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GDP-Employment Elasticities across Developing Economies

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Abstract

Economic growth is often associated with welfare gains through job creation. However, the number and quality of new job opportunities created in a growing economy vary across countries and sectors, due in great part to changes in labor productivity. This paper provides estimates of country and sector-specific GDP-employment elasticities based on data from the past two decades, including an evaluation of the predictive power among alternative methodological approaches. The results show that employment elasticities of growth vary significantly across countries and sectors, but are in most cases below 1.0, implying that employment grows less than GDP due to increasing productivity. Across sectors, agriculture has mostly lower elasticity values, becoming negative for more than one-third of developing countries. In addition, increases in labor productivity are associated with reductions in informal employment. These empirical results are in line with the implications of a theoretical model about the relationship between GDP growth, job creation, and labor productivity in economies with varying levels of productivity and informality.

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GDP-Employment Elasticities across Developing Economies[1]

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1. Introduction

The effect of economic growth on job creation has been a prominent topic in macroeconomics and development economics. It is particularly important in the context of developing countries where job creation is viewed as a critical outcome of investment activity - both public and private - driving poverty reduction and welfare improvements. However, while there is a large body of literature studying this relationship, from Solow (1956) to Acemoglu and Restrepo (2018), most theoretical models and empirical estimates are based on the experience and data from developed countries. When focusing on employment growth generated by private investment activities, there is expected variation across countries and sectors. Along these lines, this paper introduces a theoretical model to understand the relationship between GDP growth, job creation, and labor productivity in economies with different levels of productivity and informality. The model is used to interpret the implications of empirically estimated GDP-employment elasticities as well as the estimated effects of labor productivity improvements on informality. In this regard, differentiating the types of employment generated by economic growth is especially relevant in the context of developing economies, where a high share of the working poor is not able to meet their daily needs despite engaging in informal activities that are characterized by below-subsistence remuneration and provide limited or no employment benefits.

The theoretical model expands the literature on modeling informality, including Lucas (1978), Rauch (1991), Aghion et al. (2005), Gollin (2008), Sharma (2009), and De Paula and Scheinkman (2011). It follows existing studies on ability or labor productivity that drive labor market participants' decisions on whether to become: (i) formal sector entrepreneurs, (ii) workers in the formal sector, or (iii) informal sector entrepreneurs; and provides a theoretical framework to understand the impact of productivity improvements on output and employment across the formal and informal sectors in developing economies. In summary, the model shows that in economies with sizable informality, employment growth is lower than economic growth, and that there is a negative relationship between informality and labor productivity.

This paper implements alternative methodologies to estimate the GDP-employment elasticities empirically for three aggregate sectors (agriculture, manufacturing, and services) across developing economies. First, a Social Accounting Matrix (SAM) multiplier approach (Khan et al., 1989), which under strong assumptions (i.e., fixed technology, prices and capital output ratios) implies that GDP growth leads to proportional changes in employment, and therefore the GDP-employment elasticity equals 1. This is an estimation approach used by many practitioners working with Input-Output (IO) and SAM frameworks to assess the effects of different shocks to the economy. However, this approach tends to significantly overestimate employment growth relative to GDP growth across sectors and countries.[4]

The second method uses an econometric-based approach to estimate the relationship between employment growth and GDP growth. This follows various studies in the literature. For instance, Kapsos (2005) applies a panel estimation in levels with country and sectoral dummies, Sahin et al. (2015) estimate a cointegration relationship, while Crivelli et al. (2013) use a panel in levels with lags of the dependent variable and country specific dummies.[5] The estimated elasticities in these studies differ substantially, influenced by the specific country and sector of analysis and the chosen regression specification. While the results of these studies vary substantially, it is important to note that the key challenge of these approaches is the endogeneity bias in the estimators generated by the simultaneous causality of employment and economic growth.

The third estimation method is derived from distributional properties of employment and GDP. Following Klenow and Rodriguez (1997), it can be shown that the expected growth in employment conditional on observed growth in GDP equals the covariance of employment growth and economic growth divided by the variance of GDP growth.[6] Finally, the fourth estimation approach follows a direct and straightforward calculation of the GDP-employment elasticities as the average ratio of annual percentage growth in employment to the annual percentage growth in GDP. This method does not impose any structural assumptions on the underlying variables and can be implemented for time series of different length.[7]

To evaluate these estimation methods' predictive power, a cross-country data panel for developing economies in the period 2000-2016 was used based on the value added and employment data from the World Development Indicators and International Labor Organization. Within-sample as well as out-of-sample GDP-employment elasticity estimates were produced under each methodology and used to estimate employment growth based on observed GDP growth. The results of this analysis show that the fourth approach based on average ratio of annual percentage changes in employment and GDP exhibits

[4] For example, following this approach (using macro data from Eurostat and the World Bank World Development Indicators), the observed 50 percent of GDP growth in European Union countries during 1995-2005 implies 50 percent growth in employment, in contrast with the 10 percent actual growth in employment observed over the same period.

[5] Other works in the area include Kaldor (1966), Parikh (1978), Rowthorn (1975a,b), Saget (2000), Döpke (2001), Kapsos (2006), Pattanaik & Nayak (2014), or Olusoji (2016).

[6] We thank Aart Kraay for his help on identifying this alternative estimation method. It is important to note that this approach is underlined by the assumption that the growth of employment and productivity are bivariate normal.

[7] Okun's law (Okun, 1962) offers an alternative way to compute employment elasticities based on the documented inverse relationship between the unemployment rate and GDP growth (see Ball et al., 2017 for a recent summary). While there have been sector-focused versions (Goto and Bürgi, 2020), one key challenge in applying this approach in the context of developing countries is that unemployment rates alone do not describe labor market supply-demand gaps, given sizable informal employment and inefficient labor use across different sectors. In this case, GDP growth leads to a combination of job creation and increased labor productivity. In developing countries significantly lagging behind the frontier economies, employment effects would be dampened.

superior predictive power relative to other methodologies. Furthermore, the results show that average GDP-employment elasticities vary substantially across countries and sectors – ranging between 0.0 and 1.0 for more than 80 percent of countries, and between 0.25 and 0.75 for more than half of countries – in manufacturing and services. Agriculture shows a different pattern: estimated average elasticities show lower values than for manufacturing and services, 60 percent of countries have values less than 0.25 (and negative for about one-third of countries), while only 30 percent of countries have values ranging between 0.25 and 0.75. This is explained largely by the dominance of smallholder farming in agriculture across developing economies, which have in general low productivity and follow different dynamics related to labor demand, compared to other sectors.

In addition to the GDP-employment relationship, there are several studies focused on the relationship between employment levels and labor productivity. One distinct feature highlighted by these studies, in the context of developing countries, is the role of informal employment. Capp et al. (2005), Elstrodt et al. (2002), Farrell (2004), Kenyon et al. (2005), and Palmade (2005) found that informality is among the key factors driving productivity differences between developing and developed countries as it affects investment decisions and reduces growth potential of economies. In this context, increases in GDP can be decomposed into productivity and employment gains (World Bank, 2010). While productivity gains increase wages and could lift people from informal jobs into formal ones, they might not necessarily increase employment. Maloney (2001) and Loayza and Rigolini (2011) found strong and negative relationships between informality and productivity.

To complement the analysis of GDP-employment elasticities, the paper estimates the relationship between labor productivity and informal employment. For this purpose, a consistent measure of informality is used across countries which includes the self-employed and non-paid employees (which can account for more than 60 percent of total employment in low-income countries).[8] This measure is subsequently applied to a new standardized global micro dataset (I2D2) harmonized and assembled by the World Bank Group (see Appendix 1).[9] The empirical results show that an increase in labor productivity is associated with a reduction in informality, consistent with the theoretical model predictions.

[8] This measure does not comprehensively capture the extent of informal employment in developing countries, as it does not take into consideration those workers who work for informal enterprises or formal enterprises while still maintaining informal employment status. In practice, informality measures vary across developing countries and are heavily influenced by the availability of relevant indicators in labor force surveys. The definition of informality used in this paper has the advantage of being consistent across countries and has been widely adopted in studies that employ cross-country data.

[9] The I2D2 covers 147 countries and includes agriculture, manufacturing, and services as sectors of occupation. I2D2 distinguishes four employment categories: paid employee, non-paid employee, employer and self-employed.

The remainder of the paper is structured as follows: section 2 describes the theoretical model, section 3 discusses the empirical approach, section 4 describes the data and descriptive statistics, section 5 presents the empirical results, and section 6 concludes.

2. Model

The paper introduces a theoretical model to understand the relationship between GDP growth, job creation, and labor productivity in economies with different levels of productivity and informality. The model is used to interpret the implications of empirically estimated GDP-employment elasticities as well as the estimated effects of labor productivity improvements on informality.

The model uses an economy with potential entrepreneurs, drawing from the research of Aghion et al. (2005), Gollin (2008), and Sharma (2009). It is assumed that there are two types of agents in this economy in period t: N_{Ht} with high entrepreneurial ability A_{Ht} and N_{Lt} with low entrepreneurial ability A_{Lt}. While ability captures multiple factors, ability and productivity will be used interchangeably in the model. High ability agents create firms with high productivity A_{Ht} and low ability agents can only start firms with low productivity $A_{Lt} < A_{Ht}$.[10] Agents have three possible employment options. First, they can become self-employed in the informal sector. Second, agents can start a formal business as entrepreneurs and employ other workers. Third, they can become paid workers in formal firms where they earn the *"formal wage"* ($\overline{w_{jt}} + \tau_{jt}$, where $\tau_{jt} > 0$ reflects mandatory taxes and/or contributions for formal employment), higher than the reservation wage $\overline{w_{jt}}$ of worker j (which is equal to self-employment income). The production function of firms is shown below:

$$Y_{it} = A_{it} L_{it}^{\alpha} \tag{1}$$

where Y_{it} is output of firm *i* in period *t*; A_{it} is productivity linked to entrepreneurial ability of a firm's owner; $L_{i,j,t}$ is the number of workers with ability *j* employed by firm *i*; and $0 < \alpha < 1$ ensures that there is an optimal number of workers. It is assumed that workers' ability mix does not impact the productivity of the firm, determined only by the entrepreneur's ability.

Agents maximize their payoff by choosing between becoming an entrepreneur, a wage worker or self-employed. The equilibrium in this economy is determined by the (formal) wage, (formal) firms' profits, and agents' choices. Conditional on the number of high and low ability agents there are three possible scenarios. In the first scenario, all agents with high entrepreneurial ability become entrepreneurs and

[10] This setup of firms is similar to that in Gollin (2008), but it combines productivity and capital in A.

create exactly as many jobs as there are agents with low entrepreneurial ability. In the second scenario there are too many high ability agents and thus (formal business) profits decrease to their reservation wage and a fraction of high ability agents become self-employed. In the third scenario there are too many low ability agents and thus formal wages fall to the low ability formal reservation wage and a fraction of low ability workers become self-employed. The details and derivations of each scenario is detailed in the Appendix 2. Note that as the variables can change over time, economies can transition from one scenario into another.

This economic model can be used to assess the impact of GDP growth on employment; where GDP growth is driven by increases in formal sector firms' capital or productivity (A_{Ht}), through changes in output Y_t and employment. For the purpose of this analysis, only one scenario is of interest, where a fraction of low ability workers opts for informal self-employment (scenario 3). The output per worker is disaggregated into formal and informal production:

$$\frac{Y_t}{L_t} = \frac{Y_{Ft}}{L_t} + \frac{Y_{It}}{L_t} = s\frac{Y_{Ft}}{L_{Ft}} + (1-s)\frac{Y_{It}}{L_{It}} \tag{2}$$

where s is a share of a formal sector employment and (1-s) is a share of informal sector workers in total. Variables with subscript F relate to the formal sector and I to the informal one.

In scenario 3, both formal sector employment L_{Ft} and informal sector employment L_{It} include only low ability agents. Since all informal workers in scenario 3 are self-employed, an output per worker in the informal sector is simply $\frac{Y_{It}}{L_{It}} = A_{Lt}$, which we assume not to change.[11] Under this assumption, there are only two possible channels through which productivity in the economy can increase. The first channel is an increase in the productivity of formal firms (A_{Ht}) and the second channel is an increase in the number of agents with A_{Ht}.[12] In both cases, the number of informal sector workers decreases, either because each firm hires more workers or because there will be more firms. This means that regardless of the channel, any increase in overall labor productivity goes in tandem with a decrease in the share of informal employment (under the assumption that A_L is fixed). This negative relationship is estimated and confirmed in the empirical section of this paper.

[11] In line with Loewenstein and Bender (2017).

[12] Small increases in A_{Ht} will allow profit maximizing firms to hire more workers to increase their production and profits, given unchanged wages.

This model can also help explain differences in GDP-employment elasticities across countries with and without informal employment – or in economies with higher or lower informality (see the Appendix). In scenario 3, where an economy has an informal sector mainly composed by low ability agents – as is the case in most developing countries - GDP growth does not imply an increase in formal sector wages. Instead, increases in productivity lead to an expansion of the formal sector given an abundant supply of low ability agents willing to work in the formal sector. [13] This implies a negative relationship between productivity growth and the rate of informality. In this case, net job creation in the economy will be less than (gross) job creation in the formal sector, as a fraction of new formal workers move from the informal to the formal one. Thus, increases in employment originate from the unemployed entering the formal sector. It is important to note that if all new jobs are taken by the unemployed, the change in employment would be higher than in the case with informality, assuming wages remain constant.[14] However, if some of the new workers move from the informal sector, then employment growth will be relatively lower than in the former case.

The paper draws on model implications for the empirical approach. Specifically, the relationship between GDP and employment has two components. Firstly, increases in GDP can increase employment due to unemployed people becoming employed and secondly, through a shift from the informal sector to the formal sector which does not increase employment but increases wages. GDP growth can thus be decomposed into these two employment related effects.

3. Empirical Approach to Estimate GDP-Employment Elasticities

Four alternative methodologies are implemented to generate estimates of GDP-employment elasticities (i.e. the economic growth elasticity of employment) for three aggregate sectors (agriculture, manufacturing, and services) across developing economies: a SAM multiplier approach, a cross-country regression-based approach, a (country-sector-specific) growth decomposition derived approach, and a direct calculation of average annual elasticities from country-sector time series.

[13] It can be shown that $\frac{dlnY_{Ht}}{dlnA_{Ht}} = \frac{dlnL_{Ht}}{dlnA_{Ht}} = \frac{1}{(1-\alpha)}$. This implies that $\frac{dlnw_{Ht}}{dlnA_{Ht}} = 0$, which is consistent with invariant formal wages to formal sector productivity under scenario 3 ($w_H = A_L + \tau_L$).

[14] Unemployed earn 0 wages and do not produce anything. Self-employed earn their informal sector wages and produce some output (GDP). If an informal worker becomes a formal sector worker, his previous job disappears and hence there is no increase in employment and output only increases by the difference between the formal job output and the informal job output.

3.1. SAM Multiplier Approach

This approach is popular among practitioners using Input-Output (IO) and Social Accounting Matrix (SAM) data to estimate effects on employment. In line with underlying IO and SAM multipliers frameworks, this approach implies strong assumptions, such as fixed prices and technology. For example, assuming a Cobb-Douglas production function:

$$\mathrm{Y_{ijt}} = \mathrm{A_{ijt}}\,\mathrm{K_{ijt}}^{\gamma}\,\mathrm{L_{ijt}}^{\theta} \tag{3}$$

where $\mathrm{Y_{ijt}}$ is value added, $\mathrm{A_{ijt}}$ is multi-factor productivity, $\mathrm{K_{ijt}}$ is capital and $\mathrm{L_{ijt}}$ is employment in country *i*, sector *j*, and year *t*; taking logs on both sides and differentiating with respect to time:

$$\frac{dl_{ijt}}{dt} = \frac{1}{\theta}\left[\frac{dy_{ijt}}{dt} - \frac{da_{ijt}}{dt} - \gamma\frac{dk_{ijt}}{dt}\right] \tag{4}$$

where $\mathrm{x_{ijt}} = ln(\mathrm{X_{ijt}})$. When assuming that technology is fixed $\left(\frac{da_{ijt}}{dt} = 0\right)$, the production function exhibits constant returns to scale $(\theta = 1 - \gamma)$ and capital grows in proportion to output $\left(\frac{dk_{ijt}}{dt} = \frac{dy_{ijt}}{dt}\right)$ then employment also grows in proportion to output $\left(\frac{dl_{ijt}}{dt} = \frac{dy_{ijt}}{dt}\right)$, and the GDP-employment elasticity equals 1 across country-sectors.

3.2. Regression-Based Approach

The regression-based approach estimates the correlation of changes in employment and GDP growth using cross-country time series data for the three aggregate sectors where time series on value added and employment are available: agriculture, manufacturing, and services. The econometric approach estimates the impact of GDP on employment conducting seemingly unrelated regressions, following Kapsos (2005) and using the following equation:

$$\Delta\ln(l_{ijt}) = c + \alpha\Delta\ln(y_{ijt}) + \omega X_{ijt} + \varepsilon_{ijt} \tag{5}$$

where $\Delta\ln(l_{ijt})$ is the first-difference of the logarithm of employment, $\Delta\ln(y_{ijt})$ is the first-difference of the logarithm of value added, and X_{ijt} is a vector of control variables (including export and import shares of GDP, dependency ratio for the population, human capital, population, oil rents as percent of GDP, and the share of respective sectors' value added in levels) in country *i*, sector *j* and year *t*. Equation (5) is estimated using first-differences of variables, which helps avoid estimation bias that could possibly be caused by country fixed effects.[15] Given large differences in income and country characteristics, equation (5) is estimated for all countries and for different income groups based on the World Bank's country income classification. However, it is worth noting that this regression specification has simultaneity as well as omitted variables bias that deter the results from appropriately "isolating" the effect of economic growth from all other employment growth drivers.

Within-sample estimates are produced with data for years 1992-2016, and out-of-sample estimates are produced with data for years 1992-2011 (and later compared to actual employment growth for years 2012-2016).

3.3. Growth Decomposition-Derived Approach

This approach is derived from a decomposition of GDP growth into yearly changes in employment and changes in labor productivity for individual country-sectors, based on the following identity:

$$\mathrm{Y_{ijt}} = \mathrm{L_{ijt}} * \frac{\mathrm{Y_{ijt}}}{\mathrm{L_{ijt}}} \qquad (6)$$

which implies that:

$$\Delta_t lnY_{ijt} = \Delta_t \ln\left(\frac{Y_{ijt}}{L_{ijt}}\right) + \Delta_t lnL_{ijt} \qquad (7)$$

where $\mathrm{Y_{ijt}}$ is value added and $\mathrm{L_{ijt}}$ is employment in country *i*, sector *j*, and year *t*. Following Klenow and Rodriguez (1997), taking conditional expectations on $\Delta_t lnY_{ijt}$ and assuming $\Delta_t \ln\left(\frac{Y_{ijt}}{L_{ijt}}\right)$ and $\Delta_t lnL_{ijt}$ are bivariate normal, it can be shown that

$$E\left[\Delta_t lnL_{ijt} \middle| \Delta_t lnY_{ijt}\right] = E\left[\Delta_t lnL_{ijt}\right] + \varphi\left(\Delta_t lnY_{ijt} - E\left[\Delta_t lnY_{ijt}\right]\right) \qquad (8)$$

$$\text{where } \varphi = \frac{COV\left[\Delta_t lnL_{ijt}, \Delta_t lnY_{ijt}\right]}{V\left(\Delta_t lnY_{ijt}\right)}$$

[15] The seemingly unrelated regression approach implies a gain in efficiency, as the error terms across the three sectors in individual countries are contemporaneously correlated. We also included lags of the variables in the regression. While this increases the R-squared, it reduces the importance of GDP. Since the regression-based effect is already much smaller than the actual, we decided to only make those results available upon request.

This decomposition approach can be applied to a large number of individual countries and sectors to capture country-sector-specific trends.

Similarly, within-sample estimates are produced using data for years 1992-2016, and out-of-sample estimates are produced with data for years 1992-2011 (and later compared to actual employment growth for years 2012-2016).

3.4. Average Annual Elasticities Calculated from Country-Sector Data

For each country *i* and sector *j*, the ratio of the annual percentage change in employment and the annual percentage change in value added is calculated. The estimated GDP-employment elasticities $\left(\varepsilon_{i,j}\right)$ are the average of the ratios across time, after excluding negative values and zeros.

$$\varepsilon_{i,j} = \left(\frac{1}{T}\right) \sum_{t=1}^{T} \left[\frac{\Delta_t L_{i,j,t,t+1}}{L_{i,j,t}}\right] / \left[\frac{\Delta_t Y_{i,j,t,t+1}}{Y_{i,j,t}}\right] \qquad (9)$$

Two versions of these estimates are produced to test if more up-to-date representation of the economic structure and technology embedded in the data increases predictive power. One taking the full time series available (“Simple Full”, using annual data since year 1992) and another taking only recent history into account (“Simple Short”, using annual data since year 2000). This estimation approach can also be easily applied to a large number of individual countries and sectors to capture country-sector-specific trends.

4. Data and Descriptive Statistics

World Bank World Development Indicators (WDI) and International Labor Organization’s (ILO) datasets are used for GDP-employment elasticities analysis using different methods. The data on gross value added for agriculture, manufacturing, and services were obtained from the WDI in 2010 US dollars. The ILO provides data on sectoral employment for the same three sectors. According to the ILO, employment includes all persons of working age who are in the following categories: paid employment (whether at work or with a job but not at work); or self-employment (whether at work or with an enterprise but not at work). The availability of time series data on employment only for agriculture, manufacturing, and services limits the analysis to these three aggregate sectors. Given the mix of data sources, the combined employment data across all sectors from the ILO was compared with the total employment from the WDI.

The latter is computed as a sum of population 15-64 years old and above 65 years old multiplied by the employment-population ratio of 15+ years old. The comparison indicates that some countries have more than a 10 percent deviation in employment data during one or more years over the period of 2000-2016.[16] Countries with more that 10 percent deviations are excluded from the analysis. Country and sector-specific annual GDP-employment elasticities for average elasticities approach are constructed by dividing annual employment growth by GDP growth. Similarly, changes in labor productivity are divided by GDP growth to discount the share of economic growth explained by improvements in labor productivity, following the decomposition approach. Finally, average of annual elasticities over the period 2000-2016 are used as estimates of country and sector GDP-employment elasticities.

To study the relationship between labor productivity and informal employment, sector-specific informal employment shares (in agriculture, manufacturing and services) were computed using harmonized labor force surveys using the World Bank's International Income Distribution Data Set (I2D2).[17] Informal employment is defined for the purposes of this paper as those individuals that declare to be self-employed or are non-paid employees.[18]

Several stylized facts emerge when comparing informal employment across countries, country income groups and sectors; such as prevalence of informality in low-income countries and in the agriculture sector. Figure 1 shows that lower-income countries tend to have higher informal employment than high-income ones; and this pattern is consistent across all aggregate sectors. Low-income countries have sizable employment informality and thus under-utilized labor due to the limited number of formal jobs available in the economy relative to the size of the working-age population. In most cases, informal jobs do not provide sufficient income, benefits, or certainty for workers who are either poor or vulnerable to poverty in the face of economic shocks. In addition, the share of informal employment is the highest in agriculture, reaching on average 70 to 80 percent in low-income and lower-middle-income countries. In low-income countries most of these workers are part of subsistence farmer households that are either poor or vulnerable to poverty. Manufacturing and service sectors have similar patterns across income groups, although service sectors have on average slightly higher informality compared to manufacturing.

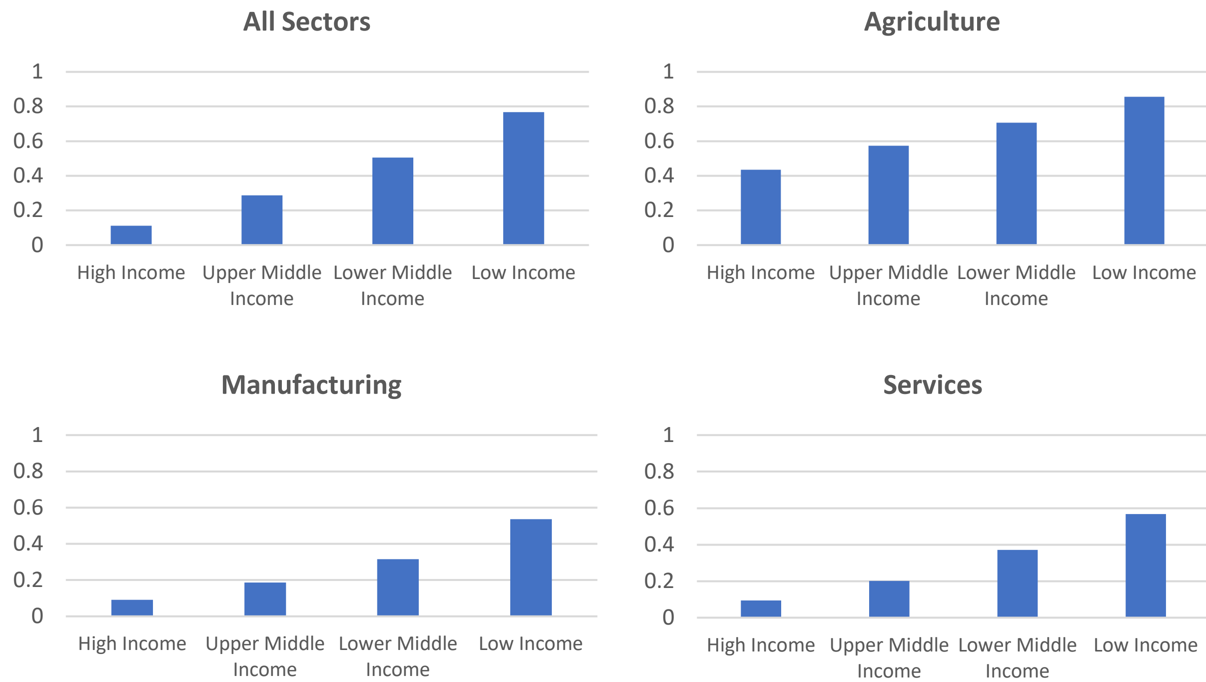
[16]These countries are excluded from the analysis and include Albania, Angola, Bangladesh, Bosnia and Herzegovina, Botswana, Burkina Faso, Cabo Verde, Comoros, Republic of Congo, Djibouti, Dominican Republic, Equatorial Guinea, Fiji, Gabon, Ghana, Guam, Guinea, Iraq, Lesotho, Mali, Mauritania, Moldova, Montenegro, Myanmar, Namibia, New Caledonia, Niger, Oman, Peru, Samoa, Serbia, Sierra Leone, Solomon Islands, Somalia, St. Lucia, Tajikistan, Turkmenistan, Uganda, and Yemen.

[17] The I2D2 a global harmonized labor force survey database that provides comparable indicators on both household and individual levels across countries and over time, from 600 surveys for 120 countries.

[18] While there are alternatives definitions of informal employment in the literature, the ability to measure it varies substantially across countries, depending on quality and availability of related indicators in labor force surveys.

Informal employment in manufacturing changes significantly across income groups, dropping from 77 percent in low-income to 11 percent in high-income countries.[19]

Figure 1. Average Share of Informal Employment by Income Groups and Sectors.



Source: Authors' computations using the I2D2 dataset.

Other indicators from the WDI and Penn World Tables are included as control variables in the econometric analysis. Among these variables are shares of sectoral value added, shares of import and export in GDP, human capital, dependency ratio, population, and real interest rates. The sectoral shares of the value added, import and export shares in GDP, and human capital index are obtained from the Penn World Table database (version 8). The human capital index is based on the average years of schooling from Barro and Lee (2013) and an assumed rate of return to education is based on Mincer equation estimates from Psacharopoulos (1994).[20] Data on dependency ratio, population, and real interest rate are taken from the WDI.

[19] An important caveat worth mentioning is that many self-employed workers in high-income countries are not necessarily informal workers although their labor productivity is low compared to the rest of the workers. Similar patterns emerge in the service sectors.
[20] Human Capital in PWT 9.0: https://www.rug.nl/ggdc/docs/human_capital_in_pwt_90.pdf.

5. Empirical Results

This section describes the empirical results of GDP-employment elasticities estimations across countries and sectors using the alternative methodological approaches described in section 3, as well as the estimated relationship between productivity growth and informality. As described in section 3, GDP-employment elasticities estimates were produced based on data for two different time periods, up to 2016 for within-sample estimations and up to 2011 for out-of-sample estimations. The estimated elasticities were compared for their predictive power on employment levels.[21]

5.1. GDP-Employment Elasticities

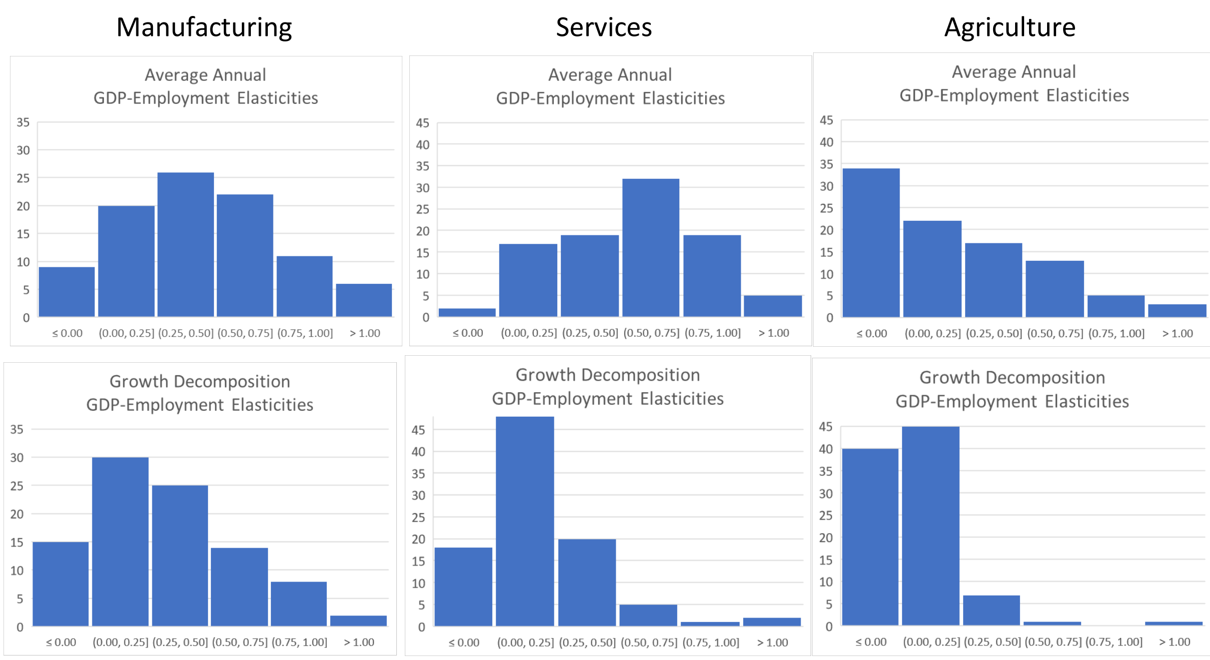
The section analyzes the range of GDP-employment elasticities estimates obtained from the different methodologies discussed in section 3. Figure 2 shows the distribution of elasticities across developing countries using available data up to year 2011 (used for out-of-sample estimations), for manufacturing, services, and agriculture.[22] For manufacturing, the average annual elasticities resemble closely a normal distribution around a median value of 0.40 (see Appendix 4 for GDP-employment elasticities for each country and sector using average annual elasticities approach). The distribution for services is less symmetric, with a median value around 0.55. 84 and 93 percent of countries' average elasticities for manufacturing and services, respectively, range between 0.0 and 1.0; while more than half of countries' average elasticities range between 0.25 and 0.75. On the other hand, growth decomposition-based estimates show a higher share of low elasticity values below 0.25, including more countries with negative values than those observed for average elasticities estimates.[23] Regression-based elasticity estimates for manufacturing and services are more widespread, with a significantly higher share of negative elasticity values around 30 percent. For agriculture, the distribution of estimated average annual elasticities has its mean and median around 0.15, as its highest mass is in negative values (36 percent) followed by low positive elasticity values below 0.25 (23 percent).[24] The decomposition and regression-based estimates are even more concentrated in negative and low-positive values. 75 and 90 percent of countries have regression and decomposition-based elasticity values below 0.25, respectively (with 40% negative values). The negative elasticities observed in the agriculture sector in many developing countries can be attributed to the prevalence of high levels of informality or subsistence farming, where employed individuals exhibit

[21] For a detailed description of data sources and construction of underlying variables, see Appendix 3.
[22] See Appendix 4 for details of the coefficients from the regression-based approach.
[23] For manufacturing 48 percent of countries have growth decomposition-based elasticity values below 0.25 (where 16 percent are negative values), while for services 70 percent of countries have growth decomposition-based elasticity values below 0.25 (where 19 percent are negative values).
[24] The distribution of average annual elasticities for agriculture also exhibits a close-to-symmetrical distribution when increasing the granularity of the histogram bins.

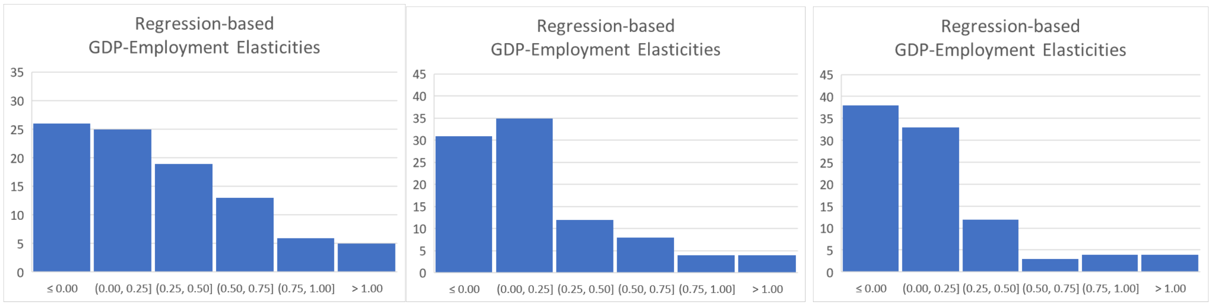
low labor productivity. This suggests that increases in GDP may primarily result in improvements in labor productivity rather than job creation. Furthermore, negative sector elasticities in some countries indicate labor movement from low-productivity to high-productivity sectors.[25]

When comparing these estimates to the full proportionality implication of the SAM-Multiplier-based approach, it is worth noting that less than 6.5 percent of country-sector elasticity estimates have values 1.0 or above for all estimation methods.[26] Moreover, in most of these distributions more than half of GDP-employment elasticity estimates are below 0.50. This is in line with the results from the theoretical model, which suggest that countries characterized by high levels of informality tend to exhibit lower employment elasticities. Furthermore, the elasticity estimates shown in Figure 2 lie in a significantly tighter range than that of other estimates provided in the literature, as by Kapsos (2005), who estimates GDP-employment elasticities ranging from -10.21 to 7.14.

Figure 2. Distribution of Estimated GDP-Employment Elasticities across Countries, by Sector

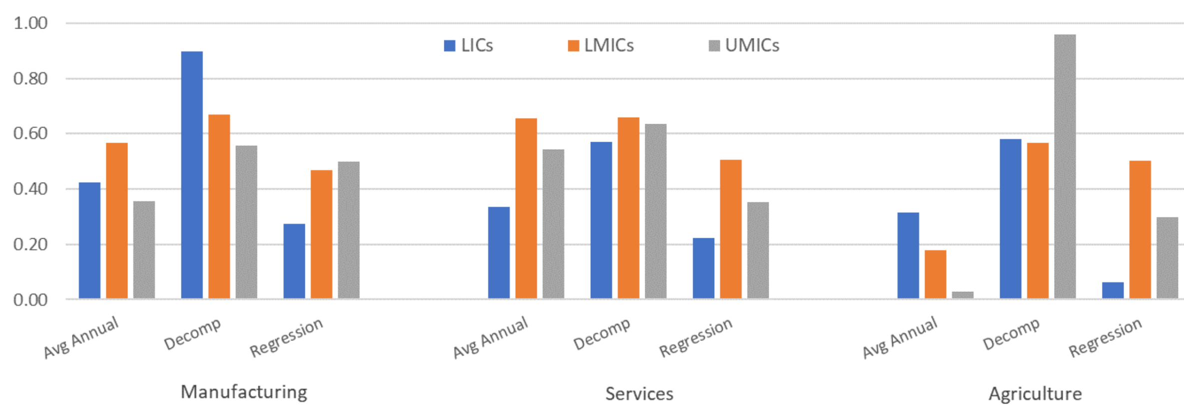


[25] In certain countries, despite the prevalence of informal employment in agriculture, job creation remains positive, potentially driven by a growing labor force that is absorbed by the agriculture sector due to a lack of more productive employment opportunities in other sectors.
[26] There are no estimated elasticities with values exactly equal to 1.0.



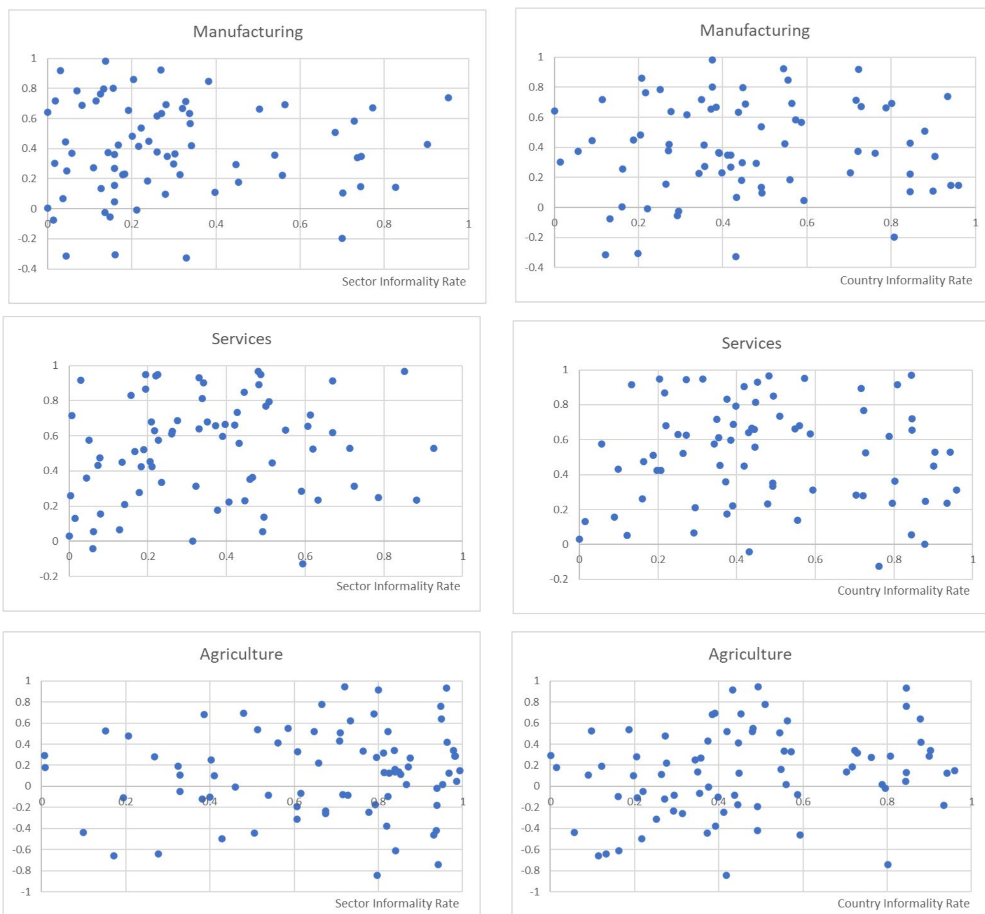
The examination of the magnitudes of the average annual sector elasticities within countries does not show a fully dominant trend in the ordering of sectors (that is, for example, that manufacturing average elasticities are in most cases higher than those for services, which are also in most cases higher than those of agriculture). Two facts are worth highlighting though: while services sectors have the highest average elasticity in 55 percent of developing countries, agriculture has the lowest average elasticity in 66 percent of countries in the sample. In both cases, this is driven by middle-income countries. It is also worth noting that there is no fully consistent trend associating the level of income (or development) with the magnitude of the median elasticity used to characterize country-income groups.

Figure 3. Median GDP-Employment Elasticities by Country Income Groups and Estimation Methodologies for Manufacturing, Services and Agribusiness



The trends of the estimated elasticities and the rate of informality across countries are further explored to investigate if among those countries with informality, the elasticity is correlated with the degree of informality. Figure 4 shows scatterplots between average annual country-sector elasticities and both, sector informality and country informality rates, for manufacturing, services, and agriculture. The empirical relationship between the GDP-employment elasticities and the level of informality is inconclusive, an empirical finding consistent with the analysis done with the theoretical model in section 2. The results remain unchanged when replicating the analysis for estimated elasticities produced by the decomposition-based and regression-based methodologies. Furthermore, the trends and relationships presented in this section remain broadly unchanged when running the analysis with elasticity estimates based on the full sample (up to year 2016).

Figure 4. Average Annual GDP-Employment Elasticities and Informality, by Sector



5.2. Predictive Power of Estimated GDP-Employment Elasticities

To evaluate the predictive power of the four estimation approaches discussed in section 3, this section uses the elasticities estimated using data until year 2011 (described in the previous section), to perform an out-of-sample evaluation of predicted employment growth based on the estimated elasticities and observed GDP growth. These predicted employment growth values are benchmarked against observed employment growth for years 2012-2016. In addition, the predictive power of average annual elasticities estimated from more recent data (years 2000-2011) is also tested. To assess and compare predictive power, Mean Absolute Prediction Percentage Error (MAE) and Root Mean Squared Prediction Percentage Error (RMSE) are computed for each of the country-sector employment predictions generated with the elasticity estimation approaches. Table 1 shows the results of this analysis.

Table 1. GDP-Employment Elasticities Predictive Power
(**bolded numbers** identify the estimation methodology with highest predictive power in each case)

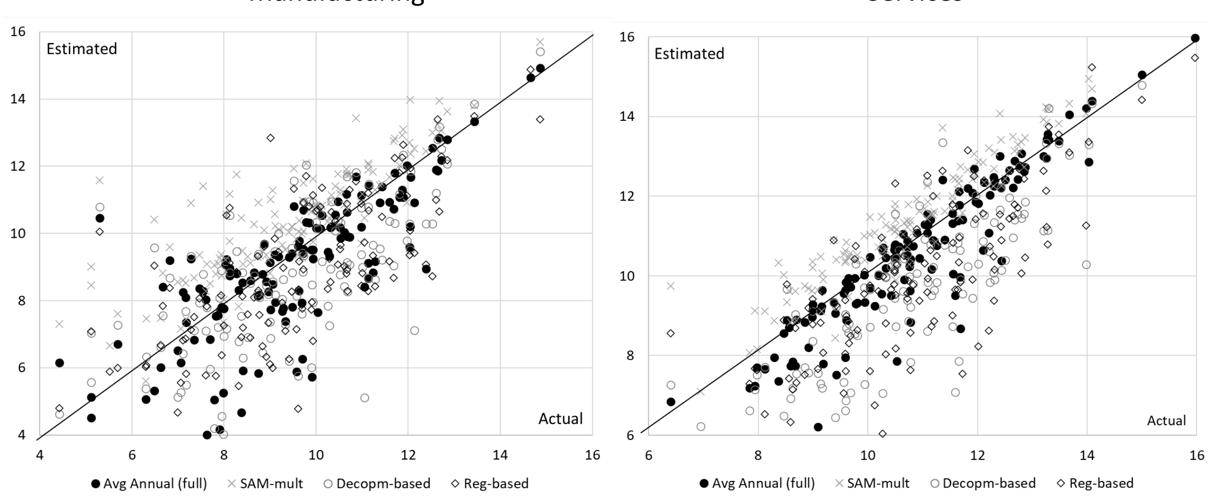
	Average Annual Elasticities		Decomposition based Approach	Regression based Approach	SAM Multiplier Approach ($E_{YL,i,j,t}$ = 1.0)
	Full Sample	Recent Sample			
Manufacturing					
MAE	**2.34**	**2.50**	3.47	2.73	8.64
RMSE	15.39	15.56	21.56	**11.28**	47.96
Services					
MAE	**0.38**	**0.43**	0.83	1.06	1.39
RMSE	**0.54**	**0.58**	1.22	1.54	2.94
Agriculture					
MAE	1.51	1.73	**1.33**	2.50	7.10
RMSE	4.31	4.78	**2.11**	8.23	17.59

The results imply that the average annual elasticity estimates have the highest predictive power, by at least one of the performance measures utilized in the evaluation, for the manufacturing and services sectors. For agriculture, the decomposition-based approach has the highest predictive power, but with MAE and RMSE values closely followed by the average annual elasticity estimates. Therefore, across sectors the average annual elasticity estimates have either the highest or second highest predictive power among the methods tested. It is worth noting that using the full or more recent (short) sample to produce annual average elasticities implies very similar predictive power. Finally, the assumption of fully proportional changes in employment to GDP underlying the SAM multiplier approach has the lowest predictive power for all sectors, with MAE and RMSE values between three and eight times larger than those computed for highest predictive power method in each case.

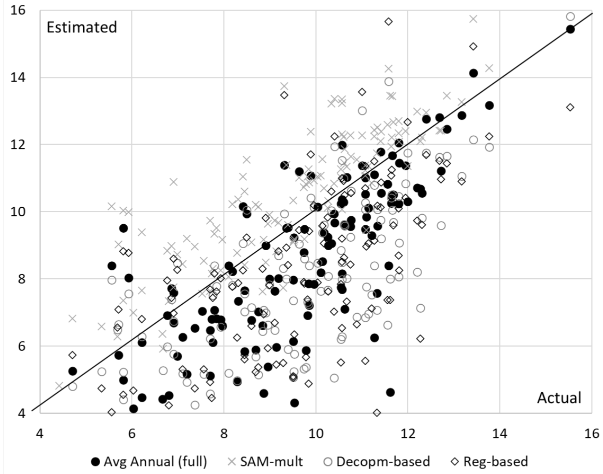
Figure 5 plots the predicted and observed employment for each sector and estimation method across countries (in logs). These results provide additional insights to those summarized in Table 1, showing how average annual elasticity estimates tend to have smaller deviations for most countries compared to other estimation approaches, and in particular for manufacturing and services. These scatterplots also show how the SAM approach significantly over-estimates the effects for most countries, while the regression-based approach mostly under-estimates the effects and exhibits large deviations. The decomposition-based approach also exhibits sizable deviations for many countries, and depending on the sector and the deviations, the summary metric used will perform better or worse, compared to the regression-based approach.

Figure 5. Actual and Predicted (2012-2016) Employment Growth by Sector

Manufacturing Services



Agriculture



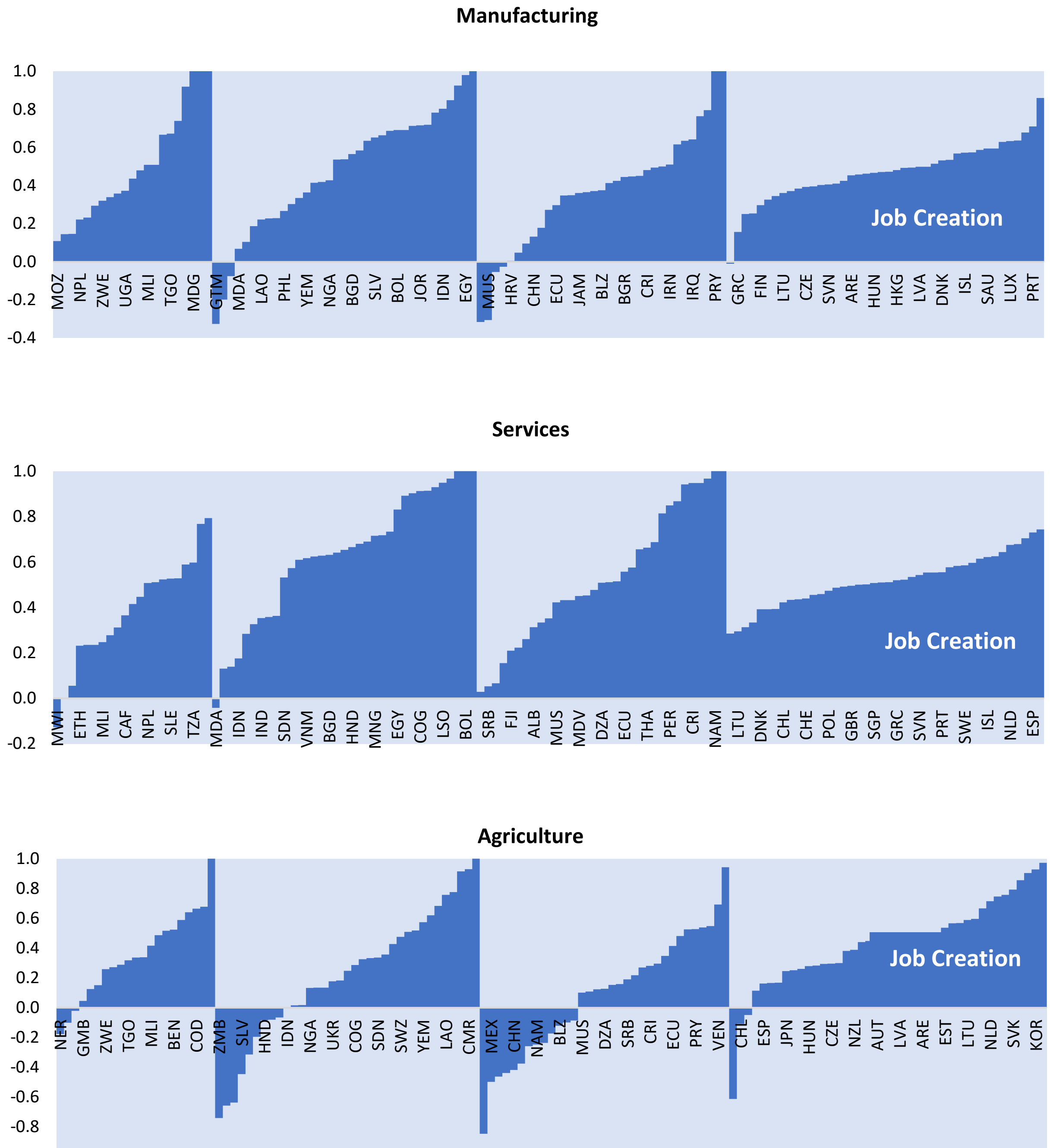
In sum, the empirical results imply that estimating country-sector GDP-Employment elasticities through a direct calculation of annual averages has the highest predictive power among all estimation methods considered and has an underlying close-to-symmetrical cross-country distribution of estimates.

5.3. Labor Productivity and Informality

As discussed in previous sections, GDP growth is not only accompanied by employment growth, but labor productivity improvements that might have welfare implications through increases in labor income driven by reductions in informal employment. In other words, productivity growth may imply higher earnings for those workers previously engaged in informal activities. This section provides empirical evidence supporting this hypothesis.

First, it is worth noting that labor productivity drives a sizable fraction of GDP growth. As shown in Figure 6, when decomposing GDP growth between employment and labor productivity growth, labor productivity improvements are a sizable fraction of observed GDP growth across developing countries. Both manufacturing and service sectors have experienced considerable improvements in labor productivity, though with considerable cross-country variation. In this regard, the data imply large differences in GDP driven employment growth across countries within each income group, in both manufacturing and services, due to differences in economic structure and improvements in labor productivity driven by technology. On the other hand, a few stylized facts emerge when decomposing GDP growth into changes in employment and changes in labor productivity in agriculture sectors. Several high-income, upper-middle and lower-middle-income countries in the sample show a reduction in employment accompanying growth in the agriculture sector. These results are in contrast with manufacturing and services.

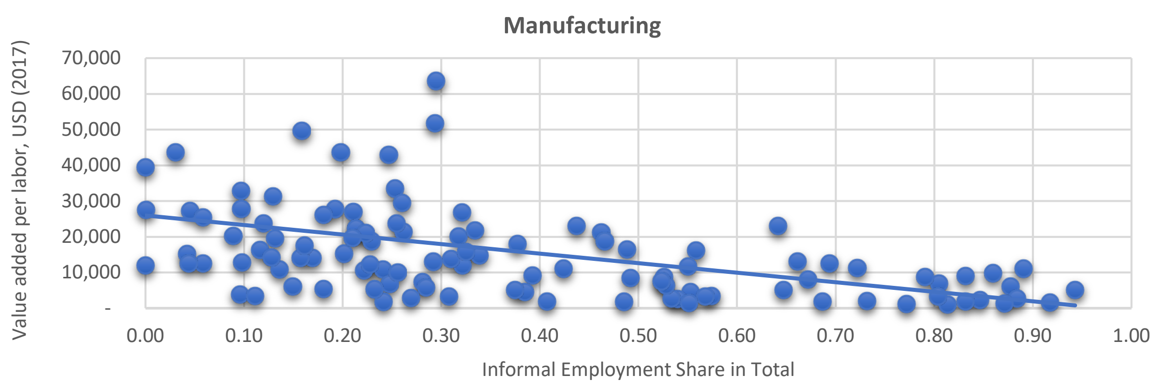
Figure 6. Contribution of Job Creation and Improvements in Labor Productivity to GDP Growth

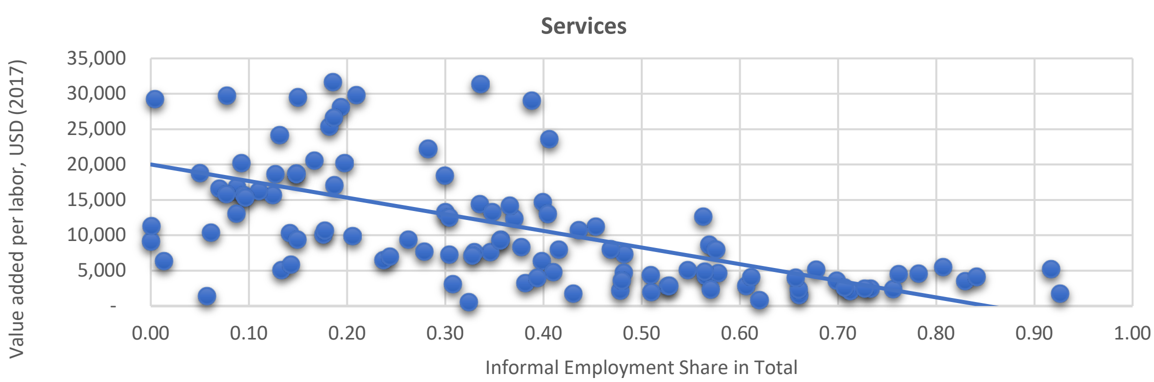


Note: Authors' calculations using the average contributions of the employment and labor productivity to GDP growth (%Y=%L +%(Y/L)) over the period of 2000-2016 based on data from the WDI and ILO.

Second, Figure 7 shows the relationship between informality and value added per worker in the manufacturing and service sectors across countries. These data suggest that countries and sectors with higher labor productivity have less informality in both manufacturing and service sectors.

Figure 7. Informal Employment and Value Added per Labor in Manufacturing and Services





To estimate the relationship between productivity growth and informality, the study follows the specification proposed by Maloney (2001) and runs the following regression model:

$$\frac{L_{jt}^{Inf}}{L_{jt}} = \alpha + \beta * log\frac{Y_{jt}}{L_{jt}} + \gamma * X_{jt} + \mu_j + \lambda_t + \varepsilon_{jt} \quad (14)$$

where L_{jt} is total employment in the economy, L_{jt}^{Inf} is informal employment, Y_{jt} is value added, X_{jt} are control variables in sector *j* and year *t*, and μ_j and λ_t are sector time fixed effects, respectively. For this estimation informal employment includes those who are self-employed and non-paid employees. Capturing non-paid employees is important, especially for low-income countries, as their number can reach more than 60 percent of total employment in countries such as Liberia, as well as in the agriculture sector where labor activities for smallholder farming are spread among household members.[27] Harmonized labor force surveys collected by the World Bank are used to derive a measure of the informal sector for this estimation, substantially expanding the sample size and including countries outside the Latin America and Caribbean region, when compared to other studies. The sample includes 87 countries, where each country has more than one survey (see Appendix 1).[28] Labor productivity is measured as a logarithm of the value added of the sector in constant prices divided by the number of total (formal and informal) workers.

The empirical results in Table 2 are in line with the theoretical model and the stylized facts discussed above, showing that productivity growth is associated with a decrease in informal employment across the three sectors considered (agriculture, manufacturing, and services). These results are consistent with Maloney (2001) and Loayza and Rigolini (2011). Columns (1)-(3) provide estimates for equation (14) without control variables for the three sectors, while columns (4)-(6) show regression results with control variables, such as export and import shares in GDP, human capital, the dependency ratio, the real interest rate, the log of population, and country fixed effects. The regression results indicate that there is a significant negative relationship between labor productivity and share of informal employment across all sectors; and the results hold in both specifications – with and without the use of control variables. This confirms that enhancements in labor productivity are associated with reduced informality and higher

[27] Informal employment using this definition differs from the ILO's reported statistics on informality as the latter includes other types of informal workers, such as paid workers who work for either formal or informal sectors. Country-specific employment informality definitions are based on the data availability about job characteristics, such as having a remuneration, contract, and social security among other benefits. Since the coverage and quality of data vary significantly across countries, this paper uses a definition that can be harmonized across countries. While this definition does not capture the entire informal sector, it allows to measure informality in a comparable way; and improves over previous definitions used by other studies like Maloney (2001) and Loayza et al. (2011) which only include self-employed workers.

[28] It is worth noting that in high-income countries, the self-employed are not necessarily part of the informal economy. Rather, they reflect economic inefficiencies or low productivity of workers that can be improved with more capital and economies of scale, ultimately affecting an overall aggregate productivity at the sector level.

earnings for workers who were previously employed in informal sectors. The estimated coefficients range from (-0.054) to (-0.077). The coefficients are slightly higher for agriculture compared to manufacturing and services in the specifications with control variables, reflecting large inefficiencies in the sector. Finally, these coefficients are lower than those reported by Maloney (2001) and Loayza and Rigolini (2011) for Latin American countries.

Table 2. Regressions results of informality and labor productivity.

	(1) Agriculture	(2) Manufacturing	(3) Services	(4) Agriculture	(5) Manufacturing	(6) Services
Labor Productivity	-0.07*** (0.017)	-0.077*** (0.022)	-0.055*** (0.019)	-0.064*** (0.018)	-0.054** (0.029)	-0.056*** (0.021)
Controls	No	No	No	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	545	543	544	532	530	531
R-squared	0.37	0.34	0.55	0.04	0.104	0.25
# Countries	87	87	87	79	79	79

Note: The first three columns show panel data regression results for each sector. The last three columns include control variables such as export and import as shares of GDP, human capital, the dependency ratio, the real interest rate and the log of population. Standard errors in brackets; * shows significance at 10% level, ** at 5% and *** at 1%.

6. Conclusion

This paper provides a theoretical framework and empirical evidence to understand and estimate the relationship between economic growth and employment growth. The results show that employment growth resulting from economic growth varies substantially across developing countries and across sectors, reflecting considerable differences in production technologies and informality. The paper estimates the GDP-employment elasticities following alternative methodological approaches and shows that elasticities estimated as the average ratio of annual percentage changes in employment and GDP based on historical data have superior performance in terms of predictive power among all the methods evaluated. The estimated elasticities using this approach imply that employment in manufacturing and services grows less than GDP growth in these sectors across developing economies, given consistent complementary growth in labor productivity. Employment growth in agriculture follows similar dynamics. Given the dominance of smallholder farming across many developing economies, large gains in productivity may imply decreasing employment as economic activity in the sector grows, and thus, a higher number of countries have negative GDP-employment elasticities for this sector. In addition, the paper shows that labor productivity growth is associated with declining informality, implying further welfare effects for households through access to better jobs.

The results of this paper have important implications for estimations of job creation and improvements in job quality resulting from policy or investment interventions to grow economic activity in different sectors across developing economies characterized by high informality. Conditional on data availability, further research in this area could explore the variation of GDP-employment elasticities for more disaggregated sectors and different kinds of occupations or worker profiles; as well as by documenting value-added employment elasticities at the firm level, for companies operating in different sectors across developing economies.

References

Acemoglu, D., and Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. American Economic Review, 108 (6): 1488-1542.

Aghion, P., Burgess, R., Redding, S., and Zilibotti, F. (2005). Entry liberalization and inequality in industrial performance. Journal of the European Economic Association, 3(2-3), 291-302.

Ball, L., Leigh, D. and Loungani, P. (2017). Okun's Law: Fit at 50? Journal of Money, Credit and Banking, 49: 1413–1441.

Basnett, Y. and Sen, R. (2013), What do empirical studies say about economic growth and job creation in developing countries? Overseas Development Institute.

Bess, R. and Ambargis, Z. (2011). Input-Output Models for Impact Analysis, BEA working paper.

Caselli, F. (2005). "Accounting for Cross-Country Income Differences," Handbook of Economic Growth,in: Philippe Aghion & Steven Durlauf (ed.), Handbook of Economic Growth, edition 1, volume 1, chapter 9, pages 679-741 Elsevier.

Crivelli, E., Furceri, D., and Toujas-Bernaté, J. (2012). Can policies affect employment intensity of growth?: a cross-country analysis, *IMF Working Paper* WP/12/218, Washington D.C.

De Paula, A., & Scheinkman, J. A. (2011). The informal sector: An equilibrium model and some empirical evidence from Brazil. R eview of Income and Wealth, 57, S8-S26.

Döpke, J. (2001). “The ‘Employment Intensity’ of Growth in Europe.” Kiel Working Paper No. 1021 (Kiel: Kiel Institute for the World Economy).

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. (2015). "The Next Generation of the Penn World Table."American Economic Review, 105(10): 3150-82.

Gasparini, L., & Tornarolli, L. (2009). Labor informality in Latin America and the Caribbean: Patterns and trends from household survey microdata. Revista Desarrollo y Sociedad, (63), 13-80.

Gollin, D. (2008). Nobody's business but my own: Self-employment and small enterprise in economic development. Journal of Monetary Economics, 55(2), 219-233.

Goto, E. & Bürgi, C. (2021). Sectoral Okun's Law and Cross-Country Cyclical Differences. Economic Modelling, 94:91-103.

Inter-American Development Bank. (2017). Better Jobs Index: An employment conditions index for Latin America. Inter-American Development Bank.

Islam, I. and Nazara, S. (2000). Estimating employment elasticity for the Indonesian economy. ILO Technical Note, Jakarta.

Islam, R. (2004). The nexus of economic growth, employment and poverty reduction: an empirical analysis. Recovery and Reconstruction Department, Geneva, ILO.

Kaldor, N. (1966). Causes of the Slow Rate of Growth of the United Kingdom: An Inaugural Lecture. Cambridge University Press: Cambridge, UK.

Kapsos, S. (2005). The employment intensity of growth: trends and macroeconomic determinants, Employment Strategy Paper 2005/12. Geneva: International Labor Office (ILO).

Kapsos S. (2006) The Employment Intensity of Growth: Trends and Macroeconomic Determinants. In: Felipe J., Hasan R. (eds) Labor Markets in Asia. Palgrave Macmillan, London.

Khan, H. A., & Thorbecke, E. (1989). Macroeconomic effects of technology choice: Multiplier and structural path analysis within a SAM framework. Journal of Policy Modeling, 11(1), 131-156. (attached)

Klenow, P. J., & Rodriguez-Clare, A. (1997). The neoclassical revival in growth economics: Has it gone too far?. *NBER macroeconomics annual*, *12*, 73-103.

La Porta, R., & Shleifer, A. (2014). Informality and development. Journal of Economic Perspectives, 28(3), 109-26.

Loayza, N. V. & Rigolini, J. (2011). Informal Employment: Safety Net or Growth Engine?, World Development, Elsevier, vol. 39(9), pages 1503-1515.

Loewenstein, W. and D. Bender. (2017). Labour Market Failure, Capital Accumulation, Growth and Poverty Dynamics in Partially Formalised Economies: Why Developing Countries' Growth Patterns are Different.

Lucas Jr, R. E. (1978). On the size distribution of business firms. The Bell Journal of Economics, 508-523.

Maloney, W. (2001). Self-employment and labor turnover in developing countries: Cross-country evidence in S. Devarajan, F. Halsey Rogers, L. Squire (Eds.), World Bank economists' forum, The World Bank, Washington, DC.

Modinat O. Olusoji, (2016). A cross causal analysis of employment and economic growth in Nigeria, The Indian Journal of Labour Economics, 59, 4, (553)

Okun, A. M. (1962). Potential GNP: Its Measurement and Significance. Reprinted as Cowles Foundation Paper 190.

Parikh, A. (1978). "Differences in Growth Rates and Kaldor's Laws" Economica, Vol. 45, No. 177, pp. 83-91.

Pattanaik, F., & Nayak, N. C. (2014). Macroeconomic Determinants of Employment Intensity of Growth in India. Margin: The Journal of Applied Economic Research, 8(2), 137-154.

Rowthorn, R. E. (1975a). What Remains of Kaldor's Law? The Economic Journal, Vol. 85, No. 337, pp. 10-19.

Rowthorn, R. E. (1975b). A Reply to Lord Kaldor's Comment. The Economic Journal, Vol. 85, No. 340, pp. 897-901.

Saget, C. (2000). Can the Level of Employment be Explained by GDP Growth in Transition Countries? (Theory versus the Quality of Data). LABOUR, 14: 623-643.

Şahin, A., Tansel, A., & Berument, M. H. (2015). Output–Employment Relationship across Sectors: A Long-Versus Short-Run Perspective. Bulletin of Economic Research, 67(3), 265-288.

Sharma, S. (2009). Entry Regulation, Labor Laws and Informality. Working paper, Enterprise Analysis Unit, World Bank, Washington, DC.

Solow, R. M. (1956). A contribution to the theory of economic growth. The quarterly journal of economics, 70(1), 65-94.

World Bank (2010). Job Generation and Growth Decomposition Tool. Reference Manual a User's Guide.

Appendix 1: Country List and Coverage in I2D2 Dataset

Country	First	Last	Total	Country	First	Last	Total
Afghanistan	2003	2007	2	Lebanon	2011	2011	1
Albania	2004	2005	2	Lesotho	2002	2010	2
Angola	1999	2008	2	Liberia	2007	2007	1
Argentina	1974	2012	22	Lithuania	2005	2008	4
Austria	2004	2008	5	Luxembourg	2004	2008	5
Azerbaijan	1995	2002	2	Madagascar	1993	2010	5
Bangladesh	1999	2010	5	Malawi	1997	2010	3
Barbados	1996	1996	1	Maldives	1998	2004	2
Belgium	2004	2008	5	Mali	1994	2003	2
Belize	1993	1999	6	Malta	2009	2010	2
Bhutan	2003	2007	2	Mauritania	2000	2008	3
Bolivia	1992	2012	14	Mauritius	1999	2012	13
Bosnia and Herzegovina	2001	2004	2	Mexico	1989	2012	13
Botswana	2009	2009	1	Mongolia	2002	2011	6
Brazil	1981	2012	28	Montenegro	2002	2004	2
Bulgaria	2001	2008	4	Morocco	1991	1998	2
Burkina Faso	1994	2009	5	Mozambique	1996	2008	3
Burundi	1998	1998	1	Myanmar	2005	2010	2
Cabo Verde	2000	2007	2	Namibia	1993	1993	1
Cambodia	1997	2012	6	Nepal	1995	2008	4
Cameroon	2001	2007	2	Netherlands	2005	2009	5
Canada	1981	2001	3	Nicaragua	1993	2009	5
Chad	2003	2003	1	Niger	2002	2011	4
Chile	1987	2011	11	Nigeria	1993	2012	4
China	2002	2002	1	Norway	2004	2008	5
Colombia	1996	2012	14	Pakistan	1992	2010	9
Comoros	2004	2004	1	Panama	1989	2012	19
Congo, Rep.	2005	2005	1	Papua New Guinea	2009	2009	1

Congo, Dem. Rep.	2004	2005	2	Paraguay	1990	2012	15
Costa Rica	1989	2009	21	Peru	1997	2012	16
Côte d'Ivoire	2002	2008	2	Philippines	1997	2011	12
Croatia	2004	2004	1	Poland	2005	2008	4
Cyprus	2005	2008	4	Portugal	2004	2008	5
Czechia	2005	2008	4	Puerto Rico	1970	2005	5
Denmark	2004	2008	5	Republic of Moldova	1998	2005	3
Djibouti	1996	1996	1	Romania	1994	2010	7
Dominican Republic	1996	2012	15	Russian Federation	2004	2009	6
Timor-Leste	2001	2010	3	Rwanda	2000	2010	3
Ecuador	1994	2012	15	São Tomé and Príncipe	2000	2010	2
Egypt, Arab Rep.	1988	2006	4	Senegal	1995	2011	4
El Salvador	1991	2009	15	Serbia	2008	2010	2
Estonia	2004	2008	5	Sierra Leone	2003	2011	2
Ethiopia	1995	2012	10	Slovak Republic	2005	2008	4
Fiji	1996	2008	2	Slovenia	2005	2008	4
Finland	2004	2008	5	Solomon Islands	1999	2005	2
France	2004	2008	5	Spain	2004	2008	5
Gabon	2005	2005	1	Sri Lanka	1993	2009	14
Gambia, The	1998	1998	1	Suriname	1999	1999	1
Georgia	1998	1998	1	Eswatini	1995	2000	2
Germany	2005	2008	4	Sweden	2004	2009	6
Ghana	1991	2012	4	Syrian Arab Republic	1997	2003	2
Greece	2004	2008	5	Tajikistan	1999	2003	2
Guatemala	2000	2011	6	Tanzania	2000	2011	5
Guinea	1994	2002	2	North Macedonia	2003	2005	3
Guinea-Bissau	1993	1993	1	Thailand	1981	2010	17
Guyana	1992	1999	2	Togo	2006	2011	2

Haiti	2001	2012	2	Trinidad and Tobago	1996	1996	1
Honduras	1991	2011	20	Tunisia	1997	2010	5
Hungary	2004	2008	5	Türkiye	2000	2010	11
Iceland	2004	2008	5	Turkmenistan	1998	1998	1
India	1983	2011	7	Uganda	2002	2010	3
Indonesia	1990	2010	20	Ukraine	2002	2005	3
Iraq	2006	2006	1	United Kingdom	2005	2008	4
Ireland	2004	2008	5	United States	1960	2010	7
Italy	2004	2008	5	Uruguay	1989	2012	18
Jamaica	1990	2002	5	Vanuatu	2010	2010	1
Jordan	2000	2010	8	Venezuela, RB	1989	2006	12
Kenya	1997	2005	2	Viet Nam	1992	2010	9
Kosovo	2000	2000	1	West Bank	1998	2008	11
Kyrgyzstan	1997	1997	1	Yemen, Rep.	1998	1998	1
Lao PDR	2002	2008	2	Zambia	1998	2010	3
Latvia	2004	2008	5				

Appendix 2. Model derivations

If agents become self-employed in the informal sector, the production function (1) still holds, but L_{it} becomes 1 and output equals productivity A_{it}. If an agent decides to start a formal sector business, (s)he will employ other agents as paid workers. Formal firms pay wages to employees equal to marginal product. Under the presence of formal labor taxes and/or contributions, the *"formal wage"* is assumed to be higher than the reservation wage $\overline{w_{jt}}$ of worker j (which is equal to self-employment income):[29]

$$\frac{dY_{it}}{dL_{it}} = \alpha \frac{Y_{it}}{L_{it}} = w_{it} = \overline{w_{jt}} + \tau_{jt} \qquad (A.1)$$

where $\tau_{jt} > 0$ reflects mandatory taxes and/or contributions for formal employment. This implies that low productivity workers will only opt to become self-employed if they cannot get a job in the formal sector, given that $w_{it} \geq A_L = \overline{w_{Lt}}$.[30]

Entrepreneurs owning a formal business will earn the following profit:

$$\pi_{it} = (Y_{it} - L_{it} w_{it}) * (1 - t) \qquad (A.2)$$

Formal business profit π_{it} is equal to the difference between output and wage payments, net of profit taxes t, which formal firms have to pay.

Formal business profits must be larger than entrepreneurs' reservation wages. Since paid workers' wages must be at least as high as a reservation wage of low ability agents ($w_{it} \geq A_L$), low ability agents will never choose to become entrepreneurs:

$$\pi_{Lt} = (A_L L_{Lt}^{\alpha} - L_{Lt} w_{Lt}) * (1 - t) \leq A_L * (1 - t) * (L_{Lt}^{\alpha} - L_{Lt}) < 0 \qquad (A.3)$$

As a result, even if a formal wage equals a reservation wage for low ability agents ($\tau_{jt} = 0$), low ability agents cannot become profitable entrepreneurs if the optimal $L_{Lt} > 1$. If the optimal $L_{Lt} = 1$, profit is weakly less than zero and thus agents will prefer to become self-employed when $\tau_{jt} > 0$ and earn a total revenue of A_{Lt}. In order to have entrepreneurs and formal sector firms in an economy, it is necessary that profits are equal or higher than the reservation wage of high productivity agents: $A_{Ht} \leq \pi_{Ht}$, which implies that the reservation wage of all high ability agents N_{Ht} is always greater than the formal wage:

$$\pi_{Ht} = (A_{Ht} L_{Ht}^{\alpha} - L_{Ht} w_{Ht}) * (1 - t) \leq A_{Ht} * (1 - t) * (L_{Ht}^{\alpha} - L_{Ht}) < 0 \qquad (A.4)$$

[29] In the absence of formal labor taxes and/or contributions, it can be assumed that formal wages are at least as high as the worker's reservation wage.
[30] In other words, the net income received by paid workers is the difference between the formal wage and τ_{jt}.

One factor ignored thus far is unemployment, which is prevalent in many developing economies with high informality. To model unemployment, it is assumed that low ability workers become unemployed when they switch firms or turn to self-employment, and that these transitions are not instantaneous.[31] Unemployed create an additional pool of potential workers in the economy who represent a fraction (ψ) of low productivity agents N_{Lt}.

Agents maximize their payoff by choosing between becoming an entrepreneur (earning π_{it}), a wage worker (earning w_{it}) or self-employed (earning A_{it}). Low ability agents never choose to become entrepreneurs as their profits are less than 0 and thus only decide between becoming a formal paid worker or being self-employed. Based on the assumption that a formal wage is at least as high as a reservation wage ($w_{it} \geq A_{Lt}$), low productivity agents are either indifferent, or strictly prefer becoming formal paid workers to being self-employed. Similarly, high ability agents never choose to become workers as it would require that $w_{Ht} \geq A_{Ht}$, which in turn implies negative profits for formal firms. Therefore, high productivity agents either become entrepreneurs or are indifferent between self-employment and entrepreneurship.

In the first scenario, all firms have the same productivity and employ the same number of workers:

$$L_{H,L,t} = \frac{N_{Lt}(1-\psi)}{N_{Ht}} \tag{A.5}$$

This immediately determines total output, formal wages, and (formal business) profits. To ensure that all conditions for this scenario are satisfied, the wage condition ($w_{Ht} \geq A_L$) for low productivity agents and the profit condition ($A_{Ht} \leq \pi_{Ht}$) for high productivity agents must hold. Unemployment in this case is given by ψN_{Lt}. Output, formal wages, and (formal business) profits in scenario 1 are the following:

$$Y_{Ht} = A_{Ht}\left(\frac{N_{Lt}(1-\psi)}{N_{Ht}}\right)^{\alpha} \tag{A.6}$$

$$w_{Ht} = \alpha A_{Ht}\left(\frac{N_{Lt}(1-\psi)}{N_{Ht}}\right)^{\alpha-1} \tag{A.7}$$

$$\pi_{Ht} = (1-\alpha)\left(A_{Ht}\left(\frac{N_{Lt}(1-\psi)}{N_{Ht}}\right)^{\alpha}\right)(1-t) \tag{A.8}$$

[31] The assumption that only low ability workers become unemployed is irrelevant for scenarios one and three below, and only matters for scenario two.

In the second scenario, there are too many high productivity agents. As high ability entrepreneurs compete for a relatively smaller number of low ability agents, the equilibrium wage increases and profits decrease. If $A_{Ht} > \pi_{Ht}$, high ability agents that become entrepreneurs have less income than self-employed high ability agents. As a result, some high productivity workers become self-employed until an equilibrium is reached with $A_{Ht} = \pi_{Ht}$.[32] All low productivity agents are (formal) paid workers in this scenario. Combining equations with the restriction on profits leads to a unique equilibrium. Unemployment in this case is given by ψN_{Lt} as in scenario 1. Formal employment, firms' output, and formal wages in scenario 2 are the following:

$$L_{H,L,t} = \left(\frac{1}{(1-t)(1-\alpha)}\right)^{\frac{1}{\alpha}} \tag{A.9}$$

$$Y_{Ht} = A_{Ht}\frac{1}{(1-t)(1-\alpha)} \tag{A.10}$$

$$w_{Ht} = \alpha A_{Ht}\left(\frac{1}{(1-t)(1-\alpha)}\right)^{\frac{\alpha-1}{\alpha}} \tag{A.11}$$

The third scenario assumes that there are many low productivity agents. In this scenario high productivity agents become entrepreneurs and hire an optimal number of (low productivity) formal paid workers at wage $w_{Ht} = \overline{w_{Lt}} + \tau_{Lt} = A_{Lt} + \tau_{Lt}$. The number of paid workers in the economy is lower than the total number of low productivity agents available, with the remaining low productivity agents becoming self-employed. Combining the formal wage condition leads to the unique equilibrium. Unemployment in this case is given by ψN_{Lt} as in the first two cases. This scenario characterizes better developing economies, as it has an informal sector and a disproportionately large number of low productivity agents. Formal employment, firms' output, and profits in scenario 3 are the following:

$$L_{H,L,t} = \left(\frac{A_{Ht}\alpha}{A_L + \tau_{Lt}}\right)^{\frac{1}{1-\alpha}} \tag{A.12}$$

$$Y_{Ht} = A_{Ht}\left(\frac{A_{Ht}\alpha}{A_L + \tau_{Lt}}\right)^{\frac{\alpha}{1-\alpha}} \tag{A.13}$$

[32] $A_{Ht} = \pi_{Ht}$ is also possible when all high ability workers are entrepreneurs, but that will fall under the first scenario.

$$\pi_{Ht} = \left(A_{Ht} \left(\frac{A_{Ht}\alpha}{A_L + \tau_{Lt}} \right)^{\frac{\alpha}{1-\alpha}} - (A_L + \tau_{Lt}) \left(\frac{A_{Ht}\alpha}{A_L + \tau_{Lt}} \right)^{\frac{1}{1-\alpha}} \right)(1-t) \qquad (A.14)$$

Derivation of the second scenario:

$$\pi_{Ht} = A_{Ht} = (A_{Ht}L_{Ht}^{\alpha} - \alpha A_{Ht}L_{Ht}^{\alpha})(1-t)$$

$$1 = (L_{Ht}^{\alpha} - \alpha L_{Ht}^{\alpha})(1-t)$$

$$\frac{1}{(1-t)(1-\alpha)} = (L_{Ht}^{\alpha})$$

$$\left(\frac{1}{(1-t)(1-\alpha)} \right)^{\frac{1}{\alpha}} = L_{Ht}$$

Derivation of the third scenario:

$$w_{Ht} = A_{Lt} + \tau_{Lt} = \alpha A_{Ht} L_{Ht}^{\alpha-1}$$

$$\frac{A_{Lt} + \tau_{Lt}}{\alpha A_{Ht}} = L_{Ht}^{\alpha-1}$$

$$\left(\frac{A_{Lt} + \tau_{Lt}}{\alpha A_{Ht}} \right)^{\frac{1}{\alpha-1}} = L_{Ht}$$

$$L_{Ht} = \left(\frac{A_{Ht}\alpha}{A_L + \tau_{Lt}} \right)^{\frac{1}{1-\alpha}}$$

$$\pi_{Ht} = (A_{Ht}L_{Ht}^{\alpha} - (A_{Lt} + \tau_{Lt})L_{Ht})(1-t)$$

$$\pi_{Ht} = \left(A_{Ht} \left(\frac{A_{Ht}\alpha}{A_L + \tau_{Lt}} \right)^{\frac{\alpha}{1-\alpha}} - (A_L + \tau_{Lt}) \left(\frac{A_{Ht}\alpha}{A_L + \tau_{Lt}} \right)^{\frac{1}{1-\alpha}} \right)(1-t)$$

This model can also help explain differences in GDP-employment elasticities across countries with and without informal employment – or in economies with higher or lower informality. In countries with no (or rather very low) informality, the impact of GDP growth on employment depends mainly on the value of

ψ. If ψ is constant, employment remains stable in response to increases in GDP. If, instead, ψ depends on A_{Ht}, then the question arises, by how much ψ decreases in response to an increase in A_{Ht}. As A_{Ht} increases, wages do not decline as firms want to hire more workers from a limited pool. The log derivative of formal wages with respect to lnA_{Ht} is the following:

$$\frac{dlnw_{Ht}}{dlnA_{Ht}} = 1 + (1-\alpha)\frac{1}{1-\psi}\frac{d\psi}{dlnA_{Ht}} \geq 0 \qquad (A.15)$$

The expression must be positive for the wage not to decrease even though the second term is negative. The log derivative of output with respect to lnA_{Ht} is shown below:

$$\frac{dlnY_{Ht}}{dlnA_{Ht}} = 1 - \alpha\frac{1}{1-\psi}\frac{d\psi}{dlnA_{Ht}} \geq 0 \qquad (A.16)$$

GDP increases more than formal wages because the log derivative of ψ with respect to A_{Ht} is negative. Furthermore, the log derivative of the number of workers with respect to lnA_{Ht} is the following:

$$\frac{dlnL_{Ht}}{dlnA_{Ht}} = -\frac{1}{1-\psi}\frac{d\psi}{dlnA_{Ht}} \quad > 0 \qquad (A.17)$$

Thus, formal employment increases as productivity increases.

$$\varepsilon_{w_h,A_h} = \frac{dlnw_{Ht}}{dlnA_{Ht}} = \frac{dlnY_{Ht}}{dlnA_{Ht}} - \frac{dlnL_{Ht}}{dlnA_{Ht}} = \varepsilon_{Y,A_h} - \varepsilon_{L,A_h} \geq 0 \qquad (A.18)$$

This implies that if an increase in productivity leads to employment growing faster than GDP ($\frac{dlnL_{Ht}}{dlnA_{Ht}} > \frac{dlnY_{Ht}}{dlnA_{Ht}}$), formal wages decline. Wage elasticity with respect to productivity $\varepsilon_{w_{h,}A_h}$ is equal to output elasticity ε_{Y,A_h} minus employment elasticity ε_{L,A_h}. Therefore, a shock that increases productivity should lead to higher output growth than employment growth, for formal wages to increase with productivity.

Appendix 3. Out-of-sample decomposition

The first approach to estimate the relationship between GDP and employment follows a conventional econometric estimation using seemingly unrelated regressions, which is estimated for three sectors (agriculture, manufacturing, and services) using the first difference of all variables. The regressions are run using data for all countries as well as separately for country groups based on the World Bank country income classification.[33] To check the robustness of the estimations, the regressions include several control variables: export and import share in GDP, dependency ratio for the population, human capital, share of respective sectors' value added, oil rents as percent of GDP, and log of population. Control variables are measured at the country-level and are sector neutral, except for sectors' share in value added. Export and import shares in GDP capture overall levels of country competitiveness, the openness of the economy, and the dependency on imports reflecting lack of country's productive capacity. The dependency ratio and the log of population capture some labor supply characteristics as well as labor supply-demand gaps. For instance, low-income countries with sizable informality and highly under-utilized labor also exhibit high population growth rates. Human capital captures labor supply basic skills to meet labor demand needs.

The results from the regression-based approach shown in Table 1 indicate that GDP-employment elasticities vary substantially across country income groups, taking values below one. The estimation results yield insignificant coefficients for agriculture in all cases. That is, employment in agriculture is unresponsive to fluctuations in value added. These findings are consistent with previous studies, such as Basnett and Sen (2013), who claim that agriculture absorbs labor surplus at the expense of reducing labor productivity. Hence, agriculture GDP growth primarily results in labor productivity improvements rather than job creation; that is higher income for farmer households.

The results show positive and significant elasticities in manufacturing, ranging from 0.227 to 0.399, when estimated in regressions with control variables for all countries and individual country-income groups, except for low-income countries where the coefficients are not significant. GDP-employment elasticities in the service sectors are also positive and significant and range from 0.056 for low-income countries to 0.188 for high-income countries, in regressions including control variables.

[33] For detailed information on the World Bank Country Income groups, see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

The low value of elasticities in manufacturing and services – as well as insignificant coefficients in low-income countries and lower values for low and middle-income countries – are in line with the theoretical model discussed in section 2, which implies limited job creation with GDP growth in countries with large informal sectors.[34] This can be explained by the existence of large informal employment in manufacturing and service sectors in low-income countries (see Appendix 3), which results in lower (total) employment compared to high-income countries as new jobs are taken up not only by unemployed but also by those who reallocate from the informal sector (and thus do not count as additional total employment).

Table A3.1. Regression Results for GDP-Employment Elasticities.

	(1) Agriculture	(2) Manufacturing	(3) Services	(4) Agriculture	(5) Manufacturing	(6) Services
All Countries	.008 (.021)	.198*** (.016)	.186*** (.012)	-.008 (.024)	.232*** (.019)	.125*** (.014)
Low Income Countries	.008 (.012)	.006 (.037)	.108*** (.025)	-.003 (.012)	.025 (.047)	.057** (.029)
Lower Middle-Income Countries	-.006 (.025)	.129*** (.032)	.119*** (.025)	-.017 (.028)	.227*** (.038)	.077*** (.029)
Upper Middle-Income Countries	-.089 (.058)	.247*** (.028)	.145*** (.024)	-.125 (.085)	.270*** (.040)	.172*** (.031)
High Income Countries	.041 (.036)	.363*** (.025)	.34*** (.023)	.034 (.038)	.405*** (.029)	.186*** (.024)

This table shows the results of a seemingly unrelated regression (SUR) for all countries in the sample as well as for country income groups, where equations for aggregate sectors are estimated jointly to gain efficiency. Each cell in columns (1)-(3) shows the result of regression of the first difference of logarithm of employment on the first difference of logarithm of real value added in each of the three sectors. Columns (4)-(6) show the results of similar regressions that include additional control variables (export and import share in GDP, dependency ratio, human capital, share of sector in GDP, oil rents as percent of GDP, and log of population). Standard errors are in parenthesis indicating significance at (*) 10%, (**) 5%, and (***) 1%.

[34] Notably, an extreme case is agriculture, a sector characterized by very high rates of informality across countries, which are larger than the informality rates in manufacturing. See The World Bank Group. 2020. The World Development Report. Trading for Development.

Appendix 4. GDP-employment elasticities across countries and sectors

Country Code	Country	Manufacturing	Services	Agriculture
BDI	Burundi	0.233	0.794	-0.102
BEN	Benin	0.300	0.749	0.533
BFA	Burkina Faso	0.145	0.312	0.151
CAF	Central African Republic	0.679	0.237	0.230
COD	Congo, Dem. Rep.	0.423	0.337	1.000
ETH	Ethiopia	0.295	0.232	0.517
GMB	Gambia, The	2.018	0.056	0.045
LBR	Liberia	0.147	0.529	0.125
MDG	Madagascar	1.060	0.001	0.641
MLI	Mali	0.509	0.248	0.417
MOZ	Mozambique	0.109	0.448	0.289
MWI	Malawi	0.359	-0.127	0.272
NER	Niger	0.740	0.236	-0.178
NPL	Nepal	0.742	0.370	0.314
RWA	Rwanda	0.920	0.769	0.337
SEN	Senegal	1.082	0.236	-0.021
SLE	Sierra Leone	0.339	0.528	0.338
TGO	Togo	0.673	0.524	0.318
TZA	Tanzania	0.668	0.598	0.679
UGA	Uganda	0.372	0.278	1.650
ZWE	Zimbabwe	0.160	0.518	-0.065
ARM	Armenia	0.315	0.275	0.016
BGD	Bangladesh	0.567	0.632	-0.081
BOL	Bolivia	0.692	1.146	0.621
CMR	Cameroon	0.104	0.719	0.930
COG	Congo, Rep.	-0.198	0.914	0.287
EGY	Egypt, Arab Rep.	0.980	0.832	0.429
GTM	Guatemala	-0.326	0.642	1.243
HND	Honduras	0.635	0.667	-0.084
IDN	Indonesia	0.804	0.176	-0.004
IND	India	0.538	0.353	-0.195
JOR	Jordan	0.717	1.039	-0.658
KEN	Kenya	0.714	0.893	0.183
KGZ	Kyrgyzstan	-0.075	0.915	-0.638
KHM	Cambodia	0.925	1.386	0.510
LAO	Lao PDR	0.222	0.655	0.758
LKA	Sri Lanka	0.416	0.610	-0.066
LSO	Lesotho	0.584	0.950	0.327
MAR	Morocco	0.187	0.681	0.016
MDA	Moldova	0.069	-0.042	0.915

MMR	Myanmar	0.229	0.285	0.135
MNG	Mongolia	0.719	0.717	0.135
MRT	Mauritania	0.849	0.139	0.333
NGA	Nigeria	0.429	0.968	0.134
NIC	Nicaragua	1.181	0.734	0.777
PAK	Pakistan	0.687	0.931	0.685
PHL	Philippines	0.268	0.904	0.518
SDN	Sudan	0.171	0.525	0.315
SLV	El Salvador	0.653	0.359	-0.446
SWZ	Eswatini	0.419	0.625	0.476
TJK	Tajikistan	0.229	0.574	0.249
TUN	Tunisia	0.783	0.628	-0.314
UKR	Ukraine	0.303	0.131	0.177
VNM	Viet Nam	0.665	0.617	0.017
YEM	Yemen, Rep.	0.996	0.688	-0.603
ZMB	Zambia	0.692	0.364	-0.741
ALB	Albania	0.048	0.313	-0.463
ARG	Argentina	0.451	0.512	0.539
BGR	Bulgaria	0.445	0.155	0.108
BLZ	Belize	0.376	0.942	-0.122
BRA	Brazil	0.636	1.204	0.218
BWA	Botswana	-0.053	0.067	-0.236
CHN	China	0.133	0.334	-0.418
COL	Colombia	1.082	0.968	0.549
CRI	Costa Rica	0.482	0.948	0.281
DOM	Dominican Republic	0.179	0.657	-0.173
DZA	Algeria	0.851	0.883	-0.353
ECU	Ecuador	0.298	0.558	0.414
FJI	Fiji	-0.026	0.210	-0.086
GAB	Gabon	0.797	0.814	0.124
HRV	Croatia	0.005	0.261	-0.099
IRN	Iran, Islamic Rep.	0.164	0.778	0.221
IRQ	Iraq	0.643	0.029	0.295
JAM	Jamaica	0.362	0.688	-0.375
KAZ	Kazakhstan	0.368	0.105	0.243
MDV	Maldives	0.349	0.451	-0.847
MEX	Mexico	0.765	0.868	-0.498
MUS	Mauritius	-0.305	0.423	0.101
MYS	Malaysia	0.067	0.603	-0.043
NAM	Namibia	0.350	1.045	-0.247
PAN	Panama	0.617	0.949	-0.259
PER	Peru	0.096	0.850	0.944
PRY	Paraguay	1.003	0.432	0.528

RUS	Russian Federation	0.372	0.576	-0.439
SRB	Serbia	-0.315	0.053	0.190
THA	Thailand	0.426	0.663	0.158
TUR	Türkiye	0.274	0.454	0.270
VEN	Venezuela, RB	0.365	0.223	0.693
ZAF	South Africa	-0.098	0.743	-0.192
ARE	United Arab Emirates	0.455	0.744	0.487
AUS	Australia	0.535	0.577	0.294
AUT	Austria	0.459	0.512	0.454
BEL	Belgium	0.385	0.583	0.487
BRB	Barbados	0.630	0.555	0.487
CHE	Switzerland	0.464	0.439	0.457
CHL	Chile	0.860	0.423	-0.109
CYP	Cyprus	0.327	0.488	0.667
CZE	Czechia	0.393	0.313	0.296
DEU	Germany	0.472	0.534	0.284
DNK	Denmark	0.533	0.393	0.301
ESP	Spain	0.679	0.731	0.163
EST	Estonia	0.568	0.286	0.537
FIN	Finland	0.298	0.523	0.598
FRA	France	0.404	0.434	0.455
GBR	United Kingdom of Great Britain and Northern Ireland (the)	0.637	0.496	0.166
GRC	Greece	0.158	0.520	0.115
HKG	Hong Kong SAR, China	0.482	0.394	0.487
HUN	Hungary	0.467	0.393	0.280
IRL	Ireland	0.596	0.627	0.260
ISL	Iceland	0.573	0.623	0.487
ISR	Israel	0.495	0.706	0.382
ITA	Italy	0.426	0.554	0.758
JPN	Japan	0.574	0.596	0.246
KOR	Korea, Rep.	0.252	0.615	0.930
LTU	Lithuania	0.362	0.295	0.589
LUX	Luxembourg	0.634	0.460	0.904
LVA	Latvia	0.500	0.335	0.486
NLD	Netherlands (the)	0.493	0.676	0.716
NOR	Norway	0.588	0.436	0.442
NZL	New Zealand	0.411	0.644	0.388
POL	Poland	0.254	0.475	-0.614
PRT	Portugal	0.711	0.556	0.252
QAT	Qatar	0.515	0.501	0.856
SAU	Saudi Arabia	0.595	0.502	0.568
SGP	Singapore	0.346	0.508	0.973
SVK	Slovak Republic	0.396	0.456	0.793

SVN	Slovenia	0.407	0.543	0.747
SWE	Sweden	0.371	0.586	0.570
TTO	Trinidad and Tobago	0.650	0.526	0.511
URY	Uruguay	-0.009	0.680	-0.049
USA	United States	0.473	0.492	0.168