015), Trinidad and Tobago (1970-2010), Tunisia (1970-2015), Uganda (1970-2015), Ukraine (1994-2015), United Arab Emirates (1973-2015), Uruguay (1970-2015), Uzbekistan (1992-2015), Vanuatu (1973-2013), Venezuela (1970-2015), Vietnam (1995-2015), Yemen (1990-2015), Zambia (1970-2009) and Zimbabwe (1976-2005).

For more recent years, we supplement the M. P. R. Lane and M. G. M. Milesi-Ferretti (2017)'s dataset—that is only available up to 2015—with data on foreign assets and liabilities from the IMF's International Investment Positions. The countries for which we rely on these statistics are the following: Afghanistan (2016-2020), Algeria (2016-2020), Angola (2003-2020), Anguilla (2016-2018), Argentina (2016-2020), Armenia (2016-2020), Bahrain (2016-2019), Bangladesh (2016-2020), Belarus (2016-2020), Benin (2016-2019), Bhutan (2016-2020), Bolivia (2016-2020), Bosnia and Herzegovina (2016-2020), Botswana (2016-2020), Burkina Faso (2016-2019), Burundi (2016-2019), Cabo Verde (2016-2020), Cambodia (2010-2020), Cameroon (2016-2019), China (2016-2020), Costa Rica (2016-2020), Cote d'Ivoire (2016-2019), Democratic Republic of Congo (2016-2019), Djibouti (2016-2020), Dominica (2016-2018), Dominican Republic (2016-2020), Ecuador (2016-2020), Egypt (2016-2020), El Salvador (2016-2020), Fiji (2016-2020), Georgia (2016-2020), Ghana

(2016-2019), Ghana (2016-2019), Grenada (2016-2019), Guatemala (2016-2020), Guinea-Bissau (2001-2019) ,Guyana (2016-2018), Haiti (2016-2019), Honduras (2016-2020), Hong Kong (2016-2020), India (2019-2020), Indonesia (2016-2020), Jamaica (2016-2020), Jordan (2016-2019), Kazakhstan (2016-2020), Kenya (2016-2018), Kosovo (2016-2020), Kyrgyzstan (2016-2019), Lesotho (2000-2019), Madagascar (2007-2018), Malawi (2016-2019), Malaysia (2016-2020), Mali (2016-2018), Morocco (2016-2020), Mauritius (2016-2019), Moldova (2002-2019), Mongolia (2016-2020), Mozambique (2016-2020), Myanmar (2016-2020), Namibia (2007-2020), Nepal (2016-2019), Nicaragua (2016-2020), Niger (2016-2019) , Nigeria (2016-2020), Pakistan (2016-2020), Panama (2016-2020), Paraguay (2016-2020), Peru (2016-2020), Philippines (2016-2020), Rwanda (2016-2019), Saint Kitts and Nevis (2016-2018), Samoa (2013-2019), Sao Tomé and Principe (2016-2020), Saudi Arabia (2016-2020), Senegal (2016-2018), Seychelles (2016-2019), Sierra Leone (2010-2017), Singapore (2016-2020), Solomon Islands (2016-2020), South Africa (2019-2020), Sri Lanka (2016-2019), Saint Vincent and the Grenadines (2016-2018), Saint Lucia (2016-2018), Sudan (2009-2019), Suriname (2016-2020), Swaziland (2014-2020), Tajikistan (2016-2019), Tanzania (2014-2019), Thailand (2016-2020), Timor-Leste (2016-2020), Togo (2016-2019), Trinidad and Tobago (2011-2020), Tunisia (2016-2020), Uganda (2016-2019), Ukraine (2016-2020), Uruguay (2016-2020), Uzbekistan (2016-2020), Vanuatu (2014-2020), Venezuela (2016), Zambia (2010-2019).

B.3 Non-financial assets

B.3.1 Agricultural land

Authors' estimates

For some countries, we rely on country-specific studies that include estimates of agricultural land and that are published in the World Inequality Database: China (Piketty, Yang, and Zucman (2019)), Ireland (Daly and Morgan (2021)), Russia (Novokmet, Piketty, and Zucman (2018)), Spain (Artola Blanco, Bauluz, and Martínez-Toledano (2020)), Sweden (Waldenström (2017)), UK (Piketty and Zucman (2014); Bauluz (2019)), US (Piketty and Zucman (2014); Bauluz (2019)). We have extended the original series for China and Russia which were available until 2015, assuming that agricultural land has remained constant as a percentage of national income during the period 2016-2020. For India, we estimate agricultural land owned by households in 2012 using the All-India Debt and Investment Survey. This is the same data source used by Kumar (2019) to estimate national wealth in India. As documented by Kumar (2019), close to all agricultural land in India is owned by the household sector. We extend these estimates for the period 2013-2020, assuming that agricultural land has remained constant as a percentage of national income at its 2012 level.

Official Non-financial Accounts

Agricultural land is only reported in official balance sheets for a few countries. In some countries, no distinction is made between Land under cultivation (AN.2112) and its three subcomponents: Agricultural land (AN.21121), Forestry land (AN.21122), and surface water used for aquaculture (AN.21123). In those cases, we approximate agricultural land using land under cultivation. In other cases, we approximate agricultural land as a residual from total land (AN.211) net of built land (Land underlying buildings and structures (AN.2111).

The countries for which official non-financial accounts are available are the following: Australia (1989-2019) (total land minus land underlying dwellings), Belgium (1995-2019), Canada (1990-2019), Czech Republic (1993-2019), Netherlands (1995-2019) (Land under cultivation), France (1978-2019) (Land under cultivation), Germany (1999-2018) (Land - Land underlying buildings and structures), Italy (2001-2017) (Land under cultivation), Japan (1994-2014) (Land under cultivation), Slovenia (1995-2019) (Land under cultivation). For details on the construction of the series of Canada, France, Germany, Italy, and Japan, see Bauluz (2019), and Bauluz and Brassac (2020).

Eurostat and FAO

In a set of European countries, we are able to estimate the value of agricultural land multiplying agricultural land area (in hectares) by land prices per hectare. We gather the data on hectares and prices from Eurostat and, in few cases, from national statistical offices.

We proceed in two steps. First, we estimate the total value of agricultural land. Second, we decompose this land across institutional sectors.

Regarding the first step. The ideal scenario would be to multiply hectares of arable land, permanent grassland, and permanent crops (the three types of agricultural land) with prices on each land type. However, prices on permanent crops are not available, reason why we approximate the price of permanent crop land using the average price of arable land and permanent grassland, as recommended by Eurostat-OECD (2015, section 8.19).[8] We follow this procedure in the following countries: Bulgaria (2003-2016), Croatia (2007-2016), Estonia (2004-2016), Greece (1995-2016), Hungary (2000-2016), Lithuania (2003-2016), Luxembourg (1995-2016), Poland (2003-2016), Romania (2003-2016) and Slovakia (2000-2016).

[8] Note that the area covered by permanent crops tends to be fairly small, as explained by Eurostat-OECD (2015, pg. 126): "in most countries permanent grassland and arable land are by far the most important types of agricultural land; their definitions are mentioned below. Areas devoted to permanent crops are usually less important, in some countries even negligible".

In some cases, we only have price information for total agricultural land area[9], and we multiply average price of total agricultural land by the sum of arable land, permanent grassland, and permanent crops (Malta (2003-2016)). We follow the same approach when both prices and land area are only available for total agricultural land, without distinguishing the share of agricultural land by types of use (Latvia (2003-2016)).

In a second step, we allocate the share of total agricultural land that is owned by different institutional sectors. For Estonia, Hungary and Lithuania, we use data on the area of agricultural land that is owned by different sectors from countries' statistical departments. For the remaining countries, we rely on FAO's World Agriculture Census (e.g. Deininger and Squire, 1998). FAO censuses report the amount of land **operated** by individual and juridical persons, respectively. Note that this information does not refer to the sector that **owns** the land. We use this information on land operated as a proxy for the sector owning the land, and allocate individually-held land to households and the remaining land to corporations. If better data on the decomposition of agricultural land across sectors become available, we will adjust our estimates accordingly.

Global Land Inequality project

Bauluz, Govind, and Novokmet (2020) estimate agricultural land and its distribution for a set of developing countries based on combining survey data and agricultural censuses. For the countries covered in their study, we use their agricultural land values estimates. Missing years are extrapolated using the growth rate of Gross Value Added in Agriculture (from FAO Statistics). Note that this project also analyzes China and India. Their estimates are consistent with those from Piketty, Yang, and Zucman (2019) and the ones we have produced based on the AIDIS survey for India.

The countries for which we rely on the Global Land Inequlity Project are the following: Bangladesh (1990-2019), Ethiopia (1990-2019), Indonesia (1990-2019), Malawi (1990-2019), Nicaragua (1990-2019), Nigeria (1990-2019), Pakistan (1990-2019), Vietnam (1990-2019).

Capitalization of Gross Value Added in Agriculture

We rely on a simple capitalization method for countries where data on Gross Value Added in Agriculture are available from FAO statistics. For the 39 countries for which we have estimates from the previous three data sources, we have compared the value of agricultural land with the Gross Value Added (GVA) in Agriculture. The ratio of land value over gross value added is 10.2, with a standard deviation of 7.5. We decide to apply this ratio in all countries for which we only have data on GVA.

To split a country's total land value across institutional sectors, we use census data from

[9]Total agricultural land area is referred in Eurostat as Utilized Agricultural Land, and it the sum of sum of arable land, permanent grassland, permanent crops, and kitchen gardens.

FAO, which generally decomposes agricultural land area across sectors. One caveat of this procedure is that this decomposition refers to the sector operating the land and not to the sector owning the land. Nonetheless, FAO also reports the share of total agricultural land that is both owned and operated by the same individual or company. In developing countries, this share is on average above 80%. Hence, we use the sectoral decomposition of land operators as a proxy for landowners.

As an alternative, we could use two existing datasets which measure agricultural land values in a large set of both developing and developed countries: (i) World Bank's *The Changing Wealth of Nations 2018* (Lange, Wodon, and Carey, 2018) and (ii) United Nation's *Inclusive Wealth Report* (Programme, 2015). These two datasets rely on a similar methodology: the Net Present Value. Although this methodology is conceptually correct, in practice, it is hard to implement with accuracy as it is particularly sensitive to assumptions on discount rates. Results from the two studies confirm that the data are not sufficiently reliable.

First, the correlation between these two datasets and estimates from our preferred sources (official balance sheets; combined estimates from Eurostat with FAO; Global Land Inequality project) is very low. Second, the two datasets obtain significantly different estimates despite using a similar methodology. Finally, some estimates are unrealistic (e.g., the ratio of agricultural land to GDP is above 20 in Mongolia, according to the UN dataset).

Overall, we believe the estimates of agricultural land values based on capitalizing GVA are a better approximation to reality. Nonetheless, these estimates should be interpreted cautiously and subject to revisions whenever better data are available.

The countries for which we rely on the capitalization of Gross Value Added in agriculture are the following: Afghanistan (1990-2019), Albania (1990-2019), Angola (1996-2019), Anguilla (1990-2019), Antigua and Barbuda (1990-2019), Argentina (1990-2019), Armenia (1990-2019), Austria (1990-2019), Azerbaijan (1994-2019), Bahamas (1990-2019), Bahrain (1990-2019), Barbados (1990-2019), Belarus (1995-2019), Belize (1990-2019), Benin (1990-2019), Bermuda (1990-2019), Bhutan (1990-2019), Bolivia (1990-2019), Bosnia and Herzegovina (1993-2019), Brunei Darussalam (1990-2019), Burkina Faso (1990-2019), Burundi (1990-2019), Cabo Verde (1990-2019), Cambodia (1990-2019), Cameroon (1990-2019), Cayman Islands (1990-2019), Central African Republic (1990-2019), Chad (1990-2019), Comoros (1990-2019), Congo (1990-2019), Costa Rica (1990-2019), Cote d'Ivoire (1990-2019), Democratic Republic of Congo (1994-2019), Djibouti (1990-2019), Dominica (1990-2019), Dominican Republic (1990-2019), Ecuador (1990-2019), Egypt (1990-2019), El Salvador (1990-2019), Equatorial Guinea (1990-2019), Eritrea (1990-2019), Fiji (1990-2019), Gabon (1990-2019), Gambia (1990-2019), Georgia (1994-2019), Ghana

(1990-2019), Grenada (1990-2019), Guatemala (1990-2019), Guinea-Bissau (1990-2019) , Guyana (1991-2019), Haiti (1990-2019), Honduras (1990-2019), Iceland (1990-2019), Iran (1990-2019), Iraq (1990-2019), Israel (1990-2019), Jamaica (1990-2019), Jordan (1990-2019), Kazakhstan (1994-2019), Kenya (1990-2019), Kuwait (1990-2019), Kyrgyzstan (1993-2019), Laos (1990-2019), Lebanon (1990-2019), Lesotho (1990-2019), Liberia (1990-2019), Libya (1990-2019), Madagascar (1990-2019), Malaysia (1990-2019), Maldives (1990-2019), Mali (1990-2019), Mauritania (1990-2019), Mauritius (1990-2019), Micronesia (1990-2019), Moldova (1993-2019), Mongolia (1990-2019), Montserrat (1990-2019), Morocco (1990-2019), Mozambique (1990-2019), Myanmar (1990-2019), Nepal (1990-2019), New Zealand (1990-2019), Niger (1990-2019), Oman (1990-2019), Panama (1990-2019), Papua New Guinea (1990-2019), Paraguay (1990-2019), Peru (1990-2019), Portugal (1990-2019), Qatar (1990-2019), Rwanda (1990-2019), Saint Kitts and Nevis (1990-2019), Saint Lucia (1990-2019), Saint Vincent and the Grenadines (1990-2019), Samoa (1990-2019), Sao Tomé and Principe (1990-2019), Senegal (1990-2019), Serbia (1993-2019), Seychelles (1990-2019), Sierra Leone (1990-2019), Solomon Islands (1990-2019), Suriname (1995-2019), Swaziland (1990-2019), Syria (1990-2019), Tajikistan (1995-2019), Tanzania (1990-2019), Thailand (1990-2019), Togo (1990-2019), Tonga (1990-2019), Trinidad and Tobago (1990-2019), Tunisia (1990-2019), Turkey (1990-2019), Uganda (1990-2019), Ukraine (1993-2019), United Arab Emirates (1990-2019), Uruguay (1990-2019), Uzbekistan (1993-2019), Vanuatu (1990-2019), Venezuela (1990-2019), Yemen (1990-2019), Zambia (1990-2019) and Zimbabwe (1990-2019).

C Methodology for Balance Sheet Completion

This section describes in details our methodology to fill the gaps in the balance sheets that we have collected. We start by describing the overall approach in section C.1 and then we expose the various steps in more details.

C.1 Notations and General Principle

Framework A balance sheet is a set of k variables, indexed by $j \in \{1, \dots, k\}$. There is one balance sheet by country $i \in \{1, \dots, n\}$, and by year $t \in \{t_{\min}, \dots, t_{\max}\}$. Let $T = t_{\max} - t_{\min} + 1$. Overall, we have $N = n \times k \times T$ variables. We will use y_{itj} to denote the value of variable j in year t and in country i.

The vector $\boldsymbol{y}_{it} = (y_{it1}, \dots, y_{itk})'$ contains all k variables for country i in year t. The vector $\boldsymbol{y}_i = (\boldsymbol{y}'_{it_{\min}}, \dots, \boldsymbol{y}'_{it_{\max}})'$ contains all k variables for all years for country i. Finally, the vector $\boldsymbol{y} = (\boldsymbol{y}'_1, \dots, \boldsymbol{y}'_n)'$ contains all variables for all years and all countries.

The components of $\boldsymbol{y}$ are not linearly independent. Within a given country and a given year, the variables are related to one another by a set of m accounting identities. Therefore, for each country i and each year t, we have:

$$\mathbf{M}\boldsymbol{y}_{it} = \mathbf{0} \tag{1}$$

where $\mathbf{M}$ is $m \times k$ matrix, filled with the values $\{0, 1, -1\}$ whose rows correspond to accounting identities.

The components of $\boldsymbol{y}$ are also not statistically independent. Within a country and a year, variables are necessarily correlated due to the conditions (1). Moreover, within a country, variables are correlated across years since each variable j correspond to a macroeconomic time series, which are known to feature persistence over time.

A flexible, yet tractable way of formalizing this setting is to model the vector $\boldsymbol{y}$ as a high-dimensional multivariate normal vector with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. That is, we assume:

$$\boldsymbol{y} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

The vector $\boldsymbol{\mu}$ represents a "default" prediction for each component of $\boldsymbol{y}$, obtained in the absence of any information about any other component of $\boldsymbol{y}$. The matrix $\boldsymbol{\Sigma}$ captures how actual values will vary around that prediction.

Note that because the variables are related by the accounting identities (1), the matrix $\boldsymbol{\Sigma}$ does not have full rank. The vector $\boldsymbol{y}$ is a degenerate case of multivariate normal distribution: it does not admit a density on the full vector space $\mathbb{R}^N$, but it does admit one over a lower-dimensional subspace of $\mathbb{R}^N$ that correspond to the set of values that satisfy the conditions (1).

Main Principle Let $\boldsymbol{y}_{\text{obs}}$ be all the observed components of $\boldsymbol{y}$, and let $\boldsymbol{y}_{\text{mis}}$ be all the missing (unobserved) components of $\boldsymbol{y}$. We will use $\boldsymbol{\mu}_{\text{obs}}$, $\boldsymbol{\mu}_{\text{mis}}$, $\boldsymbol{\Sigma}_{\text{obs}}$ and $\boldsymbol{\Sigma}_{\text{mis}}$ to denote their mean and covariance matrices. We will also use $\boldsymbol{\Sigma}_{\text{mis,obs}}$ for the covariance between $\boldsymbol{y}_{\text{mis}}$ and $\boldsymbol{y}_{\text{obs}}$.

If we know the vector $\boldsymbol{\mu}$ and the matrix $\boldsymbol{\Sigma}$, then standard results on the multivariate normal distribution allow us to know the distribution of unobserved values $\boldsymbol{y}_{\text{mis}}$, *given our knowledge* of observed values $\boldsymbol{y}_{\text{obs}}$. Namely:

$$\boldsymbol{y}_{\text{mis}}|\boldsymbol{y}_{\text{obs}} \sim \mathcal{N}(\boldsymbol{\mu}_{\text{mis|obs}}, \boldsymbol{\Sigma}_{\text{mis|obs}})$$

with:

$$\boldsymbol{\mu}_{\text{mis|obs}} = \boldsymbol{\mu}_{\text{mis}} + \boldsymbol{\Sigma}_{\text{mis,obs}}\boldsymbol{\Sigma}^{\dagger}_{\text{obs}}(\boldsymbol{y}_{\text{obs}} - \boldsymbol{\mu}_{\text{obs}}) \tag{2}$$

$$\boldsymbol{\Sigma}_{\text{mis|obs}} = \boldsymbol{\Sigma}_{\text{mis}} - \boldsymbol{\Sigma}_{\text{mis,obs}}\boldsymbol{\Sigma}^{\dagger}_{\text{obs}}\boldsymbol{\Sigma}_{\text{obs,mis}} \tag{3}$$

where $\boldsymbol{\Sigma}^{\dagger}_{\text{obs}}$ is a pseudoinverse of $\boldsymbol{\Sigma}_{\text{obs}}$ (Rao, 1973).[10] The key issue is therefore to get a proper estimate of $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$, which we explain in sections C.2 and C.3.

Illustration To illustrate the method, consider the simple case of one country, two years and three variables (y_{1t}, y_{2t}, y_{3t} for $t \in \{1, 2\}$). We assume that the covariance between the variables is:

$$\boldsymbol{\Sigma}_{\text{variables}} = \begin{bmatrix} 1 & 0.5 & 0.5 \\ 0.5 & 1 & -0.5 \\ 0.5 & -0.5 & 1 \end{bmatrix}$$

Note that this matrix does not have a full rank, and in fact implies that $y_{1t} = y_{2t} + y_{3t}$ for $t \in \{1, 2\}$. We assume a correlation of 0.5 between variables over the two years:

$$\boldsymbol{\Sigma}_{\text{years}} = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

So the full covariance matrix can be written as a Kronecker product $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}_{\text{years}} \otimes \boldsymbol{\Sigma}_{\text{variables}}$. Finally, assume that the mean of variables in both years is $(1, 0.5, 0.5)'$. Overall, we have:

$$\begin{bmatrix} y_{11} \\ y_{21} \\ y_{31} \\ y_{12} \\ y_{22} \\ y_{32} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 1 \\ 0.5 \\ 0.5 \\ 1 \\ 0.5 \\ 0.5 \end{bmatrix}, \begin{bmatrix} 1 & 0.5 & 0.5 & 0.5 & 0.25 & 0.25 \\ 0.5 & 1 & -0.5 & 0.25 & 0.5 & -0.25 \\ 0.5 & -0.5 & 1 & 0.25 & -0.25 & 0.5 \\ 0.5 & 0.25 & 0.25 & 1 & 0.5 & 0.5 \\ 0.25 & 0.5 & -0.25 & 0.5 & 1 & -0.5 \\ 0.25 & -0.25 & 0.5 & 0.5 & -0.5 & 1 \end{bmatrix} \right)$$

Let us assume that we do not observe y_{22} and y_{32}. What can we say about these two variables, given that we observe the other four? There are several potential predictors that must be accounted for: the contemporary value of y_{12}, to which y_{22} and y_{32} are related; the past values y_{21} and y_{31}, which are also correlated to y_{22} and y_{32}. The formulas (2) and (3) solve that problem in a very general way, while still acknowledging the remaining uncertainty and while still maintaining the consistency of the system of accounting identities. From these formulas, we get that y_{22} and y_{32} are jointly bivariate

[10]The use of a pseudoinverse rather than the regular inverse is required since the covariance matrix does not have full rank.

normal, and that:

$$\begin{bmatrix} y_{22} \\ y_{32} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0.5y_{12} + 0.25y_{21} - 0.25y_{31} \\ 0.5y_{12} - 0.25y_{21} + 0.25y_{31} \end{bmatrix}, \begin{bmatrix} 0.5625 & -0.5625 \\ -0.5625 & 0.5625 \end{bmatrix}\right)$$

This formulas carry many desirable and intuitive properties. The conditional mean value of $y_{22} + y_{32}$ is y_{12}, and both variables exhibit perfect negative correlation: therefore our prediction is consistent with the system of accounting identities. Both predictions are positively related to the contemporaneous value of y_{12} (which follows from the accounting identity), positively related to their own past values, but negatively correlated to the each other's past value. The conditional standard deviation of each variable is $\sqrt{0.5625} = 0.75$, compared to an unconditional standard deviation equal to 1, so we know our knowledge of y_{22} and y_{32} is 25% better than a random guess.

Discussion

C.2 Estimation of Central Prediction

C.2.1 Clustering of Countries

C.2.2 Constrained Regularized Regression

Main Regression Let c be the number of country clusters. For all $i \in \{1, \ldots, n\}$, let $c_i \in \{1, \ldots, c\}$ be the cluster to which country i belongs. For the central prediction, we run the following linear regression:

$$y_{itj} = \beta_{0tj} + \beta_{c_i tj} + e_{itj} \tag{4}$$

where e_{itj} is the prediction error. In itself, the above regression is severely overparametrized. The key to our approach will be to regularize the parameters $\beta_{0tj}, \beta_{1tj}, \ldots, \beta_{ctj}$ towards solutions with desirable properties. This is a flexible framework that allows us to not impose strong parametric assumptions (such as linear trends) while still getting robust estimates.

First, let us rewrite regression (4) in matrix form. Let $\mathbf{X}$ be the matrix with $n \times k \times T$ rows and $(c+1) \times k \times T$ columns, defined as:

$$\mathbf{X} = \begin{bmatrix} \mathbf{1}_{kT,1} & \mathbf{\Delta}_{1,c_1} & \cdots & \mathbf{\Delta}_{c,c_1} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{1}_{kT,1} & \mathbf{\Delta}_{1,c_n} & \cdots & \mathbf{\Delta}_{c,c_n} \end{bmatrix}$$

where $\mathbf{1}_{kT,1}$ is a matrix of ones with kT rows and one column, and $\mathbf{\Delta}_{c,c_i} = \mathbf{I}_{kT}$ if $c_i = c$

and $\mathbf{\Delta}_{c,c_i} = \mathbf{0}_{kT}$ otherwise. Let $\boldsymbol{e}$ be the vector of prediction errors, and let $\boldsymbol{\beta}$ be the vector of parameters. We can rewrite the regression (4) in matrix form as:

$$\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{e}$$

Regularization When estimating the model, we will regularize the parameter vector $\boldsymbol{\beta}$ towards certain, more desirable solutions. First, we will favor smooth times series over irregular ones. Second, we will favor solutions that exhibit similar trends across country clusters for the same variable. Third, we will favor solutions that exhibit similar levels across country clusters for the same variable.

Let $\boldsymbol{w} = (w_1, \ldots, w_k)'$ be a vector of strictly positive weights associated to each variable, and let $\mathbf{W} = \text{diag}(\boldsymbol{w})$. (These weights should be inversely proportional to the scale of each variable, so that each variable is penalized similarly when running the regression.)

The first regularization matrix, $\mathbf{R}_1$, can be constructed as:

$$\mathbf{R}_1 = \mathbf{I}_{c+1} \otimes \underbrace{\begin{bmatrix} 1 & -2 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & -2 & 1 \end{bmatrix}}_{(T-2)\times T \text{ matrix}} \otimes \mathbf{W}$$

This matrix calculates the second derivative over time for each variable and cluster. It is equal to zero if all time series are smooth and the trends linear.

The second regularization matrix $\mathbf{R}_2$ can be constructed as:

$$\mathbf{R}_2 = \underbrace{\begin{bmatrix} 1 & -1 & & & \\ 1 & & -1 & & \\ \vdots & & & \ddots & \\ 1 & & & & -1 \end{bmatrix}}_{c\times(c+1) \text{ matrix}} \otimes \underbrace{\begin{bmatrix} 1 & -1 & & & \\ & 1 & -1 & & \\ & & \ddots & \ddots & \\ & & & 1 & -1 \end{bmatrix}}_{(T-1)\times T \text{ matrix}} \otimes \mathbf{W}$$

It calculates the difference between between the trend (i.e., the first derivative) of a given cluster and the trend common to all clusters, for each variable.

The third regularization matrix $\mathbf{R}_3$ can be constructed as:

$$\mathbf{R}_3 = \underbrace{\begin{bmatrix} 0 & 1 & & & \\ 0 & & 1 & & \\ \vdots & & & \ddots & \\ 0 & & & & 1 \end{bmatrix}}_{c\times(c+1)\text{ matrix}} \otimes \underbrace{\begin{bmatrix} 1/T & 1/T & \cdots & 1/T \end{bmatrix}}_{1\times T\text{ matrix}} \otimes \mathbf{W}$$

It calculates the average value of the time series over time for each cluster and variable.

Equality and Inequality Constraints

C.3 Estimation of Correlation Structure between Observations

C.3.1 Correlation between Variables

Consider the vector $\boldsymbol{y}_{it}$ of k variables for a country i and a year t. We will construct a covariance structure for $\boldsymbol{y}_{it}$ that account for each variable's idiosyncratic variability, and for the set of accounting identities that they must satisfy.

A fruitful approach here is to assume the existence of a latent vector of uncorrelated variables $\boldsymbol{y}^*_{it}$. These variables have a diagonal covariance matrix $\boldsymbol{\Lambda}_{it} = \text{diag}(\lambda_{it1}, \ldots, \lambda_{itk})$. We will consider that the observed vector of variables $\boldsymbol{y}_{it}$ is the result of a projection of $\boldsymbol{y}^*_{it}$ onto the kernel of $\mathbf{M}$, i.e. onto the subspace of values that satisfy the accounting identities.

To construct the projection, define a weighted pseudoinverse of $\mathbf{M}$ as:

$$\mathbf{M}^\dagger = \boldsymbol{\Lambda}_{it}\mathbf{M}'(\mathbf{M}\boldsymbol{\Lambda}_{it}\mathbf{M}')^{-1}$$

This concept of weighted pseudoinverse is a standard generalization of the Moore-Penrose pseudoinverse (Stewart, 1989). Note that this formula applies to the case where the rows of $\mathbf{M}$ are linearly independent. This does not restrict the applicability of the method since we can drop redundant rows of $\mathbf{M}$ without changing the problem if necessary.[11]

Following standard results on matrix pseudoinverses, the matrix:

$$\mathbf{P} = \mathbf{I}_k - \mathbf{M}^\dagger\mathbf{M} \tag{5}$$

is a projection onto the kernel of $\mathbf{M}$. This projection is oblique rather orthogonal. Had we used the unweighted pseudoinverse in (5), we would have obtained an orthogonal

[11] Stewart (1989) defines it for a matrix with linearly independent *columns*. Our matrix $\mathbf{M}$ has linearly independent *rows*, so we adapted the formula accordingly.

projection. An orthogonal projection is less desirable in the present context because it would adjust all components of the vector $\boldsymbol{y}_{it}^*$, big or small, by a similar amount. The use of a weighted pseudoinverse lets us control this behavior, by encouraging larger adjustment to happen for larger variables (i.e., variables associated to a larger λ_{it}), so that every component of $\boldsymbol{y}_{it}$ experiences similar *relative* changes rather than similar *absolute* changes.

Since the covariance matrix of the unconstrained latent variables $\boldsymbol{y}_{it}^*$ is $\boldsymbol{\Lambda}_{it}$, the covariance matrix of the constrained variables $\boldsymbol{y}_{it}$ is $\mathbf{P}\boldsymbol{\Lambda}_{it}\mathbf{P}'$. For the matrix $\boldsymbol{\Lambda}_{it}$, we can assume that each variable's initial standard deviation is proportional to its value, so that $\boldsymbol{\Lambda}_{it} = \theta^2\boldsymbol{\Delta}_{it}^2$ where $\boldsymbol{\Delta}_{it} = \text{diag}(\boldsymbol{y}_{it})$. The final covariance matrix is therefore:

$$\boldsymbol{\Sigma}_{it} = \theta^2\,\mathbf{P}\boldsymbol{\Delta}_{it}^2\mathbf{P}'$$

where the coefficient θ can be adjusted to match observed variances. That is, we first extract the diagonal elements of $\mathbf{P}\boldsymbol{\Delta}_{it}^2\mathbf{P}'$, i.e. $(d_{it1}^2, \ldots, d_{itk}^2) = \text{diag}(\mathbf{P}\boldsymbol{\Delta}_{it}^2\mathbf{P}')$. Then we calculate:

$$\theta = \left(\frac{1}{N}\sum_{i,t,j}\frac{y_{itj} - \mu_{itj}}{d_{itj}}\right)^{-1}$$

By construction, this ensures that the estimated variances match the observations.

C.3.2 Correlation over Time

The Model Consider the vector $\boldsymbol{y}_{i.j} = (y_{i,t_{\min},j}, \ldots, y_{i,t_{\max},j})'$ that contains the value of the variable j in country i over all years. To model the persistence of this variable over time, we will consider the following time series model:

$$y_{itj} - \mu_{itj} = \alpha_{ij} + \underbrace{\sum_{\ell=1}^{p}\theta_\ell y_{i,t-\ell,j} + \sum_{\ell=1}^{q}\phi_\ell \eta_{i,t-\ell,j} + \eta_{itj}}_{\text{ARMA}(p,q)\text{ model} = \varepsilon_{itj}}$$

The residual $y_{itj} - \mu_{itj}$ is composed of a time-constant random effect α_{ij} and a stationary ARMA(p, q) process ε_{itj}.

Correlation Function Let $\sigma_\alpha^2 = \text{Var}(\alpha_{ij})$, $\sigma_\varepsilon^2 = \text{Var}(\varepsilon_{itj})$ and $\rho_\varepsilon(t_1, t_2) = \text{Cor}(\varepsilon_{it_1j}, \varepsilon_{it_2j})$. The covariance of the residual $y_{itj} - \mu_{itj}$ between t_1 and t_2 is:

$$\begin{aligned}\text{Cov}(y_{it_1j} - \mu_{it_1j}, y_{it_2j} - \mu_{it_2j}) &= \text{Cov}(\alpha_{ij} + \varepsilon_{it_1j}, \alpha_{ij} + \varepsilon_{it_2j}) \\ &= \sigma_\alpha^2 + \sigma_\varepsilon^2\rho_\varepsilon(t_1, t_2)\end{aligned}$$

Therefore, the correlation over time is:

$$\mathrm{Cor}(y_{it_1j} - \mu_{it_1j}, y_{it_2j} - \mu_{it_2j}) = \pi + (1-\pi)\rho_\varepsilon(t_1, t_2)$$

where $\pi = \sigma_\alpha^2/(\sigma_\alpha^2 + \sigma_\varepsilon^2) \in (0,1)$ is the share of the variance explained by the time-constant random effect. For simplicity, we will assume that this share, as well as the correlation function ρ_ε, is the same for all the variables.

Estimation of the Random Effect Because the ARMA(p,q) process is stationary, a consistent estimator of α_{ij} for sufficiently long periods of time is:

$$\hat{\alpha}_{ij} = \frac{1}{T}\sum_{t=t_{\min}}^{t_{\max}} y_{itj} - \mu_{itj}$$

For each variable, we can construct an estimate $\hat{\pi}_j$ of the fraction of the variance explained by the random effect across all countries:

$$\hat{\pi}_j = \frac{\frac{1}{n}\sum_{i=1}^{n}\hat{\alpha}_{ij}^2}{\frac{1}{T}\sum_{t=t_{\min}}^{t_{\max}}\frac{1}{n}\sum_{i=1}^{n}(y_{itj} - \mu_{itj})^2}$$

As we assume that the ratio $\hat{\pi}_j$ is the same for all variables, we can get the final estimate as:

$$\hat{\pi} = \frac{1}{k}\sum_{j=1}^{k}\hat{\pi}_j$$

Estimation of the ARMA(p,q) Model

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