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1. Introduction

In this paper we provide a methodology to assign monetary values to the different pillars of the Regional Entrepreneurship Development Index (REDI). This index can be used to describe the general stance of the entrepreneurial ecosystem of regions, based on proxies which measure different aspects/dimensions of the ecosystem. The REDI methodology provides a normalized value to describe the entrepreneurial ecosystem using natural units of the different measures as inputs to the calculation. To conduct policy modelling, one needs to link monetary values to the different pillars/dimensions. This paper presents a method to monetize the pillars of the REDI calculation.

The method we provide borrows from standard shadow pricing which is a widely used approach to assign monetary values to factors which do not have a determined market price. In principle this approach calculates the marginal contribution of a given resource to the outcome/objective of some optimization problem. If the optimization targets a monetary value such as cost or profit/payoff, the standard method is straightforward to be used. In the present setup, however, the REDI methodology starts from natural units for pillars and results in a normalized score which still does not have a monetary dimension.

Following from the challenge described above, we proceed in two steps. First, using econometric techniques, we assign a monetary value to the REDI scores. By entering the REDI scores into a production function explaining regional GDP levels, we are able to estimate the marginal contribution of the REDI to monetarized regional output. This can be taken as the marginal value of the REDI in a given region. Then, we turn to the standard principles of shadow pricing where this monetarized REDI score is traced back to its components thus allowing for a monetarization of the pillars behind the REDI.

In what follows, we first describe the data, then turn to the estimation procedure and results. After that, the shadow pricing method is described, followed by a summary of the paper.

2. Data description

2.1. Units of observation

The unit of analysis is the region. Originally our cross-section analysis consisted of 125 "mixed" NUTS regions because the REDI has been calculated for 24 countries which altogether contain a mix of 125 NUTS1 and NUTS2 regions.

It was possible to create the REDI for 24 countries in the European Union, except Bulgaria, Cyprus, Luxemburg, and Malta. In the case of 10 countries, REDI data were calculated at NUTS1 level (Austria, Belgium, Greece, France, Germany, Italy, Netherlands, Poland, Romania, and the United Kingdom). For four additional countries, only country level classification was possible. These are the Czech Republic, Latvia, Lithuania, and Estonia. For the remaining 10 countries, REDI were calculated at NUTS2 level (Croatia, Denmark, Finland, Hungary, Ireland, Portugal, Spain, Slovenia, Slovakia, and Sweden). In the case of Portugal, only those five NUTS2 level data were available which belong to the Continente NUTS1 region. For Spain, the two small African continent NUTS1 regions, Ceuta and Melilla were also excluded.

First, we conducted the regression analysis alone for the 125 NUTS regions. However, it was problematic that in the case of 28 regions (5 Danish NUTS2, 12 British NUTS1, 2 Croatian NUTS2, 8 Swedish NUTS2, and 1 Spanish NUTS2) capital stock data were missing. Since the exclusion of the listed regions would have resulted in a significant loss of data (22.4% of the dataset), we decided to calculate them. Finally, it was not possible to calculate capital stock data for three NUTS2 regions (for the Croatian HR03 and HR04, and the Spanish ES70). Thus, the final database included information for a mix of 122 EU NUTS regions. Note that the representativeness of the sample is ensured insofar as it includes 24 European countries (*Table 1*).

However, due to inconsistent regression results, a further modification of the sample was required. The analysis of the regression results highlighted that the *low sample size*, and on the other hand the *low variability in some variables* that cause serious problems. Consequently, we are required to (1) collect *all NUTS2 level data* for the 24 countries (consequently the sample size has increased to a total of 254), and additionally (2) *pool data* for the determined two years(2011, 2014), whereby we were able to achieve a satisfactory sample size (n=508).

So far the REDI has been calculated for two time periods: (1) the *REDI 2013* for 2007-2011 and the *REDI 2017* for 2012-2014. Thus, as regards other variables of the cross-sectional analysis, we collected data for 2011 and 2014 (i.e. for the last year of the two periods for which the REDI has been calculated).

Table 1. - Number of REDI regions by country

Country		Basic Class.	No. of regions (in REDI)	No. of NUTS2 regions
AT	Austria	NUTS1	3	9
BE	Belgium	NUTS1	3	11
HR	Croatia	NUTS2	3	no data
CZ	Czech Republic	NUTS1	1	8
DK	Denmark	NUTS2	5	5
EE	Estonia	NUTS2	1	1
FI	Finland	NUTS2	5	4
FR	France	NUTS1	8	22
DE	Germany	NUTS1	16	38

EL	Greece	NUTS1	4	13
HU	Hungary	NUTS2	7	7
IE	Ireland	NUTS2	2	2
IT	Italy	NUTS1	5	21
LV	Latvia	NUTS2	1	1
LT	Lithuania	NUTS2	1	1
NL	Netherlands	NUTS1	4	12
PL	Poland	NUTS1	6	16
PT	Portugal	NUTS2	3	5
RO	Romania	NUTS1	4	8
SK	Slovak Republic	NUTS2	4	4
SI	Slovenia	NUTS2	2	2
ES	Spain	NUTS2	17	16
SE	Sweden	NUTS2	8	8
UK	United Kingdom	NUTS1	12	40
Total			125	254

2.2 Dependent variable

This study measures territorial performance via *gross domestic products* (GDP). In the regression model, we used GDP at current prices (million purchasing power standards, PPS) per capita data. We collected the GDP data for 2011 and 2014 (i.e. for the last year of the two periods for which the REDI has been calculated).

Table 2. – Dependent variable

Code	Description
GDP_PPS_2011_perCap	GDP 2011 (million purchasing power standards, PPS)
GDP_PPS_2014_perCap	GDP 2014 (million purchasing power standards, PPS)

Note:

* "The purchasing power standard, abbreviated as PPS, is an artificial currency unit. Theoretically, one PPS can buy the same amount of goods and services in each country." (Eurostat).

2.3 Independent variables

The explanatory variables used in this study come from two sources. First, regional figures related to *employment (L)* and *population density (DENSITY)* were obtained from Eurostat. Also, *capital stock (K)* data were derived from Eurostat's gross fixed capital formation data and calculated by using the PIM method[1]. Second, the variable measuring the quality of the entrepreneurial ecosystem across European regions is the *Regional Entrepreneurship and Development Index (REDI)*. The first version of the REDI index based on the 2007-2011 GEM APS dataset was created by Szerb et al (2013), and with the support of the European Union ('Financial and Institutional Reforms to build an Entrepreneurial Society' (FIRES), Horizon 2020 project), the latest REDI scores with an additional extended time period 2012-2014 data were created with the objective of scrutinizing and understanding the entrepreneurial ecosystem in Europe (Szerb et al., 2017). REDI can range from the potential values of 0 to 100. The higher the regional REDI score, the better the quality of the entrepreneurial ecosystem is.

[1] "The perpetual inventory method (PIM) is a method of constructing estimates of capital stock and consumption of fixed capital from time series of gross fixed capital formation. It allows an estimate to be made of the stock of fixed assets in existence and in the hands of producers which is generally based on estimating how many of the fixed assets installed as a result of gross fixed capital formation undertaken in previous years have survived to the current period." (OECD, 2001).

Table 3. – Description of independent variables

Code	Indicator	Unit	Source
L	Employment	thousand, from 15 to 64 years	Eurostat
K	Capital stock	thousand PPP, 2000=100	own cal.*
REDI	Regional Entrepreneurship and Development Index	composite index	own cal.
Control variables			
DENSITY	Population density	Inhabitants per square kilometer	Eurostat
CAPITAL	Capital city	[0; 1], it take the value of 1 for capital city	Eurostat

Note: *It is calculated from gross fixed capital formation data (million €) using PIM method.

Table 4. – List of the independent variables

Code	Description
L_2011_perCap	EMPLOYMENT (2011, thousand)
L_2014_perCap	EMPLOYMENT (2014, thousand)
K_2011_perCap	CAPITAL STOCK (2011; thousand)
K_2013_perCap	CAPITAL STOCK (2013; thousand)
REDIunit2013_perCap	REDI score (unit) 2013
REDIunit2017_perCap	REDI score (unit) 2017
DENSITY_2011	Density 2011
DENSITY_2014	Density 2014
CAPITAL	Capital city (dummy)

Note:

REDI2013, REDI2017: the super-index REDI is simply the arithmetic average of the three sub-indices: $\mathrm{REDI_i} = \frac{1}{3}(\mathrm{ATT_i} + \mathrm{ABT_i} + \mathrm{ASP_i})$ where i = 1, 2, …, n is the number of regions.[2]

REDIunit2013, REDIunit2017: in this case, the super-index REDI is calculated as the sum of the 14 penalized pillar scores.

Also in the case of the independent variables, we collected the data for 2011 and 2014 (i.e. for the last year of the two periods for which the REDI has been calculated). All input variables are population standardized per 1,000 residents.

In the different model specifications, we included two control variables related to urbanization. Urbanization economies are a type of agglomeration externality that refers to considerable cost savings generated through the locating together of people, firms, and organizations across different industries (Parr 2002; McCann 2013). Therefore location in large or densely populated cities may offer serious advantages. In our study, we follow the practice by Meliciani and Savona (2015) and assess the role of urbanization by introducing *regional population density (DENSITY)* and a dummy for regions with a *capital city (CAPITAL)*.

3. The econometric model

The following general multiple linear regression models was tested in order to estimate the effect of the entrepreneurial ecosystem on territorial performance. The regression analysis departs from a model that includes the basic factors (labor and capital) of a simple production function completed with the REDI which reflects the interaction between individuals and their contexts that determines

[2] For additional information on the calculation of REDI see: http://www.projectfires.eu/wp-content/uploads/2017/07/FINAL-D4.4-Template-Report-Pan-European-database_V4.4.pdf

the weights of economic and societal benefits of entrepreneurship (Audretsch and Belitski, 2017). The econometric model used in this study has the following forms:

$$LnGDP\_PPS\_perCap_i = \beta_0 + \beta_1 LnL\_perCap_i + \beta_2 LnK\_perCap_i + \beta_3 LnREDIunit\_perCap_i + \beta_4 LnDENSITY_i + \beta_5 CAPITAL_i + \varepsilon_i \quad (1)$$

where i = 1, 2, …, n is the number of regions

In equations (1) performance refers to the GDP at the regional level, β_i are parameter estimates estimated for the independent variables, and ε is the normally distributed error term that varies across regions.

Table 8 shows the results of regression calculation. Before the estimation of the parameters the necessary assumptions of linear regression were checked:

(1) Regarding the dependent and independent variables:

- their normal distribution
- independence from each other/checking for multicollinearity

(2) Regarding the residuals:

- normal distribution of residuals
- the variance of the residuals/test of heteroscedasticity

Descriptive statistics are presented in *Table 5*. To ensure estimation accuracy we first have checked the skewness of the variables. The skewness statistic indicates how symmetrically distributed is a set of observed values (Greene, 2003). In the case of seven variables the absolute value of skewness – a measure of the asymmetry of distribution – exceeds the absolute value 2.

For dealing with skewed data and in order to make data conform more closely to the normal distribution we applied the log transformation method. *Table 6* contains the descriptive statistics of the variables after applying the above-mentioned transformation method.

Table 5. – Descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
GDP_PPS_perCap	508	7.46878	169.61111	26.4997376	12.14122038	5.466	.108	56.831	.216
REDIunit_perCap	508	.00044	.03869	.0052656	.00476303	2.609	.108	9.984	.216
L_perCap	508	.19432	.62141	.4271724	.05674142	-.569	.108	.654	.216
K_perCap	508	17.28	207.08	71.0064	25.34820	1.359	.108	4.408	.216
DENSITY	508	3.30	10780.30	442.6335	1182.01554	6.073	.108	42.639	.216
CAPITAL	508	0.00	1.00	.0906	.28725	2.862	.108	6.216	.216

Table 6. – Descriptive statistics after log transformation

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LN_GPD_PPS_perCap	508	2.01	5.13	3.2070	.36304	.272	.108	2.237	.216
LN_REDIunit_perCap	508	-7.73	-3.25	-5.5665	.81064	-.074	.108	-.123	.216
LN_L_perCap	508	-1.64	-.48	-.8602	.14230	-1.125	.108	2.290	.216
LN_K_perCap	508	2.85	5.33	4.2025	.35137	-.267	.108	.955	.216
LN_DENSITY	508	1.19	9.29	5.0935	1.21384	.631	.108	1.664	.216
CAPITAL	508	0.00	1.00	.0906	.28725	2.862	.108	6.216	.216

The associated correlation matrix is presented in the Appendix (*see Table A1*). Predictor variables that are highly correlated provide little independent explanatory ability. This pattern is known as multicollinearity. If the absolute value of Pearson correlation is greater than 0.8, collinearity is very likely to exist. The condition is not fulfilled for any of the variables, therefore we can assume that multicollinearity is not very likely to exist. Also, collinearity diagnostics (see the tables in the Appendix) does not confirm multicollinearity. Several eigenvalues are higher than 0, indicating that the predictors are not intercorrelated, and that small changes in the data values may lead to large changes in the estimates of the coefficients.

The condition indices are computed as the square roots of the ratios of the largest eigenvalue to each successive eigenvalue. Values greater than 15 indicate a possible problem with collinearity, and greater than 30, a serious problem. In our case, one of these indices are larger than 30, suggesting a serious problem with collinearity (CAPITAL).

However, to evaluate the threat of multicollinearity, we computed the Variance Inflation Factor (VIF) for all variables. In our models, none of the VIF values exceed 10—a generally accepted rule of thumb for assessing collinearity—were observed. The average VIF for the finally selected model was 1.172 (range: 1.108-1.279). The results for this diagnostic test do not raise collinearity concerns.

In order to make valid inferences from our regression, the residuals of the regression should follow a normal distribution. The well-known tests of normality are namely the Kolmogorov-Smirnov Test and the Shapiro-Wilk Test. The Shapiro-Wilk Test is more appropriate for small sample sizes (< 50 samples). If the value of the tests is greater than 0.05, the data is normal. If it is below 0.05, the data significantly deviate from a normal distribution. Using *GDP per capita (at current prices, PPS)* the residuals of the regression does not show a normal distribution.

One of the assumptions made about residuals in OLS regression is that the errors have the same but unknown variance. When this assumption is violated, the problem is known as heteroscedasticity. Applying the *Breusch-Pagan-Koenker Test*[3] we could identify the presence of heteroscedasticity in our data. This test assumes that the error terms are normally distributed and

[3] http://spsstools.net/en/syntax/syntax-index/regression-repeated-measures/breusch-pagan-amp-koenker-test/

tests whether the variance of the errors from a regression is dependent on the values of the independent variables. Natural log transformations of variables were tried, but the heteroscedasticity remained.

Table 7. – Breusch-Pagan-Koenker test for heteroscedasticity

	Model_508
Breusch-Pagan test for Heteroscedasticity (CHI-SQUARE df=P)	71.357
Significance level of Chi-square df=P (H0:homoscedasticity)	.0000
Koenker test for Heteroscedasticity (CHI-SQUARE df=P)	58.290
Significance level of Chi-square df=P (H0:homoscedasticity)	.0000

This means that ordinary least squares no longer produces the best linear unbiased estimators (BLUE). An alternative and highly appealing method of reducing the effects of heteroscedasticity on inference is to employ a heteroscedasticity-consistent standard error (HCSE) estimator of OLS parameter estimates (White, 1980; Hayes and Cia, 2007). With this approach, the regression model is estimated using OLSs, but an alternative method of estimating the standard errors is employed that does not assume homoscedasticity.

Table 8 shows the results using the HC3 estimators[4]. Note that the standard errors are quite similar for the predictors. We can be pretty confident that there is a relationship between the explanatory variables (L, K, REDI and DENSITY, CAPITAL) and GDP because the regression estimate is statistically different from zero, regardless of how the standard error is estimated. In sum, when heteroscedasticity is managed using the HC3 estimator, the partial relationship between the independent variables and the dependent variable is statistically significant.

In order to calculate the shadow prices for the REDI pillars we must calculate the elasticity between REDI score units and regional GDP levels. For this purpose we selected **model_508** with the estimated REDI regression coefficient: **0.0584*** (p =0,0000).**

Given this estimated elasticity between the REDI scores and GDP levels, we have a monetarized value for the REDI. More precisely, we are able to calculate the effect if a marginal increase in the REDI on the monetary value of regional output, which serves as a starting point to monetarizing the REDI pillars. In what follows, we show how the shadow pricing approach was implemented in this setting to assign monetary values to the REDI pillars.

[4] Hayes, A. F., & Cia, L. (2007): Using heteroscedasticity-consistent standard error estimators in OLS regression: An introduction and software implementation. *Behavior Research Methods*, 39 (4), 709-722.
http://www.afhayes.com/spss-sas-and-mplus-macros-and-code.html

Table 2. – OLS Regression Analysis Estimating GDP Using Standard Error Estimates Assuming Homoscedasticity (OLSE) and Not Assuming Homoscedasticity (HC3)

	Model_508				
	OLSE			HC3	
	b	SE	P	SE	P
Dependent variable	LnGDP_PPS_perCap				
Independent variables					
Constants	1.515	.150	*.000*	1.5152	*.0001*
Ln_K_perCap	.524	.026	*.000*	.5235	*.0000*
Ln_L_perCap	.794	.069	*.000*	.7939	*.0000*
Ln_REDIunit_perCap	.058	.012	*.000*	.0584	*.0000*
Ln_DENSITY_perCap	.094	.008	*.000*	.0964	*.0000*
CAPITAL	1.515	.031	*.003*	.0939	*.0149*
F-test	248.691			143,63	
Adjusted R^2	.710				
Average VIF	1.172				
Observations	508				

Note: Robust standard errors are in brackets. *, **, *** indicate significance at the 10%, 5% and 1%, respectively.

4. Shadow pricing

In this section we describe how we calculated shadow prices for REDI pillars. The basic concept behind these calculations is that using the results from the estimations described previously, we are able to assign monetary value to the REDI pillar units. Given the econometric framework established in the previous section, we have an estimation of the elasticity between REDI score units and regional GDP levels. Let this elasticity be ε^{GDP}, showing the percentage change in regional GDP level given a 1% change in the regional REDI score unit. If Y_i is the GDP level in region i, then the monetary value of a 1% increase in regional REDI score unit is

$$v_i = \frac{\varepsilon^{GDP}}{100} Y_i \tag{1}$$

In what follows we introduce the shadow pricing logic, starting with the relevant elements of REDI calculation, through how optimization can be interpreted in the REDI context, to the derivation of the final shadow prices.

4.1. The starting point: REDI normalized pillar values

In this approach, we start from the REDI calculations. As described previously, the calculation of the REDI for all regions follows the steps below:

1. Start from individual and institutional variables for the 14 pillars, and normalize these values to the 0-1 interval.
2. Multiply the institutional and individual variables to get the raw pillar values.
3. A 95 percentile capping ensures that extreme values do not distort the results.
4. Capped pillar values are normalized to the 0-1 interval.
5. Capped and normalized pillar values are transformed in a way that pillar averages across regions are equalized (and equal to the average values across pillars).
6. The Penalty For Bottleneck method is applied to get penalized pillar values.
7. Pillar values are summed up to achieve REDI score units for regions.

In this exercise we start from step 5 above. This means that for every region i and pillar p we have a $y_{i,p}$ transformed pillar score between 0 and 1.[5]

Let's use the term $\hat{y}_i = \min(y_{i,1}, y_{i,2}, \dots, y_{i,14})$ to denote the minimal pillar value in region i. Then the penalized pillar values are calculated as:

$$h_{i,p} = \hat{y}_i + \left[1 - e^{-(y_{i,p} - \hat{y}_i)}\right] \tag{2}$$

Finally the REDI score units applied in this exercise and also used in the econometric estimations is the sum of the penalized pillar values:

$$S_i = \sum_p h_{i,p}$$

[5] The transformation procedure ensures that $\sum_i y_{i,p} / R = \bar{y}$ for all p (R is the number of regions).

(3)

4.2. The REDI as a maximization problem

The method we use takea advantage of the standard shadow pricing principle, which is based on the following extreme value problem:

$$f(\mathbf{x}) \to max$$

$$g(\mathbf{x}) = b$$

(4)

where $\mathbf{x}$ is a vector of control variables, $f(\mathbf{x})$ is the objective function, b is some resource constraint and $g(\mathbf{x})$ is a constraint function. The problem above imposes one constraint on the optimization but it can be generalized to an arbitrary number of constraints. It is known from standard optimization theory that the shadow price with respect to the constraint b (also known as the Lagrange multiplier of the constraint) reflect the change in the objective function (given an optimal allocation of $\mathbf{x}$) if the constraint is relaxed by a unit. Given that the objective function describes a cost-minimization or profit maximization problem, these shadow prices associate a monetary value to the natural resource units which constrain the problem.

Using the standard shadow pricing principle in our context, we must convert the REDI methodology into a maximization/minimization problem. Our approach, we start from the average equalized, normalized pillar values $y_{i,p}$ for every region. As a result of the average equalization procedure, these values can be regarded as brought to a common denominator, or in other terms, reflecting the scores of pillar elements on a common scale. Now one maximization problem is set for every region i. The average equalized and normalized pillar scores $y_{i,p}$ for region i are considered as the control variables, so in the general setup (5) $\mathbf{x} = (y_{i,1}, y_{i,2}, \ldots, y_{i,14})$. Also, the resource constraint is the sum of observed pillar values: $b_i = \sum_p y_{i,p}$. To sum up, we interpret the REDI calculation logic as follows. Every region possesses some b_i amount of resources that can be used to enhance entrepreneurial activity in the region by allocating it to the different pillars of the model (entrepreneurship ecosystem). In this shadow pricing method, we are looking for an optimal allocation of the resources in a given region which does not necessarily coincide with the actual observed allocation.

The objective function converts the equalized pillar scores into the REDI score units using the penalty for bottleneck principle as follows. As a result, the optimization problem for region i is as follows:

$$\sum_p \hat{y}_i + \left[1 - e^{-(y_{i,p} - \hat{y}_i)}\right] \to max$$

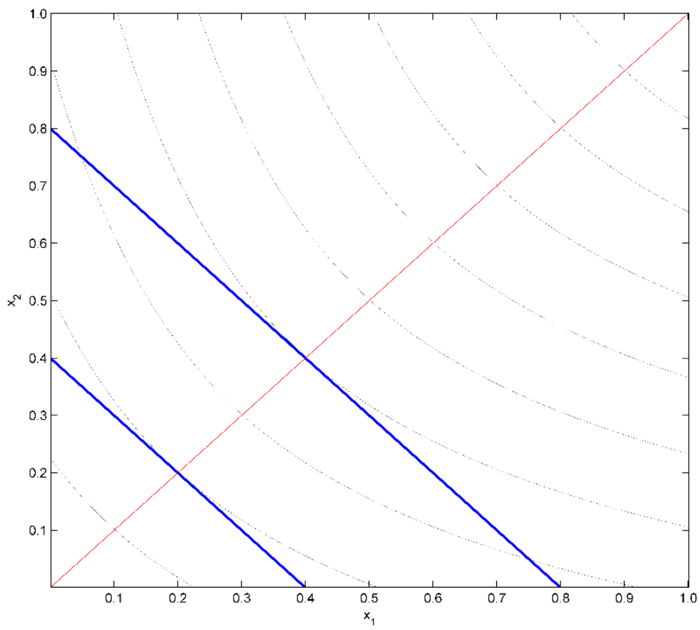
$$\sum\nolimits_p y_{i,p} = b_i$$

(6)

where $\hat{y}_i = \min(y_{i,1}, y_{i,2}, \ldots, y_{i,14})$ as before.

Given the objective function in (6), it is easy to show that for any constraint b_i the optimal solution is $y_{i,p} = b_i/14$ for all p, given that there are 14 pillars. The key to this result is the symmetry of the pillars in the objective function and the terms containing the minimal pillar value.

To prove this result, assume that we have an allocation which satisfies $y_{i,p} = b_i/14$ for all p. Then impose a reallocation so that $y_{i,p}$ decreases by some Δb while an $y_{i,q}$ increase by this same amount so that the resource constraint is still satisfied. All other pillars are unchanged. If the initial symmetric allocation was not optimal, this reallocation could increase the objective function. As the latter is additively separable in the $h_{i,p}$ penalized pillar scores, it is sufficient to analyze the change in the terms corresponding to pillars p and q. With the reallocation, the $\hat{y}_i$ minimum terms decreases by Δb as it takes the smallest pillar value. As this enters the objective function symmetrically for all pillars, the value of the objective function decreases by $14\Delta b$. As pillar p (where the score decreased) becomes the bottleneck with the minimal value, the term in the bracket for this pillar is 0, because $y_{i,p} = \hat{y}_i$. As for pillar $y_{i,q} = \hat{y}_i + 2\Delta b$, the term in the bracket for this pillar becomes $1 - e^{-2\Delta b}$. Before the reallocation, the symmetric allocation rendered the terms in the bracket to 0 for all pillars, so it follows that the change in the allocation increases the bracketed term for pillar q, but less than $2\Delta b$. To conclude, the reallocation decreases the objective function by $14\Delta b$ on the one hand and increases it by less than $2\Delta b$ on the other, so the objective function definetly decreases. It follows that the symmetric allocation is an optimal allocation.



1. Figure – A visual representation of optimal allocation

The logic above can be easily represented visually if we restrict the number of pillars to two. Figure 1 shows this solution. The black lines in the figure represent isoquants of the objective function in (6) with two arguments $y_{i,1}$ and $y_{i,2}$. This means that along a black curve the different allocations of the pillars 1 and 2 yield the same REDI score unit. The closer a black curve is to the top-right corner, the higher the REDI score unit it represents. The blue lines represent the resource constraint given b_i.

Again, the closer the blue line is to the top-right corner, the more relaxed the constraint is. Along the blue line, the sum of the two pillar values are the same, while its allocation on the two pillars change.

It is easily visible in Figure 1 that due to the symmetry of the objective function the resource constraints hit the highest REDI score unit in the middle of the graph, under a balanced allocation of the resources on the two pillars. The red diagonal line shows all the optimal allocations under different resource constraints. The penalty for bottleneck principle ensures that in an unbalanced allocation one can always improve the REDI score with a reallocation towards a more balanced structure while the symmetry of the pillars drives the optimal allocation to perfect balance.

4.3 Using the shadow pricing logic

As shown in the previous section, the structure of the REDI ensures that given b_i amount of resources in region i which can be allocated to the different pillars, the optimal allocation is $y_{i,p} = b_i/14$ for all pillars p. Now assume a change in the resource constraint from b_i to b_i'. As a result, the optimal allocation changes to $y_{i,p}' = b_i'/14$ for all pillars p. Using the objective function in (6) it is easy to show that given the optimal allocation, the REDI score is simply $S_i = \sum_p y_{i,p} = b_i$.[6] So if the resource constraint changes, the optimal REDI score also changes to $S_i' = b_i'$. As described in the previous sections, the monetary value of a percentage change in the REDI score units is v_i. If the change in the REDI score (assuming optimal resource allocation) is a result of a change in the resource constraint, the monetarized change in the REDI score is the shadow price of the resource. The shadow price of the resource is then

$$V_i = \frac{S_i'}{S_i} v_i \tag{7}$$

An important difference between this solution and the forward logic is that the latter one provides a different shadow price for all pillars in a given region, while the optimization method presented here provides one shadow price for a given region for the 'general' resource which is assumed to be allocated to the different pillars.

Table A3 contains the results for the shadow prices obtained with the optimization method described above. The average value across regions is 2.381 thousand EUR, while the minimal and maximal values are 1.512 and 4.059 thousand EUR respectively. These values mean that if a pillar value (resource) changes by 1 basis point (0.01 on the 0-1 scale), per capita GDP in PPS in the region is expected to change by this amount.

5. Discounting with fiscal multipliers

The V_i values calculated in (7) and sampled in Table A3 show how the GDP per capita in a region is expected to change for a small change in the resource constraint. These values, although having monetary dimension, are more of an output or result of investing resources into the entrepreneurial environment than being the cost of these investments. How the cost of such investments can be determined is not a straightforward task.

[6] The reason for this is that under the optimal allocation bottlenecks are eliminated so the bracketed term in the objective function in (6) vanishes.

Our approach in this respect is to use fiscal multipliers. As our interest is basically policy driven, we concentrate on policy interventions resulting in improvements in the REDI pillars, which means relaxing regional resource constraints in the context of the shadow pricing (optimization) setup. Without directly assigning monetary costs to improving specific REDI pillars, we assume that there is a general efficiency of such policies – these are usually expressed in the form of multipliers: spending 1 EUR on specific purposes, what increase can be achieved in economic output/income. The merit of using multipliers is that such values are widely available and they provide a general/aggregate measure of how policy efforts turn into economic outcome.

Given that the multiplier relevant for region i is m_i (meaning the one unit of government spending in region i results in an m_i unit increase in regional GDP), we can use this value to calculate backwards: how much spending is required in order to achieve a given amount of increase in the GDP. If the result of an investment in any pillar p in region i is V_i as in (7), then the "policy cost" of achieving this monetary result can be expressed as

$$MV_i = \frac{V_i}{m_i} \tag{8}$$

One challenge in determining the multipliers is that there are many of them. Multipliers typically differ with respect to the fiscal instrument (e.g. government consumption, different taxes, etc.), whether it is temporary or permanent and also the horizon of the output effect taken into account (e.g. short or long term effects on GDP.

In this study we take two comprehensive sources of country-level multipliers into account: a report of the European Central Bank (Kilponen et al., 2015), which uses country-level DSGE models to estimate multipliers and the report of the OECD (Barrell et al., 2012) which uses a standardized econometric method for the same purpose. These reports provide country-level estimates of fiscal multipliers for a set of countries[7] and several fiscal instruments[8]. The ECB report provides estimates for temporary and permanent interventions, but the OECD estimations are given only for temporary policies.

This diversity in the reported fiscal multipliers requires a careful choice among them. First of all, our goal is to use as detailed data as possible, which drives the choice at the first hand to use country-level multipliers wherever possible. A constraint in this respect is that the two reports contain different countries (with some overlap). In order to have the largest coverage, we take both reports and take the multipliers wherever the country is reported. If it is reported in both reports, the average of the two multipliers are used. Latvia, Lithuania, Hungary, Poland, Romania and Slovakia are not covered by either of the reports. As the ECB provides values for the Eurozone, these can be used for Euozone members within these remaining countries, while the rest is assigned an average value of the CEE countries. This approach also narrows down the fiscal instruments to be used – only government consumption is comparably provided by both reports. This instrument is in line with our

[7] From the 23 countries covered by the REDI, 17 appears in one of the reports while 10 appears in both.

[8] The OECD report cotains government consumption, government benefits (transfers), direct and indirect taxes. The ECB report estimates multipliers for government consumption, labor income tax, capital income tax and consumption tax.

purpose on the other hand: the fiscal instruments used to promote entrepreneurial ecosystems are mainly (but of course not exclusively) expenditure-side tools which are accounted for as government spending.[9] Finally, as only the ECB report contains permanent multipliers and its long run effects, the primary choice of using the most diverse set of reported values for different countries narrows down the time span as well only to temporary interventions and short run effects.[10] Finally, the standard way of presenting multipliers is the estimated effect of a restrictive fiscal impulse – as we are working with a positive, expansionary effect with more resources spent on specific purposes, we use the assumption that the reported multipliers are symmetric so that the same, but opposite effect is expected after a fiscal expansion as after a restrictive one.

1. táblázat – Estimated multipliers for different countries in the REDI sample

Country	ECB estimation	OECD estimation	Final value
Belgium	0,93	0,17	0,55
Czech Republic	0,54		0,54
Denmark		0,53	0,53
Germany	0,52	0,48	0,50
Estonia	0,83		0,83
Ireland		0,33	0,33
Greece	0,90	1,07	0,99
Spain	0,50	0,71	0,61
France	0,92	0,65	0,79
Italy	0,79	0,62	0,71
Latvia			0,98
Litvania			0,98
Hungary			0,68
Netherlands	0,74	0,53	0,64
Austria		0,53	0,53
Poland			0,68
Portugal	0,85	0,68	0,77
Romania			0,68
Slovenia	0,66		0,66
Slovakia			0,98
Finland	0,78	0,64	0,71
Sweden	0,60	0,39	0,50
United Kingdom		0,74	0,74
Eurozone	0,98		0,98
New members in 2004	0,68		0,68
Average	0,74	0,58	0,69

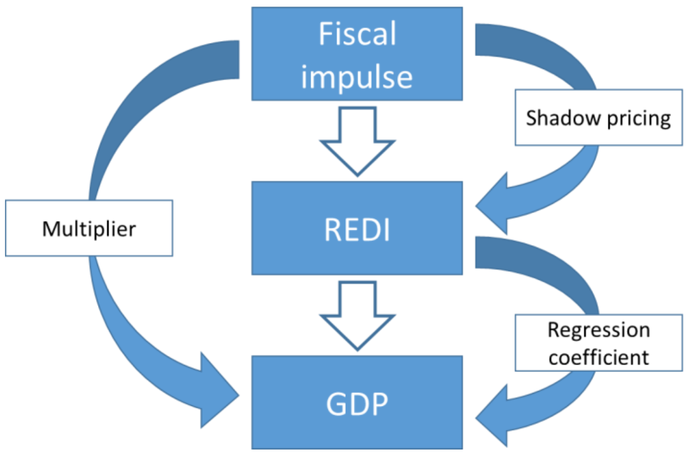
Table 1 above shows the original ECB and OECD estimations of multipliers, together with the final values used in our calculations. The values mean that given a 1% increase in government spending (as a ratio to the GDP), GDP is expected to increase by the given percentages. As these values lay below one, they mean that spending 100 EUR from the government budget results in a less than 100 EUR increase in the GDP. Or reversely, in order to achieve a 100 EUR increase in economic output, the government has to spend more than 100 EUR.

[9] Another approach could be using government transfers, but this would narrow down the basis for multiplier data to the OECD report.
[10] Although there is some variation, the long run effects do not differ too much from the short run effects.

Table A3 contains the results of these calculations. The Direct Shadow Price column shows the raw shadow prices according to (7), before accounting for the fiscal multipliers. On average this comes out at 2.38 EUR per capita. After discounting with the multiplier we get higher numbers (as described above, 1 EUR spent by the government yields less then 1 EUR on GDP), with an average of 3.75 EUR per capita (Discounted Shadow Price column) across the sample. Given the population level of regions, we can easily aggregate up these per capita levels (Aggregate Shadow Price column). This results in a 7.61 million EUR shadow price for the average region: according to our logic, spending this amount of money equals the release of the REDI resource constraint by 0.01 unit. In other terms, this is the price of 0.01 REDI units.

The logic of the calculations

Our logic behind the method is illustrated in Figure 1. Fiscal impulse is assumed to affect the REDI score which is then assumed to affect the GDP level. From the measurement point of view, multipliers grasp the relationship between fiscal impulses and the GDP. The regression coefficient reflects the relationship between REDI and GDP. Using these two values, our shadow pricing logic quantifies the third relationship between fiscal impulse and REDI, thereby allowing for an estimate of the fiscal cost of changing the REDI score in a region.



6. Summary and limitations of the method

Although the methods presented above provide relatively easy ways to assign monetary values to the pillars of the REDI, they have clear limitations.

- The values attained do not reflect real costs. Although the best way would be to systematically evaluate the cost of increasing the values of different pillars, this would require a substantial amount of information on how public and private resources spent on a diverse set of activities contribute to the improvement of the actually measured proxies of the different pillars. As this is a resource-intensive task with questionable results, we turned to the shadow pricing principle, which is used to assign somewhat 'artificial' prices, values to the natural units of some resources.
- Although the best way to proceed in shadow pricing would be to focus on the cost side, that would mean setting up a cost function which eventually results in the same problems as mentioned in the previous point. Our approach thus builds on a value-side calculation. By linking the REDI scores to regional GDP levels, we are able to estimate how much an increase

in a given pillar's score (forward method) or the pillar scores together (optimization method) contribute to regional production in monetary terms. Instead of being a cost level, this estimate shows the value of the improvement in the pillars for the region.

- Although the optimization method is methodologically more compact and builds on standard shadow pricing, it requires the assumption that the resources are allocated in an optimal way across the pillars, i.e. pillars are balanced. As a result, shadow price calculations use a situation (optimal allocation) as the starting point which does not coincide with actually observed allocation/structure of the REDI pillars in the regions.

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Appendix

Table A1. – Correlation matrix

		LN_GPD_PPS_perCap	LN_K_perCap	LN_L_perCap	LN_REDIunit_perCap	LN_DENSITY	CAPITAL
Pearson Correlation	LN_GPD_PPS_perCap	1,000					
	LN_K_perCap	,653	1,000				
	LN_L_perCap	,567	,234	1,000			
	LN_REDIunit_perCap	,290	,206	,319	1,000		
	LN_DENSITY	,462	,109	,270	-,121	1,000	
	CAPITAL	,247	,151	,111	-,073	,220	1,000

Table A2. – Collinearity Diagnostics

Model		Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	LN_K_perCap	LN_L_perCap	LN_REDIunit_perCap	LN_DENSITY	CAPITAL
1	1	5,030	1,000	,00	,00	,00	,00	,00	,00
	2	,885	2,385	,00	,00	,00	,00	,00	,92
	3	,051	9,921	,00	,00	,11	,01	,61	,05
	4	,018	16,609	,02	,17	,09	,25	,14	,00
	5	,013	19,481	,00	,01	,66	,63	,23	,00
	6	,002	46,996	,98	,83	,13	,11	,02	,02

Table A3. – Results of shadow pricing per region with the forward and optimization methods (million EUR)

Region Name	Region Code	Direct Shadow Price	Country-level multipliers	Discounted Shadow Price	Population	Aggregate Shadow Price
		(PPS EUR per capita)	-	(PPS EUR per capita)	(Thousand capita)	(Million PPS EUR)
Ostösterreich	AT1	2,1359	0,53	4,0300	1343,28	5,4134
Südösterreich	AT2	2,4996	0,53	4,7163	891,60	4,2050
Westösterreich	AT3	2,9013	0,53	5,4742	746,55	4,0867
Région de Bruxelles-Capitale	BE1	3,5952	0,55	6,5366	1154,80	7,5485
Vlaams Gewest	BE2	2,3493	0,55	4,2715	1303,28	5,5669
Région wallonne	BE3	1,9381	0,55	3,5238	680,03	2,3963
Czech Republic	CZ	2,2138	0,54	4,0997	1305,96	5,3540
Baden-Württemberg	DE1	2,4114	0,50	4,8228	2713,02	13,0844
Bayern	DE2	2,3179	0,50	4,6357	1942,48	9,0048
Berlin	DE3	1,9968	0,50	3,9937	3351,69	13,3856
Brandenburg	DE4	1,9768	0,50	3,9535	2454,90	9,7056
Bremen	DE5	3,0162	0,50	6,0323	654,54	3,9484
Hamburg	DE6	3,2707	0,50	6,5414	1726,70	11,2950
Hessen	DE7	2,2345	0,50	4,4691	2263,65	10,1164
Mecklenburg-Vorpommern	DE8	2,4702	0,50	4,9404	1605,24	7,9305
Niedersachsen	DE9	2,3266	0,50	4,6533	1946,89	9,0595
Nordrhein-Westfalen	DEA	2,3673	0,50	4,7346	3591,17	17,0027
Rheinland-Pfalz	DEB	2,0921	0,50	4,1843	1379,35	5,7716
Saarland	DEC	2,4369	0,50	4,8738	996,14	4,8550
Sachsen	DED	1,9717	0,50	3,9434	1337,79	5,2754
Sachsen-Anhalt	DEE	2,2043	0,50	4,4087	2269,62	10,0060
Schleswig-Holstein	DEF	2,1644	0,50	4,3287	2808,40	12,1568
Thüringen	DEG	2,3425	0,50	4,6850	2177,08	10,1996
Hovedstaden	DK01	2,0847	0,53	3,9334	1725,52	6,7871
Sjælland	DK02	1,5238	0,53	2,8750	818,21	2,3523
Syddanmark	DK03	1,9040	0,53	3,5925	1201,61	4,3168
Midtjylland	DK04	1,7423	0,53	3,2874	1269,41	4,1730
Nordjylland	DK05	1,6891	0,53	3,1870	580,46	1,8499
Estonia	EE	1,7294	0,83	2,0837	1322,30	2,7552
Voreia Ellada	EL1	3,0902	0,99	3,1372	771,94	2,4218
Kentriki Ellada	EL2	3,6790	0,99	3,7350	543,04	2,0283
Attiki	EL3	3,7454	0,99	3,8024	3928,20	14,9368
Nisia Aigaiou, Kriti	EL4	3,4002	0,99	3,4520	386,78	1,3352
Galicia	ES11	2,8543	0,61	4,7179	2760,14	13,0219
Principado de Asturias	ES12	2,6546	0,61	4,3878	1067,51	4,6840
Cantabria	ES13	2,9206	0,61	4,8274	589,27	2,8447
País Vasco	ES21	3,1236	0,61	5,1630	2174,99	11,2295
Comunidad Foral de Navarra	ES22	3,3462	0,61	5,5309	636,77	3,5219
La Rioja	ES23	3,5798	0,61	5,9170	317,99	1,8816
Aragón	ES24	3,3786	0,61	5,5844	1337,75	7,4705

Comunidad de Madrid	ES30	2,6844	0,61	4,4371	6386,13	28,3358
Castilla y León	ES41	2,9643	0,61	4,8997	2520,35	12,3490
Castilla-la Mancha	ES42	2,9794	0,61	4,9247	2087,23	10,2790
Extremadura	ES43	2,6401	0,61	4,3638	1099,35	4,7974
Cataluña	ES51	2,9401	0,61	4,8597	7453,89	36,2239
Comunidad Valenciana	ES52	2,6436	0,61	4,3695	4977,52	21,7494
Illes Balears	ES53	3,1923	0,61	5,2765	1104,00	5,8253
Andalucía	ES61	2,3393	0,61	3,8666	8360,56	32,3273
Región de Murcia	ES62	2,7104	0,61	4,4800	1460,46	6,5429
Canarias (ES)	ES70	2,9635	0,61	4,8983	2089,83	10,2366
Länsi-Suomi	FI19	1,9828	0,71	2,7927	1367,14	3,8180
Helsinki-Uusimaa	FI1B	2,2761	0,71	3,2058	1558,71	4,9969
Etelä-Suomi	FI1C	1,8259	0,71	2,5717	1159,34	2,9815
Pohjois- ja Itä-Suomi	FI1D	1,8688	0,71	2,6321	1299,50	3,4204
Île de France	FR1	2,6516	0,79	3,3778	11942,86	40,3410
Bassin Parisien	FR2	2,2214	0,79	2,8298	1797,81	5,0875
Nord - Pas-de-Calais	FR3	2,0046	0,79	2,5536	4059,26	10,3656
Est (FR)	FR4	2,1246	0,79	2,7065	1795,64	4,8600
Ouest (FR)	FR5	2,1271	0,79	2,7097	2925,41	7,9270
Sud-Ouest (FR)	FR6	2,1324	0,79	2,7164	2404,04	6,5304
Centre-Est (FR)	FR7	1,7745	0,79	2,2605	4104,42	9,2782
Méditerranée	FR8	1,9861	0,79	2,5301	2764,30	6,9939
Jadranska Hrvatska (Adriatic Croatia)	HR03	2,2184	0,79	2,8260	1409,57	3,9834
Kontinentalna Hrvatska (Continental Croatia)	HR04	2,2522	0,79	2,8691	2858,38	8,2009
Közép-Magyarország	HU10	3,3785	0,68	4,9929	2968,25	14,8202
Közép-Dunántúl	HU21	3,3095	0,68	4,8909	1080,97	5,2869
Nyugat-Dunántúl	HU22	3,3828	0,68	4,9993	989,25	4,9455
Dél-Dunántúl	HU23	2,4520	0,68	3,6237	928,60	3,3650
Észak-Magyarország	HU31	2,2224	0,68	3,2843	1185,20	3,8925
Észak-Alföld	HU32	2,5468	0,68	3,7637	1483,20	5,5823
Dél-Alföld	HU33	2,7028	0,68	3,9942	1292,92	5,1642
Border, Midland and Western	IE01	1,5118	0,33	4,5812	1242,51	5,6922
Southern and Eastern	IE02	2,3303	0,33	7,0615	3363,58	23,7520
Nord-Ovest	ITC	3,6554	0,71	5,1850	4090,54	21,2095
Sud	ITF	3,1381	0,71	4,4512	2217,17	9,8690
Isole	ITG	3,0191	0,71	4,2824	3224,74	13,8097
Nord-Est	ITH	4,0595	0,71	5,7581	2205,95	12,7021
Centro (IT)	ITI	3,3831	0,71	4,7987	3167,93	15,2020
Lithuania	LT	2,2386	0,98	2,2843	2992,85	6,8365
Latvia	LV	1,9105	0,98	1,9494	2034,96	3,9670
Noord-Nederland	NL1	2,2640	0,64	3,5654	574,88	2,0497
Oost-Nederland	NL2	1,9500	0,64	3,0709	1207,50	3,7082
West-Nederland	NL3	2,1567	0,64	3,3963	2069,37	7,0283
Zuid-Nederland	NL4	2,0808	0,64	3,2768	1866,14	6,1150
Region Centralny	PL1	2,1367	0,68	3,1576	4254,12	13,4329

Region Poludniowy	PL2	1,9177	0,68	2,8340	3988,48	11,3034
Region Wschodni	PL3	1,8674	0,68	2,7598	1653,45	4,5631
Region Pólnocno-Zachodni	PL4	1,9179	0,68	2,8343	2157,50	6,1151
Region Poludniowo-Zachodni	PL5	1,9000	0,68	2,8078	2060,39	5,7852
Region Pólnocny	PL6	1,7716	0,68	2,6181	1955,43	5,1195
Norte	PT11	2,1858	0,77	2,8573	3667,91	10,4804
Algarve	PT15	2,5993	0,77	3,3978	446,63	1,5176
Centro (PT)	PT16	2,3460	0,77	3,0667	2305,60	7,0705
Lisboa	PT17	2,5553	0,77	3,3402	2815,10	9,4030
Alentejo	PT18	2,3612	0,77	3,0865	750,88	2,3176
Macroregiunea unu	RO1	2,1004	0,68	3,1041	2536,58	7,8737
Macroregiunea doi	RO2	1,7938	0,68	2,6509	2975,84	7,8886
Macroregiunea trei	RO3	3,1718	0,68	4,6874	2507,89	11,7554
Macroregiunea patru	RO4	2,1511	0,68	3,1789	1970,13	6,2629
Stockholm	SE11	2,3627	0,50	4,7732	2109,82	10,0705
Östra Mellansverige	SE12	1,6317	0,50	3,2963	1587,57	5,2331
Småland med öarna	SE21	2,1325	0,50	4,3081	815,58	3,5137
Sydsverige	SE22	1,5589	0,50	3,1493	1412,08	4,4471
Västsverige	SE23	1,8025	0,50	3,6414	1901,32	6,9235
Norra Mellansverige	SE31	1,9845	0,50	4,0090	828,00	3,3194
Mellersta Norrland	SE32	2,0934	0,50	4,2291	368,96	1,5604
Övre Norrland	SE33	1,9293	0,50	3,8975	509,21	1,9847
Vzhodna Slovenija	SI01	1,7496	0,66	2,6509	1096,56	2,9068
Zahodna Slovenija	SI02	2,1262	0,66	3,2215	959,16	3,0899
Bratislavský kraj	SK01	3,6744	0,98	3,7494	609,45	2,2851
Západné Slovensko	SK02	2,7515	0,98	2,8076	1837,68	5,1595
Stredné Slovensko	SK03	2,3390	0,98	2,3867	1348,21	3,2178
Východné Slovensko	SK04	2,1937	0,98	2,2385	1609,30	3,6023
North East (UK)	UKC	1,6977	0,74	2,2943	1310,20	3,0059
North West (UK)	UKD	1,8899	0,74	2,5539	1376,81	3,5163
Yorkshire and The Humber	UKE	1,6563	0,74	2,2382	1328,20	2,9728
East Midlands (UK)	UKF	1,6067	0,74	2,1712	1561,65	3,3907
West Midlands (UK)	UKG	1,7063	0,74	2,3059	1864,02	4,2982
East of England	UKH	1,5447	0,74	2,0874	1969,32	4,1107
London	UKI	2,9505	0,74	3,9872	1449,06	5,7777
South East (UK)	UKJ	1,7095	0,74	2,3101	2215,32	5,1177
South West (UK)	UKK	1,5242	0,74	2,0598	1455,35	2,9977
Wales	UKL	1,6856	0,74	2,2779	1474,81	3,3595
Scotland	UKM	2,0218	0,74	2,7322	1207,75	3,2998
Northern Ireland (UK)	UKN	1,6617	0,74	2,2455	1822,80	4,0931
Average		2,3811	0,66	3,75	2026,58	7,6126