Issue No. 14 (June 2020)

Inequality Matters

Quarterly updates on inequality research, LIS micro data releases, and other developments at LIS

MESSAGE FROM THE EDITOR

Dear readers,

LIS is very excited to release annualised data for the United States in the LIS Database (US91 to US18 based on the CPS-ASEC). With the United States, LIS has now annualized the second long series next to Germany (DE91 to DE16). In addition, we are happy to announce the inclusion of a short annual series for Lithuania (LT09-LT17). For more data announcements in LIS for Greece, Russia, and South Africa, please see our 'data news' section.

With the addition of wealth data for South Africa (ZA15 & ZA17), we add the first upper middle income country to the LWS Database. Also, three datasets from the 3rd wave of the HFCS data have been harmonised to the LWS variable list (FI16, GR18, and SK17).

Following the success of continued collaboration between ERF and LIS, we are delighted to announce the release of the new ERF-LIS Database – 27 datasets from seven MENA region countries have been made accessible through LISSY. These datasets were acquired from the ERF – Harmonized Household Income and Expenditure Surveys (HHIES) database and harmonised according to the LIS template following the same naming convention and standards applied to the LIS datasets.

In our latest inequality research articles, Pedro Salas Rojo and Juan Gabriel Rodríguez use Machine Learning techniques to explore the role of any inheritances received in shaping wealth distribution in five OECD countries. Following Marco Ranaldi's ICI index (available in the previous issue), Roberto Iacono and Elisa Palagi study how the heterogeneity in the factor income shares of individuals compares in the Nordic countries. Using the newly released data series from Lithuania, Gintare Mazeikaite takes a closer look at the poverty trends among the elderly.

Finally, the newly released web-based version of LISSY, which includes graphing functionalities, is exemplified by Josep Espasa Reig.

More exciting news on our interactive visualisation tool - ***Data Access Research Tool* (DART)** are coming soon!

Enjoy reading! *Jörg Neugschwender*

IN THIS ISSUE

View all the newsletter issues at: www.lisdatacenter.org/newsletter
Subscribe here to our mailing list to receive the newsletter and news from LIS!
Interested in contributing to the *Inequality Matters* policy/research briefs? Please contact us at : neugschwender@lisdatacenter.org

The Role of Inheritance on Wealth Inequality: A Machine Learning Approach

Pedro Salas Rojo, (Complutense University of Madrid, Instituto Complutense de Análisis Económico (ICAE))
Juan Gabriel Rodríguez, (Complutense University of Madrid, Economics of Inequality and Poverty Analysis (EQUALITAS))

The debate: The role of inheritance in shaping wealth distribution

There is a general academic consensus that wealth inequality is on the rise (Zucman, 2019). Several factors seem to have contributed to this persisting trend. For instance, the development of financial markets since the 1980s has widened the possibilities for investment at the top of the distribution, thereby increasing their profits. Other authors blame shrinkages in progressive taxation, hindering the effect of distributional policies. Different approaches also suggest that the rising skill premium associated with wages, when accumulated, has led to a number of CEOs accumulating massive stocks of wealth derived from capital gains. However, there is still a matter causing dissent: the role of inheritance in shaping wealth distribution.

On one side, authors such as Karagiannaki (2017) find that inheritances decrease wealth inequality. Through a case-study of the UK, a counterfactual distribution of wealth excluding the value of the bequests received shows that, overall, wealth is much more unequally distributed than inheritances. In this manner, the intergenerational transmission of assets produces a net equalizing effect. However, other authors such as Piketty and Zucman (2015) suggest otherwise. Both authors explain how the annual flow of bequests and gifts, as a percentage of national income, have greatly increased in the last few decades, following the rising share of wealth at the top. Consequently, inheritance would be one of the main vehicles through which wealth inequality is transmitted and increased through generations.

In order to provide more empirical evidence on the actual role of inheritance in wealth distribution, we take a different approach. In this article, we analyze how the bequests received affect the opportunities people have for accumulating wealth. To this end, we use the Luxembourg Wealth Study (LWS) database provided by the Luxembourg Income Survey (LIS), analyzing five countries: Canada, Italy, Spain, the UK and the US.

The measurement of opportunities to acquire wealth

Any social or economic outcome such as wealth, income or health status is a result of the interaction between at least two sets of factors. On the one hand, people face exogenous barriers beyond their control, such as sex at birth, parental education, race or the value of any inheritances received. From this point on, following the seminal work of Roemer (1993), we will call them *circumstances*. On the other hand, the remaining factors are considered to be endogenous as they are within the individuals' set of choices. This is the case, for instance, for the number of hours worked or nutritional habits. We call these *efforts*.[1]

Based on circumstances, we can divide any society into exhaustive and mutually exclusive groups, also called *types*. For instance, if we were to consider that the only relevant circumstances in a given society were sex at birth (men, women) and race (black or white), we could generate four types, namely: white men, white women, black men and black women. This society would face equality of opportunity if, and only if, the distribution of economic results was independent from belonging to one type or another. In contrast, if we find prevalent differences between types, we can blame these exogenous factors for conditioning and distorting opportunities for individuals to achieve that particular economic outcome.

Following these ideas, we decompose inequality into two components. The first component collects the between-types inequality, exclusively explained by the different circumstances faced by the individuals. This is what we call *Inequality of Opportunity* (IOp). The second is the within-type component and is explained by the different efforts exerted by individuals sharing the same circumstances. It is called *Inequality of Efforts* (IE).

The demarcation of both components is important for social justice as it allows us to isolate and analyze the effect of 'unfair' inequality (Rawls, 1971). Moreover, authors such as Marrero and Rodríguez (2013) find that IOp is negatively related to economic growth, as unequal opportunities provoke inefficient allocations of human capital.

In this framework, we consider inheritances and gifts to be circumstances, as they are exogenous shocks received by the individual and is independent of their behavior. Accordingly, we generate different types based on the distribution of inheritances and later decompose total inequality into two components: the part of inequality exclusively explained by the different bequests received and a residual component that includes all remaining uncontrolled circumstances and efforts. This procedure allows us to calculate the share of total inequality explained by inheritances, measuring its actual relevance in the wealth distribution.

The empirical implementation: A Machine Learning approach

Constructing types with discrete variables (race, gender or parental education) is straightforward, as its categories are generally well defined. However, for continuous variables such as the value of the inheritances received, we need to perform a prior discretization. Here we face a choice of procedure. Should we divide the bequests distribution by the median, the terciles, or separate the top decile from the rest? Given the right-skewness of the inheritances distribution, its partition into types is quite tricky, since it could drive the results obtained in the final analysis. In fact, as we describe in the results section (below) we find that by-hand discretizations lead estimates of wealth IOp that are not robust.

To palliate this lack of robustness, we adopt a statistic criterion based on Machine Learning algorithms which split the inheritances received in a consistent way (see also Brunori *et al*., 2019). In particular, among the algorithms proposed, we lean towards the *conditional inference random forests* (Hothorn *et al.*, 2006). Based on the conditional distribution of wealth over the continuous circumstance, inheritances, this algorithm applies several statistical tests covering all potential discretizing points. In addition, using a multiple fold cross-validation procedure, we tune an endogenous coefficient of significance, which also erases the researchers' criteria over the statistical tests performed.

With this algorithm, we discretize the continuous variable under consideration selecting as the final cut points only those for which the types create the most statistically meaningful groups. As a consequence, we are able to extract all the information contained in the distribution of the variables and, at the same time, maximize the out of sample validity.

Main Results: inheritances are important for wealth inequality

The data used is taken from the LWS database (LIS), which includes a complete record of assets and inheritances received. This allows us to employ three different wealth definitions, estimating for each one of them the between-type component of inequality explained by inheritances. Particularly, we analyze financial wealth (consisting of deposits, equities, investment funds and other liquid assets), non-financial wealth (consisting of real estate, garages and other properties) and the sum of both, giving total wealth.

To introduce the matter, Table 1 deploys wealth inequality according to the Gini index for the five countries analyzed. As reported frequently, the United States is the most unequal country regardless of the wealth definition under consideration, while the European countries show the lowest estimates, Canada being in between. These results also highlight the high value that characterizes wealth inequality in general, and financial wealth in particular. For this reason, financial wealth is sometimes considered one of the main causes behind (and also derived from) the rise in capital income inequality.

The first part of our analysis consists of criticizing the use of by-hand discretizations. Thus, Table 2 shows the share of total wealth inequality (that is, the share attributed to the between-type component) explained exclusively by inheritances. Notice that types are constructed according to three different discretization methods. First, we use the median; second, we adopt terciles; third, we separate the individuals at the top quartile from the rest of the distribution.

We observe that the different construction of types generates quite different results. For instance, in the US, if we use the median to generate types, around 35% of total wealth inequality is explained by the value of inheritances received. However, if we use terciles to split the population into types, this share rises to a remarkable 47.23%. These results demonstrate that the criterion for separating individuals into types is a fundamental decision in the measurement of the role of inheritances across wealth distribution. The implementation of Machine Learning techniques to generate statistically meaningful types is clearly justified.

Figure 1 represents the share of total, financial and non-financial wealth inequality (Gini index) explained by inheritances for our five countries. The construction of types is now non-discretionary and based on the conditional inference random forests algorithm previously mentioned. The associated paper demonstrates these results to be robust for several different specifications.

We find that, in Canada, around 57% of financial wealth inequality is explained by the inheritances received, while the ratio falls to 36% for non-financial wealth and 42% for total wealth. In Italy, these values range between 37% and 44%. Interestingly, the UK is the country where the reported inheritances received seem to matter the least: around one third of financial wealth inequality is explained by this circumstance, a ratio falling to 16% and 13% for total and real estate inequality, respectively.

Most notably, our results show that for Spain and the US the value of the inheritances received significantly affect the opportunities of people to accumulate wealth. Particularly in Spain, around 69% of total and 65% of financial wealth inequality is solely explained by the inheritances received, while a remarkable 76% of non-financial wealth inequality is attributed to this circumstance. The US shows similar estimates, interchanging the values for financial and non-financial wealth.

Overall, we find the distribution of inheritances to be a remarkable component of total inequality. However, the importance seems to vary greatly across countries: while it is clearly the most important factor behind wealth distribution in Spain and the US, in other countries, such as Italy and Canada, there seem to be several other important factors shaping wealth distribution. In particular, for the UK, we find that inheritances are relatively unimportant, although not irrelevant by any means, especially for financial wealth.

Table 1: Wealth inequality (measured by Gini)

Country	Canada	Italy	Spain	United Kingdom	United States
Total Wealth	70.66	59.00	59.24	58.70	80.28
Financial Wealth	83.70	73.96	84.13	79.19	91.60
Non-financial Wealth	74.90	60.61	60.20	58.67	82.17

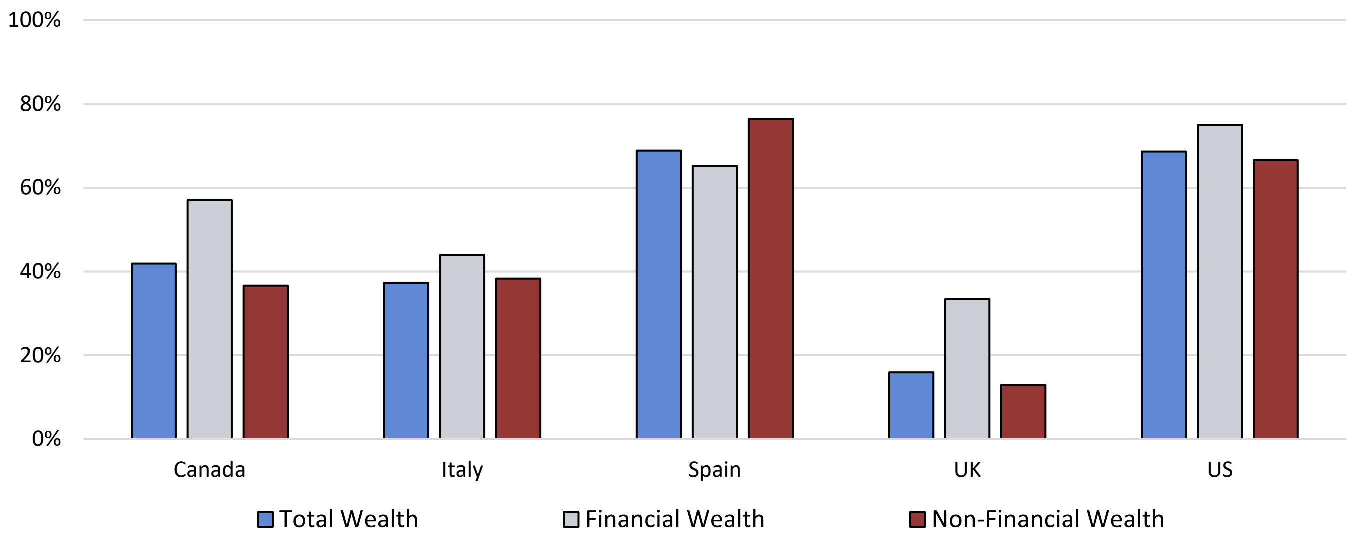
Source: Own elaboration using Luxembourg Income Study (LIS) Database/Luxembourg Wealth Study (LWS) Database.

Table 2: The share of total wealth inequality (Gini) explained by inheritances

Country	Canada	Italy	Spain	United Kingdom	United States
Gini	70.66	59.00	59.24	58.70	80.28
Inheritances viewed as the median	32,73%	29,54%	42,20%	11,69%	35,03%
Inheritances viewed as terciles	42,17%	38,44%	59,81%	17,14%	47,23%
Inheritances viewed as third quartile	34,31%	23,59%	25,71%	7,04%	32,09%

Source: Own elaboration using Luxembourg Income Study (LIS) Database/Luxembourg Wealth Study (LWS) Database.

Figure 1: Share of wealth inequality (measured by Gini) explained by inheritances



Source: Own elaboration using Luxembourg Income Study (LIS) Database/Luxembourg Wealth Study (LWS) Database.

Complementary analysis: Does parental education provide further insights?

Looking at the results deployed in Figure 1, we propose to consider not only the distribution of inheritances but also the effect of another exogenous factor: parental education. The relation between this variable and wealth distribution shows a prevalent academic consensus. Highly educated parents, in general, transmit their social and human capital to their offspring, facilitating their access to higher levels of education, at better universities, and in which they can develop more profitable social networks. As a result, the opportunities of those individuals with highly educated parents are increased, easing their wealth accumulation through a different channel not necessarily fully captured by inheritances (Palomino et al., 2019). In addition, both circumstances may reinforce each other, so the effect calculated for inheritances could actually reflect, at least in part, the effect of parental education. For this reason, it is convenient to analyze the joint effect of both factors.

For this task, Figure 2 plots the share of wealth inequality for the three previous wealth definitions explained by both circumstances together: parental education and inheritances. Unfortunately, we do not have information of the former variable for either Canada or Spain, so Figure 2 only presents the results for Italy, the UK, and the US.

We find that, in Italy, more than 60% of financial inequality is explained by the differences in parental education and inheritances received, which also explain up to 52% of total and non-financial wealth inequality. The share attributed to both circumstances also rises in the UK. Now, 49% of financial inequality is explained by them, the ratio rising to around 30% for the other two wealth definitions. Thus, for both countries there is a clear effect of both circumstances on wealth distribution. On the contrary, the already elevated ratios of

Figure 2: Share of wealth inequality (measured by Gini) explained by inheritances and parental education

Source: Own elaboration using Luxembourg Income Study (LIS) Database/Luxembourg Wealth Study (LWS) Database.

the US do not vary significantly. It seems that, in this country, the intergenerational transmission of opportunities is essentially captured by the information derived from the distribution of inheritances received.

Conclusion

In this article we use Machine Learning techniques to explore the role of any inheritances received in shaping wealth distribution in five OECD countries. We find this variable explains at least 60% of total, financial and non-financial wealth inequality in Spain and the US. It also explains a remarkable share (more than 40%) in Canada and Italy, while its role is much less important in the UK. Moreover, we find that parental education also accounts for a notable portion of wealth inequality in Italy and the UK but does not add relevant information in the case of the US.

Our results are consistent with the literature that observes important cross-country differences in the factors shaping wealth distribution. Despite finding that inheritance distribution clearly affects the opportunities of individuals for acquiring wealth, we would discourage a deterministic view of the relationship between inheritances and wealth inequality. Rather, we suggest that specific taxation structures, capital flows, general investment behavior and other deep structural factors may be behind the varying opportunities for acquiring wealth across countries.

1 The role of luck has also received attention from the literature but, for the sake of simplicity, it is disregarded in this article.

References

Brunori, P., Peragine, V. and Serlenga, L. (2019). 'Upward and Downward Bias when Measuring Inequality of Opportunity', Social Choice and Welfare, 52, 635-661.

Hothorn, T., Hornik, K. and Zeileis, A. (2006). 'Unbiased Recursive Partitioning: A Conditional Inference Framework', Journal of Computational and Graphical Statistics, 15, 651-674.

Karagiannaki, E. (2017). 'The Impact of Inheritance on the Distribution of Wealht: Evidence from Great Britain', Review of Income and Wealth, 63.

Marrero, G. A. and Rodríguez, J. G. (2013). 'Inequality of Opportunity and Growth', Journal of Development Economics, 104, 107-122.

Palomino, J. G., Marrero, G. A., Nolan, B. and Rodríguez, J.G. (2019). 'Inheritances, Family Background and Wealth Inequality', Oxford University, mimeo.

Piketty, T., and Zucman, G. (2015). 'Wealth and Inheritance in the Long Run', Handbook of Income Distribution, 2, 1303-1368.

Rawls, J. (1971). 'A Theory of Justice', Harvard University Press, Cambridge.

Roemer, J. E. (1993). 'A Pragmatic Approach to Responsibility for the Egalitarian Planner', Philosophy and Public Affairs, 20, 146-166.

Zucman, G. (2019). 'The Triumph of Injustice: How the Rich Dodge Taxes and How to Make Them Pay', Norton and Company, New York.

Still the Lands of Equality? On the Heterogeneity of Individual Factor Income Shares in the Nordics

Roberto Iacono, (Norwegian University of Science and Technology (NTNU), Faculty of Social and Educational Sciences)

Elisa Palagi, (Institute of Economics and EMbeDS, Scuola Superiore Sant'Anna, Pisa (Italy))

As far as standard measures of income inequality are concerned, the Nordic countries rank among the most equal economies in the world. We study whether and how this picture changes when the focus is on inequality of income *composition*, meaning the heterogeneity in the factor income shares of individuals. Income composition inequality is measured in our study through the ICI index introduced in Ranaldi (2020).

If we divide individual income into labour and capital, income composition inequality is high whenever the bottom and the top of the total income distribution separately own the two income sources. As an example, whenever the total factor income of wealthy individuals is made up of a higher share of capital income relatively to the poor, income composition inequality is high. Such an economy approaches the ideal-type Milanovic (2017) defines as *classical capitalism*. In contrast, whenever individuals across the total income distribution own equal shares (with respect to their own total factor income) of capital and labor income, income composition inequality is low. The latter defines a situation of *new capitalism* in which both rich and poor individuals own different sources of income. Notice that even in a world in which income composition inequality were to be low, there would still be individuals with higher total incomes than others, and significant inequalities might therefore persist.

In order to provide estimates of income composition inequality for the Nordic countries we utilize the LIS (2020) data, which is harmonized and allows a cross-country comparison. For all of the four countries under analysis, the source of the data included in the LIS database is derived from the national statistical institutes, with relatively high population coverage.

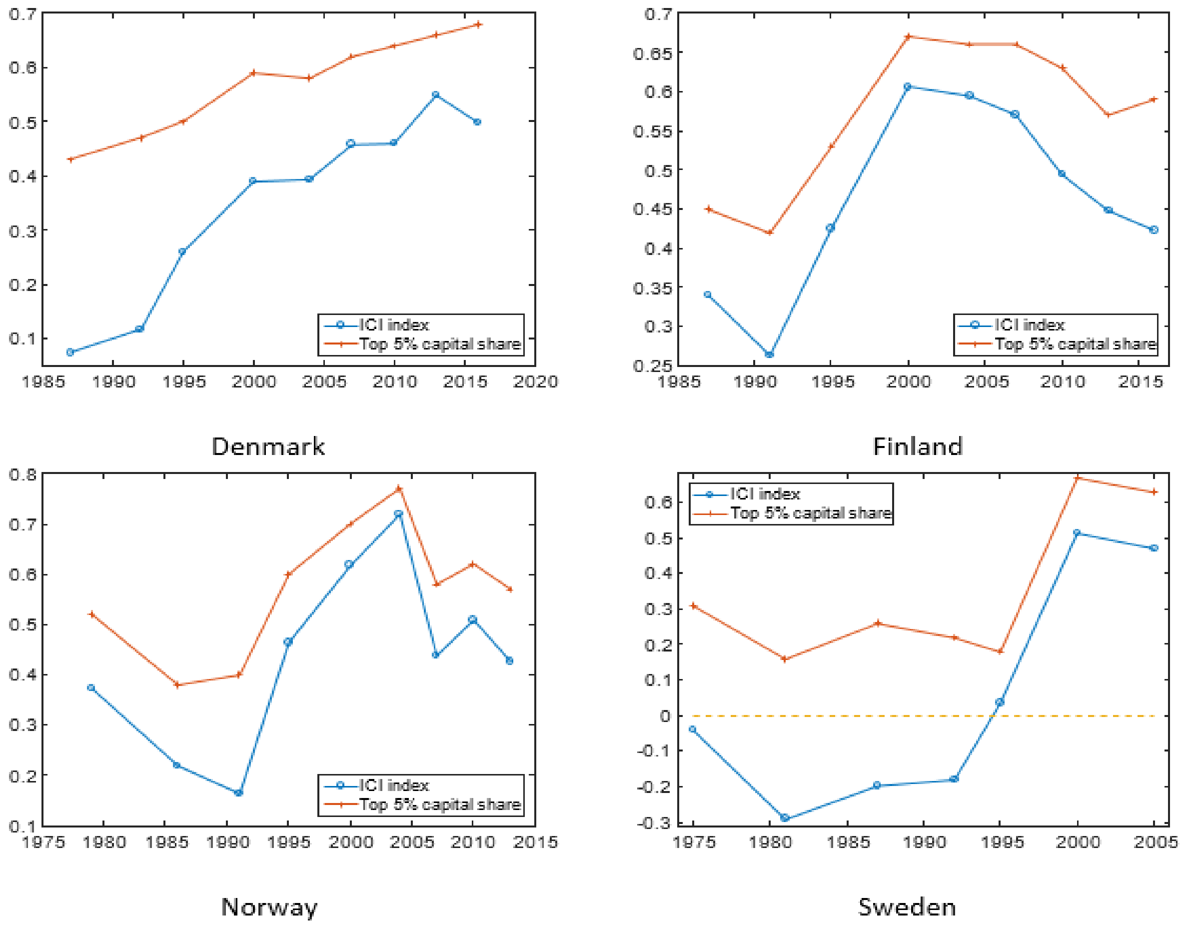
In the core of the paper we adopt a single baseline definition of income, based on the LIS factor income, hence excluding transfer income.[1] The use of market factor income, rather than net disposable income, allows us to measure the pre-tax concentration of factor incomes across the income distribution.

We define capital income (Π) as the sum of property income (Π_{pr}), comprising rental income, interest, dividends and capital gains and the capital component of net self-employment income (Π_{se}). Labor income (W) includes wage income (W_{wa}) and the labor component of net self-employment income (W_{se}).

As regards the unit of analysis, we employ household-level data adjusted by the LIS (2020) database sample weight (*hpopwgt*). Then we multiply the LIS (2020) household weights by the number of household members (given by the variable *nhhmem* in the LIS (2020) data variable list).

We highlight the structural change that has been taking place in all the Nordic countries since the early 1990s, visible from Figure 1, with rising inequality in the composition of individual incomes due mostly to a shift in capital incomes towards the top of the distribution. In fact, the evolution of capital shares accruing to the top 5% in the distribution of total factor income is closely related to the trends in the ICI index. This result indicates that in the last decades the Nordic countries have been moving towards the ideal-type of economic system of *classical capitalism*, as defined by Milanovic (2017).

Figure 1: Income Composition Inequality index



Note: For each of the four countries under analysis, we plot the series of the elasticities, obtained by using the series of the μπ and μw. The vertical reference line signals the introduction of the DIT system: 1993 for Denmark and Finland, 1992 for Norway, 1991 for Sweden.

Table 1: Summary of results by country

		Income Composition Inequality				
Country	Period	Variation (weak/strong) or sign (high/low)				
		Cap. share (variation)	mu_p (variation)	mu_w (variation)	ICI index (sign)	Gini (variation)
Denmark	1987 – 2016	+ (weak)	- (strong)	- (weak)	+	+ (strong)
	1987 – 1995	+ (strong)	- (strong)	- (weak)	+ (low)	- (weak)
	1995 – 2009	- (strong)	- (strong)	- (weak)	+ (low)	+ (weak)
	2009 – 2013	+ (strong)	- (weak)	- (weak)	+ (high)	+ (strong)
Finland	1987 – 2016	+ (weak)	- (strong)	- (weak)	+	+ (strong)
	1990 – 2007	+ (strong)	- (strong)	- (weak)	+ (high)	+ (strong)
	2008 – 2013	- (weak)	+ (weak)	- (weak)	+ (high)	+ (weak)
Norway	1979 – 2013	+ (weak)	- (strong)	- (weak)	+	+ (weak)
	1979 – 1991	+ (weak)	+ (weak)	+ (weak)	+ (low)	- (strong)
	1991 – 2005	+ (strong)	- (strong)	- (strong)	+ (high)	+ (strong)
	2005 – 2013	+ (weak)	+ (weak)	- (weak)	+ (high)	+ (weak)
Sweden	1975 – 2005	+ (weak)	- (strong)	- (weak)	-/+	+ (strong)
	1975 – 1995	+ (strong)	- (strong)	- (weak)	- (low)	+ (strong)
	1995 – 2005	- (weak)	- (strong)	+ (weak)	+ (high)	- (weak)

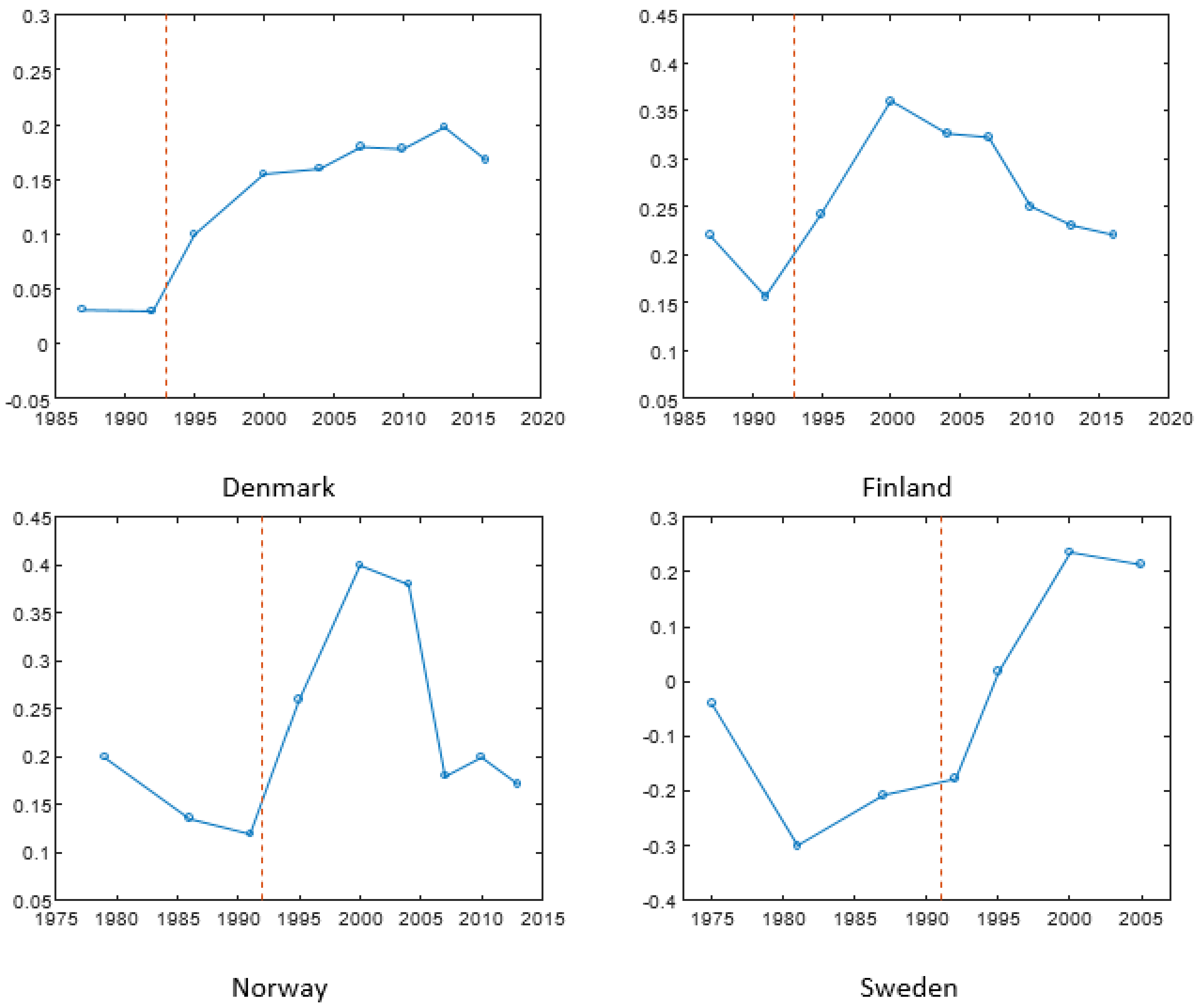
What is also striking is that the start of the increasing trend in income composition inequality in all the Nordic economies corresponds to the years of the introduction of Dual Income Taxation reforms in the 1990s. These reforms reduced tax rates on capital incomes, shrinking the progressivity of the rates or even reducing them to a proportional flat tax. In Figure 2 we plot the elasticities of the Gini coefficient to changes in the aggregate capital share of income estimated from the index. The vertical lines correspond to the introduction of the DIT system in the different countries. What this figure shows is that a reduced progressivity in the tax system, and an increased asymmetry in factor taxation, might not only increase income inequality directly but also indirectly by increasing the elasticity of personal income inequality to changes in the capital share of income. It also suggests that the ICI index is able to capture increasing asymmetries in taxation, which is typically not directly observable from the Gini coefficient.

Our estimates of the degree of income composition inequality also allow a descriptive analysis of the role of functional distribution as a determinant of personal income inequality in the Nordics. Piketty (2014)'s finding of capital having made a comeback and the related prediction that an increased capital share of income would imply higher personal income inequality has spurred an interesting debate. Bengtsson and Waldenström (2018) in a cross-country study find that the relationship between share of capital and personal income inequality varies across time and countries. Milanovic (2017) defines two necessary and sufficient conditions for the prediction being true. Ranaldi (2020) summarizes these two conditions into one, namely a high degree of income composition inequality.

We summarize the main results of the paper in Table 1. For each country and period under study, the table shows the variation in the aggregate net capital share[2], the evolution of the areas below the concentration curves respectively for capital income (μ_p) and labor income (μ_w), these being the building blocks affecting the sign and magnitude of the ICI index. Finally, the table presents the variation in the market Gini coefficient.[3]

We show that for Denmark in the period 2009–2013, Finland 1990–2007, and Norway 1991– 2005, rising capital shares of income contributed to changes in personal income inequality, whilst for Sweden the evidence leads to disregard the capital share as a

Figure 2: Elasticities and Dual Income Taxation



Note: For each of the four countries under analysis, we plot the series of the elasticities, obtained by using the series of the μ_π and μ_w.
The vertical reference line signals the introduction of the DIT system: 1993 for Denmark and Finland, 1992 for Norway, 1991 for Sweden.

determinant of income inequality. In the summary of results shown in Table 1, the shaded sub-periods refer to years in which we observe an increasing aggregate capital share together with high levels of the ICI index and rising income Gini coefficients. The high level of the ICI index suggests that in those periods the capital share has been a relevant determinant of personal income inequality in these countries. The other sub-periods are characterized by either an ICI index that is quite low in absolute value and close to 0 or by limited variations in the capital share.

Given the non-constant and country-specific nature of the relation between functional and personal income inequality, the approach used in this work represents a way to study this heterogeneity in depth. Moreover, the income composition inequality index proposed by Ranaldi (2020) might represent an important source of information for the design and the understanding of the results of broader cross-country analysis on the topic.

We argue that if the trends of increased heterogeneity among individual factor shares uncovered in this work persist, and if these are coupled with more significant increases in the aggregate capital share, the transmission from the functional to the personal distribution of income might represent an important factor potentially increasing personal income inequality in the Nordic economies in the future.

1 *In the paper we perform a robustness check by including transfer income and it turns out that the trends in the evolution of the index do not change significantly.*

2 *The series for the capital share of income (value added net of capital depreciation minus compensation of employees) are obtained from the Bengtsson-Waldenström Historical Capital Shares Database (Bengtsson and Waldenström, 2018). Capital share is computed as the sum of capital incomes (interest, profits, dividends, realized capital gains), divided by value added calculated at factor cost, net of capital depreciation.*

3 *The series of the Gini coefficients in the Nordic countries are all retrieved from the World Inequality Database, WID.World (2020). The Gini coefficients are computed from pre-tax national income, the unit of analysis being individual adults (equal-split series)*

References

Bengtsson, E. and Waldenström, D. (2018). Capital Shares and Income Inequality: Evidence from the Long Run. *The Journal of Economic History*, 78(3):712–743.

Luxembourg Income Study (LIS) Database, http://www.lisdatacenter.org (multiple countries; January 2020 - April 2020). Luxembourg: LIS.

Milanovic, B. (2017). Increasing capital income share and its effect on personal income inequality. In Boushey, H., de Long, B., and Steinbaum, M., editors, *After Piketty: The agenda for economics and inequality*, pages 235–239. Harvard University Press.

Piketty, T. (2014). *Capital in the 21st century*. Harvard University Press.

Ranaldi, M. (2020). Income Composition Inequality. Stone Center for Socio-Economic Inequality Working Paper Series, no.7, City University of New York (CUNY).

WID.World (2020). World Inequality Database. *https://wid.world/data*.

Why Is Old-Age Poverty on the Rise in Lithuania? A First Look at the Annual LIS Data Series for 2009-2017

Gintare Mazeikaite, (LIS)

In the recent LIS working paper, Ebbinghaus, Nelson and Nieuwenhuis (2019) looked at poverty trends in old age in a number of high-income OECD countries. They found a steady decline in old-age poverty in the 2000s in most of the countries analysed, leading to a convergence in poverty rates among the working age population and the elderly. Contrary to these trends, LIS Key Figures[1] show that old-age poverty in Lithuania has been on the rise since 2010. The newly released annualised LIS data series from Lithuania for 2009-2017 gives us an opportunity to have a closer look at the poverty trends among the elderly and identify some of the factors behind these trends.

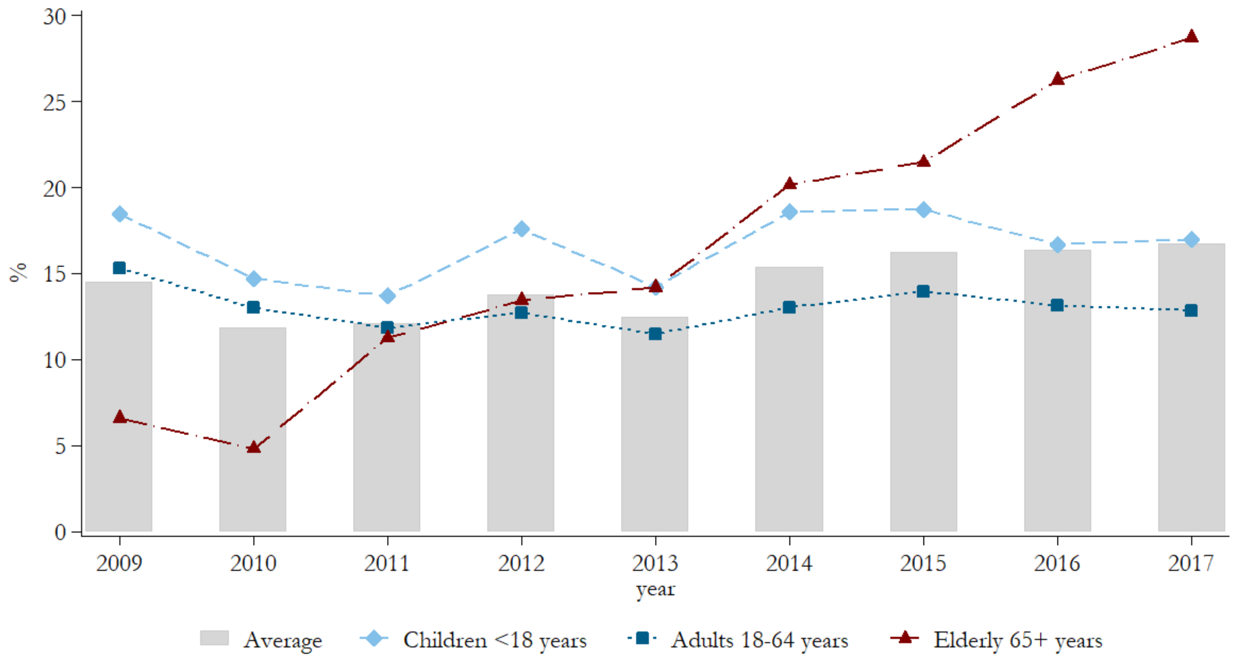
Social insurance in Lithuania can be dated back to 1926 but a universal state pension insurance scheme was not implemented until 1995[2]. During the Soviet period of 1945-1990, Lithuania did not have a separate social insurance budget. Old-age, survivors and invalidity pensions were granted from the USSR state budget to individuals reaching retirement age (50 years old for women and 55 years old for men) and persons who had completed full years of service. After the establishment of the Central State Social Insurance Board in the independent Lithuania (SoDra), a pension reform took place in 1995. Initially, the system took over the retirement age from the Soviet system but this was gradually increased.

Currently, Lithuania has a two-tier public pension scheme, comprised of a flat-rate benefit and an earnings-related component, adjusted each year based on the growth rate of the wage fund. In 2014, a voluntary funded pension scheme became available, enabling residents to channel a part of their social insurance contributions into private pension funds. The minimum number of years of social insurance contributions required to qualify for a public pension is 15 years. In 2017, the retirement age was 63 years and 6 months for men and 62 years for women[3], and a full rate basic pension was granted with 30 years of contributions. In the same year, the basic pension was 120 EUR per month and the average pension with full insurance contribution record was 291.1 EUR per month (Navicke and Cizauskaite, 2018; SoDra, 2020)[4]. The inadequacy of these old-age benefits and the high poverty rates among the elderly have led to a pension reform in 2018 (European Commission, 2018).

Figure 1 shows trends in relative poverty in the Lithuanian population and by age groups. Income is measured by adding all personal and household income after taxes and transfers and adjusting for household composition using the LIS equivalence scale (square root of the household size). Individual equivalised income is then compared to the relative poverty line equal to 50% of the median equivalised disposable income in a given year. While poverty rates of children and adults under 64 years old fluctuated in the period 2009-2017, a nearly five-fold increase in poverty in old age was responsible for a slight upward trend in poverty in the Lithuanian population. This means that the elderly at the bottom of the income distribution did not see their incomes rise at the same rate as individuals in the middle of the national income distribution.

Figure 2 offers a potential explanation for increasing poverty rates among the elderly. As the Lithuanian economy started recovering from the Great Recession of 2008, monthly wages were steadily rising. This happened not only due to the growth in the economy but also due to institutional changes in the minimum wage, which was raised from 232 EUR in 2012 to 380 EUR in 2017. At the same time, pensions remained largely unaffected. The basic monthly pension stood at 105 EUR until

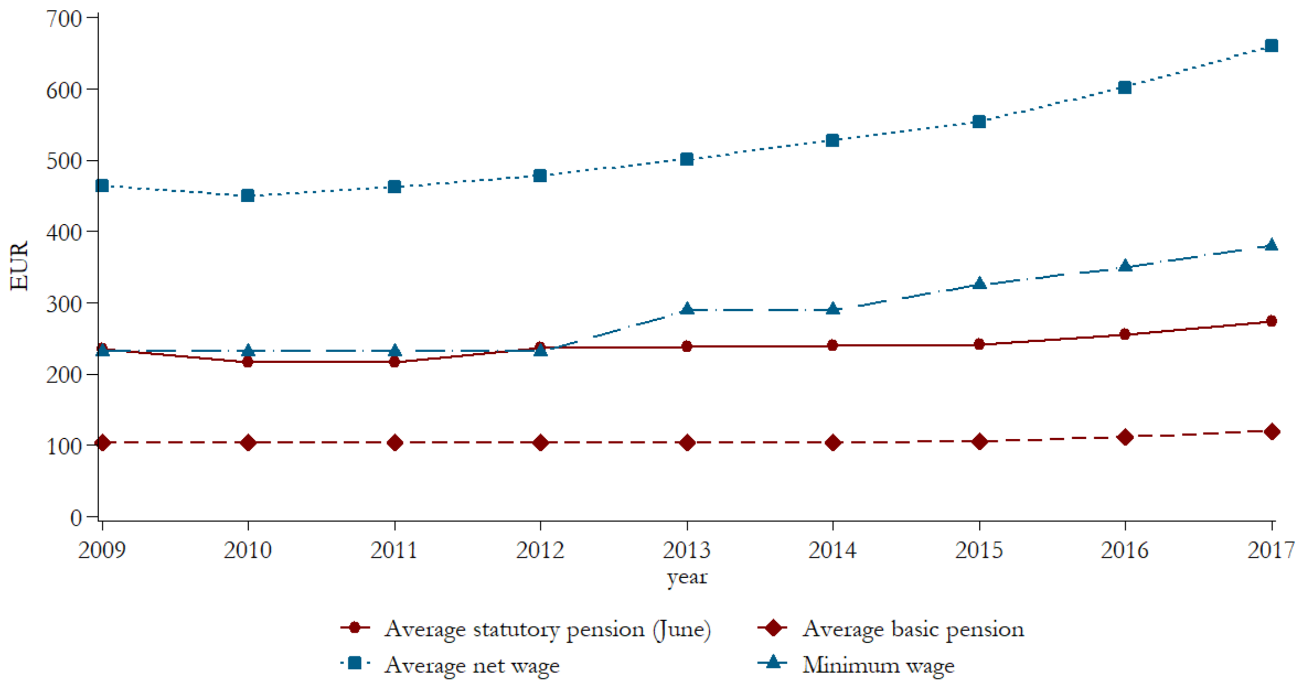
Figure 1. Relative poverty rate in Lithuania in 2009-2017 by age group



Note: The figure shows trends in relative poverty by age group. Poverty is defined as income below 50% of median equivalised household disposable income in a given year.

Source: Luxembourg Income Study (LIS) Database.

Figure 2. Monthly pension and wage in Lithuania in 2009-2017, EUR



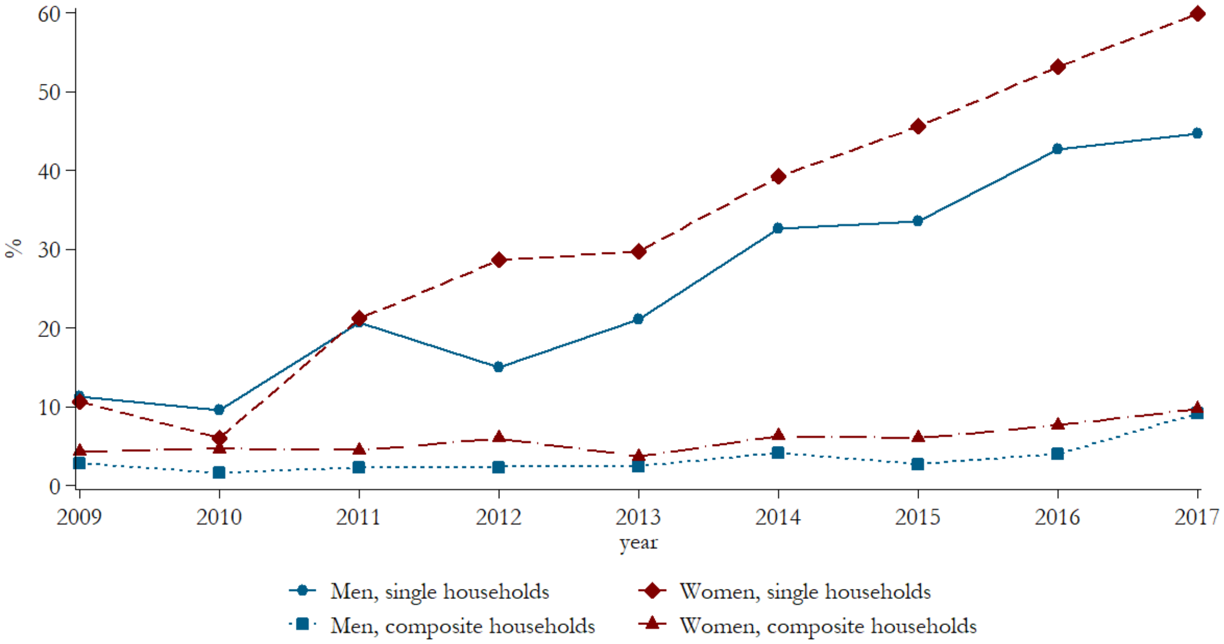
Note: Basic monthly pension and minimum monthly salary amounts were retrieved from Lazutka, Navicke, and Salanauskaite (2012) and Navicke and Cizauskaite (2018). Average statutory pension was retrieved from SoDra (2020). Average net wage was retrieved from Statistics Lithuania (2020).

2015 and was increased only slightly until it reached 120 EUR in 2017. Due to this, the rise in the old-age pensions did not keep up with the income growth of the majority of the population, which is why we see a steady increase in the relative poverty rates among the elderly in 2010-2017.

Whether the elderly were more likely to become poor during the analysed period depended largely on the household composition. Figure 3 shows that while poverty rates among the elderly living in composite households rose only slightly, it was the elderly living alone who suffered the most. The increase in relative poverty was especially pronounced for women in single households. By 2017, about 60% of women living alone were in relative poverty, compared to less than half of men living alone. The differences in poverty rates among elderly women and men are not surprising: women tend to have shorter employment histories and earn lower incomes compared to men, which result in lower old-age pensions. However, though present, the gender gap in old-age benefits in Lithuania is not considered large from an EU perspective (European Commission, 2018).

Lastly, Figure 4 shows the differences in the composition of disposable income among old-age individuals by poverty status. First, we see that poor individuals primarily rely on old-age pensions as their source of

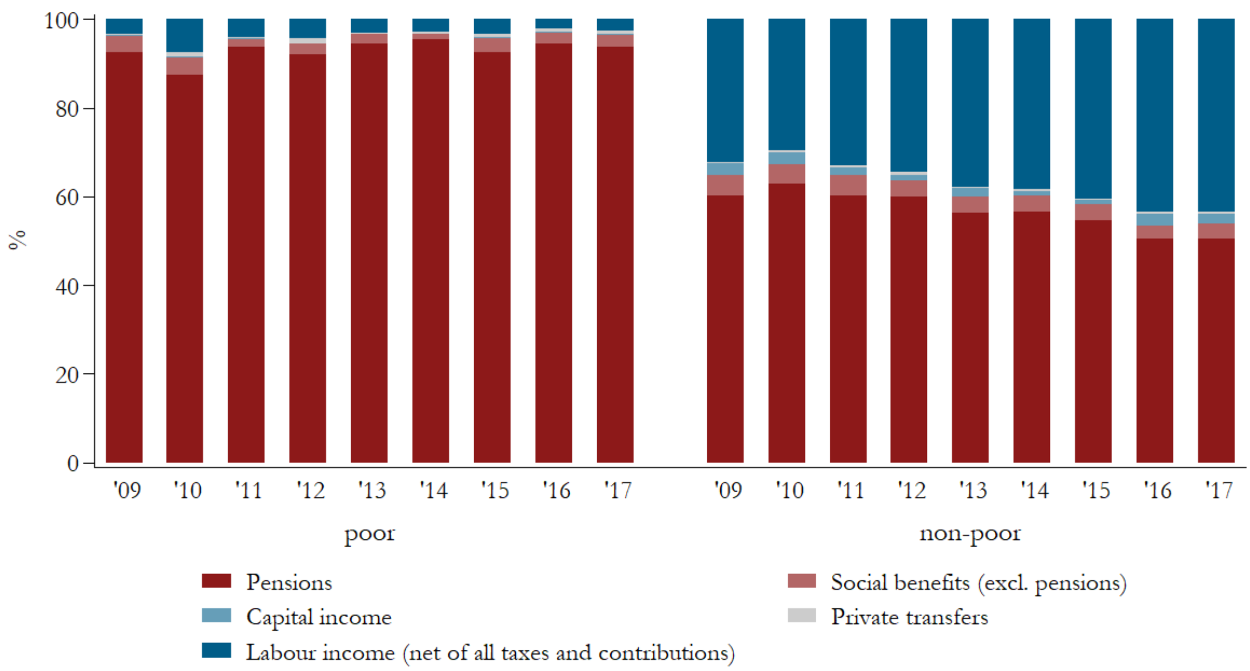
Figure 3. Relative poverty rate among the elderly in Lithuania in 2009-2017 by sex and household type



Note: Poverty is defined as income below 50% of median equivalised household disposable income in each country in a given year

Source: Luxembourg Income Study (LIS) Database.

Figure 4. Composition of disposable income among the elderly by poverty status in Lithuania in 2009-2017, %



Note: Pensions include private and public old-age pensions, social assistance pensions, survivor benefits and work injury pensions granted to individuals older than the statutory retirement age. For the sake of simplicity, all taxes and social insurance contributions are subtracted from labour income. Poverty is defined as income below 50% of median equivalised household disposable income in each country in a given year.

Source: Luxembourg Income Study (LIS) Database.

income. Only less than 10% of their income came from other sources such as labour, capital, private transfers and other social transfers. On the other hand, among the elderly living above the poverty line, pensions comprise less than two-thirds of disposable income, while labour income comprises around 30%. Second, in the period 2009-2017, the share of labour income among non-poor elderly individuals steadily increased, while it slightly declined among the poor. This suggests that while pensions stagnated, the only way for those who were close to the poverty line not to fall into poverty was to increase income from other sources, mainly labour. This does not mean that the elderly had to necessarily go back to work; it merely explains that old-age individuals living in composite households were much better protected against poverty than the elderly living alone due to the labour income of other household members. In addition to this, the share of capital income in total disposable income among non-poor individuals was higher than among poor individuals, which suggests that poverty can be reduced by promoting savings in old-age.

Overall, we found that stagnating pensions and increasing wages in the Lithuanian economy were largely responsible for the steady growth in relative poverty rates in old age in Lithuania during 2009-2017. Even though the statutory minimum wage was gradually raised from 2013 on, pension benefits saw only a marginal increase starting from 2016. In particular, old-age individuals living in single households and primarily relying on pension income were significantly more likely to fall into poverty, especially single women. Since 2018, several pension reforms have taken place in order to address the inadequacy of income protection in old age, including an increase in the basic pension[5]. Due to this, we might see a reversal of the poverty trend among the elderly from 2018 on, once the new waves of LIS data for Lithuania become available. However, ensuring adequate income protection in old age will remain a challenge in Lithuania in the coming years as the country struggles with increasing old-age dependency ratios.

1 *LIS Key Figures can be accessed at: https://www.lisdatacenter.org/data-access/key-figures/*

2 *A more detailed description of the history of the social insurance system in Lithuania is available on the website of the Central State Social Insurance Board https://www.sodra.lt/lt/socialinis-draudimas/sodros-istorija.*

3 *Retirement age in Lithuania has been gradually increasing year on year by 2 months for men and 4 months for women until it reaches 65 years in 2026.*

4 *Public pensions in Lithuania are not subject to personal income tax and social security contributions (OECD, 2019).*

5 *For example, between April 2017 and April 2020, the average statutory pension increased from 274 to 376 EUR (SoDra, 2020).*

References

Ebbinghaus, B.; Kenneth N.; Nieuwenhuis, R. (2019). 'Poverty in Old Age', LIS Working Papers Series, No.777.

European Commission (2018). The 2018 pension adequacy report: Current and future income adequacy in old age in the EU. Volume II: country profiles, https://doi.org/10.2767/653851.

SoDra (2018). Socialinis draudimas Lietuvoje 1926 - 1940 metais, Retrieved from: https://www.sodra.lt/lt/socialinis-draudimas/sodros-istorija.

SoDra (2020). Statistical data website: Pensions, Retrieved from: https://atvira.sodra.lt/en-eur/.

Lazutka, R.; Navicke, J.; Salanauskaite, L. (2012). 'EUROMOD country report: Lithuania (LT), 2007-2011', Retrieved from: https://www.euromod.ac.uk/sites/default/files/country-reports/year3/CR_LT_2007-2011_final.pdf.

Navicke, R. and Cizauskaite, A. (2018). 'EUROMOD country report: Lithuania (LT), 2015-2018." (2018)', Retrieved from: https://www.euromod.ac.uk/sites/default/files/country-reports/year9/Y9_CR_LT_Final.pdf.

Statistics Lithuania (2020). Indicators database, Retrieved from: https://osp.stat.gov.lt/statistiniu-rodikliu-analize#/.

OECD (2019). Pensions at a Glance 2019: Country profiles – Lithuania (2019), https://doi.org/10.1787/b6d3dcfc-en.

R-Charts in LISSY X: A Short Guide

Josep Espasa Reig ✉, (LIS)

In the beginning of June 2020 LIS has launched a quite innovative version of LISSY, a fully web-based interface that includes graphing functionality. For all non-users of LIS databases, since LIS' early days, LISSY is the heart of data services at LIS. LISSY is the remote execution system that allows researchers to access LIS and LWS microdata remotely. Users of this interface can write and submit statistical requests in R, SAS, SPSS and Stata. This latest update includes the option to display charts on screen and export them as image, to review earlier jobs in a multiple jobs window, to download of all results in PDF/TXT/PNG format, and to import of syntax files into the job editor panel.

Thus in order to get you started working with the new LISSY, we have produced an example of R code that allows users to easily import and clean LIS and LWS data as well as to produce some basic indicators. The whole code can be found and downloaded online. In this short exercise, we will:

1. Show how to perform data transformations in R;
2. Use these data and estimate Gini coefficients;
3. Plot and export examples of the Lorenz Curve.

Curious? Ok so let us look at each point in more detail.

The first thing that we need to do is to start the R session by loading the required packages and functions. For this exercise we load the following R packages:

```
# Prepare session

library(dplyr)
library(magrittr)
library(purrr)
library(ggplot2)

all_lissyrtools_scripts <- fs::dir_ls("/media/user/lissyrtools/")

invisible(purrr::map(all_lissyrtools_scripts, ~ source(.x)))
```

The code above loads four packages and then reads all the functions stored within the 'lissyrtools' directory. Additional documentation on these functions, such as arguments and examples of use can be found here.

The 'read_lissy_files()' function will let you import one or multiple files, specified as a character vector in the first argument (named 'files'). Under the hood, the function returns a list with the imported files as elements. In this example, the list is stored as 'lissy_datasets' and would contain six elements, one for each imported dataset. The second argument of the function ('full_year_name') will allowyou to obtain the names of the files with four digit years (e.g. 'ca2017h' instead of 'ca17h'). This can be convenient when performing certain actions, as four digit years can be more easily sorted.

```
## Read files
lissy_datasets <- read_lissy_files(files = c("ca17h", "de16h", "ee13h",
                                             "fi16h", "fr10h", "it16h"),
                                   full_year_name = TRUE)
```

Now that we have imported the datasets we will prepare them for analysis. For this, 'lissyrtools' offers a set of 'transform_' functions such as the ones in the following chunk of code:

```
## Data management
lissy_datasets %<>%
  transform_negative_values_to_zero(variable = "dhi") %>%
  transform_equivalise(variable = "dhi") %>%
  transform_top_code_with_iqr(variable = "dhi", times = 3) %>%
  transform_weight_by_hh_size(variable = "dhi")
```

In case you are not familiar with the R package 'magrittr', '%>%' and '%<>%' are pipes that allow to pass the result of one function as the first argument of the next one. Additionally, '%<>%' stores the result back to the left-hand-side object passed. Functions in 'lissyrtools' are compatible with these pipes as they make the code much easier to read. The 'tidyverse' website has great articles on the use of pipes in R code.

The 'transform_' functions above, process the files previously stored as 'lissy_datasets' with the following:

- 'transform_negative_values_to_zero(variable = "dhi")' recodes all negative values to zero in the selected variable 'dhi' - Disposable household income.
- 'transform_equivalise(variable = "dhi")' adjusts the selected variable by square root of the number of household members.
- 'transform_top_code_with_iqr(variable = "dhi", times = 3)' applies an upper limit to the variable. This corresponds to 3 times the Interquartile Range of the variable transformed using the natural logarithm.
- 'transform_weight_by_hh_size(variable = "dhi")' multiplies the weight by the number of people in the household.

Notice that, as we used the '%<>%' pipe, all transformations are automatically stored back to 'lissy_datasets'.

The computation of estimates can be done with the 'print_indicator()' function as shown below. Before that, we might want to perform a last transformation – 'transform_adjust_by_lisppp'- which adjusts by a combination of CPI and PPP (see our page on PPP Deflators) to make data in different currencies, countries and years comparable. The 'print_indicator()' function can currently compute the mean, median, percentile ratio, and Gini coefficient. If there are missing values in the variable, 'na.rm = TRUE' should be specified. Otherwise the function will return NAs as estimates. This is done so users don't compute estimates and accidentally ignore missing values.

```
## Compute estimates
lissy_datasets %>%
  print_indicator(variable = "dhi", indicator = "gini", na.rm = TRUE)
```

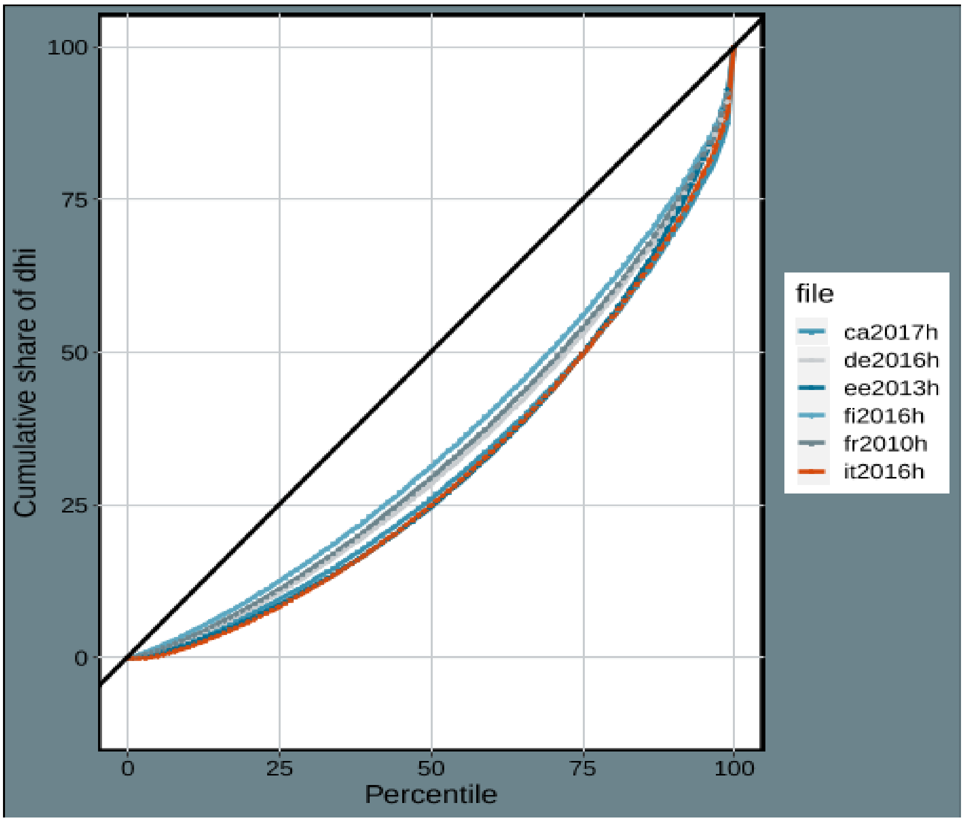
The previous code prints out the estimated Gini coefficients for the files in 'lissy_datasets'.

```
  ca2017h   de2016h   ee2013h   fi2016h   fr2010h   it2016h
0.3131517 0.2960957 0.3536698 0.2580440 0.2895518 0.3398615
```

Now, we will explore the possibilities that the new version of LISSY offers by producing some graphs. The following two chunks of code produce two different plots. Thus, they should be written on separate LISSY jobs. Otherwise, LISSY overwrites the later graph with the first one.

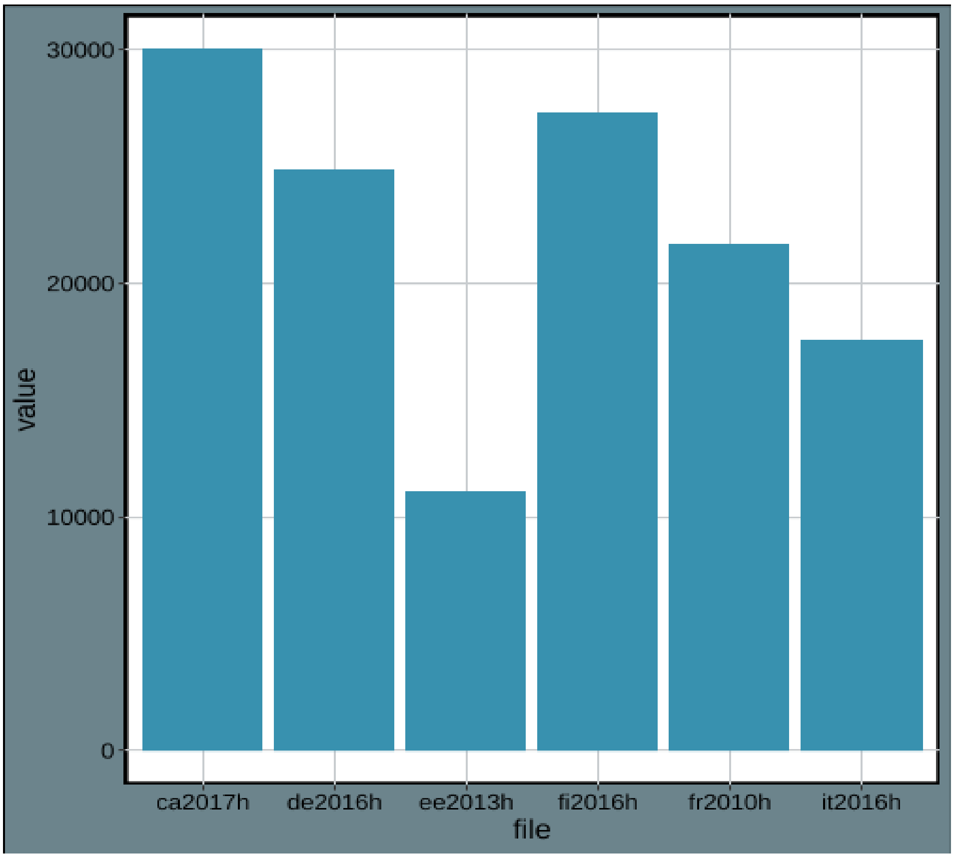
We can plot the Lorenz curve for a variable of all imported datasets with the 'plot_lorenz_curve()' function. Again, you must make sure that missing values are explicitly removed. The function also has an optional 'plot_theme' argument, which currently supports only a limited number of options.

```
## Plot Lorenz Curve
lissy_datasets %>%
  plot_lorenz_curve(variable = "dhi", na.rm = TRUE, plot_theme = "lis")
```



Similar to ‘print_indicator()’, the ‘plot_indicator()’ function computes and displays the plot for a function. In the code below we apply again the deflation adjustment and then choose the median as indicator. The graph obtained from LISSY is shown below the code.

```
## Plot Median
lissy_datasets %>%
  transform_adjust_by_lisppp(variable = "dhi") %>%
  plot_indicator(variable = "dhi", indicator = "median", na.rm = TRUE, plot_theme = "lis")
```



We hope that we could show you with this short data exercise, how easy cross-national data can be explored. For questions or suggestions about the code above, please email our data support team at usersupport@lisdatacenter.org. We are eager to receive your feedback.

Data News / Data Release Schedule

Data Releases– Luxembourg Income Study (LIS)

Greece

One new dataset from Greece, **GR16** (Wave X) has been added to the *LIS Database*.The dataset is based on the 2017 wave of the Greek **Survey on Income and Living Conditions (EU-SILC)**, carried out by Hellenic Statistical Authority (El.Stat.).

In addition, the previous datasets of the series (GR95, GR00, GR04, GR07, GR10, and GR13) have been slightly revised for consistency, including notably the allocation of tax adjustments to income taxes in GR95, GR00 and GR04. Please note that in the whole series of Greek data, variable *hxitax* (income taxes) includes only tax adjustments; in GR04, GR07, GR10 and GR13, income taxes are available only together with social contributions (in variable *hxitsc*: income taxes and contributions), whereas datasets GR95 and GR00 are net datasets (taxes and contributions are not at all available).

Lithuania

LIS has annualised the series of Lithuanian data. In addition to LT10 and LT13, now 7 more datasets are available from the **Lithuanian Survey of Income and Living Conditions (SILC)** carried out by Statistics Lithuania. As a result, Lithuanian data now cover the whole period 2009-2017 in the *LIS Database*.

A few consistency revisions have been applied to the previously available datasets, LT10 and LT13.

Russia

One new dataset from Russia **RU17** (Wave X) has been added to the *LIS Database*. The dataset is based on the 2018 **Survey of the Population Income and participation in Social programs (PIS)** carried out by the Federal State Statistics Service (Rosstat).

In addition, earlier datasets of the PIS series (RU11-RU16) underwent some revisions, including the addition of more details in the income section and the slight adjustment of the labour force status.

South Africa

We are delighted to announce that two new datasets from South Africa, **ZA15** (Wave X) and **ZA17** (Wave X), have been added to the *LIS Database*. The datasets are from the 4th and 5th Waves of the **National Income Dynamics Study (NIDS)**, carried out by the Southern Africa Labour and Development Research Unit (SALDRU) at the University of Cape Town.

In addition, LIS has carried out extensive revisions to the income section of the previously available versions of ZA08, ZA10, and ZA12, including: the simulation of taxes, social contributions and gross wages on the basis of annual tax rate tables, and the imputation of all missing income components using predictive mean matching or hot deck techniques.

United States

LIS is happy to announce that the CPS-ASEC data have been annualised from 1991-2018, with the addition of 19 datasets to the *LIS Database*, **US92** (Wave III)**, US93** (Wave IV)**, US95** (Wave IV)**, US96** (Wave IV)**, US98** (Wave V)**, US99** (Wave V)**, US01** (Wave V)**, US02** (Wave V)**, US03** (Wave VI), **US05** (Wave VI), **US06** (Wave VII), **US08** (Wave VII), **US09** (Wave VIII), **US11** (Wave VIII), **US12** (Wave IX), US14 (Wave IX), **US15** (Wave X), **US17** (Wave X), and **US18** (Wave XI).

In addition, the previously available datasets have been fully re-harmonised using the latest data versions available at the Bureau of Labor Statistics (BLS) / U.S. Census Bureau and the latest harmonisation standards. Thus some minor differences occur in the income section as compared to the previous versions available in the *LIS Database*.

Data Revisions – Luxembourg Income Study (LIS)

Palestine – As of the Summer Data Release 2020 also variable area_c is also available in PS17.

Education Recode Updates

The French and Danish series in the LIS Database underwent consistency revisions in the education section. In France these changes refer only the variables educlev and edyrs, whereas in Denmark also the more aggregated variable educ is affected.

Data Releases – Luxembourg Wealth Study (LWS)

Finland

One new dataset from Finland, **FI16** (WaveIX), has been added to the *LWS Database*. The dataset is from the 2016 wave of the **Household Wealth Survey (HWS) / Household Finance and Consumption Survey (HFCS)**, which is carried out by Statistics Finland in collaboration with the Household Finance and Consumption Network (HFCN) of the European Central Bank (ECB).

In addition, some corrections were applied to the earlier datasets of the series, namely corrections to variables secjob and *relation* (where married and cohabiting spouses were separated).

Greece

One new dataset from Greece, **GR18** (Wave XI) has been added to the *LWS Database*. The dataset is based on the third wave of the **Greek Household and Finance Consumption Survey (HFCS)** carried out by the National Bank of Greece and coordinated by the Household Finance and Consumption Network (HFCN) of the European Central Bank (ECB).

In addition, a few corrections were applied to the earlier datasets of the series: corrections were carried out to variables *nhhmem13*, *secjob*, and *relation* (where married and cohabiting spouses were separated).

Slovakia

A new dataset from Slovakia **SK17** (Wave X) has been added to the *LWS Database*.

The dataset is based on the third wave of the **Slovak Household and Finance Consumption Survey (HFCS)** carried out by the National Bank of Slovakia and coordinated by the Household Finance and Consumption Network (HFCN) of the European Central Bank (ECB). In addition, a few corrections were applied to the earlier datasets of the series: corrections were carried out to variables *nhhmem13* and *secjob*, and spouses were split in married and cohabiting spouses in variable *relation*; in SK14 only, minor consistency corrections were also carried out in the balance sheet variables.

South Africa

We are delighted to announce that South Africa has been added to the *LWS Database*, **ZA15** (Wave X), and **ZA17** (Wave X). **T**he datasets are from the 4th and 5th Waves of the **National Income Dynamics Study (NIDS)**, carried out by the Southern Africa Labour and Development Research Unit (SALDRU) at the University of Cape Town.

Data Revisions – Luxembourg Wealth Study (LWS)

Japan - Variables *hxmort* (mortgage instalments), *hxloan* (installment for other loans), and *hhouscost* (housing costs) have been corrected in JP04.

Release of the ERF-LIS Database

Based on the Memorandum of Understanding between LIS and the Economic Research Forum (ERF), LIS is delighted to announce the addition of 27 datasets from seven MENA region countries, namely Egypt, Iraq, Jordan, Palestine, Somalia, Sudan, and Tunisia. These datasets were acquired from the ERF – Harmonized Household Income and Expenditure Surveys (HHIES) database and harmonised according to the LIS template following the same naming convention and standards applied to the LIS datasets. In addition, a set of other variables were kept from the ERF – HHIES database concerned with dwelling conditions, ownership of durables, and more detailed expenditure variables. These datasets are now accessible through LISSY by selecting `ERFLIS' as project. More information about the ERF-LIS Database is available here. The new datasets are:

Egypt

Six new datasets from Egypt, **EG99** (Wave V), **EG04** (Wave VI), **EG08** (Wave VII), **EG10** (Wave VIII)**, EG12** (Wave IX), and **EG15** (Wave X), have been added to the ERF-LIS Database. The datasets are based on the ERF Harmonised Household Income and Expenditure Surveys (HHIES) version of the **Household Income, Expenditure and Consumption Survey (HIECS)** carried out by the Central Agency for Public Mobilization and Statistics (CAPMAS).

Iraq

Two new datasets from Iraq, **IQ07** (Wave VII) and **IQ12** (Wave IX), have been added to the ERF-LIS Database. The datasets are based on the ERF Harmonised Household Income and Expenditure Surveys (HHIES) version of the **Iraq Household Socio-Economic Survey (IHSES)** carried out by the Central Statistical Organization (CSO), and the Kurdistan Regional Statistics Office (KRSO).

Jordan

Five new datasets from Jordan, **JO02** (Wave V), **JO06** (Wave VII), **JO08** (Wave VII), **JO10** (Wave VIII), and **JO13** (Wave IX)**,** have been added to the ERF-LIS Database. The datasets are based on the ERF Harmonised Household Income and Expenditure Surveys (HHIES) version of the **Household Expenditure and Income Survey (HEIS)** carried out by the Department of Statistics (DoS).

Palestine

Ten new datasets from Palestine, **PS96** (Wave IV), **PS97** (Wave IV), **PS98** (Wave V), **PS04** (Wave VI), **PS05** (Wave VI), **PS06** (Wave VII), **PS07** (Wave VII), **PS09** (Wave VIII), **PS10** (Wave VIII), and **PS11** (Wave VIII) have been added to the ERF-LIS Database. The datasets are based on the ERF Harmonised Household Income and Expenditure Surveys (HHIES) version of the **Palestine Expenditure and Consumption Survey (PECS)** carried out by the Palestinian Central Bureau of Statistics.

Somalia

One new dataset from Somalia, **SO16** (Wave X), has been added to the ERF-LIS Database.The dataset is based on the ERF Harmonised Household Income and Expenditure Surveys (HHIES) version of **Somali High Frequency Survey (HFS)** carried out by Somalia Statistics , Directorate of National Statistics.

Sudan

One new dataset from Sudan, **SD09** (Wave VIII), has been added to the ERF-LIS Database. The dataset is based on the ERF Harmonised Household Income and Expenditure Surveys (HHIES) version of the **National Baseline Household Survey (NBHS)** carried out by Sudan Central Bureau of Statistics.

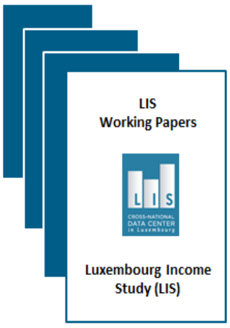
Tunisia

Two new datasets from Tunisia, **TN05** (Wave VI) and **TN10** (Wave VIII)**,** have been added to the ERF-LIS Database. The datasets are based on the ERF Harmonised Household Income and Expenditure Surveys (HHIES) version of the **National Survey on Household Budget, Consumption and Standard of Living (EBCNV)** carried out by Statistics Tunisia, the National Institute of Statistics.

LIS/LWS Data Release Schedule

	Autumn 2020	**Winter 2021**
LIS Database		
Belgium		Annual data BE03-BE17
Estonia	EE16	
Iceland		IS13/IS16
Ireland	Annual data IE02-IE17	
Israel		Annual data IL02-IL18
Laos		LA02/07/12
Latvia	LV13/LV16	
Luxembourg		LU16
Mali	ML14/ML18	
Netherland		NL15/NL16/NL17
Norway	NO16	
Panama	PA16	
Slovakia		SK14/SK15/SK16/SK17
South Korea	KR14/KR16	
Switzerland	Annual data CH06-CH17	
Vietnam		VN93/98/02/04/06/08/10
United Kingdom		UK17/15/14/12/11/09/08
LWS Database		
Chile		CL07/12/14/17
Estonia		EE13/EE17
Norway	NO16	
United Kingdom	UK13/UK15/UK17	

Working Papers & Publications



Focus on 'Are Increasing Earnings Associations Between Partners of Concern for Inequality? A Comparative Study of 21 Countries' **LIS WP No.793 by** ***Diederik Boertien*** **(Center for Demographic Studies (CED, Barcelona)), Milan Bouchet-Valat (French Institute for Demographic Studies (INED, Paris))**

Are increasing associations between partners' earnings of concern for inequality? A comparative study of 21 countries Abstract Research on whether earnings similarity matters for inequality between couples has come to a great variety of results. Some studies conclude that earnings similarity barely impacts inequality, whereas others find that changes in earnings similarity have considerably increased inequality between households. In this paper, Boertien and Bouchet-Valat argue that studies on the topic answer three similar yet distinct questions: How high would inequality be if people partnered at random? Did changes in earnings similarity over time, including changes in employment rates, contribute to inequality? Did changes in the association between partners' earnings, net of general changes in employment rates, contribute to inequality? Previous research provides relatively consistent answers once divided according to these three questions, but whether changes in earnings similarity are of concern for inequality remains unclear. The authors argue that whether this is the case depends on the kind of processes that produce changes in earnings similarity, and whether these processes affect inequality through other pathways too. Using data from the Luxembourg Income Study on 21 countries Boertien and Bouchet-Valat decompose changes over time in earnings inequality and show that even though the correlation in earnings between partners increased in most countries, this only amplified inequality on some occasions. In several countries, increases in the earnings correlation are driven by general changes in employment rates. Given that these increases in employment equalized earnings across households through other pathways, the inherently connected increases in the earnings correlation are of less concern from an inequality perspective.

LIS working papers series

LIS working papers series - No. 786
Assessing the Social Welfare Effects of Government Transfer Programs: Some International Comparisons
by Nanak Kakwani, Xiaobing Wang, Jing Xu, Ximing Yue

LIS working papers series - No. 788
Migration and Inequalities around the Mediterranean Sea
by Björn Nilsson, Racha Ramadan

LIS working papers series - No. 789
Fuel Poverty Exposure and Drivers: A Comparison of Vulnerability Landscape Between Egypt and Jordan
by Fateh Belaid

LIS working papers series - No. 790
Education Gap and Youth: A Growing Challenge in the MENA Region
by Reham Rizk, Ronia Hawash

LIS working papers series - No. 791
Still the Lands of Equality? On the Heterogeneity of Individual Factor Income Shares in the Nordics
by Roberto Iacono, Elisa Palagi

LIS working papers series - No. 792
Bottom Incomes and the Measurement of Poverty and Inequality
by Vladimir Hlasny, Lidia Ceriani, Paolo Verme

LIS working papers series - No. 793
Are Increasing Earnings Associations Between Partners of Concern for Inequality? A Comparative Study of 21 Countries
by Diederik Boertien, Milan Bouchet-Valat

LIS working papers series - No. 794
Capital and Labor Income Pareto Exponents across Time and Space
by Tjeerd de Vries, Alexis Akira Toda

LIS working papers series - No. 795
Inequality, Redistribution and Crisis: a Comparative Analysis of 5 Countries
by Rosa Melfi

LIS working papers series - No. 796
De-routinization of Jobs and Polarization of Earnings – Evidence from 35 Countries

by Maximilian Longmuir, Carsten Schröder, Matteo Targa

News, Events and Updates

LISSY Upgrade – New Graphing Functionality!

LIS is happy to announce the launch of a new version of LISSY which includes a fully web-based interface and graphing functionalities. LISSY is a an execution system that allows researchers to access LIS and LWS microdata remotely. Through its web-based interface, users can write and submit statistical requests in R, SAS, SPSS and Stata.

Main Features of the Upgrade:

This upgrade includes the following features:

- Java application no longer required
- graphing functionality, on screen and exportable as image
- possibility to review earlier jobs in a multiple jobs window
- download of all results in PDF/TXT/PNG format
- direct import of syntax files into the job editor pane.

Access upgraded LISSY here.

To get started with LISSY:

- Self-Teaching Packages, available in R, Stata, SAS, and SPSS here.
- Information about LISSY registration, available here.
- Information on Job Submission and LISSY coding best practices, available here.

For questions and inquiries, contact LIS User Support.

New access to the harmonised ERF-LIS Database through LISSY

Following the success of the ERF-LIS conference on "Inequality Trends around the Mediterranean", and the signature of a second MoU with the Economic research Forum (ERF), in June 2020 the harmonised ERF-LIS database has been made available to all the LIS users and the ERF affiliates by its integration into the LISSY system. This development has opened up new dimensions at LIS in terms of i) addition of new countries from the MENA region (Jordan, Iraq, Sudan, Somalia, and Tunisia), ii) increase of the number of data points of existing countries in LIS (Egypt, and Palestine), and iii) possibility to include consumption-based datasets where the income modules are either completely absent, or still developing (Somalia, Tunisia, and old Palestinian data points).

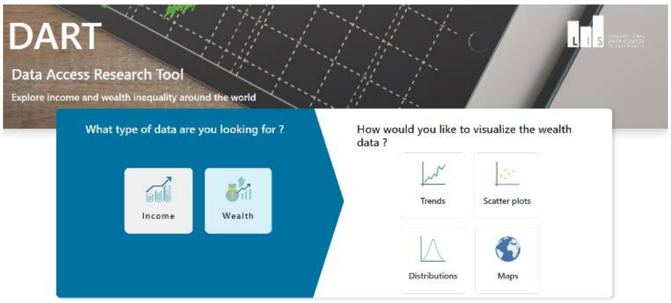
LIS is hiring!

LIS is currently seeking applications for a Microdata Expert (2-year contract). The position involves supporting the National Statistical Office of Luxembourg (STATEC) in the production of the national EU-SILC data:

The successful candidate will have a MA in statistics, sociology, economics, econometrics, demography, or another social science, to be familiar with the EU-SILC data and the commonly agreed EU indicators is a strong asset, to have extensive experience working with microdata using standard statistical software (preferably SAS) is required, as is attention to detail, command of spoken English is required. Luxembourgish and French is an asset.

Interested applicants should submit a cover letter and a Curriculum Vitae to Lucie Scapoli, search@lisdatacenter.org . More information available here.

The New LIS Data Access Research Tool (DART). Stay Tuned!



LIS is approaching the finalization of its new interactive visualization tool (DART), to be released soon. The main features of Dart are i) no prior knowledge of any statistical package or coding skills is required as it is designed to serve all kinds of users, ii) visualization of data on income and wealth through different charting types (Trends, Scatter plots, Distributions, and Maps) for the main income/wealth aggregates and income/wealth indicators to be disaggregated by different characteristics, over time and for different countries, iii) the aggregated data used to generate the plotted graph(s) can be displayed in table format, iv) In addition, all the produced graphs/tables can be easily exported and downloaded in pdf, and excel formats respectively, v) while retaining table-making options, DART provides beyond bi-variate cross-tabulations.

Stay tuned for its official launch soon.

The LIS Introductory Summer Workshop 2020 goes online!

Due to the current outbreak of Coronavirus (COVID-19) and the ensuing uncertainty regarding travel arrangements, the 2020 LIS Summer Workshop has been cancelled. The LIS team is currently working on preparing online tutorials, in addition to scheduled interactive sessions to be available in July. Stay tuned for more information!

Visiting Scholars

Due to the COVID-19 outbreak and the measures taken in different countries, scheduled approved visits through the InGRID-2 programme was postponed to be re-scheduled until June 2021.

Stone Center – Public Scholarship

In May, Janet Gornick and Nathaniel Johnson co-authored an essay titled: "Income Inequality in Rich Countries: Examining Changes in Economic Disparities". The essay, which reports results based on the LIS microdata, was published by the *Social Science Research Council,* in their series of curated essays known as *Items*. Janet Gornick subsequently discussed core findings from the essay with the Stone Center's communications team.

Stone Center – "Inequality by the Numbers" Workshop Converted to Videos

The Stone Center's sixth annual weeklong summer workshop on inequality research and methods – "Inequality by the Numbers" – was scheduled for June but had to be canceled. Many of the scheduled lecturers generously agreed to record 30-minute videos replacing their planned lectures. Lecturers in this series include Janet Gornick, Leslie McCall, Branko Milanovic, Paul Krugman, Salvatore Morelli, James Parrott, Jordon Conwell, Lane Kenworthy, Michael Kraus, Nancy Folbre, William Solecki, Florencia Torche, and more. The videos will be made available online in July, with no password or registration needed.

CROSS-NATIONAL DATA CENTER in Luxembourg

Editor: Jörg Neugschwender
Layout and Design: Heba Omar & Jörg Neugschwender
Photo credit: Cover @ ibreakstock/fotolia.com