Inequality, growth and industry structure: Evidence from Armenia

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Abstract

We use regional (marz) level data from the Armenian National Statistical Service for the period 2004-2010, to estimate the impact of economic fundamentals on income inequality and poverty. Our results suggest that per capita growth decreases both inequality and poverty. The Armenian industry structure experiences rather drastic changes in its transition, however, our results indicate that certain components in the industry significantly affect the evolution of inequality and poverty. In particular, an increase in share of agriculture leads to higher inequality and lower poverty. We suggest certain channels to explain established causalities, using a theoretical model. We also check for several specifications to ensure reliability of our results.

Keywords: Income Inequality, poverty, growth, industry structure.

1 Introduction

Over the last two decades Armenia has made substantial steps in liberalizing politico-economic environment via continuation of reforms, committed at the early stage of independence. In particular, the economy has experienced sound economic growth, severely disrupted by the world financial crisis in 2008. The Armenian authorities have succeeded to sustain high growth rate and consistently decreasing inequality and poverty along this period, with significant help of international organizations.

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Despite satisfactory aggregate economic indicators, challenges the economy faces in its transition remain actual. Armenia heavily depends on remittances, which effectively transfers external shocks to domestic markets. Trade imbalance with the rest of the world is another channel by which the economy faces external shocks. High concentration in domestic markets together with strong dependence of foreign currency inflows create high foreign exchange risk.

Real earnings in private sector bear all the inefficiencies the country experiences. The link between the financial and real sectors is very strong and inefficiencies in one sector are propagated to another. In general, the allocation of economic resources among industry sectors, which eventually determines the industry structure, may or may not be efficient. In this paper we are interested in the concept of *efficiency in distributional sense*, which accounts both for average performance and dispersion around the average. Inefficient use of resources will create an industry structure, which does not sustain efficiency. This statement tautological, but given the fact that we might be able to check only the second link, namely, whether a certain industry structure explains existing inefficiencies, we can conclude on the efficiency of the use of resources. As our concept of inefficiency hinges on inequality, we implicitly assume that the process of allocation/use of resources government has a distinct role.

Then, the following question can be posed: Is this vulnerability of the Armenian economy due to the transition phase or there are some imbalances in the industry structure, as a primary cause of inefficiencies discussed above? Put differently, should we care about the industry structure or the latter effectively adjusts to the dynamics of the economy? There is a strong volatility in the industry structure in the period 2000-2010,[1] which may or may not be efficient from both aggregate welfare and distributional viewpoints. Too much volatility conveys a warning message that it is potentially due to inability for the domestic economy to accommodate external shocks.

[1] We in fact concentrate on the second decade since the Armenian independence, as the early stage of development lacks in regularities and data of acceptable quality.

One can be pragmatic and argue that the volatility of the industry structure can be explained by the fact that small and medium size entrepreneurs, comprising majority in the economy, are able to adjust demand shocks wherever they come from. However, it is hard to imagine that an agricultural farm can effectively adjust its technologies and move to construction or service industry. There is indeed certain extent of mobility among entrepreneurs, but they stay within an industry at least in the short period, say, couple of years.

Another potential source of volatility may stem from the fact that the industry is export oriented, capable of supplying wide range of products. That is, the industry is able to appropriate different composition of external demand. In reality, the Armenian economy is not distinguished by its large product diversity for tradable goods and this hypothesis cannot survive either.

If following to the literature, efficient changes in the industry structure are explained along the development path. The U.S. economy, starting from the low level of income, patterns higher demand on agricultural goods, relative to the industry and service. As the country becomes richer, demand composition changes in favor of industry and service. Agents move from agriculture to industry in the medium stage of development and later on from industry to service. This is reflection of Engel's law, which states that consumption basket composition changes over time due to decreasing weight of agriculture in it. The model by Rebelo et al (1993) explains such dynamics of demand decomposition, simply assuming non-homothethic preferences for agents. Another channel to explain this artifact is to allow interaction demand and supply, assuming non-homothetic and learning by doing (Matsuyama 2002), respectively.

These novelties cover decades of development and naturally does not address the questions we raise here. However, it is useful to think about the possibility of the industry structure change due to preferences in the demand side or technologies in the supply side. Different elasticities for the poor and the rich due to non-homothetic preferences may induce significant industry structure change, if inequality is (i) high enough and (ii) highly volatile. Nevertheless, we think this link is very likely to be in the long run, while it should be negligible in the short run. Explaining the dynamics of industry structure by preferences and technologies will eventually lead to identification of causality from inequality to industry structure. This direction of causality is beyond the scope of this work. We will instead explore whether the evolution of the Armenian industry structure can explain significant variation in inequality measures.

Beside exploring the causal relationship between the industry structure and inequality measures, we provide another dimension which may explain inequality dynamics. Our data, disaggregated at the marz level, enables to identify spatial dependence of the variables under discussion. A simple question whether growth or inequality measures can be in part explained by their spatial factors is interesting. A traditional inequality/growth analysis discards the spatial dimension very often, resulting in loss of highly valuable information. Here we embed the spatial factor, making our analysis richer.

Marz level data enables to increase number of observations and retrieve the overall picture of the Armenian economy, controlling for unobserved heterogeneity. To our knowledge, this work is the first attempt to look at the complex relationships among growth, inequality measures and industry structure for Armenia. We start with data inspection, which will help us understand basic relations of these variables in terms of correlations and get useful insights on their dynamics.

We consider as a baseline model a static causal relationship between industry shares and growth in the right hand side and inequality/poverty measures in the left. As simple it is, certain specifications in this class of regression models survive the main diagnostic tests, namely, zero autocorrelation in errors and normality test. We take fixed effects approach since regions in Armenia apparently sustain time invariant differences. When needed, we embed a lagged exogenous variable, in order to further improve the model.

Numerous specifications will be provided, in order to extract the true relationship and causality directions for the main variables. In particular, we will make use of Bourgignon's (2003) approach, explaining poverty rate by inequality and growth measures, among other controls. As the author states, policy is indirectly incorporated in these relationship in form of development strategy, addressed to inequality and growth targets and their interaction.

In order to carefully study the impact of agricultural share on income inequality, we split our sample into two parts according to the sign of agricultural share change, and learn the underlying relationship, drawing sensible scenarios based on simulated static general equilibrium model[2].

As a part of sensitivity analysis, we report bootstrap based estimates for our specification. Overall, we are satisfied from the outcome of bootstrap analysis, as in most of the cases they fit to our estimates.

The paper has the following structure. We study statistical properties of our data in Section 2. Section 3 covers econometric analysis. Sensitivity of our estimates are analyzed in Section 4. Section 5 concludes. All graphs and tables are relegated in Appendix.

2 Data description

We use data from the National Statistical Service, Republic of Armenia (NSSRA). For the construction of Gini coefficients and poverty rates we use Household Survey micro database from 2004 to 2010, which is representative for population and includes from 4000 to 8000 households, depending on a year. We take marz level industry, construction, agriculture and service shares, as well as employment shares for these industries. As NSSRA is not publishing marz level GDP, we construct this data[3]. We have 77 observations in total (7 years and 11 marzes).

In this Section we describe the data in detail, using correlations, kernel based distributions, inequality and poverty measures. We demonstrate dynamics for these variables providing useful insights on how the Armenian economy evolves over time from the prospect of our interest.

We start with inspection of contemporaneous correlations for two inequality measures

[2]As we plan to enrich the model in certain directions, such as allowing monopoly power and opening the economy, we abstain from placing the details of the model and comparative statics results. Of course, it can be provided by request.

[3]For details contact authors.

calculated from (i) households' income and (ii) expenditures and then transformed to per-capita values, the poverty rate and the real GDP growth rate. Correlation values with corresponding significance levels are in Table 5, where $Gini1$ and $Gini2$ are the two inequality measures based on households' income and expenditure, Pov is the poverty rate, $\%GDP$ is the growth rate of the real GDP, and the remaining four variables, Ind, Agr, $Const$ and $Serv$, stand for industry, agriculture, construction and serivce shares in the real GDP, respectively. All variables are in marz levels. The two Gini coefficients are strongly correlated, while the poverty rate patterns weak correlation with inequality measures and almost zero co-movement with the GDP growth rate.

Industry shares sum to unity and an increase of a certain agricultural share results in a shrink of some other industry share(s). Quick inspection of contemporaneous correlations indicates strong correlation between agriculture and the remaining three industry sectors In average, almost the half of GDP is produced in the agricultural sector and the latter is very sensitive to any structural change in the economy. Agriculture remains a dominant sector in 8 marzes out of 11 (Figure 1).

We check for relative productivities for industries, as a ratio of an industry and employment shares in a marz. If the ratio is higher than one, the productivity of that industry is higher relative to an average productivity in an economy[4]. Figure 3 shows the average values of relative productivities. This measure for agriculture falls short from 1, indicating that productivity in agriculture falls short from the average productivity in the economy.

2.1 The dynamics of inequality and poverty measures

For the period 2000-2008, the Armenian authorities have succeeded to report improvement on inequality, poverty and growth indicators, at least in aggregate measures. Figure 4 indicates rather impressive growth rate, constantly decreasing poverty rate[5] and somewhat

[4] If productivity in agriculture is lower than the overall productivity in the economy, we have $A/E^a < GDP/E$, where A and E^a stand for agriculture and employment in that sector, and E is the overall employment in the economy. Inequality can be rewritten as $A/GDP < E^a/E$, or $(A/GDP)/(E^a/E) < 1$.

[5] Poverty rate is the poverty headcount ratio at US \$2 a day, as a percentage of population, PPP adjusted.

decreasing Gini coefficient. Disaggregated data at marz level enables to inspect the evolution of dispersion of these variables, in addition to averages. In our analysis marzes have equal shares, while aggregate measures of the above variables put population weights for marzes. As a matter of the fact, if we estimate a certain relationship with corresponding findings using aggregate data, it may well differ from the findings of panel based estimation of the same specification. This approach helps statistically evaluate how effectively policies have been addressed towards *balanced regional development*, a central concept to a long run growth strategy for Armenia[6].

As a first step to this direction, we plot kernel based densities for inequality, poverty and growth indicators for three subsamples, $2005-2006$, $2006-2007$ and $2008-2010$. For the first two subsamples we have 22 observations and for the last 33 observations. We are interested in both aggregate values and dispersion in terms of averages and standard deviations, respectively. Figure 5 shows that there has been equalization of income over time. In the period $2007-2008$, $Gini1$ index differences among marzes have been substantially decreased, while during the financial crisis it has been expanded back. We obtain a similar qualitative pattern for $Gini2$.[7]

The dynamics of the poverty rate is more complex. The average poverty rate has been decreased from 29.69 percent in $2004-2005$ to 22.60 percent in $2006-2007$. Poverty differences among marzes have also been mitigated, reflected in a decrease of standard deviation by 0.71. However, this improvement was not proportional - certain marzes have failed to catch up with the average level of poverty reduction, resulting in a bimodal distribution in $2006-2007$ (see Figure 5.2). This pattern has been preserved during the crisis period, with higher average and standard deviation, 27.48 and 7.34, respectively. Poverty rate is more dispersed than inequality measures, suggesting that there might be marzes where vast majority of the society is poor.

[6]The Armenian government has endorsed set of measurements embedded in an official document "Balanced regional development", aimed at creating equal opportunities for all regions to develop infrastructures and production capabilities.

[7]Summary statistics for inequality, poverty and growth variables are in Table 1-4, for the total sample and the three subsamples, respectively. $Gini3$ variable is an income based Gini index, calculated for households.

We also plot densities for three subsamples in Figure 7-9, comparing dynamics of two inequality measures, $Gini1$ and $Gini2$ and poverty rate. Expenditure based Gini index is shifted to the left and has a lower variance relative to income based Gini index, indicating that income redistribution has contributed to equalization both in average and differences in consumption among marzes. Figure 10 confirms this evidence for some marzes, such as Aragatsotn, Ararat, Kotayk and Shirak. The high growth period $2006-2007$ helped these marzes decrease poverty, but this has not been sustained during the crisis. It is also useful to look at the difference between inequality index and poverty rate. We take $Gini2$ for this exercise to stress the policy component. If this difference is positive, then poverty has been decreased more than inequality[8]. Figure 11 shows this second order effect for marzes. As we see, financial crisis hindered further decrease in poverty with higher rate than inequality decrease. Of course, this result is conditional on the measure of poverty.

The inspection of the distributional dynamics of growth reflects the destructive role of the crisis for the economy. The average growth and its standard deviation for the period 2006-2007 are 11.33 and 7.88, respectively. The corresponding values in$2008-2010$ are 4.15 and 15.11. Obviously, financial crisis not only retarded the overall growth of the economy, but also widened the growth differences among the regions.

3 Estimation

The core models of our interest can be defined as follows:

$$Inequality = G(growth, industry\ shares, productivity\ shares); \tag{1}$$

$$Poverty = P(GDP, industry\ shares, productivity\ shares). \tag{2}$$

for poverty. We use logarithmic transformation of variables so that the functions G and P have mutliplicative form, and the estimated coefficients are (constant) elasticities. We

[8]Denote $d_t \equiv Gini2_t - Pov_t$ with $\Delta d_t \equiv d_t - d_{t-1} = (Gini2_t - Gini2_{t-1}) - (Pov_t - Pov_{t-1}) = \Delta Gini2_t - \Delta Pov_t$. If poverty decreases (increases) with higher (lower) rate, then $\Delta Pov_t < \Delta Gini2_t$ so that $\Delta d_t > 0$.

concentrate much on explaining contemporaneous causalities, and the basic argument is that there is much short run exogenous volatility in the industry structure, conditioned by external factors and weather for agriculture. A short term drift in the industry is exogenous almost by definition, otherwise a structural change in the economy would pattern a strong trend with negligible deviations from it. We do not claim that there are no tendencies in the industry structure, but our primary concern is to explain the dynamics of inequality and poverty by mostly exogenously driven part of structural change and growth. If there is, however, a long term component in variables, it will be captured as well, since in fact we explore long term cointegration relationship in most of the specifications. We do not detrend our variables, but instead allow to capture comovements, which in part owes to persistence in the data generating process. The main reason why we do not decompose our data into trade and stochastic components, is a very limited time span.

We learn the extent of persistence in main variables, using Bias-corrected the least squares dummy variable (LSDV) method[9], to estimate AR(1) processes. Inequality measures are relatively less persistent than poverty, and for the latter time dummies are very informative. Industry structure patterns persistence, but it is far from being strong. Service is best explained by its previous value, while construction patterns the lowest persistence. There is much volatility mostly due to drastic down-shift in 2008, but as we have corresponding upturns in inequality and poverty, we do not identify a structural change in the model after the the financial crisis, 2008-2010.

Three basic components are involved in the dynamics of certain industry: absolute growth, relative growth and productivity. We decompose the product of an industry i as follows:

$$Y_i = \frac{Y_i/L_i}{Y/L}\frac{L_i}{L}Y, \tag{3}$$

where Y_i and Y are the product of industry i and the total product, both in a given marz. L_i and L are respective employment levels.

[9] The Stata routine has been written by Bruno 2004.

We then take logarithms, as all variables in our model,

$$\ln Y_i = \underbrace{\ln(Y_i/L_i) - \ln(Y/L)}_{(i)} + \underbrace{\ln(L_i/L)}_{(ii)} + \underbrace{\ln Y}_{(iii)}, \tag{4}$$

where (i) is the relative productivity measure and (ii) is the employment share, both in logarithms. The third component captures the level (growth) of marz GDP, while the first two capture deviation from that aggregate output. We in fact create three variables, which can be effectively embedded into a regression model, allowing different sources for the overall impact of an industry product on a dependent variable. We can further manipulate with the first component as follows:

$$\ln(Y_i/L_i) - \ln(Y/L) = \ln(Y_i/Y) - \ln(L_i/L), \tag{5}$$

where the first component, $\ln(Y_i/Y)$, is the industry share. Denoting relative industry share, productivity, employment share and marz out by ind, ind_p, ind_e and gdp, respectively, we may can write the following conventional regression model:

$$y = \alpha_0 + \alpha_1 ind_p + \alpha_2 ind_e + \alpha_3 gdp + ... \tag{6}$$

Then it is easy to realize, that the model can be written in the following form:

$$y = \alpha_0 + \alpha_1 ind + (\alpha_2 - \alpha_1) ind_e + \alpha_3 gdp + ... \tag{7}$$

As a benchmark model in this context, we use 7, as we want to explicitly disentangle an industry share from an employment share of that industry. Controlling for the employment share, and the overall growth in a marz, we have α_1 as a partial effect of the industry share due only to productivity increase. We also estimate the model in the form of 6, in order to test for significance of α_2.

Regression model for inequality. We suggest four different specifications for inequality model. Reported estimates are in Table 6 with standard errors in parentheses. Dependent variable is the Gini index, based on per capita incomes. All variables are in log form. The index *sp* stands for *spatial*, indicating that the variable captures spatial dimension. For example, $gini_{sp}$ is a spatial index for inequality, constructed as convex combination of *gini* values for neighboring marzes with equal shares. The spatial variable of Gini index is not significant, however it corrects the distribution and clears the autocorrelation in the error term. Specification 1 (henceforth S1) is baseline: the impact of growth and industry structure on inequality. We can choose only 3 industry shares, as the forth share becomes redundant. We use GDP growth for inequality model and the level for poverty model, following to the literature[10]. We then extend the model including lags for industry shares (S2), sectoral employment shares (S3) and productivities (S4).

A good news is that growth mitigates inequality. Growth seems to be pro-poor, signaling that government policies aimed at boosting growth will also decrease income differences. Negative significance of growth passes 95 % test in 3 specification out of 4.

A higher (lower) share in agriculture increases (decreases) inequality. Positive causality is observed for construction as well. Service expansion instead (contraction) sustains lower inequality. One should be careful with invoking *cetirus paribus* condition for shares. If we consider 1 percent increase in agriculture, there should be corresponding decrease only in the industry (manufacturing), since construction and service shares should be fixed at some (average) level. This limits the scope of interpretation of results to large extent.

Sudden increase in agricultural sector will creates inequality, if underlying technologies are disequalizing (increasing return technologies). In particular, a productivity increase will lead to higher inequality, since few rich households, as capital (in forms of land, machines, technologies and crops) owners, will absorb the significant share of the value created. S3 and S4 indicate that an increase in agricultural share is due to higher productivity, which we think is mostly projected to weather condition. In particular, S3 shows that higher inequality

[10]Inequality is sensitive to the growth rate, while poverty mostly depends on the stage of development.

is sustainable with higher output and lower employment shares in agriculture.

We later provide a structural analysis, to identify whether estimated results are consistent with (i) increase of agricultural share, (ii) decrease of agricultural share or both. At the moment we report that agricultural share has a positive impact on inequality.

Positive link between construction and inequality can be due to large income differences in construction. This sector may help the poor catch up, but it is rather pro-rich, as large profits are generated by capital owners, while wages of employees, though higher than the average in the economy, are miserable relative to these profits.

The only sector, which has negative causal relationship with inequality, is service. This relationship is in terms of service productivity, since sectoral employment share turns to be insignificant and service share is basically driven by productivity. Although in the financial sector productivity is very high, average productivity in service is the lowest[11] (Figure 3). Growth in service extends to low productivity spheres and translates into wage increase, entailing lower income inequality.

Regression model for poverty. The dynamics of poverty turns to be more persistent and rather explained by factors beyond our control. As a result, the industry structure has no primary effect on it. We report estimated results form 6 specifications in Table 7. We again start with the benchmark model, GDP and industry shares involved (S1). An increase in income per capita helps poor depart from the poverty trap. Negative significant coefficients are obtained in 4 specifications out of 6. However, each next specification somewhat rejects the previous one and, to our view the best specification is the last one. In this specification growth is not significant. The share of agriculture, on the other side, remains significant except in S5, in which the spatial factor of poverty is dominant.

As in the case of inequality, here as well productivities are the main driving factors of industry shares, when explaining poverty. Agriculture is the only sector, where employment share has a significant impact on poverty: once fixing the share of agriculture, higher employ-

[11]Services include food, transport, health, educational and financial services (the list is not exhaustive), and there is high diversity among these sectors in terms productivity and earnings.

ment in rural areas deepens poverty, as it will depress productivity and wages will slow down (S2). When introducing the lagged GDP, we somewhat capture persistence in the poverty dynamics, also making current inequality significant. This perfectly fits to Bourgignon's (2003) specification, which defines the government's development strategy within the interaction of growth and inequality, both being determinants the level of poverty in an economy.

As a next step, we add spatial factor of poverty in S5. This makes the industry structure and growth insignificant and improves R^2 more than twice. Poverty seems to be well explained by geographical location of regions. However, hypothesis that remote regions consistently pattern high poverty, does not survive. For instance, in Syunik and Tavush marzes, the one located in south and the other in north and both without border with Yerevan, poverty is relatively low for different reasons. Mining sustains low inequality in Syunik, while much of the labor force in Tavush are engaged in seasonal work outside Armenia. Their locations are important in determining poverty, but the underlying factors differ.

As a final step we check for time dummies. They leave out the spatial factor and explain the evolution of poverty almost alone. From 2005 to 2008 poverty has been consistently decreased due to factors, external to our model and captured by the year dummies. We think the central factor is remittances. Prior to financial crisis, the economy has been fed by continuously growing remittances, helping poor families to move out from the poverty region. The spatial factor is implicitly involved in this narrative. Remote regions are isolated from urban areas and especially from capital Yerevan and its surrounding metropolitan area, and households face difficulties to find a job or sell their agricultural product. As a solution to this long term problem, they choose seasonal work outside the country, generating remittances for families located in these regions. Obviously, remittances involve spatial factor, and when they are incorporated into the model via time dummies, this factor becomes redundant. What about Syunik marz? Mining has grown in these period as well, but if it had some impact on poverty, it should have been reflected in marz GDP. As we do not have significant coefficient for GDP, this channel is not common for the whole economy and instead year dummies dominate. Apart from year dummies, inequality and agriculture shares are significant, which only stress their important role in the poverty dynamics. High inequality deepens poverty, indicating that pro rich policies definitely hurt poor and the government should be careful when designing policies aimed at consolidation of resources[12].

We next learn robustness of our esimates, which involve the use of alternative measures for inequality, different scenarios for agricultural share and bootstrap analysis for all specifications.

4 Sensitivity analysis

Alternative measure for inequality. We have different measures for inequality, for which we can check our specifications from Table 6. Gini index, calculated on individuals' expenditures, seems to be very noisy and is not consistently explained by the class of models we suggest. Another income based measure of Gini, $gini_h h$, which is for households, survive almost all specifications. We report the estimates in Table 8.We continue to use the spatial factor of the original Gini coefficient, $gini_{sp}$, which controls for statistical properties of the error term. In addition to the significance of estimates obtained in Table 6, service productivity is significant in specification S4. This further supports our argument that high productivity in service captures low productivity spheres and translate into higher wages, thus mitigating inequality. The lag of agricultural share pattern 99% significance and its negative coefficient is likely to involve long run prospect. We dare to use the term "long run", because if we add higher, the second and third lags in S3, they take negative coefficients, though insignificant. The share of agriculture has uniformly decreased from 55% in 2004 to 41.7% in 2010, and this may generate inequality, if high productivity is consistent with high inequality and there is a structural change from low to high productive industries. We have the latter evidence in terms of relative productivities and agriculture is the least productive

[12]For example, creation of farms which assumes concentration of large areas in hands of few households will naturally increase inequality. Our poverty model conveys a message that this will entail excessive poverty. A possible channel is that net benefits from land consolidation will accrue to farm owners, while wages of labor will even fall short from earnings raised by production prior to consolidation, making poor households even poorer.

after services, but we do not have data on sectoral inequlities (and poverty). Unfortuntely, our time span is very limitted to analyse lng term channels.

Positive and negative changes of agricultural shares. In our specifications, when explaining inequality, we obtain positive coefficient for the agricultural share. We have provided a channel, which can explain how even a sadden increase in agriculture may deepen inequality. Good weather conditions will widen income differences between capital and labor owners, if higher productivity of capital will be effectively exploited and create much higher revenues relative to wages. What if in most of the years for marzes we have decrease in agriculture? As noted in the previous subsection, it is indeed so and we need to consider scenarios, in which this fact is embedded.

In order to study some of possible scenarios we hypothesize, a simple general equilibrium is constructed with two sectors. Each sector involves two types of households, labor and capital owners. Labor owners are poor, relative to capital owners. Sector A is agriculture and Sector B is industry (manufacturing). If households want to move from agriculture to industry, they pay participation cost, which is convex with zero costs. Production functions are Cobb-Duglas, which is equalizing by construction[13]. As our model does not pattern any non-convexities, in the long run perfect relative equality will sustain, defined over factor shares, relative productivities and participation costs structure.

We consider initial inequality in terms of factor ownership. Factor quantities are normalized and labor force is measured in terms of efficient labor units. Capital factor owners are rich relative to labor factor owners. After production takes place and gross incomes are are disclosed, income distribution can be constructed and compared with initial factor distribution. The Gini indexes are used measure inequality change in the economy. We have labor mobility from agriculture to industry and final numbers of *individuals* in agriculture and industry are calculated and used constructing Gini indexes[14].

[13]Cobb-Duglas production function patterns unit elasticity of substitution, and a factor with lower stock will earn higher marginal return, ensuring that poor will earn higher margin and catch up with the rich.

[14]We are careful to control for the effect of convex participation cost, when updating number of households (individuals) in each sector. If, say, 20 percent capital flows from agriculture to industry, we assume that

We assume high poverty and low inequality for agriculture, relative to industry, which we believe is peculiar for Armenia. In order to generate relevant scenarios, we make comparative statics analysis on productivities of agriculture and industry, as well as on factor shares. The model, in particular, shows that if there is high productivity in agriculture, then inequality both in agriculture and industry decreases, hence income inequality decreases in the economy[15].

On the other side, if there is increase in productivity in agriculture, it has no any impact on sectoral and economy income distributions. It is explained by the fact that factor mobility costs are convex and *all* households have access to improved technology in the industry.

What if capital share in production increases in industry. A decrease in share and income inequality in agriculture will follow. There will be lower inequality, because part of capital owners will move to industry, while some of labor owners will return to agriculture. There is also a left shift of income distribution in agriculture - poverty deepens. Income inequality in industry will increase, because capital owners are now getting higher return, relative to labor owners, who are shifted to the left. This shift exactly mitigates overall inequality, as we observe a right shift and higher variance of income distribution in industry.

Two scenarios are identified, in one of which the share of agriculture increases due to high productivity in agriculture, and in another the share of agriculture decreases due capital share increase in industry. In both cases overall inequality decreases. Now turn to the real economy. In order to identify whether positive causal relationship is preserved for both directions of agricultural share change, we divide the sample into two mutually exclusive parts - observations in which a marz specific agriculture share has increased are separated from the remaining observations, in which agriculture share has decreased. We loose the year 2004, as growth agricultural share is identified from 2005.

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each household transfers its 20 percent capital, and corresponding number of individuals from households move to industry, but not 20 percent of all households move to industry.

[15]The exercise enables to analyze the change of income inequality, as we compare income distributions for initial and final values of parameter specification. In general, income inequality is lower, that production factor inequality for any parameter configuration due to convex technologies. However, as we compare final outcomes of different specifications, inequality may increase within a sector and/or in the whole economy.

Estimated results are reported in Table 9. Somewhat surprisingly, the sign changes from minus to plus, when moving from agriculture share increase to its decrease. Although we do not report year dummies due to very small number of observations, they are significants signaling that an increase of agricultural share is mostly explained by good weather conditions in those years. This is a productivity shock, as the underlying technologies remain the same within a year. Our simple model described above provides a channel by which inequality is mitigated in effect. As the same product and even more can be produced with less production factors involved, departure from agriculture to industry will expand. Still agricultural share increases, and higher wages and capital returns will result in income equalization both in sectors and in the economy.

When agricultural share decreases - the last two columns of 9 - inequality decreases as well[16]. This can be consistent with introduction of capital intensive technologies in the industry. As described above, there will be decrease in agricultural share and the final shape of income distribution will sustain lower inequality.

We do the same exercise with the poverty left hand side, but minus sign of agricultural share remains negative and it becomes insignificant when adding spatial factor and/or year dummies.

Bootstrap analysis. As noted earlier, our analysis is much sensitive to limited number of observations. Error autocorrelation and normality are of our concern, and bootstrap analysis enables to estimate how properly these two conditions are satisfied for our specifications. Bootstrap has an advantage relative to the Monte Carlo method that one need not know the underlying data generation process. We use the most common form of bootstrapping, which is based on resampling residuals.

As expected, those specifications which pass autocorrelation and normality tests[17], also survive bootstrap based estimation. In particular, specification 3 in Table 6 does not pass normality test and this is reflected by its bootstrap counterpart, Table 11, S3. As part of

[16] We need to move the shares to the negative direction, which entails lower inequality in the left hand side.

[17] We use Wooldridge test for autocorrelation and Shapiro-Wilk and Shapiro-Francia tests for normality.

our sensitivity analysis refers to agriculture, poor performance of agricultural is particularly reflected in bootstrap estimates. Agricultural share passes only 85% significance level in 3 specifications out 4, Table 11. Bootsstrap based results are more consistent with original estiamtes when using the alternative measure of inequality, $gini_hh$. Finally, regression models for poverty almost entirely sruvive bootstrap test at the same significance level.

Conclusion

In this paper we estimate the impact of industry structure and growth on income inequality and poverty for the Armenian economy, using marz level data. Due to very short time span, 2004-2010, we concentrate on the short run, simultaneous causal relationship. Our results suggest that per capita growth decreases both inequality and poverty within a year. The industry structure, though its high volatility, has significant impact on inequality and poverty dynamics. In particular, agricultural share in the whole industry has an asymmetric impact on inequality. When agriculture grows faster than marz GDP, it mitigates income inequality within a marz. We interpret this result by the help of general equilibrium model, specifying a productivity shock to agriculture. Both poor and rich are better off, but due to equalizing technologies, marginal return for the poor will be higher relative to that for the rich. In simple words, farm owners offer higher wages to labor force in rural areas, which help the latter to catch up with the rest of the economy. A decrease in agriculture can be due to investments in more capital intensive technologies in the industry, which will entail partial move of capital owners from agriculture to industry. With some complex distributional interactions, the model shows that the overall income inequality will decrease. This is quite a realistic scenario, as Armenia experiences adoption of capital intensive technologies.

We provide an interesting novelty for the evolution and determinants of poverty. The spatial factor is central in this context. When time dummies are incorporated in the model, they turn to be so powerful that make spatial factor insignificant. We argue that time dummies capture remittances, which help especially poor improve her wellbeing. The key argument is that those regions which are rather isolated from the rest of the economy, receive more remittances as more labor from these regions take seasonal work option. Apparently, spatial factor is involved in this channel, and consequently, when time dummies are added to the model, this factor becomes redundant.

We use bootstrap analysis to check the validity of our estimates. Despite the very short time span and nontraditional approach we have taken to analyze the link between inequality/poverty and the main fundamentals of the economy, bootstrap exercise indicates that in most of the specifications our estimates are reliable. As expected, the estimated coefficients of agricultural share in the inequality model are trembling, and our detailed study helps understand the underlying causality.

5 Appendix

5.1 Descriptive statistics

Table 1: Summary statistics for 2004-2010

Variable	Mean	Std. Dev.	Min.	Max.
Gini1 (income based, per capita)	34.44	4.472	25.104	51.235
Gini2 (expenditure based, per capita)	32.283	3.75	20.329	40.791
Gini3 (income based, per household)	36.091	3.735	26.735	46.862
Poverty rate	26.715	6.778	15.43	41.93
GDP growth rate	8.728	13.181	-27.144	50.298

Table 2: Summary statistics for 2004-2005

Variable	Mean	Std. Dev.	Min.	Max.
Gini1 (income based, per capita)	36.536	4.854	28.403	51.235
Gini2 (expenditure based, per capita)	33.975	3.992	23.912	40.791
Gini3 (income based, per household)	38.415	2.528	34.653	43.722
Poverty rate	29.692	5.905	19.77	40.45
GDP growth rate	12.986	12.641	-2.769	50.298

Table 3: Summary statistics for 2006-2007

Variable	Mean	Std. Dev.	Min.	Max.
Gini1 (income based, per capita)	33.705	3.154	28.689	38.907
Gini2 (expenditure based, per capita)	32.402	2.638	27.366	35.994
Gini3 (income based, per household)	35.469	3.69	26.735	41.372
Poverty rate	22.596	4.619	15.43	31.49
GDP growth rate	11.334	7.88	-2.52	23.626

Table 4: Summary statistics for 2008-2010

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Gini1 (income based, per capita)	33.532	4.611	25.104	46.908
Gini2 (expenditure based, per capita)	31.076	3.859	20.329	36.509
Gini3 (income based, per household)	34.955	3.834	27.919	46.862
Poverty rate	27.477	7.339	17.19	41.93
GDP growth rate	4.153	15.109	-27.144	32.669

Table 5: Cross section correlaton: contemporaneous relationship

Variables	Gini1	Gini2	Pov	%GDP	Ind	Agr	Const	Serve
Gini1	1.000							
Gini2	0.518	1.000						
	(0.000)							
Pov	0.330	0.238	1.000					
	(0.003)	(0.037)						
%GDP	-0.050	-0.082	0.057	1.000				
	(0.666)	(0.480)	(0.621)					
Ind	-0.020	-0.059	0.069	0.040	1.000			
	(0.860)	(0.608)	(0.553)	(0.727)				
Agr	-0.039	-0.124	0.121	-0.024	-0.622	1.000		
	(0.735)	(0.283)	(0.294)	(0.833)	(0.000)			
Const	0.000	0.085	-0.222	0.089	-0.073	-0.677	1.000	
	(0.999)	(0.464)	(0.053)	(0.443)	(0.529)	(0.000)		
Serve	0.125	0.303	-0.175	-0.097	-0.097	-0.660	0.710	1.000
	(0.278)	(0.007)	(0.128)	(0.400)	(0.402)	(0.000)	(0.000)	

5.2 Graphs

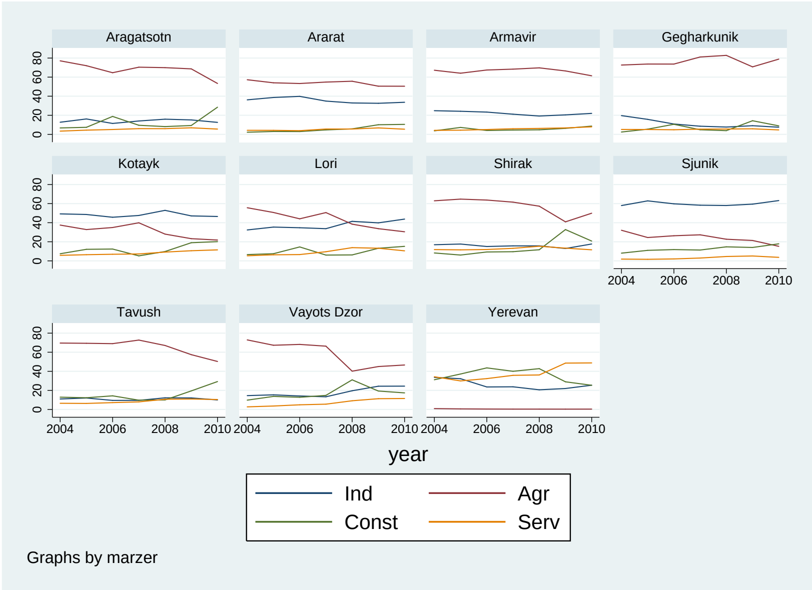

Figure 1: Industry shares for marzes

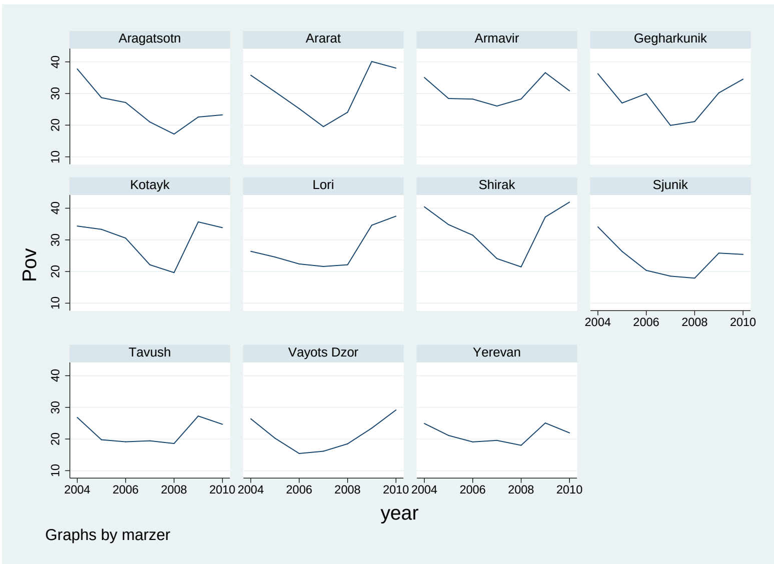

Figure 2: Poverty rate for marzes

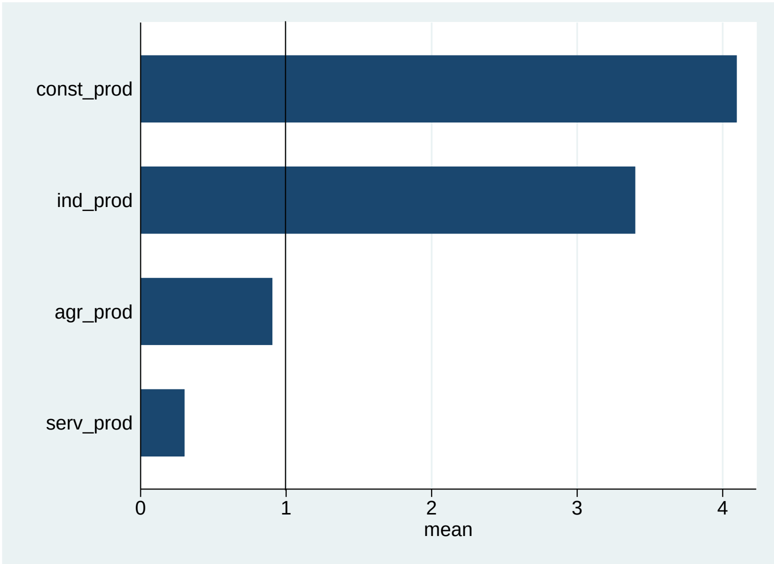

Figure 3: The means of relative productivities

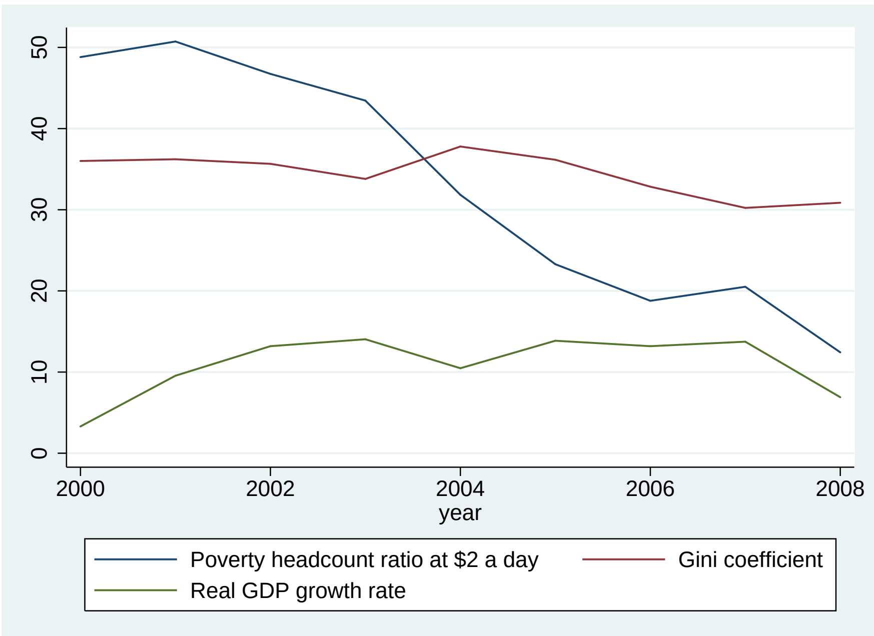

Figure 4: Aggregated data for GDP, poverty index and Gini coefficient for Armenia. *Source:* World Bank.

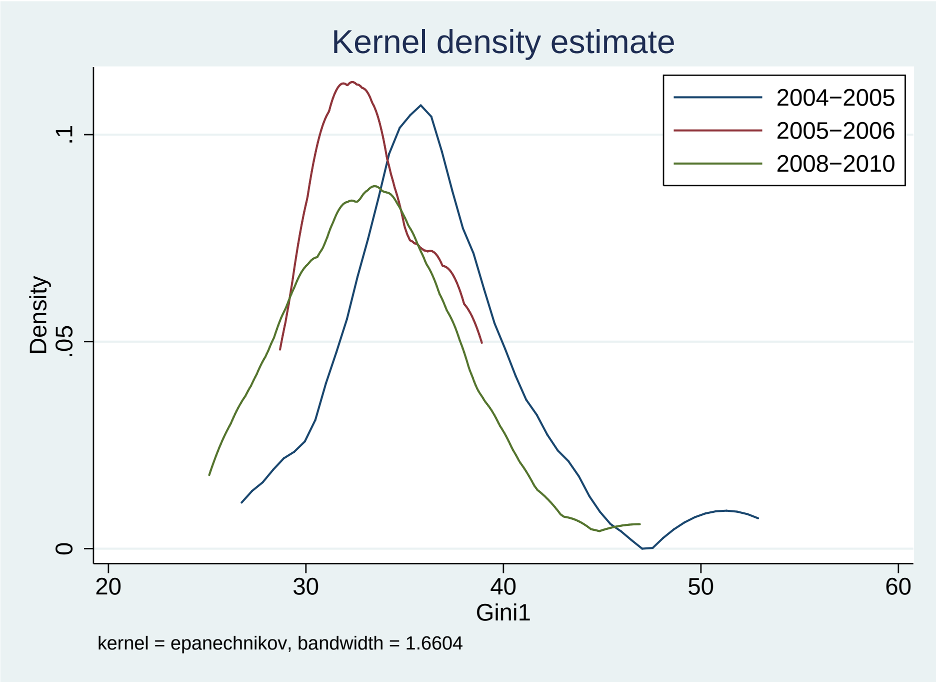

Figure 5: Distributions for income based Gini coefficient

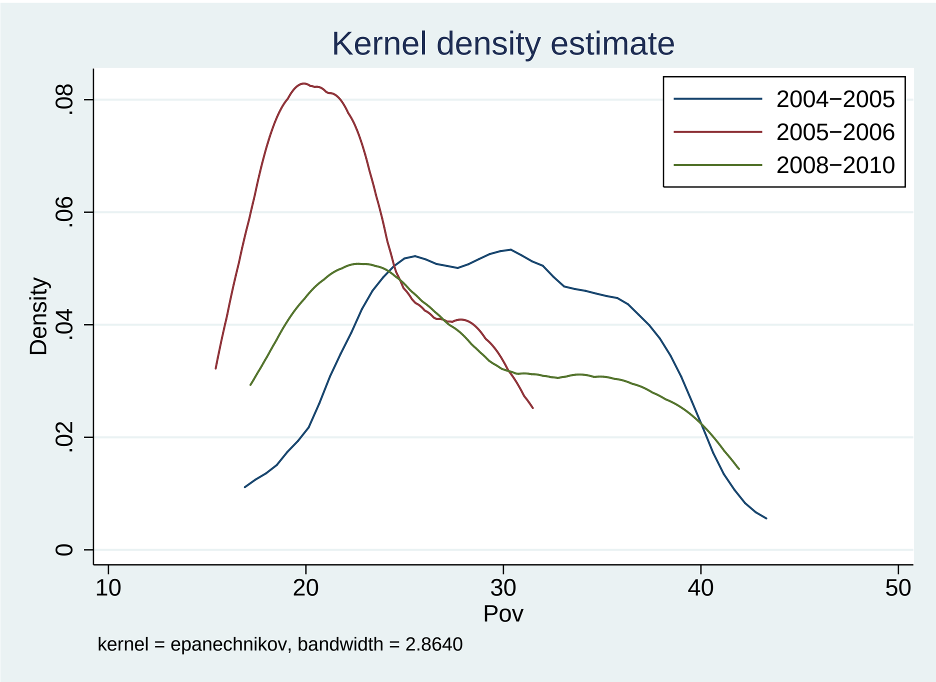

Figure 6: Distributions for poverty rate

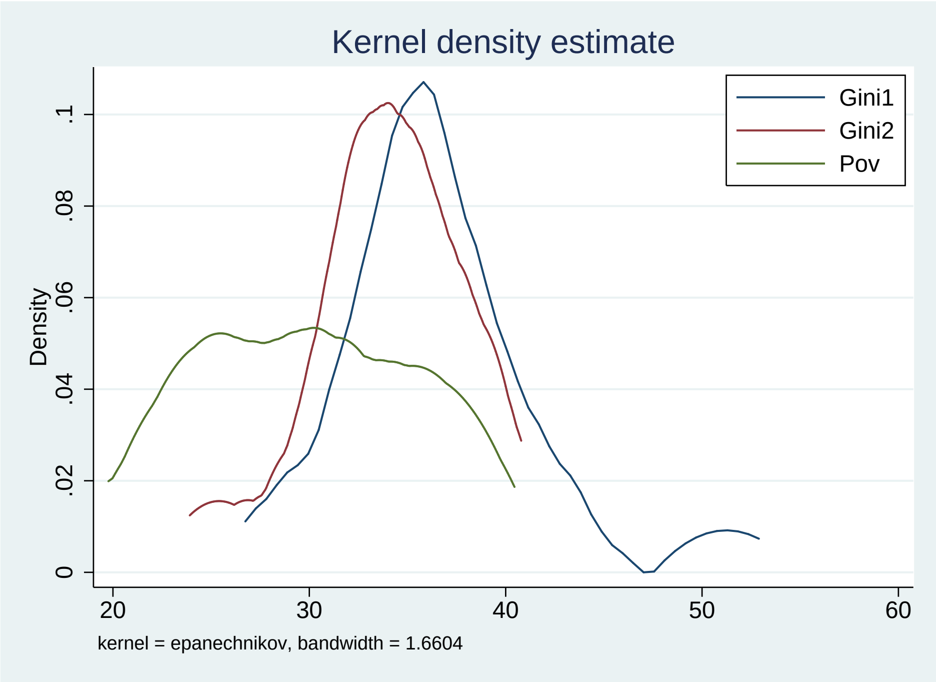

Figure 7: Distriubrions of Gini coefficients and poverty rate for the period 2004-2005

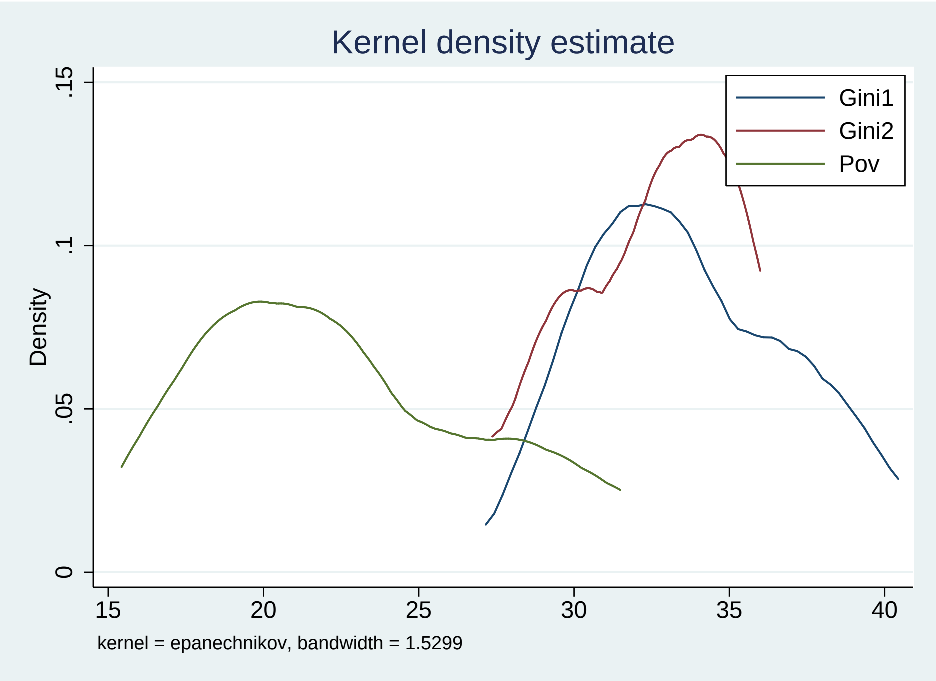

Figure 8: Distriubrions of Gini coefficients and poverty rate for the period 2004-2005

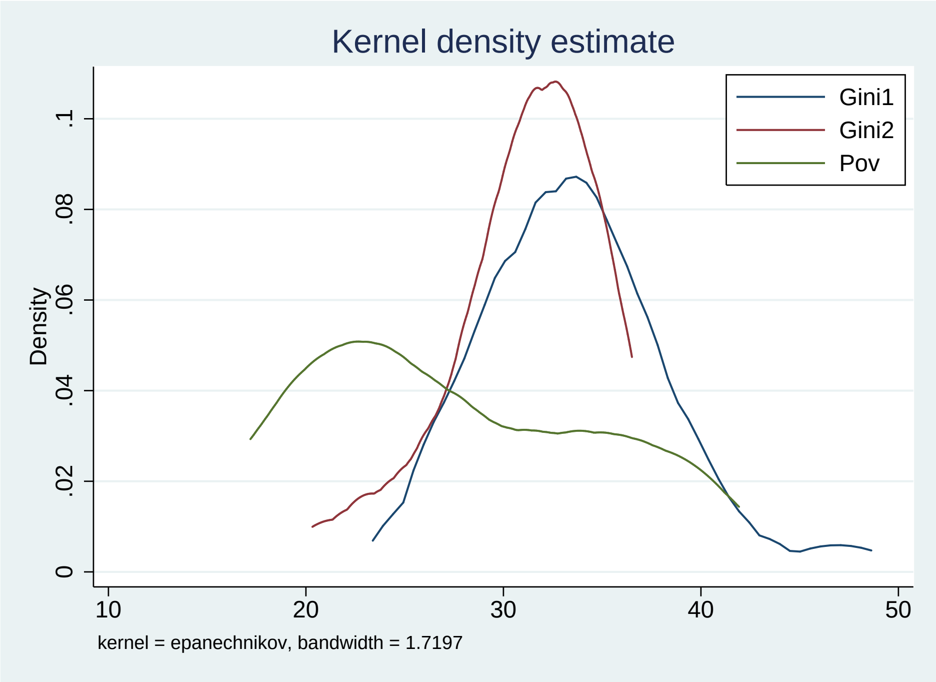

Figure 9: Distriubrions of Gini coefficients and poverty rate for the period 2004-2005

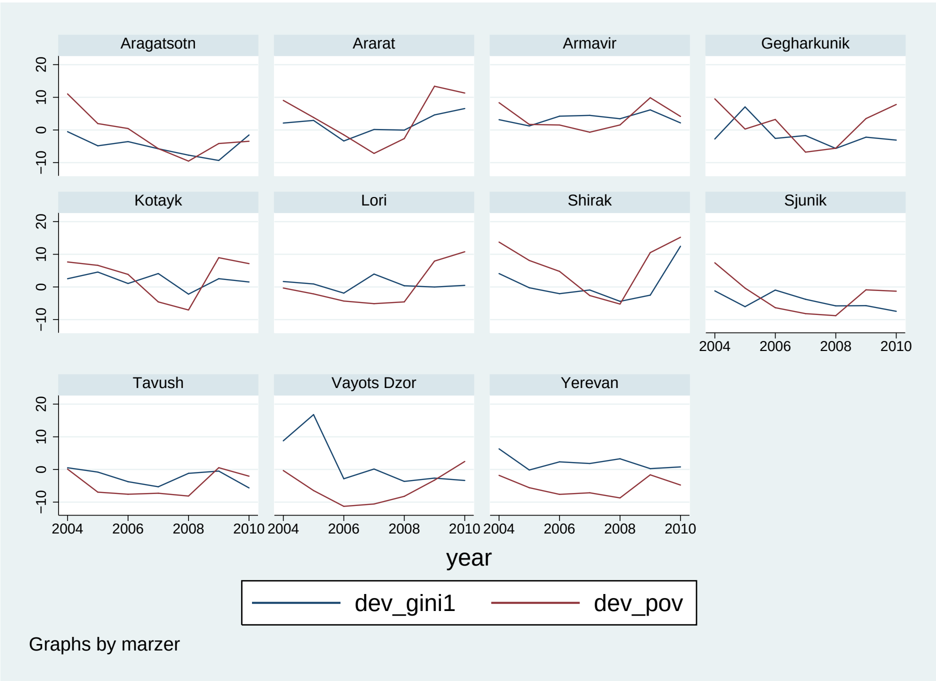

Figure 10: Deviations from average inequality (Gini1) and poverty

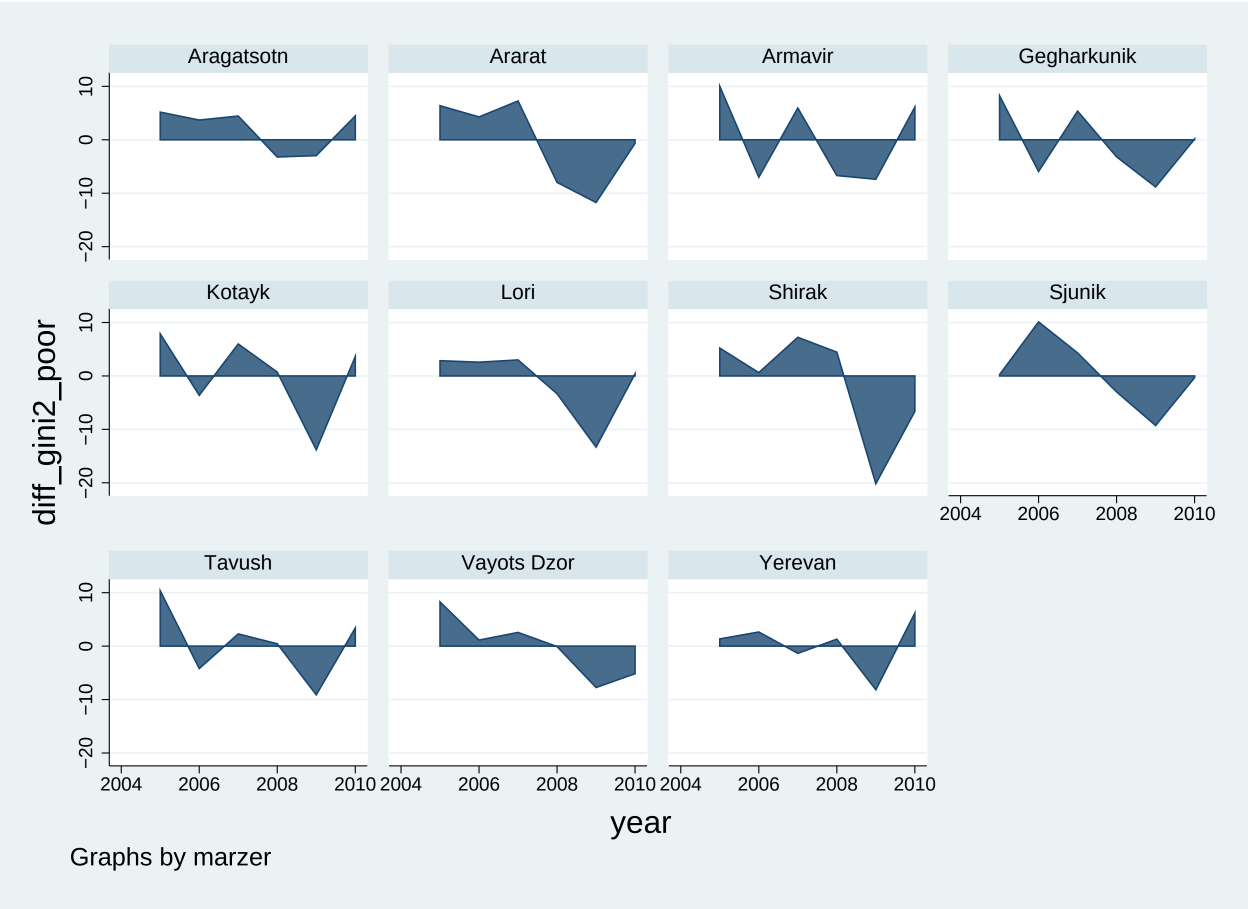

Figure 11: Difference in Gini2 and poverty changes. Positive values indicate overweight of poverty decrease.

Table 6: Regression outcomes for inequality.

Dependent: gini	(1)	(2)	(3)	(4)
$gini_{sp}$	.253 (.252)	.213 (.234)		
gdp	-.218** (.106)	-.227** (.094)	-.111 (.084)	-.212** (.099)
agr	.118** (.052)	.277** (.115)	.304** (.134)	
$const$	.068* (.036)	.099** (.050)	.082* (.045)	
$serv$	-.149** (.074)	-.147* (.087)		
$agr(-1)$		-.219** (.096)		
$pov(-1)$			.203*** (.071)	
agr_e			-.245** (.099)	
$const_e$			-.043** (.022)	
ind_e			-.320*** (.098)	
agr_p				.156** (.064)
$const_p$				.037 (.023)
$serv_p$				-.119 (.073)
pov				.167*** (.040)
N	77	66	66	77
R^2: within	.272	.282	.341	.372

$^{*}-90\%,^{**}-95\%,\ ^{***}-99\%$

Table 7: Regression results for poverty.

Dependent: pov	(1)	(2)	(3)	(4)	(5)	(6)
$gini$				.860***	.517**	.384**
				(.235)	(.217)	(.193)
gdp_{level}	-.532***	-.492***	-.349***	-.527***	-.199	-.232
	(.126)	(.134)	(.120)	(.121)	(.157)	(.188)
pov_{sp}					.747***	-.132
					(.079)	(.169)
agr	-.435***	-.526***		-.426***	-.241	-.197*
	(.152)	(.165)		(.081)	(.155)	(.116)
$const$	.172***	.151**		.131***	.018	.041
	(.060)	(.061)		(.044)	(.027)	(.031)
$serv$	-.203**	-.227**				
	(.101)	(.096)				
agr_e		.316**				
		(.154)				
agr_p			-.529***			
			(.198)			
$const_p$			.100***			
			(.029)			
$serv_p$			-.145			
			(.095)			
$year_{2005}$						-.225***
						(.054)
$year_{2006}$						-.303***
						(.081)
$year_{2007}$						-.434***
						(.103)
$year_{2008}$						-.450***
						(.101)
$year_{2009}$						-.051
						(.082)
$year_{2010}$						-.046
						(.086)
N	77	77	77	77	77	77
R^2: within	.244	.261	.239	.344	.718	.775

* – 90%, ** – 95%, *** – 99%

Table 8: Regression outcomes for inequality (alternative measure)

Dependent: $gini_{hh}$	(1)	(2)	(3)	(4)
$gini_{sp}$	.193	.150		
	(.220)	(.185)		
gdp	-.206**	-.214***	-.082	-.209**
	(.093)	(.074)	(.072)	(.084)
agr	.094*	.259**	.340**	
	(.052)	(.103)	(.150)	
$const$	.063*	.099**	.091**	
	(.038)	(.050)	(.044)	
$serv$	-.214***	-.205**		
	(.080)	(.093)		
$agr(-1)$		-.213***		
		(.076)		
$pov(-1)$			.240***	
			(.076)	
agr_e			-.256**	
			(.119)	
$const_e$			-.048**	
			(.020)	
ind_e			-.298***	
			(.107)	
agr_p				.147**
				(.065)
$const_p$				.036
				(.024)
$serv_p$				-.174**
				(.081)
pov				.181***
				(.046)
N	77	66	66	77
R^2: within	.357	.338	.407	.489

$^* - 90\%, ^{**} - 95\%, ^{***} - 99\%$

Table 9: Positive and negative changes in agricultural shares.

	$gini$ $\Delta agr > 0$	$gini_{hh}$ $\Delta agr > 0$	$gini$ $\Delta agr < 0$	$gini_{hh}$ $\Delta agr < 0$
gdp	.180	.324***	-.109*	-.080
	(.129)	(.103)	(.065)	(.079)
agr	-.451**	-.463***	.303*	.339**
	(.181)	(.148)	(.166)	(.163)
$serv$	-.141*	-.195***	1.019**	1.178*
	(.081)	(.073)	(.515)	(.641)
$const$			.137**	.148**
			(.070)	(.072)
agr_e	5.586***	4.486***	-.095*	-.081
	(.379)	(.493)	(.054)	(.059)
$serv_e$	2.183***	2.119***	1.019**	1.178*
	(.162)	(.211)	(.515)	(.641)
N	22	22	44	44
R^2	.802	.881	.386	.398

$^{*} - 90\%$, $^{**} - 95\%$, $^{***} - 99\%$

Table 10: Bootstrap for specifications in Table 6. Number of replications is 10000.

Dependent: gini	(1)	(2)	(3)	(4)
$gini_{sp}$	.253	.213		
	(.266)	(.307)		
gdp	-.218*	-.227*	-.111	-.212**
	(.114)	(.123)	(.106)	(.102)
agr	.118	.277*	.304**	
	(.085)	(.172)	(.149)	
$const$	.068**	.099**	.082*	
	(.035)	(.048)	(.044)	
$serv$	-.149**	-.147*		
	(.069)	(.093)		
$agr(-1)$		-.219*		
		(.131)		
$pov(-1)$			.203**	
			(.079)	
agr_e			-.245	
			(.411)	
$const_e$			-.043	
			(.045)	
ind_e			-.320**	
			(.156)	
agr_p				.156**
				(.078)
$const_p$				.037*
				(.024)
$serv_p$				-.119*
				(.061)
pov				.167***
				(.049)
N	77	66	66	77
R^2: within	.272	.282	.341	.372

$^{*}-85\%,^{**}-95\%,\ ^{***}-99\%$

Table 11: Bootstrap for specifications in Table 8. Number of replications is 10000.

Dependent: $gini_{hh}$	(1)	(2)	(3)	(4)
$gini_{sp}$	.193	.150		
	(.243)	(.273)		
gdp	-.206*	-.214*	-.111	-.212**
	(.108)	(.115)	(.109)	(.102)
agr	.094	.259*	.304**	
	(.082)	(.169)	(.147)	
$const$	.063*	.099**	.082*	
	(.035)	(.047)	(.044)	
$serv$	-.214***	-.205**		
	(.071)	(.095)		
$agr(-1)$		-.213*		
		(.124)		
$pov(-1)$			.203**	
			(.080)	
agr_e			-.245	
			(.416)	
$const_e$			-.043	
			(.044)	
ind_e			-.320**	
			(.155)	
agr_p				.156**
				(.078)
$const_p$				.037*
				(.024)
$serv_p$				-.119**
				(.060)
pov				.167***
				(.048)
N	77	66	66	77
R^2: within	.272	.282	.341	.372

$^{*}-85\%,^{**}-95\%,\ ^{***}-99\%$

Table 12: Bootstrap for specifications in Table 7. Number of replications is 10000.

Dependent: pov	(1)	(2)	(3)	(4)	(5)	(6)
gini				.860***	.517**	.384*
				(.286)	(.219)	(.206)
gdp_{level}	-.532***	-.492***	-.349**	-.527***	-.199*	-.232
	(.148)	(.155)	(.137)	(.137)	(.116)	(.152)
$poor_{sp}$					.747***	-.132
					(.091)	(.320)
agr	-.435**	-.526**		-.426**	-.241*	-.197
	(.215)	(.236)		(.167)	(.125)	(.133)
const	.172**	.151*		.131*	.018	.041
	(.080)	(.082)		(.070)	(.045)	(.050)
serv	-.203*	-.227*				
	(.116)	(.116)				
agr_e		.316				
		(.402)				
agr_p			-.529***			
			(.196)			
$const_p$			.100*			
			(.053)			
$serv_p$			-.145			
			(.118)			
$year_{2005}$						-.225***
						(.084)
$year_{2006}$						-.303***
						(.109)
$year_{2007}$						-.434***
						(.165)
$year_{2008}$						-.450***
						(.169)
$year_{2009}$						-.051
						(.085)
$year_{2010}$						-.046
						(.095)
N	77	77	77	77	77	77
R^2	.244	.261	.239	.344	.718	.775

* – 90%, ** – 95%, *** – 99%