

Inequalities in the relationship between long-term and health care for the elderly

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Short Abstract

In this paper, with the help of adjusted Oaxaca-Blinder regression decompositions, we estimate the contributions of individual factors to inequalities that arise in the receipt of health care and are related to measures in the field of long-term care for the elderly.

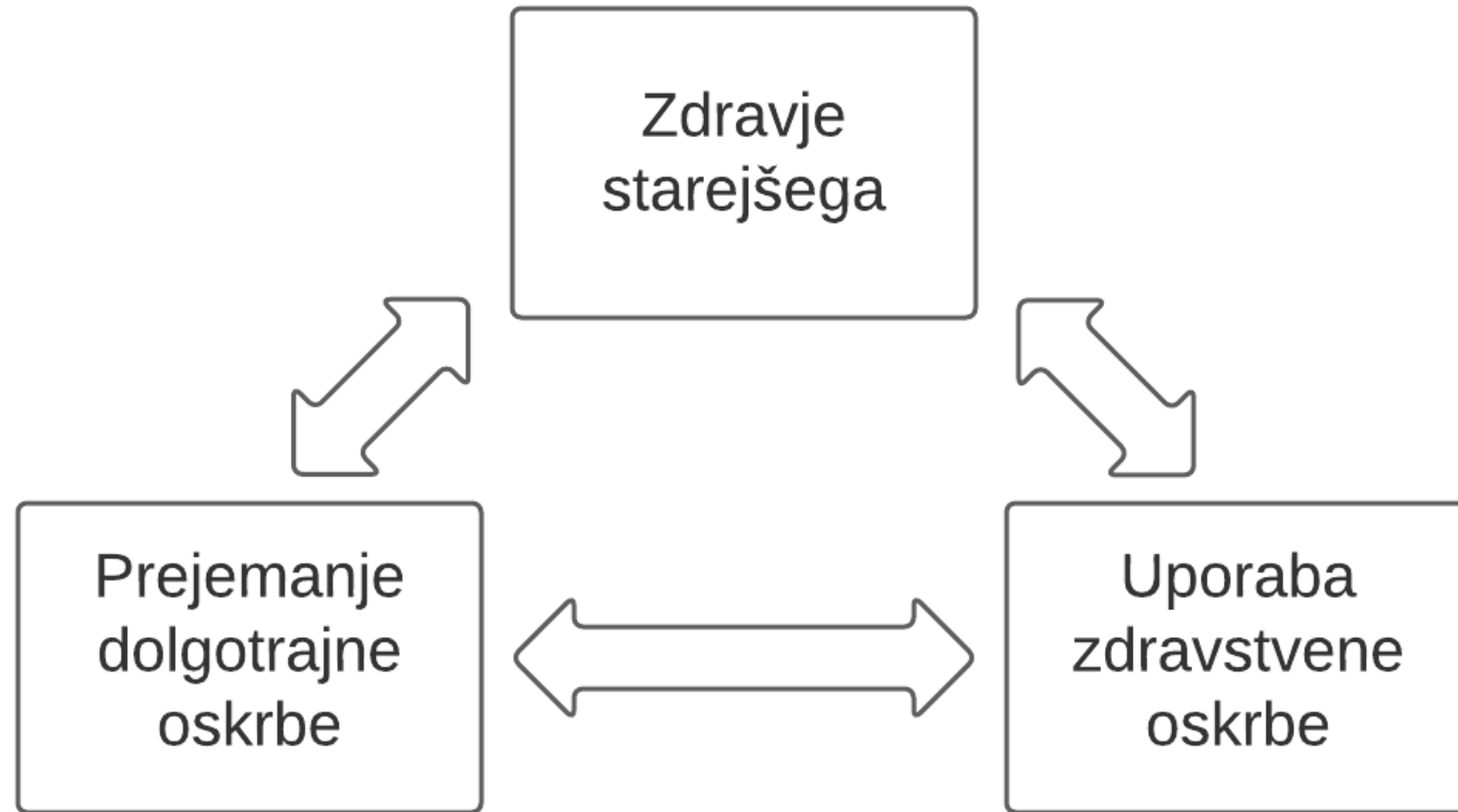
Introduction to the problem

- In this paper, we address causal relationship between long term care and health care utilization of the elderly with a novel approach developed in Srakar et al. (2020). The expansion of long-term care (LTC) may improve health system efficiency by reducing hospitalisations, and pave the way for the implementation of health and social care coordination plans. We draw upon the longitudinal evidence from Survey of Health, Ageing and Retirement in Europe (SHARE) to assess the causal estimates of the effects of receiving different types of LTC on health care utilization and derive their regression decomposition by main factors.
- We analyze the causal problem with health indicators as mediators. To solve for multiple reverse causality we utilize cross-lagged panel models, a form of longitudinal mediation analysis. The results confirm positive effects of LTC provision on reducing health care utilization with both direct and indirect significant effects in most criteria. Oaxaca-Blinder type decomposition confirm the key role of income, education and gender for the relationship under study. The article provides an interesting methodological possibility, not used so far in the analysis of the relationship between long term care and health care and important results in terms of inequalities in the studied relationship.
- The ageing of countries' populations, and in particular the growing number of the very old that is occurring in most industrialised countries, is increasing the need for long-term care (LTC) services. LTC is defined as "a range of services required by persons with a reduced degree of functional capacity, physical or cognitive, and who are consequently dependent for an extended period of time on help with basic activities of daily living" (Colombo et al., 2011).
- The combination of population ageing and social change suggests that in the coming years, there will be a greater demand for formal LTC (e.g. personal care, community care and institutional care provided in people's homes or nursing homes and assisted living facilities) funded by government programmes, private LTC insurance or individuals' out-of-pocket payments. However, such a shift in the type of LTC has important economic implications
- In the article, we want to add to the literature by solving the reverse causality between long term care provision and health care utilization in a manner which would be more feasible and not needing exogenous change and natural or quasi-natural experiments. To this end, we use a novel empirical approach to this problem, longitudinal mediation analysis, which controls for reverse causality with a longitudinal approach. We use panel data of Survey of Health, Ageing and Retirement in Europe (SHARE) for Slovenia in Waves 4-7. For the decomposition analysis we use mediation analysis decomposition method derived in Deschacht (2018).

Dataset used and main statistics

- The Survey of Health, Ageing and Retirement in Europe (SHARE) is a multidisciplinary and cross-national panel database of micro data on health, socio-economic status and social and family networks of about 140,000 individuals aged 50 or older (around 380,000 interviews). SHARE covers 27 European countries and Israel.
- SHARE Wave 4 was the first time this survey was conducted in Slovenia, therefore no previous information on the country was available for analysis. To map the initial situation of older Slovenians, we use Slovenian data from the SHARE Waves 4-7. The Slovenian SHARE survey uses a randomised sample stratified by age, sex, origin (native born or foreign born) and regional distribution as of 1 January 2010. The sample is representative of the 50+ aged population of the country and provides a sufficient number of cases for subgroups to be analysed. The sample size and the response rate (Bergmann et al., 2019) were relatively high compared with other countries participating in this wave.
- The data used in this analysis are based on the main survey respondents and their partners aged 50 and above who were interviewed in at least three waves among waves 4-7 of the SHARE study in Slovenia. With regard to the other variables, the analysis included missing values and 'don't know' responses. The final sample for our analysis after excluding the non-responses was 1,354 people.

Short description of method used



Short description of the method used - solution

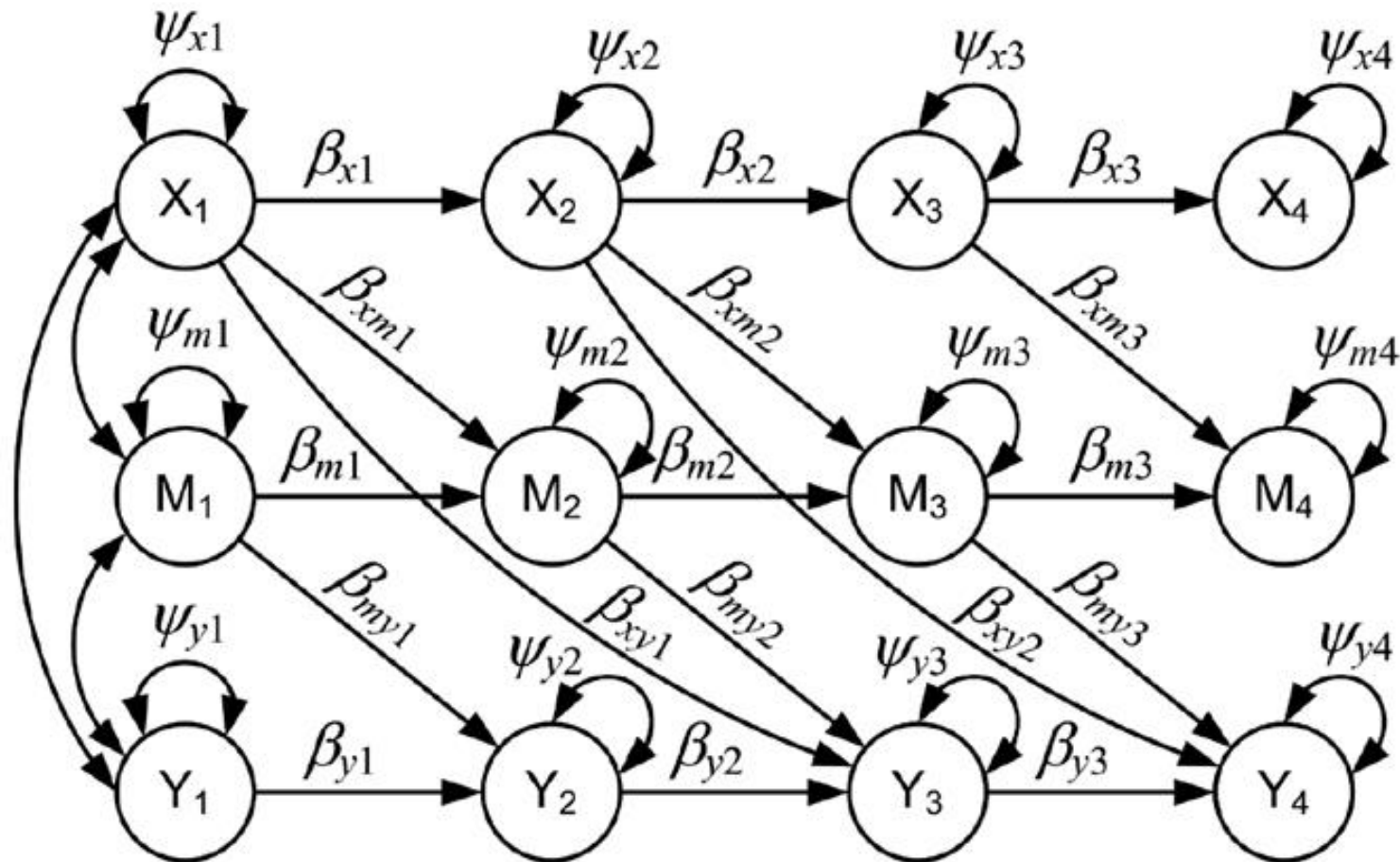


Table 1: Main variables, used in the analysis, by three types (dependent, mediating, independent/source)

Dependent variable	Description
No. of hospitalisations	Number of hospitalisations in a hospital overnight during the last twelve months
Probability of hospitalisation	Response to the following question: »During the last twelve months, have you been in a hospital overnight? Please consider stays in medical, surgical, psychiatric or in any other specialised wards.«
Length of hospitalization	Length of hospitalization in days
No. of taken medications	Number of taken medications as a sum of answers to the following question: »Do you currently take drugs at least once a week for problems mentioned1?«
Mediator	Description
ChronDis	Count variable, counting number of chronic diseases
Depression	Count variables, having the value of the score on the Euro-Depression scale
Self-rated health	Ordinal variable ranked according to a five-point scale: (1) ‘excellent’, (2) ‘very good’, (3) ‘good’, (4) ‘fair’ and (5) ‘poor’
Source – Type of care	Description
Informal care outside of household	Binary variable, having the value of 1 if the respondent is receiving care from another person living outside of respondent's household; and 0 otherwise
Informal care within household	Binary variable, having the value of 1 if the respondent is receiving care from another person living inside of respondent's household; and 0 otherwise
Formal care	Binary variable, having the value of 1 if the respondent is receiving any type of formal care; and 0 otherwise

1 The drugs include the following: 1. Drugs for high blood cholesterol; 2. Drugs for high blood pressure; 3. Drugs for coronary or cerebrovascular diseases; 4. Drugs for other heart diseases; 6. Drugs for diabetes; 7. Drugs for joint pain or for joint inflammation; 8. Drugs for other pain (e.g. headache, back pain, etc.); 9. Drugs for sleep problems; 10. Drugs for anxiety or depression; 11. Drugs for osteoporosis; 13. Drugs for stomach burns; 14. Drugs for chronic bronchitis; 15. Drugs for suppressing inflammation (only glucocorticoids or steroids); 97. Other drugs, not yet mentioned

Results

<i>Mediator: Nr. of chronic diseases</i>	LMA	ProbHosp	NrHosp	LgthHosp	NrMedic
InfCareWtin	Direct				
	Indirect	-0.0065	-0.0180	-0.1091	-0.0330
	Total	-0.0065	-0.0180	-0.1091	-0.0330
InfCareOut	Direct	-0.0550	-0.2370	-2.1000	-0.2110
	Indirect	0.0001	-0.0005	-0.0065	0.0021
	Total	-0.0549	-0.2370	-2.1065	-0.2089
InfCareIntens	Direct	-0.0240	-0.0680	-0.6930	-0.0630
	Indirect	0.0003	0.0004	0.0025	0.0026
	Total	-0.0237	-0.0676	-0.6905	-0.0604
InfCareTot	Direct			-2.1960	
	Indirect	-0.0019	-0.0057	-0.0358	0.0049
	Total	-0.0019	-0.0057	-2.2318	0.0049
FormCare	Direct			-2.3720	
	Indirect	-0.0027			-0.0267
	Total	-0.0027		-2.3720	-0.0267
FormHomeC	Direct		-0.5530		
	Indirect				-0.0432
	Total		-0.5530		-0.0432
FormHelp	Direct			-3.7390	
	Indirect	-0.0032			0.0271
	Total	-0.0032		-3.7390	0.0271
FormMeals	Direct		-0.3130	-3.7860	-0.8380
	Indirect	-0.0048			0.0064
	Total	-0.0048	-0.3130	-3.7860	-0.8316
Overall	F+InfWO	-0.0641	-0.2555	-4.5876	-0.2686
	F+InfT	-0.0046	-0.0057	-4.6038	-0.0218

<i>Mediator: Euro Depression score</i>	LMA	ProbHosp	NrHosp	LgthHosp	NrMedic
InfCareWtin	Direct				
	Indirect	-0.0047	-0.0120	-0.3773	
	Total	-0.0047	-0.0120	-0.3773	
InfCareOut	Direct		-0.1846	-1.8617	-0.1004
	Indirect				-0.0188
	Total		-0.1846	-1.8617	-0.1193
InfCareIntens	Direct	-0.0389	-0.0927		
	Indirect			-0.0324	-0.0063
	Total	-0.0389	-0.0927	-0.0324	-0.0063
InfCareTot	Direct			-1.8924	
	Indirect	-0.0058		-0.0909	-0.0250
	Total	-0.0058		-1.9834	-0.0250
FormCare	Direct			-1.2111	
	Indirect	-0.0005	0.0161		-0.0562
	Total	-0.0005	0.0161	-1.2111	-0.0562
FormHomeC	Direct		0.1456	-0.2681	
	Indirect		0.0240		
	Total		0.1696	-0.2681	
FormHelp	Direct	0.0301		-0.2381	-0.0817
	Indirect		0.0073		
	Total	0.0301	0.0073	-0.2381	-0.0817
FormMeals	Direct	-0.0927	-0.0264		
	Indirect		0.1289	0.1030	-0.1413
	Total	-0.0927	0.1025	0.1030	-0.1413
Overall	F+InfWO	-0.0051	-0.1805	-3.4502	-0.1754
	F+InfT	-0.0062	0.0161	-3.1945	-0.0811

<i>Mediator: Self-rated health</i>	LMA	ProbHosp	NrHosp	LgthHosp	NrMedic
InfCareWtin	Direct				
	Indirect				-0.0006
	Total				-0.0006
InfCareOut	Direct	-0.0490	-0.2130	-1.9480	-0.2360
	Indirect				-0.0079
	Total	-0.0490	-0.2130	-1.9480	-0.2439
InfCareIntens	Direct	-0.0240	-0.0640	-0.6660	-0.0800
	Indirect				-0.0025
	Total	-0.0240	-0.0640	-0.6660	-0.0825
InfCareTot	Direct			-2.0770	-0.2110
	Indirect				-0.0014
	Total			-2.0770	-0.2124
FormCare	Direct		-0.2490	-2.4790	-0.2800
	Indirect	0.0043			0.0313
	Total	0.0043	-0.2490	-2.4790	0.0313
FormHomeC	Direct		-0.5660		
	Indirect	0.0061			0.0313
	Total	0.0061	-0.5660		0.0313
FormHelp	Direct		-0.3420	-3.7550	
	Indirect	-0.0014			0.0106
	Total	-0.0014	-0.3420	-3.7550	0.0106
FormMeals	Direct			-3.9540	-0.8110
	Indirect	-0.0057			-0.0117
	Total	-0.0057		-3.9540	-0.8227
Overall	F+InfWO	-0.0447	-0.4620	-4.4270	-0.2132
	F+InfT	0.0043	-0.2490	-4.5560	-0.1811

Results - decomposition

Table 1: Results of Oaxaca-Blinder mediation decomposition analysis

		NrHosp				NrMedic			
		Gender	Age	Income	Education	Gender	Age	Income	Education
InfCareWtin	<i>Direct</i>	-0.0013	-0.0020	-0.0015	-0.0012	-0.0059	-0.0106	-0.0101	-0.0069
	<i>Indirect</i>	-0.0011	-0.0015	-0.0018	-0.0013	-0.0103	-0.0073	-0.0058	-0.0091
	Total	-0.0025	-0.0036	-0.0033	-0.0026	-0.0162	-0.0178	-0.0158	-0.0160
InfCareOut	<i>Direct</i>					0.0006	0.0006	0.0005	0.0007
	<i>Indirect</i>	-0.0174	-0.0172	-0.0140	-0.0129	-0.0522	-0.0470	-0.0433	-0.0413
	Total	-0.0174	-0.0171	-0.0140	-0.0129	-0.0516	-0.0464	-0.0428	-0.0406
FormCare	<i>Direct</i>	0.0001	0.0001	0.0001	0.0001	0.0007	0.0008	0.0005	0.0008
	<i>Indirect</i>	-0.0060	-0.0049	-0.0050	-0.0047	-0.0130	-0.0146	-0.0113	-0.0172
	Total	-0.0060	-0.0049	-0.0049	-0.0046	-0.0123	-0.0138	-0.0108	-0.0164

Source: Own calculations.

Conclusions

- The article uses a novel approach to analyze relationship between long term care provision and health care utilization, being able to solve the complex causal scheme, clearly mediated through the effects on health. The approach resolves the causal scheme through longitudinal modelling, being able to include all cross-relationships in the model structure.
- We use this method to access the inequalities contributing to this relationship, in terms of gender, age, income and education. We decompose the longitudinal direct and indirect effects for the mediator of chronic diseases and dependent variables number of hospitalizations and number of medications.
- Among the decomposition variables (which have been standardized to prevent the size effect), we do not see many significant differences, the most important on in terms of informal care inside household is age in all specifications, followed by income, gender and education (the last ones being of the opposite ordering for number of medications. For the informal care outside household and formal care, gender is the predominant component, which shows up most for the informal care outside household (for number of medications) and formal care (for number of hospitalizations).
- Also indirect effects, mediated through chronic diseases are significantly more important in the size of the effect than the direct ones. This shows that most of the inequalities in the access to health care that could be attributed to long term care provision are mediated through health status of an individual.
- The extensions to applications and policy analyses seem clear. As our estimates are causal, they could be multiplied by costs of each health care utilization feature (e.g. cost of hospitalization) to derive exact estimates, supporting future reforms in any country under study. Indeed, feasibility of our approach in empirical terms (as noted it does not require an exogenous change to resolve reverse causality) should provide ground for more applications. Also, the modelling could be extended in terms of variables, a clear possibility is using different individual diseases instead of a general variable for number of chronic diseases. In this case, one would get the effect mediated by each individual disease change due to long term care provision. This consideration should be provided more research in future.

Inequalities in receiving long-term care through a life course perspective

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Short Abstract

In this paper, we use the adapted Oaxaca-Blinder regression decomposition to assess the contribution of individual factors to inequalities in receiving long-term care for the elderly, especially in terms of factors influencing an individual's life course, i.e. through a long-term perspective.

Introduction to the problem

- This project builds on a theoretical premise that different early life experiences produce different family, health and economic outcomes in older age. One of the perspectives of observing and analysing the various aspects of lives of older persons is the life course perspective that interprets the level of activity in later life in view of the individual's lifestyle and activities during earlier life. The life course perspective suggests that an individual's experiences at a certain point of life may affect their lives for years or decades later (Elder, 1994; Settersten, 2003; Elder, Johnson and Crosnoe, 2004; Victor, 2013). Apart from differences in the lives of individuals, the social context – unique historical events and periods of social changes within which an individual ages strongly shape the course of ageing and older age (Danneferand and Settersten Jr., 2010; Settersten and Gannon, 2005). Differences in individual well-being accumulate over time, further intensifying in later life (Di Prete and Eirich, 2006).
- When trying to determine the relationship between earlier events and their outcomes in older age, inequalities during the life cycle need to be analysed: at family level (widowhood, divorce, etc.) or with regard to the type of employment (full time or part time, unemployment, etc.) (Dingemans and Möhring, 2019).
- Our main goal is to investigate whether and to what extent life histories, i.e. earlier-life family, health, and economic circumstances, relate to later-life long term care provision in Slovenia.
- Methodologically, we utilize a relatively novel perspective on the modelling of life-course perspective, namely retrospective panels. Research in the social sciences often relies on longitudinal data, where samples of individuals, households or families are repeatedly monitored over a period of several years. These longitudinal data allow studies of transitions, such as into and out of marriage, poverty and unemployment, which are not possible with cross-sectional surveys. They also allow more reliable statistical models to be estimated because biases due to unobservable factors, such as ability, can be alleviated when there are repeated observations on the same people (Deaton, 1997).
- However, longitudinal surveys are costly and in many countries they are restricted to small, nationally unrepresentative, samples. One response to the high cost and limited availability of longitudinal data is to use retrospective surveys. These surveys use a single interview to obtain a long-term or even lifetime history (Freedman et al, 1988). In addition to lower cost, other advantages of long-term retrospective recall are that more than one cohort can be studied at a time and sample attrition is less of a problem (Kosloski et al, 1994).
- SHARELIFE is the third wave of SHARE (Survey of Health, Ageing and Retirement in Europe) and provides life-history information about a representative sample of about 27,000 respondents aged 50 or over and living in Europe. The domains of interest include family relationships, housing, working history, health and health care. The life history nature of SHARELIFE is a novelty in social sciences, and it already generated a number of important contributions: Börsch-Supan, Brandt, Hank and Schröder (2011) and Brandt and Börsch-Supan (2013) collect studies using SHARELIFE and covering a wide spectrum of interesting topics. The way the dataset should be rearranged and used strictly depends on the research question at hand. There are at least four approaches to exploit the wealth of information available in the data.

Dataset used and main statistics

- The life history nature of SHARELIFE is a novelty in social sciences, and it already generated a number of important contributions: Börsch-Supan, Brandt, Hank and Schröder (2011), Brandt and Börsch-Supan (2013) and Mira and Weber (forthcoming) collect studies using SHARELIFE and covering a wide spectrum of interesting topics. The way the dataset should be rearranged and used strictly depends on the research question at hand. There are at least four approaches to exploit the wealth of information available in the data.
- The first approach consists of using SHARELIFE as the third wave of a traditional survey: longitudinal SHARE respondents are observed four times (in 2004/5, 2006/7, in 2008/9 with SHARELIFE and in 2010/11), therefore data can be arranged in a way to study transitions on key variables over a decade by using each wave as a separate observation. As an example, Meschi, Padula and Pasini (2013) rearrange information relative to current labour market status in SHARELIFE to be comparable with waves 1, 2 and 4 of SHARE, and then study the individual labour market participation dynamics over the period 2004-2011.
- The second approach comes from the fact that SHARELIFE collects information about events occurring throughout the respondent's life that can be related to other individual outcomes both at the time the event refers to or later in life.
- The third approach to exploit the life history nature of SHARELIFE is to build an event-dataset. Brugiavini, Pasini and Trevisan (2013) study the effect of maternity leave legislation on time spent at home after childbirth. In order to do so, they rearrange SHARELIFE into a birth-panel: each female respondent contributes as many observations as maternity episodes she experienced throughout her life. Such a dataset allows the researcher to account for characteristics that are contemporaneous to each event (e.g. age and employment status of the mother and the legislation in place at time of childbirth in a given country) and to relate this information to the sequence of successive events and to potential outcomes later in life.
- The fourth approach is to fully exploit the retrospective nature of SHARELIFE by building a "retrospective panel": each respondent contributes as many observations as there are years of age from birth to the age at which they are observed at the moment of the interview.

Brief presentation of the method

- Suppose the model to be estimated is of the following well-known form:

$$y_{it} = \beta_0 + x'_{it}\beta + z'_i\gamma + \eta_i + \varepsilon_{it}$$

- where $\eta_i = z'_i\pi + \alpha_i$ so that $E(\eta_i|z_i) = z'_i\pi$ and $\alpha_i = \eta_i - z'_i\pi$.
- An appropriate decomposition expression would therefore be (expressions in double bars denote grand averages):

$$\bar{\bar{y}}^1 - \bar{\bar{y}}^2 = (\bar{\bar{x}}^1 - \bar{\bar{x}}^2)\hat{\beta}^1 + (\bar{\bar{z}}^1 - \bar{\bar{z}}^2)\hat{\theta}^1 + \bar{\bar{x}}^2(\hat{\beta}^1 - \hat{\beta}^2) + \bar{\bar{z}}^2(\hat{\theta}^1 - \hat{\theta}^2) + (\hat{\beta}_0^1 - \hat{\beta}_0^2)$$

Results

Table 1: Results of decomposition analysis, total informal long term care

	Coef.	Std. Err.	z	P>z
explained				
gender	0.0232	0.0071	2.1714	0.0469
age	0.0011	0.0021	1.2555	0.4317
income	-0.0007	0.0011	-0.5148	0.5940
education	0.0073	0.0046	2.3318	0.0298
unexplained				
gender	-0.0418	0.0717	-0.3420	0.7282
age	-0.0063	0.0386	-0.3192	0.6423
income	-0.0559	0.0240	-2.9808	0.0038
education	0.0034	0.0254	0.1408	0.5313
_cons	0.1046	0.1538	0.4424	0.7648

Source: Own calculations.

Results

Table 1: Results of decomposition analysis, informal long term care within and outside household

	Coef.	Std. Err.	z	P>z		Coef.	Std. Err.	z	P>z
explained					explained				
gender	0.0158	0.0054	1.8726	0.0492	gender	0.0153	0.0062	1.6774	0.0596
age	0.0012	0.0017	1.1174	0.2936	age	0.0004	0.0008	1.2068	0.4345
income	-0.0010	0.0015	-0.3758	0.4871	income	-0.0014	0.0018	-0.5938	0.2874
education	0.0067	0.0072	1.9789	0.0220	education	0.0065	0.0085	1.9592	0.0275
unexplained					unexplained				
gender	-0.0384	0.0832	-0.3215	0.7282	gender	-0.0173	0.0832	-0.2604	0.6991
age	-0.0098	0.0340	-0.2617	0.1927	age	-0.0081	0.0316	-0.3010	0.2640
income	-0.0207	0.0384	-2.9539	0.0019	income	-0.0087	0.0204	-2.6200	0.0009
education	0.0053	0.0340	0.1915	0.4303	education	0.0049	0.0411	0.1398	0.5207
_cons	0.1067	0.1553	0.3274	0.8718	_cons	0.0725	0.2081	0.2062	1.0723

Source: Own calculations.

Results

Table 1: Results of decomposition analysis, formal long term care

	Coef.	Std. Err.	z	P>z
explained				
gender	0.0244	0.0027	0.5614	0.0590
age	0.0073	0.0011	4.4948	0.0008
income	-0.0104	0.0030	-3.5641	0.0035
education	0.0071	0.0103	2.1406	0.0300
unexplained				
gender	-0.0180	0.1381	-0.3359	0.3006
age	-0.0115	0.0439	-0.0933	0.2085
income	-0.0069	0.0088	-0.9238	0.0008
education	0.0023	0.0292	0.1356	0.6977
_cons	0.0283	0.2185	0.2062	0.6220

Source: Own calculations.

Conclusion

- In our study we extended previous analyses by analysing retrospective panel of SHARE using the life course perspective.
- The results of our analysis show that gender and education are significant predictors in terms of decomposition analysis for panel data, and also they are not strongly significant.
- In the unexplained part, income is strongly statistically significant predictor of our dependent variables, namely receiving and type of informal care at present.
- The decomposition which takes informal long term care within and outside household as separate dependent variables shows similar results. Both types of informal care are not significantly different in terms of inequality aspects: they are influenced by gender and education in the explained part and income in the unexplained.
- Finally, for formal care (e.g. meals on wheels), age as well as income are important predictors also for the explained part of the regression. This shows that inequality aspects for formal long term care provision are significantly influenced by most socioeconomic factors and receiving formal long term care in Slovenia is conditioned by those aspects.

Inequalities in Slovenian health care due to COVID-19

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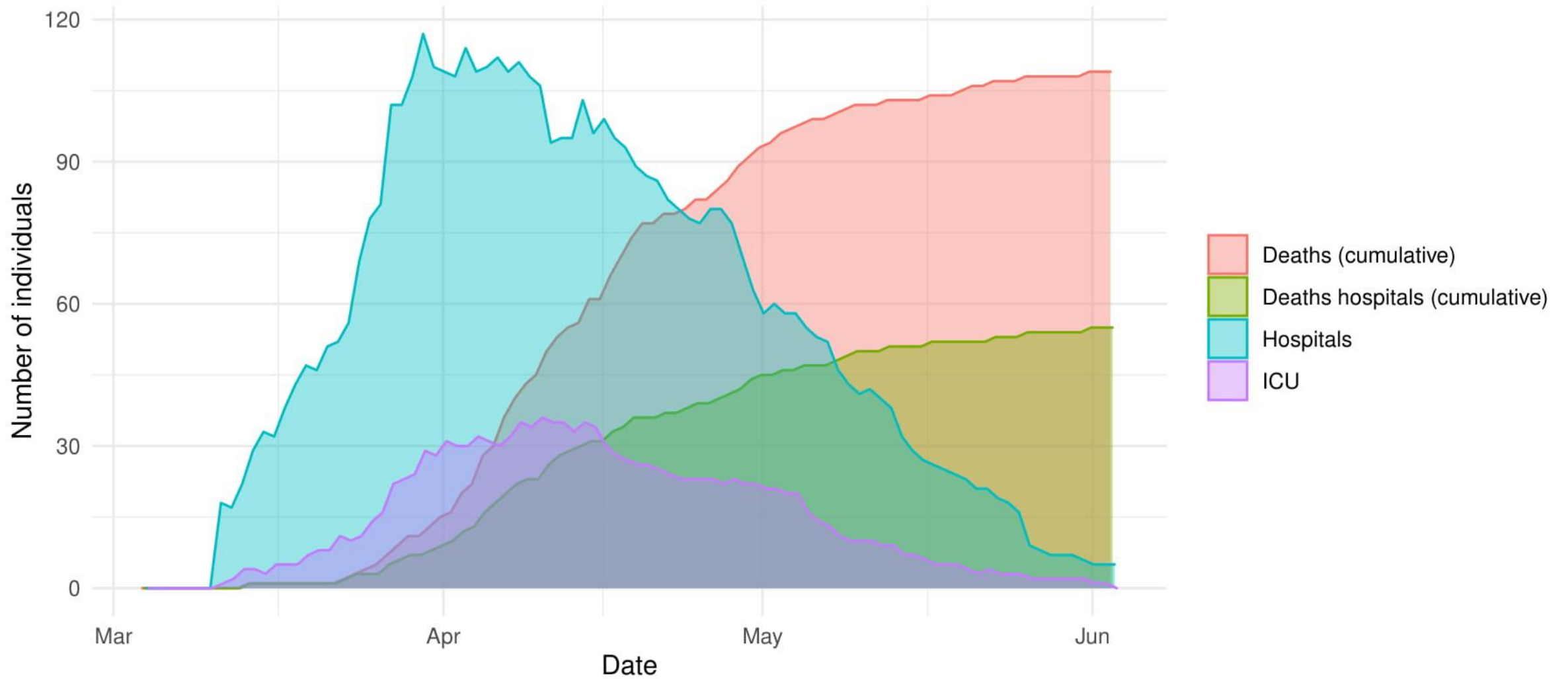
Short Abstract

In this paper, we use the basic Oaxaca-Blinder regression decomposition to assess the contribution of individual factors to health care use inequalities resulting from the current COVID-19 pandemic. To this end, we use a causal analysis based on a synthetic difference-in-differences approach (Arkhangelsky, Imbens et al., 2021)

Introduction to the problem

- As the COVID-19 pandemic spread across the world at the beginning of 2020, statistically modeling its development became of big interest. The main focus of this work was to analyze the spread of the disease and its main characteristics for Slovenia using publicly available COVID-19 data and to estimate its relationship to inequality in general health indicators.
- We estimate the causal effects of the lockdown in Slovenia (taking place on March 20th) using an recently developed difference-in-differences causal model.
- Our causal model is framed using the language of econometric causal models (Haavelmo (1944); Tinbergen (1940); Wold (1954)) and genetics (Wright, 1923) with natural unfolding potential/structural outcomes representation (Rubin, 1974; Tinbergen, 1930; Neyman, 1925; Imbens and Rubin, 2015).
- The work on causal graphs has been modernized and developed by Pearl (1995); Greenland, Pearl, and Robins (1999); Pearl (2009); Pearl and Mackenzie (2018) and many others (e.g., Pearl and Mackenzie (2018); White and Chalak (2009); Robins, Richardson, and Shpitser (2020); Peters, Janzing, and Bernhard (2017); Bareinboim et al. (2020); Hernan and Robins (2020)), with applications in computer science, genetics, epidemiology, and econometrics (see, e.g., Heckman and Pinto (2013); Hunermund and Bareinboim (2019); White and Chalak (2009) for applications in econometrics).
- The particular causal diagram we use has several “mediation” components, where variables affect outcomes directly and indirectly through other variables called mediators; these structures go back at least to Wright (1923); see, e.g., Baron and Kenny (1986), Hines, Vansteelandt, and Diaz-Ordaz (2020), Robins, Richardson, and Shpitser (2020) for modern treatments.

Introduction to the problem



Dataset used

- Several governmental and open-ended sources of data on the pandemic variables were used.
- In the experience of those countries where the spread of the virus has been most effectively curbed, correctly collected, up-to-date and transparently published data is vital for the effective response of public healthcare systems. Only then the published data can stand as the basis for understanding of what is happening, for the active self-protective behaviour of people and for accepting the urgency of the safety measures taken. Data is collected from various publicly available sources, and since Saturday, March 28, with also a direct connection with healthcare institutions and the National Institute of Public Health (NIJZ).
- They share the structured data, which is then validated and shaped into a format suitable for visualization to be presented to the public as well as for further work in model development and forecasting. As data published in the media and certain other sources may sometimes be vague and inconsistent, the table also includes notes on sources and deductions based on incomplete data.
- The following data from the NIJZ and various public sources is included in database on a daily basis (with history): number of tests performed and number of confirmed infections; number of confirmed infections by category: by age, gender, region and municipality; hospital records for patients with COVID-19: hospitalized, in the intensive care unit (ICU), in critical condition, discharged from hospital care, recovered; monitoring of individual cases, particularly those in critical activities: working in healthcare, senior citizens' homes, civil protection; healthcare system capacity: number of beds, intensive care units, respirators for ventilation. All data is collected and available in form of GSheets, CSV or via REST API. The data is used for various visualizations and statistics, such as charts, infographics and maps with information on confirmed infections and hospitalized patients on our own website.

Brief presentation of the method

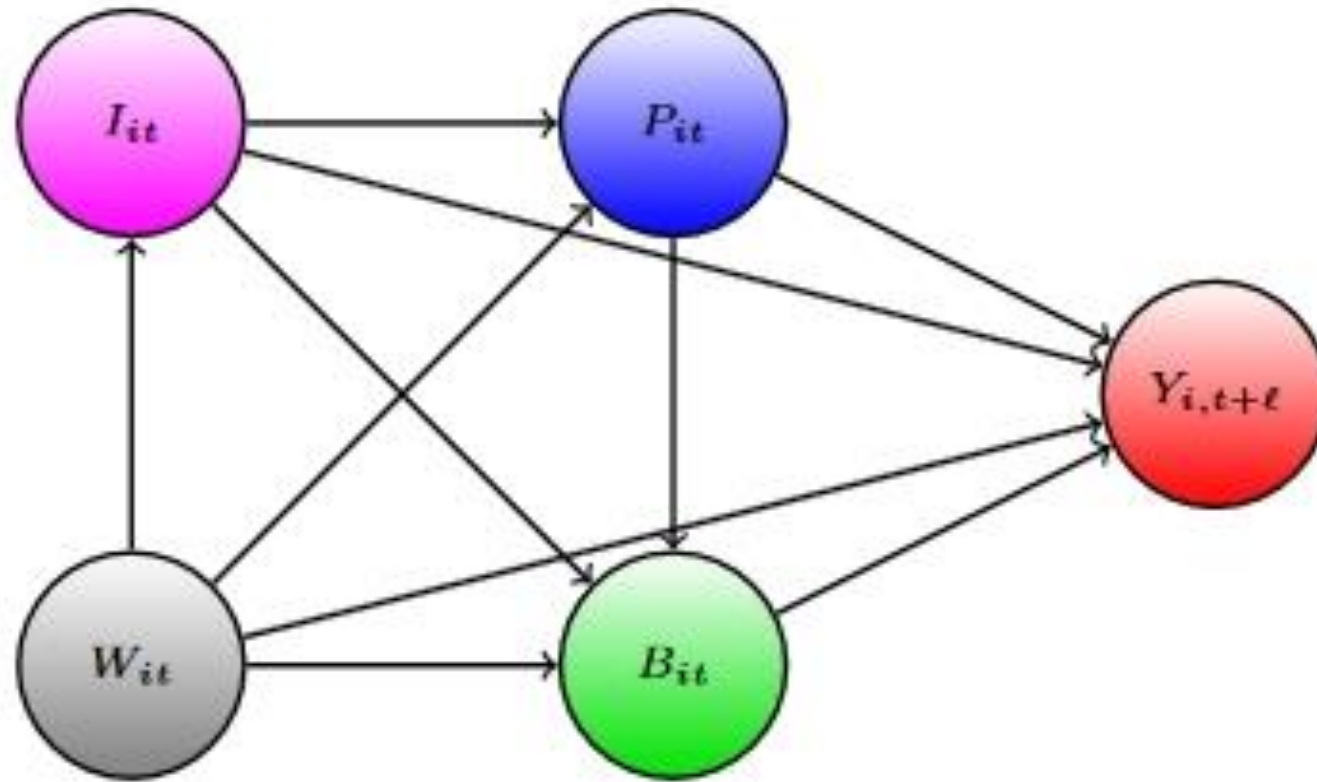


FIGURE 4. P. Wright type causal path diagram for our model.

Results and discussion

- Figure 3: Estimated causal effects of the lockdown

```
Mixed-effects REML regression
Group variable: nrkraj

Number of obs      =      5,301
Number of groups   =         57

Obs per group:
    min =          93
    avg =         93.0
    max =          93

Wald chi2(2)       =      689.34
Prob > chi2        =      0.0000

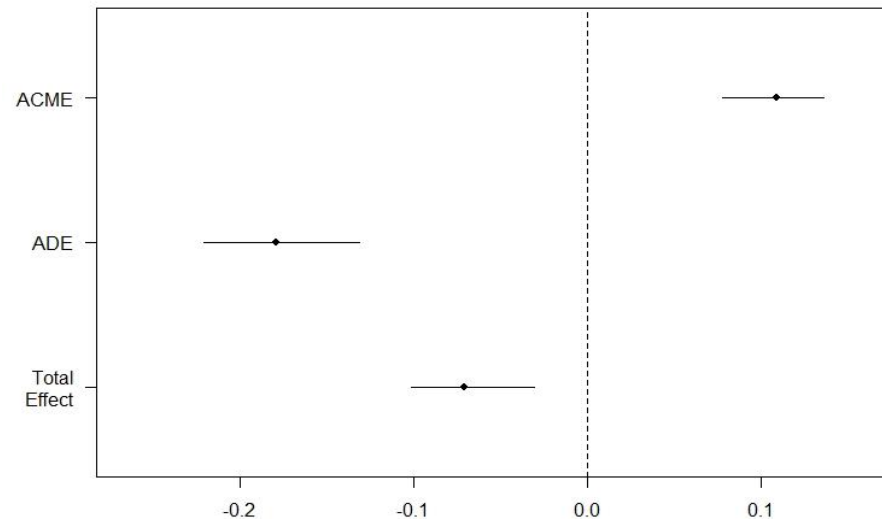
Log restricted-likelihood = -6065.2979
```

f10noviprim	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
policy	-.0471427	.0207409	-2.27	0.023	-.0877942	-.0064913
noviprim	.3280602	.0124993	26.25	0.000	.303562	.3525585
_cons	.137672	.0351177	3.92	0.000	.0688426	.2065014

- Source: Own calculations based on COVID-19 Sledilnik data.

Results and discussion

- In our model, we follow Chernozhukov et al. (2020) to estimate the causal effects of the lockdown as a policy measure on the number of the positive case using mediation analysis with the mediator being individual behaviour (which changes due to the adopted policy measure and then has an influence on the number of positive cases. Below figure shows that the total effects, as well as direct effects were indeed negative for cases per municipality each day after the pandemic took place.



Results and discussion

- The decomposition of the causal effects using basic Oaxaca-Blinder approach shows that there were statistically significant effects both in terms of endowments as well as coefficient. Furthermore, when analysis using decomposing variables of gender, age, income and education, the statistical effect was found for age, income and education – with age contribution about 40%, income 37% and education 23% to the estimated effects.

Table: Decomposition analysis of the causal effects

	Coef.	Std.	z	P> z
Differential				
Prediction_1	0.0831	0.0001	809.20	0.00
Prediction_2	0.0832	0.0001	812.05	0.00
Difference	-0.0001	0.0001	-0.42	0.67
Decomposition				
Endowments	-0.0001	0.0000	-2.42	0.01
Coefficients	0.0000	0.0000	2.45	0.01
Interaction	0.0000	0.0000	-0.42	0.67

Conclusion

- Our analysis is still **the first in Slovenia** to estimate the causal effects of the pandemic on health indicators. We were able to confirm the negative causal effect of the pandemic on number of positive cases and provided causal estimates both on the level of state in general as well as on municipal level.
- Our results were able to confirm a negative causal effect of the Slovenian lockdown on number of confirmed positive cases of COVID-19. About 76% infections and 58% deaths were avoided due to the lockdown.
- The decomposition of the causal effects using basic Oaxaca-Blinder approach showed that they were statistically significant effects both in terms of endowments as well as coefficient. Furthermore, when analysis using decomposing variables of gender, age, income and education, the statistical effect was found for age, income and education – with age contribution about 40%, income 37% and education 23% to the estimated effects.
- Beyond these findings, our paper presents a useful conceptual framework to investigate the relative roles of policies and information on determining the spread of Covid-19 through their impact on people's behavior. More broadly, our causal framework can be useful for quantitatively analyzing not only health outcomes but also various economic outcomes (Bartik et al., 2020, Chetty et al., 2020).

Data visualization



THANK YOU FOR LISTENING!

HVALA ZA POSLUŠANJE!

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