The impact of mining sector on growth, inequality, and poverty: Evidence from Armenia

Aleksandr Grigoryan*

April 11, 2013

Abstract

We use regional data for the Armenian economy to estimate the impact of the mining sector on growth, income inequality and poverty. Despite a relatively small share of mining idustry in GDP, it has an important role in shaping the evolution of the industry structure.

The main findings are as follows. An accelerated expansion of the mining sector enhances growth - a good news for policy makers to justify pro-mining policies. Mining sector, however, is likely to increase income inequality and deepen poverty in Armenia.

We study small sample properties of our estimates by bootstrap analysis. Growth models survive the test, but inequality and poverty models fail to report significant coefficients for mining. Nevertheless, the sign and magnitudes are preserved in most cases with little drop of P-values. We also check our specifications, excluding one region (Syunik marz), which absorbs a huge share of mining in Armenia. As expected, the exclusion of Syunik marz makes our models less dependent from the mining sector.

Keywords: Armenia, mining, growth, income inequality, poverty.

1 Introduction

In this paper we analyze the impact of the industry structure on growth, inequality and poverty for the Armenian economy, searching for model specifications in which the mining sector[1] has a significant role. Mining has a small share in GDP and the dynamics is rather driven by external factors. This motivates to interpret movements in mining share as an exogenous variation, which may well explain the evolution of GDP growth, income inequality and poverty measures.

*American University of Armenia (AUA); e-mail: *aleksandr@aua.am*. This work was commissioned by the AUA Acopian Center for the Environment.

[1] We use the term "mining" for the sector *Mining and quarrying* throughout the paper.

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 along this period, with significant help of international organizations. Overall, GDP and the two inequality measures (Gini index and poverty rate) move together, ensuring higher growth and less inequality/poverty in 2000-2008 (see Figure 1).[2] A recent paper by Begrakyan and Grigoryan (2012) analyze the dynamics of income inequality and poverty for Armenia, using a large set of explanatory variables.

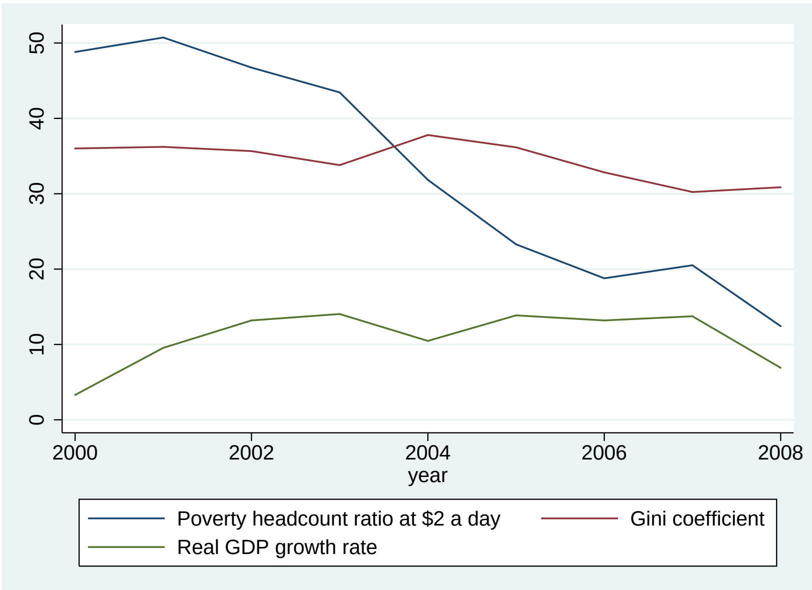

Figure 1: GDP growth, inequality and poverty for the Armenian economy. *Source:* NSS RA.

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

[2]Recent macroeconomics developments in Armenia is properly documented in, e.g., IMF (2011).

exchange risk at a very high level[3].

A separate channel the economy depends on the rest of the world, is the export of the mining product. Intuitively, high prices on ores and metals in world markets should push local producers to increase extraction of local mines and sales abroad. On the other side, mining capacities are fixed in the short run and temporary fluctuation of prices need not align current production volumes[4]. Overall, the export of mining has decreased at the early stage of crisis (2008-2009) (Figure 4)[5], but its share has even increased in GDP.

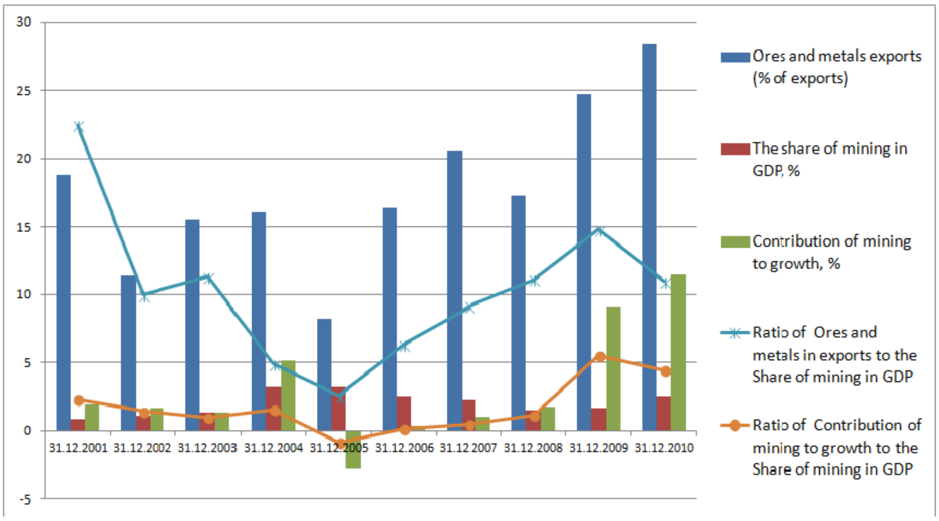

Figure 2: Mining's contrbution to export, GDP and growth

The contributions of mining to the exports, GDP and its growth are crucially different. Despite its modest share in GDP (it averages to 2 percent in 2000-2010), mining covers almost 20 percent of the total export and its contribution to growth comprises around 10 percent in 2008-2010. Figure 2 reflects these differences. There is also strong correlation between the mining share in exports and mining's contribution to GDP growth[6]. While the very small share of mining in GDP may undermine its role in explaining the evolution of the industry

[3]The impact of external imbalances on domestic prices and activity is analyzed by Oomes et al. (2009).

[4]Mining in Armenia seems to be far from its capacity utilization, however, there may be positive correlation between metal prices and the produced volumes in mining. For example, copper prices in world markets and mined volumes in Armenia have dramatically dropped during the crisis time, while the share of copper mining has increased in that period. Analysis of potential comovements/causalities in prices and mined volumes, interesting in its own, is beyond the scope of this paper.

[5]Source: Kostanyan (2011)

[6]The correlation coefficient is 0.85.

structure, its rather huge share in exports and countercyclical dynamics makes the sector central. In particular, it is interesting to observe how the mining sector helps the Armenian economy survive the crisis time[7]. Figure 3 indicates the growing share of mining in GDP growth structure in post-crisis period. From the first glance the black areas corresponding to the mining share seem to be moderate, but they amount to around 10-11 percent in 2008-2010, when accounting only for sectors, which had positive contribution to growth[8]. Two more variables are created to measure disproportionality of mining's contribution to GDP, its growth and export. These are ratios, having the mining share in denominator. In the period 2001-2005 these ratios decrease, which is more due to an increase of the mining share in GDP. After, we evidence increasing contribution of mining to export and growth, which overwhelm the increase in mining share in GDP.

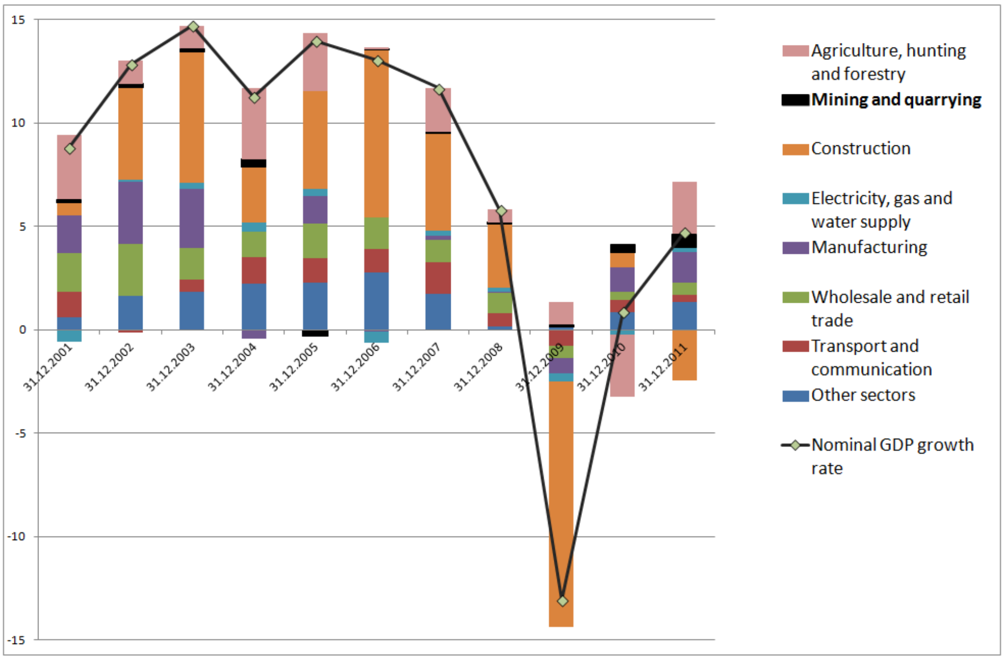

Figure 3: Growth structure for Armenia

Essential to our analysis, we ask whether consistent increase in mining share in the first period and decrease in the second until the crisis could be driven by other sectors, such as construction and/or services. Using regional level data (77 observations), we establish

[7]A statistical analysis on the role of mining in driving growth can be found in EV-Consulting (2011).
[8]Contribution of each sector involves the real growth rate of a sector and the share of it in GDP at current prices.

very poor correlation between mining and the main industry sectors[9], except with trade and service, -0.32 and -0.37, respectively. When checking for causal impacts from other sectors' share to mining, we get insignificant coefficients, except for agricultural share. These are evidences, which support to the hypothesis that mining and its share in GDP can be treated as an exogenous factor, which may have a significant power to explain GDP growth, inequality and poverty dynamics for the Armenian economy[10].

Analyzing mining's contribution to the evolution of industry structure and related macroeconomics indicators provide useful insights. However, in order to estimate the impact of mining, one needs to have a larger sample size and more details on variation of relevant variables. For this reason we make use of regional level data on the annual base, which covers the period 2004-2010. Armenia has 11 administrative districts, Yerevan (the capital) and 10 marzes[11]. In effect we have 77 observations, which allows to estimate causal impact of mining on growth, inequality and poverty.

We start with the description of our dataset and highlight some useful statistics on productivities in Section 1. Section 2 discusses econometrics methods and issues we challenge. Econometric analysis covers Section 3 and Section 5 concludes.

2 Data description

We use data from the National Statistical Service of the Republic of Armenia (NSSRA). The second source of data is Household Survey micro database from 2004 to 2010, which is representative for the whole population and includes from 4000 to 8000 households, depending on a year[12]. From annual reports by NSSRA, we take marz level manufacturing, construction, agriculture, trade and service shares, productivities and employment shares.

[9] We identify the following sectors for our analysis: mining, service, trade, agriculture, manufacturing and construction. Manufacturing involves mining.

[10] Nevertheless, our argument is far to be sufficient to exclude endogeneity of mining. We discuss the issue later in the paper.

[11] In Armenian the term "marz" stands for district (state) and we use it without translation.

[12] Household survey data is available in NSSRA website, www.armstat.am.

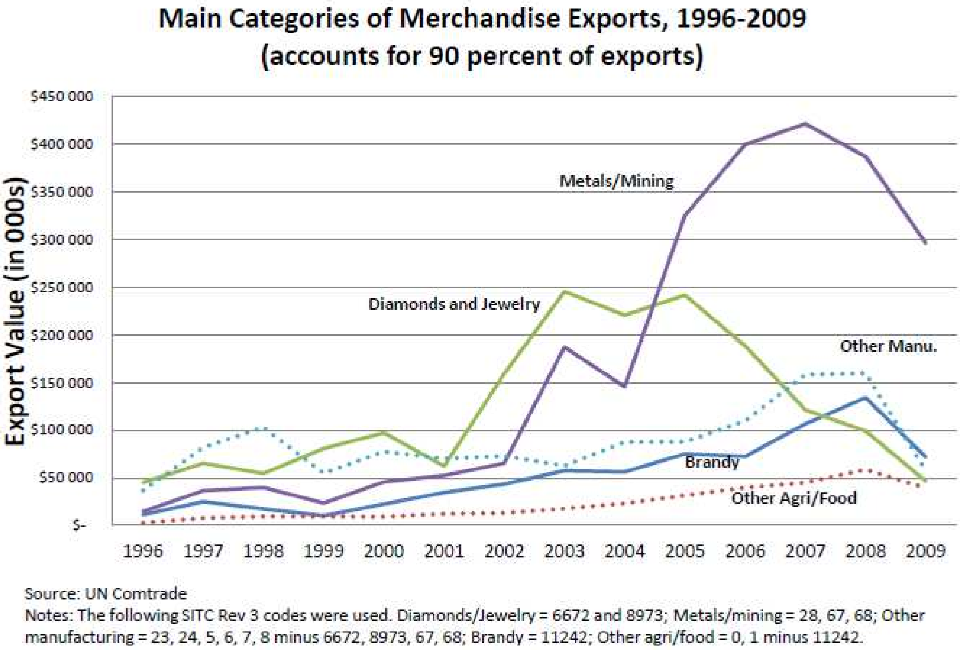

Figure 4: The main export items for Armenia. *Source:* Kostanyan (2011)

As NSSRA is not publishing marz level GDP, we construct this data[13]. From Household survay database we construct marz level data on different inequality measures, poverty rate, remittances, and wage income. Some of the variables are not used in estimated models, but we have tried to extract the highest explanatory power from the total set of variables, relevant to our model specifications. We have 77 observations in total (7 years and 11 marzes).

We construct industry shares using marz GDP and industry value added at current prices. A change in relative prices matter for consumption basket, and shares based on nominal values capture movements in relative prices. Productivities are also calculated at current prices. The GDP growth, nevertheless, is real, as the nominal factor may create effects without counterfactors[14].

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

[13]For details contact the author.

[14]Wehn taking two nominal values, the impact of common price movements will be canceled out, and the remaining effect will be due to relative price changes.

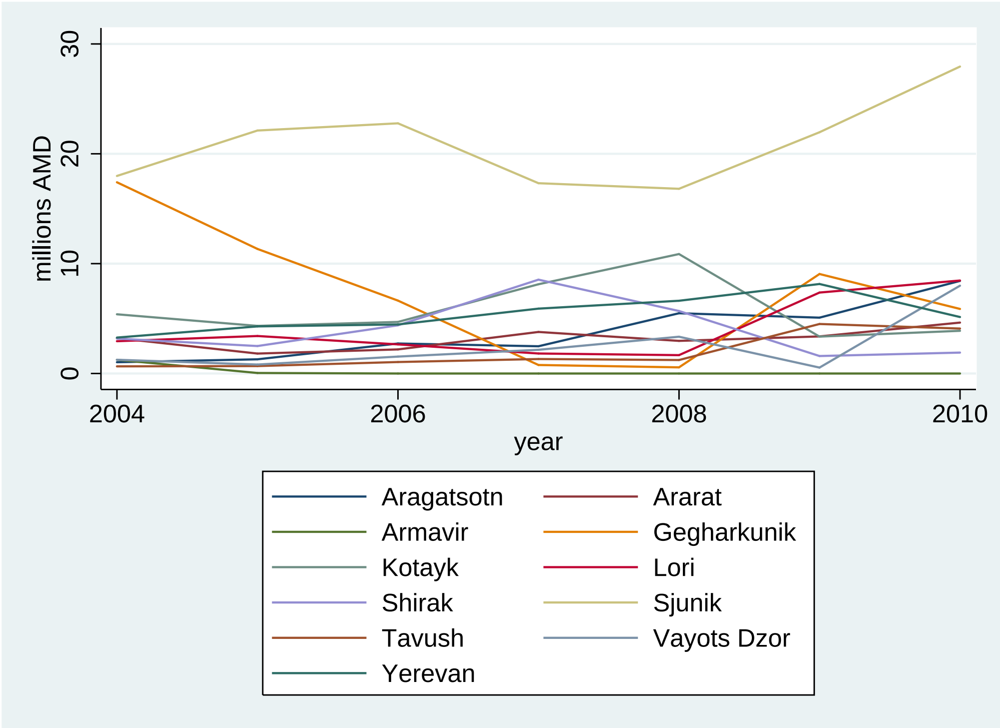

Figure 5: Mining productivities among marzes

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 for a long run growth strategy for the Armenian government[15].

Figure 5 plots productivity in the mining sector in all marzez[16]. Syunik marz is distinguished by its high productivity. Some marzes, such as Shirak and Vayots Dzor, experienced high productivity before the crises started, while there was a drop in productivity during the crisis time. Some other marzes (Gegharkunik, Lori, Syunik) pattern the opposite dynamics, low productivity before crisis and high after. Finally, there are marzes, which seem to be indifferent to the crisis shock (Tavush, Kotayk etc).

Productivity of a certain mine is (i) product and (ii) mine specific. The third factor is macroeconomic, the company may face at any time. As time unfolds, different events

[15]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.

[16]In fact, to be prices we should write in all 10 marzes and Yerevan. We treat the capital as a marz to save space.

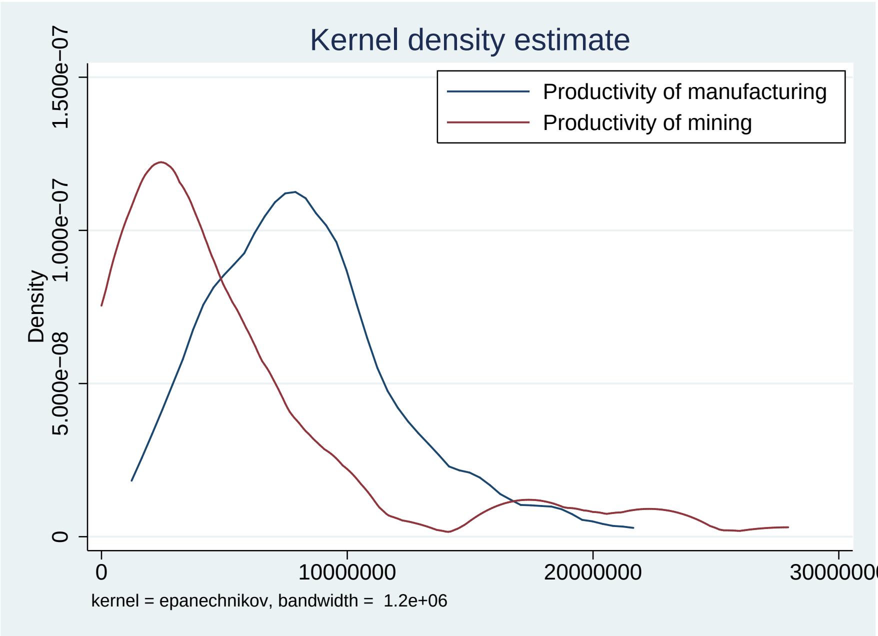

Figure 6: Productivities in mining and manufacturing

will alter initial productivities in certain ways, which will affect factor incomes, wages and profits. In order to get some insights how productivity in mining sector evolves over time, we plot distribution of marz specific productivities, manufacturing versus mining. Very rough approximation will be to use productivity distribution as a proxy for earnings distribution from the mining industry, as we do not have data for the latter.

For saving space, we only compare mining productivity with the manufacturing productivity. Also we plot dynamics of mining productivity distribution, before and during crisis period. Figure 6 reflects the fact that in average productivity in mining falls short from that of manufacturing. The second observation is that productivity variation in mining is higher than that in manufacturing among marzes. It is worth recalling that in this and forthcoming distributions all marzes have equal weights, while volumes of mining products may well differ from one marz to the other. Though very preliminary, there can be drown four observational implications from the above arguments:

1. If there is no a significant move in distribution towards a higher mean (median), then an increase in mining share is expected to deprive growth.

2. If high inequality in productivity is translated to high factor income distribution in

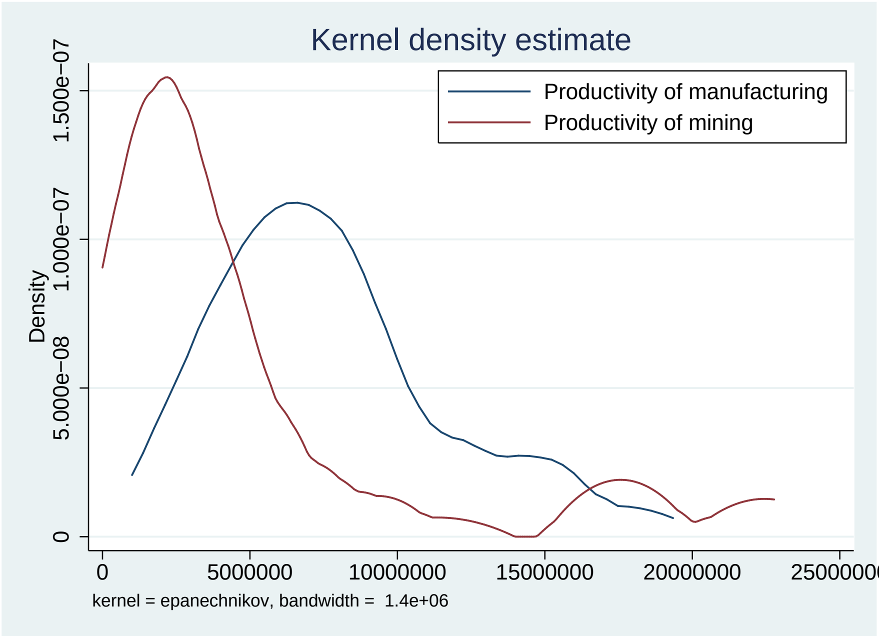

Figure 7: Productivities in mining and manufacturing in 2004-2007

mining, then it is very likely that a higher share of mining in manufacturing will further disequalize income among households.

3. If we draw a conventional poverty line for productivity, then simple expansion (not based on productivity) of mining may lead to higher poverty, as more households will be trapped in the poverty region.

4. Mining distribution is bimodal, implying that there are marzes with very high productivity, well separated from the average productivity.

These observations hinge on comparison between mining and manufacturing productivities. For an ideal comparison marz-economy specific productivity should be taken instead of manufacturing. The problem is that productivities calculated above involves intermediate goods consumption and is not corrected for shadow economy. At the moment, we only have data on marz level value added, which is net of intermediate goods consumption and accounts for the shadow economy factor.

Next we plot productivity distributions for two subsamples, 2004-2007 and 2008-2010. Figures 7 - 8 indicate the impact of crisis on mining's productivity distribution. The second mode has disappeared and the overall inequality has been mitigated - a higher mean and

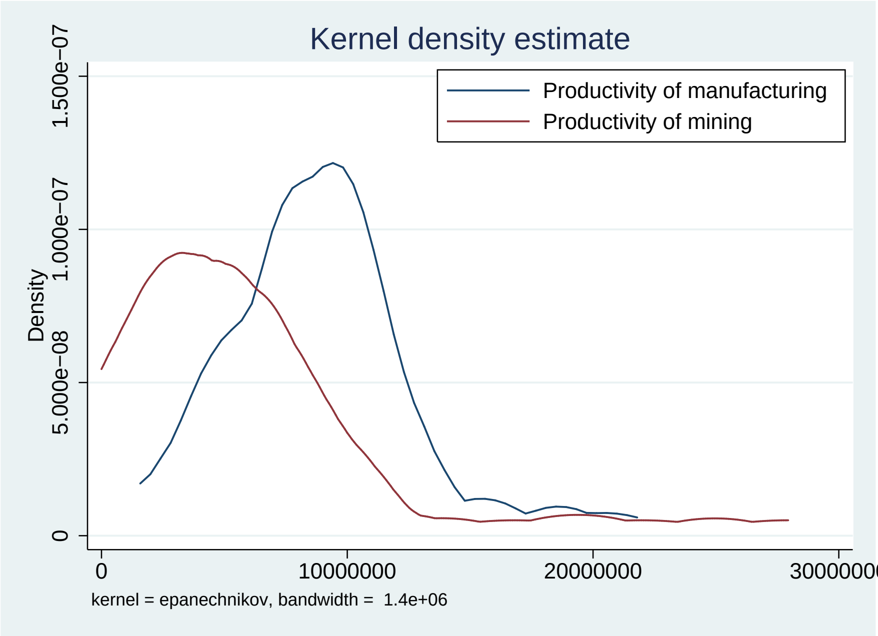

Figure 8: Productivities in mining and manufacturing in 2008-10

lower variance is reported during the crisis period. It is then very likely, that mining helped households to get out of the poverty region, if wages are paid according to productivities. We also plot dynamics of mining's productivity distribution to observe, how average productivity evolves over time. Again, we take before crisis period and the crisis time. Figure 9 indicates that we have much higher mean[17] with almost no change in standard deviation. Thus, we cannot exclude the scenario that expansion of mining may enhance growth, as the average productivity has increased, while dispersion has decreased.

We close this section by the well known fact that formal regression analysis is needed to establish causal effects, in our case, from mining sector to growth, inequality and poverty measures. In fact, our observational implications serve as hypotheses for causal analysis. Next we turn to the econometric model.

[17] 6,02 mln. versus 4,95 mln., in AMD.

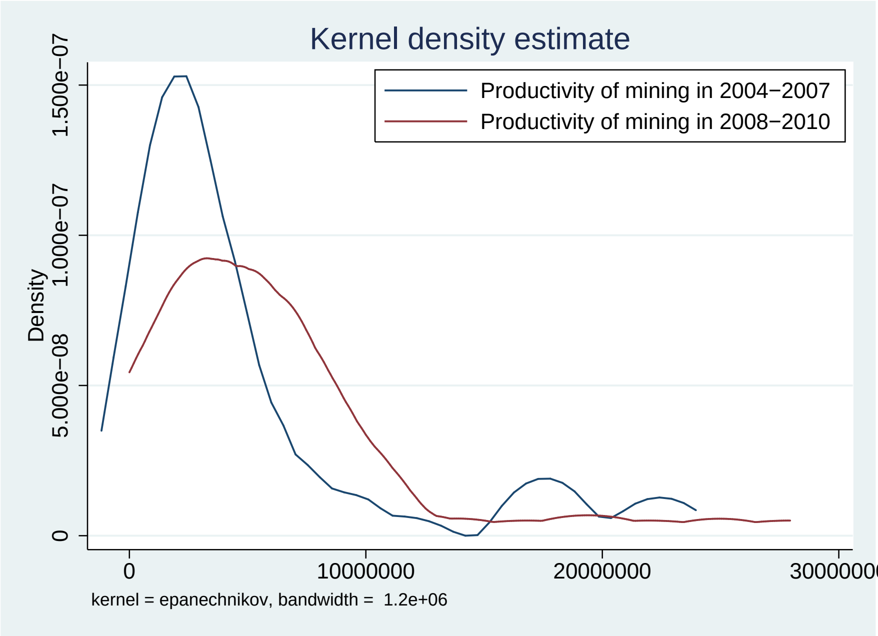

Figure 9: Dynamics of mining's productivity

3 Econometric model

The general strategy is to search within the set of linear regression models, in which mining has a significant role[18]. Our model takes the following form:

$$y_{i,t} = \alpha_0 + \beta mining_{i,t} + \alpha_1 x_{1,i,t} + ... + \alpha_k x_{k,i,t} + u_i + \epsilon_{i,t}; \tag{1}$$

where the left hand side variable $y_{i,t}$ will stand for growth, inequality and poverty, depending on a model. The variable $mining_{i,t}$ is the mining share in marz GDP, and $x_{1,i,t}, ..., x_{k,i,t}$ are all relevant variables for a given model. In particular, we will check for shares of other industries, employment shares, variables from Household survey dataset, such as remittances, as well as spatial factor of the dependent variable and time dummies. We take fixed effects approach (u_i captures fixed effects), in order to account for large unobserved differences among marzes. The error term is $\epsilon_{i,t}$. Finally, the subscripts i and t stand for a specific marz and a year, respectively.

[18]Begrakyan and Grigoryan (2012) use the same dataset, looking at unrestricted models to explains income inequality and poverty.

The model in (1) has a great potential to suffer from the endogeneity problem. The way, how the shares are constructed, introduce endogeneity. To see this, consider the following scenario. Suppose service is not included in the model, as it has no significant explanatory power on the left hand side variable. However, service expansion leads to contraction of mining share almost by construction, as shares sum to 1. Then, if the impact of mining on inequality (the dependent variable) can be sufficiently explained by the variation of service share, mining becomes endogenous. The ultimate question will be which variable is relevant to the model, as there is a functional link between mining and service shares. We control for endogeneity to some extent - mining share is very small and it seems fairly independent from most of the industry shares, as stated in Introduction.

Another issue is simultaneity in the model. Our strategy is to explain growth, inequality and poverty by exogenous drifts in industry shares and other relevant variables. 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. If there is, however, a long term component in variables, it will be captured too, since in fact we explore a 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[19], to estimate AR(1) processes. Inequality measures are relatively less persistent than poverty, and for the latter time dummies are very informative. Growth is not persistent - its lagged value is insignificant. Parallel to the benchmark model

[19]The Stata routine has been written by Bruno (2005). The general idea goes back to Kiviet (1995), who suggest to use a consistent estimator for the true parameter, in order to control for the bias, generated when estimating dynamic models by least squares.

in (1), we also check for the following relationship:

$$y_{i,t} = \rho y_{i,t-1} + (1-\rho)(\alpha_0 + \beta mining_{i,t} + \alpha_1 s^1_{1,i,t} + ... + \alpha_k s^k_{k,i,t}) + u_{i,t} + \epsilon_{i,t}, \tag{2}$$

where $s^1_{1,i,t}, ..., s^k_{k,i,t}$ are the residuals of corresponding AR(1) estimates for $x_{j,i,t}$ variables. A part of endegeneity is removed, as the current shocks are embedded in the model. However, current shocks may well be endogenous to current variables, excluded from the model. This specification is not much different from dynamic panel models studied by Arellano and Bond (1991) and Blundell and Bond (1998), among others[20].

Unfortunately, specifications in form of (2) do not yield significant estimates, and instead we use the modification of that model for the growth equation only:

$$s^{growth}_{i,t} = \alpha_0 + \beta mining_{i,t} + \alpha_1 s^1_{1,i,t} + ... + \alpha_k s^k_{k,i,t} + u_{i,t} + \epsilon_{i,t}, \tag{3}$$

where $s^{growth}_{i,t}$ is the residual from the AR(1) estimate of growth.

The last issue, we want to control for our models is the small sample size. We control finite simple properties for our models by bootstrap analysis, with the number of replications 10000. If an estimated model passes the normality test, then standard errors corrected by bootstrap will not significantly differ from the estimated once and the model will pass the test[21]. That is, we use bootstrap analysis to check models' sensitivity to finiteness of the sample[22]. For each estimated model, we report bootstrap corrected standard errors to check validity of the model. Standard errors, corrected by bootstrap are very sensitive to number of observations and for this reason we do not test our models for subsamples, as too few observations will be left for a test.

[20]We do not estimate classical dynamic panel models by GMM, as the number of cross sections is extremely small, and the estimated coefficients would suffer in huge bias.

[21]For bootstrap procedures, see Cameron and Trivedi (2010), Chapter 13.

[22]We can call it *a test for stability of a model.*

4 Estimation

Growth model

Reported estimates for different growth specifications are in Table 1. As hypothesized above, an accelerated expansion of mining is indeed growth enhancing. The significance for the coefficient is rather on the margin, but it well survives the bootstrap test. The benchmark specification (Column 1) also involves agricultural, construction and service shares, as well as export and import shares. All variables are in percentages, within the range $0 - 100$, and the estimated coefficients reflect the percentage point (pp) change for growth, as a response to 1 percentage point change in an independent variable. In particular, 1 pp increase in mining shares, say from 3% to 4%, will lead to 4.418 pp in growth.

Is this a big number? In our context, one needs to disentangle two factors which may drive growth. There can be no structural change in an economy under positive growth, as each sector grows by the same rate (balanced growth). The second factor is the change in the industry structure, and if there is a structural break in an economy, which leads to a higher growth, the corresponding causality will be established. It is possible to draw scenarios, in which 1 pp change in certain industry share, no matter how small the industry is, leads to any reasonable pp change in growth[23]. In general, the coefficient of the mining share, 4.418, is a pretty big number and comes to confirm statistical evidence from Table 2.

[23]In order to control for the impact of the sectoral growth, we need to use these components as explanatory variables.

Table 1: **Growth specifications**

	(1) benchmark	(2) boot.(1)	(3) Syunik excl-ed	(4) boot.(3)	(5) weighted	(6) shock appr.
mining	4.418*	4.418*	2.405***	2.405	4.089**	5.9624***
	(2.338)	(2.368)	(.500)	(2.105)	(2.042)	(1.251)
agr	.996***	.996**	.976***	.976**	1.145***	.826**
	(.200)	(.434)	(.175)	(.442)	(.150)	(.344)
const	1.598***	1.598***	1.692***	1.692***	1.810***	1.808***
	(.428)	(.551)	(.372)	(.533)	(.149)	(.394)
serv	2.122**	2.122	1.932*	1.932	1.277	
	(.962)	(1.292)	(1.091)	(1.341)	(.813)	
export	1.511***	1.511**	1.911***	1.911**	1.600***	.661
	(.309)	(.643)	(.371)	(.751)	(.169)	(.405)
import	-2.388***	-2.388**	-2.532***	-2.532***	-2.498***	.976***
	(.675)	(.990)	(.647)	(.971)	(.357)	(1.251)
N	77	77	70	70	77	
R^2: within	.261	.261	.323	.323	.547	

* – 90%, ** – 95% *** – 99%

Interestingly, all other covariates have much less impact on growth. This is indeed an evidence, how important mining is for growth. There is much capacity in mining to boost growth. Column 2 confirms that the benchmark specification is robust to small sample size. We estimate the same model in Column 3 without Syunik marz. The difference is striking - almost 50% of mining's contribution to growth acrues to Syunik marz. Although this estimate does not pass the bootstrap test[24], but the result seems to be reasonable. A huge share of mining industry is concentrated in Syunik, and this comes natural that mines in Syunik comprise the driving power of the mining industry for growth. We use population weights for becnhmark specification in Column 5. As we can see, the magnitudes of coefficients are almost identical. In the last column we estimate the model (3) and, interestingly, the impact of the mining share is even stronger, when persistence of both variables is controled. That is, if we explain the part of growth, which is net of inertia, then an increase in mining share, purely driven by current factors, will result in even higher

[24]A decrease in coefficient has not been accompanied by a corresponding decrease in the standard error, which is an evidence of the relevance of the Syunik marz, as its portion in the standard deviation turns to be smaller relative to the rest of the eocnomy. This can be seen, when mooving from Column 4 to 2 in Table 1.

growth.

Overall, the growth model captures common perception that mining is important for growth. As noted earlier, there is much endogeneity in the model, which mainly comes from other industry shares, but we expect that the bias of the mining coefficient is small enough to capture reality. It does, as the magnitude of the estimated coefficient reflects the huge disproportionality between the mining share in GDP and its contribution to growth, indicated in Table 2.

Inequality model

We have seen that mining is growth enhancing. Then the question is whether mining driven growth is pro-poor. Unfortunately, there is no evidence that mining expansion will help equalize income among households. The impact of mining on resource distribution is twofold. The direct effect is reflected by factor income distribution in mining, in forms of wage and profit distributions. The indirect effect is related to externalities created and amplified along the expansion of existing mines and exploitation of the new once. The damage by mining is usually underestimated and the mine owners do not totally internalize the negative consequences, resulting in deterioration of natural and local resources. This may increase inequality, as well as poverty.

Specifications for inequality models are in Table 2. All models involve mining agricultural and service shares, and a dummy variable for the year 2007. The inequality measure is the Gini index.

Mining's expansion seems to increase inequality. If there will be 10% percent in increase in value added in mining, which will lead to around 0.25 pp increase in mining share, then Gini index will increase by 0.17 pp. Again, if we want to qualify the impact, we may compare the coefficient of mining share with those of agricultural and service shares, controlling for share differences. The share of agriculture is around 11 times higher than the share of mining. Instead, the coefficient of mining share is even higher than that of agricultural share. In effect, the coefficient of mining is 14 times larger than that of agricultural share and 3.7 times larger than the coefficient of the service share.

Table 2: **Inequality specifications**

	(1) benchmark	(2) boot(1)	(3) altern.	(4) boot.(3)	(5) Syunik excl.	(6) boot.(5)
mining	.666***	.666	.670***	.670	.679***	.614
	(.102)	(.532)	(.157)	(.433)	(.129)	(.719)
agr	.542***	.542***	.688***	.688***	.545***	.690***
	(.145)	(.152)	(.202)	(.191)	(.154)	(.203)
const	.466***	.466***	.551***	.551***	.476***	.557***
	(.136)	(.163)	(.173)	(.191)	(.137)	(.197)
d_{2006}	-4.181***	-4.181***	-4.359**	-4.359***	-4.793***	-4.948***
	(1.556)	(1.385)	(1.875)	(1.537)	(1.559)	(1.608)
N	77	77	77	77	70	70
R^2: within	.302	.302	.386	.386	.323	.399

* – 90%, ** – 95% *** – 99%

The bootstrap test, however, indicates that estimated coefficients are sensitive to the sample size. The significance level is around 20% with the *P-value* ≈ 0.80 , which is still an evidence that mining has a causal impact on income inequality. When using an alternative measure for Gini index[25], we obtain similar coefficients. After, we exclude Syunik marz from our sample, but the exclusion does not lead to any significant change in the model. This is an evidence, that mining industry does not generate excessive inequality relative to the rest of the industry. Again, bootstrap test indicates that the estimated coefficients lacks in acceptable significance.

Poverty model

Begrakyan and Grigoryan (2012), using the same dataset, argue that poverty dynamics is basically explained by the spatial factor, which is further expelled, when time dummies are introduced[26]. They do not check for mining share as a separate covariate, while concentrating

[25] The difference is about weights, used to move from houseolds' income to per capita income.

[26] The authors start with a multiplicative model and use the log form. We do not use the log form of the model, as almost in non of the specifications mining is significant. The reason is that log values of very small numbers do not ensure sufficient variation and hence lack in explanatory power.

only on the main 4 sectors, agriculture, manufacturing, service and construction. It is interesting to find out that mining has a significant impact on poverty, even if we control for the spatial factor and time dummies. In the benchmark specification, 1 pp increase in mining share leads to 0.67 pp increase in the poverty rate[27]. The magnitude is very close to that in the inequality model. The causal impact of mining to inequality is almost as strong as that of the spatial factor[28]. The latter passes the bootstrap test, while mining share sustains 15 percent significance level. As in Begrakyan and Grigoryan (2012), when time dummies are introduced, the spatial factor becomes redundant. Surprisingly, the coefficient of the mining share continues to be significant, which is an evidence of the strong impact of mining on poverty.

Table 3: **Poverty specifications**

	(1) benchmark	(2) boot(1)	(3) Synik excl-ed	(4) boot.(3)	(5) year dummies	(6) boot.(5)
mining	.672** (.318)	.672 (.416)	.554 (.384)	.554 (.874)	.557** (.247)	.557 (.359)
pov_{sp}	.845*** (.110)	.845*** (.095)	.853*** (.123)	.853*** (.100)		
d_{2005}					-4.781*** (.864)	-4.781*** (1.076)
d_{2006}					-6.985*** (1.139)	-6.985*** (1.167)
d_{2007}					-10.474*** (1.347)	-10.474*** (1.230)
d_{2008}					-10.512*** (1.318)	-10.512*** (1.311)
N	77	77	70	70	77	77
R^2: within	.622	.622	.618	.618	.705	.705

* – 90%, ** – 95% *** – 99%

When Syunik marz is excluded from the sample, the impact becomes insignificant. Thus, mining in Syunik makes the industry generate poverty. An immediate conclusion is that wages in mines located in Syunik fall short to keep households out of the poverty region. This should be a serious concern for policy makers, as boosting mining, in particular in

[27] Poverty rate is the poverty headcount ratio at US $2 a day, as a percentage of population, PPP adjusted.
[28] The spatial variable is constructed as an average of inequality rates from neighboring marzes.

Syunik, will accelerate growth, but it entail higher poverty.

5 Conclusion

In this paper we search for econometric models for growth, inequality and poverty, in which mining sector has a significant role. We dare to take such an approach, as there is common perception that mining in Armenia has a specific role for the economy. First, it has served as a buffer for mitigating the disastrous impact of the world financial crisis. Second, mining comprises more than 20 percent of the Armenian exports and it has a growing tendency. Third, mining seems to be far from its capacity utilization and its share in GDP is growing too.

To our knowledge, there is no paper which quantifies the causal impact of mining (share) on growth, inequality and poverty for Armenia. Our paper is of descriptive nature, but it has certain normative implications. Variation of mining, both in terms of growth and industry share, entails social consequences. Mining sector is an externality creator, a big concern from the social viewpoint[29]. In this context the trade-off between growth (efficiency) and inequality/poverty (equity), takes an extreme form, as the two components seem to pattern zero complementarity. Our econometric analysis highlight this trade-off effectively - mining is growth enhancing, but it does bad job for inequality and poverty. That it is growth enhancing, may tempt the current government encourage further expansion of mining. This, however, conflicts with the equity consideration, and the government should draw certain policies to impose mining companies taking responsibilities of social consequences.

For controlling negative impact of mining expansion on inequality and poverty in the long run, total compensation of environmental damage by mines should be a strong precondition for exploitation. For poverty reduction in the short run, wages are of primary concern. Also, local community should definitely benefit from mining through different social programs, as a (non-exhaustive) part of mining companies' social responsibility.

[29] For the theory of externalities, see Mas-Colell et al. (1995).

Our results can be improved in different directions. A very limited time span makes the estimates highly sensitive to structural changes. We check for sensitivity by bootstrapping standard errors, but this is a poor prescription to finite sample problem. We have regional level data, but number of regions is very limited and we cannot use dynamic panel approach, by this effectively controlling for endogeneity. We make certain judgments on the extent of endogeneity we may have in models, but do not formally control for it.

Will all these deficiencies in mind, the model implied results are in line with common perceptions and concerns, present in Armenia. We believe this is the central finding of the paper, among others.

References

Manuel Arellano and Stephen Bond. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies*, 58 (2):277–97, April 1991.

Edgar Begrakyan and Aleksandr Grigoryan. Inequality, growth and industry structure: Evidence from armenia. Technical report, AUA, CBA, December 2012.

R Blundell and Steven Bond. Initial conditions and moment restrictions in dynamic panel data model. Technical report, 1998.

Giovanni S.F. Bruno. Estimation and inference in dynamic unbalanced panel data models with a small number of individuals. KITeS Working Papers 165, KITeS, Centre for Knowledge, Internationalization and Technology Studies, Universita' Bocconi, Milano, Italy, June 2005.

A. Colin Cameron and Pravin K. Trivedi. *Microeconometrics Using Stata, Revised Edition.* Number musr in Stata Press books. StataCorp LP, July 2010.

EV-Consulting. Counturs of armenia's economy in 2010: mining drives growth. *EV Periodical*, (2), April 2011.

IMF. Republic of armenia: Poverty reduction strategy paper. *IMF Country Report*, 11(191), 2011. URL http://www.imf.org/external/pubs/ft/scr/2011/cr11191.pdfl.

Jan F. Kiviet. On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics*, 68(1):53–78, July 1995.

Tigran Kostanyan. Export expansion and diversification in armenia. Technical report, World Bank, December 2011. URL http://acf.eabr.org/media/img/eng/Development_Partners/Kostanyan_eng.pdf.

A. Mas-Colell, M. Winston, and R. Green. *Microeconomic Theory*. 1995.

Nienke Oomes, Gohar Minasyan, and Ara Stepanyan. In search of a dramatic equilibrium: Was the armenian dram overvalued? IMF Working Papers 09/49, International Monetary Fund, March 2009. URL http://ideas.repec.org/p/imf/imfwpa/09-49.html.