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Could a Resource Export Boom Reduce Workers' Earnings?

The Labor Market Channel in Indonesia

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Abstract

For a decade from 2000 Indonesia underwent a natural resource export boom. Aggregate income rose, but real labor earnings stagnated. Employment rose mainly in low-skill sectors with predominantly informal employment arrangements. In this paper we reveal causal connections from the aggregate phenomenon of Dutch Disease to these labor market outcomes. We first explain broad sectoral trends, then, integrating data from several national surveys, investigate sources of variation in boom-era labor earnings. We use instrumental variables to address issues of endogeneity and selection in earnings equations.

After controlling for individual and district features we find that intensity of oil palm production, a key booming resource export, robustly predicts diminished formal employment, and that lower formality, in turn, robustly predicts lower earnings. Our findings establish causal linkages absent from prior studies, and so provide a structural dimension to ongoing debates over persistent poverty, rising inequality, and lack of educational progress in Indonesia.

Keywords: Indonesia, Dutch Disease, oil palm, formal employment, education, poverty

JEL: O15, J21, F16, I32.

1. Introduction

From the end of the Asian Financial Crisis (AFC) to the onset of the Global Financial Crisis (GFC), Indonesia enjoyed a significant boom in exports of its natural resource products. This boom helped fuel GDP growth that averaged almost 5% annually in per capita terms from 2001 to 2011, a rate sufficient to lift mean per capita income from 15% of the world average in 2001 to 20% by the end of the decade. The boom, however, was accompanied by some contradictory indicators. Most obviously among these, growth rates of manufacturing sector output and employment both declined, with especially sharp drops in more skill-intensive manufacturing industries (Coxhead and Li 2008). This change was accompanied by more rapid growth in a variety of services industries that are not notably skill-intensive. Less apparent but no less troubling, some measures of progress in educational attainment also began to slip.

Manufacturing sector expansion is an “escalator” for economic growth (Rodrik 2015), and by comparison with other regional economies Indonesia’s manufacturing slowdown appears to have occurred both at a lower level of per capita income and from a lower peak share of GDP (Coxhead 2014, Figure 1). While there are several possible contributing factors to such a slowdown, a resource export boom is a strong *a priori* candidate. The Dutch Disease model (Corden and Neary 1982) predicts that a resource export boom will cause growth in tradable sectors like manufacturing to slow, by raising input costs and reducing competitiveness relative to substitutes produced in other countries.

In a low-income economy, manufacturing growth is associated both with increased demand for human capital, and with a relative increase in formal employment contracts. Further, education is a primary channel for economic and social mobility in Indonesia as in all economies. Individuals that acquire better education can earn more, and are also more able to obtain jobs with greater tenure security and benefits, as we will discuss below. In this paper we show that the earnings of working-age Indonesian males are robustly predicted by measures of school attainment, and that a key channel for the economic benefits of schooling runs through the selection of individuals into formal employment, which in Indonesia is associated both with higher skills and higher pay for equivalent skills relative to informal employment. We also find that opportunities for formal employment are negatively associated with the relative contribution of oil palm – a key natural resource export – to the local economy. Because part of the return on schooling is attributable to its role as a means to acquire formal employment, the boom, by lowering the rate of growth of formal employment opportunities, is likely also to have reduced growth in overall *demand* for schooling. By this means we discover a structural explanation for slower progress in school attainment and lower returns to education in Indonesia in the 2000s that have been documented, but not clearly explained, in prior empirical studies.

In the remainder of this paper we first survey the relevant literature on resource booms and schooling. We then survey both macro and micro data for Indonesia, highlighting important trends in output, labor markets and schooling. Subsequently, we develop and implement an econometric strategy to test the causal claims made above. A final section returns to the broader development context and considers some options for development policy.

2: Resource boom and the labor market: a macro perspective

In this section we provide a brief survey of the macroeconomic context of our study. From 2002-12, the share of Indonesia's main resource exports (crude oil, gas, coal, copper, and palm oil) in total exports increased from 32% to 46%. This surge was driven almost entirely by two products. Palm oil production rose by almost 12% per year from 1998 to 2014,[1] and the share of palm oil in merchandise exports rose from 2% in 2000 to 9% by 2012. Coal exports rose from 3% to 14% over the same period. Meanwhile

[1] http://www.indexmundi.com, accessed 29 October 2015.

export shares of the country's key manufactures (garments, footwear, electrical goods, and computers and parts) all contracted; computers and parts even fell in nominal terms, by almost half.[2]

This was not Indonesia's first resource export boom, but it was unusual in that an agricultural product, palm oil, played a leading role relative to sectors like energy and minerals. Minerals booms have little direct impact on employment, and augment aggregate demand primarily through spending by large corporations and their owners and by government. A boom occurring in an agricultural sector where ownership and participation are widely distributed may have more direct impacts—if not on employment, then certainly on the spending of windfall gains.

Experience from natural resource export booms worldwide supports the claim that in resource-abundant economies, "natural capital appears to crowd out human capital, thereby slowing down the pace of economic development" (Gylfason 2001: 847). This argument has two parts: the boom lowers returns to existing human capital, and as a result, in the longer run also reduces incentives to invest in new human capital. A very simple model is sufficient to show the fundamental mechanisms that are thought to produce such a result. Imagine an economy using skilled and unskilled labor to produce just two outputs, natural resource products and manufactures. If skilled labor is more intensively employed in the former sector than the latter, then a rise in the latter's price will tend to lower the demand for skills, other things equal. In the longer run, if this change in the structure of labor demand persists, then individuals currently in the education system will perceive that both the skill premium (the net earnings differential attributable to additional schooling) and the probability of a skilled job have fallen. On average, these will lower incentives to acquire skills through the education system.

The complete Dutch Disease model includes a third sector producing services, assumed nontradable and thus with endogenous prices. This adds a dimension to the analysis of adjustment to an export boom,

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[2] Source of trade data: Statistics Indonesia (bps.go.id), accessed 25 October 2015.

since part of the new income generated by the boom will be spent on services, driving up both their prices and, potentially, the real returns to any factors used intensively in their production. The Dutch Disease model predicts that these changes will further reduce manufacturing sector profitability. If services were highly skill-intensive and accounted for a sufficiently large share of total skilled labor employment, their expansion could in principle more than offset the initial negative effects of the boom on skills demand and the skill premium. Conversely (and more realistically in a developing-country context), if services make only a small contribution to total skilled labor demand then their expansion and rising prices, by further reducing manufacturing sector profitability, would lower skills demand and the skill premium even more in the wake of the export boom.[3]

As foreshadowed above there is an additional complication. Indonesian wage and earnings data reveal that while the skill premium from schooling is modest at all levels, the gain from employment with a formal contract is at least as large, for every level of education. Summary data for males of working age (Table 1) show that the differences in log earnings from securing formal employment are broadly comparable at each education level to those from moving up an additional educational level. However, the likelihood that a worker with primary education will have a formal job is only 7% (=292/(292+4,015)), whereas with junior high school it is 17%, with senior high school 53%, and with tertiary education 61%.[4]

Table 1: Workers and earnings by education and employment status, 2007

The distribution of formal job opportunities also varies greatly by sector. Therefore, any change in the sectoral structure of labor demand also changes the probability of formal employment. The data suggest

[3] Moreover, in Indonesia as elsewhere in the developing world, purchases of services (including housing, health, transportation and personal services) make up a larger share of household expenditures for urban than rural households, and for wealthier households relative to poorer ones. Since skilled workers are more highly concentrated in cities and in the upper deciles of the income distribution, it follows that higher prices of services will have a greater effect on their cost of living. Other things equal, this will further reduce the real skill premium.

[4] These probabilities are based on shares calculated using SAKERNAS (National Labor Force Survey) data. Using data from Indonesian Family Life Survey (IFLS), the probabilities are 8%, 16%, 39% and 64% respectively. Data sets are described in section 3.

that this, in addition to changes in real wages discussed above, is likely to be a primary determinant of changes in earnings following a resource export boom. The additional dimension of formality in employment also has consequences for estimation, as discussed below.[5]

The structure of Indonesian output growth during the boom differed sharply in the 2000s from the manufacturing-led growth of the 1990s (Figure 1). In 1990-96, industry contributed on average half (52%) of total GDP growth, but in 2000-12 this diminished to just 35%. Services growth rose from 42% of total GDP growth in 1990-96 to 56% in the later period. The real exchange rate, a broad indicator of domestic prices relative to those in a country's trading partners, or equivalently of the prices of nontradables (mainly services) to those of other goods, appreciated by almost 4% per year during the 2000s.[6] Growth rates of output and employment in manufacturing, the engine of Indonesia's expansion in the 1990s, fell below the economy-wide rate (Table 2). In 2000-08, employment in manufacturing grew at an average annual rate of just 0.9%, or half the rate of total employment growth. Meanwhile employment in the services sectors grew at least as fast as total employment, with construction jobs expanding 4% faster and jobs in transportation and other services 2.2% and 1.9% faster, respectively.

Figure 1: Sectoral contributions to GDP growth

Table 2: Trends in sectoral output and employment growth

Indonesia was thus exhibiting symptoms of Dutch Disease in the 2000s (Thee 2011). Lower manufacturing sector profitability was exacerbated by the effects of several other negative shocks, including the after-effects of a large drop in investment during the Asian crisis (van der Eng 2009, Figure

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[5] This simple model also ignores variation in individual ability or motivation that might result in unequal rates of selection into schooling. Failure to account for selection effects imparts an upward bias to estimates of returns to schooling. Because variation in individual ability or motivation is largely unobservable, a wide range of instruments have been proposed and tested. We return to this topic in discussion of our econometric model.

[6] Source of basic data: Bank of International Settlements, BIS.org.

4); lagging public expenditures on infrastructure; and a tendency toward tightening in both trade and labor policies and policies on foreign direct investment (Wihardja 2013, World Bank 2013). All these effects are likely correlated in that they tend to reduce profits, activity levels and jobs in manufacturing. If physical and human capital are complementary inputs, then slower investment growth in manufacturing also reduces growth in the demand for skilled workers, other things equal. Of course, one important contrast between a resource export boom and an investment collapse is that whereas the former raises total income, the latter reduces it. It is therefore clear that of these influences on manufacturing growth, the resource export boom was dominant, sustaining a real GDP growth rate of about 5% per year in the post-crisis era.

What were the likely implications of the resource export boom for employment and household welfare? The boom increased total income but appears also to have altered the structure of employment and output, as described above. Resource sectors, especially oil palm and coal, expanded, as did private expenditures on income-elastic nontradables such as residential construction, health, trade and transport, and personal services. The "lagging" sectors in this Dutch Disease-affected economy were those in which firm profits were trapped between rising domestic costs and global output prices that remained flat, at best. Parts of agriculture fell into this category, and so did much of manufacturing, the most skill-intensive and technologically dynamic sector—and the one (other than government and specialized service industries such as banking, insurance and finance) with the highest rate of formal employment contracts. The International Labor Office, in a 2011 report, observed that real wages rose only very modestly in the 2000s, and that wages in informal employment slipped from 45% of the formal sector average in 2000-01 to 42% by 2009-10 (Figure 2). Household survey data from 1997, 2000 and 2007 show that relative to manufacturing wages, the median earnings of workers in private wage employment in domestic trade and personal services remained roughly constant at about 85%, while the relative earnings of self-employed workers fell sharply, especially after 2000 (Table 3).

Figure 2: Real wages by employment status, 2000-2010

Table 3: Median earnings relative to manufacturing wages

We hypothesize that the net effect of the resource export boom was to reduce the rate at which formal sector jobs were created. If supported, this may also help explain persistent low rates of school attainment in Indonesia, independent of supply-side explanations. And it may also point to a broader set of policy options for addressing educational underinvestment than are usually considered in the developing world.

3. Employment and earnings during the boom: data and estimation strategy

As discussed above, Indonesia's boom-era job growth reflected a redistribution of labor demand among industries that are heterogeneous in terms both of skills and formality. In this and the next section we use district-level data and data on individual workers to estimate sources of variation in earnings. On the basis of these estimates we are able to draw some inferences about which workers in which locations were more or less likely to gain as the result of the boom, and through which mechanisms—including family socio-economic status, individual ability and schooling, and access to formal sector employment.

3.1 Data sources and definitions

We draw on data from several sources: SAKERNAS, the national labor force survey;[7] Indonesia Database for Policy and Economic Research (INDO-DAPOER),[8] and the Indonesian Family Life Survey (IFLS).[9] We use the February 1997 round of SAKERNAS to create baseline employment variables and the February 2007 round to construct district-level estimates of median income. The dataset contains information about income earned in the previous month for both salaried and casual employees, and net profit for the self-employed.

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[7] More information about the labor force survey is available at sakernas bps.gov.id.

[8] http://databank.worldbank.org/data/reports.aspx?source=indo~dapoer-(indonesia-database-for-policy-and-economic-research)

[9] http://www.rand.org/labor/FLS/IFLS.html. The description that follows paraphrases text in Strauss et al. (2009).

The INDO-DAPOER database is compiled by the World Bank and contains district-level information on various economic, social and demographic variables (Narayan et al. 2014). The variables relevant for this paper are district-level GDP from agriculture, mining, and manufacturing and palm oil production. These variables are available from year 2000.

The IFLS is our source for individual data used in estimation. It is a longitudinal socioeconomic and health survey based on a sample of households representing about 83% of the Indonesian population living in 13 of the 26 provinces that existed at the time of the first survey wave, 1993. The survey collects data on individual respondents, families, households, and communities, and on a wide array of health and education resources and outcomes. The fourth wave, IFLS4, was administered in late 2007 and early 2008 on a sample of 13,535 households and 44,103 individuals. An important feature of the IFLS methodology is the attention given to minimizing attrition over successive waves since 1993. Average attrition (both of original respondents and of splitoff households) in IFLS4 is less than 10% overall, although the rate is somewhat higher in areas affected by armed conflict and natural disasters and in the capital city, Jakarta. Strauss et al. (2009) provide complete documentation on sampling, survey instruments, methods and protocols, and supply a breakdown of basic data about respondents.

We use IFLS data for men of working age (20-65) reported as being in the labor force. In 2007 this was 78% of men surveyed in that age group. Of those not working, 8% were attending school and smaller percentages were unpaid family workers, retired, invalids, or otherwise out of the wage labor force.

Our earnings measure is based on the IFLS 4 employment module. For those in private and government jobs, the IFLS records their monthly salary and any annual benefits paid. We convert annual benefits into monthly equivalents by dividing the benefits by 12. So, the total earnings for workers is the sum of salary and benefits. For self-employed individuals, the IFLS records monthly and yearly net profits. We derive monthly self-employment earnings by dividing the yearly profits by 12. Self-employment earnings tend to fluctuate over the course of the year, so using a monthly average of annual earnings is preferable to using data from a single recall month.

As noted earlier, the indicator of formal employment merits discussion. Formal employment status is known to be an influential factor in labor productivity and earnings (for discussion of a comparable case, Mexico, see Hanson 2010). Firms in the informal sector are less capital and technology-intensive, so human capital and labor employed by informal firms are, on average, less productive. Informal employment contracts— which may be with formal or informal firms—typically do not entail training other than on the job, and casual employees, for their part, typically have fewer incentives to give their all (including creative effort) to employers who offer no long-term commitment.

Informality lacks a universally accepted definition, despite its importance in labor market studies (ILO 2013). Another recent study using IFLS data defines formality by a combination of employment status (that is, working conditions such as contracts or benefits) and enterprise characteristics (Newhouse and Suryadarma (2011). By this definition, however, only 11% of Indonesia's nonagricultural workers are counted as in informal employment. In contrast, the International Labour Organization, using an enterprise-based definition, estimates informal employment rates for comparable countries like Brazil, Mexico, South Africa, India, Philippines and Vietnam in a range between 50% and 85% (ILO 2013, Table 2.6).

We reason that the relevant element of informality is employment status, rather than firm status. For a worker, it matters less what kind of firm employs her than whether her job is secure, pays benefits and offers other advantages. Therefore we define formality based only on employment status, not on characteristics of the employing entity. Making the best use of limited data, we count a worker as formally employed if he or she receives any benefits (bonus, pension, insurance, training, transportation, or health) as part of his or her employment, regardless of enterprise type. This definition allows for informal or casual employment contracts even within formally incorporated enterprises. By this definition, 78% of workers in IFLS4 are classified as informally employed, a figure within the ILO range cited above. These are the data as reported earlier, in Table 1.

Our definition of formality also regards all self-employed individuals as informally employed. This is because questions about job benefits were only asked of employees. This might be an issue for those self-employed with permanent employees, who might have a more secure source of income. However, this category of respondents makes up a very small fraction of the dataset, and we show below that their inclusion or exclusion does not influence the results.

Table 4 shows formal employment status by sector and occupational category. The sectoral breakdown in this table differs somewhat from that often reported in Indonesian labor market statistics.[10] We consolidate some sectors (construction and utilities, trade and transport) and distinguish between government and personal services. Our reason is that government services tend to be mostly formal as they come with fringe benefits. On the other hand, availability of formal non-government jobs depends on local economic conditions.

Panel (a) of Table 4 shows the formal employment rate of each occupational group by sector, from IFLS data. Formal employment is the norm for white-collar workers in professional, administrative and clerical occupations. For low-skill workers in non-agriculture, formal employment is widespread only in government, manufacturing and private services, while in the much larger service categories of construction, utilities, trade and transport the formality rate is only 11%. In agricultural occupations, nearly all workers are classed as informally employed. Panel (b) shows the Sakernas data on the distribution of workers across sectors and occupational categories in 1997, the year before the onset of the Asian Financial Crisis. Panel (c) shows the same data for 2007. The data are not perfectly comparable

[10] Labor market reports break sectors into agriculture, forestry, hunting, and fisheries; mining and quarrying; manufacturing; electricity, gas and water; construction; wholesale and retail trade, restaurants and hotels; transportation, warehouse and communication; financing, insurance, real estate and business services; and community, social and personal services.

across years due to changes in survey methodology, particularly expansion in categories of workers. They suggest that among production workers, growth of employment, 1997-2007, was much faster than the average in agriculture, mining, and trade/transport, while other sectors grew more slowly. Within manufacturing, production jobs expanded at only about half the rate of professional and sales/service jobs.

Table 4: Formal employment status by occupation and sector

3.2 Estimation: the earnings equation

The conventional approach to explaining earnings is that of Mincer (1974), in which a measure of earnings is explained by reference to individual age, experience and schooling. The advantages and disadvantages of this approach are very well known. For estimation purposes, perhaps the most problematic feature is the omission of unobservable cognitive and non-cognitive abilities known to play an influential role in an individual's schooling decisions. These omitted variables impart an upward bias to the estimated value of schooling (Card 1999; Heckman et al. 2006).

The empirical literature has used a variety of strategies to address the omitted variable problem. Many studies have found that early childhood health, nutrition and family socio-economic status have significant and persistent effects through childhood and in labor market outcomes (Currie 2009; Almond and Currie 2011). These effects have been found to persist even after schooling choices are taken into account (Glewwe 2001; Alderman et al. 2006; Hoddinott et al. 2008). These findings support the claim that instruments for early childhood health and nutrition are correlated with cognitive ability, an important unmeasured component of schooling and labor market outcomes. We assume that the same is true in Indonesia. We take height in 2007, mother's education and household assets as instruments for early childhood conditions serving as predictors of adult cognitive and noncognitive ability, and so of schooling and employment outcomes (Silventoinen 2003; Case and Paxson 2006; Case, Paxson and Islam 2009).[11]

Another approach in the literature has been to control for the supply of educational facilities—for example, using the distance from a respondent's home to school or college (e.g. Card 1993). This instrument too is problematic, since households may sort by location on criteria such as school access. Nonetheless we control for supply-side variation by means of province fixed effects and district-level per capita incomes. This is likely to be less controversial in Indonesia, where differences in language, culture and other cultural features keep geographic mobility across provincial boundaries relatively low.

As with schooling, there are substantial earnings premia associated with formal employment status. Also as with schooling, there are problems with the use of formal employment as an exogenous variable. Some component of formality is exogenous, being determined by industry structure, regulation, and labor market institutions beyond the influence of individuals or firms. Another component is endogenous: individuals are selected into formal jobs by virtue of ability, schooling and other forms of human capital, and other factors that make employers more willing to make contractual commitments and offer higher wages and benefits.

Our econometric strategy takes account of the foregoing issues. In our baseline earnings function estimates we exclude direct measures of schooling, replacing them with controls known to predict schooling outcomes, notably parental education and adult height, a proxy for early childhood health and nutrition, and proxies for school supply – as described above. We then use an instrumental variables strategy to take account of selection into formal employment. This approach yields precise estimates of

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[11] The IFLS records both parents' educational attainment. However these are highly correlated, so we use only that for the mother.

the value of formal employment, taking account of “macro” factors associated with availability of formal jobs in general, as well as individual-specific predictors of selection into formal employment.

Our specification of the earnings function model differs from previously published studies of educational choices and outcomes in Indonesia. Purnastuti et al. (2011, 2013) fitted a Mincer earnings equation with schooling and experience plus additional controls for tenure, location and some demographic characteristics, but no controls for ability or its predictors. Using labor force survey data for 2004, Comola and de Mello (2013) explore a multinomial model of selection into the labor force and into salaried employment based on individual characteristics and district-level indicators of economic structure. As expected, this approach yields significant estimates of constraints on female labor force participation. In an analysis of schooling choice, Newhouse and Suryadarma (2011) included proxies for ability including height, reported test scores and parental education. Other studies have used quantile regression methods to limit the heterogeneity of the sample used in estimation (e.g. Patrinos et al., 2006). In a previous earnings equation study Coxhead (2014) used height and parental education controls, but also included schooling and formal employment as exogenous regressors. None of these models address demand-side labor market phenomena.

To estimate earnings, we fit our modified Mincer equations to the data for 2007, a year well after the end of the Asian crisis era and close to the peak of the resource export boom period. We use individual data from IFLS4, with additional district-level data from SAKERNAS and INDO-DAPOER. This gives us a picture of determinants of variation in earnings in 2007.

Table 5 provides definitions of variables used in estimation, and Table 6 presents summary statistics. Earnings are measured as the log of monthly labor income in rupiah, calculated as 1/12 of reported income over the previous 12 months as discussed above. We measure education by the highest level of schooling completed (primary, lower secondary, upper secondary and tertiary).[12] Tenure is the number of years an individual reports having held a specific job. Experience is reported years in the labor force.

Table 5: Definitions of variables used in econometric analysis

Table 6: Summary statistics of labor market data

4. Results and discussion

4.1 Baseline estimates

We first report estimates of the 2007 earnings functions, using the log of monthly earnings as dependent variable. Our selection of working-age males who are reported as being in the labor force leaves open the possibility of bias due to non-random selection into the labor force. In practice, however, prior estimation of earnings and employment functions using IFLS data has revealed no significant differences between estimates obtained from OLS and those obtained from two-stage models accounting for selection into the labor force (for a review see Purnastuti et al. 2013). Our regressions control for many exogenous characteristics of individuals in the hope that any remaining variation due to unobserved traits has only random effects on earnings.

Table 7: Baseline earnings functions

In table 7 we report initial econometric exploration of the earnings function model. Column (1) reports OLS estimates of the log of monthly earnings. The explanatory variables include worker's age and tenure and their squares; dummy variables for the highest level of mother's education; log of average per capita

[12] Of course, there are significant markers of educational attainment (such as completion of a schooling stage), so using discrete educational levels rather than years allows for nonlinearities in returns. We also estimated these, but the results add little to the empirical story and we omit them to save space.

income in the district, urban dummy and a dummy for formal employment. Provincial dummy variables are also included but are not reported in the table (complete results are available on request).

In order to get an estimate of the current features of local labor market, we estimate local incomes from the SAKERNAS 2007 dataset. For each district, we compute the median log income and merge this to the individual's district of residence in 2007. Local labor market characteristics can have a direct impact on an individual's earnings and is thus included as a control in the estimation. The mean district log income is 13.3 and the standard deviation is 0.39.

We use past district characteristics as an instrument to predict the likelihood of an individual holding a formal job in 2007. These characteristics include: (1) relative reliance on resource sector (oil palm) in 2000 and (2) percentage of employees in secondary and tertiary sectors (excluding agriculture, fishing, and mining) in 1997. Reliance on the resource sector is measured by the share of oil palm production in district agricultural income and the share of mining in total district income, both computed from INDO-DAPOER. The focus on palm is motivated by the large boom in palm oil production that took place in Indonesia after 1997, as described in section 1. The percentage of non-agricultural employees in 1997 is computed from SAKERNAS 1997 for males under 30, as employment of younger individuals gives a better indication of trends in labor markets. In columns (2)-(5) of Table 7 we report estimates using an IV model. In column (2) we report the first-stage regression of the formal employment variable. The regressors are as for column (1), with the addition of three district-level measures: formal employment as a share of total employment in 1997; oil palm production as a share of total agricultural GDP in 2000; and the interaction of these two variables. The district-level formality share is estimated from SAKERNAS 1997. The definition of formality in SAKERNAS differs slightly from that in IFLS: since SAKERNAS does not report benefits, we categorize employees in the non-agricultural sector as formal. The share of oil palm in agricultural income is available from year 2000 in INDO-DAPOER.

Two assumptions underlie our instrumental variables strategy. First, district-level characteristics are uncorrelated with individual unobservables that determine selection into formal jobs. Second, after controlling for current district-specific characteristics, economic conditions in 2000 impact wages only their influence on availability of formal jobs. Given the political and economic changes that Indonesia has gone through between 1997 and 2007, district characteristics in 1997 are unlikely to have residual impact on 2007 wages.

The level of initial formal employment at district level is insignificant as a predictor of formal employment in 2007. However, the oil palm share in agricultural value-added and the interaction term of oil palm and initial formal employment are precisely estimated. Individuals in districts with a greater 1997 share of oil palm are significantly less likely to have formal jobs in 2007. The interaction term is positive and significant, showing that this effect is diminished by the extent to which the district also has a high initial rate of formal employment.

In columns (3)-(5) we report IV estimates using the instrument for formal employment. Column (3) reports IV results using the same data as for the OLS estimates in Column (1). In Column (4) we exclude individuals who are self-employed with permanent employees (n = 209). In Column (5) we include an additional control for individual initial conditions, the log of adult height. In each case the first-stage F-statistic exceeds 10, satisfying the Staiger-Stock (1997) criterion for a strong instrument. Estimation results are similar across all three specifications. In all cases, since the mean of the instrumental variable is 0.22, formal employment is associated with an earnings premium of approximately 43% after other sources of earnings variation are taken into account.

The results shown in columns (3)-(5) of Table 7 are our preferred estimates. They make use of a demonstrably strong instrument for selection into formal employment. They control for individual origins, which are known to be strong predictors of school attainment and performance, and they exclude the arguably endogenous measures of an individual's own school attainment.

To summarize, our baseline estimates confirm a significant and large role for formal employment as a determinant of individual earnings, and a significant disadvantage, in terms of access to formal jobs, for individuals in districts where oil palm production is a large component of overall agricultural activity. Individual origins, as proxied by maternal education, are strongly associated with earnings (in the OLS model) and with probability of a formal job (in the IV model). In general, younger and less experienced individuals from poorer households in poorer districts have the lowest predicted earnings and the lowest probability of formal employment, and those who reside in provinces that with high initial intensity of oil palm production are even less advantaged. Exclusion from formal employment is associated, other things equal, with average earnings about 60% those of equivalent individuals in formal employment.

4.2 Robustness checks

Thus far, we have excluded measures of individual educational attainment on the grounds that these are endogenously determined by individual, household and district variables already in the earnings equations. Nevertheless in table 8 we explore the consequences of including education, using dummies for junior high school, senior high school and college (elementary/no education is the omitted category). In columns (1) and (2) we ask whether schooling conditions the impact of formality on earnings, in a manner analogous to that of Fafchamps et al. (2009). When schooling measures are included (column (2)) the impact of formal status on earnings is somewhat smaller but remains strongly significant. Schooling alone does not account for selection into formal employment. In columns (3) and (4) we once again present an IV model, this time including individual educational attainment among the explanatory variables in both first stage and IV regressions. In column (4), only elementary schooling has an independent effect on earnings other than through effects on the instrumental variable. However, it is not clear how these results should be interpreted, given the likelihood of bias from endogenous selection into school attainment.

Moreover, in the IV earnings equation (column (4)) the formal employment premium is estimated at 74%,[13] substantially higher than results from our preferred model.

Table 8. Earnings functions with education

Bias in estimates of the earnings effects of education may arise in part from non-linear differences across education levels. In columns (3)-(5) we subdivide the IV regression by schooling levels. First-stage F statistics for these submodels indicate that the instrument is strong only in the junior high school subset. However, the mean predictions of formal employment premium, at about 40% for elementary school and junior high school graduates, and about 50% for senior high school or college graduates, are broadly consistent with those from our preferred IV models in Table 7.

Our next robustness check concerns the unequal distribution of the resource boom across locations. A concern with use of the district-level share of oil palm production as an instrument is that many districts have zero oil palm production. A total of 59 districts, out of 301 for which data is available, have non-zero palm production. As a robustness check, therefore, we exclude provinces that are least likely to have palm production from our sample. Data shows that provinces in Java, Bali, and Nusa Tenggara islands did not have any palm production. The first-stage regression is robust to exclusion of these provinces. The coefficient of interest on the second stage does change since we are excluding some high-earnings areas. Nevertheless, the underlying story remains qualitatively similar.

Table 9. Earnings functions excluding non-oil palm provinces

As a final robustness check, we consider the possibility that the share of oil palm production is picking up other aspects of district-level economic structure unrelated to the export boom. To check this, we run an additional robustness check in which we include additional district-level economic variables in the first

[13] This is because the probability of formality in this sample is 25.41%. So the expected formality premium is 291*0.254 = 74%.

stage regression. These are the shares of agriculture, mining and manufacturing in total district income. The results are seen in Table 10. The formality result on earnings remains robust and similar in magnitude to our baseline model. The influence of the oil palm sector remains robust to the inclusion of these additional structural variables.

Table 10. Earnings functions with additional district-level variables

4.3 Discussion of results

The results of these earnings function estimates echo those from other recent studies, but also add revealing details as well as a degree of econometric rigor not consistently seen in the earlier work. Purnastuti et al. (2013) compare returns to schooling from the IFLS 1993 and 2007 and conclude that returns to schooling have fallen in Indonesia. They speculate without further elaboration that this may be due to some combination of increased supply of skills, lower quality of education as schooling has expanded, and changes in the composition of labor demand. Also using IFLS data, Newhouse and Suryadarma (2011) find a marked drop in returns to categories of schooling targeted at manufacturing employment during the resource boom years. Specifically, they find that the wage premium for male vocational education, which is mainly in technical and industrial subjects, fell sharply between 2000 and 2007. The authors speculate that this may be due, among other causes, to “the declining relevance of these skills in an increasingly service-oriented Indonesian economy” (p.320). This conjecture is consistent with the predictions of a Dutch Disease model: Indonesia’s boom increased the relative rate of job creation in industries that offer low wages and below-average returns to schooling (Coxhead 2014).

Our findings are consistent with lower returns to schooling, but in contrast with the previous studies we can supply at least one definitive causal mechanism. Opportunities for skilled jobs and formal employment (which pays more, offers greater security and benefits, and rewards additional schooling investments) fell in relative terms during Indonesia's resource export boom. Palm oil was by far the fastest-growing export during the boom years, and rapid expansion of the oil palm industry had the largest labor market impacts among resource sectors. After controlling for other individual and district features we find that the intensity of oil palm production is a robust district-level predictor of diminished access to formal employment. Lower formality is in its turn a robust predictor of lower earnings for wage earners. Finally, with relatively fewer formal sector jobs being created, incentives for schooling are also diminished. These results tie the resource boom to individual earnings and human capital outcomes in a direct way. They provide microeconomic evidence for Dutch Disease, a phenomenon usually modeled only at a much higher level of generality and seldom subjected to empirical verification in household or individual data.

In the next and final section, we consider some ramifications of these findings, as well as broader implications for policy and for future research.

5. Conclusions

The Indonesian economy grew steadily during the resource boom years, and aggregate poverty declined. However, these positive indicators of progress in economic development were not uniformly matched by trends in the country's labor market. Employment shares of industries characterized by low labor productivity rose; rates of informal employment also rose, and returns to schooling declined. These trends are consistent with the expected effects of a resource export boom that reduces jobs in skill-intensive industries and expands them in industries characterized by low skill-intensity and widespread informal employment. Such trends are much less easily reconciled with those to be expected in an economy making a sustained transition through middle-income. Understanding the structural drivers of poverty and inequality, and deriving usable policy lessons from them, is a task made all the more urgent to Indonesia after the global financial crisis, as global growth rates of demand for natural resources fall back to earth.

Several recent studies have described wage stagnation and of low and falling returns to skills in Indonesia during the 2000s. Our contribution in this paper has been to establish a link to the direct and indirect effects of the resource boom, specifically the massive expansion in earnings from palm oil exports. We find that much of the structural impact of the boom in labor markets results from changes in opportunities for jobs with formal employment status. Formality is associated not only with significantly higher earnings, but also with greater security and benefits. We find that the formal employment premium in earnings is about 40% once other sources of variation have been controlled, so a lower probability of formal sector employment is associated with considerably lower expected income. Moreover, since access to formal jobs is strongly positively selected on education, the diminished promise of a formal job also reduces the expected net benefits of human capital investment.

Our findings thus provide a foundation for understanding trends in poverty, inequality, and progress in educational attainment in Indonesia during the 2000s. The labor market shift, by depressing real earnings, is likely to have retarded poverty alleviation and contributed to the clustering of household incomes around the poverty line (World Bank 2013). Indonesia's sharp rise in inequality since 2000 may well be a product of the same labor market forces: in rural areas, the income share of the poorest 40% of households has fallen by one fifth; the rural Gini has risen from 0.25 to 0.33 while the overall Gini has also risen, from 0.35 to 0.41; and poverty has risen in many urban areas (Yusuf 2013).[14] Among low and middle income countries, resource booms and a lack of dynamism in manufacturing sector growth have well-established associations with earnings inequality (Leamer et al. 1999; McMillan and Rodrik 2011; Rodrik 2013).

Despite the Dutch Disease predictions, there is nothing inherent to a natural resource export boom that rules out successful growth of other tradable industries, including skill-intensive manufacturing. Indeed

[14] The rising trend in inequality pre-dates by several years the adoption of some important policy reforms thought by some to have increased inequality—such as relaxation of fuel subsidies.

there are many counter-examples to the Dutch Disease outcome, from Southeast Asia (Coxhead 2007; Coxhead and Li 2008) and from Latin America (de Ferranti et al., 2002). Indonesia's own experience in the 1970s provides an example of how resource rents can be deployed to secure lasting economic development gains (Woo et al. 1994). Avoiding the macroeconomic effects of Dutch Disease and distributing the gains from resource-based exports is unlikely to be achieved through consumption subsidies (for example, on fossil fuels), through more restrictive trade and labor policies, or even through unconditional cash transfers—all policies adopted by Indonesian governments during the boom era. Instead, it requires a mix of investments to increase productivity and sterilization to dampen the spending effects of the boom and provide a savings cushion for when commodity prices decline. In general, long-run gains are achieved not through industry-specific interventions, but by redirecting new public and private spending toward activities—such as health, nutrition, education, rural development and infrastructure—that increase labor productivity, improve human capital, and increase returns to schooling. In Indonesia as elsewhere in the developing world, the incomes of the poor depend mainly on their labor, and thus the labor market is the most direct conduit through which to reverse poverty, inequality and lack of opportunity.

References

Alderman, H.; J. Hoddinott, and W. Kinsey, 2006. "Long term consequences of early childhood malnutrition," *Oxford Economic Papers* 58(3): 450–474.

Almond, D., and J. Currie, 2011. "Human capital development before age 5." In O. Ashenfelter and D. Card, eds: *Handbook of Labor Economics vol. 4b*. Amsterdam: North-Holland, pp. 1316-1486.

Aswicahyono, H.; H. Hill and D. Narjoko, 2011. "Indonesian industrialization: a latecomer adjusting to crises." WIDER Working paper No. 2011/53.

Card, D., 1993. "Using geographic variation in college proximity to estimate the return to schooling." NBER Working Papers No. 4483.

Card, D., 1999. "The causal effect of education on earnings" In *Handbook of Labor Economics 3A* (Amsterdam: North-Holland), pp. 1801-1863.

Case. A., and C. Paxson, 2006. "Stature and status: height, ability, and labor market outcomes." *Journal of Political Economy*, 116(3):499-532.

Case, A., C. Paxson and M. Islam, 2009. "Making sense of the labor market height premium: evidence from the British Household Panel Survey." *Economics Letters* 102: 174-176.

Comola, M., and L. de Mello, 2013. "Salaried employment and earnings in Indonesia: new evidence on the selection bias." *Applied Economics* 45 (19): 2808-2816.

Corden, W.M. and P.J. Neary, 1982. "Booming sector and de-industrialization in a small open economy." *Economic Journal* 92: 825-848.

Coxhead, I., 2007. "International trade and the natural resource 'curse' in Southeast Asia: does China's growth threaten regional development?" *World Development* 35(7): 1099-1119.

Coxhead, I., 2014. "Indonesia: returns to occupations, education and ability during a resource export boom." In P-C Athukorala, A.A. Patunru, and B. Resosudarmo (eds), *Trade, development and Political Economy in East Asia: Essays in Honor of Hal Hill.* Singapore: ISEAS.

Coxhead, I., and M. Li, 2008. "Prospects for skills-based exports in resource-rich developing economies: Indonesia in comparative perspective." *Bulletin of Indonesian Economic Studies* 44(2): 199-228.

Currie, J. 2009, "Healthy, wealthy and wise: socioeconomic status, poor health in childhood, and human capital development." *Journal of Economic Literature* 47(1): 87-122.

de Ferranti, D., G.E. Perry, D. Lederman, and W.F. Malone, 2002. *From natural resources to the knowledge economy: trade and job quality*. Washington, DC: World Bank.

Fafchamps, M.; M. Soderbom, and N. Benhassine, 2009. "Wage gaps and job sorting in African manufacturing." *Journal of African Economies* 18(5): 824-868.

Glewwe, P.; H. Jacoby, and E.M. King, 2001. "Early childhood nutrition and academic achievement longitudinal analysis." *Journal of Public Economics* 81(3): 345–368.

Gylfason, T., 2001. "Natural resources, education, and economic development." *European Economic Review* 45: 847-859.

Hanson, G., 2010. "Why isn't Mexico rich?" NBER Working Paper No.16470.

Heckman, J.J., L.J. Lochner, and P.E. Todd, 2006. "Earnings functions, rates of return and treatment effects: the Mincer equation and beyond." In E. Hanushek and F. Welch (eds): *Handbook of the Economics of Education* (Amsterdam: North-Holland), pp. 307-458.

Hoddinott, J.; J. Maluccio, J.R. Behrman, R. Flores, and R. Martorell, 2008. “Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults.” *The Lancet* 371(9610): 411–416.

ILO (International Labour Organization), 2011. *Decent Work Country Profile: Indonesia*. Geneva: ILO.

ILO (International Labour Organization), 2013. *Measuring Informality: A Statistical Manual*. Geneva: ILO.

Leamer, E.E. et al., 1999. "Does natural resource abundance increase Latin American income inequality?" *Journal of Development Economics* 59:3-42.

McMillan, M., and D. Rodrik, 2011. “Globalization, structural change and productivity growth.” NBER Working Papers No. 17143.

Mincer, J., 1974. *Schooling, Experience, and Earnings*. New York: NBER.

Narayan, A., E. Skoufias, B. Dasgupta, and K. Kaiser, 2014. “Electoral accountability and local government spending in Indonesia.” World Bank Policy Research Working Paper 6782.

Newhouse, D., and D. Suryadarma, 2011. “The value of vocational education: high school type and labor market outcomes in Indonesia.” *Bulletin of Indonesian Economic Studies* 25(2): 296-322.

Patrinos, H.A., C. Ridao-Cano, and C. Sakellariou. 2006. “Estimating the returns to education: accounting for heterogeneity in ability.” World Bank Policy Research Worlking Paper No. 4040.

Purnastuti, L., P. Miller, and R. Salim, 2011. “Economic returns to schooling in a less developed country: evidence for Indonesia.” *Proceedings: International Conference on Applied Economics 2011*.

Purnastuti, L., P. Miller, and R. Salim, 2013. “Declining rates of return to education: evidence for Indonesia.” *Bulletin of Indonesian Economic Studies* 49(2): 213-36.

Rodrik, D., 2013. “The past, present and future of economic growth.” Global Citizen Foundation, Working Paper No. 1. http://www.gcf.ch/?page_id=5758, accessed 29 November 2013.

Rodrik, D., 2015. “Premature deindustrialization.” Princeton, NJ: IAS School of Social Science, Economics Working Papers No. 107.

Silventoinen, K., 2003. “Determinants of variation in adult body height.” *Journal of Biosocial Sciences* 35(2): 263-285.

Staiger, D., and J.H. Stock, 1997. “Instrumental variables regression with weak instruments.” *Econometrica* 65(3): 557-586.

Strauss, J.; F. Witoelar, B. Sikoki, and A.M. Wattie, 2009. “The fourth wave of the Indonesia Family Life Survey: overview and field report Volume 1.” RAND Labor and Population Working Paper WR-675/1-NIA/NICHD. Santa Monica, CA: RAND.

Thee, Kian-Wee, 2011. “Indonesia: Blessed by strong economic growth and the curse of resources.” www.eastasiaforum.org.

van der Eng, P., 2009. “Capital formation and capital stock in Indonesia, 1950-2008.” *Bulletin of Indonesian Economic Studies* 45(3): 345-371.

Wihardja, M.M., 2013. “Indonesia living dangerously as it neglects economic reform.” eastasiaforum.org, 2 October 2013.

Woo, W.T., B. Glassburner, and A. Nasution, 1994. *Macroeconomic Policies, Crises, and Long-Term Growth in Indonesia, 1965-90*. Washington, DC: World Bank.

World Bank, 2013. *East Asia and the Pacific Economic Update 2013*. http://data.worldbank.org/sites/default/files/east_asia_economic_update_figures_and_tables.pdf

Yusuf, Arief A., 2013. "The evolution of inequality in Indonesia, 1990-2012." Department of Economics, Padjadjaran University: Working Papers in Economics and Development Studies No. 201314.

Figures

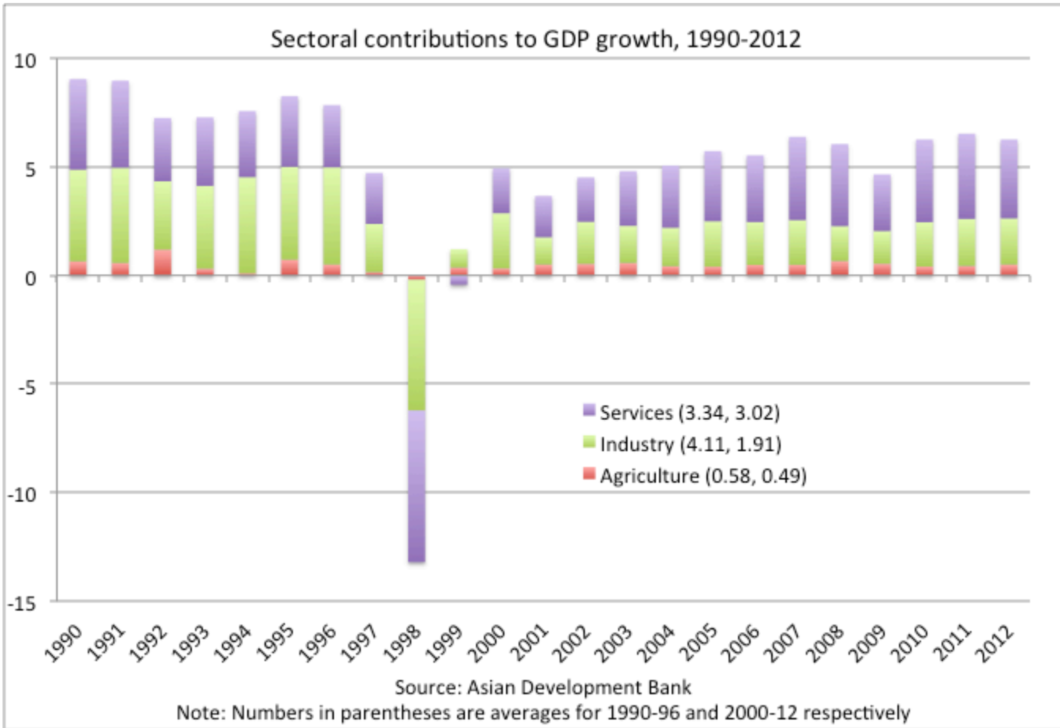

Figure 1: Sectoral contributions to GDP growth

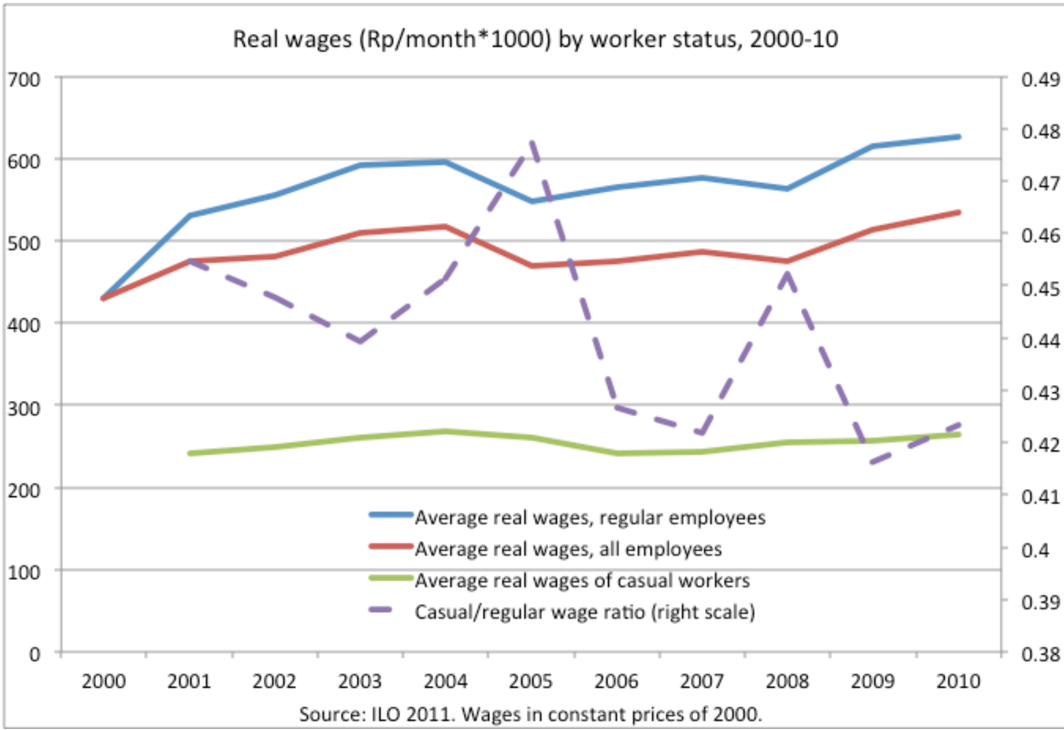

Figure 2: Average real wage trends in the 2000s

Table 1: Number of observations and average earnings by formality, 2007 males 20-65

	Number of observations		Average earnings	
	Informal	Formal	Informal	Formal
Elementary	4,015	292	12.533	13.308
Junior	1,489	252	12.807	13.51
Senior	1,765	941	13.027	13.806
University	403	638	13.454	14.277

Source: IFLS 2007

Table 2: Sectoral output and employment growth, 1990-2008

	1990-96	2000-08	Change
Output growth (% per year)			
Agriculture	3.1	3.9	0.8
Mining and utilities	5.3	1.5	-3.8
Manufacturing	11.2	5.2	-6
Construction	13.7	6.5	-7.3
Wholesale trade	8.9	5.8	-3
Transport	8.2	10.1	1.9
Other activities	6.4	5.8	-0.7
Total	7.9	5.3	-2.6
Employment growth (% per year)			
Agriculture	-1.7	0.2	1.9
Mining and utilities	6	3.7	-2.3
Manufacturing	6	0.9	-5.1
Construction	10.8	5.7	-5.1
Wholesale trade	6.5	1.7	-4.8
Transport	9.4	3.9	-5.5
Other activities	4.6	3.6	-1
Total	2.3	1.7	-0.6

Source: ADB data compiled by Aswicahyono et al. 2011.

Table 3: Median earnings/worker in wholesale/retail/personal services, relative to manufacturing wages

	1997	2000	2007
Private employment	0.88	0.85	0.85
Self-employed w/out employees	0.80	0.70	0.53

Source: IFLS.

Table 4 Formal employment status by sector and occupational category

	Occupational category			
Sector	Professional	Sales/Service	Production	Agriculture
(a) Formality by sector and occupational category, males 20-65 (%)				
Agri				0.04
Mining	1	1	0.21	
Mfg	0.61	0.52	0.35	
Cons/Util	0.48	0.63	0.11	
Trade/Trans	0.54	0.12	0.11	
Gov Serv.	0.91	0.79	0.85	
Priv Serv.	0.67	0.55	0.4	
Oth Serv	0.05	0.01	0.02	
(b) Number employed by sectors and occupational category in 1997, males 20-65				
Agri				17952523
Mining	30805	16722	571777	
Mfg	334373	190429	4844612	
Cons/Util	152522	32542	3704392	
Trade/Trans	381068	7276366	3630687	
Gov Serv.	2177050	130365	70399	
Priv Serv.	1904619	957222	1106997	
Oth Serv	154676	502849	935910	
(c) Number employed by sectors and occupational category in 2007, males 20-65				
Agri				22753091
Mining	41875	42398	713680	
Mfg	452477	497506	5679405	
Cons/Util	199613	101936	3982882	
Trade/Trans	651042	8427453	4979591	
Gov Serv.	1227412	231063	61215	
Priv Serv.	1938889	1053460	879951	
Oth Serv	203873	536707	690712	

Sources: (a) IFLS; (b) and (c): Sakernas 1997 and 2007.

Table 5: Definitions of variables used in estimation

Variable	Description	Data Source
Individual and household level variables		
Dependent variable		IFLS 2007
Log monthly income	Log of average monthly income (income last year divided by 12)	
Explanatory variable of interest:		IFLS 2007
Formality	Dummy variable equals to 1 if job provides housing, medical or transportation benefit, or any kind of training	
Other control variables		
Age and age squared		
Tenure and tenure squared	Years in current job	
Mother's education		
Basic	Up to elementary level	IFLS 2007
Junior	Junior (general or vocational)	
Senior	Senior (general or vocational)	
University	College or higher	
Log height	Log of height in cm	
District-level variables		
Log income	Median log income in district in 2007	SAKERNAS 2007
Worker 1997	Percentage of non-agricultural workers in 1997	SAKERNAS 1997
Palm Production	Palm production (in tonnes) as fraction of agricultural GDP in 2000	INDODAPOER
Mining GDP	Mining GDP as fraction of total GDP	INDODAPOER

Table 6: Summary statistics of variable used in estimation

	Num obs	Mean	Std. Dev.
Individual and household variables			
Log earnings	9101	12.962	0.015
Age	9284	40.318	0.142
Tenure	9254	10.987	0.138
Formal	9284	0.219	0.005
Mother education			
Junior	9256	0.057	0.002
Senior	9256	0.038	0.002
University	9256	0.008	0.001
Urban	9284	0.453	0.006
District level variables			
Worker 1997	250	16.59	9.17
Palm	250	0.007	0.02
Mining	250	0.076	0.168
Log income 2007	250	13.202	0.365

Table 7: Baseline earnings regressions

		IV Estimates			
	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS	First stage	All non-zero earn	No employers	W/ height
Formal	0.861***		1.958***	1.997***	1.978***
	(0.0409)		(0.544)	(0.503)	(0.552)
Worker in 1997		0.000821			
		(0.00157)			
Palm production		-4.699***			
		(0.961)			
Worker *Palm Prodn		0.518***			
		(0.101)			
Age	0.0864***	0.00228	0.0837***	0.0784***	0.0838***
	(0.00870)	(0.00351)	(0.00928)	(0.00936)	(0.00932)
Log district income	0.495***	0.118***	0.348**	0.316**	0.345**
	(0.115)	(0.0426)	(0.153)	(0.151)	(0.153)
Tenure	0.0557***	0.00937***	0.0453***	0.0460***	0.0451***
	(0.00570)	(0.00155)	(0.00750)	(0.00691)	(0.00757)
Mother Junior	0.217***	0.153***	0.0489	-0.00753	0.0451
	(0.0589)	(0.0252)	(0.103)	(0.105)	(0.104)
Mother Senior	0.296***	0.193***	0.0845	0.0357	0.0805
	(0.0670)	(0.0265)	(0.127)	(0.128)	(0.128)
Mother University	0.626***	0.279***	0.312	0.278	0.305
	(0.0961)	(0.0588)	(0.195)	(0.198)	(0.197)
Log height					0.0879
					(0.0949)
Urban	0.343***	0.118***	0.213**	0.188**	0.210**
	(0.0442)	(0.0158)	(0.0830)	(0.0797)	(0.0838)
Observations	9,063	9,238	9,063	8,854	9,063
R-squared	0.249	0.114			
F-stat 1st stage			13.32	13.32	13.31

Notes: Robust standard errors clustered at district level. Provincial dummy variables estimated but not reported.
*** p<0.01, ** p<0.05, * p<0.1.

Table 8: Earnings functions with education variables

			IV Estimates				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	OLS-excl. schooling	OLS-incl. schooling	First stage	Incl. schooling	Elem. sch only	Junior high	Senior high & above
Formal	0.861***	0.614***		2.910***	3.854**	1.590	1.806**
	(0.0409)	(0.0387)		(1.005)	(1.799)	(1.109)	(0.727)
Worker in 1997			0.00222				
			(0.00147)				
Palm production			-4.166***				
			(0.978)				
Worker *Palm Prodn			0.456***				
			(0.0963)				
Junior		0.292***	0.0607***	0.153**			
		(0.0397)	(0.0133)	(0.0777)			
Senior		0.498***	0.262***	-0.103			
		(0.0392)	(0.0165)	(0.276)			
University		0.931***	0.516***	-0.256			
		(0.0486)	(0.0233)	(0.531)			
Age	0.0866***	0.0810***	-0.000729	0.0823***	0.0568***	0.105***	0.0847***
	(0.00872)	(0.00890)	(0.00329)	(0.0115)	(0.0190)	(0.0240)	(0.0189)
Log district income	0.494***	0.395***	0.0441	0.210	0.156	0.357*	0.265**
	(0.115)	(0.106)	(0.0344)	(0.152)	(0.258)	(0.195)	(0.121)
Tenure	0.0557***	0.0599***	0.00996***	0.0370***	0.0447***	0.0573***	0.0548***
	(0.00571)	(0.00561)	(0.00146)	(0.0119)	(0.00816)	(0.0163)	(0.0175)
Mother Junior	0.216***	0.0152	0.00875	-0.00792	0.0194	-0.0515	0.0565
	(0.0589)	(0.0594)	(0.0229)	(0.0742)	(0.224)	(0.158)	(0.0791)
Mother Senior	0.296***	0.0149	-0.00743	0.0363	-0.283	0.113	0.116
	(0.0671)	(0.0613)	(0.0292)	(0.0845)	(0.759)	(0.275)	(0.0865)
Mother University	0.624***	0.241**	-0.00129	0.231		-1.061	0.370**
	(0.0962)	(0.0950)	(0.0547)	(0.151)		(0.901)	(0.145)
Log height	0.131	0.133	0.0230	0.0870	0.281	0.0606	-0.00596
	(0.100)	(0.0903)	(0.0253)	(0.0968)	(0.205)	(0.190)	(0.117)
Urban	0.342***	0.228***	0.0495***	0.104	0.104	0.134	0.122**
	(0.0443)	(0.0448)	(0.0143)	(0.0781)	(0.125)	(0.125)	(0.0602)
Observations	9,063	8,711	8,875	8,711	3,319	1,564	3,828
R-squared	0.249	0.288	0.234				
F-stat 1st stage				12.44	4.510	12.16	8.705

Notes: Robust standard errors clustered at district level. Provincial dummy variables estimated but not reported.
*** p<0.01, ** p<0.05, * p<0.1.

Table 9: Earnings functions excluding data from Java, Bali and Nusa Tenggara

VARIABLES	(1) First stage	(2) All non-zero earn	(3) No employers	(4) W/ height
Formal		1.697***	1.781***	1.704***
		(0.414)	(0.398)	(0.413)
Worker in 1997	-0.00141			
	(0.00301)			
Palm production	-5.746***			
	(0.996)			
Worker *Palm Prodn	0.615***			
	(0.105)			
Age	0.00983**	0.0415**	0.0377*	0.0408**
	(0.00469)	(0.0202)	(0.0205)	(0.0202)
Log district income	0.128**	-0.113	-0.128	-0.116
	(0.0547)	(0.286)	(0.285)	(0.286)
Tenure	0.00779***	0.0739***	0.0707***	0.0744***
	(0.00295)	(0.00794)	(0.00796)	(0.00798)
Mother Junior	0.138***	0.00269	-0.0215	-0.00591
	(0.0342)	(0.116)	(0.116)	(0.116)
Mother Senior	0.257***	-0.00571	-0.0251	-0.00716
	(0.0596)	(0.169)	(0.166)	(0.167)
Mother University	0.378***	0.0112	0.0143	0.0185
	(0.0943)	(0.324)	(0.321)	(0.329)
Log height				0.438**
				(0.170)
Urban	0.0792**	0.363***	0.316***	0.360***
	(0.0376)	(0.0891)	(0.0888)	(0.0889)
Observations	2,758	2,695	2,640	2,695
R-squared	0.109			
F-stat 1st stage		17.52	17.52	17.44

Notes: Robust standard errors clustered at district level. Provincial dummy variables estimated but not reported.
*** p<0.01, ** p<0.05, * p<0.1.

Table 10: Earnings functions with additional district-level variables

VARIABLES	(1) First stage	(2) All non-zero earn	(3) No employers	(4) W/ height
Formal		1.734**	1.834***	1.735**
		(0.684)	(0.684)	(0.684)
Worker in 1997	0.00639			
	(0.00395)			
Palm production	-5.664***			
	(1.019)			
Worker *Palm Prodn	0.614***			
	(0.114)			
Mining GDP	0.168			
	(0.261)			
Worker*Mining GDP	-0.00689			
	(0.0160)			
Agriculture GDP	0.310*			
	(0.183)			
Worker*Agriculture GDP	-0.0178***			
	(0.00677)			
Manufacturing GDP	0.218			
	(0.215)			
Worker*Manufacturing GDP	-0.00507			
	(0.00760)			
Age	0.00234	0.0839***	0.0785***	0.0840***
	(0.00351)	(0.00899)	(0.00919)	(0.00901)
Log district income	0.0689	0.378**	0.338**	0.377**
	(0.0469)	(0.167)	(0.168)	(0.167)
Tenure	0.00944***	0.0475***	0.0476***	0.0475***
	(0.00152)	(0.00820)	(0.00775)	(0.00820)
Mother Junior	0.150***	0.0824	0.0189	0.0814
	(0.0247)	(0.110)	(0.122)	(0.110)
Mother Senior	0.191***	0.127	0.0680	0.126
	(0.0265)	(0.146)	(0.156)	(0.146)
Mother University	0.278***	0.375*	0.328	0.374*
	(0.0588)	(0.208)	(0.225)	(0.208)
Urban	0.119***	0.240**	0.209**	0.239**
	(0.0165)	(0.0989)	(0.101)	(0.0988)
Log height				0.0972
				(0.0931)
Observations	9,226	9,051	8,842	9,051
R-squared	0.117			
F-stat 1st stage		15.47	15.47	15.42

Notes: Robust standard errors clustered at district level. Provincial dummy variables estimated but not reported.
*** p<0.01, ** p<0.05, * p<0.1.