

Online Appendix

A Data Description

Enterprise Survey Data We use data base on Enterprise Survey of the World Bank Group for the period 2002-2016 . Details on the methodology and data collection are available at <http://www.enterprisesurveys.org/methodology>. The data are collected on behalf of the World Bank by private contractors since they asked a range of sensitive questions and respondents are assured of confidentiality. The survey is answered by business owners and top managers with 1200-1800 interviewed in larger economies, 360 interviews are conducted in medium-sized economies, and for smaller economies, 150 interviews take place. The aim is to cover both the manufacturing and services sectors. Formal (registered) companies with 5 or more employees are targeted for interview. Services firms include construction, retail, wholesale, hotels, restaurants, transport, storage, communications, and IT. Firms with 100% government/state ownership are excluded. Most of the coverage is in the cities/regions of major economic activity.

There are two main instruments: one for manufacturing and one for services. The standard survey includes firm characteristics, gender participation, access to finance, annual sales, costs of inputs/labor, workforce composition, bribery, licensing, infrastructure, trade, crime, competition, capacity utilization, land and permits, taxation, informality, business-government relations, innovation and technology, and performance measures. The data are collected in face-to-face interviews.

We merge two standardize data sets, the Standardized data for 2002-2005 and the Standardized data 2006-2016. We describe the construction of the variables for each of the two periods.

For the 2002-2005 period, Security Costs as percentage of sales (SCAS) is computed as the sum of two variables, namely, Cost of providing security as percentage of sales and Cost of providing protection payments as percentage of sales. Loss due to theft, robbery, vandalism or arson as a percentage of sales (LDTV) is directly reported in the data set. For the 2005-2016 period, respondents indicate either the absolute amount, which one can use to compute as percentage of total sales, or directly the amount as percentage of total annual sales. SCAS and LDTV are the two type of answers combined. We disregard observed loss shares or security costs above 100% of total sales. By doing it, we lose 46 observations for LDTV and 104 observations for SCAS.

The number of employees is constructed as the sum of permanent employees and temporary employees adjusted by the average length of employment of temporary workers. We dropped 4 outliers from Malaysia which reported employment of between 100,000 and 2,000,000 workers. The largest firm after this is in China and reported about 66,000 employees. Finally, capital is computed as the sum of the net book value of machinery and equipment and the net book value of land and buildings. In most of our analysis we only use observations with data on SCAS, LDTV and size which gives us 155,915 observations.

For 2002-2005, Sector is constructed from the variable industry which specifies the sector of activity. We divide sector into four; primary sector which includes mining, manufacturing, services, and construction. For 2006-2016, data set includes information about the industry accordingly to the two-digit ISIC Rev 3.1. We use the ISIC digits 1-14 as primary sector including mining, digits 15-37 as manufacturing, the dig-

its 40-44 and 46-99 as services, and 45 as construction. The web site for the surveys (<http://www.enterprisesurveys.org/Methodology>) describes the sample process as follows:

“The sampling methodology for Enterprise Surveys is stratified random sampling. In a simple random sample, all members of the population have the same probability of being selected and no weighting of the observations is necessary. In a stratified random sample, all population units are grouped within homogeneous groups and simple random samples are selected within each group. This method allows computing estimates for each of the strata with a specified level of precision while population estimates can also be estimated by properly weighting individual observations. The sampling weights take care of the varying probabilities of selection across different strata. Under certain conditions, estimates’ precision under stratified random sampling will be higher than under simple random sampling (lower standard errors may result from the estimation procedure). The strata for Enterprise Surveys are firm size, business sector, and geographic region within a country. Firm size levels are 5-19 (small), 20-99 (medium), and 100+ employees (large-sized firms). Since in most economies, the majority of firms are small and medium-sized, Enterprise Surveys oversample large firms since larger firms tend to be engines of job creation. Sector breakdown is usually manufacturing, retail, and other services. For larger economies, specific manufacturing sub-sectors are selected as additional strata on the basis of employment, value-added, and total number of establishments figures. Geographic regions within a country are selected based on which cities/regions collectively contain the majority of economic activity. Ideally the survey sample frame is derived from the universe of eligible firms obtained from the country’s statistical office. Sometimes the master list of firms is obtained from other government agencies such as tax or business licensing authorities. In some cases, the list of firms is obtained from business associations or marketing databases. In a few cases, the sample frame is created via block enumeration, where the World Bank “manually” constructs a list of eligible firms after 1) partitioning a country’s cities of major economic activity into clusters and blocks, 2) randomly selecting a subset of blocks which will then be enumerated. In surveys conducted since 2005-06, survey documentation which explains the source of the sample frame and any special circumstances encountered during survey fieldwork are included with the collected datasets.”

The survey weights play an important role in our analysis. If weights are not given (this is the case for about 30,000 observations from the 2002-2005 data) we give a weight of $w_t=1$ to the observation which is below the mean of 37.7. In all calculations we first aggregate by country/year and then calculate means across years of the same country to get to the country values.

World Justice Project Data The website of the World Justice Project describes the construction of the index as follows. *"An effective criminal justice system is a key aspect*

of the rule of law, as it constitutes the natural mechanism to redress grievances and bring action against individuals for offenses against society. An effective criminal justice system is capable of investigating and adjudicating criminal offences effectively, impartially, and without improper influence, while ensuring that the rights of suspects and victims are protected."

The index consists of 97 variables combined to form the following seven sub-factors: criminal investigation system is effective, criminal adjudication system is timely and effective, correctional system is effective in reducing criminal behavior, criminal justice system is impartial, criminal justice system is free of corruption, criminal justice system is free of improper government influence, due process of law and rights of the accused, effective investigations, timely and effective adjudication, effective correctional system, no discrimination, no corruption, no improper government influence, due process of law. We use the aggregate score from 2013.

Government expenditure on public order and safety We use data from EUROSTAT on general government expenditure on 'public order and safety' (according to the Classification of the Functions of Government - COFOG). Eurostat collects data on general government expenditure by economic function according to the international Classification of the Functions of Government (COFOG) in the framework of the European System of National Accounts (ESA2010).

Expenditure on 'public order and safety' comprises the following categories: 'police services', 'fire protection services', 'law courts', 'prisons', 'R&D related to public order and safety' as well as expenditure not elsewhere classified. We add the numbers on 'police services', 'law courts' and 'prisons' for the year 2014 to get to our spending estimates.

Employment for public order and safety Here we downloaded the available data for the years 2003-2014 from the United Nations Office on Drugs and Crime (UNODC). This data is available from <https://data.unodc.org/>, criminal justice, system resources (accessed January 2017). We used the total count for:

"Police Personnel" means personnel in public agencies as at 31 December whose principal functions are the prevention, detection and investigation of crime and the apprehension of alleged offenders. Data concerning support staff (secretaries, clerks, etc.) should be excluded.

"Professional Judges or Magistrates" means both full-time and part-time officials as of

31 December authorized to hear civil, criminal, and other cases, including appeal courts, and to make dispositions in a court of law. Also includes authorized associate judges and magistrates.

"Prisons, Penal Institutions or Correctional Institutions" means all public and privately financed institutions where persons are deprived of their liberty. The institutions may include, but are not limited to, penal, correctional, and psychiatric facilities under the prison administration.

We use the average of all available data within each of these categories and then sum the up to calculate total employment numbers.

Penn World Table Data We also use data on Penn World Tables 8.0 from 2002 onwards. Particularly we use data on employment and population from the data and merge by country/year to countries in our sample. For survey data in 2014-2016 we use data from the last available year. Details about this data can be found in Appendix B of Inklaar and Timmer (2013).

B Protection by Organized Criminals

In countries with weak law and order, criminal networks can attract surplus from firms by offering protection, e.g. charging firms to desist from predation. We now show how this can be brought into the framework and its implications for the measurement of output loss and the misallocation of labor.

To approach this consider a situation where firm i 's protection depends on their own protection effort e_i and the protection of organized criminals c_i . We will suppose that the predation loss is now:

$$p(e_i + \psi_i c_i, g)$$

where ψ_i is a parameter which determines whether organized crime is more or less effective in reducing predation. In our base line $\psi_i = 0$ for all firms. If $\psi_i > 1$, then we will see that organized protection is relevant. In the data, we do not observe ψ_i or c_i . Let the firm's profit with organized protection c_i be

$$\Pi^i(c_i) = \arg \max_{(e,l)} p(e + \psi_i c_i, g) \theta_i (l - e) - wl$$

We will assume that the firm bargains with organized criminals over c_i and pays a

transfer $T^i(c_i)$ which can be thought of as a “payment” for protection c_i . We consider the simplest bargaining model where all of the surplus goes to the criminal network, i.e. a take or leave offer. Let $\underline{\Pi}$ be the firm’s “outside option” which could be $c_i = 0$ or joining a competing criminal network to gain protection. Thus:

$$T^i(c_i) = \Pi(c_i) - \underline{\Pi}.$$

Now define \hat{c}_i from $\psi_i p_e(\psi_i \hat{c}_i, g) \theta_i(l_i^*) = w$. If organized criminals face the same labor market as firms, then

$$c_i^* = \arg \max_c [T^i(c) - wc] = \begin{cases} \hat{c}_i & \text{if } \psi_i > 1 \\ 0 & \text{otherwise.} \end{cases}$$

is the optimal protection by criminals. Thus, if $\psi_i \leq 1$, then we have the model exactly as above with all protection being by the firm. We think of this as the case where organized crime is ineffective. With $\psi_i > 1$, then there is no firm-based protection and all protection is through organized criminals. Moreover, since organized criminals are more efficient at protecting against crime when they are active, predation will be lower than when the firm does protection.

We now consider the implications of this for our estimates of the output cost. This will be an issue only in so far as there are firms for which $\psi_i > 1$. Assuming that protection costs to organized criminals are not reported by firms in the data, then we will observe firms which do not spend on protection and yet have lower predation than otherwise. However, there is a cost to the economy due to the labor used in protection by criminal networks c_i^* . This reduces the stock of labor available for production and our estimate of the output cost based on the calculation above would be an underestimate of the true output cost. It is difficult to know by how much this is the case.¹ Credible quantitative data on organized crime across countries are hard to come by and so we cannot test this hypothesis explicitly. However, using mentions in Wikipedia we can show that, controlling for our institutional

¹Another possibility is that firms report $T^i(c_i^*)$ as part of the share of sales spent on protection. In this case, we would be including this in the calculation of the output cost but not correctly since all labor hired by the firm would be productive labor since guard protection is now being hired via organized crime. Moreover, the cost of protection would include any monopoly rent earned by the criminal network which could exceed the value of labor allocated to criminal network protection.

measure of criminal justice, firms in countries that are mentioned report systematically lower predation and protection losses. Although this awaits proper empirical testing, this is suggestive that our output measures which ignore organized crime would tend to be a lower bound on output losses.

C Using Value Added as a Productivity Measure

In our baseline estimates, we calibrate productivity from firm size. We now assess how robust our measures of output loss are to using a value-added measure of productivity computed using information on sales and input cost data from the enterprise surveys. This has the advantage of giving a direct measure of productivity. However, it suffers the usual difficulty with residual-based measures of loading more measurement error into the productivity estimate. There are good reasons to think that number of employees is measured more accurately.

We begin by estimating measure of value-added for firm i , VA_i , as the value of sales minus costs for raw materials and intermediate goods, electricity, generators and fuel. We then compute productivity and adjusted productivity as a function of $\{l_i, \sigma_i, \mu_i\}$ as:

$$\theta_i = \frac{[1 + \mu_i] VA_i}{\left[\frac{\alpha}{\alpha + \sigma_i}\right]^\alpha l_i^\alpha} \text{ and } \hat{\theta}_i = \frac{VA_i}{l_i^\alpha}$$

As our measure of l_i we use total labor cost which should pick up both variation in the quantity and quality of labor input. However, our results are essentially the same if we use total employment to measure l_i .

We use these estimates of productivity and adjusted productivity to construct firm weights θ_i/Θ and $\hat{\theta}_i/\hat{\Theta}$ to estimate output loss from equation (13). Reinforcing the point about the importance of measurement error using this method, we do find that there are sometimes very large productivity differences across firms which contain orders of magnitude. We therefore work with calculations which mitigate the influence of outliers on the estimates. We propose the following procedure. First, we exclude firms with negative VA_i and focus on the sample of countries where there are more than 500 firms included in the survey. Second, we calculate the mean level of productivity using two different methods: (i) excluding outliers that have more than 30 times the mean productivity level, (ii) including all firms. We then calculate the output loss measure as before.

Figure A4 illustrates the measures of output loss using these two different methods.

It shows how the treatment of outliers matter for estimating the output loss. Kenya, for example is estimated to have an output loss of almost 20 percent if we do not exclude outliers using the rule that we have specified but only a little over 4 percent if we do. Another example is Croatia which is estimated to have an output loss below 1 percent when outliers are excluded but is over 10 percent if they are included. In Figure A5 we focus on manufacturing and show that this apparent randomness due to outliers is mitigated although it does not disappear completely. In Figure A6 we show that if we drop outliers, focus on manufacturing and on countries with more than 500 observations our firm-size based measure and VA based measure are fairly well-aligned.

However, it is important to stress that the analysis using firm-size does not face the same problems because there are simply no such extreme outliers in the firm size data. In order to illustrate this Figure A7 plots the distribution of relative productivity, $\hat{\theta}_i/\hat{\Theta}$, for our standard firm size measure and the value-added measure described above for manufacturing in Mexico. While the productivity distribution of our firm-size measure (thick line) follows a reasonable shape with a visible region of high densities and a thick tail at higher relative productivity, the measure based on value added has a large amount of firms at extremely low values and a very long tail of high productivity firms. It is clear from this that reporting in a handful of firms would completely determine the output loss estimate in the latter case. Dropping outliers is essential when using the VA measure.

D Patterns of Protection at the Firm Level

Table A2 reports some firm level regressions to explore correlates of perceived protection. In all regressions we include country/year fixed effects, sector fixed effects for four sectors and dummy variables representing the decile of the productivity distribution that the firm is in. In columns (1) and (2), we relate $\{\varepsilon^i(g), \gamma^i(g)\}$ to some subjective questions on the perception of crime at the firm level. We find that firms that expect more protection (higher $\varepsilon^i(g)$) reduce the extent to which they report crime as an obstacle on a 0-4 scale and are less likely to say that crime is the worst obstacle the firm faces. Interestingly, $\gamma^i(g)$ is negatively correlated with reports that crime is an obstacle. Thus despite experiencing higher losses due to spending on defence, the fact that a firm is able to defend against crime appears to make it less inclined to state that predation is an obstacle to doing business.

In column (3) of Table A2 we find that firms located in the capital city perceive that they are better protected from predation. This makes a lot of sense given that many state

institutions are most robust in the capital cities of the developed countries. In column (4), the dependent variable is the protection effort elasticity $\gamma^i(g)$. Here, we find that state owned and foreign firms seem better able to defend against predation. The elasticity of defending against predation is lower in the capital city. This, together with the results in column (3), points to the possibility of some substitutability between public and private protection at the micro level.

E Simulation with Chinese Protection Parameters

We run two simulation exercises in the paper. In section 7 we apply the Chinese protection parameters, $\{\varepsilon^i(g), \gamma^i(g)\}$, to firms in other countries within the same relative productivity. To do this, we divide all firms in each country into fifty equal-size groups based on their relative productivity, $\frac{\theta_{ic}}{\Theta_c}$. We then draw values of $\{\varepsilon^i(g), \gamma^i(g)\}$ at random from the observed distribution in each productivity group in China. Third, we impose these values on firms in the same productivity group in other countries in our data. For example, we sample values of $\{\varepsilon^i(g), \gamma^i(g)\}$ for the least productive firms in China and then impose them on the least productive firms in Afghanistan. Specifically, we calculate

$$\frac{e_i}{l_i} = \frac{\gamma^i(g)}{\alpha + \gamma^i(g)}, l_i \approx L \left(\frac{\theta_i}{\Theta} \right)^{\frac{1}{1-\alpha}}$$

and the probability in equation (14). Note that the second equation is an approximation as we use $\frac{\theta_i}{\Theta}$ to back out the counter-factual firm size with the Chinese parameters. Since China is relatively close to the non-crime scenario this approximation has very little impact on the final loss estimate.² We then use the draws $\{\varepsilon^i(g), \gamma^i(g)\}$ to calculate $\frac{\hat{\theta}_i}{\hat{\Theta}}$ from

$$\frac{\hat{\theta}_{ic}}{\hat{\Theta}_c} = \frac{\frac{\theta_{ic}}{\Theta_c} \left[\varepsilon^i(g) \left(l_i \frac{\alpha + \sigma_i}{\alpha} \right)^{\gamma^i(g)} \right]^{1-\alpha}}{\left(\sum \pi_i \left(\frac{\theta_{ic}}{\Theta_c} \left[\varepsilon^i(g) \left(l_i \frac{\alpha + \sigma_i}{\alpha} \right)^{\gamma^i(g)} \right]^{1-\alpha} \right)^{\frac{1}{1-\alpha}} \right)^{1-\alpha}}$$

²We verify this by comparing l_i/L to $\left(\hat{\theta}_i/\hat{\Theta} \right)^{\frac{1}{1-\alpha}}$.

and replace the no-crime output in equation (13) by these new values. In this way we compare the output under the Chinese parameters with the actual output to calculate gains and losses.

Since some countries have quite small sample sizes we repeat this procedure five hundred times and calculate the mean and the standard deviation of the gains/losses in output as a form of "bootstrapping". We only report results if the gain or loss is larger than 1.65 times the standard deviation. Section 8 uses the same procedure except that we do not distinguish different productivity levels due to sample sizes being quite small. In that section, we also focus exclusively on the construction sector.

F Capital Stock in the Constant Elasticity Model

In this Appendix, we discuss the dependence of the capital stock on the parameters $\{\varepsilon^i(g), \gamma^i(g)\}$ in the constant elasticity model. Let $\{w, r\}$ be the factor prices for labor and capital respectively, then solving for the factor demands in this case yields:

$$l_i = \frac{\alpha\eta}{w} A \left(\theta_i p^i(e_i, g) \left(\frac{\sigma_i + \alpha}{\alpha} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

and

$$k_i = \frac{(1-\alpha)\eta}{r} A (\theta_i p^i(e_i, g))^{\frac{1}{1-\eta}} \quad (1)$$

where $A = \left[\left(\frac{\alpha\eta}{w} \right)^\alpha \left(\frac{(1-\alpha)\eta}{r} \right)^{1-\alpha} \right]^{\frac{\eta}{1-\eta}}$ is an economy-wide constant. In this case, observe that we have two dimensions to the productivity distortion. For capital $\hat{\theta}_i^k = \theta_i p^i(e_i, g)$ which is decreasing in the share of output loss. For labor we have $\hat{\theta}_i^l = \theta_i p^i(e_i, g) \left(\frac{\sigma_i + \alpha}{\alpha} \right)^{1-\eta}$ which is increasing in σ_i .³ Notice that the adjustment in productivity has a general firm-specific part and a labor-specific part from the distortion in the labor market due to employing guard labor as security.

³Note that

$$\frac{l_i}{L} = \frac{\left[\theta_i \frac{1}{1+\mu_i} \left(\frac{\sigma_i + \alpha}{\alpha} \right)^{1-\eta} \right]^{\frac{1}{1-\eta}}}{\sum_j \left[\theta_j \frac{1}{1+\mu_j} \left(\frac{\sigma_j + \alpha}{\alpha} \right)^{1-\eta} \right]^{\frac{1}{1-\eta}}}$$

Hence, as in the core model, adjusted firm-level productivity is reflected in labor shares.

We now turn towards discussing how capital stock changes with the parameters $\{\varepsilon^i(g), \gamma^i(g)\}$. We start from equation (1) for the optimal capital stock which implies that if $p^i(e_i, g)$ increases capital stock will increase. Looking at comparative statics, we need to allow for e_i to be endogenous.

Note that in the constant elasticity model we have

$$p^i(e, g) = \begin{cases} \varepsilon^i(g) \times e_i^{\gamma^i(g)} & \text{for } \varepsilon^i(g) \times e_i^{\gamma^i(g)} \leq 1 \\ 1 & \text{otherwise.} \end{cases}$$

We assume an interior solution for e_i which implies that if $\varepsilon^i(g)$ increases then $p^i(e_i, g)$ increases as long as e_i does not fall. Using the first order condition for the choice of e_i :

$$\frac{p_e^i(e_i, g)}{p_i(e_i, g)} = \frac{\eta\alpha}{l_i - e_i} = \frac{\gamma^i}{e_i}$$

which implies that e_i does not change with $\varepsilon^i(g)$ for fixed l_i and that k_i is increasing in $\varepsilon^i(g)$.

The first order condition for firm's optimal labor supply is given by

$$\theta_i \frac{\alpha\eta}{w} p^i(e_i, g) \left[(l_i - e_i)^\alpha k_i^{(1-\alpha)} \right]^\eta = l_i - e_i. \quad (2)$$

Substituting in (1) and using the constant elasticity formula for $p^i(e_i, g)$, substituting in $l_i - e_i$ from (2) and collecting terms we obtain:

$$\gamma^i(g) = e_i^{\frac{1-\eta-\gamma^i(g)}{1-\eta}} C_i$$

where C_i is a constant at the firm level. This implies that e_i is increasing in γ^i as long as $\gamma^i + \eta < 1$. Since $p_i(e_i, g)$ is an increasing function of e_i , we can conclude that the optimal capital stock k_i is increasing in $\gamma^i(g)$.

G Size of the Enterprise Sector

Here we show that if we assume that ω is fixed, i.e. there is no general equilibrium response in the sector that is supplying labor to the formal enterprise sector, then a back-of-the-envelope calculation suggests that the output loss could be about double that which we estimated above. To formalize this point, let L^* be labor allocated to the enterprise sector

without predation/protection and \hat{L} be the amount with predation/protection. Write output as:

$$Y^* = (L^*)^\alpha \Omega \text{ and } \hat{Y} = \hat{L}^\alpha \hat{\Omega}$$

where $\Omega = \Theta \sum_i \pi_i \left(\frac{\theta_i}{\Theta}\right)^{\frac{1}{1-\alpha}}$ and $\hat{\Omega} = \Theta \sum_i \pi_i \frac{\theta_i}{\Theta} \left[\tau + \frac{(1-\tau)}{1+\mu_i}\right] \left(\frac{\hat{\theta}_i}{\hat{\Theta}}\right)^{\frac{\alpha}{1-\alpha}} \left(\frac{\alpha}{\alpha+\sigma_i}\right)^\alpha$ using equations (9) and (10) in the main text. Now labor allocation to the enterprise sector will equate the marginal product of labor in the enterprise sector to the outside wage, i.e.

$$\omega = \alpha (L^*)^{\alpha-1} \Omega = \alpha \left(\hat{L}\right)^{\alpha-1} \hat{\Omega}.$$

From this we have an expression for the relative size of the labor force in the distorted and undistorted cases given by:

$$\frac{\hat{L}}{L^*} = \left(\frac{\hat{\Omega}}{\Omega}\right)^{\frac{1}{1-\alpha}}. \quad (3)$$

Now let M be the total workforce and denote aggregate productivity as $Z \in \{\Omega, \hat{\Omega}\}$. Then with $\tau = 0$ we have that aggregate labor demand to the enterprise sector is:

$$L = \left(\frac{\alpha Z}{\omega}\right)^{\frac{1}{1-\alpha}} \quad (4)$$

and the level of national income is:

$$\begin{aligned} Y(Z) &= \omega M + L^\alpha Z - \omega L \\ &= \omega M + (1-\alpha) Z^{\frac{1}{1-\alpha}} (\alpha/\omega)^{\frac{\alpha}{1-\alpha}} \end{aligned}$$

after using (4). Given the economy as specified here, this is the sum of labor earnings at the fixed wage, ω , plus profit generated in the enterprise sector which we are implicitly assuming is the source of all profits. Our expression for the loss from predation/protection is now:

$$\begin{aligned} \Delta &= \frac{Y(\Omega) - Y(\hat{\Omega})}{Y(\Omega)} \\ &= \frac{\Omega^{\frac{1}{1-\alpha}} (1-\alpha) \left(\frac{\alpha}{\omega}\right)^{\frac{\alpha}{1-\alpha}}}{(1-\alpha) \Omega^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{\omega}\right)^{\frac{\alpha}{1-\alpha}} + \omega M} \left[1 - \left(\frac{\hat{\Omega}}{\Omega}\right)^{\frac{1}{1-\alpha}}\right]. \end{aligned}$$

To give a back-of-the-envelope measure of this and its effect on our core output loss mea-

sure, we can estimate $\frac{\Omega^{\frac{1}{1-\alpha}}(1-\alpha)\left(\frac{\alpha}{\omega}\right)^{\frac{\alpha}{1-\alpha}}}{(1-\alpha)\Omega^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{\omega}\right)^{\frac{\alpha}{1-\alpha}}+\omega M}$ from the profit share in GDP. Putting this together, then to a first-order approximation, we have the following expression for the aggregate output loss as:

$$\Delta \simeq \frac{\alpha}{1-\alpha} \left[1 - \left(\frac{\hat{\Omega}}{\Omega} \right) \right].$$

H Covariance between Firm-Size and Productivity

A popular way of looking at the extent of misallocation suggested by Bartelsman et al (2013) is through measuring the covariance between firm size and productivity. We now explore this approach exploiting the fact that we have direct measures of distortions to work with. For this purpose, we no longer use the constant elasticity specification but revert to general model of the protection technology.

As a preliminary step, we first check whether large firms are more or less heavily affected by predation/protection distortions by examining the covariance between firm size, μ_i and σ_i . This is important in light of the discussion in section 7. Comparing the within-country covariance between firm size and μ_i allows us to look at whether countries which are more heavily affected by predation are less likely to prevent predation in large firms. Thus the covariance between firm size and μ_i is positive and relatively high in Mexico, Afghanistan and Sierra Leone even though it is negative on average. But we can go one step further by looking at differences across sectors within the same country. Column (1) of Table A3 shows that, controlling for country fixed effects, the predation loss, μ_{is} , is decreasing with firm size while protection spending σ_{is} is increasing with firm size. In other words, larger firms tend on average to lose a smaller share of their output to predation but hire more unproductive labor.

The covariance between firm size and productivity allows us to summarize these distortions. We look at two covariance measures suggested by the model. The covariance between labor productivity and firm size can be written as:

$$cov \left(\log \frac{y_{is}}{l_{is}}, \log \frac{l_{is}}{L_s} \right) = cov \left(\log \frac{w}{\alpha_s + \sigma_{is}}, \log \frac{l_{is}}{L_s} \right). \quad (5)$$

This formula reveals immediately that, in absence of other distortions, the covariance

depends upon the relationship between σ_{is} and l_{is} .⁴ If larger firms hire more labor for protection, we would expect the covariance in (5) to be lower, i.e. labor productivity would be a weaker predictor, all else equal, of the number of workers that a firm employs.

An alternative way to look at this is to use the covariance between firm size and overall firm productivity instead. In terms of our notation this covariance is

$$cov\left(\log\frac{\theta_{is}}{\Theta_s}, \log\frac{l_{is}}{L_s}\right) = cov\left(\log\frac{(1+\mu_{is})(l_{is})^{1-\alpha_s}\left(\frac{\alpha_s}{\alpha_s+\sigma_{is}}\right)^{1-\alpha_s}}{\Theta_s}, \log\frac{l_{is}}{L_s}\right) \quad (6)$$

where Θ_s and L_s are fixed at the country/year/sector level. The covariance will depend mainly on the variance of firm size, l_{is} , within a sector. Firm level distortions have two opposing effects on our estimates of productivity through the term $\frac{1}{(1+\mu_{is})}\left(\frac{\alpha_s+\sigma_{is}}{\alpha_s}\right)^{1-\alpha_s}$. Predation losses, μ_{is} , lower the optimal firm size while protection spending, σ_{is} , increases firm size by increasing the amount of labor that a firm hires. The change in the covariance induced by predation and protection will depend on whether such distortions are correlated with a firm's productivity.

We calculate the covariances in (5) and (6) within each sector/country/year under the assumption that the labor share, α_s , varies by sector.⁵ Two patterns are worth noting. First, both the median and mean covariance in (5) are negative. This implies that larger firms tend to protect themselves more. Second, the covariance in (6) decreases in α_s as the formula suggests, i.e. more labor intensive sectors have a lower covariance. Thus, the covariance between firm productivity and firm size is higher in manufacturing than in construction.

Table A3 shows that a lower covariance between firm size and productivity in a sector is associated with a higher estimated loss of output due to predation. We would expect this if we regard predation as inducing a misallocation of labor across firms with heterogeneous productivity levels.⁶ The pattern holds for the covariance in (5) as shown in columns (2) and (3) and for the covariance in (6) as shown in columns (4) and (5). The findings, except

⁴Note that in (5), the wage rate, w and sector labor shares L_s are fixed at the country/year/sector level.

⁵We drop sector/country/years with less than 10 firms.

⁶In interpreting this, we should emphasise that we are only looking at the marginal misallocation that is being attributed to the distortion in the labor market due to predation. Our benchmark measure of $\frac{\theta_i}{\Theta}$ takes any other sources of misallocation and/or productivity loss as given.

for in column (5), are robust to controlling for country/year and sector fixed effects and constitute an economically meaningful relationship; an increase of 4 percentage points in the output loss in column (3) is associated with a decrease of the covariance between labor productivity and firm size by one standard deviation.

The mechanism at work here is worth elaborating further. The negative covariance in columns (2) and (3) is driven by the fact that protection spending is positively correlated with firm size. This is not entirely surprising in our framework as it is protection which leads a firm to expand its level of employment. This negative relationship becomes more pronounced if we relate output losses to the covariance measure given by equation (6). If we use the constant elasticity model, we know that this is not due to the fact that large firms are better protected by the state but is due to the fact that they spend more on protection. This also highlights the importance of including endogenous firm protection effort in the analysis of the distortions caused by predation. Our finding that large firms are less protected in some countries, for example, is a direct consequence of having protection spending in the model – absent protection spending we would observe a lower level of the distortions due to predation for larger firms.

Hopenhayn (2014) suggests that for distortions to matter for TFP they must lead to rank reversals in the firm size distribution. The fact that we observe measures of the distortion allows us to look at this directly. To do this, we calculate Spearman’s rank correlation coefficients between $\frac{\theta_{ic}}{\Theta_c}$ and $\frac{\hat{\theta}_{ic}}{\hat{\Theta}_c}$ and plot the result with our output loss estimate at the country level in Figure A11. There is a very strong negative relationship between our output loss measure and the rank correlation confirming the idea that the rank correlation is indeed a way of thinking about distortions which affect output losses.

I Incentive Effects on Productivity

Suppose that

$$\theta_i = \frac{\theta_i}{1 - \kappa} (I_i)^{1-\kappa}$$

where I_i is managerial effort whose cost is the wage. Then managerial effort maximizes:

$$\frac{\theta_i}{1 - \kappa} (I_i)^{1-\kappa} \left[(l_i)^\alpha \left(\frac{\alpha}{\alpha + \sigma_i} \right)^\alpha \frac{1}{1 + \mu_i} \right] - w [I_i + l_i].$$

The first order condition for such effort is

$$\underline{\theta}_i (I_i)^{-\kappa} \left[(l_i)^\alpha \left(\frac{\alpha}{\alpha + \sigma_i} \right)^\alpha \frac{1}{1 + \mu_i} \right] = w,$$

where we have used the envelope condition for the choice of l_i . Combining this with $l_i = \left(\frac{\hat{\theta}_i \alpha}{w} \right)^{\frac{1}{1-\alpha}}$ and $\hat{\theta}_i = \theta_i \frac{1}{(1+\mu_i)} \left(\frac{\alpha+\sigma_i}{\alpha} \right)^{1-\alpha}$ from the main text yields:

$$\underline{\theta}_i (I_i)^{-\kappa} \left[\left(\frac{\alpha}{w} \frac{\underline{\theta}_i}{1 - \kappa} (I_i)^{1-\kappa} \frac{1}{1 + \mu_i} \left(\frac{\alpha}{\alpha + \sigma_i} \right)^{\alpha-1} \right)^{\frac{\alpha}{1-\alpha}} \left(\frac{\alpha}{\alpha + \sigma_i} \right)^\alpha \frac{1}{1 + \mu_i} \right] = w$$

Collecting terms

$$(\underline{\theta}_i)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{w(1-\kappa)} \right)^{\frac{\alpha}{1-\alpha}} (I_i)^{\frac{\alpha-\kappa}{1-\alpha}} \left(\frac{1}{1 + \mu_i} \right)^{\frac{1}{1-\alpha}} = w$$

This implies that

$$I_i^* = \text{constant}_i \times \left(\frac{1}{1 + \mu_i} \right)^{\frac{1}{\alpha-\kappa}}.$$

So higher μ_i results in lower managerial effort if $\alpha > \kappa$. The relative productivity is scaled down by a factor:

$$\left(\frac{1}{1 + \mu_i} \right)^{\frac{1-\kappa}{\alpha-\kappa}}$$

which, given the parameter values supposed in the exponent, is approximately 1.96. This additional term can then be added to the calculations.

References

- [1] Bartelsman, Eric, John Haltiwanger and Stefano Scarpetta, [2013], "Cross-Country Differences in Productivity," *American Economic Review*, 305-334.
- [2] Hopenhayn, Hugo A., [2014], "On the Measure of Distortions," typescript, UCLA.
- [3] Inklaar, Robert and Marcel Timmer, [2013] "Capital, Labor and TFP in PWT 8.0".

Table A1: Estimated Output Loss and Homocide Rate

VARIABLES	(1) estimated output loss	(2) estimated output loss
homocide rate (per 100,000 population)	32.08* (16.26)	128.4** (56.97)
country fixed effects	no	yes
Observations	155	155
R-squared	0.056	0.733

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "estimated ouptut loss" is estimated under the assumption of heterogenous firms.

Table A2: Protection and Crime as an Obstacle

VARIABLES	(1) degree to which crime is an obstacle (0-4)	(2) crime is worst obstacle	(3) perceived protection	(4) protection effort elasticity
perceived protection	-0.127*** (0.0104)	-0.0121*** (0.00284)		
protection effort elasticity	-0.0302*** (0.0111)	-0.00696*** (0.00255)		
foreign owned firm			0.00678 (0.0130)	0.0304*** (0.0107)
state owned firm			-0.00918 (0.0206)	0.0302** (0.0153)
firm in capital			0.00622*** (0.00237)	-0.00705*** (0.00228)
firm productivity decile dummies	yes	yes	yes	yes
country/year fixed effects	yes	yes	yes	yes
sector fixed effect	yes	yes	yes	yes
Observations	152,549	108,659	124,563	124,563
R-squared	0.246	0.088	0.106	0.096

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All estimates assume alpha=0.66. "perceived protection" is the estimate of the epsilon parameter. "protection effort elasticity" is the estimate of the gamma parameter. Both variables are weighted by their standard error.

Table A3: Covariance Between Firm Size and Productivity

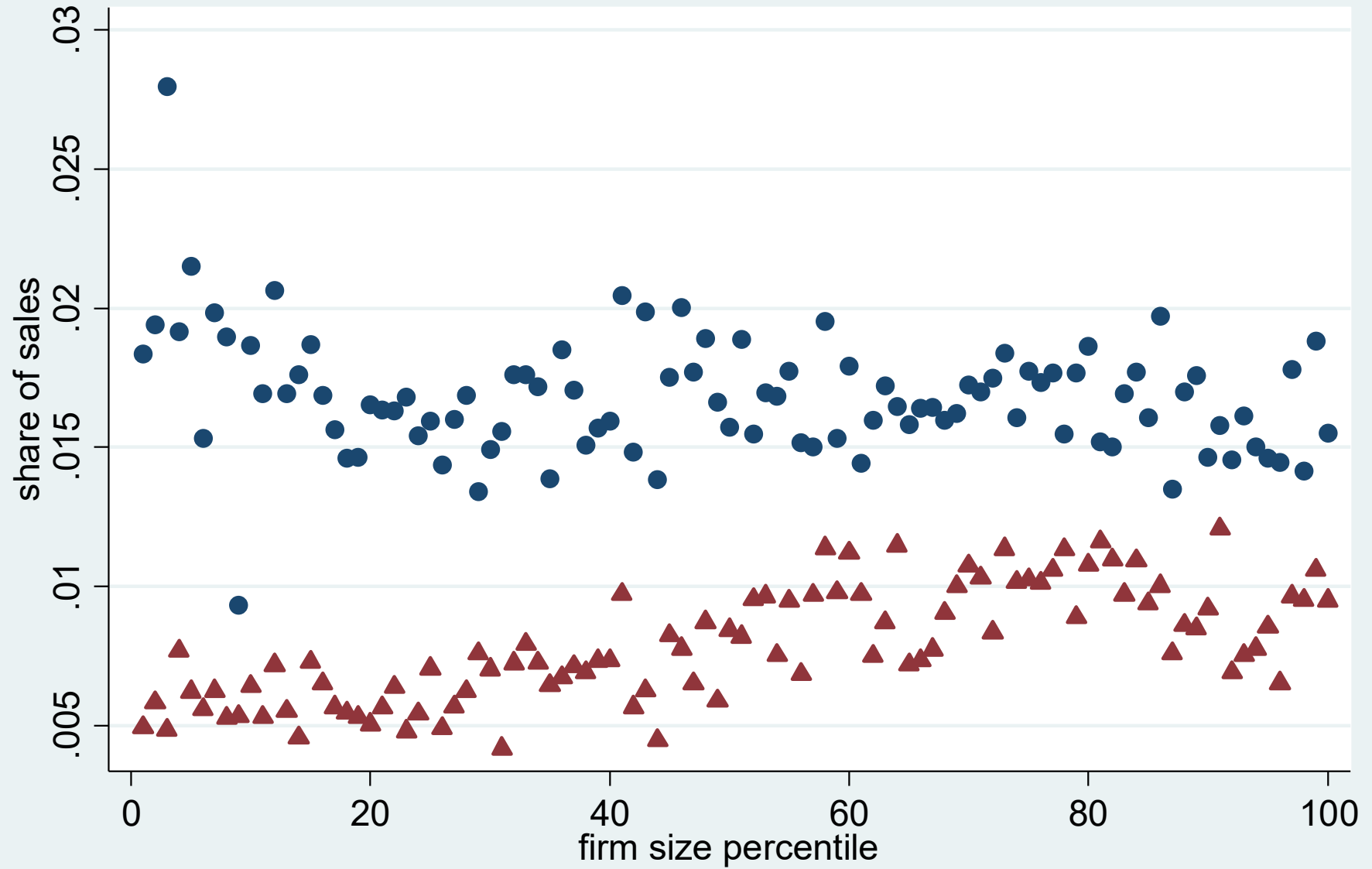
VARIABLES	(1) ln(firm size)	(2) covariance (size, output per worker)	(3) covariance (size, output per worker)	(4) covariance (size, firm productivity)	(5) covariance (size, firm productivity)
loss due to theft, robbery, vandalism or arson as a percentage of total annual sale	-0.732*** (0.160)				
percentage of total annual sales paid for security	0.615*** (0.150)				
estimated output loss in sector		-0.208*** (0.0524)	-0.334*** (0.0632)	-1.256** (0.503)	-0.414 (0.637)
country/year/sector fixed effects	yes	no	no	no	no
country/year fixed effect	no	no	yes	no	yes
sector fixed effects	no	no	yes	no	yes
Observations	154,852	842	842	842	842
R-squared	0.230	0.137	0.609	0.014	0.764

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "covariance (size, firm productivity)" is the covariance between log firm size and estimated log relative theta at the sector level. "covariance (size, output per worker)" is the covariance between log firm size and $-\log$ of spending on protection plus the sector labor share ($\gamma + \alpha$).

Table A4: Estimated Output Loss by Country

country	homogenous firms	heterogeneous firms	country	homogenous firms	heterogeneous firms
Afghanistan	2.37%	5.95%	Liberia	4.74%	5.34%
Albania	2.11%	1.86%	Lithuania	1.65%	1.57%
Angola	4.85%	5.94%	Macedonia	2.81%	2.28%
Antigua and Barbuda	1.09%	1.06%	Madagascar	2.66%	2.19%
Argentina	1.53%	1.40%	Malawi	5.68%	5.92%
Armenia	1.42%	1.84%	Malaysia	1.88%	3.67%
Azerbaijan	2.45%	2.88%	Mali	1.78%	2.47%
Bahamas, The	2.32%	3.60%	Mauritania	2.12%	1.93%
Bangladesh	0.94%	0.65%	Mauritius	1.31%	2.73%
Barbados	0.16%	0.21%	Mexico	1.95%	4.32%
Belarus	1.30%	1.07%	Micronesia, Fed. Sts.	2.45%	3.35%
Belize	0.82%	0.70%	Moldova	1.93%	1.96%
Benin	1.45%	1.77%	Mongolia	2.59%	2.35%
Bhutan	1.47%	1.42%	Montenegro	2.38%	3.75%
Bolivia	1.84%	1.87%	Morocco	0.44%	0.48%
Bosnia and Herzegovina	1.48%	1.65%	Mozambique	2.70%	3.57%
Botswana	3.01%	2.76%	Myanmar	0.25%	0.93%
Brazil	2.12%	2.12%	Namibia	2.90%	3.33%
Bulgaria	1.59%	1.40%	Nepal	1.40%	1.54%
Burkina Faso	2.45%	4.15%	Nicaragua	3.21%	3.05%
Burundi	1.93%	1.75%	Niger	3.14%	1.78%
Cambodia	9.91%	12.58%	Nigeria	3.43%	3.73%
Cameroon	6.76%	4.15%	Pakistan	1.71%	1.67%
Cape Verde	4.10%	4.68%	Panama	1.52%	2.02%
C.African Rep.	4.07%	5.60%	PapuaNewGuinea	5.14%	3.61%
Chad	3.77%	4.33%	Paraguay	2.44%	3.10%
Chile	1.13%	1.28%	Peru	3.22%	2.74%
China	0.84%	0.93%	Philippines	2.29%	2.62%
Colombia	1.23%	1.42%	Poland	1.28%	1.23%
Congo, Dem. Rep.	3.33%	5.13%	Portugal	2.74%	1.78%
Congo, Rep.	5.55%	4.63%	Romania	1.68%	1.98%
Costa Rica	1.38%	1.09%	Russian Federation	2.09%	2.39%
Cote d'Ivoire	4.15%	4.73%	Rwanda	2.28%	3.19%
Croatia	0.78%	0.94%	Samoa	5.37%	6.88%
Czech Republic	1.78%	1.62%	Senegal	1.60%	2.26%
Djibouti	1.84%	1.58%	Serbia	1.89%	1.99%
Dominica	0.48%	0.93%	Sierra Leone	2.12%	9.15%
Dominican Republic	3.01%	3.23%	Slovakia	1.70%	1.36%
Ecuador	3.82%	3.46%	Slovenia	0.83%	0.66%
Egypt	0.83%	1.41%	Solomon	2.94%	2.40%
El Salvador	3.74%	2.74%	South Africa	1.61%	1.56%
Estonia	1.17%	1.80%	South Korea	0.06%	0.01%
Ethiopia	0.77%	1.13%	South Sudan	3.69%	4.66%
Fiji	1.51%	1.92%	Spain	0.48%	0.95%
Gabon	2.24%	1.47%	Sri Lanka	1.18%	1.81%
Gambia, The	6.12%	5.39%	St. Kitts and Nevis	2.17%	1.41%
Georgia	1.49%	1.55%	St. Lucia	0.29%	0.72%
Germany	2.06%	1.22%	St. Vincent and the Gr	1.56%	2.10%
Ghana	2.05%	2.43%	Sudan-North	2.30%	3.30%
Greece	1.95%	0.53%	Suriname	1.00%	0.52%
Grenada	2.51%	3.23%	Swaziland	5.38%	6.84%
Guatemala	3.08%	3.08%	Sweden	0.38%	0.38%
Guinea	2.60%	3.63%	Tajikistan	2.54%	2.95%
Guinea-Bissau	1.67%	1.47%	Tanzania	4.00%	4.60%
Guyana	1.78%	1.99%	Thailand	0.33%	0.34%
Honduras	4.05%	5.30%	Timor-Leste	4.62%	4.91%
Hungary	0.57%	1.00%	Togo	2.75%	2.53%
India	2.19%	1.65%	Tonga	2.10%	3.27%
Indonesia	0.89%	1.08%	Trinidad and Tobago	1.65%	1.74%
Iraq	0.83%	0.92%	Tunisia	1.17%	0.78%
Ireland	0.34%	0.19%	Turkey	1.04%	1.62%
Israel	0.12%	0.41%	Uganda	3.10%	3.27%
Jamaica	1.66%	1.37%	Ukraine	2.35%	2.27%
Jordan	0.32%	0.25%	Uruguay	1.25%	0.98%
Kazakhstan	2.52%	2.13%	Uzbekistan	0.76%	0.86%
Kenya	3.48%	3.11%	Vanuatu	4.12%	9.43%
Kosovo	4.95%	4.22%	Venezuela, R.B.	3.94%	3.54%
Kyrgyz Republic	3.05%	2.83%	Vietnam	0.90%	1.09%
Lao PDR	1.45%	1.40%	West Bank and Gaza	2.31%	2.60%
Latvia	1.25%	0.86%	Yemen, Rep.	0.89%	1.57%
Lebanon	0.68%	0.87%	Zambia	4.11%	5.50%
Lesotho	5.36%	9.66%	Zimbabwe	2.05%	1.94%

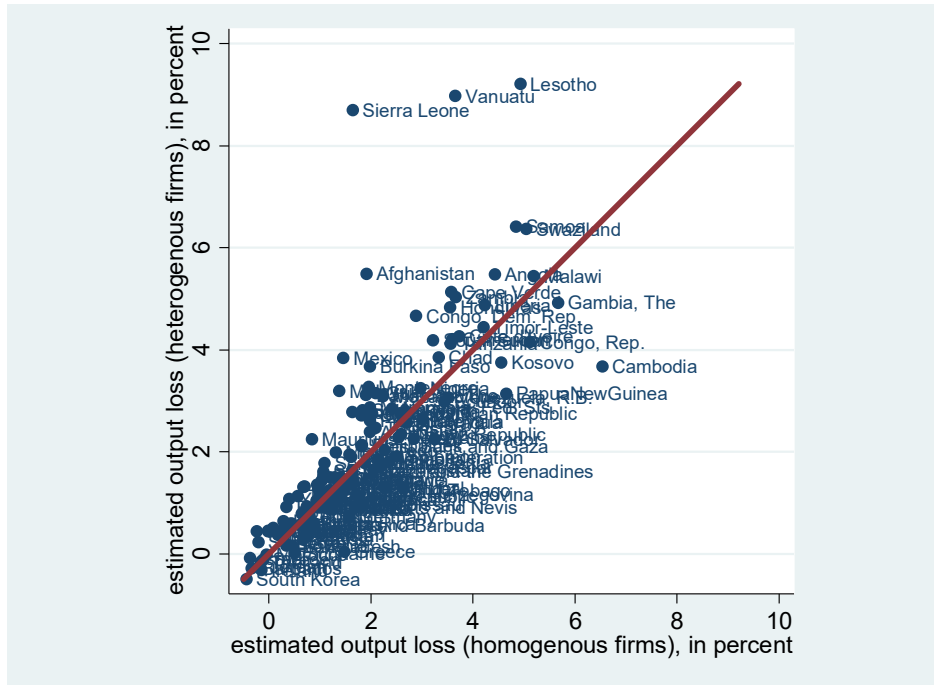
Figure A1: Predation Loss and Spending on Security Across Firm Size



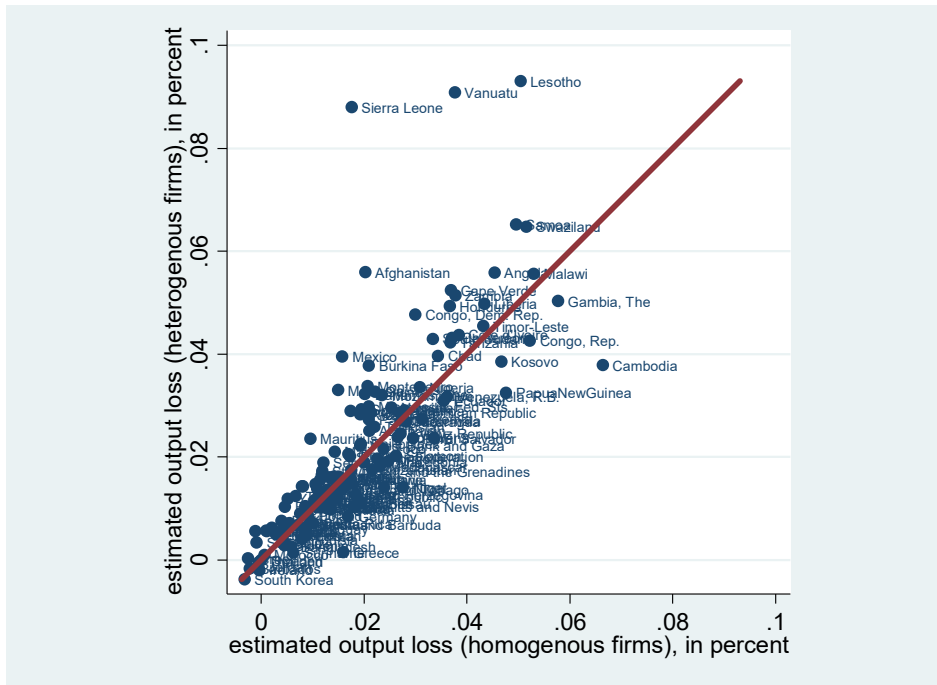
● spending on security ▲ loss from predation

Figure A2: Productivity Weights but China or Sweden as Benchmark

a) China as a Benchmark

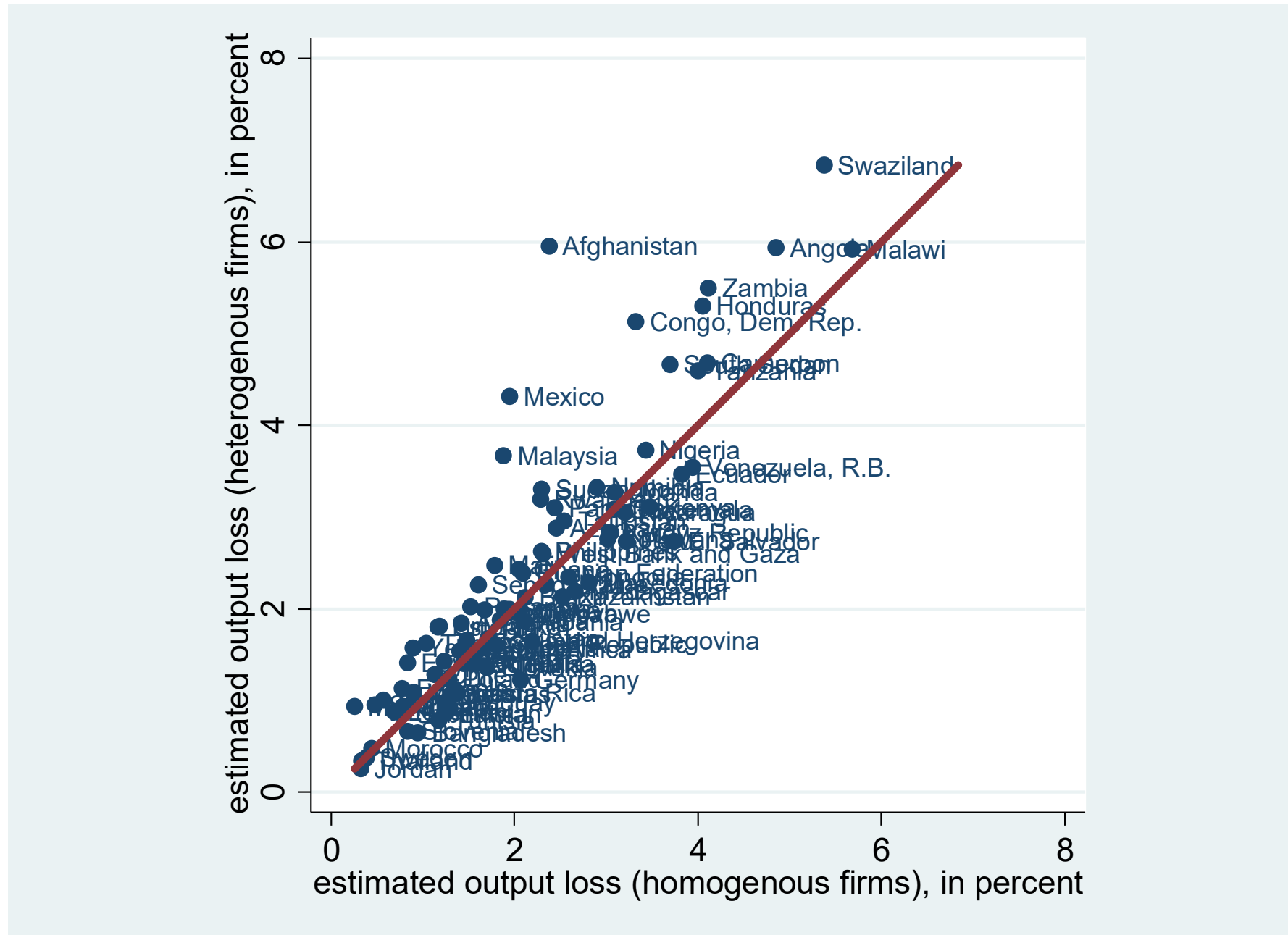


b) Sweden as a Benchmark



Notes: Figure contrasts the output loss, Δc , from equation (12) on the x-axis with the output loss, Δc , from equation (13). In each case we first calculate the output loss for each country/year and then take the mean value for the respective country. The red line represents the points at which the two losses are the same. The Central African Republic dropped as an outlier. Panel a) takes the crime loss in China as a benchmark. Panel b) takes the crime loss in Sweden as a benchmark.

Figure A3: Estimated Output Losses (Countries with 500+ Observations)



Notes: Figure contrasts the output loss, Δc , from equation (12) on the x-axis with the output loss, Δc , from equation (13). In each case we first calculate the output loss for each country/year and then take the mean value for the respective country. The red line represents the points at which the two losses are the same.

Figure A4: Non-Robustness to Dropping Outliers (all sectors)

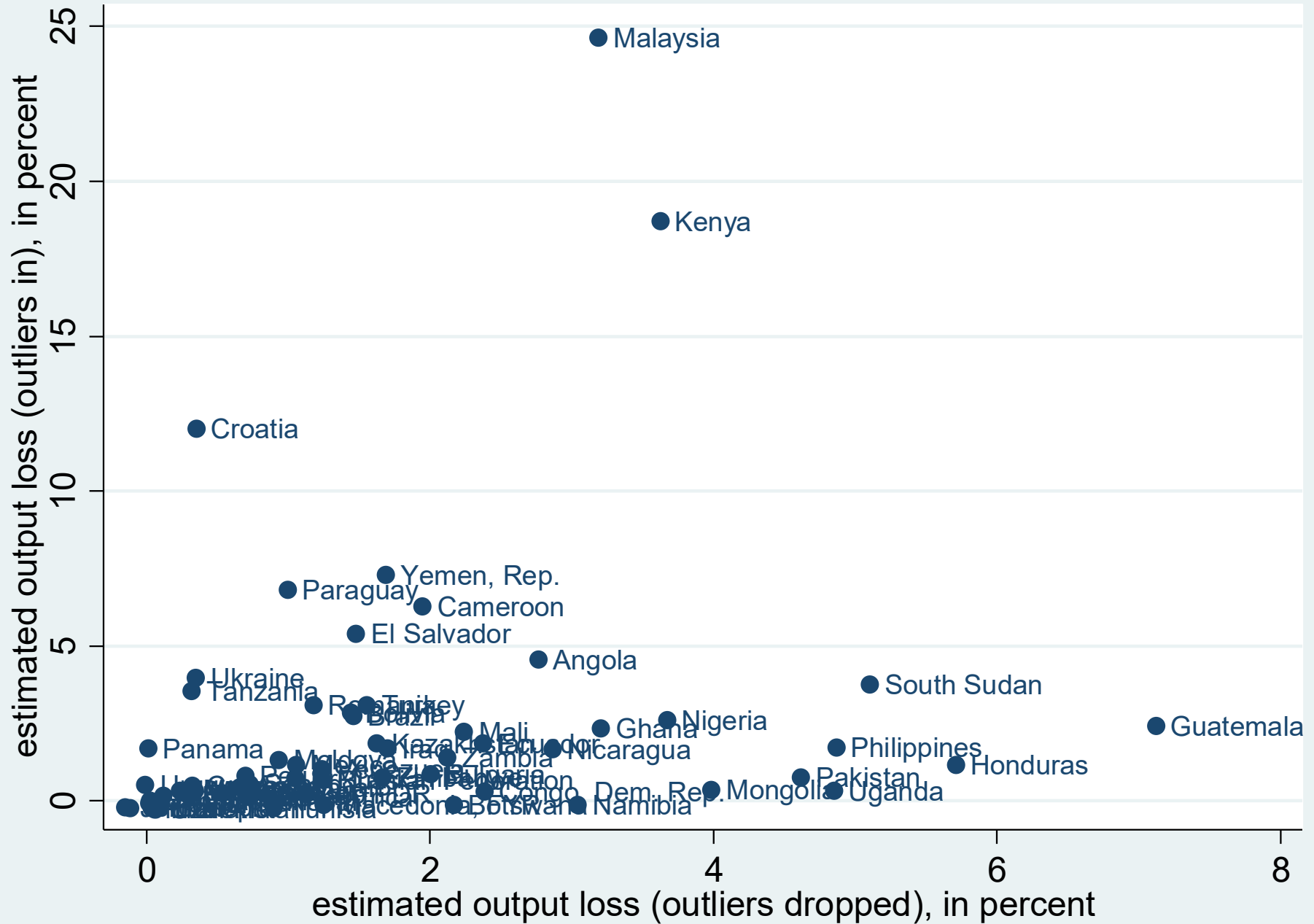


Figure A5: Non-Robustness to Dropping Outliers (manufacturing, 500+ observations)

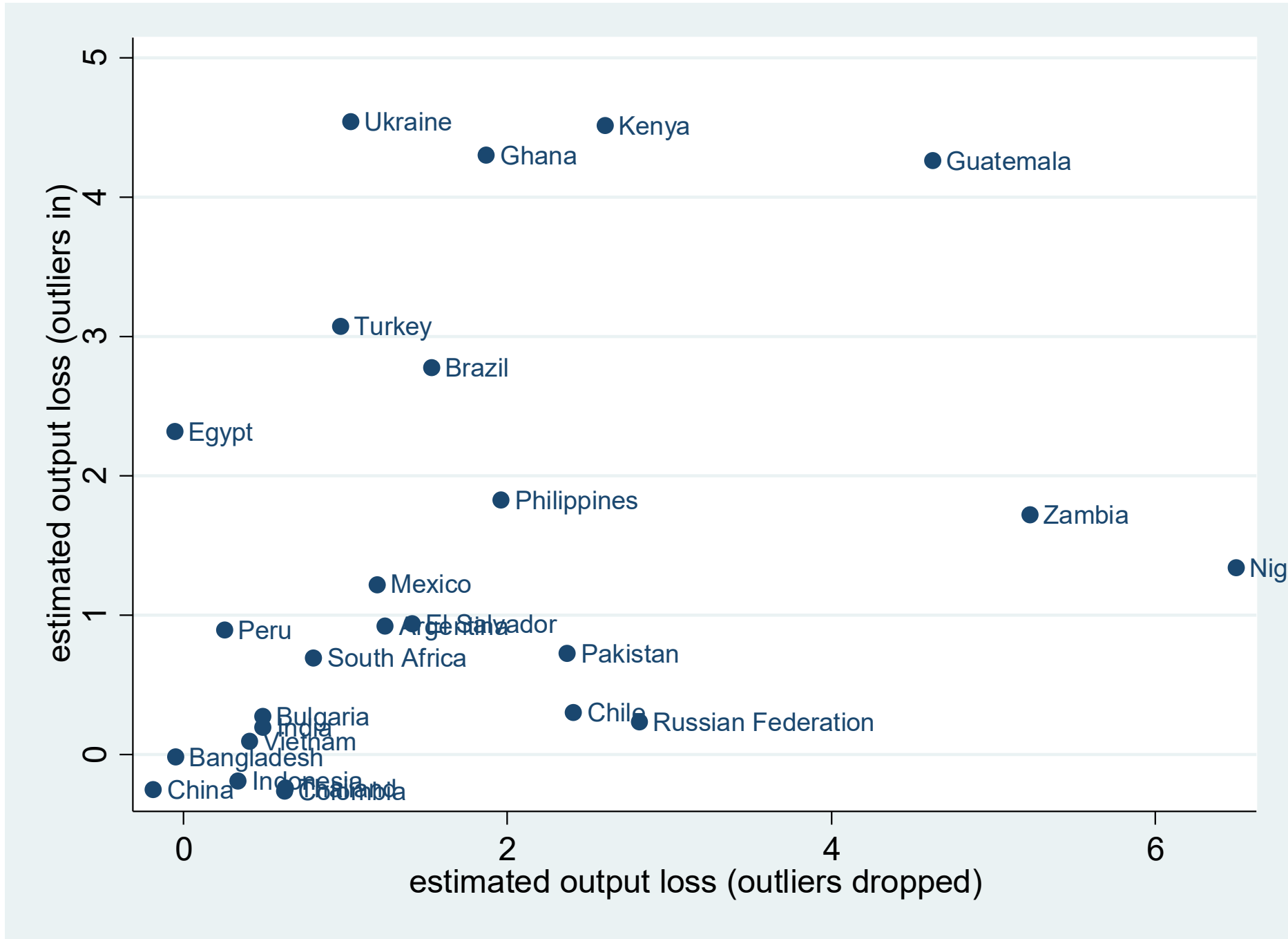


Figure A6: VA-Based Measure and Size-Based Measure (manufacturing, 500+ observations)

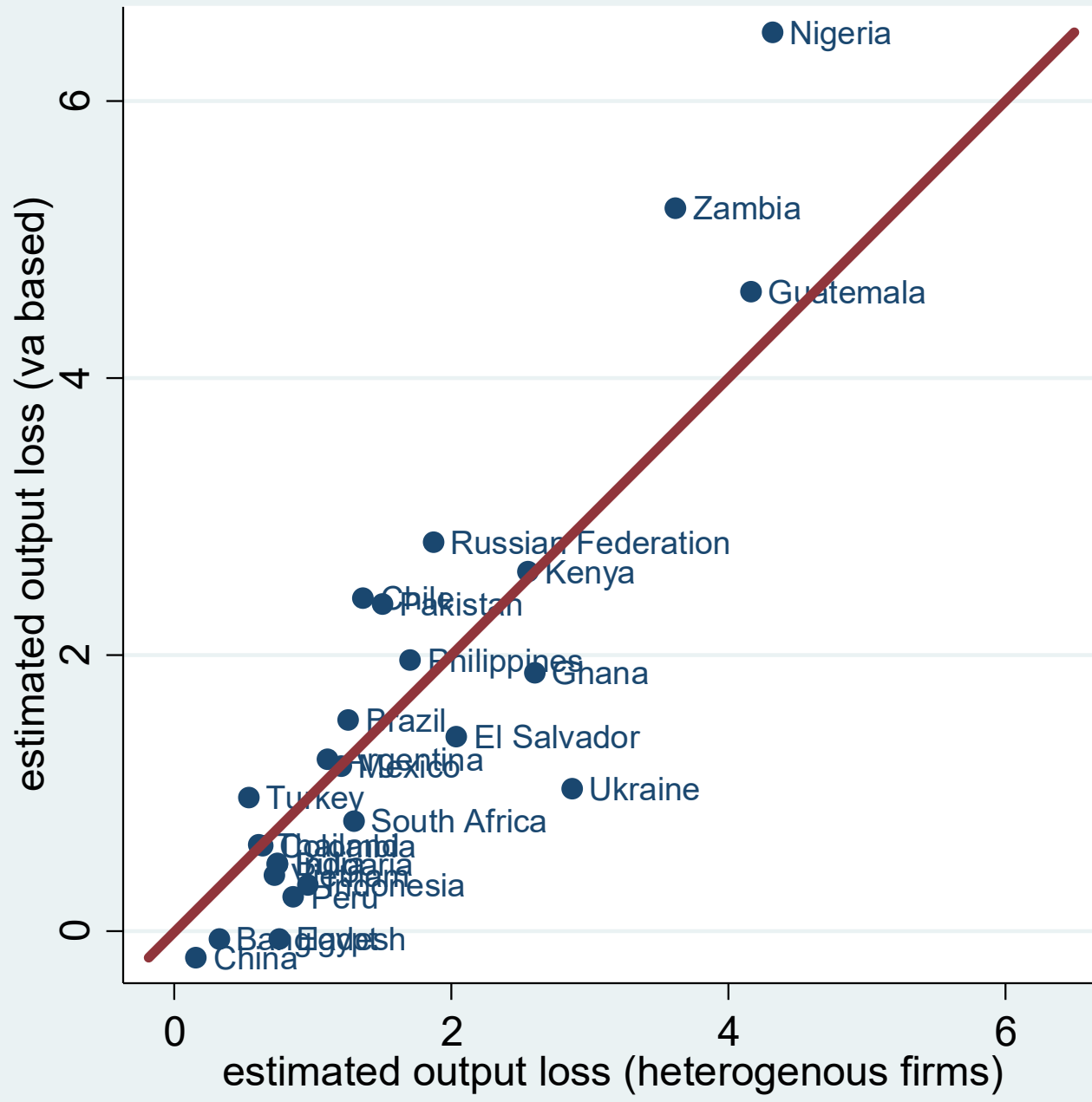


Figure A7: Relative Productivity Weights in Manufacturing in Mexico

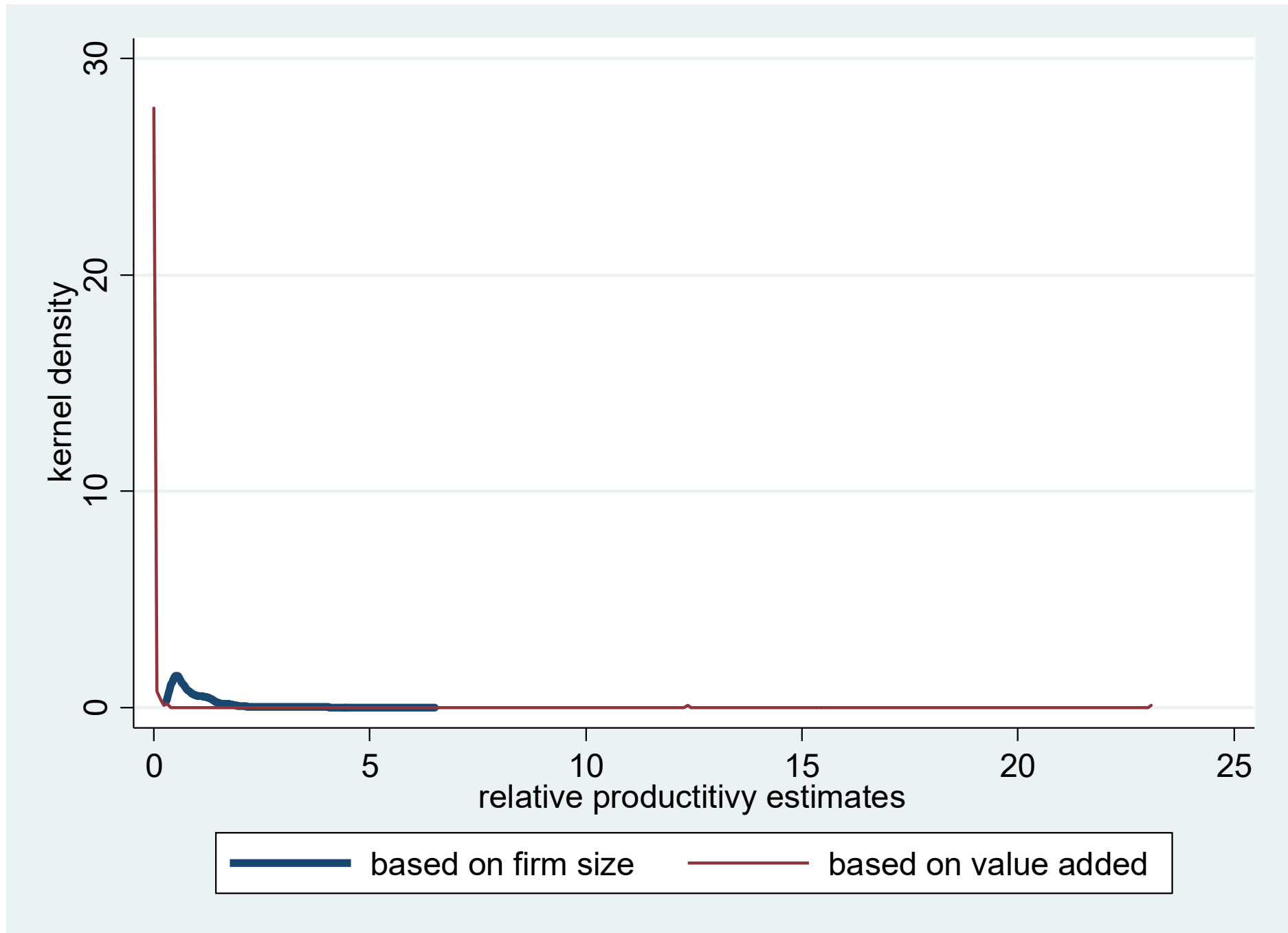


Figure A8: Re-Allocation Effect

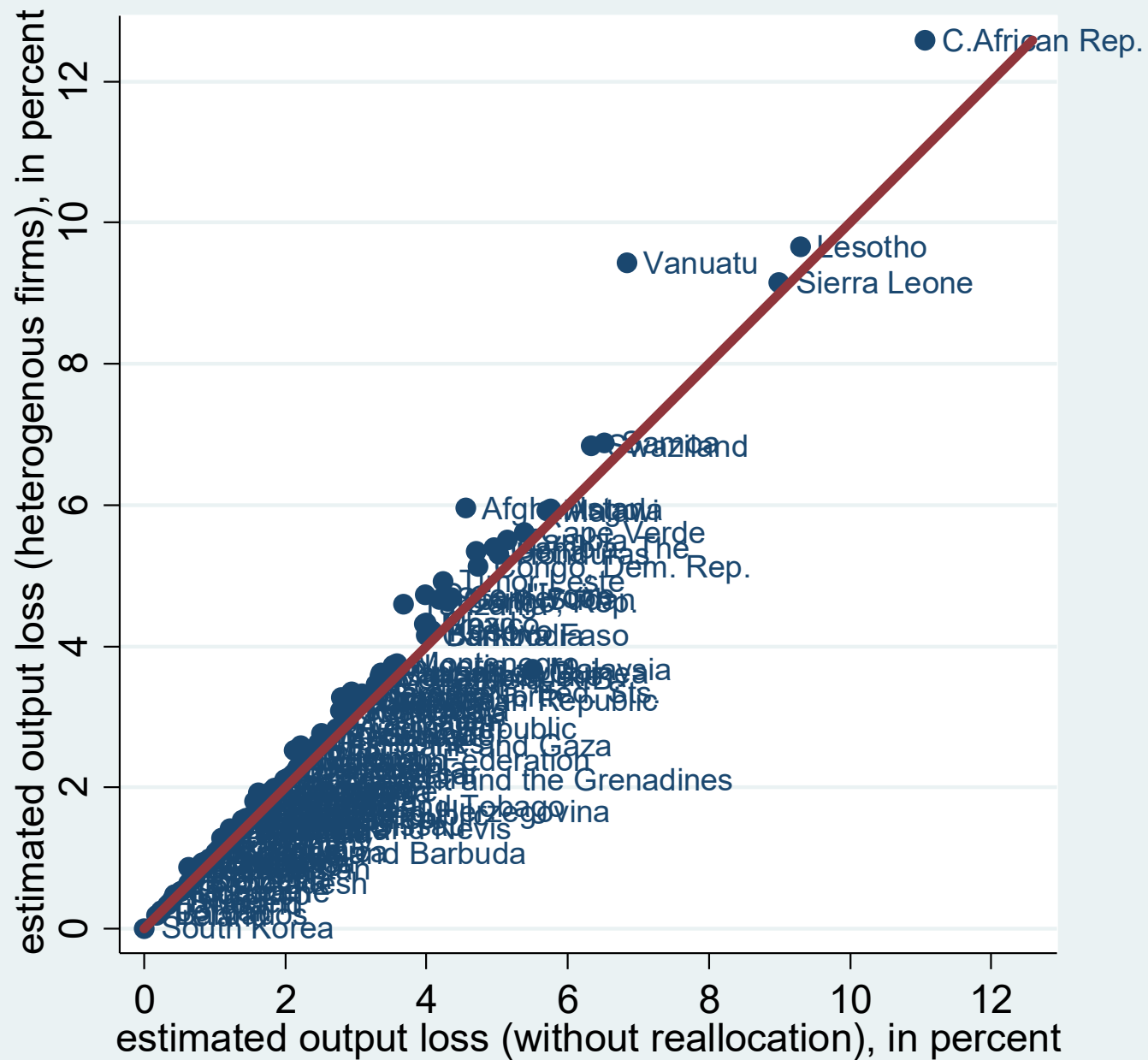
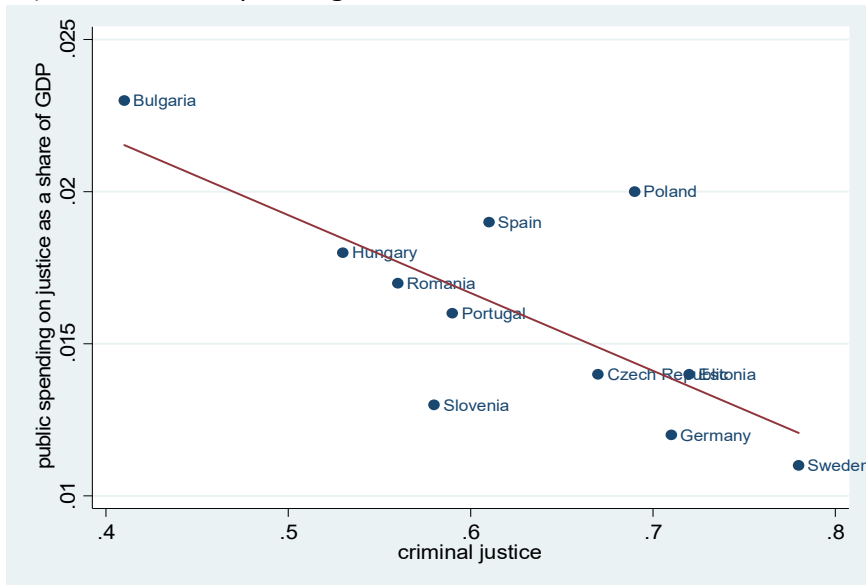
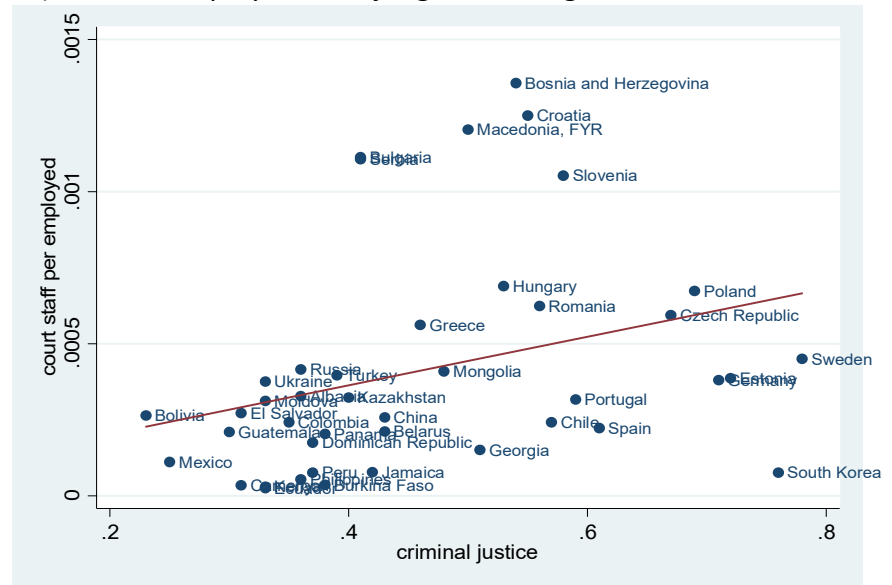


Figure A9: Justice Resources and Criminal Justice

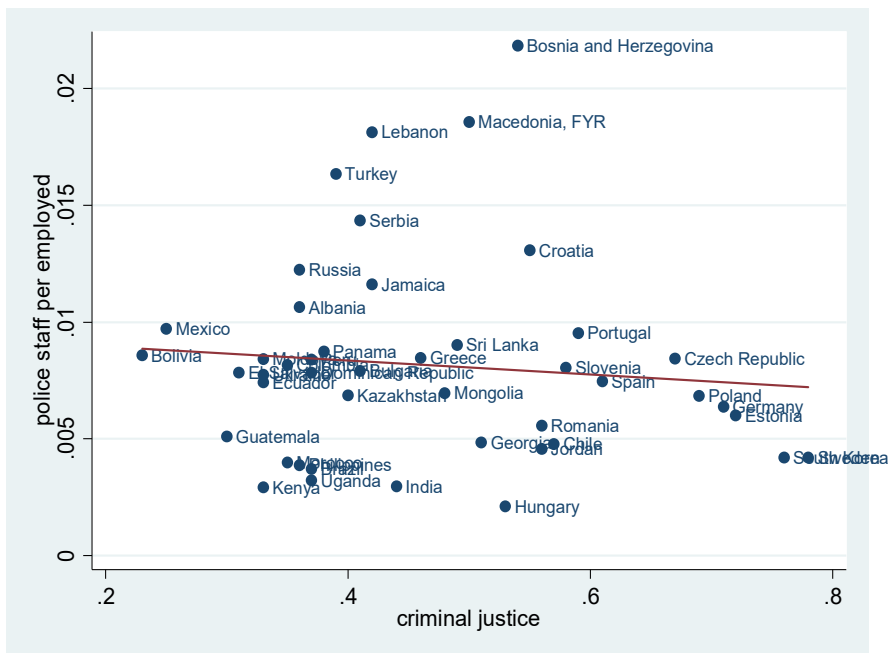
a) Data on total spending from Eurostat



b) Data on employment of judges and magistrates from UNODC



c) Data on employment of police from UNODC



d) Data on employment of prison staff from UNODC

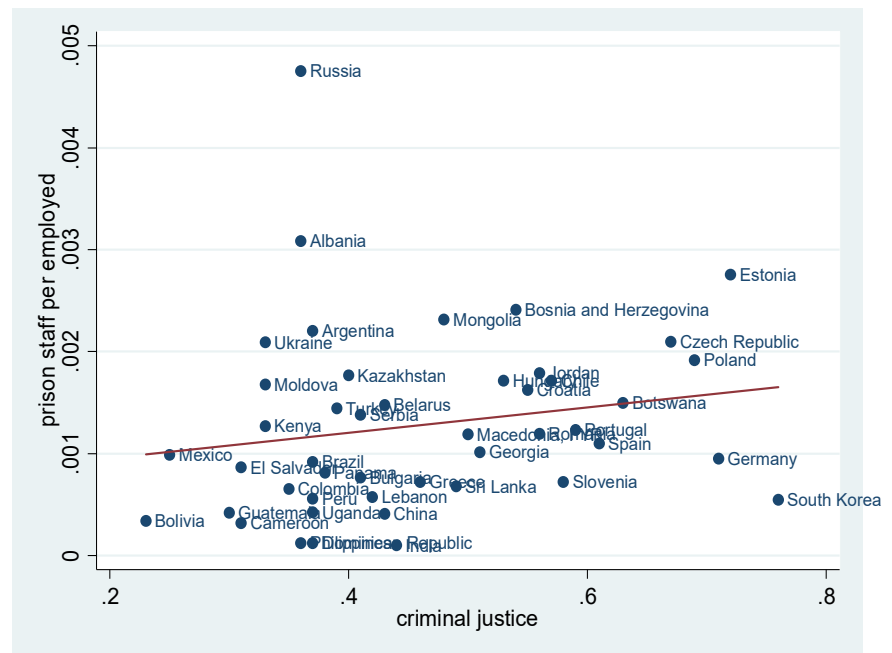


Figure A10: Protection Estimates by Firm Productivity

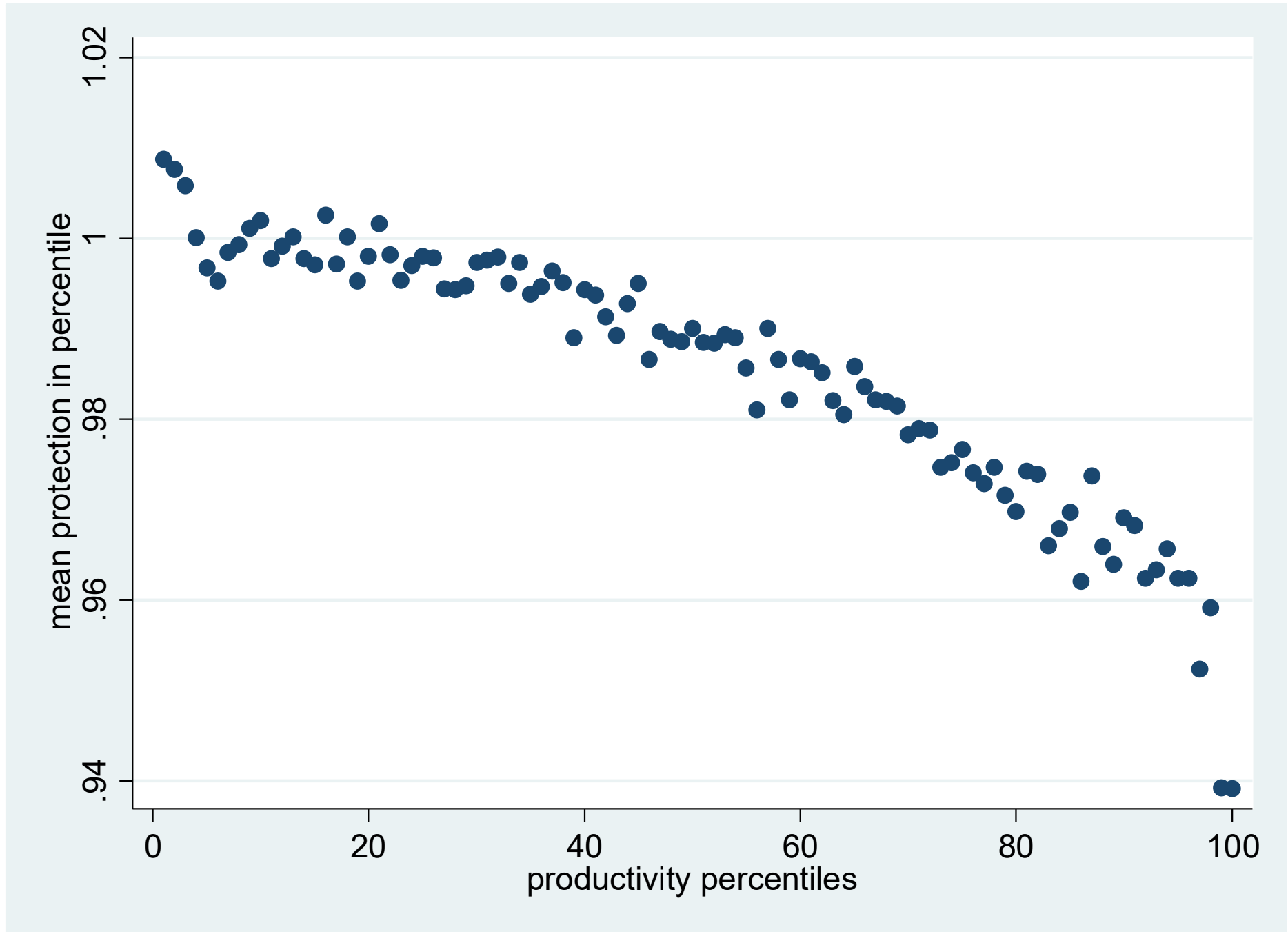


Figure A11: Spearman's Rank Correlation as a Proxy for Distortions

