This is the accepted version of Arena M., Azzone G., Dell'Agostino L. & Scotti F. (2022), Precision policies and local content targets in resource-rich developing countries: The case of the oil and gas sector in Mozambique, Resource Policies, Vol. 76
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Published Journal Article available at: https://doi.org/10.1016/j.resourpol.2022.102597

# Precision policies and Local Content targets in resource-rich developing countries: the case of the oil and gas sector in Mozambique

**Abstract**

This paper aims to understand whether and to what extent firm-level data can "precisely" support the definition of Local Content (LC) targets for international oil and gas companies in resource-rich developing countries. The paper addresses this topic with reference to a specific, publicly available dataset developed by the World Bank Enterprises Survey (ES) Unit and uses the case of Mozambique to demonstrate the informative potential of firm-level data for policy-making. Specifically, we compare the LC estimates obtained using firm-level data with those obtained using sector-level data (input-output tables). Based on this comparison, we demonstrate that firm-level data provide a more accurate representation of the capability of the domestic supply chain to provide inputs to the oil and gas industry, while input-output tables lead to a significant overestimation of LC. Overall, our findings suggest that firm-level data can provide a more precise basis for supporting the design of LC policies and the Enterprise Survey for Mozambique could represent a reference model for data collection to be extended to other resource-rich developing countries to support target definition.

**Keywords:** Precision policies; Firm-level data; Local content; Oil and gas; Mozambique.

## 1. Introduction

In recent years, the growing availability of more detailed and timely data has been a game changer in many regulated sectors (Maciejewski, 2017), leading to the adoption of so-called "precision policies". Compared to a "standard" public policy, a precision policy aims to define a set of interventions that takes into account the specific characteristics and expectations of homogeneous groups of users (or even a single user, if data are available), enabling a more efficient and effective usage of public resources (Azzone, 2018).

In the energy sector, precision policies have progressed very differently between developed countries, especially those with a negative energy balance, and resource-rich developing countries, which often count on the availability of energy sources for their economic development.

In the former, the diffusion of smart grids, smart meters, sensors, digital devices and the "Internet of Things" made large amounts of data on energy demand easily available, supporting the implementation of precision policies aimed at optimizing energy consumption and at reducing the environmental impact of energy production, transformation and distribution (Grolinger et al., 2016).

In the latter, instead, demand-supply optimization is only one aspect of energy policies. Here, the issues connected to the exploitation of energy resources have a key role and policy makers tend to focus on policies at the intersection between energy, industrialization and economic diversification as instruments to support long-term growth (Adewuyi and Oyejide, 2012; Emmanuel, 2016; Ovadia, 2016; Yanıkkaya and Turan, 2018; Kalyuzhnova and Belitski, 2019). In these countries, the adoption of precision policies is more complex for two main reasons. First, to support policy formulation the analysis of actual data has to be combined with estimations necessary for evaluating the future consequences of current decisions (answering to questions such as: how will world energy needs change over time? What will the impact of new plants be on the rest of the country's economy?). Second, many developing countries do not have reliable and complete datasets and the cost of collecting information is extremely high, leading to the "poor numbers-poor policy" dilemma (Jerven, 2013) or the "data deprivation" phenomenon (Serajuddin et al., 2015). Emblematic from this point of view is the case of African countries, which have a significant place in the global energy value chain, also thanks to recent discoveries in Sub-Saharan Africa (e.g., Ghana, Mozambique, Tanzania), but face huge

challenges in the design and implementation of effective policies also due to the lack of good-quality data (Balchin, 2015).

The relevance of this problem has been underlined repeatedly by the World Bank, which has strongly advocated the use of big data for the design of policies for energy access, energy efficiency and economic development. Not by chance, the World Development Report 2021 (World Bank, 2020)—World Bank annual flagship publication—is dedicated to the role of *Data for Development*, identifying in high-quality data the basis for effective policy-making and public service delivery. In addition, to support such policy and delivery, the World Bank has collected and made available to policy makers, practitioners and researchers, different types of datasets that can at least partially compensate for the absence of data from national statistics offices.

Moving from these considerations, this paper focuses on a key issue for resource-rich developing countries, analysing how available data can be used to determine Local Content (LC) targets for the multinational companies that want to develop oil and gas projects in these countries. The attention around this topic has significantly increased in recent years since LC—generally considered as the contribution of a multinational company to local development through the purchase of local goods and services and the development of skills—can activate long-term and sustainable economic development, leveraging on production links that connect different industrial sectors (NRGI, 2015). To enable this process, Local Content Policies (LCPs) often contain targets expressed in terms of the minimum share of local inputs of goods, services and workforce that multinational companies must (or are invited to) satisfy in their projects. Defining these targets accurately can prevent establishing objectives that are unambitious (and thus do not maximize the effects on the economy of the country) or, on the contrary, unattainable due to a lack of available skills among local suppliers (and discouraging for potential investors).

Although there is not a commonly accepted model for LC target definition[1], various scholars agree that policy makers should set LC targets consistent with the existing local capabilities in order to maximize the

[1] The first conceptual model for LC development focused on the petroleum industry was proposed by Kazzazi and Nouri (2012). They identify local policies, infrastructures, environment and capabilities as the main factors influencing LC

effects on the economy (Tordo et al., 2013; Ramdoo, 2015; Adedeji et al., 2016). Hence it is crucial for the design of effective policies to clarify which are the most appropriate data to measure these capabilities.

Against this background, the purpose of this paper is to show how a specific dataset based on firm-level data can support resource-rich developing countries in "precisely" defining LC targets for international oil and gas companies (IOCs). We will discuss the topic with reference to a specific, publicly available dataset developed by the World Bank Enterprises Survey (ES) Unit through a special survey designed for Mozambique. More specifically, the paper aims to answer two research questions:

1. Does the World Bank ES dataset for Mozambique enable setting LC targets more accurately than alternative data sources (i.e., conventional national accounts)?

2. Can the World Bank ES special survey for Mozambique represent a model for data collection to support LCP definition in other resource-rich developing countries characterized by a limited availability of reliable statistical data?

The case of Mozambique demonstrates the informative potential of firm-level datasets for policy design. The country represents a paradigmatic case of the importance of energy resources for local development, as it is part of the new resource boom in Africa and the offshore gas discoveries in the Rovuma fields could host the largest investment project in Sub-Saharan Africa, estimated at around USD 100 billion (Roe, 2018). LCPs are on top of the agenda of Mozambican policy makers, who aim to leverage oil and gas activities to generate long-term socio-economic development. At the same time, Mozambique is emblematic also of the difficulty in accessing data since the country is characterized by low statistical capacity (World Bank: Statistical Capacity Indicator Dashboard).

The rest of the paper is articulated into four sections. Section 2 presents the state of the art on LC targets, highlighting the main limitations of current approaches exploited for supporting LC target definition. Section 3 illustrates the data with special attention on the ES on Mozambique, and describes the methodology adopted to identify the LC target to be assigned to an oil and gas project through a precision policy. Section

development. However, their aim is to provide governments with a broad integrated framework of all the variables that affects LC, rather than to identify LC targets.

4 shows the empirical results obtained for the Mozambique case study and compares the targets estimated through firm-level data from ES against those obtained using traditional approaches. Section 5 contains conclusions about the possible generalization of results.

## 2. Background

LCPs are regulations introduced in resource-rich developing countries to leverage natural resources to promote economic diversification and maximise the potential for the development of local economies (Ovadia, 2015; Nwapi, 2016). To stimulate industrialization and long-term growth, LCPs aim to activate productive linkages between the extractive sector and the economy as a whole through the use of domestic intermediate goods and services and the recruitment of the local workforce in oil and gas projects (IPIECA, 2011). Therefore, the definition of the expected shares of local inputs—i.e., the LC targets—that IOCs must (or are invited to) satisfy, is a central element in the design of an LCP and an issue subject to lively debate in the LCP literature.

On the one hand, most authors suggest adopting quantitative and mandatory LC targets to encourage IOCs to use locally sourced goods, services and workforce beyond what they would normally do (White, 2017; Roe, 2018; Pereira et al. 2018), arguing that otherwise IOCs generally tend to import a larger share of their production inputs and devote limited concern to the activation of domestic development. On the other hand, the application of these targets might generate additional costs for IOCs when domestic companies are less efficient than international suppliers, with consequently lower tax revenues for national governments (Hansen et al., 2016; Rui et al., 2018). Comprehensive studies argue that although LCPs are designed with the objective of correcting market failures and generating productive externalities, they limit the decision space of IOCs, producing inefficiencies and misallocation of resources (Esteves et al., 2012; Kolstad and Kinyondo, 2017). For instance, Hufbauer et al. (2013), analysing the case of Nigeria, conclude that mandatory LC targets are responsible – due to production distortions and technical inefficiencies – for an average annual loss in government revenues, between 2011 and 2020, of almost 6 $ billion (nearly 10 per cent of total government revenues). From an international trade perspective, Stone et al. (2015) pinpoint that LC

requirements reduce world trade, especially in intermediates goods, leading to market distortions. Nwapi (2016) points out that these negative effects of LCPs are particularly strong when there is a misalignment between LC targets and the local business environment, or, in other words, when the national economy is not able to provide IOCs with local inputs coherently with LC targets.

Due to these limits of LCPs, some resource-rich developing countries are introducing alternative policies to LC requirements with the idea of reducing government intervention and promoting competition (Kolstad and Kinyondo, 2017). However, these alternative approaches can also be ineffective in achieving local economic development. For instance, in Tanzania oil and gas regulation lacks specific targets, monitoring mechanisms, incentives or sanctions to protect and support the infant domestic industry. Hansen et al. (2016) and Kolstad and Kinyondo (2017) identify these lacks as one of the key factors that limited the establishment of relevant backward and forward linkages between domestic companies and IOCs that still import a large share of inputs. According to Roe (2018), in Mozambique, weak institutions and a vague LCP may be the main causes of the likely failed achievement of the IMF's over-optimistic GDP growth rate forecasts of 24% between 2021 and 2025 (IMF, 2016)[2].

To balance these issues, a promising solution could be to set targets more consistent with existing local capabilities (Tordo et al., 2013; Aoun and Mathieu, 2015; Ramdoo, 2015), in order to stimulate IOCs to purchase in the country all inputs that can be produced efficiently (Heum et al., 2011; Kazzazi and Nouri, 2012; Adedeji et al., 2016). The availability of data able to assess the actual capacity of local firms is hence key to setting optimal LC targets (Klueh, 2009; Acheampong et al., 2016; Pereira et al., 2018), avoiding both unambitious LC targets with limited incentive for IOCs to identify local suppliers (Nwapi, 2015), and unattainable LC targets that cannot be satisfied by the domestic business environment, discouraging potential investors (Teka, 2012).

[2] Specifically, Roe (2018) observed that in 2018 there is no evidence of a growth spurt in Mozambique and that since 2013 growth has been weaker than at any time in the past 20 years. Looking at a relevant downward adjustment of the IMF growth projections and analysing other macroeconomic and national account data, Roe (2018) concludes that the double digit growth rates projected by IMF in 2016 are unlikely to happen in the next years.

Available datasets for the assessment of local supply capabilities differ according to their unit of analysis. A first group of datasets provides information at the *sector* level (*sector-level datasets*), usually through national Input-Output tables (hereinafter IOTs) (Tordo et al., 2013). IOTs represent the economy as articulated in a number of sectors and provide a schematic representation of all flows of domestic intermediate goods and services among these sectors, with a separate indication of imports (see Timmer et al., 2012 for a schematic outline of IOTs and an introduction to the basic relationship within IOTs). In this way, IOTs offer information about the amount and type of intermediate input needed in the production of one unit of output in a given sector provided within a country (Leontief, 1936). Once the size of a new oil and gas project is known, such information can thus be used to estimate the amount of input needed by the project and—theoretically—available in the country.

Conveniently, sector-level datasets are available in most developing countries. However, the reliability of this approach has been increasingly questioned. For instance, using IOTs from the Global Trade Analysis Project (GTAP) database[3], Tordo et al. (2013) calculate the LC levels for the oil and gas sector of 48 countries as the ratio of domestic intermediate goods and services to total intermediates. Tordo et al. (2013) estimate an expected level of local content of 80% or more for 25 countries, between 40% and 79% for 17 countries, while only 6 countries have a LC level between 20% and 39%. However, the authors point out that these figures are significantly higher than those actually achievable in practice and reported in real-case studies (Nordås et al., 2003; Tordo and Anouti, 2013). They attribute such discrepancies to the IOTs used for the analysis, characterized by different sources, base years and sectoral details. Indeed, in many developing countries IOTs have a low level of sectoral disaggregation and oil and gas is usually considered within the mining and quarrying sector, together with the mining of coal, metals and other products. However, these extractive activities use different technologies and inputs, with different potential for LC. Consequently, IOT data on the mining and quarrying sector do not provide a precise representation of the needs of oil and gas companies and of the availability of suppliers in the country.

[3] The GTAP initiative offers IOTs for a number of countries derived from a world input-output table obtained merging international trade statistics with a collection of national IOTs. The release used by Tordo et al. (2013) is the GTAP8, which includes data for 2004 and 2007, covers 129 regions and 57 sectors with an aggregated upstream oil and gas sector. At present, the GTAP10 database offers IOTs for 121 countries, 65 sectors and 4 base years (2004, 2007, 2011 and 2014). For further details see https://www.gtap.agecon.purdue.edu/databases/v10/index.aspx.

In contrast, in a few countries, national authorities in charge of the design and implementation of LCPs created project-level datasets. An example of this type of dataset is used by Furtado et al. (2017) for the revision of Brazilian LC targets. The authors exploited the LC shares for each equipment item and service certified by firms accredited by the National Petroleum Agency in order to measure the socio-economic impact of an oil and gas project. Specifically, using oil and gas projects data available from Petrobras—the National Oil Company—they define the cost structure of an average project identifying the cost associated with the 110 products listed in the Resource and Uses Table provided by the National Statistical Institute (IBGE). Then, they multiply the budget for each product by the corresponding LC share certified by the National Petroleum Agency and finally associate these products to the 55 economic activities listed in the Brazilian IOT to estimate the domestic impact of the project. Such an approach allows the identification of realistic targets, as the information is both country and product/service specific. Clearly, it requires a large set of data concerning past oil and gas projects, which is feasible in well-established extractive countries, as in the case of Brazil presented by Furtado et al. (2017). However, this approach is not realistic in countries that have recently entered the oil and gas industry, including in Sub-Saharan regions, and are not equipped with consistent statistical infrastructures.

In these contexts, a possible solution is provided by firm-level datasets that are becoming increasingly available and whose quality is improving. Concerning developing countries, a relevant dataset is the World Bank Enterprise Survey (ES). This is provided by the Enterprises Analysis Unit of the World Bank, which conducts extensive enterprise surveys to make firm-level data available. The ES represents a rich source of information about firms that operate in non-agricultural, formal private sectors in more than 140 countries. Specifically, it reports the main business characteristics of surveyed companies in manufacturing and services and discloses details about the business environment in which these firms operate. Moreover, in every country some core sectors are selected on a 'case-by-case' logic for a special survey, whose results are included in the ES dataset. In Mozambique, the increasing importance of energy resources for local economic development led the World Bank to include also mining and quarrying in the standard ES, selecting this sector as the focus of the survey. Hence, the ES for Mozambique includes some specific questions about the share of domestic inputs used for production and allows the identification of a subset of firms that are suppliers of

the extractive sector. These ES firm-level data for Mozambique seem to be well suited for supporting the definition of LCPs and especially for setting LC targets in the oil and gas sector. As follows, we analyse if and how they can be applied to provide more accurate estimates of LC targets than IOTs (which represent the "standard" approach in countries like Mozambique with a limited availability of reliable statistics).

## 3. Data and methodology

LC targets can be expressed in two different ways.

According to a first, more common definition, LC is the "*share of goods and services provided by first tier domestic suppliers against IOCs total supplies*" (Tordo et al., 2013; and Furtado et al., 2017). We call it Gross LC, as it measures the actual impact of a project on local companies only if all domestic suppliers do not use imported inputs. Usually, such assumption is not verified in practice, hence the Gross LC overestimates the effect of the IOC on local economy.

For this reason, some countries set LC targets taking into consideration the quantity of domestic purchases at different levels of the supply chain, offsetting the value of imports of goods and services provided by "further-level" suppliers. For instance, in Mexico, the LCP refers to the *value of Mexican goods used by the IOC, including only the proportion of domestic materials "incorporated" into the goods, specifically excluding the value of imported materials along different levels of the supply chain* (Asali et al., 2015). We define the LC measure obtained by offsetting suppliers' imports as Net LC.

Net LC can be determined at different levels of precision and completeness. On the one hand, we can just focus on the effect of first-tier suppliers, determining Net LC as the difference between Gross LC and import of first tier suppliers. On the other hand, we could take into account the whole supply chain, as in the Mexican case. The latter approach improves the quality of results, but requires a larger set of data, which can hardly be available in energy-rich and data-poor countries. Accordingly, we will limit our analysis to the former approach, measuring Net LC as the *share of goods and services provided by first-tier domestic suppliers, net of their imports, against IOCs total supplies*. However, our results can be easily extended to a more extensive definition of Net LC.

Below, we outline how Gross LC and Net LC can be calculated relying on the IOT and the ES datasets. To this aim, we first describe the two data sources and the data pre-processing activities needed to make the datasets comparable; then, we present in detail the methodology adopted to compute LC targets.

### 3.1 Data sources and preprocessing

Our first data source is the Eora database that provides IOTs for the years 1990-2015 for 190 countries, covering many developing regions and offering a valuable alternative for countries—such as Mozambique—whose national statistical offices do not disclose IOTs (Lenzen et al., 2012; Lenzen et al., 2013)[4]. Specifically, for Mozambique the Eora IOT is designed according to industry outputs and presents a detailed breakdown of 25 sectors at 2-digit level of the International Standard Industrial Classification (ISIC) of all economic activities (see Lenzen et al., 2013). We use the average data of the three most recent years (2013-2015) to prevent bias due to yearly fluctuations[5].

Our second data sources are the two Mozambique ESs compiled by the World Bank in 2018 with reference to the previous fiscal year[6]. One is the standard ES that covers 601 firms in non-agricultural, formal

[4] Although in many countries IOTs have been incorporated into the System of National Accounts using internationally accepted statistical standards, these tables are not publicly available in many developing countries. Only recently, some international datasets - such as Eora - are trying to solve this data gap. The Eora multi-region input-output database provides a time series of high resolution IOTs complemented with environmental and social satellite accounts for 190 countries for the period 1990-2015, assembling data from different national and international data sources. The database is compiled from the best available national supply and use tables or national IOTs that are linked through international trade statistics and balanced through an optimization exercise. For further details, see https://www.worldmrio.com/.

[5] Although the local production structure and the linkages among sectors tend to be stable in the short term, the quantity of imports for each sector could be subject to larger fluctuations, leading to sectoral standard deviations in terms of the share of sectoral LC from IOTs with ranges between 0.93% and 7.14% over the time frame 2013-2015 for Mozambique. In order to prevent that our estimates of LC are affected by the contingencies of a single specific year, which might not be fully representative of the domestic production structure, we use the average of the three most recent years (2013-2015).

[6] Given the high stability of the main relationships underlining IOTs, the misalignment between the period covered by IOTs (2013-2015) and the year of the ES (2017) can be considered negligible.

Mozambican private sectors and comprises manufacturing (ISIC Revision 3.1 - group D), construction (group F), services (groups G and H), and transport, storage, and communications (group I). The other focuses on 49 firms from the extractive sector (mining and quarrying according to ISIC nomenclature) usually not surveyed in the standard ES and compiled by the World Bank specifically for this country according to the above-mentioned special survey decided 'case by case'[7]. Data collection for both surveys is based on the same questionnaire and covers standard business characteristics such as access to finance, annual sales, costs of inputs/labor, capacity utilization, and taxation. Moreover, it includes some country-specific questions that are well-suited to estimate the share of LC. First, Mozambican enterprises are required to declare the share of inputs of domestic origin used in production, which represents the share of inputs purchased from domestic suppliers over total inputs and is a good proxy of their Gross LC (Questionnaire variable d12a: "In the last complete fiscal year, what percentage[8] of this establishment's purchases of material inputs or supplies were of domestic origin?"). Second, local firms have to state if they are suppliers of goods and services to companies in the extractive sector or not (Questionnaire variable MZd2: "In last complete fiscal year, did this establishment sell products or provide services to companies in Oil & Gas and/or Mining sectors?"). We will show below how to use this information to estimate the Net LC. In addition, for each firm the dataset provides the ISIC code at 4-digit level of the main product traded and its share with respect to total annual sales, allowing us to distinguish oil and gas firms (operating in the extraction of crude petroleum and natural gas) from companies operating in other extractive sub-sectors (i.e., mining and agglomeration of hard coal; mining of non-ferrous metal ores, except uranium and thorium ores; quarrying of stone, sand and clay; extraction of salt; other mining and quarrying).

[7] The sample for the 2018 Mozambique ES was selected using stratified random sampling and three levels of stratification were used (industry, establishment size, and region). Firms included in the survey have at least five employees and operate in the manufacturing and services sectors. The ES use a stratified sampling technique and the resulting samples are representative of a country's private sector, excluding firms with 100 percent state ownership. For all methodology details, see https://www.enterprisesurveys.org/en/methodology

[8] We note that these percentages are computed based on monetary values of material inputs and not on physical values (number of purchased material inputs).

**Table 1 - Composition of the sample by sector**

| ISIC code (2 digit) | Sectors | N° of Firms | |
|---|---|---|---|
| | | Full sample | *of which* Extractive sector suppliers |
| 10,11,12,13,14 | Mining and Quarrying | 42 | 17 |
| 15, 16 | Food and Beverages | 84 | 11 |
| 17, 18, 19 | Textiles and Wearing Apparel | 22 | 0 |
| 20, 21, 22 | Wood and Paper | 40 | 4 |
| 23, 24, 25, 26 | Petroleum, Chemical and Non-Metallic Mineral Products | 24 | 1 |
| 27, 28 | Metal Products | 64 | 7 |
| 29-33 | Electrical and Machinery | 13 | 5 |
| 34,35 | Transport Equipment | 2 | 2 |
| 36 | Other Manufacturing | 35 | 3 |
| 45 | Construction | 41 | 14 |
| 50 | Maintenance and Repair | 29 | 10 |
| 51 | Wholesale Trade | 23 | 8 |
| 52 | Retail Trade | 104 | 15 |
| 55 | Hotels and Restaurants | 79 | 19 |
| 60-63 | Transport | 32 | 17 |
| 64 | Post and Telecommunications | 5 | 0 |
| 65-74 | Financial Intermediation and Business Activities | 6 | 2 |
| | **Tot.** | **645** | **135** |

*Source: Author's calculations on ES data.*

Combining the two ES datasets and excluding only five observations with missing values for the share of inputs of domestic origin, we obtain a sample composed of 645 companies (over 99% of the firms in the original dataset), 135 of which are suppliers of the extractive sector (representing about 21% of our sample).

Finally, we match our ES firm-level data with IOT data to make comparable the results coming from the two alternative data sources. In doing so, we are forced to reduce the level of detail of the ES dataset by

assigning to each firm the corresponding IOT sector (defined at the 2-digit level of the ISIC classification) based on the 4-digit ISIC code of the main product. In this way, in both datasets data aggregation is at the 2-digit level of ISIC, in line with the Eora IOT sectoral breakdown. The result is an ES firm-level sample that covers 17 of the 25 IOT sectors (Tab. 1).

## 3.2 LC estimation

### *3.2.1 Gross LC*

Gross LC (GLC) is a measure of the share of goods and services provided by first-tier domestic suppliers against IOC total supplies (Tordo et al., 2013; and Furtado et al., 2017).

Based on IOTs, the GLC of a sector is determined following Tordo et al. (2013) as the ratio between domestic purchases of intermediate goods and services of the sector and total purchases of intermediate goods and services of the sector, which include also imported inputs. Hence, for each sector *i*, GLC is obtained according to Eq.1:

$$GLC_i\ (IOTs) = \frac{Purchases\ of\ Domestic\ Intermediate\ Goods\ and\ Services}{Total\ Purchases\ of\ Intermediate\ Goods\ and\ Services}. \quad (1)$$

In general, using ES firm-level datasets, we could obtain the same measure by aggregating data from the firms belonging to each sector *i*, following Eq. 2:

$$GLC_i\ (ES) = \frac{\sum_{j=1}^{n} Purchases\ of\ Domestic\ Intermediate\ Goods\ and\ Services}{\sum_{j=1}^{n} Total\ purchases\ of Intermediate\ Goods\ and\ Services}, \quad (2)$$

where n is the number of firms in sector *i*. However, we cannot use Eq. 2 in the case of Mozambique, as only 284 companies out of 650 provide the absolute value of the cost of domestic intermediate goods and services

(Questionnaire variable: n2e)[9]. For a larger number of companies (645), the dataset only contains the average share of the purchases of domestic intermediate goods and services out of total purchases (Questionnaire variable: d12a). In this case, we can provide a different measure of the GLC (Eq. 3):

$$GLC_i(ES) = \frac{\sum_{j=1}^{n} Percentage\ of\ Domestic\ Inputs}{Number\ of\ firms\ in\ sector\ i}. \quad (3)$$

Eq. 3 introduces a possible bias because it does not take into account firm size and, consequently, the absolute value of domestic goods and services. In Section 4.1, we analyse this issue for the Mozambican case and discuss the robustness of our results.

*3.2.2 Net LC*

As we clarified above, we measure Net LC (NLC) as the share of goods and services provided by first-tier domestic suppliers net of their imports against IOC total supplies. NLC has to be estimated with reference to a specific project, since it requires knowing the industries where suppliers operate. Specifically, we perform our exercise starting from a given total GLC of a project and use three groups of data to determine NLC: (1) the project cost structure; (2) the share of domestic purchases of the IOC for each activated sector; and (3) the share of imports of each activated sector.

The project cost structure defines which sectors are activated by the project and their relative weight in terms of incidence over the total cost of the project ($q_i$). In this paper, we refer to a "reference" oil and gas

[9] In order to identify possible reasons for the high non-response rate for this Questionnaire variable, Appendix A presents a twofold descriptive analysis that investigates (i) the non-response rate for other questions, focusing on those related to financial indicators, and (ii) the main firm characteristics, comparing firms who did answer Questionnaire variable n2e with firms who did not answer).

project that is going to be realized in Mozambique, for which public information is available: the Rovuma Liquefied Natural Gas (LNG) Project situated on the Afungi Peninsula in Cabo Delgado Province[10].

The share of domestic purchases of the IOC for each activated sector ($x_i$) defines how the GLC is distributed among the sectors activated by the project. The linear combination between the incidence over the total cost of the project of each activated sector ($q_i$) and the sectoral shares of domestic purchases of the IOC ($x_i$) should equal the total GLC of the project according to Eq.4:

$$GLC = \sum_{i=1}^{n} q_i x_i \quad where \quad x_i \in [0,1], \sum q_i = 1, \tag{4}$$

where *i* represents the sectors activated by the oil and gas project.

To solve Eq. (4), where the unknown variables are the shares of domestic purchases $x_i$, we introduce an additional hypothesis, assuming that the share of domestic purchases in each sector is proportional to the portion of local production in the corresponding sector on the local market ($y_i$). More specifically, the higher the local production, the larger the share of domestic purchases in the considered sector. To this aim, we first define $y_i$ as the incidence of the sectoral domestic production over the sum between sectoral imports and domestic production (Eq. 5):

$$y_i = \frac{out_i}{out_i + im_i}, \tag{5}$$

where $out_i$ is the total output of sector *i*, obtained from IOTs (in line with GLC elaborations we use the average of the period 2013-2015) and $im_i$ is the value of imports of goods and services at country level that can be

[10] Phase 1 of the Rovuma Liquefied Natural Gas (LNG) Project is currently being realized by Mozambique Rovuma Ventures, a joint venture owned by ExxonMobil, Eni and CNPC. Detailed information and reports are available on the website https://www.exxonmobil.co.mz/en-MZ/About/Who-we-are/Rovuma-LNG#Overview.

associated to a specific sector *i*, obtained from the UN Comtrade dataset (average 2013-2015)[11]. Second, we assume that the ratio between the share of domestic purchases of the IOC and the portion of local production is constant across sectors (Eq. 6):

$$\frac{x_i}{y_i} = k. \tag{6}$$

Combining Eq. (4) and (6)[12] we determine k and consequently all the $x_i$, which represent the GLC generated by the IOC in each activated sector. Finally, we multiply the share of local purchases of the IOC, weighted by the incidence of activated sectors over the total project value ($x_i\, q_i$), by the portion of domestic inputs purchased by each activated sector ($GLC_i$) to offset the quantity of imports of first-tier suppliers (Eq. (7):

$$NLC = \sum_{i=1}^{N} q_i\, x_i\ \ GLC_i. \tag{7}$$

[11] It is noteworthy that IOTs record for each sector the imported production inputs, regardless of the sector of origin of those inputs. This means that the imports associated to a sector in IOTs encompass imports procured by the underlying sector across different sectors. Consequently, the factor $im_i$, which represents the quantity of goods and services belonging specifically to the single sector i that is imported, cannot be computed through IOTs. For this reason, we rely on international trade data – i.e., UN Comtrade data (https://comtrade.un.org/)- that provide enough information to identify the value of imports of goods or services belonging to a specific given sector. In more detail, since trade data record the imported goods and services by product and not by sector, it is necessary to associate each imported input with its own production sector and then sum the value of the inputs produced by the same sector. We perform this step according to the international classifications of trades goods (SITC) and services (EBSOP).

[12] Combining Eqs. (4) and (6) we obtain: $GLC = k \sum_{i=1}^{n} q_i y_i$ leading to $k = \frac{GLC}{\sum_{i=1}^{n} q_i y_i}$. Finally, from Eq. (6) we compute: $x_i = k * y_i \quad \forall\, i.$

## 4. Results

This section presents the results of the analysis for both GLC and NLC.

### 4.1 Analysis of Gross LC

Table 2 shows the GLC obtained from IOTs and ES dataset for all sectors. The table compares the results for the full sample, including all firms interviewed by the World Bank, the "Extractive sectors suppliers" subset, encompassing only companies that provide inputs to the extractive industry and the "Other firms" subset, with all firms not included in the "Extractive sector suppliers" subset. The comparison of the results obtained for these different data sources and sets of firms sheds light on the peculiarities of the extractive industry, and more specifically the oil and gas industry, with respect to other sectors in terms of local purchases and capability of activating local supply chains.

First, for each industry sector, the GLC of the ES full sample (Eq. 3) reflects the sectoral average value of the sample and proxies from a firm-level perspective the average value of the country obtained by IOT (Eq. 1), making the two results comparable. The comparison of GLC for the ES full sample and the IOTs seems to confirm that IOTs generally overestimate this share in most sectors. In some cases, this phenomenon is very evident, as for example in transport and transport equipment and in wholesale and retail trade. There are only two exceptions represented by the wood and paper and other manufacturing, for which GLC estimated using IOTs is lower than using the ES. In other cases, the two figures are more aligned. In particular, GLC for the mining and quarrying sector obtained from ES data is in line with that from IOTs, around 78%.

Second, focusing on the comparison of the different ES subsets, for the extractive sectors suppliers, GLC is lower than in the full sample suggesting that extractive firms require a higher share of imported inputs compared with the sectoral average. This result is in line with the literature, which highlights that most of the Mozambican firms are not able to meet the high international standards required for being part of the extractive industry supply chains (AfDB et al. 2016) and that the space for the few competitive formal local enterprises who can qualify as the business partners of foreign direct investments projects in the oil and gas sector is extremely limited (Da Costa, 2012). This outcome is even clearer observing GLC shares of the Other

**Table 2 - GLC by sector from different sources and sub-sample (%)**

| Sectors | IOTs Avg. 2013-2015 | ES Full sample | ES Extractive sector suppliers | ES Other firms |
|---|---|---|---|---|
| Mining and Quarrying | 78.49 | 78.86 | 63.53 | 89.28 |
| Food and Beverages | 84.52 | 85.92 | 71.82 | 88.04 |
| Textiles and Wearing Apparel | 72.46 | 72.73 | - | 72.73 |
| Wood and Paper | 71.66 | 85.13 | 47.50 | 89.31 |
| Petroleum, Chemical and Non-Metallic Mineral Products | 70.64 | 59.92 | 60.00 | 59.91 |
| Metal Products | 69.25 | 68.50 | 36.86 | 72.39 |
| Electrical and Machinery | 70.58 | 60.31 | 43.00 | 71.13 |
| Transport Equipment | 73.36 | 30.00 | 30.00 | |
| Other Manufacturing | 75.41 | 90.83 | 66.67 | 93.09 |
| Construction | 90.79 | 78.29 | 70.36 | 82.41 |
| Maintenance and Repair | 66.65 | 61.31 | 69.70 | 56.89 |
| Wholesale Trade | 84.14 | 58.26 | 35.63 | 70.33 |
| Retail Trade | 92.03 | 67.86 | 52.93 | 69.69 |
| Hotels and Restaurants | 86.63 | 82.38 | 75.53 | 84.55 |
| Transport | 84.65 | 58.13 | 46.47 | 71.33 |
| Post and Telecommunications | 88.93 | 77.00 | - | 77.00 |
| Financial Intermediation and Business Activities | 70.94 | 64.17 | 100.00 | 46.25 |

*Source: Author's calculations on Eora and ES data*

**Table 3 - Gross LC in the Mining and Quarrying sector by ISIC code**

| ISIC code | Sectors | IOTs % | ES Full sample % |
|---|---|---|---|
| C | Mining and Quarrying | 78.49 | 78.86 |
| | *of which* | | |
| 1010 | Mining and agglomeration of hard coal | | 57.86 |
| 1110 | Extraction of crude petroleum and natural gas | | 10.00 |
| 1320 | Mining of non-ferrous metal ores, except uranium and thorium ores | | 82.86 |
| 1410 | Quarrying of stone, sand and clay | | 92.14 |
| 1422 | Extraction of salt | | 97.86 |
| 1429 | Other mining and quarrying n.e.c. | | 66.40 |

*Source: Author's calculations on Eora and ES data.*

firms' sub-sample, that show higher values for most of sectors. An exception is maintenance and repair[13], where GLC of the extractive sector suppliers is higher than GLC of other firms; it is interesting to note that, in this specific case, GLC estimated from ES survey is also higher than GLC estimated from IOTs.

More generally, this pattern suggests that the extractive sector has peculiar characteristics with respect to the other industries in the local value chain, experiencing - with few exceptions - significantly lower levels of local purchases.

Moreover, taking full advantage of the ES database, we analyse the difference that emerges moving to a higher granularity level from IO sectors (ISIC code, 2 digit) to the ISIC code at 4 digits. In this way, we can investigate GLC associated to the different sub-sectors that compose the extractive sector. Focusing on

[13] Moving from sectors (ISIC code, 2 digit) to the ISIC code at 4 digits for maintenance and repair, we identify that the difference between sub-samples is driven by the "Sale, maintenance and repair of motorcycles and related parts and accessories" sub-sector, where the Extractive sector suppliers have a higher GLC share compared with Other firms. In general, this sub-sector is characterized by a high share of local resellers of domestic inputs for the Extractive sector, while it mainly provides imported inputs to other sectors (Baez et al., 2018).

mining and quarrying, Table 3 shows how a similar GLC at sectoral level hides a high heterogeneity among sub-sectors, from a maximum value of about 98% in the extraction of salt to a minimum of 10% in the extraction of crude petroleum and natural gas. This result corroborates the weaknesses of IOTs that aggregate heterogeneous industries within the mining and quarrying sector. IOTs significantly overestimate the percentage of domestic purchases of oil and gas, which is a capital-intensive industry requiring technologically complex inputs that in developing countries can hardly be provided by the local supply chain in large quantities.

To summarize, GLC estimated from IOTs (i.e., the share of domestic production inputs over total inputs) is around 78.5% for the mining and quarrying sector and this percentage falls to 63.5% when GLC is estimated from ES extractive sector suppliers, and drops sharply to 10% focusing specifically on the extraction of crude petroleum and natural gas sub-sector in the ES. The GLC obtained from the ES for the oil and gas sub-sector is consistent with those obtained from some publicly available data about two ongoing oil and gas projects in Mozambique. For the Rovuma LNG Project, the Standard Bank Group (2019) reports the estimates of the share of domestic input over total investment to be around 9% in the construction phase and 10% during the operational phase. The Mozambique LNG Project is targeting an expenditure of USD 2.5 billion in goods and services from local suppliers out of USD 20 billion in investments – that is, a GLC near 12.5%[14]. Moreover, all these estimates for Mozambique are in line with the preliminary assessment by the World Bank Group (2016) of an LNG project in Tanzania, a country near Mozambique in terms of level of development and oil and gas maturity[15]. In Tanzania, out of a total LNG investment projected to be around USD 17 billion, the potential for GLC is expected to be in the range of USD 1.4 billion, accounting for around 11% of the total demand for goods and services.

[14] For information about the Mozambique LNG project, see: https://www.mzlng.total.com/en

[15] These countries figure among the Least Developed Countries (LDCs) according to UN classification (https://www.un.org/development/desa/dpad/least-developed-country-category/ldcs-at-a-glance.html), which means that Mozambique and Tanzania are low-income countries with severe structural impediments to sustainable development and low levels of human assets. Both countries entered the oil and gas market in recent years, after the discovery of large, deep-sea, natural gas reserves, without any previous experience in the sector.

**Table 4 - Share of local inputs (GLC) by sector: Full vs Restricted dataset**

| Sectors | IOTs | ES Full dataset | | ES Restricted dataset | |
|---|---|---|---|---|---|
| | % | Firms (n°) | % | Firms (n°) | % |
| Mining and Quarrying | 79.66 | 42 | 78.86 | 34 | 52.93 |
| Food & Beverages | 87.84 | 84 | 85.92 | 77 | 64.46 |
| Textiles and Wearing Apparel | 73.66 | 22 | 72.73 | 18 | 32.91 |
| Wood and Paper | 72.75 | 40 | 85.13 | 28 | 85.64 |
| Petroleum, Chemical and Non-Metallic Mineral Products | 71.21 | 24 | 59.92 | 24 | 20.51 |
| Metal Products | 69.71 | 64 | 68.50 | 58 | 13.15 |
| Electrical and Machinery | 71.44 | 13 | 60.31 | 11 | 94.72 |
| Transport Equipment | 74.28 | 2 | 30.00 | 2 | 3.39 |
| Other Manufacturing | 77.09 | 35 | 90.83 | 29 | 98.31 |
| Construction | 91.62 | 41 | 78.29 | 1 | 100.00 |
| Financial Intermediation and Business Activities | 72.44 | 6 | 64.17 | 2 | 100.00 |

*Source: Author's calculations on Eora and ES data.*

To confirm the robustness of the results, for a restricted sample of 284 firms, GLC is estimated also based on Eq. 2, exploiting Questionnaire variable: n2e – i.e. "Cost of raw materials and intermediate goods used in production in the last fiscal year". This allows us to deal with potential bias related to the firm size and the overall value of inputs locally purchased. The comparison of GLC estimated from the restricted dataset, based on Eq.2, and GLC estimated from the full dataset, based on Eq. 3 is reported in Table 4. Obviously, this comparison is particularly significant for those sectors with the same firms in both the restricted and the full datasets, as in the *petroleum, chemical and non-metallic mineral products* and *transport equipment*. In these sectors, GLC share computed from the ES restricted dataset, based on Eq. 2, are clearly lower than those obtained from the ES full dataset, based on Eq. 3 and from the IOTs, confirming the relevance of ES survey data for obtaining a more accurate definition of LC targets.

This first result suggests that the usage of sector-level datasets might lead policy makers to set LC targets which are far from the real potential of the domestic market and which do not reflect the capabilities of the local economic and industrial structure. This offers a strong empirical support to the use of firm-level data – such as the Mozambique ES – in the definition of LC targets of the oil and gas industry, especially in countries characterized by a limited availability of reliable statistics.

**4.2 Analysis of Net LC**

The NLC allows a deeper analysis considering that local first-tier suppliers might import some portions of the inputs used in the production of goods and services they provide to oil and gas companies. In this way, we try to further refine the real quantity of local purchases induced by an oil and gas project. However, as anticipated, the calculation of the NLC requires some assumptions concerning (1) the sectors activated by the project and (2) how local purchases are distributed across those sectors. This makes our results indicative, rather than precise estimates, of how of LC might change when taking into account the level of imports in the purchases of first-tier suppliers.

To identify the main sectors activated by an oil and gas project, we rely on the cost structure of the Rovuma LNG project in terms of sectoral incidences over the total investment, as reported in Table 5.

We first calculate the NLC considering the GLC results from both IOT and ES and distribute the share of local purchases by applying the methodology described in Section 3.3.2 using the portions of local production ($y_i$) reported in Table 6.

Table 7 presents the results in terms of NLC obtained assuming the GLC of the project equal to the GLC of the mining and quarrying sector from IOT (78.49 %) and the sectoral $GLC_i$ from the same source. Likewise, Table 8 shows the results obtained assuming the GLC of the extraction of crude petroleum and natural gas from ES (10.00 %) and the sectoral $GLC_i$ resulting from its extractive sector supplier sub-sample. The comparison of the results reported in the two tables clearly highlights that IOT data determine an overestimation of NLC (as for the GLC). This overestimation emerges from the computation of the share of

**Table 5 - Sectoral composition of Rovuma LNG Project (CAPEX)**

| Input supplier sectors | Cost structure ($q_i$) |
|---|---|
| Metal Products | 34% |
| Electrical and Machinery | 17% |
| Transport Equipment | 5% |
| Construction | 20% |
| Other Manufacturing | 2% |
| Financial Intermediation and Business Activities | 22% |

*Source: Standard Bank Group (2019) study*

**Table 6 - Portion of local production on the local market by sector ($y_i$)**

| Input supplier sectors | $y_i$ |
|---|---|
| Metal Products | 27.0% |
| Electrical and Machinery | 38.6% |
| Transport Equipment | 34.8% |
| Construction | 47.2% |
| Other Manufacturing | 82.5% |
| Financial Intermediation and Business Activities | 63.6% |

*Source: Author's calculations on Eora and Comtrade data.*

domestic purchases for each activated sector ($x_i$)**;** as expected, to obtain a project GLC of 78.49%, every sector should contribute to the total GLC with a higher $x_i$ than those required to obtain a GLC around 10%.

Finally, we exploit all the publicly available information about the Rovuma LNG project to estimate its NLC. Specifically, since according to the Standard Bank Group (2019) the largest share of equipment and machinery will be imported, we exclude these sectors from the domestic inputs that make up the GLC of the project (9%) to solve Eq. (4) using Rovuma LNG project data. Table 9 allows a comparison of the results obtained using the sectoral $GLC_i$ from both IOT and ES, observing that LC falls from a gross level of 9% to a NLC in the range between 6.9% using IOT and 6.6% with ES data, which means that the NLC of the project is

**Table 7 – NLC of a reference project using IOT data**

| i | Input supplier sectors | Sectoral structure ($q_i$) (%) | Local purchases by sector ($x_i$) (%) | $GLC_i$ (from IOT) % | $NLC_i$ % |
|---|---|---|---|---|---|
| 1 | Metal Products | 34.00 | 54.62 | 69.25 | 12.86 |
| 2 | Electrical and Machinery | 17.00 | 78.06 | 70.58 | 9.37 |
| 3 | Transport Equipment | 5.00 | 70.52 | 73.36 | 2.59 |
| 4 | Construction | 20.00 | 95.63 | 90.79 | 17.36 |
| 5 | Other Manufacturing | 2.00 | 100.00* | 75.41 | 1.51 |
| 6 | Financial Intermediation and Business Activities | 22.00 | 100.00* | 70.94 | 15.61 |
| | **Total** | **100.00** | | | **59.29** |

*Source: Author's calculations on Eora data. * To solve Eq (4) we adopt an iterative algorithm. It means that if we obtain $x_i$ >1, we impose a share of local purchases of 100% for the underlying sector and then divide the residual GLC among the other sectors following the same methodology adopted in the first step.*

**Table 8 - NLC of a reference project using ES data**

| i | Input supplier sectors | Sectoral structure ($q_i$) (%) | Local purchases by sector ($x_i$) (%) | $GLC_i$ (from ES) % | $NLC_i$ % |
|---|---|---|---|---|---|
| 1 | Metal Products | 34.00 | 6.34 | *36.86* | 0.79 |
| 2 | Electrical and Machinery | 17.00 | 9.06 | *43.00* | 0.66 |
| 3 | Transport Equipment | 5.00 | 8.18 | *30.00* | 0.12 |
| 4 | Construction | 20.00 | 11.10 | *70.36* | 1.56 |
| 5 | Other Manufacturing | 2.00 | 19.39 | *66.67* | 0.26 |
| 6 | Financial Intermediation and Business Activities | 22.00 | 14.95 | *100.00* | 3.29 |
| | **Total** | **100.00** | | | **6.69** |

*Source: Author's calculations on ES data.*

**Table 9 - NLC of the Rovuma LNG project (CAPEX) (%), with IOT and ES data**

| i | Input supplier sectors | CAPEX (USD bln) | GLC decomposition (USD bln) | NLC | | | |
|---|---|---|---|---|---|---|---|
| | | | | IOT | | ES | |
| | | | | $GLC_i$ % | USD bln | $GLC_i$ % | USD bln |
| 1 | Metal Products | 11.15 | 0.79 | *69.25* | 0.55 | *36.86* | 0.29 |
| 2 | Electrical and Machinery | 5.58 | - | *70.58* | - | *43.00* | - |
| 3 | Transport Equipment | 1.64 | - | *73.36* | - | *30.00* | - |
| 4 | Construction | 6.56 | 0.81 | *90.79* | 0.74 | *70.36* | 0.57 |
| 5 | Other Manufacturing | 0.66 | 0.14 | *75.41* | 0.11 | *66.67* | 0.09 |
| 6 | Financial Intermediation and Business Activities | 7.22 | 1.21 | *70.94* | 0.86 | *100.00* | 1.21 |
| | **Total** | **32.80** | **2.95** | | **2.25** | | **2.16** |
| | ***% over Total*** | | ***9%*** | | ***6.9%*** | | ***6.6%*** |

*Source: Author's calculations on Rovuma LNG project, IOT and ES data.*

around ¾ of its GLC. These results provide further evidence of the actual potential of the local supply base when considering the quantity of imports from first-tier suppliers and might be taken as a reference by policy makers for the definition of realistic LC targets well aligned with the development level of the country's industrial supply capacity.

## 5. Conclusion

This paper explores whether and to what extent detailed firm-level data can support the design of LCPs, with special reference to the definition of LC targets of oil and gas projects. To this aim, we exploit the World Bank ES for Mozambique, which provides information on a large set of firms from the manufacturing, services and extractive sectors and allows us to distinguish extractive sector suppliers from other firms. In particular, we compare ES data and IOT as sources for the two indicators conventionally used for expressing LC targets, namely GLC and NLC.

The results of our empirical investigations contribute to the LC literature demonstrating how firm-level data collected for Mozambique offer a more accurate understanding of the productive characteristics of the domestic business environment, better supporting the definition of LC targets in the oil and gas sector within a "precision policy" perspective. Specifically, our results show that the GLC in the extraction of crude petroleum and natural gas is significantly different compared with other extractive sub-sectors and confirm that in a developing country the extractive sector suppliers have a lower GLC than other firms. As a consequence, IOT data lead to a significant overestimation of GLC. This result is also reflected in the estimate of NLC, which considers import effects along the supply chain.

These results indicate that firm-level data, like those provided by the ES on Mozambique, can support the policy maker in evaluating more precisely the effects along the supply chain, especially when firm-level data are combined with detailed project data about domestic purchases by sector. This type of information can be relevant for policy makers not only for setting LC targets, but also for monitoring the progress that different industries are experiencing thanks to a project or a strategic investment.

In our view, ES data are a powerful instrument to narrow the data gap that affects developing countries, and they support the design of data-driven policies, constituting an important element to address the poor data-poor policy dilemma. Specifically, our findings suggest that the World Bank special survey for Mozambique, with its focus on extractive sectors, could represent a reference model for data collection to be extended to other resource-rich developing countries to support their LCP definition - integrating the set of data that countries can exploit to assess the capability of the domestic supply chain - starting with those with the lowest statistical capacity.

In principle, a potential criticism associated to the use of ES survey data for policy-making is that survey participants could opportunistically misreport data concerning the share of inputs sourced domestically and other LC sensitive data (e.g., number of employees). However, such risk is limited, for several reasons. First, the development of oil and gas projects requires a direct negotiation with the national authorities and LC is

often one important issue in this process[16]. Second, LC is often part of IOCs' corporate social responsibility strategies and it is used to demonstrate the sustainability of their business; as a consequence, LC data are often reported in official and publicly available documents used by firms in their external communication and can be audited. Finally, the quality of ES data is certified by the World Bank: the Enterprise Survey Unit has designed the ES survey to obtain accurate responses and, in every country, makes efforts to ensure that information is actually reliable (e.g. in Mozambique, special effort was made to make sure that data about permanent and temporary employment was not missing for most establishments; please see the ES Implementation report (World Bank, 2020)).

Finally, it is noteworthy that our exercise takes a snapshot of LC in Mozambique reflecting its productive structure at a given moment. However, in the medium-term, the expansion of oil and gas extractive activities could affect the structure of the economy in terms of sectoral composition and production capacity (Nchor and Konderla, 2016). Therefore, LC targets should be regularly updated taking into account the transformation of the local business environment in order to maximize production linkages and activate long-term and sustainable economic development. Accordingly, to support as effectively as possible LCP definition and implementation, firm-wide surveys do not only have to provide specific information on the oil and gas sector and its suppliers but must be repeated over time to monitor the development of the country's production capacity.

[16] Specifically, the direct negotiations between the IOC and the national authorities cover the construction as well as the operation of the oil and gas plants. Therefore, the IOC has no incentive in underreporting data about the share of inputs sourced domestically since declaring a LC share lower than that the IOC is currently able to reach, would mean reducing its negotiating power. Moreover, also the overreporting hypothesis could be excluded due to the risk of a revision of the LCP based on IOCs declaration about their LC share. If national authorities would decide to set new LC target using data with a strong upward bias, IOCs might not be able to meet them.

**Appendix A**

To identify the reasons for the high non-response rate of the Questionnaire variable n2e (Cost of raw materials and intermediate goods used in production in the last fiscal year), we first investigate the non-response rate of other questions in the ES, focusing on those related to financial indicators (Table A.1). Second, we compare the main characteristics of firms answering to the Questionnaire variable n2e with respect to those of firms not answering to this question (Table A.2), in order to analyze the heterogeneity between the two groups of companies.

Table A.1 shows that the full sample discloses data related to total annual sales (variable: d2) and only a limited number of firms does not provide information concerning the total labour cost (variable: n2a) and the total cost of electricity (variable: n2b). The non-response rate increases for questions related to the cost of intermediates inputs (n2e), the amount of finished goods/materials bought to resell (n2i) and the total cost of sales (n2p). Finally, a very high percentage of firms answer questions about net profit or losses (MZn8). Overall, we find evidence that firms tend to answer more general questions related to their business, while the non-response rate becomes higher as required information concerns specific or sensitive data.

Table A.2 highlights that responding and non-responding firms to the Questionnaire variable n2e have similar characteristics in terms of age and size. Moreover, firms in the two groups are comparable in terms of percentage of domestic, foreign ownership and legal status. They appear homogenous also with respect to the portion of companies with internationally recognized quality certifications, financial statements certified by an independent external auditor, and a direct export of at least 20%.

We formally analyse the presence of statistical differences between the two groups through a t-test, where we compare the distribution of responding and non-responding firms for the above-mentioned characteristics[17]. Overall, there are no remarkable differences, as for all the variables we are not able to reject that the two groups have the same mean. The only exception is Questionnaire variable b2c, where we

[17] We perform the t-test for all numerical variables displayed in Table A.2. We do not perform the t-test on binary and categorical variables.

**Table A.1 – Questionnaire variables about figures: non-response rate**

| Questionnaire variable | | Percentage of firms who did NOT answer | |
|---|---|---|---|
| | | ES Full sample | ES Extractive sector suppliers |
| d2 | In last fiscal year, what were this establishment's total annual sales? | 0.00% | 0.00% |
| n2a | Total labor cost (incl. wages, salaries, bonuses, etc) in last fiscal year | 1.40% | 0.00% |
| n2b | Total annual costs of electricity in last fiscal year | 6.36% | 5.19% |
| n2e | Cost of raw materials and intermediate goods used in prod. in last fy | 55.97% | 64.44% |
| n2i | Total annual cost of finished goods/materials Bought to resell in last fy | 86.51% | 92.59% |
| n2p | Total cost of sales in last fiscal year | 54.26% | 64.44% |
| MZn8 | Net profit or losses of this establishment | 6.67% | 2.96% |

*Source: Author's calculations on ES data.*

find that non-responding firms tend to have slightly higher presence of government/state ownership. Due to the high comparability of the two groups, our robustness check in section 4.1 should fairly represent the LC generated by the local business environment, reducing the risk that our results might be significantly affected by firms with specific characteristics.

**Table A.2 – Main firms' characteristics**

| | Questionnaire variable | Unit | Firms who did answer n2e question | Firms who did NOT answer n2e question (or answer Don't know) | Total | t-test (p-value) |
|---|---|---|---|---|---|---|
| b5 | Age of the establishment (years) | Mean | 17.58 | 16.77 | 17.13 | 0.795 |
| | | *Std. Dev.* | *14.24* | *14.27* | *14.25* | |
| l1 | Size (employees) | Mean | 59.27 | 54.55 | 56.63 | 0.597 |
| | | *Std. Dev.* | *115.88* | *108.85* | *111.93* | |
| a6a | Size (sampling size) | % Small | 45.77 | 48.20 | 47.13 | |
| | | % Medium | 33.10 | 31.86 | 32.40 | |
| | | % Large | 21.13 | 19.94 | 20.47 | |
| b2a | Proportion of private domestic ownership (%) | Mean | 63.95 | 65.44 | 64.79 | 0.714 |
| | | *Std. Dev.* | *44.53* | *43.52* | *43.94* | |
| b2b | Percent of firms with at least 10% of foreign ownership | % | 22.54 | 23.06 | 22.83 | 0.737 |
| b2c | Percent of firms with at least 10% of government/state ownership | % | 0.35 | 2.22 | 1.40 | 0.013** |
| b1 | Percent of firms with legal status of: | % Shareholder company | 9.15 | 7.48 | 8.22 | |
| | | % Sole Proprietorship | 64.44 | 60.66 | 62.33 | |
| | | % Partnership or Limited partnership | 26.14 | 31.86 | 29.46 | |
| b8 | Percent of firms with an internationally recognized quality certification | % | 10.56 | 11.91 | 11.32 | |
| k21 | Percent of firms with an annual financial statement reviewed by external auditors | % | 44,37 | 45.71 | 45.12 | |
| d3c | Percent of firms with a direct export of at least 20% | % | 11.97 | 13.30 | 12.71 | 0.945 |

*Source: Author's calculations on ES data; *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01*

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