Comparison of Assistance Policies for Vulnerable Groups Based on Markov Models

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Abstract. Employment assistance for vulnerable groups involves basic living security and sustained income growth. This group dynamically transitions between unemployment, temporary employment, low-income employment, and high-income employment. The mechanisms and durations of these three types of assistance measures differ, making it difficult to reflect the phased effects of policies at a single point in time. This paper constructs a four-state Markov reward model with a common benchmark of no new policy implementation. It sets up scenarios of living allowances, job support, and education and training, and uses a time-varying transition matrix to describe the gradual formation of training effects. The model compares policy paths over 12, 36, and 60 months from four dimensions: unemployment rate, cumulative discounted benefits, employment quality, and high-income employment rate. The robustness of the policy ranking is tested through 5000 parameter simulations. Numerical simulations show that the three types of policies each have phased advantages in terms of living security, employment entry, and employment quality improvement. Early income security, concurrent job matching, and subsequent skills enhancement can form a continuous assistance path, providing a quantitative basis for phased allocation of policy resources.

Keywords: Vulnerable groups; Markov chain; Employment assistance; Education and training; Robustness analysis

1 Introduction

Assistance to vulnerable groups should not only alleviate unemployment and income interruption, but also improve their ability to achieve stable employment and sustained income growth. The beneficiaries of assistance will continuously shift between unemployment, temporary employment, low-income employment and high-income employment, and the policy effect will thus manifest as a change in state over a period of time. Finite-state Markov chains can be used to characterize this process using state distribution and transition probability [1]; cumulative reward and discounted reward criteria can incorporate the employment status benefits of each period into the same evaluation scale [2].

© The Author(s) 2026
B. P. Siba et al. (eds.), *Proceedings of the 2026 5th International Conference on Public Service, Economic Management and Sustainable Development (PESD 2026)*, Advances in Economics, Business and Management Research 411,
https://doi.org/10.2991/978-94-6239-825-2_56

Living allowances, job support, and education and training are common policy tools in assisting vulnerable groups, but they intervene in the employment process at different stages. Living allowances primarily ease financial pressure stemming from income interruptions; job support directly improves unemployed individuals' prospects for securing work and stable employment; and education and training enhance subsequent job options and income levels through skill accumulation. Because the three types of policies differ in their target groups, transmission mechanisms, and speed of implementation, the same policy may exhibit different effects at different stages of implementation. Comparing only the number of unemployed or high-income employed individuals at a single point in time easily overlooks the continuous migration of beneficiaries between various employment and income states, and fails to simultaneously reflect short-term living security and medium- to long-term employment quality. Therefore, it is necessary to examine the phased effects of different assistance measures from the perspective of dynamic state transitions and multi-term evaluations, establishing a unified analytical basis for the sequential arrangement and combined use of policy tools.

Research on poverty and employment vulnerability has shifted from static identification to dynamic transformation. Cappellari and Jenkins used a first-order Markov model to identify low-income status dependence [3]; Ward used panel data from rural China to distinguish between temporary poverty and persistent poverty [4]. Domestic research has focused on poverty persistence, vulnerability to relapse into poverty, multidimensional poverty dynamics, and household transformation in underdeveloped rural areas [5-8], indicating that continuous migration is an important measure for observing the effectiveness of assistance.

Employment support literature reveals the time-dependent differences in policy tools. Meta-analysis of proactive labor market projects shows that the average impact of projects is close to zero in the short term, becomes more positive after two to three years, and human capital projects have higher medium- to long-term benefits [9]. McKenzie reviews training, wage subsidies, and employment services in developing countries [10]; Crépon and van den Berg discuss project heterogeneity, implementation process, and cost-benefit [11]. Randomized experiments in Colombia and Turkey examined the impact of training on employment income and employment quality [12-13]. Accordingly, job support and education and training adopt different transfer directions and speeds of action.

Cash transfer experiments have shown that subsidies can improve household consumption and psychological well-being relatively quickly [14]; the six-country comprehensive assistance experiment shows that consumption support and asset and training linkage can lead to sustained improvement [15]. Based on this, this paper incorporates direct welfare, employment entry and long-term employment quality into a common benchmark chain to compare the three types of policies. The monthly changing training matrix adopts a time non-homogeneous Markov chain [16].

Existing research has provided empirical evidence on poverty dynamics, labor market programs, and cash transfers, respectively. However, these three types of policies typically use different samples, observation periods, and effectiveness indicators, making it difficult to directly compare the phased effects of these policies within the same

group and to answer which policy tools should be prioritized at different stages of assistance. Based on this research gap, this paper compares the policy effects of living allowances, job support, and education and training under a unified state space, initial distribution, and evaluation period. It focuses on examining the differences between short-term living security, employment entry, and medium- to long-term employment quality, providing a comparable analytical framework for the sequential arrangement and combined use of these three types of policies.

2 Problem Analysis and Model Setting

2.1 State Division and Initial Conditions

This paper categorizes employment and income status into four states based on the main employment situation at the end of each month: A (unemployment) refers to those who are willing to work but have not yet obtained a job; B (temporary employment) refers to those whose employment relationship is unstable and whose income fluctuates greatly; C (low-income employment) refers to those whose employment is relatively stable but whose income is still at a low level; and D (high-income employment) refers to those whose income and employment stability are both relatively high. A, B, C, and D are fixed to represent the above states throughout the paper, and D is the relatively high-income state within the model.

The initial population of 10,000 participants is distributed across the four states as follows: 2000 in A, 3000 in B, 3400 in C, and 1600 in D, corresponding to the initial state distribution $\pi_0 = (0.20, 0.30, 0.34, 0.16)$. The time step was 1 month, simulating 60 months, and key results were extracted at months 12, 36, and 60.

The state classification considers both employment stability and relative income level: the difference between state A and the others is whether or not one has obtained employment; the difference between B and C is whether employment and income fluctuations tend to stabilize; and the difference between C and D is income level. At the end of each month, classification is performed based on the dominant employment and income situation, so the states are mutually exclusive and cover all research subjects. A transition from A to B, from B to C, and from C to D represents progressive improvement, while a reverse transition indicates a deterioration in employment or income.

2.2 Symbols and Evaluation Indicators

Table 1 summarizes the main symbols used in the model and their corresponding meanings and value ranges.

2.3 Policy Mechanisms and Basic Assumptions

The transition matrix adopts a “common benchmark - policy adjustment” setting. $P^{(0)}$ represents the natural monthly transition without new policies, while $P^{(s)}$ $P^{(j)}$, and $P^{(e)}$are adjusted according to the mechanisms of living allowances, job support,

and education and training, respectively. Each matrix maintains diagonal element dominance, the transition probability of adjacent states is higher than the transition probability of cross-level states, and each row of elements is non-negative and sums to 1. Table 2 outlines the mechanism of action and direction of parameter adjustment for each of the three policy types.

Table 1. Main symbols and their meanings

symbol	meaning	Values or dimensions
S_t	Employment and income status at the end of month t	A, B, C, and D have fixed meanings.
π_t	The state distribution row vector at the end of month t	Sort by (A, B, C, D), and the sum of the elements is 1.
k	Policy Scenario Index	0、s、j、e, corresponding to the baseline, living allowance, job support, and education and training scenarios in order.
$P^{(0)}, P^{(s)}, P^{(j)}$	Benchmark, living allowance and job support transfer matrix	4×4. Rows and columns are ordered by (A, B, C, D).
$P^{(e)}$	Target matrix after education and training are fully effective	4×4The row and column order is (A, B, C, D).
$P_t^{(e)}$	The time-varying matrix used in the education and training scenario in month t	Obtained by $P^{(0)}$ weighting $P^{(e)}$
w_t、τ	Training effectiveness achievement weight and time delay parameter	$w_t \in [0,1]$, $\tau = 12$ months
q、b	Employment status rewards and subsidies are direct welfare rewards	Sort by (A, B, C, D)
δ、T	Monthly discount factor and evaluation period	$\delta = 0.995$T can be 12, 36, or 60 months.
$I(\cdot)$	Indicator Function	The value is 1 if the condition is true, and 0 otherwise.

Table 2. The Mechanism of Action and Parameter Adjustment Direction of Three Types of Policies

Policy Scenario	Main target	Direction of transition probability adjustment	Expected performance
Baseline Scenario	All objects	Maintaining the natural flow of employment and income status	As a unified comparison benchmark
Living allowance	Group A (unemployed) and Group C (low-income employed)	Reduce the probability of transitioning to a worse state, and moderately increase the probability of retention and upward movement to adjacent states.	Early direct welfare improvements were relatively rapid.

Policy Scenario	Main target	Direction of transition probability adjustment	Expected performance
Job support	Group A (unemployed) and Group B (temporary employment)	Decrease the probability of continuing in state A and increase the probability of entering state C or D.	The proportion of short-term unemployment has decreased rapidly.
Education and Training	Groups B (temporary employment) and C (low-income employment)	The probability of shifting to D (high-income employment) increases over time.	Improvement in the quality of employment in the medium and long term

The model assumes a population size of 10,000 during the study period, with each person in one state per month; a fixed monthly matrix is used for baseline, living allowance, and job support, while a time-varying matrix is used for education and training; living allowance is included in direct welfare rewards for the first 12 months. Transition probabilities are used as replaceable scenario parameters and can be updated subsequently using regional panel or administrative tracking data.

Scenario parameters are set according to three principles: "clear mechanism direction, comparable adjustment range, and satisfied probability constraints." The baseline matrix retains a high probability of state persistence; living allowances transfer some of the probability of deterioration to the current state or move it to adjacent states; job support transfers the persistence probability in rows A and B to columns C and D; education and training focuses on adjusting rows B and C and sets a gradual implementation process. All adjustments are completed within the same row, therefore the policy matrix maintains the properties of a random matrix, and numerical differences can be directly interpreted as changes in monthly transfer opportunities. Matrix adjustments prioritize the state rows directly affected by the policy, and each probability change corresponds to a specific object and transfer direction, facilitating re-estimation using regional data.

3 Mathematical Model Construction

3.1 State Transitions and Policy Matrix

Let $p_{ij} = \Pr(S_{t+1} = j \mid S_t = i)$ denote the conditional probability of transitioning from state i to state j, where $i, j \in \{A, B, C, D\}$. Any transition matrix satisfies $p_{ij} \geq 0$ and the sum of elements in each row is 1. For the scenario without a time-varying term k, t the state distribution for the month is recursively derived as follows:

$$\pi_{t+1} = \pi_t P^{(k)}, \qquad k \in \{0, s, j\}$$

$P^{(0)}$ This represents the natural monthly transfer when there are no new policies. Employment status is continuous, so the diagonal element is the largest, and D (high-income employment) maintains a high retention rate. The specific transition probabilities of the baseline scenario are shown in Table 3.

Table 3. Baseline Scenario Transition Matrix $P^{(0)}$

S_t for the current period/S_{t+1} for the next period	A Unemployment	B Temporary employment	C. Low-income employment	D High-income employment
A Unemployment	80.0%	10.0%	8.0%	2.0%
B Temporary employment	8.0%	78.0%	11.0%	3.0%
C. Low-income employment	4.0%	6.0%	84.0%	6.0%
D High-income employment	2.0%	2.0%	4.0%	92.0%

The living allowance matrix primarily reduces the probability of deterioration in states A (unemployment) and C (low-income employment), and increases the probability of moving to adjacent states and retaining favorable states; the job support matrix focuses on reducing the probability of persistence in states A (unemployment) and B (temporary employment), and increasing the probability of entering state C (low-income employment) or D (high-income employment).

The specific transition matrix for the living allowance scenario is presented in Table 4. Table 5 reports the full transition matrix for the job support scenario. Taking scenario A as an example, in the baseline scenario, the probability of an unemployed person remaining in scenario A next month is 0.80. The probability drops to 0.78 in the living allowance scenario and 0.66 in the job support scenario, with the latter simultaneously increasing the combined probability of transitioning from A to B, C, or D to 0.34. For scenario B, the probability of job support transitioning to C or D increases from 0.14 to 0.255, reflecting the direct contribution of job information, employment matching, and employment services to employment stabilization. The adjustments to the living allowance across different scenarios are relatively gradual, primarily aimed at reducing the downside risk for the unemployed and low-income groups and improving the retention rate of those in favorable scenarios.

Table 4. Living allowance transfer matrix $P^{(s)}$

S_t for the current period/S_{t+1} for the next period	A Unemployment	B Temporary employment	C. Low-income employment	D High-income employment
A Unemployment	78.0%	11.0%	9.0%	2.0%
B Temporary employment	6.0%	79.0%	12.0%	3.0%
C. Low-income employment	2.5%	4.5%	86.0%	7.0%
D High-income employment	1.0%	1.5%	3.5%	94.0%

Table 5. Job support transfer matrix $P^{(j)}$

S_t for the current period/S_{t+1} for the next period	A Unemployment	B Temporary employment	C. Low-income employment	D High-income employment
A Unemployment	66.0%	18.0%	13.0%	3.0%
B Temporary employment	4.5%	70.0%	20.0%	5.5%
C. Low-income employment	2.5%	5.0%	84.0%	8.5%
D High-income employment	1.2%	1.8%	5.0%	92.0%

3.2 The Time-Change Shift in Education and Training

Analysis shows that the effects of human capital projects are more pronounced in the medium to long term [9]; randomized experiments in Colombia and Turkey provide evidence that training affects employment income and employment quality [12-13]. This paper first sets up a complete effectiveness matrix $P^{(e)}$, and then connects $P^{(0)}$ and $P^{(e)}$ with the realization weight w_t. $w_1=0$ in the first month, and increases month by month thereafter; the larger τ is, the slower the training effect takes shape. This structure belongs to a time-nonhomogeneous Markov chain [16]. The target transition matrix after education and training takes full effect is given in Table 6.

$$P_t^{(e)} = (1 - w_t)P^{(0)} + w_t P^{(e)}, \qquad w_t = 1 - \exp\left[-\frac{t-1}{\tau}\right]$$

Table 6. Matrix after education and training take effect $P^{(e)}$

S_t for the current period/S_{t+1} for the next period	A Unemployment	B Temporary employment	C. Low-income employment	D High-income employment
A Unemployment	74.0%	11.0%	11.0%	4.0%
B Temporary employment	5.0%	68.0%	19.0%	8.0%
C. Low-income employment	2.5%	4.5%	79.0%	14.0%
D High-income employment	1.0%	1.5%	4.5%	93.0%

The baseline time lag parameter is set to $\tau = 12$ months. As w_t rises with time, the probability of remaining in states A, B, and C gradually decreases, while the probability of transitioning to state D (high-income employment) gradually increases.

Under the setting of $\tau = 12$ the given settings, the achievement weights for months 12, 36, and 60 are approximately 0.60, 0.95, and 0.99, respectively. Therefore, the training scenario in the first year simultaneously incorporates significant baseline mobility and some training effects, while after three years it essentially approximates the target matrix. The target matrix increases the probability of transitioning from B to D from 0.03 to 0.08, and the probability of transitioning from C to D from 0.06 to 0.14, corresponding to an increased opportunity to enter more stable, higher-paying positions after skill accumulation.

3.3 Reward Evaluation and Calculation Methods

Let there be an employment status reward vector $q = (0, 0.30, 0.60, 1.00)$and a living allowance direct welfare reward vector $b = (0.25,\ 0.15,\ 0.07,\ 0)$, both (A, B, C, D) sorted and scaled using a normalized relative welfare scale. The discounted cumulative welfare for policy scenario k over T months is calculated as:

$$R^{(k)}(T) = \sum_{t=0}^{T} \delta^t \pi_t q + \sum_{t=1}^{\min(T,12)} \delta^t I(k = s)\pi_{t-1} b$$

The monthly discount factor δ is set to 0.995. The first item is the cumulative employment status reward, and the second item is the direct benefits of the cumulative living allowance over the first 12 months. This paper compares $R^{(k)}(12)$the unemployment rate in the 12th month, the employment status quality index in the 36th month, and the high-income employment rate in the 60th month. The employment status quality index is assigned q values based on employment stability and income level, resulting $\pi_t q$ in a range of 0 to 1. b The direct subsidy benefits captured by vector b are concentrated on three categories (A, B, and C), and decrease as employment income improves.

4 Numerical Experiments and Result Analysis

4.1 Dynamic Paths

Figure 1 illustrates the 60-month state distribution paths of the three types of assistance policies. The model simulates 60 months from π_0 the start. Job support reduces the unemployment rate most quickly in the early stages, dropping to 6.32% in the 12th month and approaching 5.83% after the 36th month; living allowances reduce the unemployment rate to 11.30% in the 12th month and 9.51% in the 60th month; education and training reduce the unemployment rate to 12.58% at month 12; as training effects gradually emerge, the rate falls to 6.94% and 6.37% at months 36 and 60, respectively.

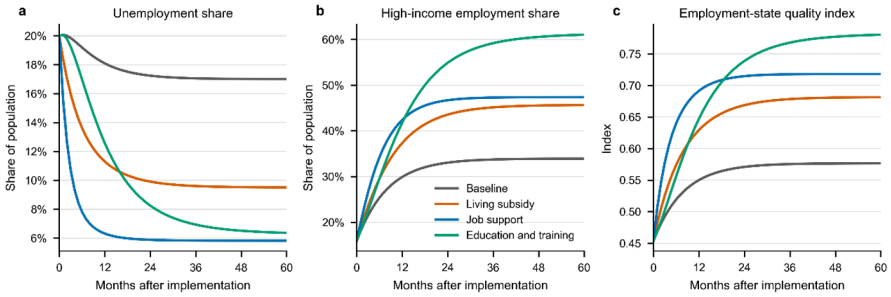


Fig. 1. The 60-month status path of the three types of assistance policies

The proportion of high-income employment shows different paths. At month 12, the high-income employment rate under the job support scenario was 42.40%, and that under the education and training scenario was 41.81%; in the 36th month, education and training rose to 59.16%, and in the 60th month, it reached 61.01%, while job support and living allowances were 47.37% and 45.63% respectively during the same period.

Compared to the baseline scenario, all three policy categories improved employment distribution in the 12th month. Job support reduced the unemployment rate by 11.78 percentage points from 18.10% and increased the high-income employment rate by 12.47 percentage points; living allowances reduced the unemployment rate by 6.79 percentage points; and education and training, even before fully taking effect, increased the high-income employment rate by 11.88 percentage points. By the 60th month, education and training had increased the high-income employment rate by 27.09 percentage points relative to the baseline scenario, and the employment status quality index improved from 0.577 to 0.780, with a significant expansion in long-term growth.

4.2 Policy Implications

Table 7 presents the evaluation results of the three policies across different time horizons.

Table 7. Evaluation results for different timeframes

plan	12-month unemployment percentage	12-month discount cumulative benefits	36-month employment status quality index	60-month high-income employment percentage
Baseline Scenario	18.10%	6.46	0.575	33.91%
Living allowance	11.30%	8.18	0.678	45.63%
Job support	6.32%	7.75	0.718	47.37%
Education and Training	12.58%	6.97	0.768	61.01%

Table 7 and Figure 2 show that job support achieved the lowest unemployment rate of 6.32% in the 12th month, living allowances achieved the highest cumulative welfare benefit of 8.18 in the first 12 months, and education and training achieved the highest employment status quality index of 0.768 in the 36th month and the highest high-income employment rate of 61.01% in the 60th month. These three types of policies correspond to early welfare guarantees, rapid employment entry, and medium- to long-term employment quality improvement, respectively. In terms of timeline, living allowances first stabilize basic living standards, job support expands employment entry, and education and training subsequently promotes further improvement in employment quality and income levels.

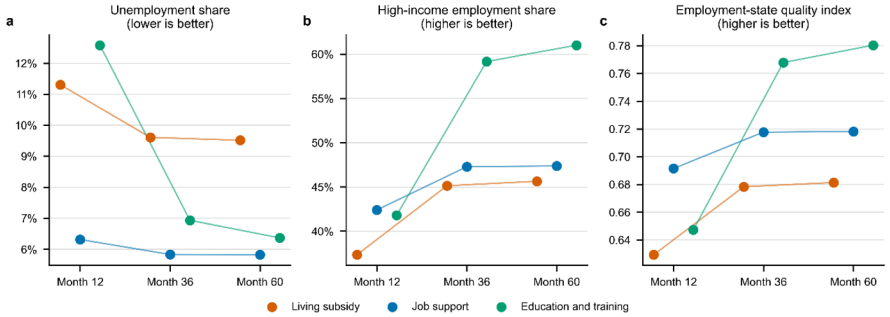


Fig. 2. Comparison of Three Types of Support Policies

Based on this, a phased assistance arrangement can be formed: for the first 6-12 months, basic expenditures are stabilized with living allowances, and job development, employment services and matching support are provided at the same time; after entering employment, education and training that are in line with job requirements are continued to be provided to promote the transfer of B (temporary employment) and C (low-income employment) to D (high-income employment). International evidence of comprehensive assistance projects also supports the formation of a continuous policy chain of consumption support, employment promotion and capacity building [15].

4.3 Robustness Analysis

Table 8. Monte Carlo simulation results

Evaluation Objectives	Living allowance	Job support	Education and Training
12-month discount cumulative benefits	94.5%	5.5%	0.0%
12-month unemployment percentage	1.4%	97.7%	0.9%
36-month employment status quality index	2.3%	9.5%	88.1%
60-month high-income employment percentage	3.4%	3.9%	92.7%

Robustness analysis was performed using 5000 Monte Carlo simulations. The initial state proportions and matrix rows were extracted from the Dirichlet distribution, the concentration parameters of the Dirichlet distribution were set to the range of 300–450, and the training lag τ varied uniformly between 5 and 12 months. The four evaluation indicators were recalculated for each simulation, and the results are shown in Table 8.

Living allowances ranked first in cumulative 12-month cash benefits in 94.5% of the simulations, while job support yielded the lowest unemployment rate in 97.7% of the simulations. Education and training ranked first in the 36-month employment status quality index and the 60-month high-income employment rate, with 88.1% and 92.7% of the experiments respectively. Figure 3 further shows the median and 95% empirical range of policy differences as a function of training time lag.

Experimental results show that short-term welfare and short-term employment are the most stable conclusions; medium- and long-term indicators are more sensitive to changes in training lag and transfer probability, but education and training still maintain a significant majority advantage. As training lag increases, the difference between education and training and job support for long-term high-income employment gradually narrows, indicating that course duration, skill development speed, and job availability jointly determine the time to realize long-term benefits.

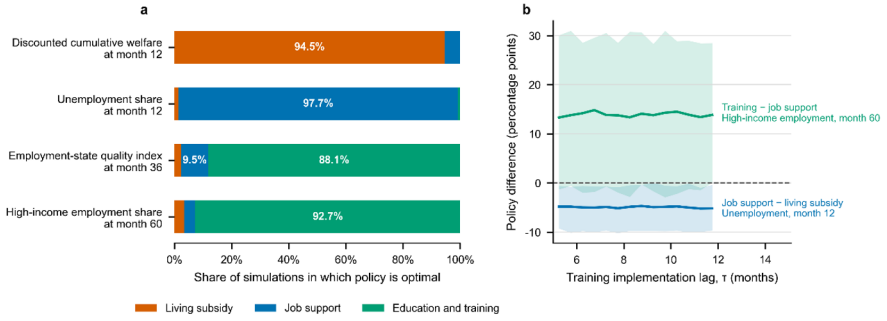


Fig. 3. Robustness Analysis

5 Conclusion

This paper constructs a four-state Markov reward model based on a common benchmark chain, comparing living allowances, job support, and education and training under the same initial distribution and time scale. A, B, C, and D represent unemployment, temporary employment, low-income employment, and high-income employment, respectively. A fixed transition matrix describes the monthly effects of living allowances and job support, while a time-varying transition matrix describes the process of education and training from participation and skills formation to job matching. A discounted reward function connects the benefits of employment status with the direct welfare of living allowances.

Numerical results show that the policy advantages vary with objectives and timeframes: job support reduced the unemployment rate to 6.32% in month 12, living allowances achieved a cumulative 12-month discounted benefit of 8.18, and education

and training achieved an employment status quality index of 0.768 in month 36, increasing the proportion of high-income employment to 61.01% in month 60. In 5000 parameter simulations, the short-term benefit advantages of living allowances, the short-term employment advantages of job support, and the long-term high-income advantages of education and training were established in 94.5%, 97.7%, and 92.7% of the samples, respectively. Policy implementation can be based on this to form a continuous arrangement of initial income security, concurrent job matching, and subsequent skills enhancement, and the tasks at each stage can be tracked using the unemployment rate, employment status quality, and the proportion of high-income employment.

Future research could organize employment registration, low-income population monitoring, and training tracking records into state pairs for adjacent periods, and use maximum likelihood, Bayesian update, or hierarchical Markov models to estimate the regionalization transfer matrix, setting grouping parameters according to age, education level, care burden, and labor demand. Further incorporating policy costs would allow for comparison of the reduction in unemployment rate and improvement in employment quality per unit of resources, providing a basis for selecting specific regional support programs.

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