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Growth, Growth Accelerations and the Poor: Lessons from Indonesia[1]

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Abstract. We study the impact of growth and growth accelerations on poverty and inequality in Indonesia using a new panel dataset covering 26 provinces over the period 1977-2010. This new dataset allows us to distinguish between mining and non-mining sectors of the economy. We find that growth in non-mining significantly reduces poverty and inequality. In contrast, overall growth and growth in mining appears to have no effect on poverty and inequality. We also identify growth acceleration episodes defined by at least four consecutive years of positive growth in GDP per capita. Growth acceleration in non-mining reduces poverty and inequality whereas growth acceleration in mining increases poverty. We expect that the degree of forward and backward linkages of mining and non-mining sectors explain the asymmetric result. Our results are robust to state and year fixed effects, state specific trends, and instrumental variable estimation with rainfall and humidity as instruments.

JEL classification: I32, N15, O11, O13, O49

Key words: growth; growth accelerations; mining, non-mining, poverty; inequality

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1. Introduction

Global growth since 2006 has been sluggish. Yet growth in the emerging market economies over this period has been steady. Indonesia along with India and China has been one of the strong performers during this period growing at an average rate of over 5 per cent. This however begs the question how much of this steady growth has been beneficial to the poor. In spite of some agreement on the desirability of growth, there is however no consensus on whether growth is good for the poor. At one end of the spectrum the argument is against growth as any potential benefits of growth for the poor are eroded or offset by an increase in inequality that often accompanies growth. At the other end of the spectrum the argument is in favour of growth as it is perceived to be raising living standards of the poor and non-poor proportionately. Addressing this puzzle with facts has significant bearing on whether the Millennium Development Goal of halving global poverty by 2015 is achieved. In particular, addressing this puzzle in Indonesia is crucial given its large population and being the third largest developing country after China and India.

In this paper we revisit the issue of growth and its impact on the poor. We study the impact of growth and growth accelerations on poverty and inequality in Indonesia using a new panel dataset covering 26 provinces over the period 1977-2010.[3] This new dataset allows us to distinguish between mining and non-mining sectors of the economy which yields novel and asymmetric results. Indonesia, like many other developing countries has a substantial mining sector. Therefore, to study the impact of growth on the poor in Indonesia, it is crucial to disentangle the impact of mining growth from non-mining growth. We find that growth in non-mining significantly reduces poverty and inequality. In contrast, overall growth and growth in mining appears to have no effect on poverty and inequality. We are also able to

[3] Note that these are Indonesian provinces, excluding East Timor, till 1999. Since then several provinces have split into two or more new provinces and so by now there are 34 provinces in Indonesia. In this paper, for the sake of continuity we grouped new provinces into their original provinces.

estimate causal effects of growth on poverty and inequality as we use instrumental variable estimation with rainfall and humidity as instruments for growth. We find some evidence of heterogeneous impact of growth on poverty and inequality across states.

We also identify growth acceleration episodes defined by at least four consecutive years of positive growth in GDP per capita. This allows us to analyse the effect of rapid and sustained growth experiences by provinces on poverty and inequality. Few would disagree that understanding the cause and effects of sustained growth accelerations is perhaps the most important policy issue in development economics. Growth acceleration in non-mining reduces poverty and inequality whereas growth acceleration in mining increases poverty. These asymmetric results are perhaps best explained by the fact that the link between the poor and the mining sector is lot less relative to the link between the poor and the non-mining sector (especially agriculture and urban services) in Indonesia.

Using the timeline of growth accelerations, we are able to test the timing and durability of the effects. We find growth accelerations start to have an impact on the poor only three years after an episode. However, these effects do not appear to be durable over the very long term.

Overall our results are robust to the inclusion of state and year fixed effects and state specific trends as controls. They are also robust to the inclusion of schooling, employment, credit, government spending, and political fractionalization as additional controls.

We make the following five contributions in this paper. First, we compile a new panel dataset on poverty and growth in Indonesia covering 26 provinces over the period 1977-2010. To the best of our knowledge, this is the largest provincial level panel dataset available for Indonesia. Second, we are able to distinguish between the effects of mining and non-mining growth on poverty and inequality. This distinction yields new results. Third, using rainfall and humidity as instruments for growth we are able to arrive at causal estimates of growth on poverty and inequality. This is unlike any other previous studies on Indonesia. Fourth, by identifying growth acceleration episodes we are able to study its effect, timing and durability. These issues are of key policy significance and yet they were never studied before. Fifth, despite the fact that Indonesia is the third largest developing country in the world, studies of the effects of her economic growth on her poor are rare. This study aims to fill this important gap.

In spite of the importance of Indonesia in global poverty reduction, the literature on the effects of growth on poverty and inequality in Indonesia is relatively thin. Two recent studies deal with this topic.[4] Sumarto and Suryahadi (2007) examines the role of agriculture in poverty reduction in Indonesia and finds agriculture to be of significance. Suryahadi et al. (2009), in contrast, investigate the relationship between growth and poverty reduction over the period 1984 to 2002 by focusing on the sectoral composition and rural-urban divide of growth and poverty. They find growth in rural agriculture is the most effective channel for reducing rural poverty. They also find growth in rural and urban services reduce poverty in most sectors and locations. None of these studies however analyse the effect of mining and non-mining growth on poverty and inequality. None of them also analyse the effects of growth accelerations.

Our study is related to a large literature on the impact of growth on poverty. Some studies analyse the impact of growth on poverty using a global sample and find that growth is good for the poor (Datt and Ravallion, 1999; Dollar and Kraay, 2002; Loayza and Raddatz, 2006; and Ravallion, 2012). For example, Dollar and Kraay (2002) using a sample of 92 countries spanning four decades show that average incomes of the poorest quintile rise proportionately to overall average income. Others focus on the same question using Indian

[4] Other studies on related topics are Levinsohn et al. (2003), Suryahadi et al. (2003), Suryahadi and Sumarto (2003), McCulloch et al. (2007), and Suryahadi et al. (2008). Almost all of these studies present poverty estimates during the economic crisis in Indonesia.

and Chinese data (Ravallion and Datt, 1996; Datt and Ravallion, 1998, 2002; Foster and Rosenzweig, 2005; Ravallion and Chen, 2007).[5] For example, Ravallion and Datt (1996) using Indian time series data spanning the period 1951 to 1991 find that agriculture and informal services sector growth contributes most to poverty reduction. Foster and Rosenzweig (2005) in contrast use Indian village and household panel data for the period 1982 to 1999 and find that agricultural productivity growth and factory employment contrbutes to poverty reduction.

Our study is also related to a large theory and empirical literature on growth and inequality. The comparative empirical literature on this topic flourished after the publication of Deininger and Squire (1996) inequality dataset. The theory literature in contrast stems back to Alesina and Rodrik (1994). Some of the notable studies on this topic are Persson and Tabellini (1994), Deininger and Squire (1998), Barro (2000), Forbes (2000), Banerjee and Duflo (2003), and Easterly (2007). Aghion and Williamson (1998) and Aghion et al. (1998) present excellent surveys of the early literature.

Finally, our study is related to a growing literature on inequality measurement using top income shares (Banerjee and Piketty, 2005; Leigh and van der Eng, 2007; Roine *et al.*, 2009) and the causes and consequences of growth accelerations (Hausmann et al., 2005). Atkinson *et al.* (2009) present an excellent survey of the former.

The remainder of this paper is organized as follows: Section 2 analyses the effects of mining and non-mining growth on poverty and inequality. First, it introduces our econometric model and discusses the virtues of our growth, poverty and inequality measures. Second, it reports results relating to the consequences of growth. Section 3 analyses the effects of growth accelerations and reports relevant results. It also reports results on the timing and durability of the growth acceleration effects. Section 4 concludes.

[5] There are some exceptions who study countries other than India and China. Warr (2006) study Southeast Asia, Christiansen and Demery (2007) study Africa, and Warr and Wang (1999) study Taiwan.

2. Mining and Non-mining Growth and the Poor

2.1 The Model

To estimate the effect of province-specific growth on poverty, we relate poverty in province i at time t (H_{it}) to province specific fixed effects plus time trend $(\alpha_i + \beta_i t)$, time-varying shocks that affect all Indonesian provinces (ϕ_t), province-specific growth in GDP per capita (Y_{it}) or Mining GDP per capita (Y_{it}^{M}) or Non-Mining GDP per capita (Y_{it}^{NM}), and a vector of additional covariates ($\mathbf{X}_{it}$) which includes political fractionalization index, schooling, employment, real government spending and credit. The province specific fixed effects (α_i) control for province specific time invariant unobservable such as religion, culture or linguistic differences. The time trends $(\beta_i t)$ on the other hand control for province specific time varying unobservable such as different growth trajectory. We estimate the following model.

$$H_{it} = \alpha_i + \beta_i t + \phi_t + \gamma Y_{it} + \Phi \mathbf{X}_{it} + \varepsilon_{it} \qquad (1)$$

Our coefficient of interest is γ which estimates the average effect of one percentage point increase in Y_{it} on H_{it}.

Even though growth in mining GDP per capita (Y_{it}^{M}) is likely to be mainly influenced by exogenous factors such as international commodity prices and subsoil resource discovery, growth in non-mining GDP per capita (Y_{it}^{NM}) could be endogenous. In other words, causality could run in the opposite direction from H_{it} to Y_{it}^{NM}. This would bias the estimate of our coefficient of interest γ. To address this issue we also instrument Y_{it}^{NM} by using exogenous variations in rainfall and humidity. For the instrumental variable estimation method to adequately address this issue, the instruments used are required to be correlated with the suspected endogenous variable Y_{it}^{NM} and uncorrelated or orthogonal to the error term ε_{it}. The latter criterion is often referred to as the exclusion restriction. Rainfall and humidity are exogenous geography based instruments correlated with Y_{it}^{NM} and they are unlikely to affect poverty through channels other than GDP per capita. They also pass all the diagnostic tests to be valid instruments.

To estimate the effect of province specific growth on inequality we estimate the following model.

$$G_{it} = \alpha_i + \beta_i t + \phi_t + \delta Y_{it} + \Lambda \mathbf{X}_{it} + v_{it} \qquad (2)$$

2.2 Data

Our dataset covers the period 1977 to 2010 and 26 provinces. Note that currently there are 34 provinces in Indonesia. In this paper, for the sake of continuity we grouped new provinces into their original 26 provinces that existed till 1999. Due to data limitations, not all specifications have the same number of observations and the panel is unbalanced. Figure 1 presents a map of Indonesia and Appendix A1 presents a list of provinces included in our dataset.

Poverty (H_{it}) here is measured by the poverty head count ratio. Poverty head count is the percentage of poor people residing in a province at a particular point is time. We source this measure from several volumes of the Statistics Indonesia's 'Statistical Yearbook of Indonesia'. The head count ratio here is calculated using the Indonesian provincial poverty line set by Statistics Indonesia.[6] This is a point of departure from Suryahadi et al. (2009) who use household consumption survey data from the *Susenas* survey and region specific poverty lines developed by Pradhan et al. (2001) to calculate poverty estimates. Appendix A2 presents the data appendix with details on the variables used and table 1 reports summary statistics. We found Jakarta in 1996 to be the least poor province in our sample with a poverty

[6] Note that in 1996 Statistics Indonesia adjusted their methodology to calculating provincial poverty line in Indonesia. This change is taken into account by the year dummies in our models.

head count ratio of 2.48 per cent. In contrast Irian Jaya/Papua in 1999 records the highest poverty rate of 54.75 with more than half of the population below the poverty line.

Inequality (G_{it}), in contrast, is measured by the Gini coefficient reported by the Statistical Yearbook of Indonesia for the period 1977 to 2010. These inequality measures are consumption expenditure based and calculated from several rounds of household surveys. In our sample, Jakarta in 1999 is the most unequal province with a Gini coefficient of 46 per cent and Sulawesi in 2007 is the least unequal province with a Gini coefficient of 18 per cent. Inequality across Indonesian provinces and over time also appears to be fairly uniform as the overall variation in Gini coefficient in our sample is close to 4 per cent.

We also source the real GDP per capita (Y_{it}) data and the Non-Mining GDP per capita (Y_{it}^{NM}) data from several issues of the Statistical Yearbook. The Mining GDP per capita (Y_{it}^{M}) data is calculated to be the difference between overall GDP per capita (Y_{it}) and Non-Mining GDP per capita (Y_{it}^{NM}). All GDP here are real and measured in 2002 constant prices. Riau in 1977 is the fastest growing province in our sample and Jawa Barat in the same year is the slowest growing province. Maluku in 2000 records the fastest mining GDP per capita growth.

We also use rainfall and humidity as instruments for non-mining GDP per capita. Rainfall or average annual precipitation is measured in millimetres and humidity is the relative humidity expressed in percentages. Note that relative humidity is expressed in percentages as the ratio of absolute humidity relative to maximum possible humidity for that temperature. Both variables are sources from the Statistics Indonesia.

Finally, we also use schooling, employment, real government spending relative to GDP, credit to the private sector relative to GDP as additional control variables. Schooling and employment data are sourced from several issues of the Statistical Yearbook. Government spending and credit data are sourced from the Ministry of Finance database.

We also create a political fractionalization index using election data from Sudibyo, (1995), Kristiadi et al. (1997), Suryadinata (2002), and Apriyanto (2007). Following Alesina et al. (1999) this variable measures the probability of two individuals voting for different political parties in the national legislative elections. If the probability is too low then there is too little political diversity in the electorate and vice versa. We argue that low diversity is reflective of lack of political competition and democracy.

2.3 Evidence

In table 2, we relate growth to poverty. In column 1 we estimate the effect of growth in GDP per capita on poverty measured by the head count ratio. We control for state fixed effects, year dummies and state specific trends. The coefficient estimate is not significantly different from zero. Using the new dataset in columns 2 and 3 we are able to distinguish between growth in mining GDP per capita (Y_{it}^{M}) and growth in non-mining GDP per capita (Y_{it}^{NM}). In column 2 we find that an increase in the growth rates of mining GDP per capita reduces poverty but the effect is not statistically significant. In column 3 an increase in the growth rate of non-mining GDP per capita also reduces poverty and the effect is statistically significant. In order to gauge the magnitude of the effect, let us focus on Irian Jaya/Papua in 1999, the poorest province in our sample with more than half of the population below poverty line. Our estimate predicts that a one percentage point increase in the growth rate of non-mining GDP per capita in Irian Jaya/Papua in 1999 would have reduced the poverty head count ratio from 54.75 to 54.75-6.22=48.53. This amounts to pulling 134682 individuals (6.22 per cent of the Irian Jaya/Papua population in 1999) out of poverty and hence is a large effect.

The effect that we report in column 3 may not be causal. The causality could run in the opposite direction from poverty to non-mining growth. Poverty could distort the political economy of income distribution in a society which in turn could harm growth by creating an investment unfriendly environment. In order to tackle the causality challenge, in column 4 we estimate the model using instrumental variable estimation method and rainfall and humidity as instruments for non-mining growth. Rainfall and humidity are geography based and are often strongly correlated with economic performance (especially agriculture) in developing countries. They are also unlikely to affect poverty through channels other than non-mining GDP growth. Therefore, they are suitable instruments. We notice that the size of the coefficient declines marginally however it remains negative and strongly significant. This indicates that what we are picking up is a causal effect.

In table 3, we estimate equation 2, the effect of growth on inequality. In column 1, we relate GDP per capita growth to inequality. The effect is negative but insignificant. In column 2, we estimate the effect of growth in mining GDP per capita on inequality. The effect is again negative but insignificant. In column 3, we look at the effect of growth in non-mining GDP per capita on inequality. The effect is negative and significant. Our estimate indicates that a percentage point increase in the growth rate of non-mining GDP per capita would reduce the Gini coefficient by 2.1 per cent. To put this into perspective, our estimates predict that an extra 1 per cent growth in the non-mining GDP per capita in Bengkulu would reduce her inequality level (a Gini coefficient of 31 per cent in 1977) to that of Sumatera Selatan (a Gini coefficient of 29 per cent in 2002). To be certain that we are estimating causal effects, we estimate the model using instrumental variable method in column 4. We use rainfall and humidity as instruments for growth in non-mining GDP per capita. The negative effect survives and the magnitude of the coefficient appears to be marginally different.

In table 4 we check the robustness of our non-mining growth, poverty and inequality results in the presence of additional covariates. In columns 1-5 we check the robustness of our poverty result in the presence of political fractionalization, schooling, employment, real government spending, and credit as additional control variables respectively. Political fractionalization is an indicator of democratic accountability. Higher degree of political diversity is likely to be correlated with more democratic accountability. Democratic accountability in turn could influence both non-mining GDP growth and poverty. Schooling, employment, real government spending, and the availability of credit could also have direct effects on both poverty and growth. In all the cases reported in columns 1-5 our main result survives. The magnitude of the coefficient varies between -5.96 to -6.66 which are very close to our preferred estimate of -6.22 reported in column 3 of table 2. This exercise is repeated in columns 6-10 with inequality as the dependent variable and we end up with similar results. The magnitude of the coefficients here are also close to our preferred estimate of -0.021 reported in column 2 of table 3.

We also check whether there is significant heterogeneity in the poverty and inequality elasticities of growth across certain selected provinces. This is done by estimating the coefficients on the regression of non-mining growth on poverty (head count ratio) and inequality (Gini coefficient) using time series data over the period 1977-2010 carried out for the eight selected provinces. Note that growth, poverty and inequality here are stationary. These results are reported in Figures 2 and 3. The dots show the point estimates, and the bars indicate 95% confidence intervals. In Figure 2, we find that the poverty elasticity of growth in Jawa Burat is very small whereas the same in Sulawesi Tengah is large and over 80 per cent. In Figure 3, Yogyakarta and Nusa Tenggara Timur registers an increase in inequality due to non-mining growth whereas the remaining six provinces all register a reduction in inequality.

3. Growth Accelerations and the Poor

3.1 The Model

After estimating the growth elasticities of poverty and inequality in section 2, here we focus on the related question whether the speed and sustainability of growth matters for poverty and inequality reduction. In other words, we focus on the effects of growth accelerations on poverty and inequality. To estimate the effect of province-specific growth accelerations on poverty, we relate poverty in province i at time t (H_{it}) to province specific fixed effects plus time trend $(\alpha_i + \beta_i t)$, time-varying shocks (ϕ_t), province-specific growth accelerations in GDP per capita $(\hat{Y}_{it})$ or Mining GDP per capita $(\hat{Y}_{it}^{M})$ or Non-Mining GDP per capita $(\hat{Y}_{it}^{NM})$. We estimate the following model.

$$H_{it} = \alpha_i + \beta_i t + \phi_t + \theta \hat{Y}_{it} + e_{it} \tag{3}$$

Our coefficient of interest is θ which estimates the average effect of growth accelerations in GDP per capita $(\hat{Y}_{it})$ on H_{it}. Similarly to estimate the effect of growth accelerations on inequality, we estimate the following model.

$$G_{it} = \alpha_i + \beta_i t + \phi_t + \mu \hat{Y}_{it} + \omega_{it} \tag{4}$$

3.2 Measuring Growth Accelerations

In order to estimate the distributive impact of growth accelerations, it is crucial to define and accurately measure growth accelerations. Here we identify a growth acceleration episode in a particular province if it experiences at least four consecutive years of positive growth in GDP per capita. This is identified by assigning the value 1 to the growth accelerations variable $(\hat{Y}_{it})$ for the corresponding years. The variable takes the value 0 for all other years.

One could argue that simply having positive growth in GDP per capita may not amount to growth acceleration. Growth acceleration requires something stronger. We account for this argument by defining growth acceleration episodes by at least four consecutive years of more than 2 per cent growth in GDP per capita. Our results are robust to this alternative definition. Results are not reported here to save space but are available upon request.

Another point of view is that growth acceleration needs to be more sustained than just four consecutive years of growth. We account for this by using six and eight years as cut off and our main results survive.

3.3 Evidence

In table 5, we examine the effect of growth accelerations on poverty. In column 1 we look at the effect of growth accelerations in GDP per capita on poverty. We do not find any evidence of an impact on poverty. In column 2 we relate growth accelerations in mining GDP per capita to poverty. We find that growth acceleration episodes in the mining sector on average tend to increase the poverty headcount ratio by 1.72 per cent. This implies that a mining growth acceleration episode in Irian Jaya/Papua would push an additional 37,243 individuals into poverty. In contrast, in column 3 we observe that, a growth acceleration episode in the non-mining sector on average would reduce poverty headcount ratio by 1.68 per cent. This implies that a non-mining growth acceleration episode in Irian Jaya/Papua would pull an additional 36,377 individuals out of poverty. This asymmetric result is consistent with theories that the mining sector has very little backward and forward linkages and hence tends to benefit a privileged few directly linked with mining. The non-mining sector and especially urban services and agriculture in contrast are the hub of core occupations of the poor and therefore growth in these sectors tend to benefit the poor more (Suryahadi et al., 2009).

In table 6, we focus on the effects of growth accelerations on distribution. In column 1 we find that growth accelerations in GDP per capita reduces inequality. The effect however is not significant for growth accelerations in mining GDP per capita (column 2). In column 3 we notice that the overall negative effect is coming from growth accelerations in the non-mining GDP per capita. So overall we learn that sustained growth in GDP per capita driven by non-mining activities in the economy produces more progressive redistributive outcome.

In table 7 we look at the timing and durability of these reported effects. In addition to learning about timing, this exercise allows us to make informed judgements on causality. In columns 1-3 we deal with timing and durability issues related to the poverty estimates. In column 1 we define three binary variables. The variable '3 years pre $\hat{Y}_{it}$' takes the value 1 for 3 years before a growth acceleration episode, the variable '3 years post $\hat{Y}_{it}$' takes the value 1 for 3 years after a growth acceleration episode, and the variable '4 years onwards post $\hat{Y}_{it}$' takes the value 1 for 4 year onwards after a growth acceleration episode till the next episode (if there was any). These variables are 0 otherwise. We find that the coefficient on '3 years post $\hat{Y}_{it}$' is positive and significant suggesting that it takes 3 years for the effect of a growth acceleration episode on poverty to kick in. Also note that the coefficient on the variable '3 years pre $\hat{Y}_{it}$' is statistically insignificant. This implies that the effect on poverty was not present 3 or more years prior to the growth acceleration episode. Therefore what we are picking up here is indeed causal. The effect is observable only up to 3 years post the acceleration episode as the coefficient on the '4 years onwards post $\hat{Y}_{it}$' variable is not significant. Therefore the effect is not durable over the very long term. The absence of long term durability has important policy implications. It emphasizes the importance of a sustained growth strategy in order to tackle poverty and reduce inequality in developing countries. We repeat this estimation process for the mining and non-mining sectors in columns 2 and 3 and the results are qualitatively identical.

In columns 4-6 we repeat this exercise using inequality as the dependent variable. The results are similar. We find evidence of causal effects as the effects were not present before the acceleration episodes. We also notice that it takes 3 years for the effect to kick in and the effect on average is not durable beyond 3 years since the episode.

4. Concluding Remarks

An accelerated and sustainable process of economic growth is often touted as one of the most important policy issue in economics in order to tackle poverty and create a fairer society. The devil however is in the details as not all forms of growth turn out to be beneficial for the poor. In this paper we study the impact of growth and growth accelerations on poverty and inequality in Indonesia. Many developing countries are resource rich and therefore their growth performance is susceptible to the fluctuations in international commodity prices. Furthermore, the resource sector in developing countries may not have sufficient backward or forward linkages to the rest of the economy to benefit the poor. Therefore a booming resource sector may not often translate into a reduction in poverty. In this context it is important to distinguish between growth in the resource and non-resource sectors of the economy while analysing pro-poor growth. A new panel dataset covering 26 provinces over the period 1977-2010 allows us to distinguish between mining and non-mining sectors of the economy. We find that growth in non-mining significantly reduces poverty and inequality. In contrast, overall growth and growth in mining appears to have no effect on poverty and inequality. We also identify growth acceleration episodes defined by at least four consecutive years of positive growth in GDP per capita. Growth acceleration in non-mining reduces poverty and inequality whereas growth acceleration in mining increases poverty.

Our results emphasizes the importance of the non-mining sector in delivering pro-poor growth in Indonesia. This is in line with results reported by other studies of pro-poor growth on India and other developing countries. A large concentration of the poor in these countries are in agriculture and urban services. Therefore policies to support agriculture, urban services and manufacturing tend to have the most direct impact on poverty and inequality. The mining sector in contrast is capital intensive and therefore generates very little employment. The mining revenues in developing countries also tend to concentrate within a network of politically connected elites. As a result the poor aften do not benefit from a mining boom.

Our results also emphasize the importance of policies to support sustainable growth. A four year growth acceleration episode (or four consecutive years of positive growth) affects poverty and inequality only for the following three years. Therefore in order to reduce poverty it is important for developing countries to grow their economy sustainably.

Even though we emphasize the importance of non-mining growth and sustainable growth in poverty reduction, our results do not provide any guidance on the appropriate policy mix. However our results do highlight the role of non-resource growth as much as any other poverty reducing policies.

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Appendices:

A1. List of Provinces in the Sample:

Aceh, Sumatera Utara, Sumatera Barat, Riau, Jambi, Sumatera Selatan, Bengkulu, Lampung, Jakarta, Jawa Barat, Jawa Tengah, Yogyagarta, Jawa Timur, Bali, Nusa Tenggara Barat, Nusa Tenggara Timur, Kalimantan Barat, Kalimantan Tengah, Kalimantan Selatan, Kalimantan Timur, Sulawesi Utara, Sulawesi Tengah, Sulawesi Selatan, Sulawesi Tenggara, Maluku, Irian Jaya/Papua.

A2. Data Appendix:

Poverty $[H_{it}]$: Percentage of the population in the province who are living below the Indonesian provincial poverty line set by Statistics Indonesia. *Source:* Statistics Indonesia, 1978-2011.

Inequality $[G_{it}]$: Inequality measured by the Gini coefficient reported by the Statistical Yearbook. *Source:* Statistics Indonesia, 1978-2011.

Real GDP per capita $[Y_{it}]$: Real Gross Domestic Product per capita at the provincial level measured in 2002 constant prices. *Source:* Statistics Indonesia, 1978-2011.

Non-mining GDP per capita $[Y_{it}^{NM}]$: Real non-mining Gross Domestic Product per capita at the provincial level measured in 2002 constant prices. *Source:* Statistics Indonesia, 1978-2011.

Mining GDP per capita $[Y_{it}^{M}]$: Real mining Gross Domestic Product per capita calculated as the difference between real GDP per capita and non-mining GDP per capita. *Source:* Author's calculation.

Schooling: Years of schooling. *Source:* Statistics Indonesia, 1978-2011.

Employment: Employment rate. Source: Statistics Indonesia, 1978-2011.

Credit: Credit to the private sector as a share of GDP. *Source:* Ministry of Finance Database, 2011.

Real Government Spending: Real total provincial government spending as a share of GDP. *Source:* Ministry of Finance Database, 2011.

Political Fractionalization Index: Diversity index of political party voters among political parties competing in the national legislative elections in 1977, 1982, 1987, 1992, 1997, 1999 and 2004. This is the probably of finding two voters who voted for different political parties. The index is calculated using the Alesina et al. (1999) methodology. *Source:* Sudibyo (1995), Kristiadi et al. (1997), Suryadinata (2002), Apriyanto (2007) and Author's calculations.

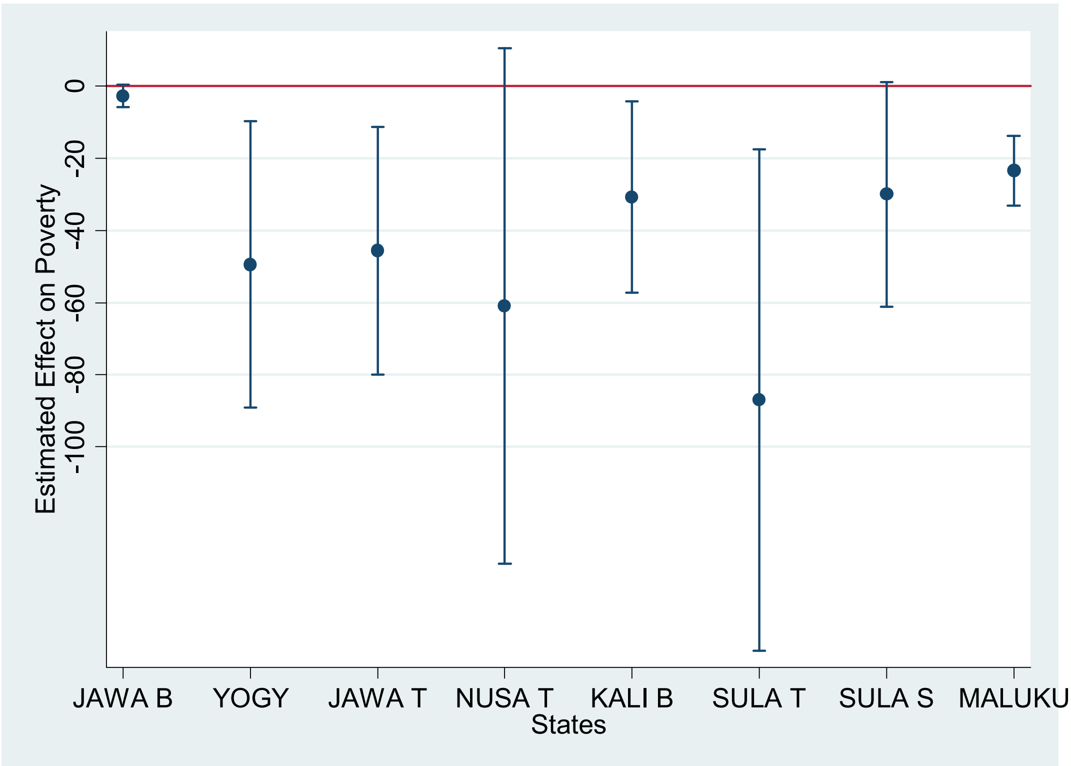
Rainfall [$\ln(Rain_{it})$]: Log of annual precipitation (amount of rain) measured in millimetres. *Source:* Statistics Indonesia, 1978-2011.

Humidity [$\ln(Humid_{it})$]: Average yearly humidity. *Source:* Statistics Indonesia, 1978-2011.

Figure 1: Provincial Map of Indonesia

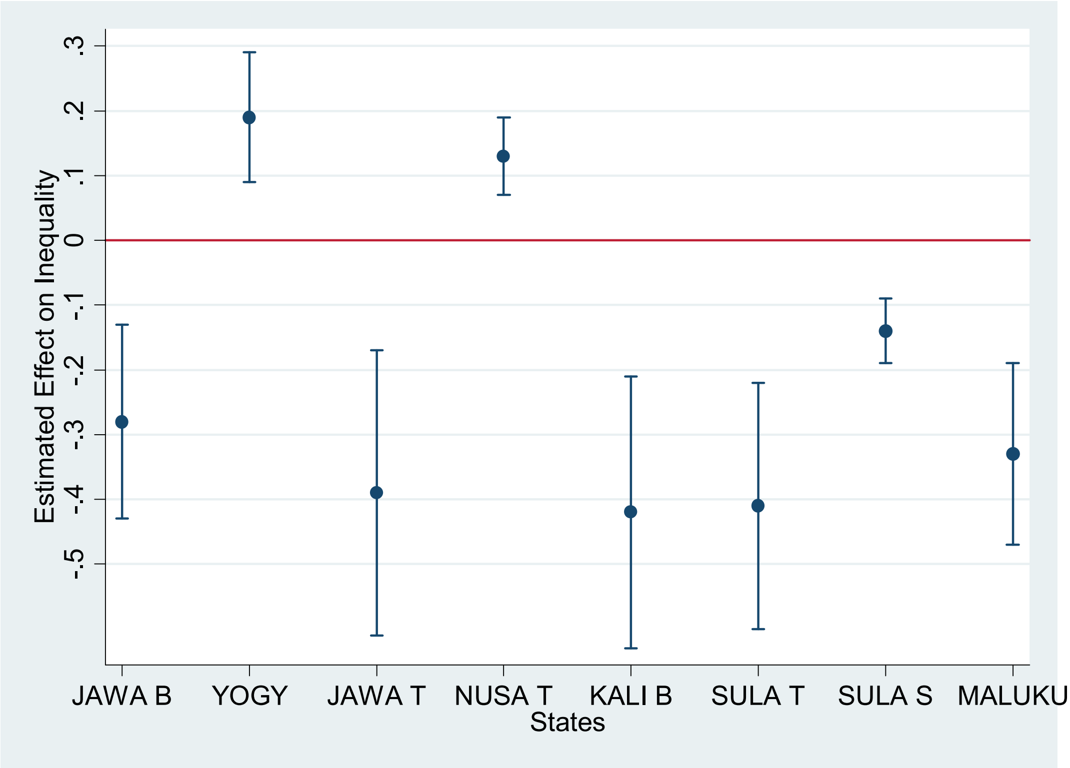
Note: This is a map of Indonesia in 2011, in which there are 33 provinces in the country. Up till 1999, Riau Islands was still part of Riau, Bangka-Belitung was part of South Sumatra, Banten was part of West Java, Gorontalo was part of North Sulewasi, North Maluku was part of Maluku, West Sulawesi was part of South Sulawesi and West Papua and Papua were previously Irian Jaya. In 2012, East Kalimantan was split into East Kalimantan and North Kalimantan. At present there are 34 provinces in Indonesia. For the sake of continuity we grouped new provinces into their original 1999 provinces in our dataset. The map is sourced from the Indonesia Project of The Australian National University.

Figure 2: Non-mining Growth and Poverty: Estimated Effects by Selected Provinces



Notes: The figure shows the coefficients on the regression of non-mining growth on poverty (head count ratio) using time series data over the period 1977-2010 carried out for the 8 selective states. Both growth and poverty here are stationary. The dots show the point estimates, and the bars indicate 95% confidence intervals. The states included are Jawa Burat (JAWA B), Yogyakarta (YOGY), Jawa Timur (JAWA T), Nusa Tenggara Timur (NUSA T), Kalimantan Burat (KALI B), Sulawesi Tengah (SULA T), Sulawesi Selatan (SULA S), and Maluku (MALUKU). Standard errors in the regressions are robust.

Figure 3: Non-mining Growth and Inequality: Estimated Effects by Selected Provinces



Notes: The figure shows the coefficients on the regression of non-mining growth on inequality (gini coefficient) using time series data over the period 1977-2010 carried out for the 8 selective states. Both growth and inequality here are stationary. The dots show the point estimates, and the bars indicate 95% confidence intervals. The states included are Jawa Burat (JAWA B), Yogyakarta (YOGY), Jawa Timur (JAWA T), Nusa Tenggara Timur (NUSA T), Kalimantan Burat (KALI B), Sulawesi Tengah (SULA T), Sulawesi Selatan (SULA S), and Maluku (MALUKU). Standard errors in the regressions are robust.

Table 1. Summary Statistics.

	Mean	Standard Deviation (overall)	Standard Deviation (between provinces)	Standard Deviation (within provinces)	Min	Max	Number of Obs.
Inequality $[G_{it}]$	0.30	0.037	0.26	0.17	0.18	0.46	832
Poverty $[H_{it}]$	18.87	8.37	7.67	6.19	2.48	54.75	884
Growth in GDP per capita $[Y_{it}]$	0.001	0.29	0.27	0.18	-2.97	1.39	883
Growth in non-mining GDP per capita $[Y_{it}^{NM}]$	0.03	0.14	0.12	0.10	-2.96	0.62	680
Growth in mining GDP per capita $[Y_{it}^{M}]$	0.04	0.13	0.11	0.09	-2.89	0.62	680
Rainfall $[\ln(Rain_{it})]$	7.36	0.94	0.46	0.83	2.19	9.01	723
Humidity $[\ln(Humid_{it})]$	4.38	0.07	0.03	0.06	4.01	4.54	767

Notes: The panel dataset covers the time period 1977-2010 and 26 Indonesian provinces. The Data Appendix provides detailed definition and source of the key variables used.

Table 2. The Effect of Growth on Poverty

	Dependent Variable: Poverty $[H_{it}]$			
	(1) Fixed Effects Estimate	(2) Fixed Effects Estimate	(3) Fixed Effects Estimate	(4) Instrumental Variable (IV) Estimate
Growth in GDP per capita $[Y_{it}]$	0.32 (1.17)			
Growth in mining GDP per capita $[Y_{it}^{M}]$		-3.78 (4.59)		
Growth in non-mining GDP per capita $[Y_{it}^{NM}]$			-6.22** (2.98)	-6.10** (3.00)
State fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes	Yes
Instruments				$\ln[Rain_{it}]$, $\ln[Humid_{it}]$
F-stat on EI				21.6/15.2
Angrist-Pischke *F-stat*				39.8/22.1
Partial R^2 on EI				0.31/0.27
Stock-Yogo critical values				13.46/7.49
States	26	26	26	26
Observations	837	670	670	638
Adjusted R^2	0.79	0.85	0.85	

Notes: The dependent variable is Poverty head count ratio $[H_{it}]$ in state i at time t observed annually between 1977 and 2010. Standard errors, in parentheses, are robust and clustered at the state level. '*F*-stat on EI', 'Angrist-Pischke *F*-stat', 'Partial R^2 EI', and 'Stock-Yogo critical values' indicates *F*-statistic on excluded instruments, Angrist-Pischke multivariate *F*-statistic on excluded instruments, Partial R^2 on excluded instruments and Stock-Yogo critical values respectively. Fuller's modified LIML estimator with $\alpha = 1$ (correction parameter proposed by Hausman et al., 2005) is used in column (4). Reported Stock-Yogo critical values in column (4) are the 5 percent significance level critical values for weak instruments tests based on, respectively, 30 percent and 5 percent maximal Fuller relative bias. The null of weak instruments is rejected in the case that the *F*-statistic on the excluded instruments exceeds the Stock-Yogo critical value/s.

* p<0.10, ** p<0.05, *** p<0.01

Table 3. The Effect of Growth on Inequality

	Dependent Variable: Inequality $[G_{it}]$			
	(1) Fixed Effects Estimate	(2) Fixed Effects Estimate	(3) Fixed Effects Estimate	(4) Instrumental Variable (IV) Estimate
Growth in GDP per capita $[Y_{it}]$	-0.003 (0.004)			
Growth in mining GDP per capita $[Y_{it}^{M}]$		-0.015 (0.021)		
Growth in non-mining GDP per capita $[Y_{it}^{NM}]$			-0.021** (0.010)	-0.023** (0.010)
State fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes	Yes
Instruments				$\ln[Rain_{it}]$, $\ln[Humid_{it}]$
F-stat on EI				28.4/19.6
Angrist-Pischke *F-stat*				44.1/30.6
Partial R^2 on EI				0.42/0.23
Stock-Yogo critical values				13.46/7.49
States	26	26	26	26
Observations	822	640	640	621
Adjusted R^2	0.77	0.75	0.76	

Notes: The dependent variable is Inequality $[G_{it}]$ measured by the Gini coefficient in state i at time t observed annually between 1977 and 2010. Standard errors, in parentheses, are robust and clustered at the state level. '*F*-stat on EI', 'Angrist-Pischke *F*-stat', 'Partial R^2 EI', and 'Stock-Yogo critical values' indicates *F*-statistic on excluded instruments, Angrist-Pischke multivariate *F*-statistic on excluded instruments, Partial R^2 on excluded instruments and Stock-Yogo critical values respectively. Fuller's modified LIML estimator with $\alpha = 1$ (correction parameter proposed by Hausman et al., 2005) is used in column (4). Reported Stock-Yogo critical values in column (4) are the 5 percent significance level critical values for weak instruments tests based on, respectively, 30 percent and 5 percent maximal Fuller relative bias. The null of weak instruments is rejected in the case that the *F*-statistic on the excluded instruments exceeds the Stock-Yogo critical value/s.
* p<0.10, ** p<0.05, *** p<0.01

Table 4. The Effect of Growth on Inequality and Poverty: Robustness with Additional Covariates

	Dependent Variable: Poverty $[H_{it}]$					Dependent Variable: Inequality $[G_{it}]$				
	(1) Fixed Effects Estimate	(2) Fixed Effects Estimate	(3) Fixed Effects Estimate	(4) Fixed Effects Estimate	(5) Fixed Effects Estimate	(6) Fixed Effects Estimate	(7) Fixed Effects Estimate	(8) Fixed Effects Estimate	(9) Fixed Effects Estimate	(10) Fixed Effects Estimate
Growth in non-mining GDP per capita $[Y_{it}^{NM}]$	-6.18**	-6.66**	-5.97**	-6.21**	-5.96**	-0.021**	-0.021**	-0.020*	-0.021**	-0.020**
	(2.90)	(2.81)	(2.90)	(2.97)	(3.00)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Political Fractionalization Index	Schooling	Employment	Real Government Spending	Credit	Political Fractionalization Index	Schooling	Employment	Real Government Spending	Credit
States	26	26	26	26	26	26	26	26	26	26
Observations	670	670	658	670	635	640	640	633	640	612
Adjusted R^2	0.85	0.86	0.85	0.85	0.87	0.75	0.76	0.75	0.76	0.75

Notes: The dependent variables are Poverty $[H_{it}]$ (for columns 1-5) and Inequality $[G_{it}]$ (for columns 6-10) measured by head count ratio and Gini coefficient respectively in state i at time t observed annually between 1977 and 2010. Standard errors, in parentheses, are robust and clustered at the state level.
* p<0.10, ** p<0.05, *** p<0.01

Table 5. The Effect of Growth Accelerations on Poverty

	Dependent Variable: Poverty $[H_{it}]$		
	(1) Fixed Effects Estimate	(2) Fixed Effects Estimate	(3) Fixed Effects Estimate
Growth Accelerations in GDP per capita $[\hat{Y}_{it}]$	0.54 (0.89)		
Growth Accelerations in mining GDP per capita $[\hat{Y}_{it}^{M}]$		1.72** (0.86)	
Growth Accelerations in non-mining GDP per capita $[\hat{Y}_{it}^{NM}]$			-1.68** (0.79)
State fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes
States	26	26	26
Observations	837	670	670
Adjusted R^2	0.79	0.85	0.85

Notes: The dependent variable is Poverty head count ratio $[H_{it}]$ in state i at time t observed annually between 1977 and 2010. *Growth Accelerations* $[\hat{Y}_{it} / \hat{Y}_{it}^{M} / \hat{Y}_{it}^{NM}]$= 1 if a state experiences at least four consecutive years of positive growth in GDP per capita, = 0 otherwise. Standard errors, in parentheses, are robust and clustered at the state level.
* p<0.10, ** p<0.05, *** p<0.01

Table 6. The Effect of Growth Accelerations on Inequality

	Dependent Variable: Inequality $[G_{it}]$		
	(1) Fixed Effects Estimate	(2) Fixed Effects Estimate	(3) Fixed Effects Estimate
Growth Accelerations in GDP per capita $[\hat{Y}_{it}]$	-0.008*** (0.003)		
Growth Accelerations in mining GDP per capita $[\hat{Y}_{it}^{M}]$		-0.006 (0.005)	
Growth Accelerations in non-mining GDP per capita $[\hat{Y}_{it}^{NM}]$			-0.007** (0.003)
State fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes
States	26	26	26
Observations	822	640	640
Adjusted R^2	0.77	0.76	0.79

Notes: The dependent variable is Inequality $[G_{it}]$ measured by the Gini coefficient in state i at time t observed annually between 1977 and 2010. *Growth Accelerations* $[\hat{Y}_{it} / \hat{Y}_{it}^{M} / \hat{Y}_{it}^{NM}] = 1$ if a state experiences at least four consecutive years of positive growth in GDP per capita, = 0 otherwise. Standard errors, in parentheses, are robust and clustered at the state level.
* p<0.10, ** p<0.05, *** p<0.01

Table 7. Distributional Consequences of Growth Accelerations: Timing and Durability of the Effects

	Dependent Variable: Poverty $[H_{it}]$			Dependent Variable: Inequality $[G_{it}]$		
	(1) Fixed Effects Estimate	(2) Fixed Effects Estimate	(3) Fixed Effects Estimate	(4) Fixed Effects Estimate	(5) Fixed Effects Estimate	(6) Fixed Effects Estimate
3 years pre $\hat{Y}_{it}$	0.55			-0.002		
	(0.65)			(0.004)		
3 years post $\hat{Y}_{it}$	3.54*			-0.014**		
	(1.74)			(0.007)		
4 years onwards post $\hat{Y}_{it}$	2.47			-0.011		
	(2.28)			(0.010)		
3 years pre $\hat{Y}_{it}^{M}$		0.91			-0.0003	
		(1.10)			(0.006)	
3 years post $\hat{Y}_{it}^{M}$		2.37**			-0.005	
		(1.05)			(0.005)	
4 years onwards post $\hat{Y}_{it}^{M}$		0.29			0.003	
		(1.92)			(0.007)	
3 years pre $\hat{Y}_{it}^{NM}$			0.47			0.002
			(0.83)			(0.006)
3 years post $\hat{Y}_{it}^{NM}$			-0.31**			-0.004**
			(0.15)			(0.002)
4 years onwards $\hat{Y}_{it}^{NM}$			-0.16			0.002
			(0.17)			(0.006)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes	Yes	Yes	Yes
States	26	26	26	26	26	26
Observations	837	670	670	822	640	640
Adjusted R^2	0.79	0.84	0.84	0.76	0.76	0.76

Notes: The dependent variables are Poverty $[H_{it}]$ (for columns 1-5) and Inequality $[G_{it}]$ (for columns 6-10) measured by head count ratio and Gini coefficient respectively in state i at time t observed annually between 1977 and 2010. *Growth Accelerations* in GDP per capita/Mining GDP per capita/Non-mining GDP per capita $[\hat{Y}_{it} / \hat{Y}_{it}^{M} / \hat{Y}_{it}^{NM}]= 1$ if a state experiences at least four consecutive years of positive growth in GDP per capita, = 0 otherwise. *3 years pre* $[\hat{Y}_{it} / \hat{Y}_{it}^{M} / \hat{Y}_{it}^{NM}]= 1$ for 3 years before the Growth Acceleration episode, *3 years post* $[\hat{Y}_{it} / \hat{Y}_{it}^{M} / \hat{Y}_{it}^{NM}]= 1$ for 3 years after the Growth Acceleration episode, and *4 years onwards post* $[\hat{Y}_{it} / \hat{Y}_{it}^{M} / \hat{Y}_{it}^{NM}]= 1$ for 4 year onwards after the Growth Acceleration episode till the next episode (if there was any). These variables are 0 otherwise. Standard errors, in parentheses, are robust and clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01