Heterogeneous Firms and Corruption
A Firm-Level Analysis on Emerging Markets*

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Abstract

Using the World Bank Enterprise Surveys and an extension of the Helpman et al. (2004) framework, I test whether host country corruption influences the composition of local exporters and multinational enterprise (MNE) affiliates. In this setting, a firm's 'type' is assumed to be determined by an exogenously drawn productivity level and country–specific fixed costs. I find evidence that greater degrees of host corruption cause underlying fixed costs to rise, reflected by differences in average firm productivity, both at the country and country–industry levels. In particular, local corruption contributes to increased exporter fixed costs for both domestic firms and MNEs, costs which only relatively more productive firms can afford. A one unit intensification of corruption is associated with 2.53% to 4.81% and 1.41% to 2.53% higher average productivity across remaining exporting MNE affiliates and domestically-owned firms, respectively, relative to domestically-owned non-exporters. These findings suggest corruption to be a detriment to export participation across firms.

JEL classification: D24, D73, F23, J24
Keywords: Firm-level data, firm heterogeneity, productivity, corruption.

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1. Introduction

Studies surrounding the influence of institutional corruption on economic activity often find effects to be ambiguous, depending on which underlying mechanism is examined. On one hand, lower public expenditure could place a burden on a given economy and lead to lower national growth rates (Shleifer and Vishny, 1993). Bribery, inefficient judicial systems, poor maintenance of property rights or a general failure of law enforcement are all factors through which corruption may hamper growth (Mauro, 1995; Olken, 2007; Potter and Tavits, 2011; Dincer, 2019). Conversely, it is possible that particular components of growth, such as trade and investment, are stimulated by corruption. For example, corruption havens may form in which the poor enforcement of labor rights draws in foreign direct investment (Edmonds and Pavcnik, 2006; Davies and Voy, 2009). Government contracts, where the bidding process is susceptible to bribery, may make it easier for the most productive firm to win the bids (Lui, 1985; Kaufmann and Wei, 1999).

I focus on a particular mechanism in which host country variation in corruption adjusts the fixed costs of entry, export participation, and inward FDI at the firm-level, which is reflected by changes in the composition of firms across a large set of developing countries. I center this study on developing countries since corruption is more prevalent (Svensson, 2005) and exports are a greater contributor to growth (Melo and Robinson, 1992).[1]

To understand this mechanism, consider how firm-level trade participation is influenced more generally. Economic development is commonly pursued through increased trade openness, which allows entrant firms to access export markets and existing exporters to upscale operations (Clerides et al., 1998; Bernard and Jensen, 1999). Such policy adjustments result in country-specific resources reallocating to relatively more productive firms through competitive market forces (Pavcnik, 2002). These resource reallocation insights have coincided with an increased focus on firm- and plant–level analyses. One particularly well supported theory is that of self-selection, in which only sufficiently competitive firms, with higher exogenously drawn levels of productivity, can afford access to foreign markets due to their associated exporting fixed costs (Pack, 1988; Aw and Hwang, 1995; Melitz, 2003). Through an extension of this framework by Helpman et al. (2004), which I will refer to as HMY (2004) going forward, multinational enterprises (MNEs) producing goods in a given host country must be more productive than exporting firms to afford greater investment fixed costs.

I extend HMY (2004) such that my framework is still characterized by heterogeneous firms with exogenously drawn productivity levels but endogenous fixed costs are influenced by variation in host country corruption levels. Similarly to HMY (2004), differences in a country's fixed costs establish productivity rankings across firm types, which are increasing in the order of non-exporters, exporters and MNEs. For a given country, I deviate from HMY (2004) by focusing attention on MNEs affiliates formed through inbound FDI, rather than MNE parent firms that generate outbound FDI. Additionally, I distinguish between MNEs seeking proximity to a given country's domestic market and MNEs establishing export platforms. In this setting, a country's fixed costs of various firm-type profit functions are each potentially exposed to underlying corruption in that same country.

[1]This trend of trade driving growth in developing countries has also accelerated compared to developed countries. For example, total exports of developing countries have increased from 33.2 percent of global exports in 2005 to 41.9 percent in 2015. Available at https://unctadstat.unctad.org/EN/Index.html (accessed 25 July 2021).

Among developing countries, where MNEs more frequently form through inward rather than outward FDI (Luo and Tung, 2007), I highlight whether specific fixed costs of entry, exporting and factory overheads are influenced by variation in corruption exposure at the firm–level. Using a net effects model based on Davies and Jeppesen (2015) in which country-specific fixed costs influence average productivity, I test how average productivity differences across firm-types vary with local corruption levels.

The findings of the baseline model I specify suggests that productivity rankings are consistent with my extension to the HMY (2004) framework. MNEs affiliates, formed through inward FDI, and domestically–owned exporters are, on average, more productive than domestically–owned non-exporter firms. Respectively, these differences reflect 12.4 to 52.4 per cent and 10.9 to 32.2 per cent greater levels of productivity, depending on the explicit productivity measure used. Upon distinguishing between MNEs by exporter status, MNEs with export platforms top every productivity ranking, ranging between 20 to 55.8 percent more productive than the non–exporting domestic firms. In contrast, average productivity among domestic exporters and non-exporting MNEs are often indistinguishable, with the latter group maintaining productivity levels 2.8 to 26 percent higher than domestic non–exporters. These results suggest that only exporting MNE affiliates should be considered "top-dogs" in a developing country setting. Distinguishing the sample of firms by sub-regions, Latin America, Eastern Europe, Central Asia and Sub-Saharan Africa all yield these same patterns individually. South-East Asia yields a particularly elevated average productivity across its domestically-owned exporters.

Extending the baseline regression specification to account for variation in host country–specific and host country–industry–specific corruption, my results suggests that this form of resource misallocation weighs significantly on export participation both for domestic firms and MNEs. Among domestically-owned exporters, a one-unit increase in the country–industry corruption score in year t, C_{iht}, is associated with a 1.39% to 2.47% lower average productivity levels.[2] When all else is held constant, MNE affiliates maintaining export platforms reflect, on average, 2.47% to 4.59% percent lower average productivity, given a one-unit increase in corruption which is synonymous to lower degrees of corruption. According to the extended framework I specify, this would suggest that given a host's greater control of corruption, the fixed costs maintaining an export platform in a host country lower. This allows less productive MNE affiliates based in this host country to afford participating in trade, lowering average productivity among the exporting MNE cohort.

The rest of the paper proceeds as follows. Section 2 explores the related literature and highlight the contributions of this study. Section 3 details the conceptual framework of this paper. This in turn will motivate the specification of my baseline and extended regressions used to assess productivity rankings across firm-types and the impact of a greater control over corruption on average productivity levels, respectively. Section 4 describes the data set and details how productivity & corruption are measured at the firm-level and country–industry level, respectively. Section 5 presents the results and details two robustness tests for potential selection bias. Section 6 provides concluding remarks.

[2] A maximum score of 10 represents a country being at the lowest degree of corruption. This measure of corruption for industry h in country i is estimated based on a combination of country–level corruption scores from Transparency International, which ranks how much control a nation has over corruption, and firm-level survey responses from the World Bank in which firms specify how much of an obstacle corruption is to their business activities. Further details of this measure are provided in Section 4 and the appendix.

2. Related Literature

In this section I highlight my contributions to several strands of literature, such as studies of heterogeneous firms & export participation, the impact of institutional and market frictions on international trade and challenges with respect to measuring corruption.

The findings of this study contribute to a set of empirical firm–level analyses, examining whether firms' inherent productivity determines their ability to engage in trade and FDI. Within this literature, this paper is closest in spirit to Melitz (2003), Helpman et al. (2004), Nocke and Yeaple (2007) and Tintelnot (2017), which establish models of heterogeneous firms endogenously self-selecting into various modes of foreign market activity. As highlighted by Greenaway and Kneller (2007) and displayed in Table 1, many of the empirical studies of their productivity rank propositions are country–specific with a particular focus on developed countries. For example, in a plant-level study based on U.S. firms, Bernard et al. (2003) finds supportive evidence of higher average labor productivity ratios among exporters relative to non-exporters. Using the U.S. Bureau of Economic Analysis firm-level data, Ramondo et al. (2016) finds matching patterns for non-exporters and exporters, while only the largest firms engage in foreign direct investment as MNE's. In contrast, I provide substantial support to the external validity of firm rankings in a cross-country setting while focusing on developing countries.[3]

Table 1: Evidence of Relative Productivity of Exporters and Multinationals

Author	Sample	Methodology	Exporter vs. Non-Exporter	MNE vs Exporter
Arnold & Hussinger (2005)	Germany, '96–'02	K-S Tests of Stoch Dom	+	+
Castellani & Zanfei (2007)	Italy, '94–'96	OLS	0	+
Girma et al. (2004)	Ireland, '00	K-S Tests of Stoch Dom	0	+
Girma et al. (2005)	UK, '90–'95	K-S Tests of Stoch Dom	+	+
Head & Ries (2003)	Japan, '89	OLS	0	+
Kimura & Kiyota (2004)	Japan, '94–'00	OLS	+	+
Wagner (2005)	Germany, '95	K-S Tests of Stoch Dom	+	+

Source: Greenaway and Kneller, 2007. "Firm Heterogeneity, Exporting and Foreign Direct Investment"

I also add to a wider literature examining the impact of institutional and market frictions on international trade. This body of work departs from the traditional assumption in the trade literature that resources are efficiently and instantaneously reallocated across firms. For example, Manova et al. (2015) finds that variation in financial market imperfections can impede firms' ability to engage in international trade. Under more rigid labor market conditions, frictions limit the reallocation of workers between firms in response to particular trade policies (Ruggieri, 2019; Kim and Vogel, 2020). In the presence of firm heterogeneity and potential resource misallocation, Berthou et al. (2020) displays how efficient institutions, factor and product markets amplify the gains from import competition but dampen those from export access. Using the World Bank Enterprise Surveys

[3] More specifically, this study uses firm-level data across over 140 unique countries, of which 120 are developing, and 242 country–year groups.

(WES), both Davies and Jeppesen (2015) and Olney (2016) find that larger trade costs and greater corruption in host countries, respectively, leads to lower productivity differences between exporters and non-exporters while raising differences between direct and indirect exporters. Narayan and Bui (2021) find higher degrees of corruption discourage bilateral export flows in Vietnam, though the underlying mechanism through which this occurs are not detailed. I provide a distinct extension to these studies by using a firm–type set inclusive of MNEs affiliates formed through inward FDI and a micro-founded framework that assesses the impact of frictions, in the form of host country corruption, on the fixed costs of export participation and inbound FDI.

My findings overlaps most directly with a variety of studies dovetailing firm-level outcomes and the influence of host country corruption. While these studies have guided my selection of country–level corruption measures[4], the majority explain differences in investment flows. Local investment is inhibited by an anticipated "extra tax effect" or more generally through a risk of rent-seeking behaviour by local officials (Beekman et al., 2014), resulting in less domestic firms reaching a scale in which they can approach export markets. Using firm-level data across 22 transition economies, Javorcik and Wei (2009) finds that the probability of inward FDI occurring in a host country is negatively associated with the degree of corruption present. Gastanaga et al. (1998) identifies corruption, among other factors, as a deterrent to FDI inflows. Wei (2000) uses bilateral country-level data to assess the impact of corruption on FDI, finding that a shift from 1990-1 Singaporean to Mexico's prevailing corruption level would reduce FDI in a manner equivalent to raising corporate tax rates by over 20 percentage points. Egger and Winner (2005) suggests corruption attracts FDI, using similar bilateral data and appealing towards easing administrative restrictions.

Differences across these FDI studies may be explained by Wu (2006), using a concept of "corruption distance", a difference in acceptance of existing corruption levels between host and parent countries. While MNEs with the capacity to engage in bribery can disregard this activity, MNEs accustomed to operating in transparent environments find it difficult to overcome the administrative complexities these additional requirements introduce.[5] En masse, the results I present suggest that the majority of MNE affiliates are not compatible with a given host country's extent of corruption and inward FDI, intended for developing export platforms, is inhibited by corruption among developing countries.

An additional contribution of this paper is my refinement of a country–industry measure of corruption exposure, which I have not encountered in the aforementioned literature on corruption influencing firm–level outcomes.[6] Not only do I prepare a measure of corruption more reflective of the exposure associated with individual firms, but the manner in which I prepare this variable allows it to be comparable across firms in a cross–country setting. Results using these more specific corruption measures are largely supportive of my other findings, while dismissing the significance of non-exporting MNE firms' productivity, relative to non-exporting domestic firms. This suggests a particularly direct inhibition of trade participation as a result of intensified corrupt activities.

[4] To measure corruption, these papers often use a Kaufmann-Kraay-Zoibo (KKZ) index developed by Kaufmann et al. (1999) and the Transparency International (TI) corruption index. For country level corruption, this study uses the TI measure of corruption perceptions, highly correlated with the KKZ.

[5] Given that I do not observe the parent country of MNE affiliates, I cannot control for interactions between host and parent country "corruption distance" and leave this pursuit open to future research.

[6] This measure is generated to address concerns regarding the use of an aggregated country–level corruption measure that ignores distinct differences in exposure across industries of a given country.

3. Methodology

In the following section, I detail my extension of the HMY (2004) framework, which pivots to focus on inbound rather than outbound FDI and features the choice of establishing an export platform by the affiliate MNE hosted in country i. This model establishes four firm types, distinguished by combinations of exporter and MNE status, and their associated minimum productivity levels in a setting where countries share symmetric characteristics. I then provide specifications of the baseline and extended regressions this framework would motivate use of. I include country, industry and year fixed effects to relax the symmetric assumptions featured in the model, but continue to assume productivity is exogeneously determined per firm while average productivity per firm-type is endogenously determined by fixed costs causing firms self-selecting into specific profitable operations.

3.1. Conceptual Framework

Under a HMY (2004) setting, there are N countries, in which monopolistic firms use labor to produce a variety of goods in $H + 1$ sectors. The subset of H sectors produce a differentiated set of goods while the single numeraire sector requires 1 unit of labor per quantity of homogeneous good produced. To enter the market in country i, a firm faces an initial sunk cost of entry, f_i^E labor units. Entry firms then draw their particular productivity level from a specified distribution $G(a)$, with shape parameter k_h and scale parameter b.[7] Upon observing productivity, a firm may decide to exit the market or produce for the domestic economy and bear a fixed cost of plant overheads, f_i^D.

Of the surviving firms, conventional theory has those producing for a foreign market face a proximity-concentration trade–off, which determines their status as either an exporter or a multinational enterprise. This trade–off captures a choice between higher fixed costs of outward foreign direct investment and higher variable costs due to exporting. I deviate from the standard model at this point. To assess impact of host country-specific conditions on fixed costs, I include MNE affiliates formed through inward FDI from parent country k rather than HMY's (2004) 'home-grown' MNEs from i engaged in outward FDI to country k. This allows for every firm–type's operations to be exposed to the corruption levels prevailing in host country i. Relative to firms which only supply the domestic market, exporting firms bear an additional fixed cost of exporting to country j, f_{ij}^X, and increased variable costs in the form of an 'iceberg' transport cost. This form of attrition on traded goods means $\tau^{ij} > 1$ labor units are required to provide one labor unit of output to foreign destination j.

A firm headquartered in parent country k operates as an MNE in host country i by establishing operations through inbound FDI, which bears a fixed cost of investment, f_{ki}^I. This measure incorporates the fixed overhead costs of maintaining a factory abroad, handling the required translations & filings of key application documents and the costs of forming local distribution and servicing networks. Of those MNEs which are productive enough to afford these fixed costs of operating abroad, a subset will treat country i as an export-platform, in which they also consider exporting to country j in addition to supply goods locally to country i. Firms capable of affording both foreign direct investment fixed costs and those required to establish an export platform can afford $f_{ki,ij}^{IX}$.

[7]In most cases this takes the form of a Pareto distribution, which is frequently noted as a good fit for real-world distributions of firm size relative to other possible distributions (Melitz and Redding, 2013).

I suggest that these fixed costs experienced in country i are endogenously determined by various country–specific factors, such as corruption, C_i. This is motivated by Antras et al. (2017), which uses the corruption level of host countries when estimating the fixed costs of inbound FDI in a quantitative setting.[8] In this case, variation in corruption determines the composition of firms engaged in non-exporting, exporting and foreign direct investment, where $\{f_i^D, f_{ij}^X, f_{ki}^I, f_{ki,ij}^{IX}\}$ is represented by $\{f_i^D(C_i), f_{ij}^X(C_i), f_{ki}^I(C_i), f_{ki,ij}^{IX}(C_i)\}$.

Under CES consumer preferences, the elasticity of substitution is $\varepsilon = 1/(1-\alpha) > 1$, where α is the inverse of the markup factor available to these monopolistic firms. The demand function for a particular good from sector h is $A_i(p_i^h)^{-\varepsilon}$, where A_i represents the demand level of a country and p_i^h is the price of the good.[9] Given that the firms face monopolistic competition with a drawn labor coefficient a, the price-per-unit-output $p_i = w_i a/\alpha$, where w_i is the prevailing wage. The output of a given firm is $q_i^h = A_i(p_i^h)^{-\varepsilon} = A_i(w_i a/\alpha)^{-\varepsilon}$. Revenue, $r_i^h = p_i^h q_i^h = A_i(w_i a/\alpha)^{1-\varepsilon}$. Given the markup factor, costs would be $c_i^h = \alpha p_i^h q_i^h = \alpha A_i(w_i a/\alpha)^{1-\varepsilon}$. For variable profits, the difference between revenue and marginal costs is $\pi_i^{*h} = r_i^h - c_i^h = (1-\alpha)A_i(w_i a/\alpha)^{1-\varepsilon}$. Using these expressions, the profit functions for our four firm activities are as follows:

$$\pi_i^D = (w_i a)^{1-\varepsilon}(1-\alpha)A_i\left(\frac{1}{\alpha}\right)^{1-\varepsilon} - f_i^D(C_i) = (w_i a)^{1-\varepsilon}B_i - f_i^D(C_i) \tag{1}$$

$$\pi_{ij}^X = (\tau_{ij} w_i a)^{1-\varepsilon}(1-\alpha)A_j\left(\frac{1}{\alpha}\right)^{1-\varepsilon} - f_{ij}^X(C_i) = (\tau_{ij} w_i a)^{1-\varepsilon}B_j - f_{ij}^X(C_i) \tag{2}$$

$$\pi_{ki}^I = (w_i a)^{1-\varepsilon}(1-\alpha)A_i\left(\frac{1}{\alpha}\right)^{1-\varepsilon} - f_{ki}^I(C_i) = (w_i a)^{1-\varepsilon}B_i - f_I(C_i) \tag{3}$$

$$\pi_{ki,ij}^{IX} = (\tau_{ij} w_i a)^{1-\varepsilon}(1-\alpha)A_j\left(\frac{1}{\alpha}\right)^{1-\varepsilon} - f_{ki,ij}^{IX}(C_i) = (\tau_{ij} w_i a)^{1-\varepsilon}B_j - f_{ki,ij}^{IX}(C_i) \tag{4}$$

where π_i^D denotes profits of sales in the domestic market, π_{ij}^X represents profits of exports to country j, π_{ki}^I captures MNE profits from sales in the domestic market, and $\pi_{ki,ij}^{IX}$ represents profits of MNE's originating from k and based in i, operating an export platform to country j. Since $\varepsilon > 1$, $a^{1-\varepsilon}$ increases monotonically with productivity levels $1/a$, all four activities see profits rise with productivity levels across the support range of $\{a_i^D, +\infty\}$. In addition, the model assumes that the following inequality holds:

$$(\tau^{ij})^{\varepsilon-1} f_{ki,ij}^{IX}(C_i) > f_{ki}^I(C_i) > (\tau^{ij})^{\varepsilon-1} f_{ij}^X(C_i) > f_{ij}^D(C_i) \tag{5}$$

This first inequality ensures lower productivity MNE firms generate greater profits exclusively from producing for the domestic market, while higher productivity MNEs find maintaining export-platforms profitable. The last inequality ensures that there exists some portion of firms that only supply the domestic economy. As per Melitz (2003), these assumptions contribute to a setting where exporters must also produce for the domestic market. This allows for each firm's profit function can be separated into portions earned

[8] The study focused on treating FDI activity as a means of sourcing foreign inputs within an organization. It uses US firm-level data, combined with country characteristics including "control of corruption", to determine structural estimates of country-level fixed costs. These in turn are used as structural parameters to model patterns in trade and sourcing potential.

[9] $A_i = \beta^h E_i / (\int_0^{n_i^h} p_i^h(v)^{1-\varepsilon} dv)$, where β^h represents the share of income spent on sector h, E^i is the aggregate expenditure level of country i and the integral captures the price level across n_i^h varieties v in sector h. This demand level is exogenous from the supplier's perspective.

by domestic sales based in country i (π_i^D, π_{ki}^I) and export sales attributed to country j ($\pi_{ij}^X, \pi_{ki,ij}^{IX}$). Setting (1)-(4) equal to zero, the model identifies four cut-offs at which firm–types are determined.

$$(a_i^D)^{1-\varepsilon} = (w_i)^{1-\varepsilon}\frac{f_i^D(C_i)}{B_i} \qquad (a_{ij}^X)^{1-\varepsilon} = (\tau_{ij}w_i)^{1-\varepsilon}\frac{f_i^X(C_i)}{B_j}$$
$$(a_{ki}^I)^{1-\varepsilon} = (w_i)^{1-\varepsilon}\frac{f_{ki}^I(C_i)}{B_i} \qquad (a_{ki,ij}^{IX})^{1-\varepsilon} = (\tau_{ij}w_i)^{1-\varepsilon}\frac{f_{ki,ij}^{IX}(C_i)}{B_j}$$

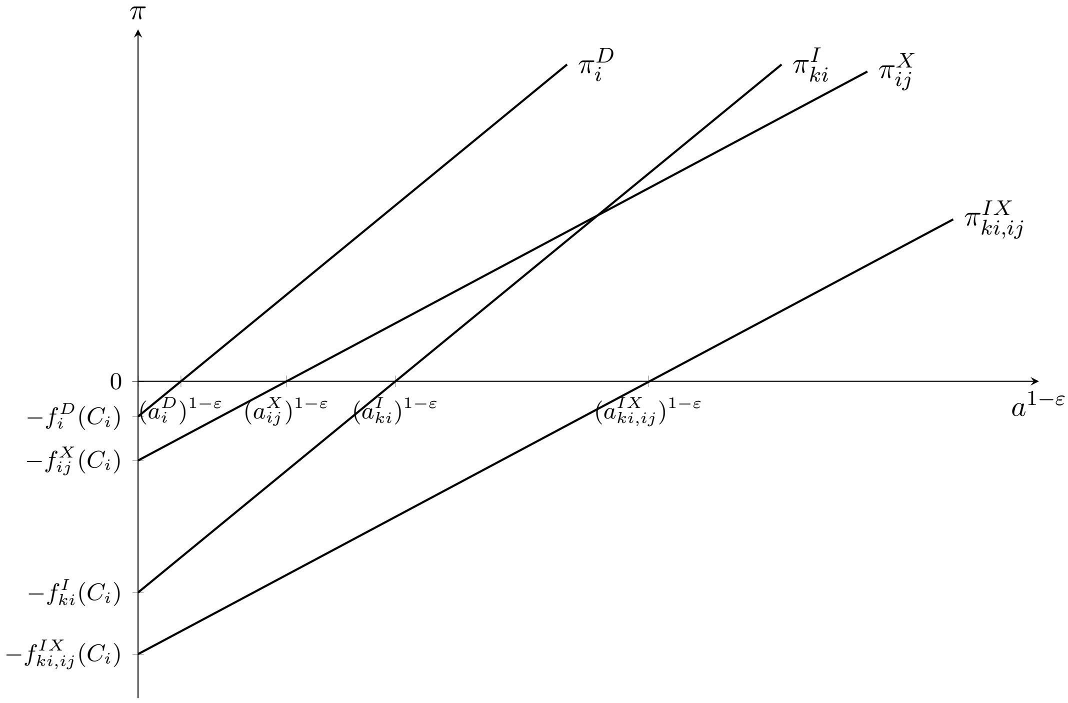
In order to highlight the comparative statics of fixed costs, consider a simplification to the model in which all countries share symmetric characteristics and wages are normalized to 1. In this case $B_i = B_j \ \forall \ i,j \in N$. As displayed in Figure 1, these assumptions result in two pairs of parallel profit functions for both domestic and export activities. In this setting the productivity distributions that firms draw from are identical across the J included countries. Under common productivity distributions across countries and symmetric trade costs, the cutoff between export status and outward FDI from country k to country l are identical to our country of interest, i. Assuming inward FDI is based on factory setup (greenfield investment) and foreign affiliates inherit the productivity of their parent firm, then the productivity of firms engaged in inward FDI will dominate exporters from a given country. Among inward FDI, because you need an additional fixed cost to export, firms engaged in inward FDI and export–platforms represent the highest productivity establishments.

Should a firm draw productivity below $(a_D^i)^{1-\varepsilon}$, they will immediately exit the market. For productivity draw $(a_i^D)^{1-\varepsilon} \leq a^{1-\varepsilon} < (a_{ij}^X)^{1-\varepsilon}$, the firm exclusively selling goods to the domestic market, identifying our least productive cohort of firms as domestically-orientated non-exporting firms. Higher draws of productivity within $(a_{ij}^X)^{1-\varepsilon} \leq a^{1-\varepsilon}$ will see firms supply the domestic economy as well as export goods to a particular country j. In this setting of symmetric countries, every country would receive exports of such firms. Only the most productive firms, MNEs, maintain productivity levels such that $a^{1-\varepsilon} > (a_{ki}^I)^{1-\varepsilon}$, which are high enough to afford the associated fixed costs $f_{ki}^I(C_i)$ and derive a profit from engaging in FDI for country i. Similarly to their domestically–owned counterparts, if $(a_{ki,ij}^{IX})^{1-\varepsilon} \leq a^{1-\varepsilon}$ then MNEs will establish an export-platform in i, targeting country j.

As highlighted in (5) and Figure 1, adjustments to fixed costs have selection effects in which firms of varying levels of productivity will be forced to exit markets. Should export-related fixed costs rise, this would be reflected through an increase in $f_{ij}^X(C_i)$ and $f_{ki,ij}^{IX}(C_i)$ and cause π_{ij}^X and $\pi_{ki,ij}^{XI}$ to shift downward for every given level of productivity $a^{1-\varepsilon}$. The required minimum productivity thresholds to maintain exporter status increase from the set $\{(a_{ij}^X)^{1-\varepsilon}, (a_{ki,ij}^{IX})^{1-\varepsilon}\}$ to $\{(a_{ij}'^X)^{1-\varepsilon}, (a_{ki,ij}'^{IX})^{1-\varepsilon}\}$. Firms on the margin of exporting to j would cease these activities, lowering ij export market participation. Assuming no response in overhead investment costs, average productivity among the now larger set of non-exporters is higher, as is average productivity across the set of exporting firms.

Consider instead a case in which overhead costs of setup rise, in which case we would expect to observe an increase in $f_i^D(C_i)$ and $f_{ki}^I(C_i)$. Given that the required minimum productivity thresholds to maintain activities in country i rises from the set $\{(a_i^D)^{1-\varepsilon}, (a_{ki}^I)^{1-\varepsilon}\}$ to $\{(a_i'^D)^{1-\varepsilon}, (a_{ki}'^I)^{1-\varepsilon}\}$, low productivity firms are forced out of the market among both domestically–owned and MNE non-exporters. This contributes to a rise in average productivity across firms exclusively servicing the domestic market.

Figure 1: Profit functions by activity



These changes in underlying fixed costs may be partially driven by local country factors specific to i, such as accessibility to key documents necessary to engage in business start-up, meeting the legal requirements necessary to ship goods abroad or receiving permission to pursue foreign investment through legal transactions of property rights. The positive co-movement of fixed costs featured in my assessment is not guaranteed. For example, we may observe heterogeneity such that local officials are more likely to lean on small domestic start-ups rather than more established multinational organizations seeking to establish greenfield investment or joint ventures.[10] Under such circumstances in which MNEs are shielded from potential increases in fixed costs, we may observe ambiguous cases such that $f_i^D{'}(C_i), f_{ij}^X{'}(C_i) > 0$ & $f_{ki}^I{'}(C_i), f_{ki,ij}^{IX}{'}(C_i) \leq 0$.

In each of these settings, interference at an institutional or local level by appointed officials in the form of required informal payments may limit the affordability of business ventures relative to a counterfactual where such systems are infeasible to maintain. Conversely, if corruption is instead reflected through poor labor rights enforcement, the initial cost in establishing a factory may be far less extensive (e.g. lower safety standards that are completely ignored by adequately compensated regulators). In such a setting, the trade–off could shift a given profit function upward in Figure 1 and allow less efficient firms to thrive in a corrupt setting. This composition change in active firms would lower average productivity, given an increase in the degree of corruption for a country.

[10]Evidence suggests that developing nations separately prioritize their administrative and tax duties of large firms to dedicated offices. For example, Indonesia moved the top firms in each region into "Medium-Sized Taxpayer Offices" with high staff-to-taxpayer ratios, resulting in associated tax revenue more than doubling (Basri et al., 2021).

In the next section I detail how I apply a cross–country, firm–level empirical strategy to both test theoretical productivity rankings across firm types and infer composition changes in average productivity per firm–type, given variation in corruption. These changes and their implied influences on underlying fixed costs are interpreted using the conceptual framework I have outlined.

3.2. Empirical Strategy

Using the assumptions and firm-types of my conceptual framework, I empirically test two hypotheses established by the model. The first hypothesis uses the baseline specification to examine whether implied productivity rankings across my firm-types are consistent with the economic theory I apply. The extended specification tests if variation in corruption significantly influences fixed costs, which is reflected by differences in average productivity between firm–types, given variation in the corruption measure. For my baseline and extended fixed effects models, I follow a specification based on Davies and Jeppesen (2015) to test both hypotheses.

In my baseline regression, I regress four separate firm-level measures of productivity[11], lnY_{fhit}, on indicators for firm–types and on firm-specific controls through a fixed effects model.

$$\begin{aligned} lnY_{fhit} = \beta_0 + \beta_1 \text{HomeExp}_{fhit} + \beta_2 \text{MNEDom}_{fhit} + \beta_3 \text{MNEExp}_{fhit} \\ + \beta_4 X_{fhit} + \theta_h + \theta_i + \theta_t + \varepsilon_{fhit} \end{aligned} \tag{6}$$

where firm f operates in industry h and country i at survey year t. Dummy variables identify whether firm f is a domestically-owned exporters, HomeExp_{fhit}, MNE non-exporters, MNEDom_{fhit}, or MNE exporter MNEExp_{hit}.[12] X_{fijt} represents a vector of firm level controls, which includes the logarithm of firm age, *lnage*, a dummy variable, *qcert*, equal to 1 if an establishment has an internationally-recognized quality certification, a dummy variable, *license*, equal to 1 if a firm uses technology licensed from a foreign-owned company, a dummy variable, *import*, equal to 1 if the firm directly imports goods, and lastly a dummy variable, *multi*, equal to 1 if less than 100 percent of total annual sales originate from the firm's primary product.

Given the assumptions applied in Section (3.1), I would expect that each particular firm–type maintains average productivity levels that are significantly higher than our reference group of domestically–owned non–exporters and $0 < \beta_1 < \beta_2 < \beta_3$. While I assume underlying productivity levels of firms are individually exogenous, the distributions by which they draw these levels from may be dependent on the country, industry and year in question. By controlling for these underlying differences across groups, whether that be by country, industry or year, these fixed effects map the empirical specification that is otherwise non-symmetric across countries and industries back to my model setting. Standard errors are clustered at the industry level, unless otherwise specified.

[11] These productivity measures include labor productivity, approximate total factor productivity and two residual productivity prescribed by the World Bank, the provider of the observed data. For more details on how productivity is measured, see the next section.

[12] Based on the prevailing literature on MNEs, I use a conventional cut-off of 10 percent foreign ownership for their identification (Almeida, 2007; Farole and Winkler, 2012; Javorcik, 2015).

Upon establishing baseline support for implied productivity rankings across firm-type, I then use the following extended model to assess the impact of lower country-level corruption (higher Cor_{it}) on differences in average productivity across firm types:

$$\begin{aligned} lnY_{fhit} = \beta_0 + \gamma_0 Cor_{it} + \beta_1 \text{HomeEXP}_{fhit} + \beta_2 \text{MNEDom}_{fhit} + \beta_3 \text{MNEExp}_{fhit} \\ + \gamma_1(\text{HomeExp}_{fhit} * Cor_{it}) + \gamma_2(\text{MNEDom}_{fhit} * Cor_{it}) \\ + \gamma_3(\text{MNEExp}_{fhit} * Cor_{it}) + \beta_4 X_{fhit} + \theta_h + \theta_i + \theta_t + \varepsilon_{fhit} \end{aligned} \tag{7}$$

The coefficients of interest, γ_i, convey the association between country–level corruption and average firm–level productivity. The higher the value of Cor_{it}, the less corrupt the country is, with continuous values ranging between 0 (extreme corruption) to 10 (little to none). If $\gamma_1 < 0$, a one unit increase in the corruption measure (less acts of corruption) is associated with a lower average productivity among domestically-owned, exporting firms, implying lower associated fixed costs and greater participation rates. Signs across γ_0, γ_1, γ_2 and γ_3 provide insights into which specific fixed costs may be affected through the necessary selection mechanisms requirement to explain changes in average productivity.

While the theory I provide allows for ambiguous movements in fixed costs as a result of variation in corruption, surrounding studies establish relevant priors useful for framing causal effect. For example, Javorcik and Wei (2009) would lead me to expect that increased host corruption has a negative effect on FDI inflows, which my framework would explain through elevated fixed costs of factory overheads. Such increases would limit participation of relatively less productive MNEs, leading to higher average productivity among this firm type. This would be reflected through a negative γ_3 estimate, since a marginal increase in Cor_{it} reflects a lower degree of corruption.

The use of a country-specific measure as my covariate of interest limits the variation of corruption. To address introduce greater variation and limit a possible source of bias, I use a country-industry measure of corruption, C_{iht}, which incorporates added variation based on firm-weighted country-industry level indications of direct exposure to corruption as "an obstacle to current operations". In the next section, I describe the data set used to test these regressions and provide further detail on measures corruption and productivity.

4. Data & Key Measures

I use the Enterprise Surveys data set provided by the World Bank, which I henceforth refer to as WES data.[13] This cross-country administrative data is a set of pooled cross-sections of firm-level observations from 2005 to 2020, which provides details the numbers of employees, sales revenue, and balance sheet information with respect to capital. I identify over 90,000 manufacturing firms from 145 countries, of which 120 are operating in developing countries. Country-year data, such as exchange rates and consumer price indices used for deflating and expressing values in USD, are sourced from the World Development Indicator (WDI) database. Upon cleaning the data for key variables and merging it with country-level data, I have generated estimates of productivity for 63,389

[13] Access was provided by the World Bank Group, Enterprise Analysis Unit, 2021. The sampling methodology for Enterprise Surveys is stratified random sampling. The strata for Enterprise Surveys are firm size, business sector, and geographic region within a country. Further details are available at enterprisesurveys.org/en/methodology

firms distributed across 242 country-year groups.[14] Productivity is measured using four separate estimates that list as labor productivity, approximate TFP, value-added TFP and output-based TFP, all of which are detailed further in Section 4.2. Since the data is a set of pooled cross-sections, firms are not observed repeatedly over time. This limits the scope of the study's ability to apply more precise measures of productivity while the cross-country aspect of my analysis strengthens its appeal with respect to external validity.

Survey questions also inquire about the ownership of firms and their trade activity, which allows me to distinguish specific firm–types. I identify firms as either non-exporting domestically-owned firms, exporting domestically-owned firms, or multinational enterprises (MNEs), in order to mirror the identified firms in my conceptual framework. The data does not provide details regarding whether domestically-owned firms maintain foreign affiliates abroad, therefore firms engaged in outbound FDI are not identified in the data. This paper instead distinguishes between foreign-owned MNEs that are either domestically orientated or engage in exporting.

4.1. Corruption Measure

The key regressor featured in my analysis is a host country's corruption level. There are a number of corruption indices available at this level of variation, all reflecting subjective perceptions of corruption. To reduce the impact of the idiosyncratic errors of individual respondents, the majority of studies interested in this regressor use measures of corruption that capture a pool of information from several existing sources of indices through simple averages or statistical extraction methods (Javorcik and Wei, 2009; Rohwer and Hulsewig, 2009; Ramirez, 2014).

The two prominent examples include Kaufmann et al. (1999) which yields a 'control of corruption measure' and Transparency International's (TI) corruption perception index (CPI). The former measure has since been adapted for the World Governance Indicators (WGI) and reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests (Kaufmann et al., 2010). CPI is a composite indicator that takes an average across various measures of perceived corruption in the public sector and reflects views from institutional experts and various business executives on the state of bribery, diversions of public funds, use of public office for private gain, nepotism in public service and state capture for a given country i in year t.[15] Given that these two measures are 96 percent positively correlated, and the latter more specifically focuses on underlying costs such as bribery, I use a rescaled measure of CPI that ranges from 0 to 10 for a host country corruption regressor.

In Table 2, I display the share of firms belonging to each respective "firm–type" group and a weighted-average of country-specific corruption levels across a set of developing regions. For each region, weights are assigned based on the number of firms observed

[14] For details regarding how the data was cleaned, see Appendix A.

[15] The calculation of CPI values incorporates a quality control mechanism which consists of parallel independent measurements being conducted by two in–house researchers and two academic advisors which TI states as having no affiliation to the organization. Each of the 13 sources included in the CPI are standardized, rescaling all series with a range of 0-100 where a 0 represents the highest level of perceived corruption, and 100 represents the lowest level of perceived corruption. Each country's CPI is a simple average of all the available rescaled scores.

in each included country. This table highlights that as corruption worsens the share of domestically-owned exporting firms (HomeExp) to total firms declines across regions. Should corruption be contributing towards higher fixed costs of trade, this pattern would be expected. Due to a lack of MNEs in South Asia, I assign South Asian and the East Asian Pacific firms to a single "South-East Asia" region in Section 5.2.

Table 2: Firm Type Shares across Regions

Firm Type	**HomeDom**	**HomeExp**	**MNEDom**	**MNEExp**	**Corr**	**# Firms**
E. Europe & C. Asia	0.61	0.28	0.03	0.07	4.02	20,168
Latin America	0.67	0.21	0.04	0.07	3.80	15,728
M.E. & N. Africa	0.72	0.19	0.04	0.05	3.48	7,387
South Asia	0.81	0.17	0.01	0.01	3.31	11,554
East Asian Pacific	0.70	0.15	0.06	0.09	3.25	9,958
Sub-Saharan Africa	0.73	0.10	0.10	0.06	3.07	12,123

Note: **HomeDom** represents domestically-owned non-exporters. **HomeExp** represents domestically-owned exporters. **MNEDom** and **MNEExp** represent non-exporting and exporting MNEs, respectively.

Thus far, I have focused on a country–level measure of corruption, which assumes homogenous exposure to corruption across industries within a given country. Given that fixed costs of entry, exports and inward FDI possibly vary at the country–industry level (Bernard et al., 2007), I introduce a country–industry measure of host country corruption. This measure is estimated through firm-level variation in the WES data set combined with the TI series of country-level corruption. One WES survey question asks *"To what degree is corruption an obstacle to the current operations of this establishment?"* with a 99% response rate. Responses range from 0, 'No Obstacle', to 4 ,'Very Severe'. Differences in these ordinal categorical variable responses are informative within a given country, and allow for comparison of which sets of firm groups (industries) exhibit particularly high or low exposure to prevailing corruption.

While these categories of WES responses are informative in capturing industry differences for a given country, cross-country differences are unclear. For example, a "very severe" response by a firm in a highly corrupt country could imply starkly different conditions compared to the same response by a firm based in a relatively less corrupt country. To ensure these categorical responses still account for relevant differences in perception across countries, I use country corruption (TI) as a base value and apply a rescaling method informed by percentage-based deviations from cross-industry WES-informed average responses for each given country. This measure, C_{iht}, introduces greater variation in my main regressor and incorporates added information more reflective of firm-specific experiences. Though individual perceptions of the meanings behind these categorical responses may differ across firms, these same patterns are likely to be exhibited across industries when taking averages of firm responses. As a result, this approach has an added quality of 'averaging out' idiosyncratic differences in perceptions of questions asked across firms. For further details on the available questions and rescaling method used, see Appendix B.

4.2. Revenue-based Productivity

To measure productivity, I use a number of approaches applied by previous literature. I include measures such as labour productivity (log of deflated sales per employee in USD), residual TFPs estimated through fixed effect models, and an approximate total factor productivity measure. Due to the pooled cross-sectional nature of the WES data set, I cannot generate measures that rely on unique firms being repeatedly identified across time.

For labor productivity (LABP), I measure total sales levels in USD using the year's average exchange rate and deflate for price inflation using the consumer price index for the country each firm stems from. This measure is then divided by the number of employees employed by each firm to obtain a sales revenue per employee proxy for labor productivity. This measure (sales/employees) is commonly used throughout the trade literature, but often acts as a simple proxy of productivity before introducing more accurate residual-based estimates of productivity (Alfaro et al., 2018). Approximate total factor productivity (ATFP) uses a standard log-linearized production function based on labor and capital proposed by Griliches (1998) and applied in Head and Ries (2003) and Tomiura (2007). As per these studies, I use the same $\frac{1}{3}$ capital share of output, which follows Hall and Jones (1999) and Boyle and McQuinn (2004).

$$\begin{aligned} Y_{fjt} &= \Phi^{\text{ATFP}} L_{fjt}^{\frac{2}{3}} K_{fjt}^{\frac{1}{3}} \\ Y_{fjt}/L_{fjt} &= \Phi^{\text{ATFP}} (K_{fjt}/L_{fjt})^{\frac{1}{3}} \\ ln(Y_{fjt}/L_{fjt}) &= ln(\Phi^{\text{ATFP}}) + \frac{1}{3} ln(K_{fjt}/L_{fjt}) \\ ln(\Phi^{\text{ATFP}}) &= ln(Y_{fjt}/L_{fjt}) - \frac{1}{3} ln(K_{fjt}/L_{fjt}) \end{aligned} \tag{8}$$

While use of a production function is helpful, the rigid composition of ATFP still may be of some concern as it assumes a homogeneous distribution of factor inputs across countries and industries. Empirical evidence suggests that when accounting for different types of capital assets, varying degrees of capital shares across countries depend on country income levels (Inklaar et al., 2019).

I address this concern by estimating two additional productivity measures, using of a pair of country-year fixed effect models and then interpreting the residual as an estimate of total factor productivity.[16] This approach exploits contributions of factors of production up to the second moment through flexible polynomial functions. All of the sales revenue, material input, capital and labor cost measures provided by firms are deflated and converted into USD according to the year the data was provided. The estimated residual is associated with the total factor productivity of the firm. The value-added TFP measure (VAKL) sets value added as total sales revenue less input costs as the dependent variable. For explanatory variables, I apply using polynomial of capital and labor. The second of these two productivity estimates measures an output-based total factor productivity measure (YKLM), using sales revenue as the dependent variable and material inputs, labor and capital as the three contributing factors of production.

[16] A methodology is provided by the World Bank Group, Enterprise Analysis Unit, 2021. "Firm Level Productivity Estimates", which I apply for firms from 2005 to 2019.

The set of regression functions are as follows:

$$ln(\mathrm{Y}_{fjt}^{\mathrm{VAKL}}) = \alpha + \beta_1 L_{fjt} + \beta_2 K_{fjt} + \beta_3 L_{fjt}^2 + \beta_4 K_{fjt}^2 + \beta_5(L_{fjt} * K_{fjt}) + \theta_j + \theta_t + \nu_{fjt}^{\mathrm{VAKL}} \tag{9}$$

$$\begin{aligned} ln(\mathrm{Y}_{fjt}^{\mathrm{YKLM}}) = \alpha &+ \gamma_1 L_{fjt} + \gamma_2 K_{fjt} + \gamma_3 M_{fjt} + \gamma_4 L_{fjt}^2 + \gamma_5 K_{fjt}^2 + \gamma_6 M_{fjt}^2 \\ &+ \gamma_7(L_{fjt} * K_{fjt}) + \gamma_8(L_{fjt} * M_{fjt}) + \gamma_9(K_{fjt} * M_{fjt}) + \theta_j + \theta_t + \nu_{fjt}^{\mathrm{YKLM}}, \end{aligned} \tag{10}$$

where observed performance measures of value-added $ln(\mathrm{Y}_{fjt}^{\mathrm{VAKL}})$ and output $ln(\mathrm{Y}_{fjt}^{\mathrm{YKLM}})$ are observed for a given firm f, in country j, at year t. Value-added is represented by the log of sales revenue less material input costs, deflated and adjusted to USD values. Output is the log of sales revenue, deflated and adjusted to USD values. L_{fjt}, K_{fjt} and M_{fjt} represent labor costs, the net value of capital and material input costs.[17]

Well-documented statistical issues, such as simultaneity and selection bias, are often associated with these cross-sectional productivity measures.[18] Methods such as the Olley and Pakes (1996) and Levinsohn and Petrin (2003) semi-parametric input-based approaches can resolve some of these identification issues and have used extensiveness in the trade literature (Pavcnik, 2002; Van Biesebroeck, 2005; De Loecker, 2007; Halpern et al., 2015; De Loecker et al., 2016). However, these methods require panel data on firms and the associated output elasticities of perfectly variable inputs are challenging to identify, resulting in strict or implausible assumptions (De Loecker and Syverson, 2021).

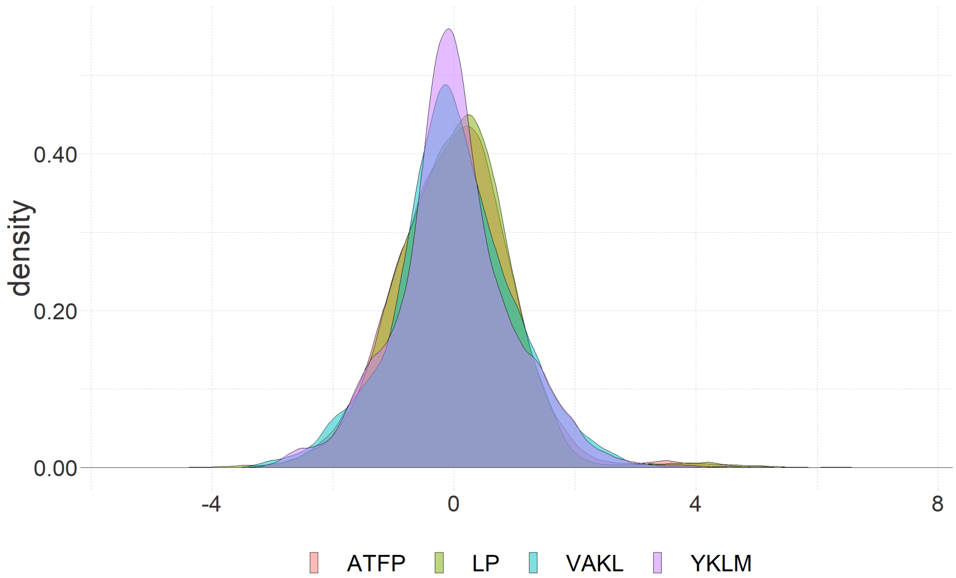
I standardized these productivity measures and display their distributions in Figure 2. Labor productivity and ATFP share a 91.4% positive correlation. Labor productivity shares a 23.2% & 18.2% positive correlation with respect to value-added and output-based residuals, respectively. Between value-added and output-based residual measures of productivity, I observe an 88.7% positive correlation. There is notable skewedness in the VAKL & YKLM distributions, which would appeal to the extreme-distributions often used in explaining extensive margins of firm-level export participation. In the Melitz setting, a Pareto distribution for exogenous firm-level productivity draws delivers a well-documented good fit to the observed firm size distributions (Melitz and Redding, 2013). For these reasons, I rely on VAKL and YKLM as my preferred measures of productivity.

Using two corruption measures, which vary at the country and country-industry level, and productivity measures both consistent with the distributions prescribed by Melitz models and appropriate in a cross-sectional firm-level setting, I proceed with estimation. The next section details the results of these model specifications and highlights the implications of variation in host country corruption on average productivity across firm-types in a developing country setting.

[17] Multiple capital values are available. I have used a measure representing the replacement value of capital as informed by the given firm.

[18] Unobservables can lead to issues of selection bias and simultaneity when attempting to estimate a production function. Additionally, as Katayama et al. (2009) highlights, pass-through effects, unob -served factor heterogeneity and mark-up variations can result in firms with low efficiency yet high profit margins "outperforming" highly efficient yet less profitable firms under a biased measure.

Figure 2: Distribution of Productivity Estimates



5. Results

To address the validity of productivity rankings on a cross-country basis, I assess equation (6) using a set of fixed effect models for each of the four productivity measures. Furthermore, I present results suggesting that these patterns persist across regions, I apply the same equation to five specific blocks of countries: Latin America, South-East Asia, Eastern Europe & Central Asia, the Middle East & North Africa and Sub-Saharan Africa. Lastly, I present results of the extended model and highlight that adjustments in host country corruption are driving fixed costs higher for both domestically-owned and MNE exporters. In comparison, there is no significant variation in average productivity among non-exporters which suggests that corruption has no significant impact on factory overhead fixed costs.

5.1. Productivity Rankings, Pooled

For the pooled samples, results indicate that productivity rankings are consistent with my conceptual framework. Upon controlling for firm-level covariates and industry, country and year fixed effects, multinational firms exhibit greater productivity than their domestically-owned counterparts, with domestically-owned exporters significantly more productive than non-exporting firms. Furthermore, when distinguishing between MNEs by export status, it appears that the conventional form of exporting MNEs are the driving force for this higher average productivity level for a given country-industry-year.

As displayed in the tables below, productivity rankings are consistent across labor productivity, appproximate TFP, value-added TFP and output-based TFP. I emphasize particular focus on columns (3) and (6) of each table, in which I incorporate all relevant fixed effects. Differences in the productivity of MNE non-exporters and domestically–owned exporters are often not statistically different. In the pursuit of conciseness, I maintain use of firm-specific controls but exclude their associate covariates from presented results.

Table 3: Labor Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
HomeEXP	0.435*** (0.074)	0.425*** (0.069)	0.284*** (0.056)	0.439*** (0.076)	0.430*** (0.070)	0.288*** (0.057)
MNE	0.449*** (0.099)	0.485*** (0.080)	0.440*** (0.047)			
MNEDOM				0.351*** (0.061)	0.382*** (0.053)	0.384*** (0.032)
MNEEXP				0.530*** (0.140)	0.570*** (0.113)	0.485*** (0.070)
lnage	0.135*** (0.017)	0.180*** (0.015)	0.079*** (0.012)	0.133*** (0.017)	0.179*** (0.016)	0.079*** (0.012)
qcert	0.564*** (0.048)	0.561*** (0.042)	0.336*** (0.026)	0.558*** (0.046)	0.555*** (0.041)	0.333*** (0.025)
license	0.177*** (0.030)	0.167*** (0.028)	0.184*** (0.017)	0.176*** (0.031)	0.165*** (0.028)	0.182*** (0.017)
import	0.297*** (0.037)	0.228*** (0.043)	0.191*** (0.028)	0.294*** (0.036)	0.225*** (0.042)	0.189*** (0.027)
multi	0.155*** (0.021)	0.009 (0.021)	−0.015 (0.015)	0.155*** (0.021)	0.009 (0.021)	−0.015 (0.015)
Fixed Effects						
Industry	✓	✓	✓	✓	✓	✓
Year		✓	✓		✓	✓
Country			✓			✓
N	63,389	63,389	63,389	63,389	63,389	63,389
R^2	0.119	0.187	0.551	0.119	0.187	0.551

Notes: Observations are at the firm level. All columns are all reflective of the baseline model. Standard errors clustered at the industry level are shown in parentheses. Firm type dummies are: **HomeEXP**, domestically-owned exporters, **MNEDOM**, non-exporter MNEs, and **MNEEXP**, MNEs maintaining export platforms. *** at 1%, ** at 5%, * at 10% level.

Table 4: Approximate TFP, Baseline Regression

	(1)	(2)	(3)	(4)	(5)	(6)
HomeEXP	0.330*** (0.051)	0.327*** (0.040)	0.229*** (0.035)	0.336*** (0.053)	0.334*** (0.041)	0.236*** (0.036)
MNE	0.350*** (0.079)	0.353*** (0.059)	0.341*** (0.031)			
MNEDOM				0.211*** (0.050)	0.207*** (0.041)	0.243*** (0.024)
MNEEXP				0.464*** (0.117)	0.474*** (0.087)	0.421*** (0.050)
lnage	0.065*** (0.014)	0.130*** (0.013)	0.043*** (0.008)	0.063*** (0.015)	0.128*** (0.014)	0.043*** (0.009)
qcert	0.391*** (0.036)	0.369*** (0.030)	0.228*** (0.013)	0.382*** (0.034)	0.360*** (0.029)	0.223*** (0.013)
license	0.087*** (0.020)	0.064*** (0.019)	0.099*** (0.012)	0.084*** (0.021)	0.060*** (0.019)	0.096*** (0.012)
import	0.147*** (0.026)	0.131*** (0.032)	0.112*** (0.022)	0.142*** (0.025)	0.126*** (0.031)	0.109*** (0.021)
multi	0.151*** (0.016)	0.009 (0.014)	−0.003 (0.013)	0.151*** (0.016)	0.009 (0.014)	−0.004 (0.013)
Fixed Effects						
Industry	✓	✓	✓	✓	✓	✓
Year		✓	✓		✓	✓
Country			✓			✓
N	46,222	46,222	46,222	46,222	46,222	46,222
R^2	0.083	0.179	0.452	0.084	0.179	0.453

Notes: Observations are at the firm level. All columns are all reflective of the baseline model. Standard errors clustered at the industry level are shown in parentheses. Firm type dummies are: **HomeEXP**, domestically-owned exporters, **MNEDOM**, non-exporter MNEs, and **MNEEXP**, MNEs maintaining export platforms. *** at 1%, ** at 5%, * at 10% level.

Table 5: Value-Added TFP, Baseline Regression

	(1)	(2)	(3)	(4)	(5)	(6)
HomeEXP	0.112*** (0.021)	0.110*** (0.021)	0.135*** (0.017)	0.113*** (0.021)	0.111*** (0.021)	0.138*** (0.018)
MNE	0.186*** (0.016)	0.190*** (0.015)	0.189*** (0.020)			
MNEDOM				0.164*** (0.019)	0.169*** (0.017)	0.138*** (0.025)
MNEEXP				0.205*** (0.020)	0.209*** (0.019)	0.232*** (0.020)
lnage	0.007 (0.009)	0.016** (0.007)	0.009 (0.007)	0.007 (0.009)	0.016** (0.007)	0.009 (0.007)
qcert	0.167*** (0.018)	0.149*** (0.016)	0.130*** (0.015)	0.166*** (0.019)	0.148*** (0.016)	0.127*** (0.015)
license	0.050*** (0.014)	0.044*** (0.013)	0.037*** (0.011)	0.049*** (0.014)	0.043*** (0.013)	0.035*** (0.011)
import	−0.023* (0.012)	−0.009 (0.011)	0.033** (0.013)	−0.024* (0.012)	−0.010 (0.011)	0.032** (0.013)
multi	−0.028*** (0.008)	−0.023*** (0.005)	−0.017** (0.007)	−0.028*** (0.008)	−0.023*** (0.005)	−0.017** (0.007)
Fixed Effects						
Industry	✓	✓	✓	✓	✓	✓
Year		✓	✓		✓	✓
Country			✓			✓
N	40,717	40,717	40,717	40,717	40,717	40,717
R^2	0.380	0.386	0.427	0.380	0.386	0.428

Notes: Observations are at the firm level. All columns are all reflective of the baseline model. Standard errors clustered at the industry level are shown in parentheses. Firm type dummies are: **HomeEXP**, domestically-owned exporters, **MNEDOM**, non-exporter MNEs, and **MNEEXP**, MNEs maintaining export platforms. *** at 1%, ** at 5%, * at 10% level.

Table 6: Output-Based TFP, Baseline Regression

	(1)	(2)	(3)	(4)	(5)	(6)
HomeEXP	0.058*** (0.010)	0.052*** (0.011)	0.062*** (0.008)	0.057*** (0.011)	0.052*** (0.011)	0.062*** (0.009)
MNE	0.104*** (0.014)	0.105*** (0.013)	0.093*** (0.013)			
MNEDOM				0.107*** (0.015)	0.112*** (0.014)	0.080*** (0.015)
MNEEXP				0.101*** (0.017)	0.099*** (0.016)	0.103*** (0.014)
lnage	0.015** (0.006)	0.020*** (0.005)	0.011** (0.004)	0.015** (0.006)	0.020*** (0.005)	0.011** (0.004)
qcert	0.090*** (0.012)	0.079*** (0.009)	0.067*** (0.007)	0.090*** (0.012)	0.079*** (0.009)	0.066*** (0.007)
license	0.034*** (0.009)	0.030*** (0.009)	0.024*** (0.007)	0.034*** (0.009)	0.030*** (0.009)	0.024*** (0.007)
import	−0.014* (0.008)	−0.013* (0.006)	0.007 (0.008)	−0.014* (0.008)	−0.012* (0.006)	0.006 (0.008)
multi	−0.011** (0.005)	−0.009** (0.004)	−0.009** (0.004)	−0.011** (0.005)	−0.009** (0.004)	−0.009** (0.004)
Fixed Effects						
Industry	✓	✓	✓	✓	✓	✓
Year		✓	✓		✓	✓
Country			✓			✓
N	40,012	40,012	40,012	40,012	40,012	40,012
R^2	0.472	0.480	0.534	0.472	0.480	0.534

Notes: Observations are at the firm level. All columns are all reflective of the baseline model. Standard errors clustered at the industry level are shown in parentheses. Firm type dummies are: **HomeEXP**, domestically-owned exporters, **MNEDOM**, non-exporter MNEs, and **MNEEXP**, MNEs maintaining export platforms. *** at 1%, ** at 5%, * at 10% level.

5.2. Productivity Rankings, Regions

While these findings hold when pooling the entire sample, it is of interest to examine whether various geographic blocks in the world maintain similar patterns. I separate each of the four productivity samples into five subcontinental datasets. As displayed in the labor productivity results of Table 7, Latin America, Eastern Europe & Central Asia, and Sub-Saharan Africa all strongly reflect the predictions of this extended Melitz model. It should be noted that South-East Asia and the Middle-East/North Africa maintain particularly low shares of MNE firms, as displayed in Table 2, which may explain these results' departure from otherwise consistent global productivity ranking patterns.

In the case of approximate TFP, similar findings emerge, though MNE domestic producers appear to underperform relative to their domestically-owned exporter counterparts for a given country-industry-year. Value-added and output-based TFP measures by region suggest similar productivity rankings with domestic exporters outperforming non-exporters. However, the dominance exhibited by MNE firms only persist in Latin America, Eastern Europe and Central Asia, and Sub-Saharan Africa.

These results highlight that regions with larger populations of MNE firms may be drawing up large enough samples to make more accurate inference from. Given a stronger degree of development in the South-East Asian block, I would expect similar rankings of productivity to form across firms. The overall results suggest that productivity rankings predicted by my extended framework are consistent with observed data, even when specifying across specific subcontinental regions.

Table 7: Labour and Approximate Ranking by Region

Dep Var: Labor Productivity					
	Latin America	South-East Asia	E. Eur & C. Asia	Middle East N. Africa	Sub-S Africa
HomeEXP	0.365*** (0.065)	0.353*** (0.059)	0.208** (0.075)	0.201** (0.085)	0.307*** (0.047)
MNEDOM	0.492*** (0.051)	0.249** (0.089)	0.322*** (0.053)	0.292*** (0.093)	0.386*** (0.056)
MNEEXP	0.618*** (0.068)	0.225*** (0.065)	0.512*** (0.078)	0.217 (0.166)	0.634*** (0.090)
N	13,651	15,207	17,524	6,426	10,581
R^2	0.512	0.316	0.534	0.421	0.692

Dep Var: Approximate Total Factor Productivity					
	Latin America	South-East Asia	E. Eur & C. Asia	Middle East N. Africa	Sub-S Africa
HomeEXP	0.313*** (0.033)	0.279*** (0.045)	0.122** (0.057)	0.193*** (0.048)	0.333*** (0.044)
MNEDOM	0.320*** (0.057)	0.181** (0.080)	0.286*** (0.047)	0.242** (0.108)	0.191*** (0.045)
MNEEXP	0.488*** (0.053)	0.283*** (0.050)	0.396*** (0.045)	0.211 (0.122)	0.563*** (0.077)
N	11,145	9,238	11,691	5,676	8,472
R^2	0.371	0.247	0.434	0.358	0.616

Notes: Using all fixed effects and controls. Standard errors clustered at industry level. *** at 1%, ** at 5%, * at 10% level.

Table 8: TFP Ranking by Region

Dep Var: Value-Added Total Factor Productivity

	Latin America	South-East Asia	E. Eur & C. Asia	Middle East N. Africa	Sub-S Africa
HomeEXP	0.124*** (0.023)	0.208*** (0.037)	0.111*** (0.037)	0.176*** (0.034)	0.093** (0.036)
MNEDOM	0.141** (0.049)	0.209** (0.089)	0.223*** (0.063)	0.159* (0.088)	0.045 (0.027)
MNEEXP	0.175*** (0.025)	0.195*** (0.060)	0.231*** (0.031)	0.297*** (0.056)	0.291*** (0.029)
N	9,808	8,112	10,003	5,254	7,540
R^2	0.405	0.472	0.414	0.488	0.362

Dep Var: Output-Based Total Factor Productivity

	Latin America	South-East Asia	E. Eur & C. Asia	Middle East N. Africa	Sub-S Africa
HomeEXP	0.061*** (0.011)	0.083*** (0.017)	0.047** (0.019)	0.088*** (0.015)	0.051** (0.019)
MNEDOM	0.086** (0.031)	0.104** (0.040)	0.160*** (0.039)	0.153* (0.077)	0.001 (0.023)
MNEEXP	0.104*** (0.012)	0.077* (0.038)	0.081*** (0.017)	0.159*** (0.039)	0.116*** (0.017)
N	9,455	8,020	9,874	5,255	7,408
R^2	0.489	0.596	0.508	0.584	0.486

Notes: Using all fixed effects and controls. Standard errors clustered at industry level. *** at 1%, ** at 5%, * at 10% level.

5.3. Implications of Corruption

Using the extended regression model, I examine how differences in firm–level productivity averages vary, given variation in underlying host country and country–industry levels of corruption. Table 9 presents results of equation (7) using labor productivity, ATFP, value-added TFP and output-based TFP as dependent variables. Distinguishing between firm types, it appears the productivity rankings continue to hold. Additionally, given an improvement in the corruption measure (a one unit increase), average productivity yields a significant reduction across firms. Inferring from Section 3.1, the increased control over corruption results in a reduction of fixed costs, which on average enables the survival of less productive firms now able to afford entrance into the market. This in turn causes average productivity across firms to decline.

I present results of the full regression based on Equation (7) in Table 10. Across columns (1) to (4) I pool MNE types into a single category, whereas between columns (5) and (8) I distinguish between MNEs by exporter status. The first implication of these results is that average productivity across firms declines as corruption lessens, which would correspond to a one unit increase in ‘corr’.

Examining the average change in productivity specifically among domestic exporting firms (HC), there is a signicant decline across both of the residual TFP measures. As corruption levels abate, reflected by a one unit increase in *corr*, average productivity declines by 1.4 to 2.6 percentage points while MNE exporters see a decline of 2.2 to 4.4 percentage points. This suggests that higher corruption (lower ‘corr’) introduces additional fixed costs that prevents the entry of lower productivity firms into the exporting market.

Table 9: Corruption on Productivity Measures

	LAB LABP	ATFP	VAKL	YKLM
corr	-0.243^{***} (0.039)	-0.243^{***} (0.030)	-0.074^{***} (0.022)	-0.035^{**} (0.013)
HomeEXP	0.288^{***} (0.056)	0.237^{***} (0.035)	0.139^{***} (0.017)	0.063^{***} (0.009)
MNEDOM	0.382^{***} (0.032)	0.241^{***} (0.024)	0.138^{***} (0.025)	0.080^{***} (0.015)
MNEEXP	0.483^{***} (0.069)	0.420^{***} (0.049)	0.232^{***} (0.020)	0.103^{***} (0.014)
N	63,389	46,222	40,717	40,012
R^2	0.552	0.454	0.428	0.534

Notes: Using previous fixed effects and contrls. Standard errors clustered at the industry level. Corruption varies across the host countries and years. *** at 1% , ** at 5%, * at 10% levels.

Turning to implications for multinational firms, the pooled MNE interaction term 'MC' would suggest no significant changes in the composition of multinational firm productivity levels, given variation in corruption. However, when distinguishing between differences in exporter status across MNEs, significant effects are present both for non-exporter and exporter cohorts. This suggests that the fixed costs of investment, f^I, are also augmented by variation in corruption across countries. These results suggest that a one unit increase in the corruption index, equivalent to a reduction in overall corrupt activities, is associated with significantly more productive non-exporting MNEs and significantly less productive exporting MNEs. Mismeasurement of corruption exposure may be present, given the strong assumption of homogeneous exposure across firms for a given country. In order to alleviate this concern, I utilize a more informed measure of corruption that uses firm-level survey responses to determine industry-country variation in corruption. The results correlate far more succinctly with the supporting model.

Table 10: Full Model with Net Effects

	LAB	ATFP	VAKL	YKLM	LAB	ATFP	VAKL	YKLM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
corr	-0.240^{***} (0.040)	-0.238^{***} (0.031)	-0.067^{***} (0.021)	-0.031^{**} (0.012)	-0.239^{***} (0.041)	-0.237^{***} (0.032)	-0.066^{***} (0.021)	-0.031^{**} (0.012)
HomeEXP	0.284^{***} (0.078)	0.286^{***} (0.049)	0.227^{***} (0.042)	0.110^{***} (0.022)	0.282^{***} (0.080)	0.294^{***} (0.050)	0.239^{***} (0.042)	0.116^{***} (0.022)
HC	-0.0002 (0.014)	-0.015 (0.009)	-0.024^{**} (0.009)	-0.013^{**} (0.005)	0.001 (0.014)	-0.015 (0.009)	-0.026^{**} (0.009)	-0.014^{**} (0.005)
MNE	0.513^{***} (0.060)	0.364^{***} (0.072)	0.217^{***} (0.048)	0.102^{***} (0.023)				
MC	-0.021 (0.015)	-0.007 (0.014)	-0.008 (0.009)	-0.003 (0.005)				
MNEDOM					0.597^{***} (0.071)	0.278^{***} (0.073)	0.028 (0.062)	-0.009 (0.039)
MDC					-0.064^{**} (0.025)	-0.011 (0.021)	0.032^{*} (0.015)	0.026^{**} (0.009)
MNEEXP					0.523^{***} (0.121)	0.520^{***} (0.120)	0.401^{***} (0.048)	0.189^{***} (0.023)
MEC					-0.010 (0.020)	-0.026 (0.021)	-0.044^{***} (0.010)	-0.022^{***} (0.007)
N	63,389	46,222	40,717	40,012	63,389	46,222	40,717	40,012
R^2	0.552	0.454	0.428	0.534	0.552	0.454	0.428	0.535

Notes: Using previous fixed effects and controls. Standard errors clustered at the industry level.Firm type dummies are: **HomeEXP**, domestically-owned exporters, **MNEDOM**, non-exporter MNEs, and **MNEEXP**, MNEs maintaining export platforms. Corruption varies across the host countries and years. Interaction terms: **HC** represents ($HomeEXP_{fhit} \times C_{it}$), **MC** represents ($MNE_{fhit} \times C_{it}$), **MDC** represents ($MNEDOM_{fhit} \times C_{it}$), **MEC** represents ($MNEEXP_{fhit} \times C_{it}$). *** at 1% , ** at 5%, * at 10% levels.

5.4. Industry-Specific Corruption

One appealing finding within a Melitz model setting was a contribution from Bernard et al. (2006), which highlights how falling trade costs induce reallocations of resources both within and across industries, for a given country. Given these findings, it is of interest to allow for varying degrees of exposure to corruption in the form of industry-country fixed costs. I re-apply Equation (7) but in this case replace country-wide measures of corruption with country-industry measures determined in Section 4 and detailed in Appendix B. I display the results of this adjustment in Table 11.

Productivity rankings persist across the 8 columns of results, however, in this setting it appears only exporting and foreign-owned firms are affected, with effects notably larger among exporting MNEs. Appealing to the conceptual model of this paper, reduced corruption contributes to lower export-related fixed , f_{ij}^{X} and $f_{ki,ij}^{IX}$, reducing productivity cutoffs. This is reflected by the resulting in significant average productivity decreases as a greater portion of less productive domestic firms and MNEs are now able to export. Among exporters, a one-unit change in the corruption score (max 10), contributes to a 1.4 to 2.5 percentage point (10.7%-12.3%) decline in average productivity while MNE's with export platforms experience, on average, yield a 2.5 to 4.7 percentage point (11.2%-12.5%) decline in average productivity. The analysis therefore suggests that, in line with Javorcik and Wei (2009) , FDI is discouraged by increased degrees of corruption for a given industry-country combination. Additionally, I suggest export participation falls for both parties of interest.

Table 11: Full Model with Industry Net Effects

	LAB	ATFP	VAKL	YKLM	LAB	ATFP	VAKL	YKLM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
corr_ind	−0.032 (0.037)	−0.050 (0.032)	−0.031* (0.016)	−0.010 (0.010)	−0.032 (0.037)	−0.049 (0.032)	−0.030* (0.016)	−0.010 (0.009)
HomeEXP	0.322*** (0.075)	0.305*** (0.050)	0.222*** (0.046)	0.109*** (0.023)	0.322*** (0.077)	0.313*** (0.051)	0.232*** (0.047)	0.114*** (0.024)
HC_i	−0.011 (0.015)	−0.020* (0.011)	−0.023** (0.010)	−0.013** (0.005)	−0.010 (0.015)	−0.021* (0.011)	−0.025** (0.010)	−0.014** (0.005)
MNE	0.524*** (0.070)	0.387*** (0.079)	0.244*** (0.042)	0.124*** (0.022)				
MC_i	−0.023 (0.017)	−0.013 (0.016)	−0.015* (0.007)	−0.009* (0.005)				
MNEDOM					0.559*** (0.084)	0.260*** (0.082)	0.063 (0.060)	0.028 (0.037)
MDC_i					−0.051* (0.026)	−0.005 (0.022)	0.022 (0.015)	0.015* (0.008)
MNEEXP					0.558*** (0.123)	0.560*** (0.120)	0.416*** (0.048)	0.200*** (0.024)
MEC_i					−0.019 (0.021)	−0.036* (0.020)	−0.047*** (0.010)	−0.025*** (0.007)
N	63,388	46,221	40,717	40,012	63,388	46,221	40,717	40,012
R^2	0.551	0.453	0.428	0.534	0.551	0.453	0.428	0.535

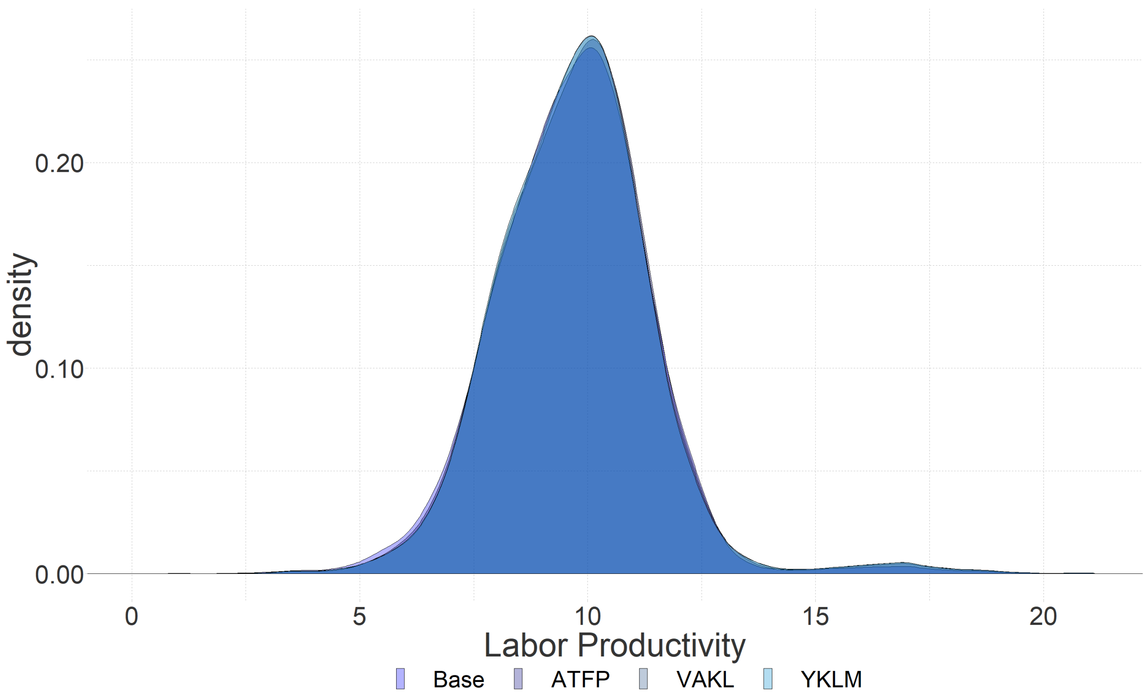
Notes: Using previous fixed effects and controls. Standard errors clustered at the industry level.Firm type dummies are: **HomeEXP**, domestically-owned exporters, **MNEDOM**, non-exporter MNEs, and **MNEEXP**, MNEs maintaining export platforms. Corruption varies across the host countries, industries and years. Interaction terms: **HC** represents ($\text{HomeEXP}_{fhit} \times C_{iht}$), **MC** represents ($\text{MNE}_{fhit} \times C_{iht}$), **MDC** represents ($\text{MNEDOM}_{fhit} \times C_{iht}$), **MEC** represents ($\text{MNEEXP}_{fhit} \times C_{iht}$). *** at 1% , ** at 5%, * at 10% levels.

5.5. Potential Selection Bias

It is possible that average productivity is higher due to the presence of selection bias in which the composition of firms able to report values of sales and employment to the survey teams may be influenced by prevailing institutional quality. In a scenario where pre-existing data requirements are less stringent in more highly corrupt countries, the only firms reporting sufficiently for this study's various productivity measures could be inherently productive or profitable enough to maintain accurate statistics, despite lax government requirements. In this case, average productivity and corruption levels could be correlated due to less productive firms not engaging as actively in data collection in relatively more corrupt countries. In such a scenario, these firms would be more likely to yield missing values of productivity within the sample and could therefore not be 'missing-at-random', contributing towards bias in the main results.

In order to assess whether greater data requirements imply higher average productivity levels as a result of selection into a thinner subset of the sample, I compare labor productivity distributions across various observed productivity subsets of the firm-level dataset. For the largest dataset, 'Base', labor productivity functions as the most readily available and least data-intensive measure, provided for across 74,842 firms. When measuring ATFP, the providing firms falls to 51,225 due to requirements for labor productivity measures in tandem with an additional requirement of capital data. Upon applying the most data-demanding method of fixed effects based on value-added and output measures, the VAKL and YKLM productivity measures yield 44,636 and 43,962, respectively. Across these groups, the distribution remains relatively static, as displayed in Figure 3, which suggests the 'missing-at-random' assumption may be valid.

Figure 3: Distribution of labor productivity across subsets



Another manner in which to identify signs of this potential selection bias is to observe changes in the percentage of firms reporting specific productivity measures given changes in corruption. Should it be the case that there is a significant relationship between variation in corruption and the percentage of firms reporting a given productivity measure, as well as a rise in average productivity as corruption intensifies, this would discredit the 'missing-at-random' assumption. To explore this possibility, I measure the percentage of firms reporting each of the four productivity measures and average productivity for each country-year group. I then take percentage point changes in the share of firms providing sufficient data for productivity measures, level changes in average productivity and changes in the Transparency International corruption measure for each of 52 countries, across the multiple years of survey data available for each country.

Regressing the change in the percentage of firms reporting a productivity measure on the change in corruption yields insignificant results. Additionally there does not appear to be a significant change in average productivity for a given country-year when observing a change in corruption. These two findings are consistent across all productivity measures as well as when the change in corruption is replaced with the level corruption in the latter year of change. Given these findings, I would suggest that the results of the paper are not influenced by selection bias to a significant degree, when accounting for potential exclusion of existing, low productivity firms, in highly corrupt nations.[19]

6. Conclusion

The findings in this paper suggest that there is a strong influence of corruption on the degree to which a given country can engage in global market activities such as exporting and foreign direct investment. In particular, these patterns suggest that greater corruption increases fixed costs of export activity, both for domestically-owned and multinational enterprises. In contrast, the prevailing level of corruption in a host country appears to not heavily influence factory level overheads. These results align closely with Javorcik and Wei (2009), in which the presence of corruption lessens the likelihood of FDI inflows, but in our case we'd specify that this seems particularly focused in effect on ventures intended to foster export-platforms abroad.

Additionally, my analysis supports the validity of the Melitz-like models in a cross-country emerging markets setting. The distinction of differences across MNE affiliates based on exporter status led to rather key results that could have otherwise been obscured, had all MNEs been assumed to draw from identical productivity distributions. This highlights a great need to take care in identifying firm types.

From a domestic policymaker perspective, the findings of this paper appear to highlight a trade off between illicit income generated from various corrupt activities and the potential for improvements in global competitiveness. To combat widespread acts of corruption, and enable firms to more easily access export markets would be equivalent to bolstering the country's performance internationally and possibly enhance the growth trajectory of these various developing economies. With respect to forthcoming work, I would add to calls for more granular firm-level data in a cross-country setting. For example, observing the parent countries of these MNE affiliates may assist in accounting for "corruption distance" in firm-level analysis and aid in distinguishing what contributes to the margin of productivity between MNEs by exporter status. Furthermore, I would anticipate that the proliferation of panel data sets using cross-country firm-level data would enable more accurate estimations of productivity, and provide a clearer picture of whether adjustments to corruption invite entries and exit among increasingly globalized firms. For now I leave these pursuits for future research to explore.

[19] In the pursuit of brevity, I exclude these 16 regression outputs from this study, though they are available on request. The cross-country regression is weighted by the total number of firms involved in any year-to-year change in productivity measures for a given country.

Appendix A Data Cleaning

The original dataset contains responses from 168,057 firms, from which I focus on 90,528 manufacturing firms with 5 or more employees. As per Davies and Jeppesen (2015), I also drop observations from Ghana, Micronesia, Zimbabwe and Venezuela due to unreliable sales figures or missing consumer price indices. Since identifying firm types is key in this study, I drop a further 1,241 firms for not disclosing their share of foreign ownership followed by 585 firms not disclosing the share of sales revenue attributed to exports. Firms from Kosovo, Djibouti, Niger, Yemen and Sudan are dropped for not maintaining any multinational enterprises in the sample. A lack of corruption data from Transparency International results in a loss of Eswatini and the West Bank/Gaza. The exclusion of these seven locations removes 1,068 firms from the sample.

The data uses the International Standard Industrial Classification of All Economic Activities (ISIC), Rev. 3.1. Manufacturers of ISIC industries 10 through to 14 include only 18 firms, insufficient for the application of industry-specific productivity estimates, industry fixed effects and clustering standard errors at the industry level. These firms are dropped from the sample as too are those with no ISIC code (1,056 observations) or firms from ISIC divisions 38 and above (18 observations).

Similarly to Davies and Jeppesen (2015), I drop 10 percent of the sample for not reporting sales figures or being deemed to have answered the questions untruthfully or provided arbitrary and unreliable figures. Sales figures are converted to USD amounts given the average exchange rate of the firms' given country of residency. These values are deflated according to the prevailing consumer price index as reported by the World Development Indicators (WDI) database. These requirements lead to the loss of firms from Antigua and Barbuda, Belize, Fiji, Senegal (2007 only), St. Kitts and Nevis, St. Lucia, St. Vincent and Grenadines, Suriname, Tonga, and Vanuatu.

Due to the sparsity of observations for some particular industries, I follow the Enterprise Survey's Analysis Unit procedure as described in their methodological note "Firm Level Productivity Estimates".[20] This combines firms from ISIC industries 15 and 16 into "Food, Beverages and Tobacco" and 23 and 24 into "Chemicals and refined Petroleum" industries. Additionally firms from ISICs 30 to 34 are labeled under a single industry which accounts for office, computing and electrical machinery, radio, television and communication equipment, medical, and precision and optical instruments. Lastly, firms in industries 34 and 35 fall under a single motor vehicle industry. Firms from the recycling industry are excluded from this analysis due to a low observation count and unique nature of this manufacturing process.

Given the multiple productivity estimates I generate and the wider of variety of data this requires, I prepare sub-samples of the raw data for each respective productivity measure. For example, the ATFP measure requires positive capital amounts, unavailable across 24,185 firms. This explains differing sample sizes across the regressions. For each of the four datasets, I use a 1.5 interquartile range cutoff which drops any mild outliers with a productivity measure lower than the 25th percentile minus 1.5 times the interquartile range (75th percentile - 25th percentile) or higher than the 75th percentile plus 1.5 times the interquartile range, for a given country.

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Appendix B Industry-Country Corruption Measure

As highlighted in Figure 4, responses range from 0, 'No Obstacle', to 4 ,'Very Severe'. For each country-industry-year set of firms, I calculate an average of the numeric value responses to this specific survey question as well as the number of firms that contributed to each average. For a given country, this presents two matrices for average firm responses and total responding firms, where rows capture given years and columns represent industries.

Inevitably some years for a given country may present no firms responses for a given industry. In these cases, I count zero firms as contributing towards this value to ensure it does not affect the weighting performed afterwards. For a given industry, I calculate the average corruption score times the number of firms providing that score and sum values across years, dividing by the total number of firms across years. This imposes the assumption that between any set of given years, the industry-specific degree of corruption relative to a country level degree of corruption remains fixed. To ensure these averages are comparable across countries, I calculate an average of these industry scores for each country then measure each industry's percentage deviation. Using the TI corruption scores, the industry-country measure is the percentage deviations times these base values.

Figure 4: WES: Corruption as obstacle to current operations of firm

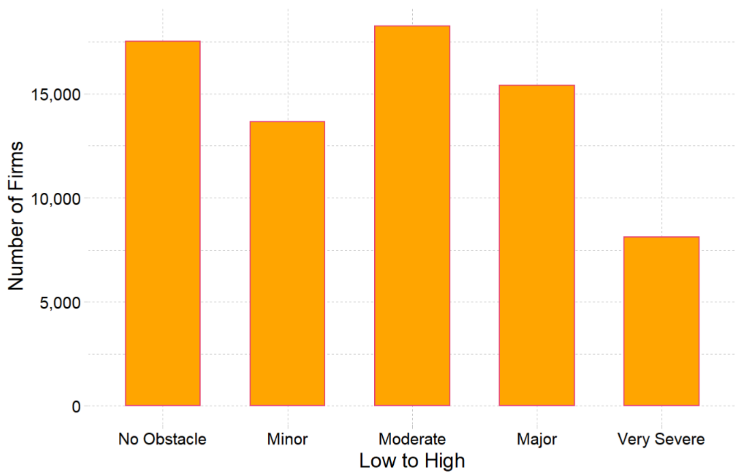

Table 4: WES Corruption Questions

Survey Question	Responses, %
Was Informal Gift/Payment Expected or Requested For Electrical Connection?	17.02
Was Informal Gift/Payment Expected or Requested in Clearing Exports Through Customs?	8.47
Was Informal Gift/Payment Expected or Requested For Construction Permit?	16.76
In Any Tax Inspection Was A Gift/Informal Payment Requested?	55.86
% Of Contract Value Avg. Firm Pays In Informal Gifts to Secure Govt Contract?	28.40
How Much Of An Obstacle is Corruption to Current Operations of Firm?	99.98
Is the the Court System Fair, Impartial And Uncorrupted?	99.16

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