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Economic Complexity and Structural Transformation: The case of Mozambique

Bjørn Bo Sørensen*, Christian Estmann*, Enilde Francisco Sarmento+, and John Rand*

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* Development Economics Research Group (DERG), University of Copenhagen, Denmark.

+ National Directorate of Economic Policies and Development, Ministry of Economy and Finance (MEF), Mozambique.

Abstract: Mozambique is one of the world's least complex economies in terms of production sophistication and diversity. This paper identifies a set of new products that via targeted industrial policy could help diversify and upgrade the Mozambican economy. First, we take a supply-side perspective and use network methods from the literature on economic complexity to identify products that are complex, require productive capabilities useful in the export of other products, and are close to Mozambique's existing productive structure. Second, we use gravity equations to account for demand-side factors by modelling which export markets and products are most feasible for Mozambique to target given product-specific trade resistance and geographically dispersed demand. We find that the broad sectoral focus of Mozambique's industrial policy is consistent with a focus on structural transformation and export promotion. The current priority given to foodstuffs, metals, and chemicals is especially important, while there is unexploited opportunities in machinery, vehicles and transport equipment. We also find a significant potential for Mozambique to export target products to its neighbouring countries. The paper constitutes the first comprehensive study on economic complexity and structural transformation in Mozambique that systematically accounts for both supply and demand-side factors.

Key words: Economic complexity, trade, export upgrading, structural transformation, Mozambique

JEL classification:

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1 Introduction

Since its independence from Portugal in 1975, Mozambique has undergone several remarkable transformations. In the mid-1980s it transitioned from a planned to an open economy. The country achieved peace from a devastating war in 1992, and it introduced multi-party democracy in 1994. In the wake of these progressions, the Mozambican economy has grown at an impressive average annual rate around 7.8 per cent until 2016. The rapid growth in the past decades was partly a consequence of a very low base as a starting point: 44.4 per cent of the Mozambique's GDP per capita was destroyed between 1975 and 1986 as a consequence of the war (Cruz et al. 2018). It was, however, also fuelled by high inflows of foreign aid and foreign direct investments (FDI); investments in health, education, and infrastructure; institutional reforms; and good weather conditions (Cruz and Mafambissa 2016). In addition, a booming extractives sector and the Mozal aluminium smelter mega-project have driven a strong export growth. In 2015, however, Mozambique entered a macroeconomic crisis with a sharp decline in economic growth rates and an explosion of public debt, rising from 40 to 130 per cent of GDP since 2012 (Cruz et al. 2018; Dietsche and Esteves 2018).

In this paper, we argue that in order to achieve sustained economic growth in the future Mozambique needs to invest in the productive capabilities necessary for the country to diversify and upgrade its economy and export structure. The argument draws on economic complexity theory, stating that economic growth occurs as countries accumulate productive capabilities enabling them to produce and export a diverse set of complex products. Supporting the theory, empirical evidence shows that a country's diversification in sophisticated export products is a strong predictor of economic growth (Hidalgo and Hausmann 2009; Hausmann et al. 2013). The theory implies that economic growth follows a structural transformation process whereby productive resources are moved from low-complexity to high-complexity activities.

Nowhere is the quest for improving economic complexity more important than in Mozambique. The country remain one of the world's least complex economies despite past decades' impressive growth rates. That is, the majority of Mozambique's growth cannot be attributed to structural change. For instance, Jones and Tarp (2015) find that recent aggregate growth has been driven by productivity growth within the capital-intensive mining sector and by employment growth in low-productive service activities. Overall, though, labour reallocation have played only a modest role in Mozambique's post-conflict productivity growth and the majority of its labour force continuous to rely on low-productivity agricultural activities. To improve the prospects of sustained economic growth over the long-term, we argue that industrial policy needs to ignite structural transformation, not replicate previous decades' focus on attracting large-scale international investments into the extractive industries.

Recent government policies do acknowledge the need to move away from a reliance on primary commodity sectors and diversify export products and markets. The Industrial Policy and Strategy (2016-2025) has the objective to "make industry the main vehicle for achieving prosperity and well-being". It outlines seven priority sectors to achieve this goal: *i)* Food and agro-industry, *ii)* Clothing, textiles and footwear, *iii)* Non-metallic minerals, *iv)* Metallurgy and manufacture of metal products, *v)* Wood and furniture processing, *vi)* Chemistry, rubber and plastics, and *vii)* Paper and printing. These priority sectors are selected based on national priority, contribution to the current production level, the origin of raw materials used in production, job creation, import substitution, export potential, potential to generate upstream and downstream linkages, and ease of policy implementation.

In this paper, we identify an alternative set of new products and sectors that may be targeted by industrial policy with the explicit aim to diversify and upgrade Mozambique's economy and boost its export revenue. First, we take a supply-side perspective and use network methods from the literature on economic complexity to identify products that are complex, require productive capabilities useful in the export of other products, and are close to Mozambique's existing productive structure. We find that Mozambique's industrial policy is broadly in line with a structural transformation agenda – especially the priority given to agriculture and metal products. However, the sector identified to hold the largest potential for Mozambique – Machinery and electronics– is not currently prioritized in the Industrial Policy and Strategy (2016-2025). Products in this sector are complex, well-connected, and Mozambique is already exporting some of them, although without a revealed comparative advantage (RCA). Instruments[1] and Vehicles and transport equipment constitute two other product sectors identified to hold an unaddressed potential.

Second, we use gravity equations to account for demand-side factors by modelling which export markets and products are most feasible for Mozambique to target given product-specific trade resistance and geographically dispersed demand. The results indicate synergies between the structural transformation potential of different sectors and their exports potential. For current priority sectors, demand conditions for target products are particularly favourable in Agriculture, Metals, and Minerals. We also find the export potential to be very high in Machinery and electronics and Vehicles and transport equipment, underlining the need for industrial policy to consider their inclusion as priority sectors. In terms of export markets, we estimate that Mozambique's largest current trade partners are generally the ones with the highest potential to import its target products. The pay-off from export market diversification is, thus, limited. Yet, we do find a potential for Mozambique in exporting to its neighbours and other Southern African countries. Exploiting and expanding the free trade agreement under the South African Development Community (SADC) seem important for Mozambique to realise this potential, which deviates somewhat from the country's current trade strategies.

The paper draws on *theoretical ideas* from the literature on economic complexity, *methodological approaches* from empirical work on international trade (gravity models) and economic complexity (network science), and *empirical results* from previous literature attempting to identify key sectors in Mozambique's structural transformation process. We contribute directly to the latter two dimensions of the literature, but discuss all three in turn below.

Theoretically, our core argument relies on two seminal ideas developed in the literature on economic complexity. First, the wealth of nations is a function of the set of productive capabilities that countries possess and are able to combine for productive purposes. One can think of 'capabilities' as an umbrella-term capturing everything from the factors of production (labour and capital) to institutional quality and productive knowledge. Countries with more productive capabilities are able to produce many sophisticated goods and they tend to have a higher level of income (Hidalgo and Hausmann 2009). Second, this implies that countries diversify into new economic activities, undergo structural transformation, and grow when they acquire and combine capabilities in new ways (Hausmann and Klinger 2007; Hidalgo et al. 2007). This process of structural transformation is an incremental, path-dependent process due to two simple characteristics of productive capabilities. One, many capabilities are product specific due to phenomena such as asset specificity and tacit knowledge. Two, the capabilities employed in the production of different goods are complementary to varying degrees. It is thus less costly for countries undertake 'related diversification', gradually moving into economic activities similar to what they already know how to do. Besides path-dependency, the nature of productive capabilities also explains why the

[1] Identified instruments include *i)* Other parts for machines and appliances, *ii)* Machines for testing the mechanical properties of materials, *iii)* Musical instruments, wind, and *iv)* Instruments designed for demonstrational purposes (see Table A1-A4).

structural transformation process may entail hick-up problems for developing countries that only know how to produce goods, whose capabilities do not complement other activities (Hausmann and Klinger 2007; Hidalgo et al. 2007).

Methodologically, we propose a new method to rank the attractiveness of products and export destinations by combining the supply-side-focused complexity analysis with a structured demand-side analysis based on gravity models, ranking their revenue-generating trade potential. In combination, the two analyses constitutes a coherent methodological framework that considers both *i)* demand and supply-side factors, *ii)* the importance of diversification (extensive margin) and the export potential of new industries (intensive margin), and *iii)* the need for long-term structural transformation as well as the pressing issue of export revenue generation.

Our supply-side analysis follows the methodology employed in a number of studies taking the ideas in economic complexity as a starting point to guide industrial policies in developed and developing countries alike. Examples include policy-reports on the Netherlands (Hausmann and Hidalgo 2013), South Africa (Hausmann and Klinger 2006a), Rwanda (Hausmann and Chauvin 2015), Jordan (Hausmann et al. 2019), Panama (Hausmann, Morales, and Santos 2016; Hausmann, Santos, and Obach 2017), Myanmar (Ayres and Freire 2014), Uganda (Hausmann et al. 2014), and Southern Africa (Hidalgo 2011). The main objective in these studies is clear: in order to achieve economic growth countries need to diversify and upgrade their productive structure by acquiring new capabilities. While it is impossible to identify which exact capabilities are most important, it is possible to attach sets of capabilities to products and then target the products that rely on the most feasible set of capabilities. Specifically, industrial policy should ideally target products that force countries to acquire new and sophisticated capabilities (complex products) and products that ease further diversification by relying on capabilities that are useful in many different production processes. Importantly, however, industrial policy should simultaneously take into account what countries already know how to do well in order to maximize the efficiency of the structural transformation process.

The economic complexity methodology, and hence most of the empirical studies mentioned above, are silent on the question of which products (and destinations) hold the highest potential to generate export revenue. This is a non-trivial shortcoming, especially for countries like Mozambique, whose trade deficit and low GDP per capita forces government policies to favour interventions with a not-too-distant payoff. Evidently, addressing these issues is an important objective in the Industrial Policy and Strategy 2016-2025, which include export potential and import substitution as two core criteria in the selection of priority industries. We take a demand-side perspective to address this shortcoming, using gravity models from the international trade literature to map the export potential of products (and markets) in Mozambique. For instance, our estimates of a product's export potential is a function of importer-capacities in all countries other than Mozambique (such as country-product-specific demand and competition) and Mozambique's accessibility to those import-destinations (given by factors such as distance). The approach is closely related to work in the economic geography and trade literature that uses equations from trade models to measure "total demand exposure" in a location as a function of the demand from other locations and the accessibility of those (see for example Head and Mayer (2004), Redding and Venables (2004), and Hanson (2005)). In contrast to these studies that measure the total demand exposure across locations, we are only interested in the total demand exposure in Mozambique. Therefore, we let our estimates vary across products and attempt to single out the most important destination driving demand in Mozambique.

Empirically, the key products and sectors identified in this paper complements the results from previous studies aiming to identify important sectors in Mozambique's structural transformation process. Two sectors has gained particular attention in the literature. First, the benefits of developing the agricultural and agro-processing sectors have been analysed in a series of computable general equilibrium (CGE) studies. Jensen and Tarp (2004) estimate that simultaneous productivity improvements in Mozambique's agricultural sector and agro-industry sectors (food-processing and textiles) will lead to significant economic expansion, noting strong synergies in what they call an agricultural-development-led-industrialization strategy.[2] Other studies use dynamic CGE simulations to show that large-scale investments in the development of a biofuel sector in Mozambique has the potential to foster economic growth, increase employment, and reduce poverty (Arndt et al. 2010; Hartley et al. 2019). In general, these models corroborates our finding that investments in capabilities conducive to agriculture and agro-processing constitute a potentially important industrial strategy for Mozambique.

Second, the extractives sector in Mozambique has received much scholarly as political attention in recent years – especially since the discoveries of giant natural gas deposits in the Rovuma Basin since 2009. The net present value of the deposits has been estimated to be many times larger than Mozambique's current GDP (Toews and Vezina 2018) and their exploitation has the potential to strengthen economic growth and strengthen fiscal revenues. An IMF report even predicted that the new discoveries alone could boost the country's average real GDP growth rate to 24 per cent from 2021-24 (IMF 2016). Besides this direct effect, the impact of investment surges in the extractives sector on other sectors have been examined in several studies. Toews and Vezina (2018) show that the gas discoveries have generated a foreign direct investment (FDI) bonanza in non-extractive industries, potentially facilitating economic diversification. Dietsche and Esteves (2018) and Roe (2018) draw respectively on Mozambique's current policies and experiences from other developing countries to appraise the prospects of economic diversification fuelled by extractive industries through backward and forward linkages to the rest of the economy. Their conclusions vary from scepticism to cautious optimism. The analysis in this paper lends support to a sceptic position: we do not identify the extractives industry as an important driver in Mozambique's structural transformation process because they generally produce unsophisticated products that do not rely on capabilities complementary to those in other sectors.[3] Instead, the analysis in this paper identifies Machinery and electronics as a key industry for Mozambique. Machinery products are complex, rely on many widely useful capabilities, and they have a high export potential in Mozambique. In addition, Mozambique already has some exports in the sectors, hinting at the viability of the sector. This finding constitutes a significant contribution, as machinery does not feature on the list of priority sectors in the country's Industrial Policy and Strategy 2016-2025.

The rest of the paper is organized in three sections. Section 2 lays forth the supply-side analysis. Here, we first describe the data and methodology, before we identify target products that are feasible for Mozambique to move into as a part of its structural transformation process. The demand-side analysis is presented in the third section. We first describe the data and methodology applied to run gravity models, before we use these models to rank Mozambique's target products in accordance with their export potential. In the final section, we discuss on conclude on our findings.

[2] A recent study by Mondlane and van Seventer (2019) also finds the food-processing sector to be attractive from a distribution point of view. Based on a SAM multiplier model they find that an exogenous expansion of the sector has a strong potential to raise income in poor rural households.

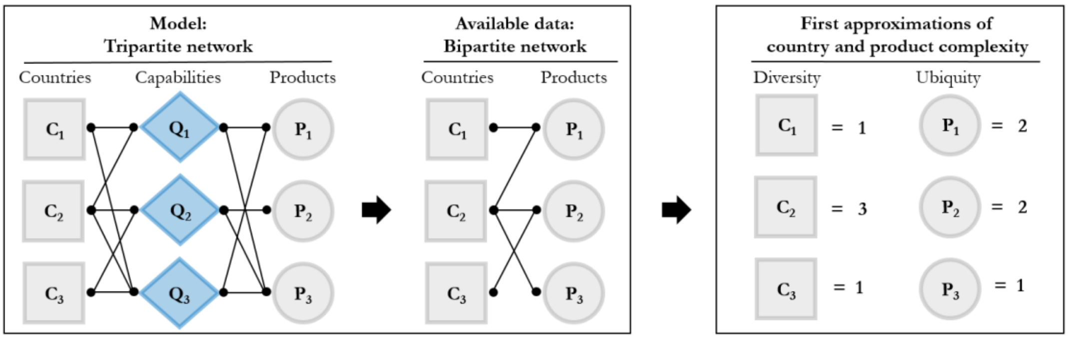
[3] That is not to say that we dismiss the significance of the extractive sector or deny its potential to boost fiscal revenues and growth over the coming decades. Rather, we argue that the enclave-characteristic of the sector means that its take-off is unlikely to drive structural transformation. Industrial policy targeting the sector for its transformative power is likely misguided.

2 Supply-side analysis

2.1 Data

The supply-side analysis is built on country-product level world trade data from United Nations Statistical Division (COMTRADE) and cleaned by The Growth Lab at Harvard University using the Bustos-Yildrim Method (2019). The method exploits the fact that trade flows are reported twice (once by exporters, once by importers) to correct for inconsistencies in reporting while taking into account the reliability of each countries' trade records. After dropping observations on services and products not specified according to kind, the dataset covers 242 countries and 1241 products from 1995-2018 using 4-digit product codes from the 1992 revision of the United Nations Harmonized System (HS). We undertake an additional cleaning process in order to reduce noise in the data. First, we drop all products with global exports of less than USD 10 million on average from 2015-18. Second, we exclude countries exporting less than USD 1 billion on average over the same time-span. We further use population data from the World Development Indicators (World Bank 2020) to drop all small countries with less than 1.25 million inhabitants in 2018 (including countries with no population data).[4] Fourth, we drop Chad, Iraq, and Macau due to questions on unreliable trade data (Hausmann et al. 2013). Finally, we keep only countries with trade data in all years. Our final sample covers 131 countries and 1221 products.

Figure 1: The hidden capabilities layer



Source: From Sørensen (2020), originally based on Cristelli et al. (2013).

2.2 Methodology: economic complexity

Measuring the complexity of countries and products

Quantifying something as fuzzy as the set of capabilities different countries' hold, and the capabilities it take to produce and export different products, is naturally a tricky exercise. While the exact method applied in the literature varies (see Hidalgo and Hausmann (2009) and Tacchella et al. (2012) for two prominent examples) they all build on the same intuition. Countries are connected to products via capabilities in a tripartite network as shown in Figure 1. While it is impossible to observe these capabilities directly, it is possible to infer the amount of complementary capabilities layered in countries and products through a bipartite network linking countries to the products they are able to export. Saltarelli et al. (2020) find that countries' export patterns mirrors their domestic production structures in manufacturing and sectors producing physical goods. This indicates that countries' exports serve as reasonable approximations not only of their *export capabilities*, but of their *productive capabilities* (economic complexity) in general. Countries able to export many products can be assumed to possess a larger set of complementary

[4] Applying a population threshold between 1.2 and 1.25 million is standard in the literature (see for example Albeaik et al. (2017) and Hausmann et al. (2013)).

capabilities. A first approximation of countries' complexity is therefore their export diversity. On the other hand, products exported by only a few countries are likely to require many hard-to-acquire capabilities. The ubiquity of products (i.e. the number of countries able to export them) can therefore be assumed to be inversely correlated to their complexity.

We follow the approach in Hausmann et al. (2013) and construct the country-product adjacency matrix M from international trade data. Each row represent a country c and each column a product p. We define a country to be linked to a product if it exports that product competitively. Formally, each element in the adjacency matrix, M_{cp}, take the value of one if c has a revealed comparative advantage (RCA>1) in exporting p at time t or an average over the past four years, and zero otherwise:

$$M_{cp} = \begin{cases} 1 \quad if \quad RCA_{cp}^{t} > 1 \quad or \quad \left(\frac{1}{4}\sum_{i=0}^{4} RCA_{cp}^{t-i}\right) > 1 \\ 0 \quad otherwise \end{cases} \tag{1}$$

where

$$RCA_{cp}^{t} = \frac{X_{cp}^{t}}{\sum_{c} X_{cp}^{t}} / \frac{\sum_{p} X_{cp}^{t}}{\sum_{c,p} X_{cp}^{t}} \tag{2}$$

and X^{t}_{cp} is country c's total export of product p at time t. When calculating RCA_{cp}^{t}, we follow the standard set by Hausmann et al. (2013) and average the denominator over three years. Yet, we also smooth the entire RCA_{cp}^{t} over four years when populating the adjacency matric - equivalent to the length of the average business cycle in many developing countries (Rand and Tarp 2002) – to avoid a scenario where it drops below the threshold of one in a given year due to world price fluctuations, exchange rate volatility, or business cycles. Going forward we drop the time-period subscripts to avoid notational clutter, but the variables remain time-dependent.

From M we can formally derive the diversity of countries and the ubiquity of products in each time period:

$$Diversity = k_{c,0} = \sum_{p} M_{cp} \tag{3}$$

$$Ubiquity = k_{p,0} = \sum_{c} M_{cp} \tag{4}$$

Ubiquity and diversity are, of course, imperfect approximations of product and country complexity. Take diamonds as an example. Only a few countries are able to export them, but they are not especially difficult to mine and they are often exported by countries (such as Botswana) that do not export many other goods. To account for these inconsistencies, it is possible to correct our initial proxy for the complexity of diamonds by accounting for the diversity of the countries producing diamonds. Similarly, we can correct our initial country complexity measure by accounting for the ubiquity of the products that a country is able to produce. Put differently, it is possible to use one of the above equations to correct the other through an algorithm that jointly and iteratively calculates the average value of the measures obtained in the previous iteration of the algorithm. This approach is called the Method of Reflections (Hidalgo and Hausmann 2009) and can by mathematically formulated as:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \, k_{p,N-1} \tag{5}$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_c M_{cp}\, k_{c,N-1} \tag{6}$$

where $k_{c,N}$ and $k_{p,N}$ are country and product complexity after N iterations of the algorithm. Inserting Equation 6 into 5:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} \frac{1}{k_{p,0}} \sum_{c'} M_{c'p}\, k_{c',N-2}$$

$$k_{c,N} = \sum_{c'} k_{c',N-2} \sum_p \frac{M_{c'p}\, M_{cp}}{k_{c,0} k_{p,0}}$$

$$k_{c,N} = \sum_{c'} k_{c',N-2}\ \widetilde{M}^C_{c,c'} \tag{7}$$

where

$$\widetilde{M}^C_{c,c'} = \sum_p \frac{M_{c'p}\, M_{cp}}{K_{c,0} K_{p,0}}$$

Notice that the solution to Equation 7 can be formulated as an eigenvector problem. We first write Equation 7 in vector notation:

$$\vec{\mathbf{k}}_{\mathrm{N}} = \widetilde{\mathbf{M}}^{\mathrm{C}} \times \vec{\mathbf{k}}_{\mathrm{N-2}} \tag{8}$$

where $\vec{\mathbf{k}}_{\mathbf{N}}$ is a vector whose cth element is given by $k_{c,\,N}$ and $\widetilde{\mathbf{M}}^{\mathbf{C}}$ is a matrix with the (c,c')th element given by $\widetilde{M}^C_{c,c'}$. Taking N to infinity (equivalent of running an algorithm for ∞ iterations), there is a perfect rank correlation between $\vec{\mathbf{k}}_{\mathbf{N}}$ and $\vec{\mathbf{k}}_{\mathbf{N-2}}$. In other words, $\vec{\mathbf{k}}$ remains fixed up to a scalar factor, λ:

$$\widetilde{\mathbf{M}}^{\mathrm{C}} \times \vec{\mathbf{k}} = \lambda \vec{\mathbf{k}} \tag{9}$$

It follows that $\vec{\mathbf{k}}$ is the eigenvector of $\widetilde{\mathbf{M}}^{\mathbf{C}}$ and λ is the corresponding eigenvalue. The eigenvector capturing the largest variance in the system is the one associated with the second largest eigenvalue (the eigenvector associated with the largest eigenvalue is just a vector of ones). This vector is defined as the Economic Complexity Index (ECI) for countries (Hausmann et al. 2013). We use the ECI to obtain the Product Complexity Index (PCI) by substituting ECI for $k_{c,\,N-1}$ in Equation 6.[5]

Measuring the relatedness of, and distance to, products

To construct a measure of the degree to which products hold complementary capabilities, we construct the Product Space network following Hidalgo et al. (2007). In this network, each node represents a product and each weighted link measures the proximity between two products, that is, the extent to which they rely on similar capabilities. Proximities are calculated based on the simple idea that if many countries exporting one product are simultaneously able to export another, these two products must rely on many complementary capabilities. Technically, we estimate the

[5] This is equivalent to repeating the procedure above, plugging Equation 5 into 6, and obtaining the eigenvector associated with the second largest eigenvalue.

proximity φ between product p and p' as the minimum of the pairwise probabilities that a country c exports one of the products with a RCA above one, given that it also exports the other with a RCA above one:

$$\varphi_{p,p'} = \min\{P(M_{c,p} = 1 | M_{c,p'} = 1), P(M_{c,p'} = 1 | M_{c,p} = 1)\} \tag{10}$$

which is equivalent to

$$\varphi_{p,p'} = \frac{\sum_c M_{c,p} M_{c,p'}}{\max(k_{p,0} k_{p',0})}$$

where M is the matrix described above and $k_{p,0}$ is the ubiquity of product p as defined in Equation 4.

To capture the "capability gap" between a particular product p and a country *c's* current productive knowledge, we calculate a measure of distance, $d_{c,p}$, to product p. It is the sum of proximities between p and all the products that country c is currently not making, normalized by the sum of proximities between product p and all other products:

$$d_{c,p} = \frac{\sum_c (1 - M_{c,p'})\, \varphi_{p,p'}}{\sum_{p'} \varphi_{p,p'}} \tag{11}$$

Measuring opportunities for further diversification

Since export diversification and upgrading is a path-dependent process, it is important to quantify whether Mozambique is well-positioned in the Product Space allowing it to easily jump into new and complex products. To do so, we construct the Complexity Outlook Index (COI) for country c following Hausmann et al. (2013):

$$COI_c = \sum_p (1 - d_{c,p})(1 - M_{c,p}) PCI_p \tag{12}$$

where $d_{c,p}$ is the distance for country c to product p, M is the country-product matrix, and *PCI* is the Product Complexity Index defined above. *COI* measures how close a country's current capabilities lie to not-yet-produced products, weighted by the complexity of those products. A high *COI* means that a country is well-positioned to diversify into new and complex export products.

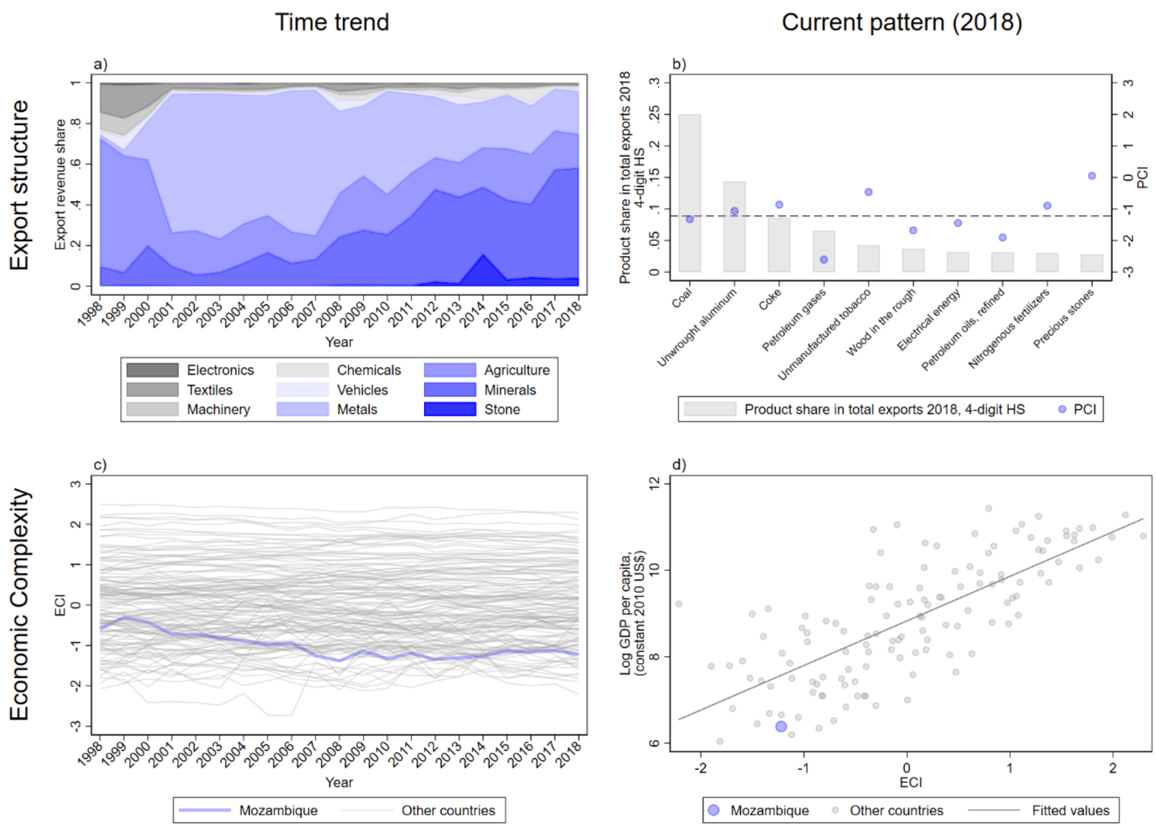
It is also possible to calculate how much a particular not-yet-produced product p would add to country *c*'s diversification options. The Opportunity Gain Index (OGI) measures the how much *COI* would change for country c if it were to acquire the capabilities necessary to export product p competitively. Formally, we define OGI as:

$$OGI_{c,p} = \sum_{p'} \frac{\varphi_{p,p'}}{\sum_{p''} \varphi_{p',p''}} (1 - M_{c,p'}) PCI_{p'} \tag{13}$$

2.3 A history of economic complexity in Mozambique

In this section, we draw on the variables and networks presented above to provide a brief overview of Mozambique's past and present export structure and economic complexity, while subsequently discussing the country's potential for future diversification.

Figure 2: Current and historical exports patterns and economic complexity in Mozambique

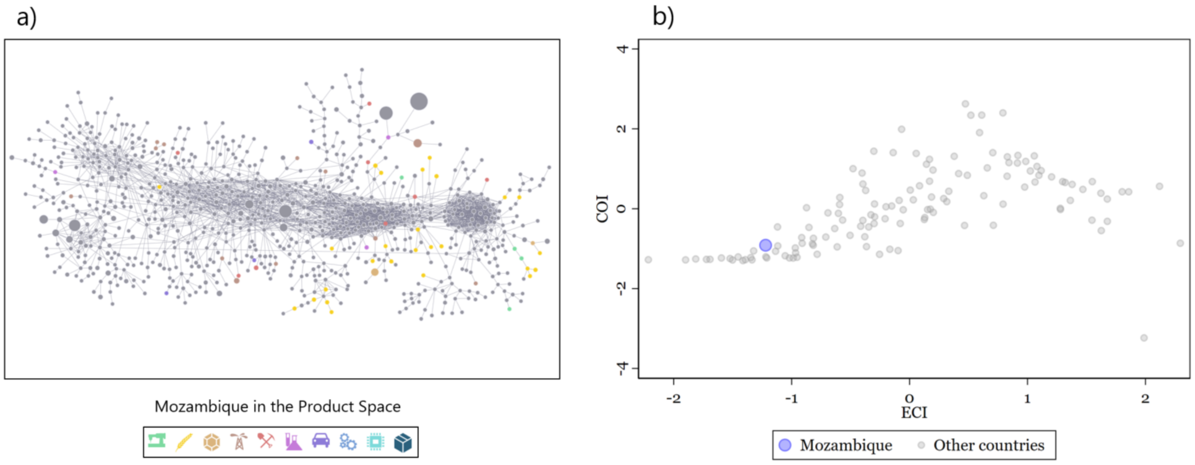


Notes: a) Products are grouped in accordance with the approach outlined in Harvard's online Atlas of Economic Complexity (2019). Product group 'Other' is left out of the figure. Each product group's share is calculated based on the total export volume of included products.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019) and World Development Indicators (World Bank 2020).

Since the peace deal in 1992 and the turn to multi-party democracy in 1994, Mozambique has experienced impressive economic growth. Yet, the economic growth has not been followed by structural change. The country's export dynamics over the past decades pay testimony to this structural deadlock. On one hand, Mozambique has seen strong growth in export volumes. Volume growth has primarily been driven by exports of unwrought aluminium from the Mozal aluminium smelter at the turn of the millennium and the gradual take-off of the country's fossil fuels exports. These shifts are clearly visible in Figure 2.a, showing the split between the country's exports in primary product sectors from 1998-2018. The product sector contributing most to export revenues has changed from agriculture (mainly crustaceans, cashew nuts, and wood), through metals (almost exclusively unwrought aluminium), and finally to minerals (primarily fossil fuels such as petroleum oil and gasses, coke, and coal). On the other hand, Mozambique's portfolio of exported products has not changed substantially from an economic complexity point of view. The combined share in total exports of low-complexity natural resources and primary commodities has remained high and constant over time (approximately 90%). It is not just that Mozambique's export basket is, and has been, unsophisticated. It is also undiversified. In 2004, unwrought aluminium accounted for more than 65% of total exports. In 2018, almost 75% of the country's exports came from just 10 products (see Figure 2.b). These products all have PCI scores at or below average (zero) and do not substantially add to the complexity of the Mozambican economy as a whole. Thus, industrial policies focused on the intensive margin of trade, that is, boosting the export volume of these marque products may increase Mozambique's export revenues, but they will not increase the country's economic complexity.

The trends described above signals that Mozambique has been unable to acquire the new productive capabilities necessary to diversify and upgrade its export basket. As a consequence, the country has remained one of the world's least complex economies for the past 20 years (see Figure 2.c). In fact, its position in the economic complexity index has worsened since 1998, dropping from the 93th to 117th place out of 131.[6] This has clear consequences for economic development. Figure 2.d plots the positive relationship between GDP per capita and ECI. Complex countries enjoy a higher standard of living. Although Mozambique ranks among the worst performers on both scales, the graph also paint an optimistic picture of the future growth potential of Mozambique. In short, ECI has been shown to be a key determinant of economic growth as countries tend to converge towards the values predicted by the simple linear fit shown in the figure (Hausmann et al. 2013). That is, the residuals hold information about countries' future growth rates. Countries located under the regression line – like Mozambique – have a lower level of GDP per capita than what is expected given their current capabilities. On average, these countries are projected to enjoy higher future growth rates than the countries above the regression line (Hausmann et al. 2013). On one hand, this indicates that Mozambique may enjoy high growth rates in the coming years. On the other hand, it also implies that the country is even better set up for growth if it is able to increase its economic complexity further.

Figure 3: Mozambique's opportunities for structural transformation (2018)



Notes: a) Each node represents a product at the HS 4-digit level (rev. 92). Nodes are connected based on the similarity of the capabilities it takes to export them. Each node is sized in proportion to world trade in that product. Coloured nodes represents products that Mozambique exported with a RCA>1 in 2018.
Source: a) From the Online Atlas of Economic Complexity (2019). b) Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Given the current structure of Mozambique's economy, how is the country positioned to diversify, upgrade, and increase its level of economic complexity? Figure 3.a shows that Mozambique's exports are located in the outskirts of the Product Space (only products where Mozambique has a

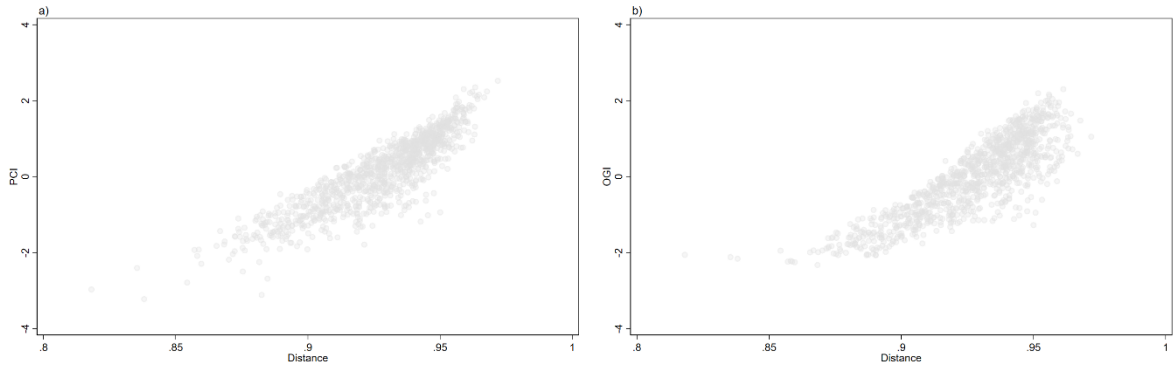
[6] Authors' own calculations based on based on trade data from The Growth Lab at Harvard University (2019).

RCA>1 are coloured). Thus, the products Mozambique currently knows how to export require very few capabilities that are useful in order to export other products. Consequently, it will be very difficult for Mozambique to learn to export many new and sophisticated products, suggesting that its road to a complex economy is challenging. This idea can formally be measured through the COI (Equation 12), indicating the extent to which countries are located close to new products, weighted by the complexity of those products. Figure 3.b shows the relationship between countries' COI and ECI. It is clear that Mozambique is poorly positioned to diversify into complex products when compared to other countries. That said, the inverted U-shaped relationship between COI and ECI indicates that the opportunities for diversification tends to increase as low-complexity economies acquire more and more productive capabilities. In other words, it is potentially very rewarding to accept the initial cost necessary to acquire new capabilities to produce new products, because it lowers the cost of future diversification.

2.4 Selecting target products

In order to increase Mozambique's economic complexity, industrial policies should ideally support the production of highly complex product (high PCI) and products that rely on capabilities used in many other products, thereby opening up paths to future diversification (high OGI). Unfortunately for Mozambique, products with these characteristics tend to lie further away from its current productive knowledge (measured by distance, $d_{c,p}$, from Equation 11). Figure 4 visualizes the trade-off between PCI/OGI and distance. Each dot in the figure represents one of the 1,111 products that Mozambique did not produce with a RCA>1 in 2018.

Figure 4: Mozambique's trade-off between a) PCI and Distance and b) OGI and Distance



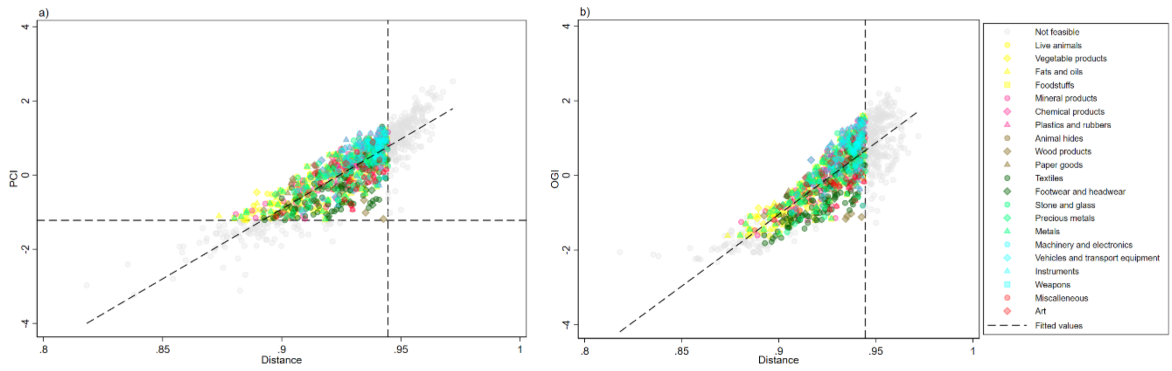
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

In the following, we identify a broad set of "feasible products" given the criteria mentioned above. We also discuss how to narrow the set of feasible products down to a set of "target products" using weights.

Feasible products

To identify feasible products, we apply a two-step filter to discard some of the 1,111 products depicted in Figure 4. Our approach, and the final set of feasible products, are depicted visually in Figure 5. First, we remove all products with a complexity score lower than Mozambique's level of complexity. These products rely on unsophisticated capabilities that will not help Mozambique upgrade its productive structure. Second, we follow the approach in Hausmann and Chauvin (2015) and remove products with very high-distance scores. These products are so detached from Mozambique's current productive knowledge that it would be very difficult and costly to attain the full set of capabilities needed in their production. Specifically, we remove all products beyond the 75th percentile (this is a judgement call, as no clear cut-off exists). We define Mozambique's feasible products as the ones that are highlighted in both Figure 5.a and 5.b.

Figure 5: Identifying the set of feasible products for Mozambique



Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Choosing a weighting scheme

The filtering process described above is clearly inadequate. While it narrows Mozambique's feasible Product Space down to a set of 731 attractive products, it is too broad for meaningful policy targeting. Therefore, it is necessary to device an identification procedure to select a smaller number of "target products" from the pool of "feasible products". One intuitive way to do this is to exclusively focus on products lying above the fitted lines in Figure 5. Investing in a product lying under the line is inefficient, as it would always be possible invest in another product located at a similar distance with a higher PCI/ OGI. This approach is, however, still too broad, classifying 388 products as feasible. Furthermore, such approach does not take an active stand on whether Mozambique should put a higher value on a low distance, a high PCI, or a high OGI.

Following the approach adopted in the literature (see for instance Hausmann et al. (2014), Hausmann and Chauvin (2015), and Hausmann et al. (2019)), we address these issues by assigning a weight to each variable. The weighting scheme-approach entails creating a new index in which each products' score is computed based on a weighted sum of the normalized values of distance, PCI, and OGI. Normalizing the variables makes it possible to compare the variables directly and assign an importance to each through weights.[7] In this way, it is possible to reduce the dimensionality of the problem and conduct a comparison at the product-level. Note that when we talk about assigning a weight to distance, we are in fact assigning a weight to its inverse, density, measuring Mozambique's closeness to a product. From the new summary index, it is possible to select any number of target products, always including the products that score highest in the index. Specifically, we create two indexes based on two weighting strategies – a Leverage & Support

[7] Specifically, we apply the following normalization procedure:

$$var_p^{norm} = \frac{var_p - var^{mean}}{var^{sd}},$$

Where var_p denotes the non-normalized value either distance, PCI, or OGI for product *p*. var_p^{norm} is the normalized value of var_p. var^{mean} and var^{sd} is the mean and standard deviation of var, respectively. The normalization gives each variable (distance, PCI, and OGI) a mean of zero and a standard deviation of one.

strategy and a Diversify & Scale strategy – picking the 25 most important products from each (see Table 1 below).

Table 1: Weighting scheme

Strategy	Component	Weights		
		Distance	PCI	OGI
Leverage & Support (0.1<RCA<1)	Low-Hanging Fruits	0.45	0.25	0.30
	Strategic Bets	0.20	0.20	0.60
Diversify & Scale (RCA<0.1)	Low-Hanging Fruits	0.65	0.15	0.20
	Strategic Bets	0.50	0.10	0.40

Source: Authors' own creation.

The main issue with the weighting scheme-approach lies in the selection of feasible weights. Previous studies sharing our approach have constructed weighting schemes more or less arbitrarily (see for instance Hausmann et al. 2017). As no better selection strategy is currently available, we follow this approach, but find it necessary to stress that the choice of weights in this paper remain more an art than a science – they stem from a somewhat subjective and political choice. We motivate the choice of weights by three simple propositions informed by theory, empirical analyses, and Mozambique's industrial strategy. These are describe below. To be as transparent as possible, we conduct a volatility analysis showing how the choice of target products vary with changing weights, described in the last subsection of the supply-side analysis.

Proposition 1: It is easier for Mozambique to develop a comparative advantage in a product if it already exports that product (without a revealed comparative advantage). Furthermore, distance matters less for Mozambique's ability to gain a comparative advantage in a product if it already exports that product non-competitively. Therefore, Mozambique should employ two weighting schemes. One weighting scheme should target products where Mozambique has no current exports, giving a higher weight to nearby products. We call this weighting scheme the Diversify & Scale strategy as it focuses on identifying completely new product sectors that Mozambique can diversify into. Another weighting scheme should target products that Mozambique currently exports non-competitively, where distance has a smaller weight and PCI and OGI are weighted higher. We call this second weighting scheme the Leverage & Support strategy because it focuses on identifying, leveraging, and supporting the capabilities that already allow Mozambique to export certain products with an RCA below one.

Proposition 1 is rooted in the simple idea that market actors can be assumed to have better information about the potential for exporting new products in Mozambique than the state. The analysis in this paper does not change this. Therefore, industrial policies should utilize market signals to identify product sectors that show export potential and then address the key constraints and enablers necessary to develop a comparative advantage in these sectors.

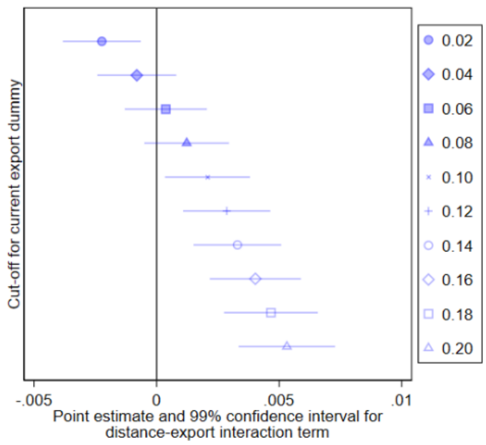
We test the intuition behind Proposition 1 in Table 2. It shows the results from a linear probability model predicting product appearances between 2015-18 based on 2014 values of distance and a dummy variable, D^{Export}, taking the value one if Mozambique's RCA in a product was between 0.1 and 0.99 in 2014. The dependent variable, product appearances, takes the value one if a product was absent (RCA<1) from a country's export basket in year *t-1* but appeared (RCA>1) in year *t*. We run the regression only on products that were absent in 2014. The model fits our intuition. Column 1 shows that countries are less likely to move into distant products, but more likely to gain a comparative advantage in a product, if they are already exporting that product non-competitively. In the regression, we have standardized the distance variable to have a mean of zero and a standard deviation of one. Thus, a country that is one standard deviation further away from a product has a 0.03 lower probability of starting to export that product with a comparative advantage over the coming four years. In the second column, we introduce an interaction term, showing that the negative effect of distance on product appearance is less pronounced if the product is already exported in a country.

In order to reduce noise and actually measure whether a product is already established in a country, we let D^{Export} equal one only if 0.1>RCA<1. To check the robustness of the coefficient of the interaction term with respect to this cut-off, Figure 6 displays the coefficient plot for varying cut-offs. The plot indicates that the interaction term remains positive and significant (at the 1 per cent level) with a cut-off above 0.1. We will therefore use the 0.1 cut-off to distinguish between products in our two weighting strategy. For products with 0.1>RCA<1, we give a lower weight to distance. It should be noted that by setting a threshold as low as 0.1 to classify established export industries, we run the risk of assuming that Mozambique has capabilities in products that are in fact not produced in the country, but are imported and re-exported. We do not have data to directly check for re-exports and the results in our analysis should therefore be interpreted with this caveat in mind. The positive and significant coefficient in Table 2 does, however, provide evidence that *on average* countries find it easier to jump long distances when they already have exports above this our RCA cut-off. Guided by these results, we find it reasonable to assume that exports with an RCA above 0.1 is indicative of established export capabilities in that product.

Table 2: Effect of current exports and distance on product appearances

	Product appearances (2015-2018)	
	(1)	(2)
Values in 2014:		
Distance	-0.030***	-0.031***
	(0.001)	(0.001)
D^{Export}	0.025***	0.025***
	(0.001)	(0.001)
Distance *x* D^{Export}		0.002***
		(0.001)
Year FE	YES	YES
Country FE	YES	YES
Observations	527,008	527,008
R-squared	0.017	0.017

Figure 6: Coefficient plot of Distance *x* D^{Export} interaction term



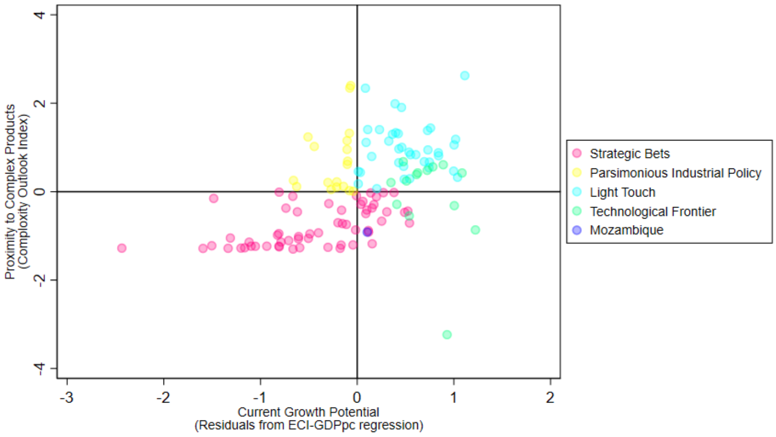
Notes: Table 2 reports robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Constant not reported. The value of Distance has been standardized.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Proposition 2: Industrial policy in Mozambique need to strike a balance between the policy objective of relatively quick and low-cost implementation and the potential for higher pay-offs in the future. To strike this balance, the weighting strategy should be split into a Low-Hanging Fruits component, where distance and PCI has a higher weight, and a Strategic Bets component, valuing long jumps into highly high-OGI products.

On one hand, Mozambique's industrial policy favours industries "whose implementation and resource allocation can develop relatively quickly" (GoM 2014). A strategy focusing on nearby products with (relatively) high PCI-scores is likely to satisfy this policy objective. First, the strategy should put a high weight on distance. Since Mozambique already possesses some of the capabilities necessary to move into nearby products, the cost of investing in the few missing links is relatively small. Furthermore, the timeline for a structural transformation process allocating factors of production to higher-complexity activities in nearby products is likely to be shorter because the productive structure of the economy does not need to change dramatically. Second, the strategy should put a relatively higher weight on high PCI products, because these will increase Mozambique's complexity immediately. High OGI products, on the other hand, influence the prospects of future diversification, but do not necessarily deliver a complexity-premium themselves.

On the other hand, theory prescribes that Mozambique to experiment with the development of comparative advantages in dense parts of the Product Space further away from its current productive structure. This argument is based on the idea that the strategic focus of industrial policy should take into account that different countries are positioned differently with respect to their opportunity to *i)* diversify and upgrade and *ii)* achieve economic growth (Hausmann et al. 2016; The Growth Lab at Harvard University 2020). Figure 7 plots countries along these two spectres. The y-axis measures how close countries are to not-yet-produced, complex products in the Product Space (COI). The x-axis measures how much countries are projected to grow, given their current GDP per capita and ECI (measured by residuals when regressing ECI on the log of GDP per capita).[8]

Figure 7: Strategic approach



Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Countries in the upper-left quadrant of this two-by-two matric should pursue a *parsimonious industrial policy*. These countries are projected to grow slowly, as they currently have a higher GDP per capita than what is warranted by their ECI. Luckily, however, the countries are located close to many complex products and their main aim should therefore be to leverage this position in order to increase their complexity. For these countries, PCI should have a relatively higher weight. Countries in the upper-right corner are placed in a "sweet-spot" close to many complex products and yet already complex enough to grow in the future. Here, governments should apply a *light touch approach*, with a balanced weighting strategy. The countries coloured in green are highly complex countries (in the 90th percentile in terms of ECI). Having exhausted most possibilities for diversification and upgrading, these countries' *frontier approach* should focus on innovation, developing entirely new products. Finally, countries placed in the lower two quadrants of the matrix are located in the outskirts of the Product Space, far from any complex cluster of products. These countries should follow a *strategic bets approach,* experimenting with long jumps into well-

[8] In contrast to Figure 2.d, positive residuals from this regression are indicative or higher economic growth rates.

connected parts of the Product Space. Thus, these countries should prioritize OGI over distance and PCI (relative to other strategies) (Hausmann et al. 2016; The Growth Lab at Harvard University 2020). Mozambique, depicted in blue, should follow this strategic bets approach.

Proposition 3: Market actors have an incentive to move into highly complex products, but a weaker incentive to move into products connected to other complex products (high externality products). Because market actors can be expected to internalise the value of PCI, but OGI to lesser extent, our weighting scheme should put a higher weight on OGI as a general rule of thumb.

Consider the simple model developed in Hausmann and Klinger (2006b), where a firm can either stick to producing product *p* or jump to a new product *p´*. The firm has an incentive to jump, if it can earn a higher price by producing product *p´*. We can assume this is the case if $PCI_{p'}>PCI_p$. However, the firm will also face a fixed cost of jumping from *p* to *p´*, because it has to acquire the new capabilities necessary to produce product *p´*. This fixed cost increases with the distance between the products, $d_{p,p'}$. The firm only jumps if the benefits of doing so outweighs the costs.[9] However, it might be socially optimal if the firm jumps, even if it incur a loss, if externalities reduce the cost of jumping into the same or related products for emulating firms. Such spillovers occur, for instance, through labour mobility.[10] Because the societal value generated by investing in a new product is not fully appropriated by the original firm, underinvestment is likely to occur in the competitive equilibrium.[11] In order to spur externalities and reach socially optimal investment levels, industrial policies should put a higher weight on the factors the market do not value appropriately (OGI). [12]

Table 3: Effect of distance, PCI, and OGI on product appearances

	Product appearances (2015-2018)			
	(1)	(2)	(3)	(4)
Distance (2014)	-0.043***			-0.044***
	(0.001)			(0.001)
PCI (2014)		-0.003***		0.002***
		(0.000)		(0.001)
OGI (2014)			-0.004***	-0.002**
			(0.000)	(0.001)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	527,008	527,008	527,008	527,008
R-squared	0.011	0.006	0.006	0.011

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Constant not reported. The values of Distance, PCI, and OGI have been standardized.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

[9] Empirically, product switching has been shown to be substantial in the US (Bernard, Redding, and Schott 2010), but in a developing country context results are more unclear (Goldberg et al. 2010) and Newman et al. (2013).

[10] Imagine if the firm wants to produce non-alloy steel in a country that has not done so before. It may have to invest heavily in the training of mechanical engineers to operate the smelters. These engineers may later be hired by emulators, when they realize that it is profitable to produce non-alloy steel in the country. The engineers may also be hired by another firm capitalising on the local supply of non-alloy steel to make wrought iron products in the country.

[11] A slightly moderated version of the model is found in Hausmann and Klinger (2007). The main conclusion remain intact.

[12] Notice that market actors are likely to assign some (inadequate) value to high-OGI products. If a firm plans to jump into several new products sequentially, it has an incentive to land the initial jumps in products that are better connected to other highly complex products. Because the model of Hausmann and Klinger (2006b) is a model of overlapping generations considering only two time periods, it does not explicitly address this scenario.

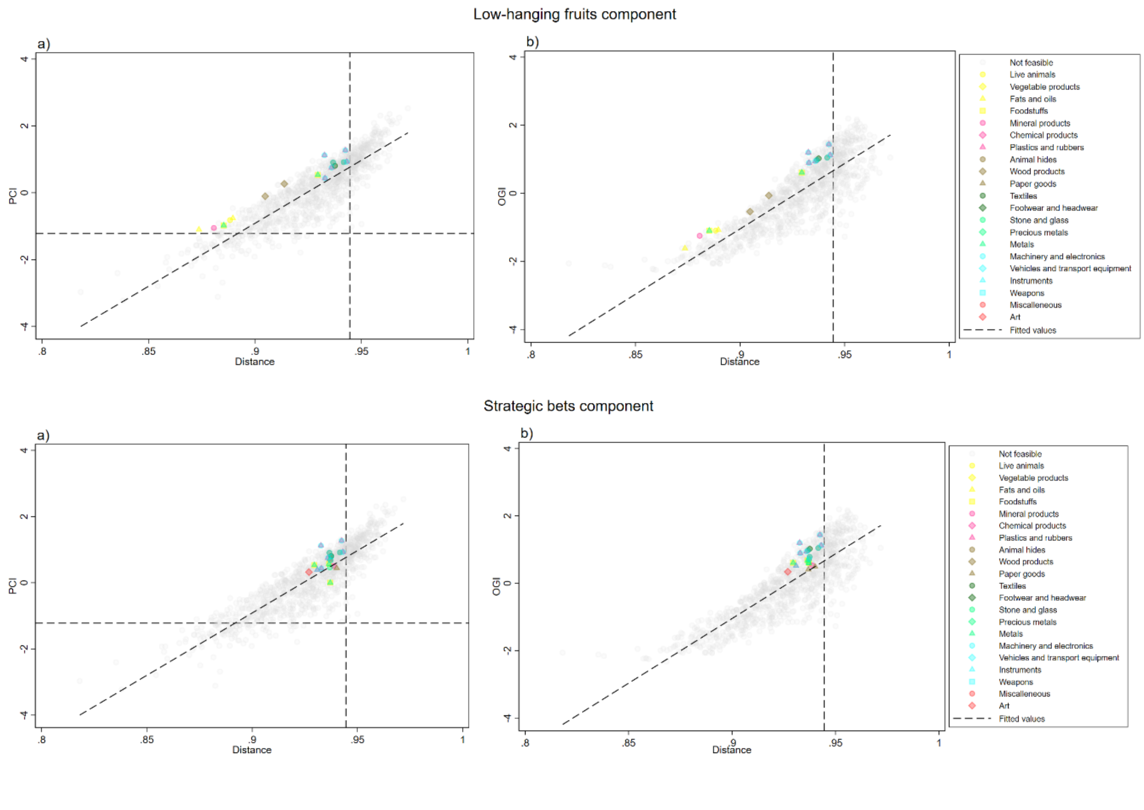
We take this idea to the data in Table 3. It shows the results from the linear probability model described above, but with 2013 values of distance, PCI, and OGI as explanatory variables. All variables are standardized and the interpretation of the coefficients are as described for Table 2 above. As we would expect, when holding distance constant, countries are more likely to move into products with high PCI scores. The same is not true for OGI. The negative coefficient shows that the probability of moving into a new product is negatively correlated with OGI. This confirms that OGI should be weighted higher than PCI.

Based on Proposition 1, 2, and 3, we adopt the weighting strategies shown in Table 1. Following Proposition 1, the strategy takes into account that Mozambique should have two overall strategies – a Leverage & Support strategy focused on already exported products and a Diversify & Scale strategy focused on developing completely new products. A higher weight is given to distance in the latter strategy. Based on Proposition 2, we split each strategy into a *Strategic Bets* and a *Low-Hanging Fruits* component in order to balance a long-term strategic focus with the objective of easier implementation and a quick transition. We assign relative high weights to distance and PCI in the latter component. Finally, because of the large externality-component in OGI, our approach always assigns higher weights to OGI compared to PCI.

Target products

We identify 25 products from each of the four strategy-component combinations listed in Table 1. Because the Low-Hanging Fruits and Strategic Bets components of each strategy identify some of the same target products, we end up identifying 84 target products for Mozambique. Figure 8 and 9 show these 84 target products, while Figure 10 counts the total number of target products identified within each product section. Tables A1-A4 in the appendix provide the full list of products for each strategy-component combination.

Figure 8: Target products in Leverage & Support strategy

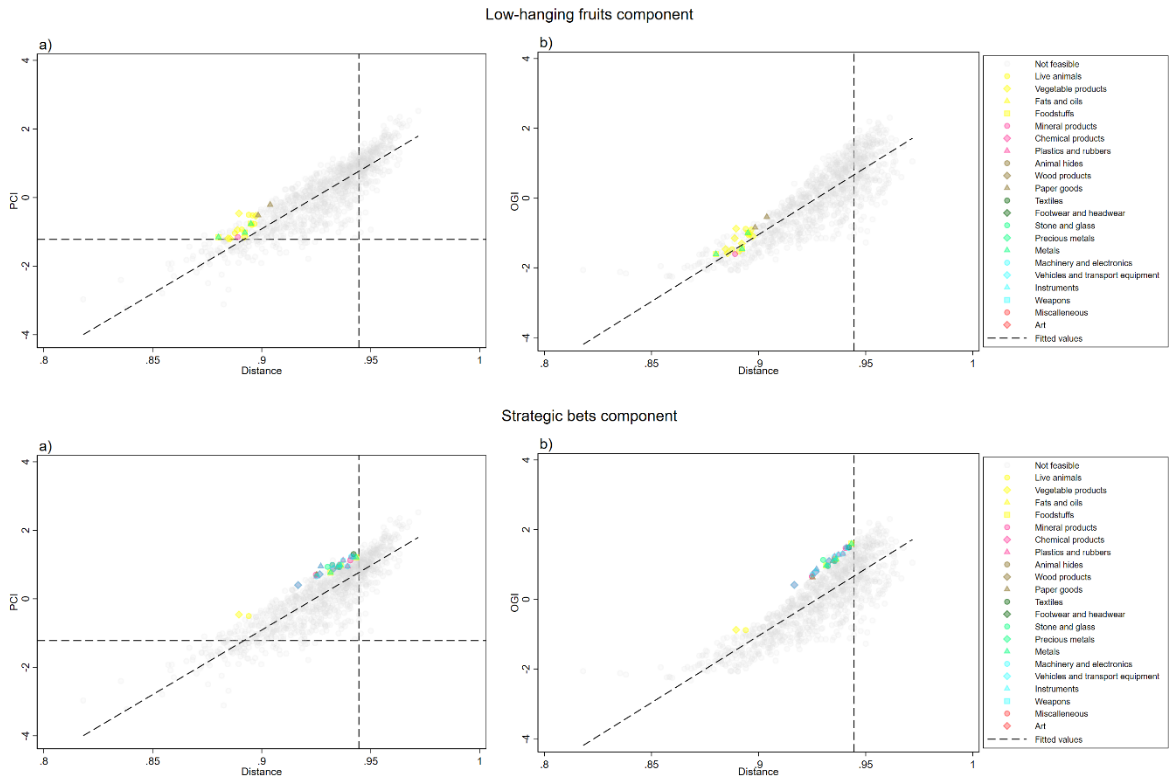


Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Figure 8 shows that the Leverage & Support strategy identifies products from a broad set of sectors. Mozambique is already exporting these products. 13 of the products identified by the Low-Hanging Fruits and Strategic Bets component are identical. This is a consequence of the fact that only 121 of the products Mozambique exports with 0.1<RCA<1 lies within the feasibility space defined in Figure 5 (for an extended discussion see the section on robustness checks below). Many of the target products have a high OGI score as well as a PCI level far beyond Mozambique's ECI. It indicates that Mozambique is already exporting some high-complexity products, although they do not currently have a comparative advantage in those. Products in the Machinery and electronics section accounts for 12 of the 37 products collaboratively identified by the two components of the strategy. The remaining two-thirds of the target products are broadly allocated between product sectors.

Figure 9 displays the target products identified with the Diversify & Scale strategy. Mozambique currently has an RCA<0.1 in these products. The most prominent product sector identified in the *Low-Hanging Fruits* component is agriculture accounting for 19 products within foodstuffs (6), live animals (6), vegetables products (6), and animal hides (1). These products are only slightly more complex than Mozambique's average complexity, but they lie close to Mozambique's productive capabilities. The *Strategic Bets* component of the Diversify & Scale strategy identifies an entirely different set of products. These are of high complexity and are located further away from Mozambique's location in the Product Space. Machinery and electrical equipment constitutes the biggest product section with 8 target products, followed by 3 target products in metals and vehicles and transport equipment. We note that both sets of products are located at Mozambique's "efficiency frontier", having large and positive residuals when fitting a linear line through the scatter plot.

Figure 9: Target products in Diversify & Scale strategy

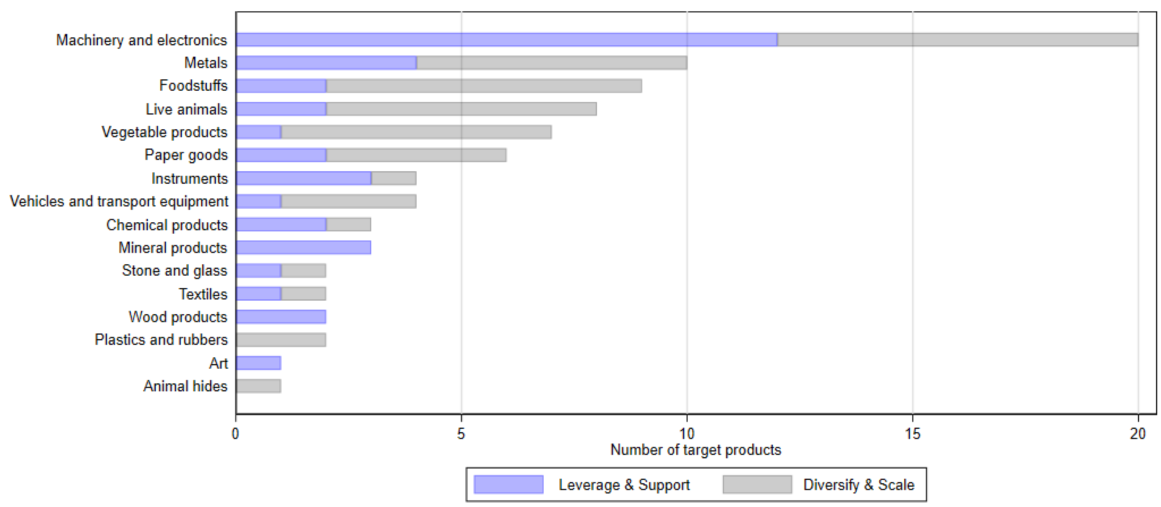


Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Figure 10 displays the total number of target products identified by the Leverage & Support and Diversify & Scale strategies within each sector. On one hand, the figure highlights that Mozambique's current industrial policy focus on multiple different sectors is warranted. The country needs to diversify production, not specialize in a narrow set of industries. Although this strategy runs contrary to traditional trade models' call for specialization, it is in line with recent empirical evidence that diversification is related a countries' growth paths and level of income (Cristelli et al. 2013, 2017; Hausmann et al. 2013).

On the other hand, Figure 10 provides an idea about which specific sectors constitute important pillars for structural transformation in Mozambique and it allows us compare these target sectors to the seven priority sectors identified in the Industrial Policy and Strategy 2016-2025. The comparison can be broken into three parts. First, we identify Machinery and electronics, Vehicles and transport equipment, and Instruments as sectors that seem highly important, but are left out of Mozambique's current industrial strategy. These products have particularly high PCI scores and are located in a dense cluster of the Product Space. It may seem far-fetched that Mozambique should bet on these highly sophisticated industries that lie far from the country's current productive know-how. However, many of the target products identified in these sectors have been identified with the Leverage & Support strategy, meaning that Mozambique is already exporting them. Understanding how industrial policy can leverage and support the capabilities that already allow Mozambican firms to produce and export these products is therefore an important policy exercise.

Figure 10: Number of target products by HS product section and strategy



Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Second, Agro-processing (Foodstuffs), Metals, and Paper goods constitute very important transformation drivers and are simultaneously included as priority sectors in the Industrial Policy and Strategy 2016-2025. In fact, agricultural production in general seem to constitute an important pillar in structural transformation efforts, accounting for a total of 25 target products (Foodstuffs (9), Live animals (8), Vegetable products (7), and Animal hides (1)). These conclusions are in line with the ones reached through CGE modelling in previous studies (Arndt et al. 2010; Hartley et al. 2019; Jensen and Tarp 2004). Metals is already a significant part of Mozambique's export basket (see Figure 2). This export volume is, however, almost exclusively driven by aluminium ingot production from the Mozal aluminium smelter (Sutton et al. 2014). Our analysis highlights that diversification of metal exports has a huge potential to drive transformation in Mozambique. One way to do so is to build on the last decades successful policies aiming to establish supply-chain linkages from Mozal to the local economy. Examples include the SME Empowerment Linkage Program, MozLink, and MozLink II – programs aiming to link local SMEs to the construction and operation phases of Mozal. Today, a large part of Mozambique's metal sector stem from SMEs in Mozal's supplier network (Sutton et al. 2014). The literature on FDI highlight that such linkages may facilitate learning spillovers and technology transfers, with the potential to help local firms develop export-capabilities in other parts of the metal sector (Bajgar and Javorcik 2020; Eck and Huber 2016; Javorcik 2004; Javorcik, Lo Turco, and Maggioni 2018; Moran 2007; Newman et al. 2015; Sørensen 2020).

Third, the priority given to Non-metallic minerals, Chemistry, rubber and plastics, Clothing, textiles and footwear, and Wood and furniture is broadly in line with the results from the analysis in this paper. Accounting for 5 (Minerals and Stone and glass), 5 (Chemicals and Plastics and rubbers), 2 (Textiles) and 2 (Wood products) target products, these sectors are not as prominent as the ones described above, but they are not completely irrelevant either. The export of mineral fuels is the single largest export category in Mozambique today (see Figure 2). Despite their enormous share in Mozambique's current export revenue, mineral fuels hold relatively few opportunities to ignite structural transformation going forward. Minerals are generally poorly connected to other products and of relatively low complexity. The limited transformative power of this sector has already been noted in Dietsche and Esteves (2018). Finally, it is noteworthy that the weighting scheme do not identify any footwear products. Thus, from a complexity-point of view, this component of the textile sector should not be included as a priority in Mozambique.

Robustness check

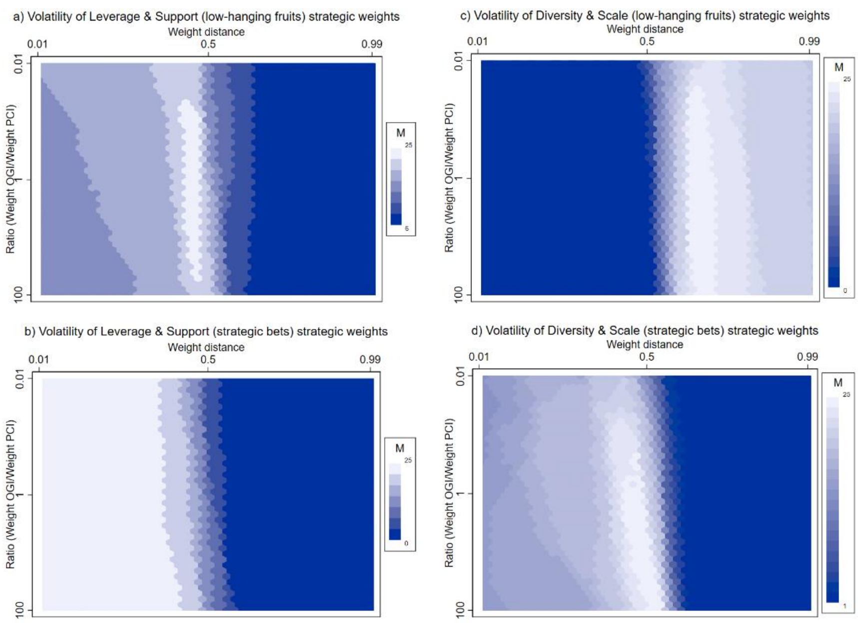
We conduct a volatility simulation to shed light on the impact of the choice of weights on the selection of target products. Figure 11 presents four bivariate histograms displaying the co-occurrence of selected target products between each of the four strategy-component combinations and other potential weighting schemes. In other words, the histograms display the overlap in target products between all possible weighting schemes and each of our four strategy-component schemes. For instance, the Strategic Bets component of the Leverage & Support strategy identifies seven target products similar to an extreme strategy putting close-to-exclusive weight on distance.

The simulation shows that the ratio of the weights assigned to OGI and PCI has only little impact on the target product selection, when holding the distance-weight constant. This is true across all four strategy-component combinations and is a consequence of the strong positive correlation between OGI and PCI (typically, more connected products are also more complex). In contrast, there is a discontinuous jump in the products identified as targets when the weight given to distance changes around 0.5. Except for the Low-Hanging Fruits component of the Leverage & Support strategy, the target products changes more or less completely when crossing the cut-off point.

The documented volatility is not a weakness of our analysis per se. In fact, we would expect the selection of target products to be correlated with the choice of weights: the essence of the weighting scheme approach is to select some products over others given their characteristics. Moreover, it is important to note the strategic interplay between our choice of weights and the discontinuous jump around the 0.5 cut-off point for the distance-weight. The Low-Hanging Fruits and Strategic Bets components of the Diversify & Scale strategy are respectively meant to capture proximate products of lower PCI/OGI and distant products of higher PCI/OGI. Because the components of the Diversify & Scale strategy give distance a weight on either side of the cut-off point, we capture exactly these two different groups of target product. Conversely, with the Leverage & Support strategy we want to exploit the fact that it is easier to develop a comparative advantage in products that are already exported (see Table 2 and Figure 6) and we are therefore primarily interested in capturing highly complex and connected – but distant – products. Consequently, we assign a distance-weight below the cut-off in both components of the Leverage & Support strategy.

At a more general level, the simulations raises questions about the robustness of the conclusions one can reach by applying a single weighting strategy, and it explains why it is common in the literature to propose a set of different weighting schemes (Hausmann et al. 2019, 2016, 2017; Hausmann and Chauvin 2015; Hausmann and Klinger 2006a).

Figure 11: Weighting scheme robustness checks



Notes: The figure shows bivariate histograms of the target product overlap between various arbitrary weighting schemes and the target products chosen by a) the Leverage & Support strategy (low-hanging fruits), b) the Leverage & Support strategy (strategic bets), c) the Diversify & Scale strategy (low-hanging fruits), and d) the Diversify & Scale strategy (strategic bets).
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

3 Demand-side analysis

The analysis thus far have focused on the supply side of Mozambique's structural transformation challenge. This section extents the analysis to take into account demand-side factors. Specifically, the section analyses *i)* which target products are likely to generate the highest export revenue and *ii)* which countries constitute the biggest export markets for these products. The analysis is based on a simple gravity model framework that accounts for product specific factors (such as transportation costs), import market factors (such as product specific demand), and exporter-import relevant factors (such as the physical distance between countries).

3.1 Data

The demand-side analysis builds on four data sources. First, we use importer-exporter-product level trade data for 2011-18 from United Nations Statistical Division (COMTRADE), compiled and cleaned be The Growth Lab at Harvard University (2019). We "square" the dataset, inserting zeroes for all missing exporter-importer-product combinations. This gives us a starting point of 555,740,352 observations. Because we run our gravity model at the product level – and only for our target products – we exclude all non-target products from the sample. Second, we obtain various inter-country distance measures and indicators for landlocked countries from the GeoDist database compiled by the Centre d'Études Prospectives et d'Informations Internationales (CEPII; Mayer and Zignago (2011)). Third, we use the CEPII Gravity dataset (CEPII 2015) to get information on regional trade agreements from 2011-15 as reported by the World Trade Organization (WTO). We update this variable with data for 2016-18 from WTO's website (WTO 2020). Finally, GDP measures are taken from the World Development Indicators (World Bank 2020). Countries that cannot be linked to all datasets are then dropped along with Chad, Iraq, and Macau (unreliable export data).[13] The final dataset contains 25,421,760 observations, based on 195 countries and the 84 target products identified in the supply-side analysis.

3.2 Methodology: gravity model

Estimating the gravity model

The aim of the demand-side analysis is to estimate a predicted trade volume of the different target products and to the different export markets. We start from a structural gravity model, following Head and Mayer (2014)[14]:

$$T_{int} = \frac{Y_{it}}{\vartheta_{it}} \frac{X_{nt}}{\varphi_{nt}} \emptyset_{in} \tag{14}$$

where T_{int} denotes the value of trade from exporter *i* to importer *n* in year *t*. Y_{it} is the value of exporters' production and X_{nt} the value of importers' expenditures in year *t*. ϑ_{it} and φ_{nt} are multilateral resistance terms while $\emptyset_{in}$ is a term for bilateral accessibility.

We estimate Equation 14 in its multiplicative form with the Poisson pseudo-maximum-likelihood (PPML) estimator, using fixed effects to control for exporters' output, importers' expenditure, and their respective multilateral resistance terms. We estimate the model separately for each target product *p* to fix the analysis at the product level and allow for product-specific slope-parameters and fixed effects (different products are, for instance, likely to have different slope parameters for dyadic distance because their transportation costs vary). The PPML regression model can be written as:

$$T_{int}^{\{p\}} = \exp\left(\alpha^{\{p\}} + \boldsymbol{\beta}^{\{p\}'} \boldsymbol{ln\emptyset_{in}} + \gamma_{it}^{\{p\}} + \theta_{nt}^{\{p\}}\right) \times \varepsilon_{int}^{\{p\}} \tag{15}$$

where $\boldsymbol{\emptyset_{in}}$ is a vector of distance measures between importer *n* and exporter *i*. It includes the log of physical distance between countries' most populated cities and a set of indicator variables for contiguity (sharing a border), colonial ties, if a language is spoken by at least nine per cent of the population in both countries, and whether two countries are part of the same regional trade agreement. γ_{it} and θ_{nt} are exporter-year and importer-year fixed effects.

[13] This contrasts to the stricter cleaning procedure we applied in the supply-side analysis in order to reduce noise and estimate the complexity values reliably. There is several reasons behind this choice. First, the complexity variables are sensitive to the inclusion of very small countries that export little. The gravity model is not sensitive to the same extent. Second, many small Sub-Saharan African countries were excluded from the supply-side dataset because they exported less than USD 1 billion on average form 2014-17. By leaving in all countries in the sample, we make sure that we can granularly identify potential export markets for Mozambique.

[14] As we work with panel data, we add the subscript *t* to the model.

Table 4 displays the average point estimates and standard errors across all 84 iterations of Model 15 (one for each target product). The average coefficients and standard errors of our preferred specification (PPML with exporter-year and importer-year fixed effects) are shown in column 4. For comparison, we also estimate the gravity model by linear-in-logs OLS and without fixed effects to control for $\frac{Y_{it}}{\vartheta_{it}}$ and $\frac{X_{nt}}{\varphi_{nt}}$. We show results from OLS regressions in columns 1 and 2. While the log-linearized OLS regression has been the workhorse in the empirical gravity literature for long, several advantages of the PPML estimator have recently been noted. First, Santos Silva and Tenreyro (2006) shows that the PPML estimator is robust to different patterns of heteroscedasticity. In contrast, linear-in-logs OLS estimates can be severely biased under heteroscedasticity. Second, the PPML model allows for easy incorporation of zero-values in the dependent variable and it produces consistent estimates even when the share of zeroes is large (Santos Silva and Tenreyro 2011). OLS estimation does not allow for incorporation of zeroes due to the logarithmic transformation of the trade flows (zero values will be undefined). As a consequence, the OLS estimations displayed in columns 1 and 2 of Table 4 discard the majority of observations in our dataset and may be biased.[15] Finally, estimating the gravity equation with PPML and fixed effects automatically produces predicted export flows, whose sum add up the trade flows observed in the data (Fally 2015).

Results from "traditional" (or "naive") gravity regressions without importer-year and exporter-year fixed effects are reported in columns 1 and 3. This approach involves the inclusion of proxies for Y_{it} and X_{nt} as well as ϑ_{it} and φ_{nt}. We follow the strategy in Santos Silva and Tenreyro (2006) and include (the log of) importer's and exporter's GDP and GDP per capita, measures of their remoteness, and dummies indicating whether they are landlocked.[16] The remoteness variables proxy for the multilateral resistance terms. The best-in-class remoteness proxies is calculated as $\left(\sum_{nt} \frac{GDP_{nt}}{Distance_{ni}}\right)^{-1}$ for exporter remoteness and $\left(\sum_{it} \frac{GDP_{it}}{Distance_{in}}\right)^{-1}$ for importer remoteness (Head and Mayer 2014). We take the log of these variables in our gravity equation so their coefficients can be interpreted as elasticities. We expect the sign of the coefficients to be positive based on the intuition that greater distance to all other countries will increase trade between two countries. It should be noted, though, that remoteness variables are all inconsistent with the theoretical concepts of multilateral resistance (Head and Mayer 2014). Instead, the use of fixed effects to control for exporters' output, importers' expenditure, and their respective multilateral resistance terms is widely acknowledged as the theory-consistent gold standard in gravity estimation today (Head and Mayer 2014). The fixed effects estimates are shown in column 2 and 4 of Table 4.

From Table 4, it can be seen that the signs of the coefficients are broadly in line with our expectations across all four specifications.[17] However, the results also highlight that the choice of

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[15] Some studies using linear-in-log OLS estimation keep zeroes by transforming the dependent variable as $\ln(T_{in} + 1)$. This method should be avoided because the results will depend on the unit of measurement and the interpretation of coefficients as elasticities is lost (Head and Mayer 2014).

[16] Even though we follow the estimation strategy in Santos Silva and Tenreyro (2006) in broad terms, our approach deviates from theirs in certain respects. First, we run the regressions on the product level, not the country level. Second, we use panel data and therefore include year fixed effects in the "traditional" gravity regressions. Third, we include the same control variables (except a dummy for trade openness), but we define some of them slightly different. For instance, we use remoteness proxies argued to be more (but not completely) consistent with theory (Head and Mayer 2014).

[17] Except the negative sign on common language under the naïve PPML model, all coefficients on the distance variables are as expected across all specification. A comparison of the average point estimates on the distance variables and their average standard errors (both robust and clustered at the exporter-importer level) reveal that most distance coefficients are also significant at the 5 per cent-level, on average, across all specifications. The coefficients of the additional controls in the naïve gravity equations are also broadly in line with our predictions, although some of them are insignificant on average. Taking point of departure in the naïve PPML estimation with cluster-robust standard

Table 4: Average coefficient estimates and standard errors across target products

	OLS $\ln\left(T_{int}^{\{p\}}\right)$	OLS FE $\ln\left(T_{int}^{\{p\}}\right)$	PPML $T_{int}^{\{p\}}$	PPML FE $T_{int}^{\{p\}}$
	(1)	(2)	(3)	(4)
Distance	**-0.81**	**-1.11**	**-0.68**	**-0.83**
	(0.03)	(0.03)	(0.05)	(0.04)
	[0.05]	[0.05]	[0.12]	[0.09]
Contiguity	**0.80**	**0.71**	**0.65**	**0.52**
	(0.07)	(0.07)	(0.10)	(0.08)
	[0.16]	[0.15]	[0.26]	[0.19]
Common language	**0.15**	**0.40**	**-0.05**	**0.34**
	(0.05)	(0.05)	(0.08)	(0.08)
	[0.10]	[0.10]	[0.21]	[0.19]
Colonial tie	**0.42**	**0.63**	**0.30**	**0.43**
	(0.07)	(0.07)	(0.11)	(0.08)
	[0.16]	[0.15]	[0.26]	[0.20]
RTA	**0.27**	**0.33**	**0.74**	**0.67**
	(0.04)	(0.05)	(0.08)	(0.07)
	[0.09]	[0.09]	[0.19]	[0.15]
Exporter's GDP	**0.62**		**0.88**	
	(0.01)		(0.02)	
	[0.02]		[0.05]	
Importer's GDP	**0.51**		**0.72**	
	(0.01)		(0.02)	
	[0.02]		[0.05]	
Exporter's GDP per capita	**0.05**		**0.03**	
	(0.02)		(0.04)	
	[0.04]		[0.09]	
Importer's GDP per capita	**0.01**		**0.05**	
	(0.02)		(0.03)	
	[0.03]		[0.08]	
Exporter's remoteness	**0.01**		**-0.04**	
	(0.04)		(0.08)	
	[0.08]		[0.19]	
Importer's remoteness	**0.45**		**0.32**	
	(0.04)		(0.08)	
	[0.09]		[0.20]	
Landlocked exporter	**-0.20**		**-0.18**	
	(0.06)		(0.10)	
	[0.12]		[0.25]	
Landlocked importer	**-0.27**		**-0.12**	
	(0.05)		(0.09)	
	[0.10]		[0.22]	
Year FE	Yes	No	Yes	No
Importer-year FE	No	Yes	No	Yes
Exporter-year FE	No	Yes	No	Yes

Notes: Dependent variable is trade volume (PPML) and log of trade volume (OLS) in the years from 2011-18. Coefficients and standard errors refers to averages across 84 regressions (one for each target product). Robust standard errors in parentheses. Standard errors clustered at exporter-importer level in brackets.
Source: Authors' own calculations based on data from The Growth Lab at Harvard University (2019), CEPII (Mayer and Zignago 2011; CEPII 2015), WTO (2020), and the World Bank (2020) as described in the data section.

errors, it seems that neither exporter's and importer's GDP per capita, remoteness, nor their status as landlocked have a significant effect on their bilateral trade in our target products.

regression specification and estimator matters. When moving from the naïve PPML (OLS) to the fixed effects PPML (OLS) regressions, the negative effect of distance on bilateral trade is 22 per cent (37 per cent) higher. This is non-negligible changes. The effect of sharing a common language and colonial ties also increases, whereas the border effect lessens. For the PPML regressions, the effect of regional trade agreements is higher in the fixed effects specification. We also note sizable changes in coefficients, when moving from the OLS to the PPML estimator. The effect of distance, for instance, decreases with 25 per cent (16 per cent) in the fixed effect (naïve) specification. The coefficients on contiguity, common language and colonial also decrease. In contrast, the change in estimator increases the effect of regional trade agreements with over 100 per cent in both the naïve and the fixed affects specifications.

In the preferred specification from column 4, distance has a strong negative effect on trade volume. A one percent increase in distance decreases the predicted volume of trade by 0.83 per cent. This effect is comparable to the one reported by in Santos Silva and Tenreyro (2006) using a PPML with fixed effects (-0.75), but is slightly lower than the general finding in the literature of a negative elasticity around unity (Head and Mayer 2004, 2014; Redding and Venables 2004). The difference may be caused by Mozambique's target products having relatively low transportation costs. The average coefficients of contiguity and common language are also close to the estimates reported by Santos Silva and Tenreyro (2006). Yet, where Santos Silva and Tenreyro (2006) find no significant effect of colonial ties on bilateral trade, our estimates show that sharing a colonial past increases the trade volume between two countries by 54.15 per cent.[18] Our estimated effect of regional trade agreements is also markedly larger than the one reported by Silva and Tenreyro (2006) (0.38 vs. 0.67).

Predicting export potential

We use the product-specific coefficients from each iteration of Equation 15 to predict the export potential of Mozambique's the different target products and the market potential of the country's different trade partners. Specifically, let the predicted export value from Mozambique to an importer *n* in product *p* at time *t*, $\hat{T}^{\{p\}}_{Moz,nt}$, be defined as:

$$\hat{T}^{\{p\}}_{Moz,nt} = \exp\left(\hat{\alpha}^{\{p\}} + \hat{\boldsymbol{\beta}}^{\{p\}'} \boldsymbol{ln\emptyset_{Moz,n}} + \hat{\theta}^{\{p\}}_{nt}\right) \tag{16}$$

where $\hat{\alpha}^{\{p\}}$, $\hat{\boldsymbol{\beta}}^{\{p\}'}$, and $\hat{\theta}^{\{p\}}_{nt}$ are respectively the estimates of $\alpha^{\{p\}}$, $\boldsymbol{\beta}^{\{p\}}$, and $\theta^{\{p\}}_{nt}$ from the PPML regression with exporter-year and importer-year fixed effects. Notice that while we apply exporter-year fixed effects to obtain consistent parameter estimates when calibrating the model, we leave them out when predicting potential trade flows in Equation 16. We do so to avoid that Mozambique's *current* (in)ability to export certain target products influence our judgement of their exportability in the *future*. We want to level the playing field, predicting which target products would generate the highest export revenue if Mozambique had an equal ability to produce each of them. In other words, we want to predict demand while taking the supply-side as given. The exercise thereby gives an indication of which target product-investments will generate the highest return in terms of export revenue.

The predicted values $\hat{T}^{\{p\}}_{Moz,nt}$ enable us to rank products in accordance with their potential to generate export revenue and countries for their potential as market destinations for the target products. First, we create a Market Export Potential (MEP) variable, which captures the total

[18] The formula to calculate this effect is $(e^{\hat{\beta}} - 1) \times 100$. $\hat{\beta}$ is the estimated coefficient.

estimated export value of all target products from Mozambique to each country *n* over a eight year time period (2011-18):

$$MEP_n = \sum_{p,t} \hat{T}_{Moz,nt}^{\{p\}} \tag{17}$$

MEP_n is a measure for the potential total trade in all target products between Mozambique and each country in the world. It allow us to evaluate which country is likely to be the biggest importer of Mozambique's target products. Cross-country variation in MEP_n comes from variation in importer characteristics, such as import demand (captured by importer-year fixed effects), and different dyadic distances between Mozambique and each country (captured by $\emptyset_{\mathbf{ni}}$).

Second, we create a Product Export Potential (PEP) variable by estimating the total predicted export value for each product over the same time period:

$$PEP_p = \sum_{n,t} \hat{T}_{Moz,nt}^{\{p\}} \tag{18}$$

PEP_p denotes the potential total trade in each target product between Mozambique and all countries of the world. Because we run Equation 16 separately for each target product, we obtain product-specific slope and fixed effect estimates ensuring cross-product variation in PEI_p. Intuitively, the variation comes from different world import-volumes across products (captured by product specific intercepts and sums of importer-year fixed effects) and different effects of distance-variables on product-specific trade. For instance, some target products may have a high transportation cost and will be difficult for Mozambique to export (captured by the coefficient on physical distance). Other products may carry a certain cultural value making it easier for Mozambique to export these products to former colonial powers or countries speaking Portuguese (captured by the coefficients on the similar language-dummy and the colonial power-dummy).

3.3 Export potential

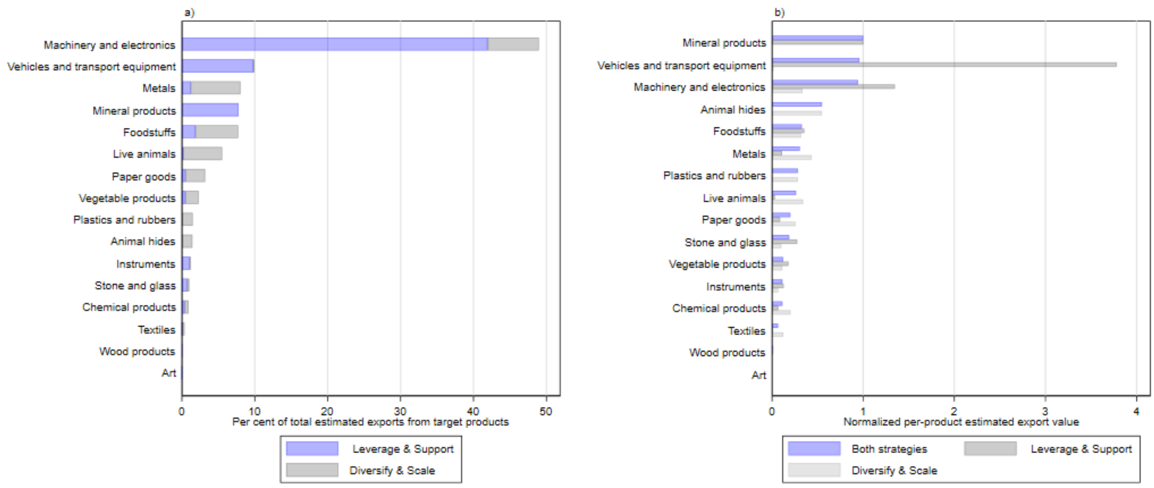
Product Export Potential

Figure 12.a displays the PEP for Mozambique's target products summed over product section and strategy. Values are reported as a percentage of total estimated exports of all target products. The figure provides a projected export revenue distribution over product sections if Mozambique were to export all target products. Not surprisingly, the export potential between product sections varies because the number of target products identified in each section varies. Therefore, 12.b displays the distribution of PEP averaged over the number of products within each section (and strategy) in order to give an idea of differences in *per product* export potential. To ease interpretation, average PEP values are normalized so to that the highest (when considering both strategies combined) take the value one, whereas the lowest take the value of zero. Figures A1-A3 in the appendix show that the results from Figure 12 (based on the PPML model with fixed effects) are highly dependent on which of the four regression models from Table 4 are used to calculate PEP scores.

Figure 12 highlights important similarities and differences between the Industrial Policy and Strategy's selection of priority sectors (partly based on their export potential) and the export revenue projections from the gravity model. First, the gravity estimates show that the current prioritization of production in Metals, Minerals, Paper goods, and Agriculture (Foodstuffs, Live animals, Vegetables, and Animal hides) is well aligned with an ambition to increase export revenue. Target products within these sectors have a high revenue potential in absolute terms. Of these product sections, Minerals, Animal hides, Foodstuffs, and Metals have the highest per product

PEP. This consolidates our finding from the supply-side analysis: there are important synergies between the structural transformation potential of these sectors and their exports potential. These sectors should remain a focus for industrial policy in Mozambique. Second, the list of priority sectors appear to omit two important export drivers: Machinery and electronics as well as Vehicles and transport equipment. The gravity model projects these product sections to account for nearly 60 per cent of total estimated exports from target products even though they "only" account for 24 of 84 target products. Both product sections are also projected to deliver some of the highest revenues per exported product. When combining these results with the ones from the supply-side analysis, the omission of these two sectors from the list of priority sectors in Mozambique seem misguided. Products within these sectors have a high potential to drive both structural transformation and export revenue. Finally, and at the other end of the spectrum, only two target products were identified in Textiles and Wood products and these products also have a very low export potential – both in absolute and per product terms. It thus seems that Clothing, textiles and footwear along with Wood and furniture processing are the least important of Mozambique's seven priority sectors.

Figure 12: Total PEP and average PEP by product section and strategy (PPML FE)



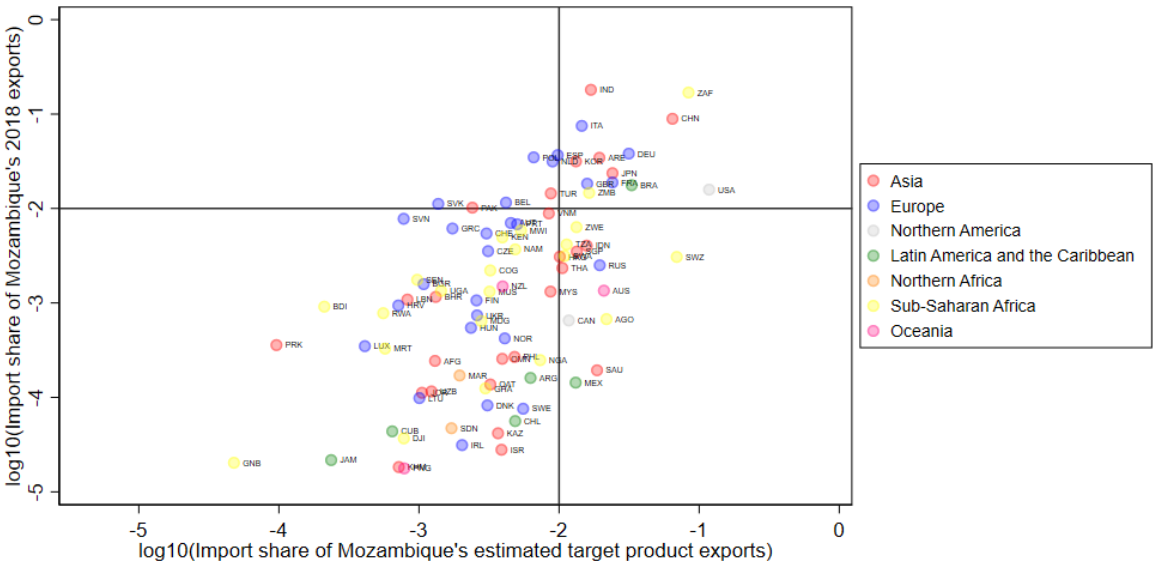
Notes: PEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

We note that that the export potential is highest in target products Mozambique already exports (identified by the Leverage & Support strategy) in Machinery and electronics, Vehicles and transport equipment, and Mineral products. From a revenue perspective, Mozambique should take advantage of the favourable demand exposure to boost the *intensive margin* of trade in these product sections. In product sections where the opposite is true (for example Metals, Animal hides, Live animals, Paper goods, Chemical products, and Plastic and rubbers), the export potential is highest in the products Mozambique is not yet exporting. Here, policies aiming to boost export revenues may be most effective when focusing on the *extensive margin*.

Market export potential

The implementation of effective export promotion policies dictates an identification of high-potential export markets. Figure 13 shows which countries the gravity model predicts as important export destinations for Mozambique's target products. The graph shows which countries are currently importing most of Mozambique's exports, and the degree to which these destinations are predicted to be important importers of Mozambique's target products. The vertical line on the graph represent each countries' import share of Mozambique's total exports in 2017. The share in imports is reported in logarithmic form ($\log_{10}$), meaning that -1 represents 10 per cent, -2 represents 1 per cent, and so forth. The horizontal axis reports Mozambique's projected export of all target products to each import market as a share of its total projected export across all target products and markets. It is calculated as the $\log_{10}$ of each importer's MEP value divided by the sum of all country's MEP values from 2011-2018.

Figure 13: Import share of Mozambique's 2018 exports versus import share of Mozambique's estimated target product exports over eight years (PPML FE)



Notes: MEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

One immediate conclusions is evident from Figure 13: there is a positive (log-)linear relationship between Mozambique's current volume of exports to other countries and these countries' predicted import share of Mozambique's target product exports. This is encouraging because it indicates that Mozambique's current trade partners can drive target product export growth. In other words, the result indicates that Mozambique does not need to penetrate new markets or change the structure of their market portfolio significantly in order to export identified target products (except when it comes to its neighbours).

Yet, there is still some room to attune Mozambique's portfolio of trade partners to accommodate export growth in target products. Countries located in the bottom-left quadrant of Figure 13 are *low-potential* export markets. These are countries with whom Mozambique currently trades little and neither are they predicted to import Mozambique's target products in high volume. Many Sub-Saharan African and Latin American countries are located in this quadrant. Notably it also includes countries such as Portugal and Vietnam. The countries in the upper-left quadrant are *hard-to-exploit* export markets. Countries located here are important for Mozambique's current trade, but they are predicted to be unimportant importers of its target products. The quadrant includes Turkey, Pakistan, Netherlands, Belgium, Spain, Poland and Slovakia. Countries located in the top-right quadrant constitute *high-potential* markets. These countries are important current markets for Mozambique and they are estimated to import the country's target products in great volumes. We note that the countries located here are big European and Asian economies, Brazil, US, Zambia, and South Africa. Finally, the bottom-right quadrant is home to *high-opportunity* markets. Mozambique do not currently trade much with these countries, but they have a high projected demand for its target products. This group of countries a substantial part of Mozambique's neighbouring countries (Eswatini, Zimbabwe and Tanzania) and other Southern African countries (Angola and Botswana). There is thus a great untapped potential for Mozambique in trading with its neighbours and other Southern African countries in new and complex products. Trade policy aimed at expanding the scope of intra-regional trade agreements such as SADC may be a way for Mozambique to realise this potential. Hong Kong, Singapore, Indonesia, Thailand, and Saudi Arabia constitutes high-opportunity Asian markets. Russia, Australia, Canada, and Mexico are also identified promising markets of Mozambique's target products.

Figures A4-A6 in the appendix replicates Figure 13 based on predicted exports from the naïve PPML and OLS regressions and the fixed effect OLS regression. The tables show that a correct model specification is crucial for drawing valid conclusions. For example, the higher absolute value of the coefficients on distance and contiguity in the OLS regressions make these models over-estimate the potential for Mozambique to export the target products to its neighbours. The naïve PPML model also overstates the border-effect and assigns inflated MEP values to Mozambique's neighbours.

4 Discussion and conclusion

Economic growth entails a structural transformation process whereby productive resources are moved from low-complexity to high-complexity activities. The discovery of a heterogeneous Product Space has highlighted that externalities and path-dependencies are inherent parts of this process (Hausmann and Klinger 2007; Hidalgo et al. 2007). The question of whether and how governments can guide this process through industrial policy has therefore gained considerable attention in many developing countries (Hausmann et al. 2014, 2016; Hausmann and Chauvin 2015; Hausmann and Klinger 2006a). This question is particularly relevant for Mozambique, whose export structure is undiversified and unsophisticated. To guide industrial policy, we have identified a set of target products that are complex, rely on productive capabilities complementary to the production of many other products, and are relatively close to Mozambique's current know-how. Acknowledging that export revenue constitutes a significant policy objective in Mozambique, a demand-side analysis has ranked target products and export markets in accordance with their predicted export potential. The main conclusions can be summarized in two steps.

First, Mozambique's current industrial policy is broadly speaking consistent with a focus on structural transformation and export promotion. The broad sectoral focus is consistent both with our findings in this paper, the general concern that Mozambique is too reliant on a the export from few extractive industries (Cruz and Mafambissa 2016; Dietsche and Esteves 2018), and the stylized empirical fact that diversification is good for growth (Cristelli et al. 2013, 2017; Hausmann et al. 2013). That said, the priority given to agricultural and metal products seem especially important when the potential for structural transformation and export growth are simultaneously considered. Our analysis also highlights unexploited opportunities especially in Machinery an electronics and Vehicles and transport equipment. Noticeably, many of the products identified in these sectors are already exported by firms in Mozambique, although in relatively small volumes. Second, gravity model estimates show Mozambique's largest current trade partners are the ones predicted to import the lion's share of its target products. Mozambique's current pattern of trade can, however, still be attuned to accommodate export growth in target products. As an example, we find a potential for Mozambique to export target products to its neighbours and other Southern African countries indicating the importance of a continued deepening of regional trade agreements such as SADC.

The results presented here have implications for industrial policy. It is therefore pertinent to stress what the core principles of such policies should (and should not) be. First, Mozambique should invest in capabilities, not products. This argument is about first principles. From the perspective of economic complexity, products are only interesting because they are signals about productive knowhow. The only reason the analysis in this paper is product-focused is that it is practically impossible to identify the exact capabilities related to all the +1200 products of the World. Thus, the sectors identified in this paper should be seen as a suggested roadmap to guide the search for the capabilities necessary for Mozambique to *diversify and upgrad*e its economy. Only if the primary focus objective is to grow *export revenue* may an explicit focus on specific products be justifiable. Second, this paper is not a call for "picking winners". The analysis has shown that opportunities exist in a wide variety of sectors. By picking some sectors above others, the government may effectively condemn potentials in non-prioritized sectors. A first principle in industrial policy should therefore be to make any interventions as broadly applicable and sector-neutral as possible (Hausmann and Klinger 2006a). When the government is doomed to choose, however, the analysis presented here have shown a structured and somewhat neutral way of prioritizing. Third, economic theory tells us that government intervention is only welfare enhancing in the presence of market failures, such as externalities in product diversification. Industrial policy should only do, what the market cannot accomplish on its own, and interventions should be guided by market signals to the extent possible. This principle has been the intention behind the Leverage & Support strategy developed in this paper.

Furthermore, the policy implications of this paper should be interpreted in relation to the limitations of the method applied. Compared to the objectives listed in the Industrial Policy and Strategy 2016-2025, our study has a more narrow focus on promoting economic complexity and export revenue. This has consequences for the industries we identify as important. For instance, we do not focus on the labour intensity of products and sectors in this paper, even though employment generation is a stated objective in Mozambique's current prioritization of industries. In related work, we explore this aspect in the context of Tanzania and find an inverse relationship between PCI and labour intensities in products (Estmann, Sørensen, and Rand 2020). This implies a trade-off between job creation and complexity, and it suggests that the Low-Hanging Fruit component of the two strategies proposed in this paper may strike the best balance between these objectives because it assigns a lower weight to PCI. Another limitation of the complexity approach relates to data availability. International trade data do not include granular information on services and it obviously miss data on any non-tradable sectors. As a consequence, we are unable to evaluate claims from other studies arguing that industries without smokestacks[19] constitute an important piece in Mozambique's diversification puzzle (Cruz and Mafambissa 2016) and that the construction sector is important for the domestic market (Cruz et al. 2018). Industrial policy should ideally consider all relevant sectors and objectives when prioritizing.

Despite these shortcomings, this paper make two contributions to the literature. We extend the methodology supply-side-focused economic complexity analysis applied in a number of studies to guide industrial policy in developing countries (Ayres and Freire 2014; Hausmann et al. 2014, 2016, 2017; Hausmann and Chauvin 2015; Hausmann and Klinger 2006a; Hidalgo 2011) with a structured demand-side analysis, ranking products in accordance with their revenue-generating trade potential. Most other studies do not consider demand-side factors at all, and none use gravity models to map the export potential of products and markets. The analysis has highlighted significant synergies between the structural transformation potential of different sectors and their potential for exports.

[19] Industries without smokestacks are industries sharing the characteristics of the manufacturing sector. Examples include sectors such as food processing and horticulture, but also tourism, ICT, and other services.

Additionally, this paper constitutes, to the best of our knowledge, the first comprehensive study on economic complexity and structural transformation in Mozambique. The complexity framework offers a different perspective to the CGE models, which have traditionally been used to evaluate the attractiveness of different sectors in the context of Mozambique (Arndt et al. 2010; Hartley et al. 2019; Jensen and Tarp 2004). These models enable a detailed evaluation of economic aggregates and the distributional consequences of one specific shock or a policy intervention in one specific sector. Such detailed response-analyses is impossible with the economic complexity analysis conducted in this paper. Its strength lies in its ability to evaluate the attractiveness of all sectors/products simultaneously. The analysis is data-driven: we make no judgement calls on which sector to focus on a priori. This can lead to new and surprising conclusions like the one found in this paper on Mozambique's opportunities in machinery production. Another strength lies in the ability to provide policy recommendations at the product-level by explicitly modelling the externalities associated with each product. A policy-relevant avenue of further research would be to combine these two models, using the economic complexity framework to identify the most promising sectors and a CGE model to evaluate the economic consequences of targeting that sector with industrial policy.

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Appendix

Table A1: Target products from Leverage & Support strategy, Low-Hanging Fruits component

HS code	Description	Product group	Rank	RCA	Density	PCI	OGI	Weighted score
8479	Machines n.e.c.	Machinery and electronics	1	0.09	-1.53	2.20	2.31	0.55
8431	Parts for use with hoists and excavation machinery	Machinery and electronics	2	0.06	-0.24	1.12	1.20	0.53
8485	Machinery parts, not containing electrical features, n.e.c.	Machinery and electronics	3	0.12	-0.68	1.27	1.44	0.44
8412	Other engines and motors	Machinery and electronics	4	0.04	-0.79	1.27	1.52	0.42
9024	Machines for testing the mechanical properties of materials	Instruments	5	0.04	-1.16	1.55	1.62	0.35
8503	Parts for use with electric generators	Machinery and electronics	6	0.16	-0.43	0.91	0.98	0.33
2501	Salt	Mineral products	7	0.01	2.41	-1.10	-1.62	0.32
4415	Packing boxes	Wood products	8	0.13	0.61	0.27	-0.06	0.32
3602	Prepared explosives, except gunpowder	Chemical products	9	0.00	2.09	-1.05	-1.25	0.30
5602	Felt	Textiles	10	0.20	-0.46	0.81	1.02	0.30
8474	Machinery for working minerals	Machinery and electronics	11	0.82	-0.39	0.76	0.94	0.29
2523	Cements	Mineral products	12	0.75	2.72	-1.43	-1.94	0.28
7602	Waste or scrap, aluminium	Metals	13	0.90	1.88	-0.98	-1.10	0.27
7302	Railway construction material of iron or steel	Metals	14	0.03	-0.10	0.53	0.61	0.27
4404	Strips and other pieces of wood	Wood products	15	0.23	1.01	-0.10	-0.54	0.27
0804	Avocados, pineapples, mangos, etc.	Vegetable products	16	0.28	3.15	-1.93	-2.24	0.26
8429	Self-propelled bulldozers, excavators and road rollers	Machinery and electronics	17	0.49	-0.25	0.43	0.90	0.26
2306	Solid vegetable oil and fat residues	Foodstuffs	18	0.69	2.03	-1.01	-1.33	0.26
8455	Metal-rolling mills	Machinery and electronics	19	0.00	-0.82	1.06	1.19	0.26
0511	Animal products n.e.c.	Live animals	20	0.42	1.75	-0.82	-1.10	0.25
8535	Electrical apparatus for > 1k volts	Machinery and electronics	21	0.14	-0.65	0.91	1.05	0.25
0106	Other live animals	Live animals	22	0.33	2.30	-1.35	-1.50	0.25
8438	Machinery for the industrial preparation of food or drink	Machinery and electronics	23	0.21	-0.71	0.93	1.12	0.25
2713	Petroleum coke	Mineral products	24	0.30	1.69	-0.76	-1.07	0.25
2202	Waters, flavored or sweetened	Foodstuffs	25	0.35	1.24	-0.35	-0.75	0.25

Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).
Notes: Density refers to the inverse of distance and is calculated as distance minus 1.

Table A2: Target products from Leverage & Support strategy, Strategic Bets component.

HS code	Description	Product group	Rank	RCA	Density	PCI	OGI	Weighted score
8479	Machines n.e.c.	Machinery and electronics	1	0.09	-1.53	2.20	2.31	1.52
9024	Machines for testing the mechanical properties of materials	Instruments	2	0.04	-1.16	1.55	1.62	1.05
8412	Other engines and motors	Machinery and electronics	3	0.04	-0.79	1.27	1.52	1.01
8485	Machinery parts, not containing electrical features, n.e.c.	Machinery and electronics	4	0.12	-0.68	1.27	1.44	0.98
8431	Parts for use with hoists and excavation machinery	Machinery and electronics	5	0.06	-0.24	1.12	1.20	0.90
8455	Metal-rolling mills	Machinery and electronics	6	0.00	-0.82	1.06	1.19	0.76
8438	Machinery for the industrial preparation of food or drink	Machinery and electronics	7	0.21	-0.71	0.93	1.12	0.72
8503	Parts for use with electric generators	Machinery and electronics	8	0.16	-0.43	0.91	0.98	0.68
5602	Felt	Textiles	9	0.20	-0.46	0.81	1.02	0.68
8535	Electrical apparatus for > 1k volts	Machinery and electronics	10	0.14	-0.65	0.91	1.05	0.68
8474	Machinery for working minerals	Machinery and electronics	11	0.82	-0.39	0.76	0.94	0.64
8429	Self-propelled bulldozers, excavators and road rollers	Machinery and electronics	12	0.49	-0.25	0.43	0.90	0.57
8803	Parts of other aircraft	Vehicles and transport equipment	13	0.35	-0.81	0.53	1.00	0.54
8545	Carbon articles for eletrical purposes	Machinery and electronics	14	0.12	-0.46	0.79	0.79	0.54
9205	Musical instruments, wind	Instruments	15	0.69	-1.61	1.11	1.03	0.52
8502	Electric generating sets and rotary converters	Machinery and electronics	16	0.61	-0.45	0.68	0.72	0.48
7302	Railway construction material of iron or steel	Metals	17	0.03	-0.10	0.53	0.61	0.45
7418	Household articles of copper	Metals	18	0.11	-0.42	0.56	0.68	0.44
6902	Bricks, tiles and similar refractory ceramic constructional goods	Stone and glass	19	0.15	-0.43	0.46	0.62	0.38
9023	Instruments designed for demonstrational purposes	Instruments	20	0.22	-0.17	0.39	0.52	0.36
2826	Flourides	Chemical products	21	0.16	-0.51	0.51	0.53	0.32
4702	Chemical woodpulp, dissolving grade	Paper goods	22	0.00	-0.43	0.71	0.41	0.30
9704	Postage or revenue stamps	Art	23	0.00	0.01	0.32	0.34	0.27
7905	Zinc plates and foil	Metals	24	0.08	-0.44	0.00	0.60	0.27
4809	Carbon paper	Paper goods	25	0.02	-0.58	0.45	0.49	0.27

Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).
Notes: Density refers to the inverse of distance and is calculated as distance minus 1.

Table A3: Target products from Diversify & Scale strategy, Low-Hanging Fruits component.

HS code	Description	Product section	Rank	RCA	Density	PCI	OGI	Weighted score
7214	Other bars of iron, not further worked than forged	Metals	1	0.01	2.12	-1.16	-1.61	0.88
2402	Cigars and cigarettes	Foodstuffs	2	0.01	1.99	-0.91	-1.39	0.88
2009	Fruit juices	Foodstuffs	3	0.05	2.09	-1.12	-1.59	0.87
1104	Worked cereal grains	Vegetable products	4	0.00	1.69	-0.46	-0.87	0.86
4104	Tanned hides of bovines or equines	Animal hides	5	0.04	1.86	-1.01	-1.40	0.78
1102	Cereal flours	Vegetable products	6	0.02	1.91	-1.19	-1.46	0.77
1209	Seeds used for sowing	Vegetable products	7	0.04	1.72	-0.95	-1.15	0.75
0805	Citrus fruit	Vegetable products	8	0.02	1.87	-1.20	-1.59	0.72
0102	Bovine	Live animals	9	0.00	1.49	-0.50	-0.88	0.72
0304	Fish fillets	Live animals	10	0.08	1.78	-1.04	-1.47	0.71
1704	Confectionery sugar	Foodstuffs	11	0.00	1.57	-0.61	-1.11	0.70
2403	Other manufactured tobacco	Foodstuffs	12	0.04	1.48	-0.61	-1.04	0.66
2207	Ethyl alcohol > 80%	Foodstuffs	13	0.00	1.67	-1.12	-1.27	0.66
0407	Eggs, in shell	Live animals	14	0.00	1.41	-0.52	-1.03	0.63
7902	Zinc waste and scrap	Metals	15	0.06	1.45	-0.77	-1.00	0.63
3301	Essential oils	Chemical products	16	0.01	1.72	-1.15	-1.60	0.62
0409	Honey	Live animals	17	0.00	1.64	-0.93	-1.53	0.62
0402	Milk, concentrated	Live animals	18	0.04	1.37	-0.77	-0.90	0.60
4819	Cardboard packing containers	Paper goods	19	0.07	1.30	-0.52	-0.84	0.60
0604	Other parts of plants	Vegetable products	20	0.00	1.58	-1.14	-1.30	0.59
0301	Live Fish	Live animals	21	0.00	1.43	-0.80	-1.07	0.59
7313	Barbed wire of iron or steel	Metals	22	0.00	1.57	-1.03	-1.45	0.58
2101	Coffee extracts	Foodstuffs	23	0.00	1.34	-0.67	-0.99	0.57
0811	Fruits and nuts, frozen	Vegetable products	24	0.00	1.34	-0.53	-1.10	0.57
4707	Paper waste	Paper goods	25	0.05	1.05	-0.21	-0.54	0.54

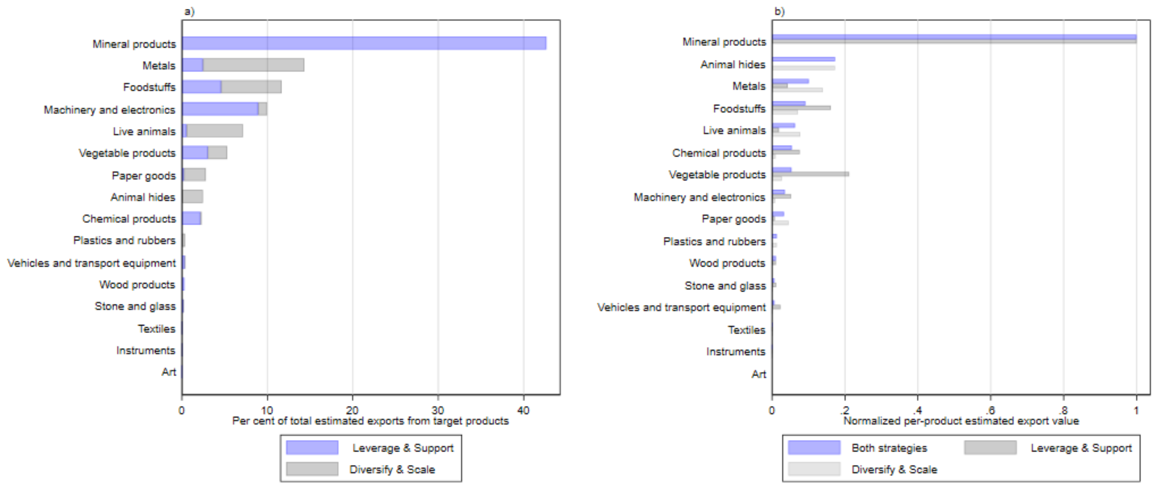
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).
Notes: Density refers to the inverse of distance and is calculated as distance minus 1.

Table A4: Target products from Diversify & Scale strategy, Strategic Bets component.

HS code	Description	Product section	Rank	RCA	Density	PCI	OGI	Weighted score
6806	Mineral wools and insulating materials	Stone and glass	1	0.03	-0.13	0.93	1.13	0.48
1104	Worked cereal grains	Vegetable products	2	0.00	1.69	-0.46	-0.87	0.45
9033	Other parts for machines and appliances	Instruments	3	0.00	0.01	0.95	0.86	0.44
8801	Gliders, hang gliders	Vehicles and transport equipment	4	0.00	0.47	0.40	0.41	0.44
8428	Other lifting machinery	Machinery and electronics	5	0.09	-0.62	1.23	1.49	0.41
8433	Harvesting or agricultural machinery	Machinery and electronics	6	0.00	-0.37	0.99	1.23	0.40
8608	Railway track fixtures	Vehicles and transport equipment	7	0.07	0.03	0.72	0.79	0.40
4008	Vulcanized rubber plates	Plastics and rubbers	8	0.01	-0.60	1.12	1.47	0.40
8709	Work trucks	Vehicles and transport equipment	9	0.00	-0.26	0.88	1.10	0.40
7307	Tube or pipe fittings of iron or steel	Metals	10	0.01	-0.72	1.21	1.60	0.40
8436	Other agricultural machinery	Machinery and electronics	11	0.00	-0.45	1.12	1.28	0.40
8432	Machinery for soil preparation or cultivation	Machinery and electronics	12	0.05	0.09	0.66	0.71	0.40
5911	Textile articles for technical use	Textiles	13	0.00	-0.67	1.30	1.49	0.39
3921	Other plastic plates, sheets etc.	Plastics and rubbers	14	0.00	0.11	0.70	0.66	0.39
8442	Machinery for making printing components	Machinery and electronics	15	0.00	-0.67	1.23	1.48	0.38
4911	Other printed matter	Paper goods	16	0.04	0.09	0.71	0.63	0.37
7211	Flat-rolled iron, width < 600mm, not clad	Metals	17	0.00	-0.19	0.76	0.97	0.37
4902	Newspapers, journals and periodicals	Paper goods	18	0.02	-0.33	0.92	1.10	0.37
8524	Tapes, cassettes, records and compact disks	Machinery and electronics	19	0.02	-0.23	0.99	0.96	0.37
7326	Other articles of iron or steel	Metals	20	0.02	-0.40	0.98	1.16	0.36
2402	Cigars and cigarettes	Foodstuffs	21	0.01	1.99	-0.91	-1.39	0.35
8468	Machinery for soldering	Machinery and electronics	22	0.08	-0.54	0.95	1.31	0.35
8546	Electrical insulators of any material	Machinery and electronics	23	0.00	-0.37	0.92	1.10	0.34
0102	Bovine	Live animals	24	0.00	1.49	-0.50	-0.88	0.34
2106	Food preparations n.e.c.	Foodstuffs	25	0.01	0.73	0.23	-0.14	0.33

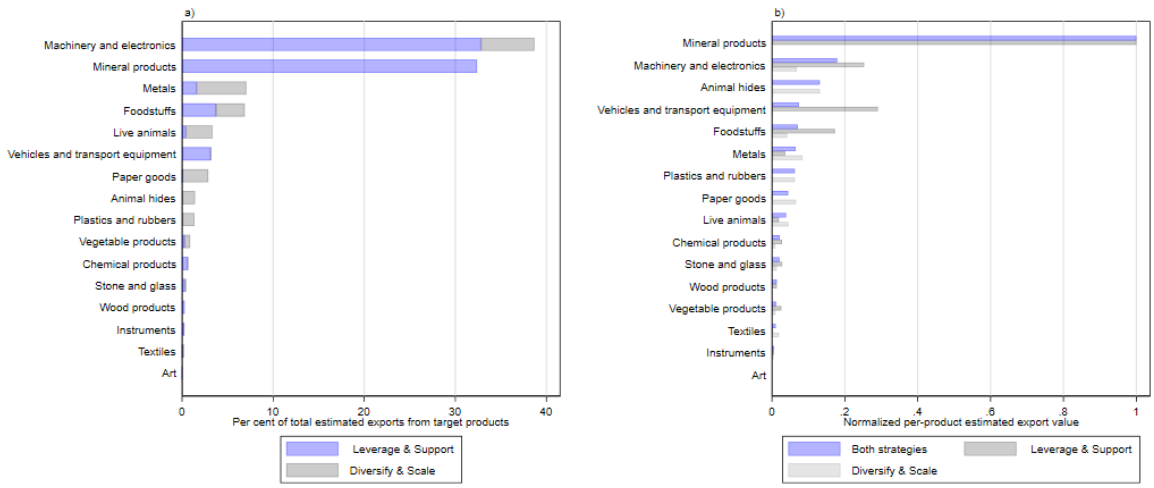
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).
Notes: Density refers to the inverse of distance and is calculated as distance minus 1.

Figure A1: Total PEP and average PEP by product section and strategy (OLS)



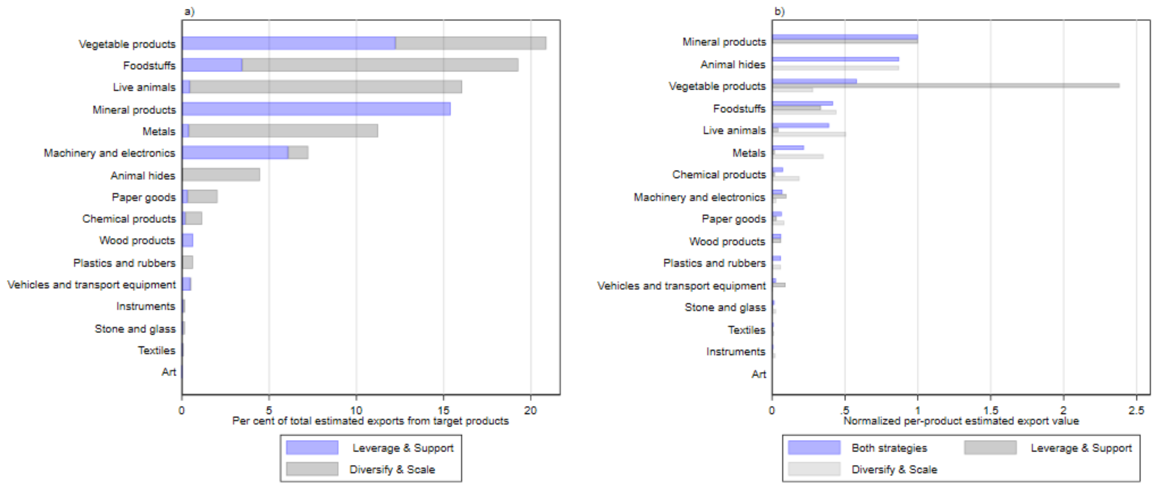
Notes: PEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Figure A2: Total PEP and average PEP by product section and strategy (OLS FE)



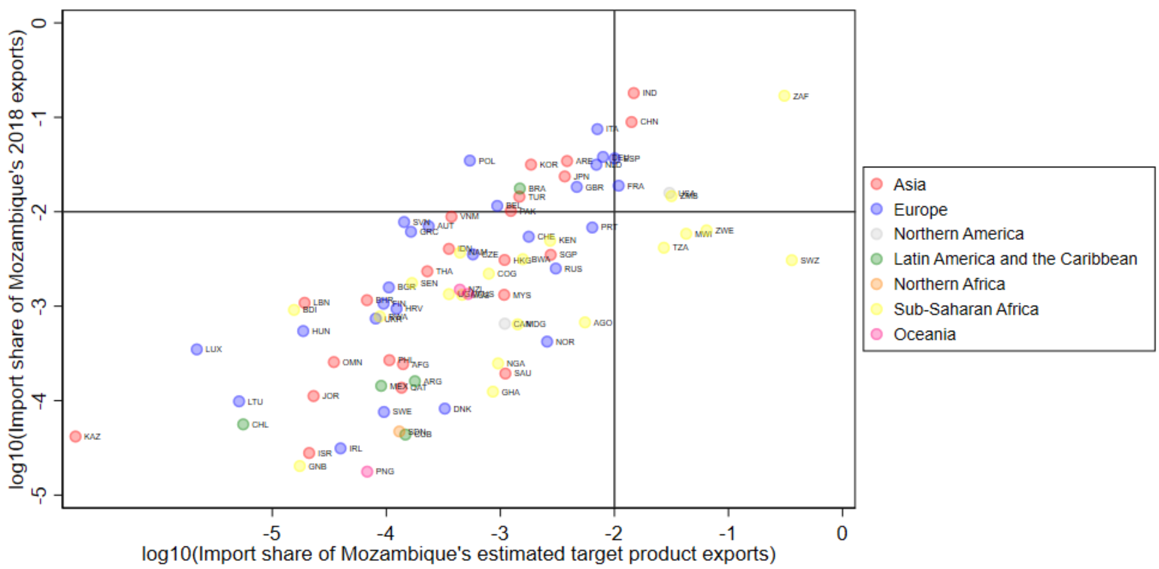
Notes: PEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Figure A3: Total PEP and average PEP by product section and strategy (PPML)



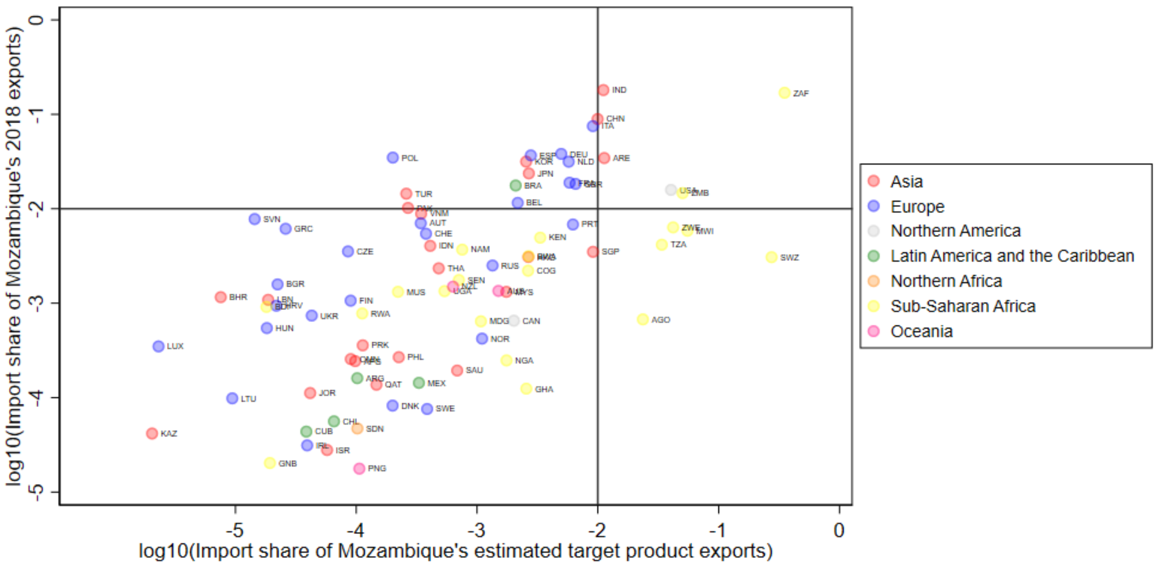
Notes: PEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Figure A4: Import share of Mozambique's 2018 exports versus import share of Mozambique's estimated target product exports over eight years (OLS)



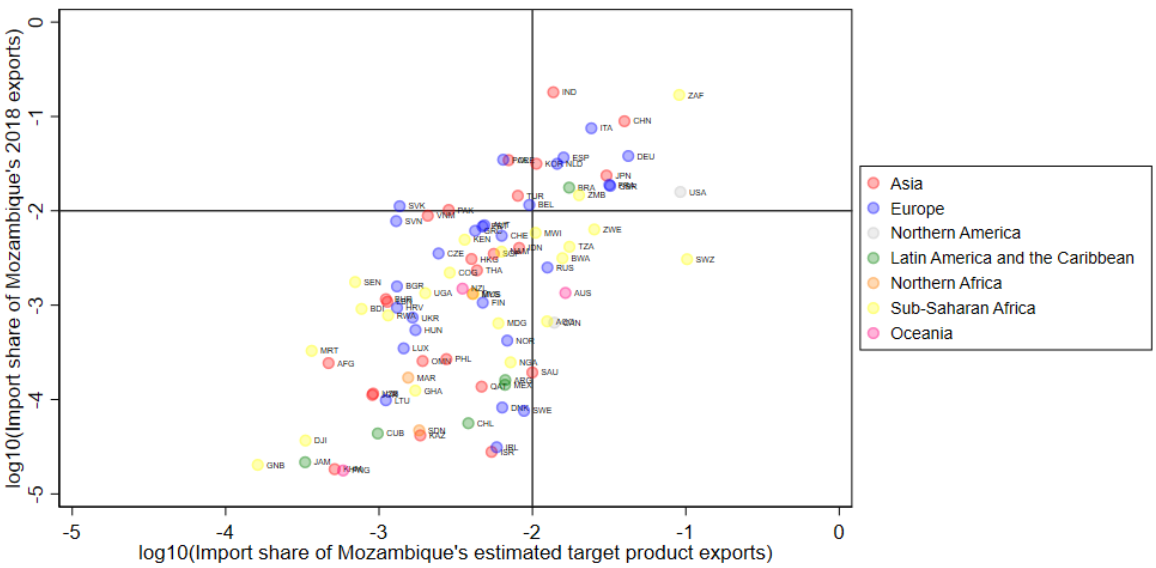
Notes: MEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Figure A5: Import share of Mozambique's 2018 exports versus import share of Mozambique's estimated target product exports over eight years (OLS FE)



Notes: MEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).

Figure A6: Import share of Mozambique's 2018 exports versus import share of Mozambique's estimated target product exports over eight years (PPML)



Notes: MEP estimates are based on the PPML regression with exporter-year and importer-year fixed effects.
Source: Authors' own calculations based on trade data from The Growth Lab at Harvard University (2019).