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Semi- Markov processes in labor market theory: The case of Switzerland

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Abstract

The mathematical base of stochastic labor markets is the theory of Markov processes, and the uncertainty is its indivisible part. In this paper, Markov processes are used to calculate the equilibrium position, the time needed to reach it, natural rate of unemployment, transition probabilities and first passage time. While the theories of uncertainty give explanation why workers transit, identify the market anomalies and best fitted Markov model. The findings showed that the semi-Markov labor model better fits Switzerland data. Furthermore, the time needed to reach the equilibrium position is 4.6 years and the right number of employed workers, unemployed and inactive workers maintain the highest rate of uncertainty reduction is 67.16 %, 1.31 % and 31.54 % respectively, where 1.31% is the natural rate of unemployment. What is also important to point out is that the percent of employed workers in Switzerland is expected to decrease from 79.4% to 67.16%, while the percent of inactive workers is projected to increase significantly, from 15.9%to 31.54%. Workers who are expected to transit to an *Inactive state* in the future and stay there for a longer time are the older works (above 45 years). In other words, the Switzerland labor market is directed toward its "bad" equilibrium. In the end, the demographic structure is considered as one of the main factors for sustainable growth. Therefore, the government is suggested to control the population growth and put into practice new-innovative youth policies,becausethe traditional pro-family policies implemented to encourage bigger families has failed to increase the fertility rates to expected levels.

1. INTRODUCTION

The mathematical base of stochastic labor markets is the theory of Markov processes, and the uncertainty is its indivisible part. In economics, uncertainty is a situation which embraces unknown and imperfect information. In other words, a state of having limited knowledge where it is impossible to precisely identify the current state, a future outcome, or more than one likely outcome.

In this paper, Markov processes are used to calculate the equilibrium position, the time needed to reach it, natural rate of unemployment, transition probabilities and first passage time. While the theories of uncertainty give explanation why workers transit, identify the market anomalies and best fitted Markov model.

In essence, the theories of uncertainty explain why the most probable path in labor markets is always that which is the shortest and keep to the steepest state that will have just the right number of employed workers, unemployed and inactive workers to maintain the highest rate of uncertainty reduction. The worker's transit from a higher uncertainty state to a lower uncertainty state and in this transit worker is reducing the uncertainty level. In literature, this is recognized as an uncertainty reduction theory. The groundwork of the uncertainty reduction theory branches of the information theory, developed by Claude Shannon and Warren Weaver in 1949. If the worker is at the lowest possible uncertainty level, it is said to be in a stable state, and if it is at a higher uncertainty level, it is said to be unstable. In other words, the lower uncertainty level of a state, the more stable worker is- the worker will not transit.

So, how to determine which Markov model fits the labor data best?

When the **Employment state** is the lowest uncertainty state than we can say that the labor market is stable/efficient because the worker will stay employed, will not transit. (positive market anomaly has been detected). In this case, the continuous-time Markov chain better fits the data. However, when the **Unemployment state or Inactive state** is the lower uncertainty state than the labor market is unstable/inefficient (negative anomaly has been detected), and semi-Markov model batter fits the data. In this case, in future, it is expected the employed workers to transit and become unemployed or inactive, depending on the state's uncertainty level.

What is also important to point out a state of lower uncertainty under one set of circumstances may be a state of higher uncertainty under other circumstances. The findings showed that the Employment state is unstable when the old dependency ratio>youth dependency ratio, but stable when the old dependency ratio<youth dependency ratio. By definition, the dependency ratio is the age-population ratio of people not in the labor force (the dependent part compresses young from 0 to 14 and/or old's above 65) and those in the labor force (the productive part compresses those from 15 to 64). This ratio is used to quantify the pressure on the productive population.

Studying the Switzerland labor market, I notice that the labor market in 2016 is highly unstable/inefficient, i.e., negative anomaly is present. Running two additional tests (Cox proportional regression model and Survival analysis), I comforted the existence of an age discrimination market anomaly. Thus, a semi-Markov process better fits the Switzerland data. The results are available in the Methodology section.

2. LITERATURE REVIEW

The standard approach in labour economic literature discusses the discrete-time Markov chains where the population is divided into three labour market states as employed (E), unemployed (U), and inactive (I). Here researchers compare changes in workers' status between two discrete periods usually a month, quarter, or a year. Based on this information they create the matrix of transition probabilities, where the rows show the workers labour market status in an initial period and the columns show the status of the same worker in future.

One of the first papers applying this labour flows analysis in practice are those of Mincer (1966), Toikka (1976), Marston (1976), Clark et.al (1979), Burdett and Mortenscn (1980), Flinn and Heckman (1982b), Coleman (1984), Mortensen and Neumann (1984), Weiner (1982), Abowd and Zellner (1985).

Moreover, several significant studies have demonstrated that the analysis of labour worker flows as well as the job flows delivers important understandings above analysis of the unemployment rate. Here we can mention the papers of Blanchard et.al. (1990), Blanchard and Diamond (1992), and Davis and Haltiwanger (1990,1999).

These empirical analyses have been accompanied by theories of job flows and workers' flows, as those have been presented in the papers of Pissarides (1986,1991), Mortensen&Pissarides (1994), Hall (2005), and Shimer (2005).

Furthermore, we have the papers of Elsby et al. (2009), Shimer (2007) and Petrongolo&Pissarides (2008). They show how the construction of unemployment flows in and out of the unemployed state allows cross-country comparisons of labour market dynamics.

The main drawback of the discrete-time approach is that in real life situation observations are influenced not just at a single instant but through the entire interval of time. In particular, the discrete-time Markov chain can tell us nothing about where those workers arrived from, their waiting time/sojourn times, or where they will go later.

The second part of this review outlines the application of semi-Markov processes.

Semi-Markov process (SMM) is more realistic description of the labor market dynamics.

If we go back in the history we notice that semi- Markov process are first studied by Levy in 1954 and Smith in 1955, while Markov renewal processes by Pyke in 1959. Today Markov process are frequently used to analyze the complex reliability problems, queuing systems, inventory theories, health service decision-making, as well as modeling economic phenomena that involve stochastic dynamics.

Semi-Markov process is used to model the hospital patient flow inside a system of networked service facilities. One such application is given by Kao (1974). He applied the semi-Markov model to analyze the dynamics of movement of patients through various care zones in hospital, such as intensive care, surgical unit and etc. Semi-Markov model application to the hospital planning can be seen also in the work of Weiss et al. (1982).

Another excellent account of this process also appears in the papers by Pirin and Sheps (1964), Sheps and Menken (1971), Hoem (1973). They developed the theory of birth as a Markov renewal process. Then, Potter (1983) has shown how this theory can be applied to micro demography. Semi-Markov models are also used in manpower planning. Such a models are proposed by Ginsberg (1971), Mehlmann (1980), McClean(1980,1986) and McClean et al. (1997).

An interesting application of the semi-Markov process in the labour flow analysis appears in the papers of Schumm (2009) and Bijwaard (2014). By Schumm the semi-Markov process allows a more realistic description of behavior of an individual in a labour market, using the German labour flow data. Here, the possible states of an individual in the labour market are unemployment or employment. On the other hand, Bijwaard approached the migrant behaviour thorough the semi-Markov process, where individuals are moving between the four states (unemployed, employed, non-participating, abroad).

Other articles published in this field are those from Kieferand Neumann (2006), Bijwaard (2009), Neumann and Westegrad-Nielsen (2012) and Janssen (2013).

3. SEMI-MARKOV PROCESSAND UNCERTINITY

In this paper, the Switzerland labor market dynamics is viewed as a **semi-Markovian process** with individuals moving between the three labor states, i.e., employed, unemployed and inactive. While, the relative uncertainty (RU) is used as a measure of the state's uncertainty level and randomness.

Semi-Markov models are considered as an extension of continuous-time Markov models in which the inter-arrival times between two states are exponentially distributed. For SMM also holds that only the current state is relevant for the transition rates, i.e., memorylessness exists. However, inter-arrival times in SMM are no longer exponentially distributed. In other words, in SMM the entire process is not memoryless as happens in a continuous-time Markov chain. Instead, the process is Markovian, i.e., memoryless, only at the specified jump instants.

In the case of Switzerland, I claim that the sojourn times in the labor market follow a semi- Markov model. In this case, sojourn times are modeled with two-parameter Weibull distribution (α, β). Indeed, the Weibull distribution is often used in practical application and well adapted to deal with various shapes of monotone hazards,

$$\alpha_{ij}(d) = \frac{\beta_{ij}}{\alpha_{ij}}(\frac{d}{\alpha_{ij}})^{\beta_{ij}-1} \tag{1}$$

whereβ is the scale parameter and α is the shape parameter. If the shape parameter α is less than 1, then the hazard rate decreases with time. If α is greater than 1, then the hazard rate increases with time. And when α is equal to 1, the hazard rate is constant.

The semi-Markov process can be considered as a special case of a Markov renewal processbecause waiting time distributions are explicit. In this section, I will review a Markov renewal process $\{\{Y_i, T_i\}: i=0,1\ldots\}$ in which random variable Yi is an embedded homogeneous Markov chain taking values in a finite state space S= {1, ., n} with transition probability $p_{ij}=P(Y_{i+1}=j|Y_i=h)$, iϵN.

If we suppose that the process is non-explosive with $0=T_0<T_1<\ldots<T_n<\infty$, N= {1,2,..}, No= {0,1,2,..} and that is time homogeneous than the Markov renewal kernel $Q(t)=Q_{ij}(d)$ satisfies:

$$Pr = (Y_{n+1} = j, T_{n+1} - T_n \leq d|Y_n = i\} = Q_{ij}(d) \tag{2}$$

For all i,j,d and independent of n, the $\{p_{ij}\}$ is defined as:

$$p_{ij=}\lim_{t\to\infty} Q_{ij}(d) \tag{3}$$

And represents the one-step probability of a Markov embedded chain at the transition times.

However, before the entrance into state *j*, the person holds for a time *x* in state *i*. The sojourn times probability distribution (G_{ij}) in state*i* during passage to *j* is related to the semi-Markov kernel element Q_{ij}, according to $Q_{ij}(d)=p_{ij}G_{ij}(d)$, or:

$$G_{ij}(s) = \int_0^\infty e^{sd}dQ(d) \tag{4}$$

To fit the semi-Markov model to the Switzerland labor flow data, the distribution of sojourn times is specified using the Maximum Likelihood estimator (MLE). The likelihood function associated is:

$$L = \left[\prod_{n=1}^{N} py_{n-1}y_n f y_{n-1}y_n(S_n)\right] x\left[G_{y_N}(U)\right]^{\delta}$$

(5)

Where N is the total number of observed transition between two states, U is the duration between the time of the last observation and T_N the time of the end of the study. Then, the indicator δ is equal to 1 if the last sojourn time U is right-censored by the end of the study. In the cases when the observation is right-censored, the survival function of the sojourn times is also taken into account.

Finally, I calculate the Shannon relative uncertainty for the possible 6 transits based on the historical waiting time data. Given the waiting times WT, the Shannon uncertainty is computed using the formula:

$$H(WT) = -\sum_{i=1}^{n} p\,(wt_i) log_b p(wt_i)$$

(6)

Where H(WT) is the uncertainty, and n is the number of different outcomes, wt_i are the workers waiting times, p is the probability of the event happening, b is the base (base 2is mostly used in inflation theory, base 2=bits).

The relative uncertainty, RU is then calculated using the formula:

$$RE = |1 - \frac{H(WT)}{H_{max}}|$$

(7)

The H_{max} in Equation 7, is the maximum value of the uncertainty:

$$H_{max} = log_2 \frac{1}{p(wt)}$$

(8)

Using a built-in function in the computer algebra package MATHEMATICA the relative uncertainty RU are computed for all of the six sojourn times, that is waiting times in state i, before the transition to another state.

4. CONSTRICTING FLOW DATA

The first step in the construction of longitudinal dataset is matching records of labor market statuses (employment, unemployment, inactivity) for the same worker over a number of continuous surveys. In the labor force surveys', I look in two section of questions: the current period information and those who provide the retroacting information. By retroacting information, I refer to those relating to the duration in a particular state (sojourn times) and those related to the worker labor market status one year ago. This will help us to attain the following nine labor flow categories: UU, UI, UE, EE, EU, EI, II, IE and IU, which are quantified by

$$F_d^{SX} = \sum_{i \in G_d^{sx}} w_{id}$$

(9)

where $w_{id}$is the sample weight of the worker i at year d, and $G_d^{xy}$is the group of workers who transit from state S ∊ {E, U, I} to state X ∊{E, U, I} at year d.

The observation period is from 1st September 1999 to 31st of Mart 2016, based on Swiss Household Panel survey: Waves 1-17 (1999-2015). The construction of longitudinal data set is done in Microsoft SQL Server 2014. Here, the year 1999 is taken as a base year and those entering or leaving the workforce are left out from the measured sample. By definition**,** the dataset is longitudinal if it tracks the same type of information of the same person or subject, over a given period. As a result, the sample data used in this paper is balanced and made of 21.230 people and 45.206 transits. The data includes the following information:

- The ID of the individual (PID), the time when he/she enters into a particular state,
- the time when he/she leaves this state,
- activity status (employed, unemployed and inactive),
- waiting time in days (sojourn times)**,**
- and censoring (0 stands for non-censored data and 1 for censored data). In particular, censoring is a condition in which the observation is only partially known. In our case the data is right censored; i.e., the data collection process ends before the event/transition has occurred.

Moreover, the matrix of frequencies of transitions between consecutive states calculate by Equation 1 is:

$$\begin{array}{cccc} & E & U & I \\ E & 13834 & 2137 & 8984 \\ U & 2274 & 417 & 573 \\ I & 9382 & 766 & 6839 \end{array}$$

(10)

Thus, there were 2274 transits to employed (E) from state unemployed (U), 9382 transits to employed (E) from state inactive (I), and 13834 subjects stayed in the state employed(E) during the data collection period.

5. METHODOLOGY AND RESULTS

Using a built-in function in the computer algebra package MATHEMATICA Weibull distribution parameters α, β are computed for all of the six sojourn times, that is waiting times in state i, before the transition to another state, as well as the jump chain p_{ij}.

Table 1. Estimated sojourn time distribution parameters and Markov embedded chain, i.e., jump chain probabilities p_{ij}

Transition i→j	Sojourn times Weibull distribution parameters	Estimation of the jump chain p_{ij}
E→U	(0.773085, 9038.76)	0.456321
E→I	(0.767036, 8032.7)	0.543679
U→E	(0.964404, 452.869)	0.608182
U→I	(1.054102,716.2979)	0.229402
I→U	(0.910175, 3511.192)	0.272991
I→E	(0.906383, 1586.98)	0.676378

Jump chain for continuous Markov Process is:

$$m = \begin{bmatrix} 0 & 0.456321 & 0.543679 \\ 0.608182 & 0 & 0.391818 \\ 0.676378 & 0.323621 & 0 \end{bmatrix} \tag{11}$$

Then using another MATHEMATICA built-in function, I determined the probability density function, which is needed in the calculation of the state transition probabilities. Using Switzerland labor market flow data, transition probabilities between states are estimated:

$$P(0) = \begin{bmatrix} 0.891658 & 0.0511828 & 0.057159 \\ 0.365339 & 0.405259 & 0.229402 \\ 0.11786 & 0.2729912 & 0.609149 \end{bmatrix} \tag{12}$$

Thus, given a person enters state 3 (inactive) at t=0, he/she has a 0.27299 probability to be 1 year later in state 2 (unemployed), probability of 0.11786 to be 1 year later in state 1(employed), and probability of 0.6091 being still in state 3(inactive).

Stationary transition matrix

$$P(55) = \begin{bmatrix} 0.676139 & 0.141768 & 0.182088 \\ 0.676139 & 0.141768 & 0.182088 \\ 0.676139 & 0.141768 & 0.182088 \end{bmatrix} \tag{13}$$

The equilibrium is expected to be reached after 55 months or 4.6 years.

Expected First Passage Times (FPT) in days:

$$FPT = \begin{bmatrix} 1.31127 & 747.924 & 719.87 \\ 163.674 & 22.8461 & 395.511 \\ 379.436 & 851.275 & 5.16504 \end{bmatrix} \tag{14}$$

FPT is the expected time until the process first enters a given state, also known as the hitting time. Thus, 163.674 days are needed for transit from unemployed to employed state.

Stationary distribution/long-run proportion is:

$$\pi 1 = 0.67158;$$

$$\pi\ 2 = 0.0130676;$$

$$\pi\ 3 = 0.315353; \tag{15}$$

The long run proportion (stationary distribution) of time that a person will be employed is 67.16 %, unemployed 1.31 % and inactive 31.54 %, where 1.31% is known as the natural rate of unemployment.

Finally, using a built-in function in the computer algebra package MATHEMATICA relative uncertainty RU are computed for all of the six sojourn times, that is waiting times in state i, before the transition to another state.

$$\mathrm{RU} = \begin{bmatrix} - & 0.529722 & 0.228305 \\ 0.274923 & - & 0.265515 \\ 0.231212 & 0.676099 & - \end{bmatrix} \tag{16}$$

Relative uncertainty (RU) matrix than is used to calculate the total relative uncertainty by each state. Thus,

$\mathbf{RU_e}$=0.274923+0.231212=0.506135;

$\mathbf{RU_u}$=0.529722+0.676099=1.205821; and

$\mathbf{RU_i}$=0.228305+0.265515=0.49282. (17)

Total relative uncertainty gives the uncertainty level by state, the randomness and distance/displacement from the equilibrium point. RU_e gives the uncertainty level in the employment state, RU_uin the unemployment state and RU_i in the inactive state.

5. DISCUSSION

Unifying the concepts of Markov models and the uncertainty reduction theorywe can easily give an answer to the following questions: *what is the equilibrium position, the time needed to reach it, which workers will transit and where, the direction of the system-toward its equilibrium position or far away it equilibrium position, market anomalies, the labor market current position (stable/efficient or not) and best fitted Markov model.*

The findings showed that the time needed to reach the equilibrium position is 4.6 years and the right number of employed workers, unemployed and inactive workers maintain the highest rate of uncertainty reduction is 67.16 %, 1.31 % and 31.54 % respectively, where 1.31% is the natural rate of unemployment.

The semi-Markov labor model better fits Switzerland data and signifies then in the next 4.6 year the percent of employed workers is expected to decrease from 79.4% [1] to 67.16%, while the percent of inactive workers is projected to increase significantly, from 15.9%[1] to 31.54%.In other words, the Switzerland labor market is directed toward its “bad” equilibrium.

However, not all transits in labor markets occur randomly, as studied by Markov models. The additional uncertainty added into the system is triggering the non-random transits. Usually, the additional uncertainty in labor markets directed towards its “bad” equilibrium, is added by the government. Actually, the government will try to remove negative market anomalies and change the future “bad” equilibrium position.

However, the problem that governmentsface is that most of its policies and regulations act out as a process inhibitor. Or in other words, the policies and regulations will slow down the process (fewer workers will transit) but does not change the position of the equilibrium. What is more, the deviation of the estimated time of reaching the equilibrium distribution is not a surprise, rather expected deviation. The government will not be a government if it does not try to get involved in the market's evolution.

Considering all this, we can state that the Switzerland labor market will reach the new, “bad” equilibrium position but no earlier than 4.6 years. Switzerland no longer is the most stable economy. The difficult period is arriving.

Who is transiting? Why are workers transiting?And What market anomalies are detected?

Figure 6 is the graphical presentation of the relative uncertainty in the Switzerland labor market. According to the uncertainty reduction theory, workers will make transitions from a state to a higher uncertainty level to a state with a lower uncertainty state. Hence, the relative uncertainty will help us to determine the states of the labor market with lowest and highest uncertainty level.

In Switzerland, as shown in Figure 8, the ***Inactive state*** is a state with lower uncertainty level (0.49282), while ***Employment state*** and ***Unemployment state*** are with the higher uncertainty level, 0.506135 and 1.205821 respectively. Accordingly, the transit ***Unemployed →*** ***Inactive*** will occur first and then ***Employed → Inactive***. Workers will tend to reach the stable state (the Inactive state), and in this path, they will realise the uncertainty to its surroundings. As a result, the percent of inactivity rate is expected to increase, and the percent of the unemployment rate and employment rate decrease in future.

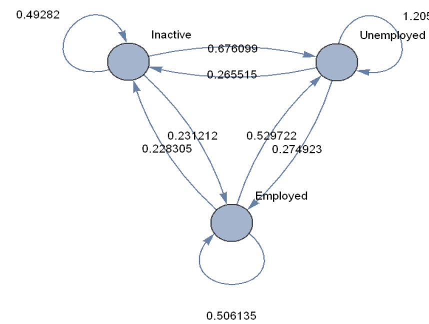

Figure 1. Relative uncertainty for SWISS labor market

Next, the ***Inactive state*** is characterized with low uncertainty which is signifying an anomaly exitance (see Figure 3). When the anomaly is detected in the ***Inactive states,*** then the anomaly is recognized as a negative. This type of anomalies is causing the path to the ***Inactive state*** to be stepped. On the other hand, the ***Employment states*** and ***Unemployment state***is characterized with higher uncertainty-no anomaly detection.

In summation, we can say that when the lowest relative uncertaintyis computed in the ***Inactive state***, as in the case of Switzerland, then the labor market is unstable/inefficient. Here, the inactive workers do not have an equal chance to transit- anomaly exists. Also, the sojourn time distribution is affected by worker’s socio-demographic covariates. Therefore, the semi-Markov process will yield better estimates. To be more specific, age discrimination is detected. Two additional tests are run to support these findings, Cox proportional regression model, and Survival analysis.

Since data is right censored, the first test that I apply is a Cox proportional regression model (Cox 1972). The Cox model handles the problem for right censoring data, a typical issue for thelabor market data (see, for instance, Tunali and Pritchett, 1997). Here the hazard rate is defined by

$$\alpha_{ij}(d|X_{ij})=\alpha_{ij0}(d)\exp(\beta_{ij}X_{ij}),\ d\geq 0,\ i,j \in E,\ i\neq j, \quad \textbf{(18)}$$

where X_{ij} is the vector of explanatory variables, β_{ij} is the vector of regression parameters associated with the transition from state i to state j, and $\alpha_{ij}(d)$ is the baseline hazard given in Equation 18.

[1] employment rate and inactive rate for Q1 2016. The data is published by OCDE Statistics, available online athttps://stats.oecd.org/index.aspx?queryid=35253

Using MATHEMATICA build-in function, I applied Cox proportion regression model. The results suggest significant interaction. In other words, during the particular period, from 1999 up to 2015, the sojourn time distribution is affected by the worker's age. In long-run all worker's do not have an equalchance to transit, i.e., they are inhomogeneous.

The second test that I apply is the Survival analysis. Using MATHEMATICA build-in function, I compared survival curves for inactive workers by gender and age. The survival lines in Figure 9 showed a significant difference. In other words, the underlying assumption of continuous-time Markov chain (workers have an equal chance to transit) is violated. Therefore, the semi-Markov model will better fit the Switzerland labor market data. Moreover, the inter-arrival rates between states are no longer exponentially distributed.

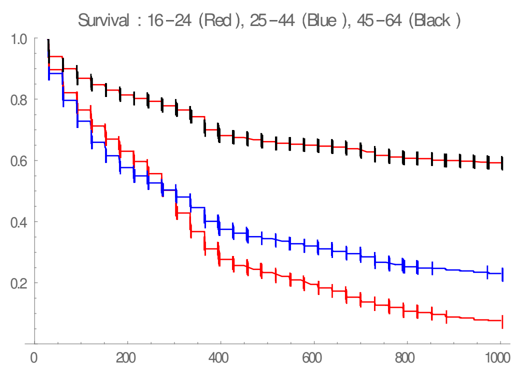

Figure 2. Survival lines for inactive workers by age

Both tests show that the workers do not have an equalchance to transit, i.e., age discrimination is detected. Furthermore, the survival lines show that older workers (above 45 years) have longer sojourn times. Hence, workers who are expected to transit to an ***Inactive state*** in the future and stay there for a longer time are the older works (above 45 years).

Labor market policies as motivating older people to work, tax reliefs for hiring older people and policies for attracting foreign high-skilled workers, will not remove the negative market anomaly and change the position of the equilibrium. These policies will only slow down the process (fewer older people will transit to Inactive state) and place the labor market in its bubble territory. When the countries are facing the problem with an aging population, the government should be extremelycautious which policies they implement in order not to upset the business and push its economy into a bigger recession. Inadequate policies can cause even more devastating breakdowns.

Why? What is causing the path toward the Inactive state to become stepper?

When the youth dependency ratio < old dependency ratio[i] than the path toward ***Inactive state*** is steeper, i.e., anegative market anomaly exists. In Switzerland, in 2015 we have the following population demographic structure:

youth dependency ratio < old dependency ratio =21.99% < 26.85% **(19)**

In this paper, the demographic structure is considered as one of the main factors for sustainable growth. So, to remove the negative anomalies and change the "bad" equilibrium position the government first needs to change the population demographic structure, which is, unfortunately, a process that demands time.

Considering all the findings, we can say that the "bad" equilibrium position toward which the Switzerland labor market is currently directed to, can't be avoided. The right number of employed workers, unemployed and inactive workers that will maintain the highest rate of uncertainty reduction, is employed 67.16 %, unemployed 1.31 % and inactive 31.54%. The only debatable matter is the time when the equilibrium will be attained.

However, the government as soon as possible should act and implement the traditional family policies more aggressively and parallel work on new- innovative ones that will have a positive effect on the fertility rate.

To be more specific, the government should put into practice new-innovative family policies, because the traditional pro-family policies implemented to encourage bigger families has failed to increase the fertility rates to expected levels. Today, both women and men want first to work and earn an income of their own before raising a family. As a consequence, the fertility rate in Switzerland in the last 50 years continuedto decrease. In 2017, it is 1.50 children per woman.[2]

When the higher fertility rates are attained, then, the government should focus on the implementation of policies that will support the development of the youth population (0-14 year-old) into a significant resource for socio-economic development via investments in education, youth-friendlyhealthcare serviced, innovation and entrep-reneurial skill development.

Finally, I claim that the adjusted demographic structure is expected to return the Switzerland's labor market to its growth path.

6. POLICY RECOMMENDATION

Currently, in Switzerland, the maternity paid leave is 98 days, or 14 weeks, from the day it starts. Second, by the

[2]The statistical data is available online athttp://www.geoba.se/country.php?cc=CH

European Commission Flash Report (ESPN Flash Report 2017/04), Switzerland is one of the OECD countries where childcare is the most expensive. In line with the OECD Family database, Switzerland is the country where childcare costs for parents are high compared to wages (OECD 2014). The government should support more working mothers.

Next, in Switzerland, the decline in the number of women of childbearing age, as well as the postponement of childbearing, is registered. The average age of first delivery of women is high, at just below 30 years old in Switzerland (SHP, 2015; OECD, 2010a; OECD 2010d).

Polices recommendation:increasing the maternity leave, support and encourage marriages after graduation, changes in the rules and the amount of the child benefit policies, higher childcare subsidies and receiving an extra incentive to babysit for retired or non-working grandmothers.

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i Dependency ratio of the population is a proportion of people who are not in the labor force, also known as the dependents to the labor force of a country, also known as the productive part of the population. The dependents add in the population under 15 years old and people aged 65 and over. The productive part of population adds in the population between 15 - 64 years. This ratio shows the pressure put by the dependent part of the population to the productive population. There are 3 types of age dependency ratios:

$$total\ dependecy\ ratio = \frac{[ages\ 0-15] + [ages\ 65-plus]}{[Population\ ages\ 16-64]} \times 100$$

$$old\ dependecy\ ratio = \frac{[Population\ ages\ 65-plus]}{[Population\ ages\ 16-64]} \times 100$$

$$youth\ dependecy\ ratio = \frac{[Population\ ages\ 0-15]}{[Population\ ages\ 16-64} \times 100$$