Large, positive, and persistent effects of ALMPs: Evidence from Slovak administrative data

Igor Liška*, Matěj Bělín*, Ondrej Buchel*

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1 Introduction and summary

This paper presents an evaluation of three different Active Labour Market Policies (ALMPs) from Slovak administrative data over the period from the second half of 2021 to March 2024. Using a matched sample of participants and non-participants to ensure common support (Heckman et al., 1997), we find in a differences-in-differences framework numerically large and statistically significant positive employment effects for all three interventions. Specifically, we focus on the following measures:

- A retraining scheme, **REPAS+**, in which participants had about 10 percentage points (pp) higher chances of being employed during the 24-months of post-intervention period compared to non-participants. The cost per supported person was approximately 800 euro on average and it took approximately 20 months to recover the costs of intervention from lowered costs of unemployment (i.e. to get the positive return on the investment, ROI).
- An internship scheme, **Youth Internship**, has led to an approximately 11.6 pp higher chance of employment during the 12-month follow-up period compared to non-participants. The cost per supported person was approximately 1,000 euro on average, and it took around 30 months to obtain the positive ROI.
- A counselling programme, **Individual Counselling for Disadvantaged Job Seekers**, in which the participants experienced approximately 13 pp higher chances of being employed during the follow-up period compared to non-participants. The cost per supported person was approximately 33 euro on average and the positive ROI was approximately 7 months.

From the policy makers' perspective, the relatively fast returns on investment are salient. All three measures have estimated positive ROI within a three-year period, which would generally be seen as attractive payback period for investment decisions (e.g. Yard, 2000). The longest positive ROI was for Youth Internship (about 2.5 years), while the positive ROI for REPAS+ was in the range of 1.5 years for the 2021 cohort and 1.7 years for the 2022 cohort. Youth Internship was the most expensive measure among the AOTPs studied, so its costs were recovered more slowly, although its effect was similar to REPAS+. Individual counselling had an estimated positive ROI at about half a year due to its low cost and positive employment effects. The length of of the payback period is mainly driven by the costs of unemployment and therefore even the more modestly-priced interventions take time to recover their costs.

2 Examined ALMPs

The analysis evaluates the effectiveness of three different active labour market measures targeting different groups of unemployed persons (REPAS+, Youth Internship, Individual Counselling for Disadvantaged Unemployed Persons). A total of 37.2 million euro was spent on these three measures in the sample period and a total of 58,628 unemployed persons participated in them. Given that these programmes were intended for unemployed persons

*Institute of Social Policy, Ministry of Labour, Social Affairs and Family of the Slovak Republic

Table 1: Basic characteristics of the examined ALMPs and their estimated impacts

ALMP	Number of job seekers treated	Money spent	Estimated effect on probability of employment	Estimated payback horizon
REPAS+	42 554	34 134 094 euro	10 pp	20 months
Youth Internship	2 531	2 668 010 euro	11.6 pp	30 months
Individual counselling	13 543	420 057 euro	13 pp	7 months

in different life situations, the effectiveness of the programme is estimated in comparison with similar unemployed persons who did not participate in any other ALMP in the sample period.

The long-term development of the Slovak labour market in terms of labour force participation and unemployment rates is rather positive compared to the Eurozone countries. However, challenges remain, for example in the areas of unemployment of the low-educated labour force, regional differences in participation and participation of young people under 29. One way to enable a more efficient allocation of labour potential is through the use of labour market policy instruments. Expenditure on active labour market policy to facilitate access to suitable employment for potential employees in Slovakia has long been well below the average of the Euro Area and other V4 countries (Czech Republic, Poland, Hungary), suggesting room for improvement for the use of such measures.

2.1 REPAS+

'Support for the retraining of job seekers' (REPAS+) is a scheme aimed at preparing unemployed persons for the labour market by providing them with the opportunity to complete a retraining course in which they will acquire new professional knowledge and skills. The job seeker under this scheme has the opportunity to choose the course and the provider of the retraining course, while the Labour Office reimburses the course fee (up to a certain amount) plus travel and food costs associated with participation. Part of the requirement for participation is to state the job position to which the job seeker would like to apply upon completion of the course and a document showing that such a position is available (e.g. a job advertisement).

REPAS+ was implemented from July 2017 to December 2023 and during this period a total of 4,865 approved courses were attended by a total of 42,554 job seekers (in case one person participated in REPAS+ more than once, we consider their last participation). Of these, 55% were women and 45% were men with an average age of 37 years. In terms of the highest level of education achieved, the largest group among the supported job seekers were high school graduates, who accounted for more than 57%. The second largest group was university graduates - 14%, followed by 13% of primary school graduates. The rest of the participants either did not have the specified education or were without education. Participants without any completed education were approximately 2%. Of the total number of REPAS+ participants, 78% were from the category of disadvantaged job seekers. A total of 34,134,094 euro were spent on REPAS+.

2.2 Youth Internship

The Youth Internship Project supports job seekers from the NEET category - i.e. young people up to the age of 29 who are not employed and are not in the process of education or vocational training. Young job seekers are supported through the participation in an internship corresponding to their education, with funding provided for this internship for three to six months. This project was implemented from September 2022 and the window for applications was closed on 31 July 2023. Of the total number of 2,531 job seekers supported during this period, 68% were women and 32% were men. The average age of the supported applicant was 23 years. The largest group among those supported was high school graduates, who made up 75% of all participants. There were 20% university graduates and only approx. 4% of participants reported primary education as the highest level of education attained. There were less than 1% of participants who had not completed primary education. In total, 2,668,010 euro were spent on this scheme in the sample period, with the average length of the completed internship lasting 4.5 months.

2.3 Individual Counselling for Disadvantaged Job Seekers

The aim of this measure was to help disadvantaged job seekers in the labour market in the aftermath of the COVID-19 pandemic. Disadvantaged job seekers were supported primarily by developing so-called soft skills, which are relevant for finding a job and increasing their own competitiveness in the labour market. These include, for example, activities to encourage the evaluation of their own skills, competencies, or, conversely, obstacles to successful participation in the labour market. The project was implemented from December 2022 and was completed on 31 December 2023, with the total amount of funds disbursed being 420,057 euro.

A total of 13,543 disadvantaged job seekers were supported within the project, of which 64% were women and 36% were men, with the structure of the disadvantaged being as follows: 2,684 fresh graduates (20%), 11,406 job seekers who never held a regular job (84%), 12,156 long-term unemployed (90%), 4,226 job seekers over 50 (31%), 4,387 job seekers with low education (32%), 457 young persons with disabilities and 461 job seekers with other types of disadvantages. We note that a job seeker may have multiple disadvantages, therefore the percentages do not add up to 100%. In terms of highest education level, 59% of those supported were high school graduates, 10% were university graduates, 26% were primary school graduates, and 5% were job seekers with no completed education.

3 Methodology

We identify the effect of ALMP on employment by matching ALMP participants and similar job seekers and then estimating the differences in differences on the matched sample.[1]

We search for a set of comparable participants and non-participants using nearest-neighbour matching with Mahalanobis distance. As matching characteristics of job seekers, we used:

- Registration date in the job seeker registry
- Age
- Gender
- Education
- Region of the Labour Office where the applicant registered + identifier for the regional capital
- Earnings from the last job + binary indicator of missing earnings
- Number of days in the job seeker registry before the start of the sample period
- Probability of successful completion of ALMP estimated by machine learning

The date of registration is important in terms of the timing of the intervention, as it is necessary to capture persons who were registered at the time when ALMP was running. For matching, we use date as a continuous variable, as we do not require that the participants and non-participants be registered on the same day. Age, gender, education, and geographic location are basic variables that characterize the individual and their local labour market. Finally, we consider historical variables that reflect previous interactions between the individual and the labour market. These variables have been shown in the literature to be crucial for correctly comparing ALMP participants and non-participants (Dehejia and Wahba, 1999). The variable "probability of successful completion of ALMP" represents a summary of several characteristics of job seekers. Specifically, this probability was estimated using a LightGBM model, the input of which consisted of the variables listed below.

[1] Doubly-robust estimation (Chernozhukov et al., 2018) on the full sample was conducted as a robustness check with similar results.

Categorical variables:

- District of registration
- Employment status prior to registration (e.g. employed/student/etc)
- Marital status
- Nationality
- Highest education attained
- Field of education
- District of permanent residence
- District of temporary residence, if any
- Previous employment sector (NACE), if any
- Previous employment position (ISCO), if any
- Number of children
- Indicated willingness to commute

Binary variables:

- Gender
- Disability
- Driver's license
- Ability to work with a PC
- Knowledge of a foreign language
- University degree
- Self-employed person
- Voluntarily unemployed
- Promise of future employment
- Interest in going abroad
- Interest in working abroad
- Interest in working as a self-employed person
- Interest in short-term full-time
- Interest in further education
- Interest in internship
- Interest in lifelong learning

Numeric variable:

- Age

The model was trained by 5-fold cross-validation. The output of the model is the estimated probability that a participant with the observed characteristics will successfully participate in a given ALMP. Since matching on a large number of variables is practically impossible, we use this summary variable to capture additional characteristics without increasing the number of matching variables. This plan is propensity-score matching, which has been extended to include additional matching variables. The literature shows that classical propensity-score matching can create highly heterogeneous pairs (King and Nielsen, 2019), which we seek to prevent by explicitly taking into account additional characteristics as suggested by Guo et al. (2020).

After identifying matched pairs,[2] we compare the employment of participants and non-participants in the period τ months after the end of the ALMP.[3] For the comparison in month τ, we use the model:

$$\mathbb{E}[\text{employed}_{it}] = \alpha_i + \alpha_m + \alpha_\tau + \beta_\tau \text{treated}_i \times \mathbb{I}[\tau = t \wedge \tau \geq -12] \tag{1}$$

where $\mathbb{E}$ is the expectation operator, employed_{it} is a binary variable equal to one if person i was registered as working by the Social Security (as an employee, contract worker or self-employed person) in the period t and zero otherwise; treated_i is a binary variable equal to one if person i was a participant in the ALMP and zero otherwise; similarly $\mathbb{I}[\cdot]$ is an indicator function equal to one if its argument is true and zero otherwise; parameters α_i, α_m, and α_τ are fixed effects for person, time period, and time relative to the end of the intervention respectively. Different specifications are tried with varying sets of fixed effects:

(a) included $\alpha_i + \alpha_m + \alpha_\tau$, where α_m is defined as fixed effects for person i's unemployment duration at time t in months;[4]

[2] There are instances when a single non-participant was matched to multiple participants. This is because Labour Offices generally aim to offer ALMP participation for eligible individuals and thus the pool of eligible non-participants is limited. Figure 1 lists the number of individuals in each group.

[3] For non-participants, the date of the intervention is taken to be the date when their matched participants were treated.

[4] Note that conditional on person fixed effect, the unemployment duration is the same as calendar time since a person who became unemployed in March will automatically have unemployment duration of two months in April. Thus, the specification with person fixed effects and calendar month fixed effects will yield numerically identical estimates to specification (a).

(b) included $\alpha_m + \alpha_\tau$ only, sans person fixed-effects, where α_m is defined as monthly fixed effects of unemployment duration;

(c) included $\alpha_m + \alpha_\tau$ only, sans person fixed-effects, where α_m is defined as fixed effects for calendar months.

Comparing specification (a), which includes person fixed-effects, with specifications (b) and (c) which do not, provides a convenient check on the success of the matching that preceded the estimation of the model in (1). To the extent that the matching found comparable participants and non-participants, their time-invariant characteristics should be equal in expectation, rendering the use of individual fixed effects superfluous. Thus, on a successful match, results from all specifications should be similar.

To obtain ROI on the ALMPs, we estimate the time horizon T at which:

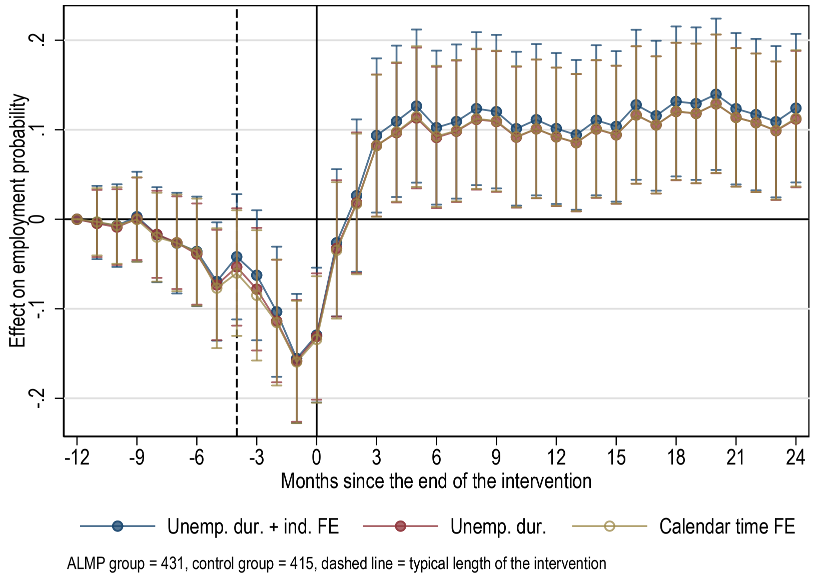
$$\text{costs of ALMP} - \underbrace{\sum_{\tau=t_0}^{T} \widehat{\beta}_\tau \times \text{costs of unemployment}}_{=\text{savings from lower unemployment}} = 0 \tag{2}$$

The results are shown in Table 1. The estimated coefficient $\widehat{\beta}_\tau$ from Equation (1) appears in Equation (2) with negative sign since it estimates the ALMP's effect on the probability of *employment*. The time period t_0 marks the start of the intervention (rather than its end) to account for the fact that participants have opportunity costs of attending ALMP rather than devoting the time spent on ALMP to job search.

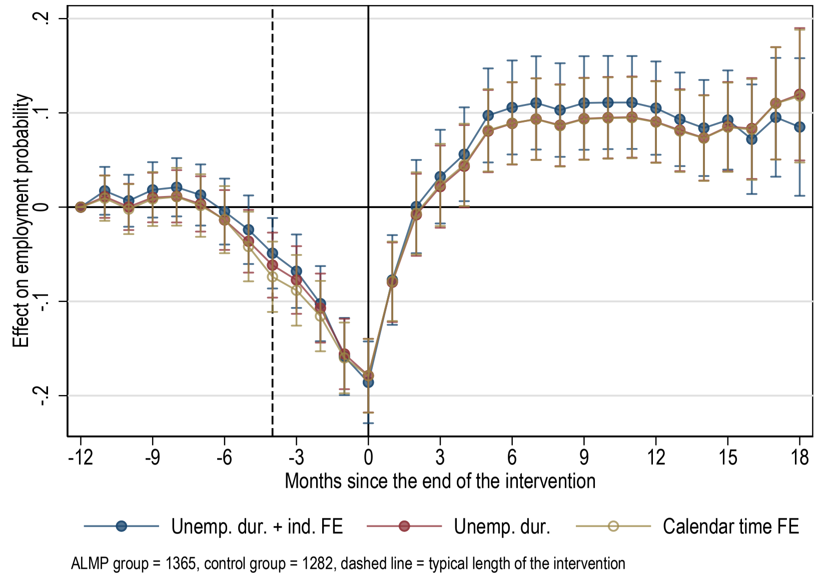
To be conservative, the costs of unemployment to the state were taken to be 600 euro per person per month, which is at the low end of the estimated costs of unemployment in Slovakia (Domonkos and König, 2015; Domonkos, 2022, after adjusting for inflation) and do not take into account any second-order costs such as unemployment scarring (e.g. Filomena, 2024). To the extent that the interventions have any positive effect at all, assuming lower costs of unemployment would lengthen the payback period T.

Figure 1: Estimated effects from Eq. (1) on matched sample

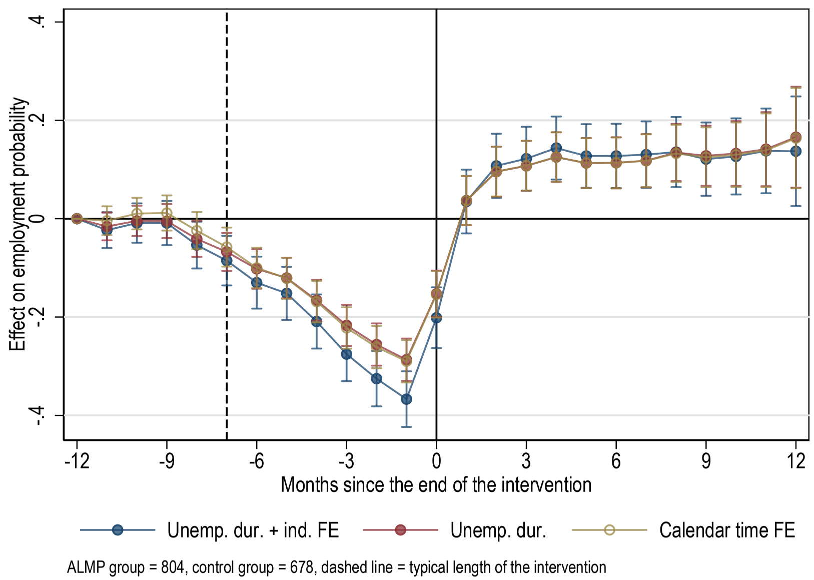
(a) REPAS+ 2021



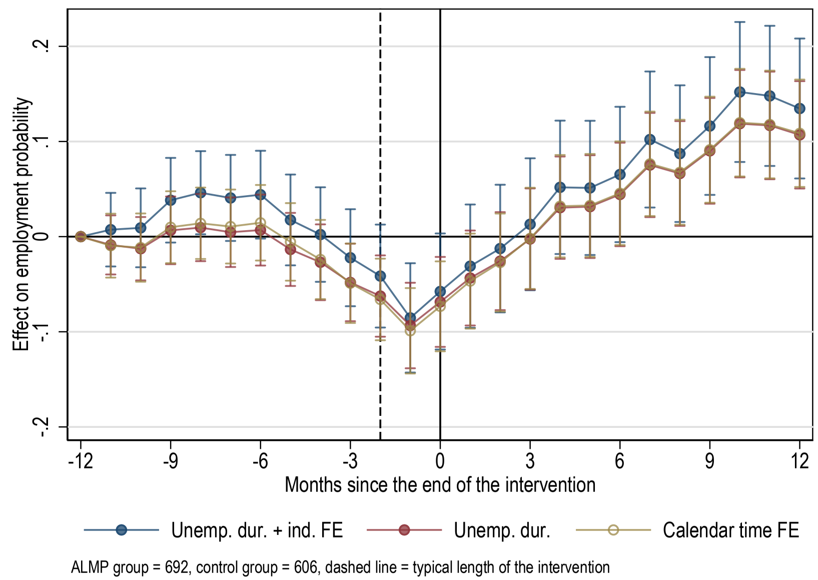
(b) REPAS+ 2022



(c) Youth Internship



(d) Individual Counselling



4 Results

4.1 REPAS+

Figure 1a graphically shows the estimated coefficients $\widehat{\beta}_\tau$ for REPAS+ participants who were treated during the second half of 2021. The coefficient for the twelfth month before the end of the intervention is normalized to zero and until the start of the ALMP we observe only small changes in employment from this baseline period, which would be consistent with the crucial 'parallel trends' assumption for difference-in-differences models.

As explained in the Methodology section, 3 sub-alternatives are presented: a variant with individual fixed effects + fixed effects (FE) for each month of the unemployment duration (blue line); a variant without individual FE but with monthly FE for each month of the unemployment duration (red line); and a variant without individual FE with constants for calendar months (yellow line).

A stable and practically zero difference compared to the baseline period has the interpretation that no differences in the trend of unemployment between ALMP participants and their matched non-participants are observed, which is an indication that the matching was successful. This is followed by the period of the ALMP itself, the typical length of which is delimited by vertical lines.[5] Here we observe reduced employment among participants compared to non-participants. This phenomenon can be interpreted as a head start of non-participants in finding a job while participants are engaged in the retraining program. Finally, we observe the period after the end of the ALMP, which is marked by a stable difference of about 10 to 13 percentage points (pp) between participants and non-participants. This is the estimated employment advantage of participants gained from the REPAS+ program.

It is important to note that the results do not change significantly depending on the inclusion of individual FEs in the model, suggesting that unobserved characteristics of individual job-seekers were adequately captured by matching.

As a robustness test, we estimated all models above on REPAS+ participants in the second half of 2022. The results are shown in Figure 1b and are substantively similar to those from the previous cohort (Figure 1a). Here, it is not possible to follow the full 24 months since the end of the ALMP, as employment data ends in March 2024, but this second sample provides us with an independent view of the effect of this intervention.

The estimated effect obtained here is appreciably higher than the effect of the older REPAS program analysed by Petráš (2018). Our results are closer to more recent estimates (Štefánik, 2021), which place the effects of the REPAS program to be between 10 pp and 15 pp in the first year after the end of the intervention.

4.2 Youth Internship

The results are depicted in Figure 1c and are analogous to those from the REPAS+ measure, and therefore the interpretation above applies. The estimated effect of the Youth Internship after 6 months from its end was 11.6pp, meaning that participants had more than 11pp higher employment rate compared to non-participants six months after the end of the internship, other things being equal. This result is again significant at the 5% level and the corresponding confidence interval ranges from 3.9 to 19.2pp. The effect seems to persist a full year after the intervention albeit with slightly larger uncertainty. However, both in terms of magnitude and significance, our results accord well with those of a similar program ("Praxou k zamestnaniu", roghly translated as "Internship-to-Employment"), which was analysed by Petráš (2023), who obtained practically the same effect. Similar results were found on older data by Štefánik et al. (2020).

4.3 Individual Counselling

The results for Individual Counselling are shown in Figure 1d and indicate slowly growing effects after the end of the intervention. Initially, the effects are insignificant, even after 6 months but after 12 months, the effect was estimated to be 13 pp with a 95% confidence interval ranging from 6 to 21pp. Thus, even the relatively modest intervention in terms of

[5]The length of ALMP can vary significantly, especially for individually targeted interventions. Further differences in the length of AOTP may arise for administrative or medical reasons. Therefore, the vertical lines in Figure 1 were drawn to encompass 90% of the observed treatment durations.

budget can have potentially large and positive impact but there is a considerable uncertainty attached to the results.

5 Conclusions

This analysis evaluated the net effectiveness of three different active labour market measures: a re-training programme REPAS+, the Youth Internship Project for young job seekers, and Individual Counselling for disadvantaged job seekers in the period from the second half of 2021 to March 2024. We identified numerically large and statistically significant positive effects of all three interventions on employment.

REPAS+ led to a 10 to 13 percentage point advantage in employment rates for participants compared to comparable non-participants. This effect is statistically significant and stable over two years after the end of the intervention.

The high efficiency and relatively quick ROI of the REPAS+ programme demonstrates the importance of developing new skills and upgrading qualifications, which is in line with the EU consensus on the need to build new skills to strengthen sustainable competitiveness, bolster social justice and build resilience in response to crises.

The effect of the **Youth Internship** measure was around 12 percentage points, which corresponds to the results from earlier studies. The results, therefore, show that among younger job seekers it is important to gain work experience that helps them find employment. Based on these findings, it would be possible to recommend expanding cooperation between schools and employers so that students can gain work experience during their studies through internships or temporary work, which will make them more attractive to employers after graduation.

The internship ALMP was the measure with the longest payback period among the studied interventions but this fact ought to be viewed in context of the ALMP's implementation. Youth Internship was evaluated in the period of the second half of 2023 and the first half of 2024, which was characterized by high employment and relatively rapid entry of graduates into the labour market. This situation meant that the counterfactual outcomes for participants were very good, "setting the bar" rather high for the ALMP. Nevertheless, positive and statistically significant effects of the internship programme were found, which supports the usefulness of this measure. A plausible conjecture in light of these results would be that an effect of an analogous measure in periods of economic slowdown would be even more pronounced. Thus, our results advocate for cooperation between the education system and the employers, whether through internships, dual education and other channels through which students and graduates gain work experience.

The effect of **Individual Counselling** for disadvantaged job seekers was estimated with high uncertainty. After half a year from the end of the counselling, no statistically significant effect was observed, but over time the effect grew to approximately 15 pp but with an uncertainty of $\pm$ almost 7 pp (at the 5% significance level). However, it should be noted that individual counselling is a relatively inexpensive measure, which compensates for the higher level of uncertainty in the measured effects. The costs of individual counselling are much lower than for other ALMPs in this study, and the shorter duration of counselling creates fewer negative effects on employment during the duration of counselling.

The results of Individual Counselling indicate that in the case of disadvantaged job seekers, even a relatively low-cost investment has a significant and positive impact. The implied policy recommendation would be to focus on training Labour Office staff so that they can be in a position to provide better quality counselling services.

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