Allocative efficiency between and within the formal and informal manufacturing sector in Zimbabwe

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Abstract

Resource misallocation has the potential to reduce aggregate total factor productivity and undermine industrial development. These effects can be particularly pronounced in emerging economies where large market frictions impede efficient resource allocation. This paper investigates the extent and nature of resource misallocation between and within the formal and informal manufacturing sector in Zimbabwe. Applying the approach developed by Hsieh & Klenow (2009) to firm-level microdata, the results reveal extensive resource misallocation in both the formal and informal manufacturing sector. Misallocation is more pronounced in informal sector firms and is associated with relatively large capital market distortions. Further, misallocation is more pronounced amongst relatively productive firms, thus exacerbating aggregate losses in total factor productivity (TFP). Estimates indicate that aggregated gains in TFP of 126.7% can be realized through efficient resource allocation.

Keywords: Misallocation, total factor productivity, informal sector

JEL Codes: E24, D24, E29, L60

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Introduction

Differences in aggregate total factor productivity (TFP) have been shown to be a key explanatory factor behind the large differences in incomes and development across countries (Asker, Collard-Wexler & De Loecker, 2014; David & Venkateswaran, 2019; Gopinath et al., 2017; Hall & Jones, 1999; Hsieh & Klenow, 2009). Traditionally, these income gaps have been attributed to differences in technologies and factor input accumulation (such as labour and capital) (Hall & Jones, 1999; Howitt, 2000). More recently, however, the contribution of resource misallocation in explaining the observed disparities in cross-country aggregate TFP has been emphasised (David & Venkateswaran, 2019; Hsieh & Klenow, 2009; Restuccia & Rogerson, 2017). In efficient markets, resources allocate across firms such that more productive firms control a larger share of the market. When output and factor market distortions impede this re-allocation, aggregate productivity falls. These misallocation effects can be large. Hsieh & Klenow (2009) calculate that China and India could experience aggregate TFP gains of between 50% and 60% should resource allocation become as efficient as in the US. Consequently, reducing the misallocation of resources is seen as one channel through which substantial increases in aggregate productivity and incomes of emerging economies can be achieved, despite the constraints they face in accessing technology, capital, and other productive resources.

This paper analyses how market distortions contribute to the misallocation of resources within and between the formal and informal[1] manufacturing sector in Zimbabwe. The analysis is guided by several broad shortcomings in the available literature. Much of the literature on misallocation and aggregate productivity has focused on advanced economies (Bartelsman et al., 2013; Hsieh & Klenow, 2009; Restuccia & Rogerson, 2017; Restuccia & Rogerson, 2008; Syverson, 2011). Yet, misallocation is expected to be much more detrimental to aggregate productivity in low-income and emerging economies where large factor and product market distortions are prevalent (Inklaar, et al., 2017). More studies on emerging economies that isolate the contributions of factor and product market distortions to resource misallocation will provide a deeper understanding of how markets function in these economies and aid the formulation of appropriate policies.

The role of the informal sector in driving misallocation has not received much attention in the literature, notwithstanding its sizeable contribution to economic activity in emerging economies. There are two different positions in this regard. The *dualist* model portrays the informal production sector as a backward traditional sector with high market frictions, low productivity, a highly segmented labour market and limited scope to drive aggregate productivity growth. On the other hand, the *structuralist* model portrays the formal and informal sectors as two competitive and integrated economic systems where the informal sector is able to trigger aggregate productivity and growth (Benjamin & Mbaye, 2012; Fields, 2011; Maloney, 1999; Mcpherson, 1996). These positions give rise to very different implications of the informal sector for resource misallocation, with very different policy recommendations. Given the prominence of the informal sector in many emerging countries (Medina & Schneider, 2018), identifying its impact on resource allocation may be central to policies that aim to raise aggregate TFP.

These considerations are particularly relevant for Zimbabwe. The country has experienced widespread interventions by the state in the operation of product and factor markets, including controls over prices and access to foreign exchange; periods of hyperinflation; restrictive labour regulations; severe

[1] Informal manufacturing firms are defined as unincorporated or unregistered enterprises engaged in the production of goods for employment or income (ILO, 2002).

constraints to access finance; and weak economic infrastructure related to the provision of water and electricity (Gunning & Oostendorp, 1999; Velenchik, 1997). Such market frictions are expected to negatively affect allocative efficiency, firm performance and aggregate TFP in the economy. Further, the economy has undergone a process of de-industrialisation and informalisation with the share of formal manufacturing in non-agricultural formal employment falling from 22% in 1992 to 8% in 2019, and the informal sector share in total manufacturing employment rising from 29% in 2011 to 69% in 2019.[2] Thus, Zimbabwe provides a suitable context to study the link between market frictions, informality and misallocation in emerging economies.

The focus on allocative efficiency in manufacturing also has broader relevance to the challenge of industrialisation in Africa. The manufacturing sector is seen as a key pillar of economic development given its level and capacity for productivity growth. However, the contribution of the manufacturing sector to aggregate output and employment in Africa has been declining (Bigsten & Söderbom, 2011; McMillan & Rodrik, 2011; Söderbom & Teal, 2004; Söderbom et al., 2006), thereby diminishing aggregate productivity (Diao et al., 2018; Kouamé & Tapsoba, 2019; McMillan et al., 2014). Whereas these studies have generally focused on sectoral shifts in the composition of employment and output, this study, by focusing on resource allocation across firms between and within the formal and informal manufacturing sector, provides a firm-level perspective of structural changes within manufacturing and the aggregate TFP gains that can be realised through more efficient allocations of resources.

To measure misallocation, the paper adopts the well-known Hsieh & Klenow (2009) (mostly referred to as HK in the rest of the paper) framework. We measure misallocation as the dispersion of total factor revenue productivity (TFPR). We further decompose TFPR to isolate the relative importance of factor and product market distortions in driving misallocation, and how this differs across the formal and informal sectors. Finally, we study the correlation between distortions and firm productivity to study whether aggregate TFP losses are exacerbated (attenuated) by distortions that penalise relatively efficient (inefficient) firms, as is emphasised by Restuccia and Rogerson (2008).

We apply these measures using firm-level data obtained from the *Zimbabwe Manufacturing Firm Survey 2015-2016*.[3] The survey was conducted with formal and informal firm owners or managers and contains detailed information on firm sales, raw materials, indirect costs, employment, capital stock, etc. It further contains information on factor and product market constraints to the operation of the firm. We find evidence of large resource misallocation in both the formal and informal manufacturing sector, but misallocation is more pronounced in informal sector firms. While both output and capital market distortions contribute to resource misallocation, the latter are strikingly large for informal firms. Further, misallocation is more pronounced amongst relatively productive firms, thus exacerbating aggregate losses in total factor productivity (TFP). Estimates indicate that misallocation reduces aggregated TFP by up to 126.7%.

The remainder of the paper is structured as follows: Section 2 presents the brief background context of the Zimbabwe manufacturing sector. Section 3 reviews the theoretical and empirical literature. Section 4 presents the methodology and data. Results are discussed in section 5 and the conclusion is presented in section 6.

[2] Formal employment data for 1992 is obtained from the Employment and Earnings series provided by Zimbabwe National Statistics Agency (ZIMSTAT). The informal and formal sector employment data for 2011 and 2019 are drawn from the 2011 and 2019 Labor Force Surveys (ZIMSTATS, 2012; 2020).

[3] For access to the data, see https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/702/study-description.

The Zimbabwe manufacturing sector

Zimbabwe is a low-income economy emerging from over a decade long economic crisis in the early 2000s. From 2000 to 2009, the Zimbabwean economy collapsed in the face of hyperinflation and severe macroeconomic imbalances. While growth initially recovered in response to the stabilisation and reduction of inflation following the dollarisation of the economy in 2009 (averaging close to 8% per annum from 2009 to 2011), it remained fragile and susceptible to continued external (e.g., lower commodity prices) and internal (government deficit, trade deficit) pressures, and an uncertain political environment.

The Zimbabwean economic crisis had a profound impact on production, industrialisation, employment and human development in the country (Confederation of Zimbabwe Industries (CZI), 2012; World Bank, 2012; World Economic Forum, 2017). According to the 2011-2012 Poverty, Income, Consumption and Expenditure Survey (PICES), 62.6% of Zimbabwean households were poor with 16.2% in extreme poverty (ZIMSTAT, 2012). During the early 1990s, Zimbabwe had one of the most advanced and diversified industrial sectors in Africa (Gunning and Oostendorp, 1999). In 1993, the manufacturing sector produced 24% of gross domestic product (GDP), provided 21% of non-agricultural formal employment and accounted for 42% of total export earnings. By 2009, when hyperinflation ended, the share of manufacturing in GDP and non-agricultural employment had fallen to 15.5% and 17.7%, respectively, as manufacturing firms contracted, exited and shed employment.[4] Despite a raft of economic policies by the government to enhance economic growth, employment, industrial development and international trade, manufacturing employment continued to decline in subsequent years, and by 2019, manufacturing's share of formal employment had fallen to 8% (ZIMSTAT, 2020).[5]

Associated with the deindustrialisation of formal employment, was a rise in the level and share of the informal sector in production and employment, including in manufacturing. In contrast to the formal manufacturing sector, total employment in informal manufacturing rose from roughly 77 000 in 2011 to 151 000 in 2019, thus surpassing the number of employees in formal manufacturing (67 000 in 2019) (ZIMSTAT, 2012; 2020).

The Zimbabwean economy has thus experienced substantial structural change over the past two decades. What is not known is whether these structural shifts have reduced aggregate productivity through increased misallocation of resources or reflect a dynamic efficient adjustment in response to relatively severe distortions within the formal economy. For example, informal firms may be less constrained by government regulations, including labour laws that impose rigidities on changes to employment in the formal firms. To provide further insight into this matter, the remainder of the paper presents an analysis of misallocation between and within the formal and informal manufacturing industry in Zimbabwe.

[4] The 2009 employment shares are based on Employment and Earnings data provided by ZIMSTAT. The national accounts data are drawn from the revised GDP 2009-2012 data provided by ZI MSTAT.

[5] These include the government's Medium-Term Plan (2011-2015), its Industrial Development Policy (2011-2015) and the National Trade Policy (2012-2016). Some of the earlier economic policies include the 1995 Economic Structural Adjustment Program (ESAP), the Zimbabwe Programme for Economic and Social Transformation, ZIMPREST (1996–2000), the 2001 Millennium Economic Recovery Programme (MERP), the 2003 National Economic Revival Plan (NERP) and the Zimbabwe Agenda for Sustainable Socio-Economic Transformation – ZIMASSET (2013-2018). See Mhone and Bond (2001) and Makina (2010) for policy details.

Theoretical and empirical literature

The concept behind misallocation, as presented by Hsieh & Klenow (2009), is that in competitive markets with no frictions, firms will pay common factor prices, resulting in the equalisation of the marginal revenue product (MRP) of factor inputs across firms with similar production functions. Should MRP for a particular factor differ across firms in a competitive market, then the higher MRP firms will bid for these factors, leading to a re-allocation of factors from low to high marginal revenue product firms, and an associated convergence in MRP across firms and an increase in aggregate output. A further consequence of this adjustment (see later for formal derivation) is that firms within the same industry will converge on equivalent levels of total factor productivity revenue (TFPR).

Factor and product market distortions, however, impede the (re)allocation of given production resources across heterogeneous firms. This will happen, for example, if the output of firms within the same industry is taxed differently or when distortions affect the cost of inputs across firms differently. These distortions impede the equalisation of marginal revenue products of capital and labour across all firms, thereby generating misallocation (Hsieh & Klenow, 2009). Further, they give rise to dispersion in TFPR across firms, with high TFPR firms being inefficiently small and those with TFPR below the industrial average inefficiently large. Empirically, therefore, the dispersion of TFPR across firms within the same industry has been used to determine the presence and extent of resource misallocation (Hsieh & Klenow, 2009).

Formally, Hsieh & Klenow (2009) illustrate these concepts by assuming an economy with heterogeneous (in total factor productivity) manufacturing firms, where each firm *i* in industry *s* produces a differentiated product using the same Cobb-Douglas production technology.[6] In optimising profits face firm-specific output distortions, τ_{Ysi} (e.g., taxes, corruption, price controls), and firm-specific capital distortions, τ_{Ksi}, that affect the cost of capital relative to labour (e.g., access to credit, credit rationing, government subsidies).[7] From these conditions, Hsieh & Klenow (2009) derive marginal revenue product of capital (MRPK) and labour (MRPL) as follows:

$$MRPK_{si} = \alpha_s \frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{K_{si}} = R\,\frac{1+\tau_{Ksi}}{1-\tau_{Ysi}} \tag{1}$$

$$MRPL_{si} = (1-\alpha_s)\frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{L_{si}} = w\,\frac{1}{1-\tau_{Ysi}} \tag{2}$$

where $P_{si}Y_{si}$ is the firm's value-added (firm's revenue less cost of raw materials), and w and R are, respectively, the unit cost of labour and capital. Thus firm-specific capital and output distortions cause the marginal revenue product of capital and labour to deviate from the market wage and cost of capital. For example, distortions that raise the cost of capital to a firm, result in firms under-utilising capital in production leading to higher MRPK relative to firms facing no distortions. Similarly, distortions that reduce the price received on sales, reduce firm output and raise MRPK and MRPL relative to non-distorted firms.

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[6] The firm's Cobb-Douglas production is given by $Y_{si} = A_{si}K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}$, where A_{si} is firm-specific productivity (TFP), and K_{si} and L_{si} are capital and labour inputs respectively. Industry output is the total of individual firm's production, aggregated according to a constant elasticity of substitution technology.

[7] The profit function is given by $\pi_{si} = (1-\tau_{Ysi})P_{si}Y_{si} - wL_{si} - (1+\tau_{Ksi})RK_{si}$ where $P_{si}Y_{si}$ is the firm's value-added (firm's revenue less cost of raw materials), K_{si} and L_{si} are capital and labour inputs respectively, w and R are the unit cost of labour and capital respectively.

Hsieh & Klenow (2009) further derive Total Factor Product Revenue (TFPR) as a weighted average of marginal revenue products, as:

$$TFPR_{si} = \varphi_s \frac{(1+\tau_{Ksi})^{a_s}}{1-\tau_{Ysi}} \quad (3)$$

where φ_s is a constant.[8] In the absence of distortions (τ_{Ksi} = 0 and τ_{Ysi}=0), TFPR for all firms converges on the constant φ_s, implying no variation in TFPR across firms within the same industry. This implies that in the absence of distortions, more capital and labour resources will be allocated to firms with relatively high total physical productivity (TFPQ) compared to those with lower TFPQ.[9] TFPR is equilibrated across these firms through product price adjustments: the low productivity firms produce less output and charge higher prices while high productivity firms produce more and charge lower prices.

The equation also shows how firm-specific output and capital-labour distortions cause deviations in TFPR across firms. For example, firm-specific increases in the cost of capital and taxes on output, distort production and factor usage decisions leading to a reduction in the firm's TFPR relative to other firms. Hence, Hsieh & Klenow (2009) use the dispersion of TFPR across firms to represent aggregate resource misallocation and allocative inefficiency.

This approach to measuring resource misallocation has been widely applied. Hsieh & Klenow (2009) apply their method to manufacturing firm data for China (1998-2005) and India (1987-1994) and find that the removal of capital and output distortions to mimic that of the United States (US), would increase aggregate manufacturing TFP by 30% to 50% in China and 40% to 60% in India. Other studies have applied the Hsieh & Klenow (2009) methodology to a wide range of (mostly developed) countries, including Calligaris (2015) for Italy; Dias et al. (2016) for the Eurozone; Gopinath et al. (2017) for South Europe; Bartelsman et al. (2013) for European Union countries; Asker et al. (2014) for US, France, Spain, Romania and Slovenia[10]; and Foster et al. (2016) for the US. While fewer studies have been conducted for emerging economies, the literature is growing. Examples include Busso et al. (2013) for 10 Latin American countries, Kalemli-Ozcan and Sorensen (2016) for 10 African countries[11]; León-Ledesma (2016) for 62 developing countries; Nguyen et al. (2016) for Turkey; and Cirera et al. (2020) for Ivory Coast, Ethiopia, Ghana and Kenya. The general finding from these studies is that market frictions lead to large aggregate TFP losses via the misallocation channel, particularly in emerging economies.

However, the Hsieh & Klenow (2009) approach faces several challenges (Bils et al., 2020; David & Venkateswaran, 2019; Bartelsman et al., 2013; Haltiwanger et al., 2018; Restuccia & Rogerson 2017; Wu, 2018). Restuccia & Rogerson (2017) argue that deviations in capital-labour ratios across firms in the same industry may reflect the heterogeneity of the production function, rather than the effect of factor market distortions. Similarly, Haltiwanger et al. (2018) and Bartelsman et al. (2013) argue that the dispersion in marginal revenue products of capital and labour may simply reflect differences in

[8] More precisely, $TFPR_{si} = \frac{\sigma}{1-\sigma}\left(\frac{R}{a_s}\right)^{a_s}\left(\frac{w}{1-a_s}\right)^{1-a_s}\frac{(1+\tau_{Ksi})^{a_s}}{1-\tau_{Ysi}}$, where a_s is the input elasticity and σ is the elasticity of substitution.

[9] This reallocation of resources continues to a point where prices start lowering for firms with higher output and rising for firms with lower output until their TFPR is equalised.

[10] These include US, France, Spain, Romania and Slovenia.

[11] They included a sample of the following African countries; Burundi, Kenya, South Africa, Senegal, Botswana, Nigeria, Uganda, Ghana, Tanzania and Zambia.

adjustment costs across producers rather than misallocation. Measurement error in the data can also drive dispersion in marginal revenue products (Bils et al. 2020; Newman et al. 2019). Restuccia and Rogerson (2008) also show that the aggregate TFP losses will be exacerbated if negative distortions penalise more efficient firms relative to less efficient ones. In this case, production of the efficient firms is constrained, while production of less efficient firms is stimulated beyond efficient levels, further reducing aggregate TFP.

An alternative approach to measuring misallocation is the Olley and Pakes (1996) (OP) decomposition technique used by Bartelsman et al. (2013). The OP decomposition separates an index of industry-level productivity (weighted firm-level productivity) into unweighted firm-level average productivity and the *covariance term*. The covariance term (known as the OP covariance) measures the covariance between firm size and firm productivity. Low levels of the covariance term signal a weak allocation of resources toward relatively productive firms.

Using this technique, Bartelsman et al. (2013) find industry productivity and size of the firm to be positively correlated in the advanced economies (US and several European countries), but with a lot of variation in the association across these countries. Using data for 52 developed and developing countries, Inklaar et al. (2017) find that more advanced economies have a lower presence of misallocation than developing economies. León-Ledesma (2016) corroborate this finding using firm data for 62 developing countries.

Relatedly, Wu (2018) developed an alternative model to measure misallocation where the aggregate TFP loss from financial constraints is proportional to the variance of the marginal revenue product of capital (MRPK) that is used as a measure of capital misallocation. The framework captures how capital market distortions, plus firm-specific financial frictions and policy distortions, affect a firm's optimal choice of capital giving rise to misallocation of capital across firms. Applying this model to China, Wu (2018) found that financial frictions account for about 30% of observed capital misallocation in China, which results in up to a 9.4% loss in aggregate TFP. The key advantage of the Wu (2018) approach, and the constructed measure of MRPK, is that it takes into account heterogeneities in production functions and market power as compared to other measures in the literature (such as HK). David & Venkateswaran (2019) also propose interesting alternative measures of misallocation to HK.[12]

Missing in studies on misallocation is the contribution of the informal sector. The evidence in this regard is mixed. La Porta and Shleifer (2008) use data for formal and informal firms obtained from the World Bank Informal and Micro Surveys and find substantially higher productivity levels in the formal sector. They conclude that aggregate TFP would rise with a reallocation of resources from the informal to the formal sector. Similarly, Kathuria et al. (2013) apply a stochastic frontier analysis to Indian manufacturing firms and find significantly higher levels of technical efficiency in formal compared to informal firms. Other studies similarly providing support of the 'dualist' theory include Baez-Morales (2015), Benjamin & Mbaye (2012), Fajnzylber et al. (2011), La Porta & Shleifer (2014) and Maloney (2004).

Value-added per worker and measures of technical efficiency, however, are not necessarily indicators of resource misallocation. Lower value added per worker may reflect constraints to access to capital, a

[12] David & Venkateswaran (2019) methodology is based on a structural general equilibrium model of firm dynamics to estimate misallocation and account for measurement error. Their model disentangles sources of capital misallocation, by looking at dispersion in average revenue product of capital and measures the contributions of technological/informational frictions and some firm-specific factors to misallocation.

common problem faced by small and informal firms (Rand & Torm, 2012; Siba, 2015). While informal firms may be relatively inefficient, in heterogeneous firm models what matters for misallocation is whether these firms account for a disproportionate share of the market given their lower productivities. Other studies have therefore directly measured misallocation. For example, Busso et al. (2013) apply the HK approach to firm data in Mexico and find that informal firms command a disproportionate share of resources given their (lower) productivity status. Lopez-Martin (2019) come to a similar conclusion using firm-level data for Mexico, Egypt, and Turkey. The paucity of available studies, however, prevents a generalisation of these findings. By focusing on Zimbabwe, this study, therefore, provides an additional data point on the association between misallocation and the informal economy.

Methodology and data

Method

This paper draws on the Hsieh & Klenow (2009) framework to measure misallocation across Zimbabwean manufacturing firms. We are particularly interested in the dispersion of $TFPR_{si}$ as a measure of aggregate misallocation in the economy and how this varies between sectors (formal vs informal) as well as firm size within these groups. For example, informal firms in the 'dualist' model will be located to the right of the $TFPR_{si}$ distribution reflecting inefficient misallocation of resources, whereas in the structuralist framework there should be no systematic differences across formal and informal firms.

Data

The empirical analysis draws on the *Zimbabwe Manufacturing Firm Survey 2015-2016*. The initial dataset consists of 195 formal manufacturing firms and 130 informal manufacturing firms that were surveyed in 2015. The sample of formal firms was stratified according to size ('small' (5-9 employees), 'medium' (10-99 employees), and 'large' (100+ employees)), industry (Food, beverages and tobacco; Wood and furniture; Metal, machinery and equipment; Textile and leather; and Chemical and rubber) and main industrial cities (Harare and surrounds; Bulawayo; Gweru, Kwekwe and Redcliff (in Midlands); and Mutare (in Manicaland)).

For the informal sector, the survey covered the Metal; Wood and furniture; and the Textile and leather industries. These are industries in which the bulk of informal manufacturing takes place. Data are only collected in Harare and Bulawayo, the two largest urban cities in Zimbabwe that account for the bulk of informal manufacturing activities. A two-stage sampling process was followed in selecting informal manufacturing firms, based on our own population estimates and constructed sample frame.[13]

To ensure comparability across formal and informal sectors, the sample of firms is restricted to industries common in both sectors, that is: metal, wood, and textiles. Further, because misallocation is an aggregate national measure, the measures of misallocation are constructed using weighted data. This is to ensure the results match the population distribution within each of these industries. We also

[13] Informal manufacturing firms in Zimbabwe are located in specific areas within the cities. In the first stage, the main areas (one or two) in each city in which informal production for each industry takes place were selected. These areas were then divided into blocks (enumerating areas) with roughly equal numbers of firms based on spatial area or building complex. Blocks were then randomly selected. In the second stage, firms within each of these randomly selected blocks were listed. A random sample of firms was then selected for interviewing purposes from the listed firms in each randomly chosen block.

compare small formal firms (1-19 employees) with informal firms as the latter only include micro and small firms. Further details on the data are provided in the appendix.

The survey data contains information on sales and production, raw material costs, indirect costs, capital stock and labour inputs among other important information. Following HK, labour input is measured by the wage bill (sum of wages, bonuses, and benefits) rather than employment, to account for differences in human capital and hours worked. The capital stock is measured by the market value of fixed assets (vehicles, machinery and equipment, and land and buildings). Value-added is computed as the difference between sales and cost of raw materials, overhead expenses, and energy costs (electricity, fuel, gas). All observations where value-added could not be calculated because of either missing or negative values (14 firms) are dropped.

The calculation of the HK measures of misallocation requires information on the elasticity of substitution (σ), interest rate (R) and industry labour and capital shares (α_s). Following HK, we set the elasticity of substitution to 3.[14] The interest rate (R) is set at 12.5% drawing from the average interest rate reported in our data for the formal and informal firms. The labour share in the production function is calculated as the mean firm share of labour expenditure in value-added ($\frac{wL_{si}}{P_{si}Y_{si}}$) for each industry. The capital share (α_s) is one minus this value.

Table 1. Summary statistics for key variables

	Formal Sector			Informal Sector		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Value added per worker (ln)	92	8.45	1.22	105	7.76	0.83
Capital/Labour ratio (ln)	92	8.50	1.38	105	5.50	1.25
Labour costs (ln)	92	11.57	1.84	105	8.30	1.00
Firm Size (employment)	92	66.63	94.91	105	3.26	1.57
Firm age (years)	92	34.23	23.53	105	8.91	6.56

Notes: For the formal sector, the summary statistics are only for overlapping industries with the informal sector (Metal, Textile and Wood) for plausible comparisons.

Table 1 presents summary statistics on the key variables in our analysis. The sample covers 92 formal manufacturing firms and 105 informal manufacturing firms. Compared to firms in the informal sector, firms in the formal sector are larger (average employment of 67 compared to 3), older (34.2 vs. 8.9 years), and more productive, as measured by the value-added per worker (a difference in logs of 0.69), reflecting the substantially higher capital-labour ratio in the formal sector firms (difference in logs of 3). As expected, the average wage bill is also substantially higher for formal firms (difference in logs

[14] If the elasticity of substitution between factor inputs differs from one, then the dispersion of the marginal product of capital and hence the gains from reallocation can change substantially. The more substitutes factor inputs are, the more technologically similar they are and the less important will relatively factor market distortions be. Intuitively, when σ is larger, TFP gaps are closed more slowly in response to the reallocation of inputs and in this case, gains are higher (Hsieh and Klenow, 2009).

of 3.3).

Results

This section presents the results of the HK model applied to the Zimbabwe manufacturing sector data. The analysis is structured in three parts. First, we present the results on the dispersion of productivity (TFPQ) and the measure of misallocation (TFPR). As argued in the earlier sections, the presence of misallocation leads to the survival of many low productivity firms that would otherwise exit operations and release resources to more productive firms (Restuccia & Rogerson, 2008). The existence of many low productive firms is the first evidence indicating the prevalence of misallocation. Likewise, high TFPR denotes firms that produce too little relative to the efficient benchmark. This implies that too few resources have been allocated towards production in the firm, therefore giving rise to misallocation.

Second, the paper presents the results on the correlation between indicators of misallocation and productivity (TFPQ). Theoretically, a positive correlation implies that misallocation disproportionately affects relatively productive firms compared to less productive firms, thus leading to higher aggregate TFP losses. Third and last, we calculate the aggregate TFP gains that can be achieved if misallocation is eliminated.

Productivity and misallocation

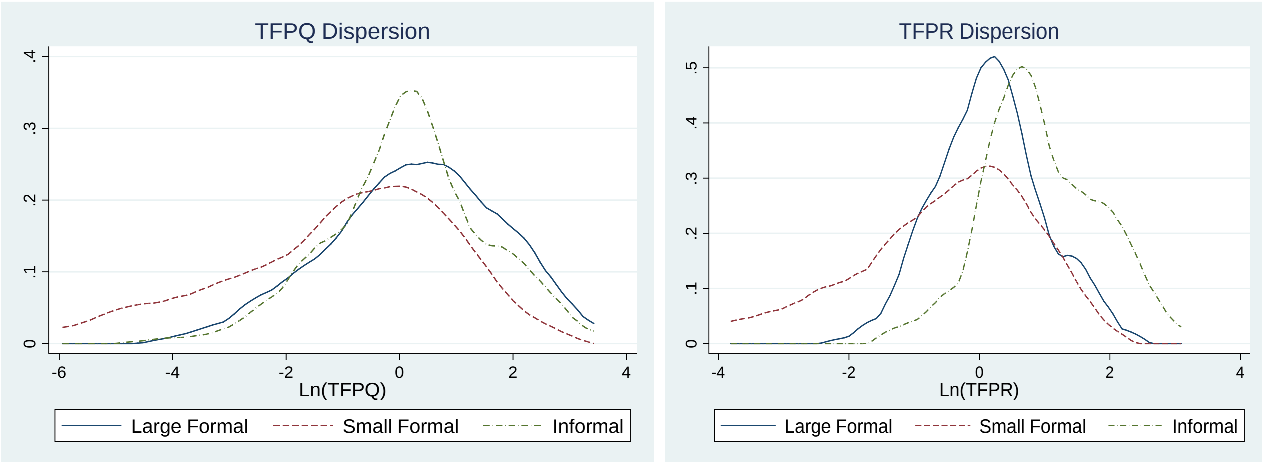
Figure 1 shows the distribution of TFPQ (in Panel A) and TFPR (in Panel B) across firms. To facilitate analysis, plant-level measures are demeaned by the industry average using the pooled data for formal and informal firms, and the natural logs of the demeaned indicators are presented (e.g., $ln(TFPR_{si}/\overline{TFPR}_s)$ and $ln(TFPQ_{si}/\overline{TFPQ}_s)$, where the overscore represents the industry mean). For a better comparison of firms of similar size, formal sector firms are split into small and large size categories.

The results in Figure 1 in Panel (A) illustrate several interesting characteristics regarding the distribution of firm productivity. While large formal sector firms are on average more productive compared to informal and small formal sector firms, there is wide variation in firm productivity within each category of firms, with a substantial overlap in the kernel densities. Firms of different sizes thus co-exist in the market, despite similar productivity levels. Comparing small formal and informal firms, there is a high degree of overlap in the productivity distributions. Further, several informal firms have productivity levels comparable to the more efficient large formal firms. The co-existence of the formal and informal manufacturing firms, together with the wide overlap in productivity, is suggestive of a structuralist as opposed to the dualist characterisation of the informal economy.

What is striking in the productivity distributions is the thick tail to the left for small formal firms indicating that a significant proportion of these firms survive despite extremely low productivity levels. Compare this with the more truncated left tail of informal sector firms indicating that similarly low productivity firms in this sector exit. These results point to the presence of distortionary policies and regulations that prompt firms in the formal sector to continue operating at low productivity levels rather than exiting or shrinking operations.

Figure 1 Panel (B) shows the distribution of TFPR, our measure of allocative inefficiency. In efficient economies with no resource misallocation, we expect the distributions of demeaned TFPR to be spiked around zero. In contrast, the figure reveals a wide dispersion of TFPR suggestive of widespread allocative inefficiency in both the formal and informal manufacturing sector. As found with the TFPQ distributions, there is a large left tail in the TFPR distribution of small formal firms.

Figure 1. Distribution of TFPQ and TFPR



Panel (A) Panel (B)

Notes: The left panel plots the distribution of $\ln(\text{TFPQ}_{si}/\overline{\text{TFPQ}_s})$ for the formal and informal manufacturing sector; the right panel plots the distribution of $\ln(\text{TFPR}_{si}/\overline{\text{TFPR}_s})$ for the formal and informal manufacturing sector. The distributions are estimated using sampling weights.

A high proportion of large firms are also characterised by low TFPR. These firms are far larger in terms of market share than they would otherwise be in situations with no market frictions inhibiting resource re-allocation. Notably, the distribution of TFPR for informal firms is further to the right side of the x-axis compared to small and large formal firms, suggesting that production in informal firms is relatively constrained despite their lower average productivity (compared to large firms). The distribution is also narrower with many firms centred around the natural log of TRPR value of 1, suggesting a more efficient allocation of resources across firms within this sector.

Table 2 presents the standard deviation of TFPQ, TFPR and of output and capital distortions. The table reveals considerable firm-level heterogeneity in productivity across the two sectors. The standard deviation of TFPQ shows a higher productivity dispersion in the formal sector (1.76) than in the informal sector (1.07), again signalling the co-existence with vastly different productivity levels.

The variance of TFPR, the primary indicator of misallocation, is also higher for formal manufacturing firms (1.11 standard deviation) compared to informal firms (0.99 standard deviations). This variation exceeds what is estimated for most other emerging economies. For example, Cirera et al. (2020) calculate standard deviations of TFPR in manufacturing that range from 0.63 to 0.78 for Côte d'Ivoire, Ethiopia, India and China, with only Ghana (0.95) and Kenya (1.52) with similar or higher variances than these results for Zimbabwe.

Table 2. Dispersion of TFPR, TFPQ and other indicators of misallocation

	ln (TFPQ)	ln (TFPR)	ln (MRPK)	ln (1+ τ_{ksi})	ln (1- τ_{ysi})
			Formal		
sd	1.76	1.11	1.78	1.61	0.68
Corr. with TFPQ	1.00	0.87	0.86	0.70	-0.59
N	92	92	92	92	92
			Informal		
sd	1.07	0.99	1.33	1.46	0.71
Corr. with TFPQ	1.00	0.90	0.78	0.45	-0.55
N	105	105	105	105	105

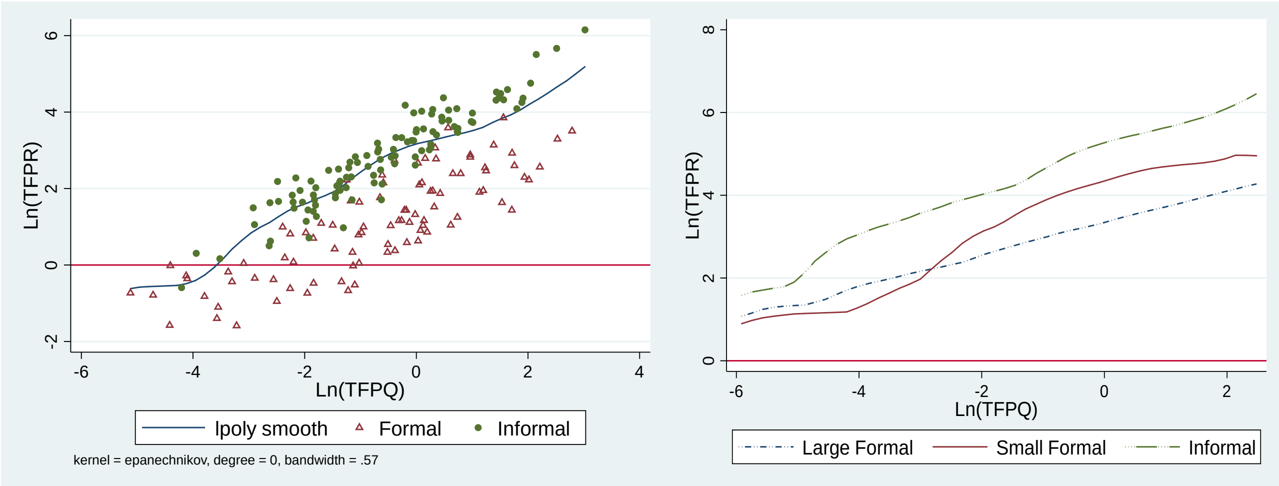
Notes: For each firm i, in industry s TFPRsi=$\frac{P_{si}Y_{si}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$, TFPQsi =$\frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$, $1+\tau_{Ksi}=\frac{a_s}{1-a_s}\frac{wL_{si}}{RK_{si}}$ and $1-\tau_{Ysi}=\frac{\sigma}{1-\sigma}\frac{wL_{si}}{(1-a_s)P_{si}Y_{si}}$. The statistics for ln(TFPQ) and ln(TFPR) are deviations from respective industry means. sd is the standard deviation and N is the number of firms.

To isolate the potential sources of this variation, Table 2 also presents the standard deviation of MRPK and the indicators of capital and output distortions. As with TFPR, we find substantial variation in the indicators across firms, and, with the exception of output market distortions, relatively high variation within the formal sector. In addition, the dispersion of the capital market distortion exceeds that of the output market distortion, suggesting relatively strong factor market constraints to re-allocation of resources. Overall, the results in Table 2 are consistent with the prevalence of high distortions that impede efficient allocation of resources across firms and in this case across the formal and informal sectors.

Correlation between misallocation and productivity

As articulated by HK, the extent of misallocation is worse, and aggregate TFP is lower when there is greater dispersion of the natural log of TFPR. One possibility is that the variance in the TFPR is driven by randomly allocated output and factor market distortions across firms. An alternative, as argued by Restuccia and Rogerson (2008), is that distortions may affect particular types of firms that and this can amplify aggregate TFP losses. This would occur, for example, when efficient firms face high negative distortions relative to less efficient ones. To assess this, Figure 2 plots the local polynomial regression of TFPQ against TFPR (demeaned and natural logged). In an economy with no distortions, the dispersion of $log(TFPR_{si}/\overline{TFPR}_s)$ should be zero and all firms would be placed along the zero TFPR line. Along this line, firms would only differ in their TFPQ. With distortions affecting firms randomly, TFPR would deviate from zero but would be evenly scattered around the zero line. A high positive correlation between productivity and indicators of misallocation would signify that negative (positive) market distortions affect relatively productive (inefficient) firms.

Figure 2. TFPR against firm productivity



Panel (A) Panel (B)

Notes: The plots show the relationship between productivity ln(TFPQ) measured as $\ln(\mathrm{TFPQ}_{si}/\overline{\mathrm{TFPQ}}_s)$ and TFPR, $\ln(\mathrm{TFPR}_{si}/\overline{\mathrm{TFPR}}_s)$. Panel (A) shows the aggregate manufacturing sector. Panel (B) shows a comparison between the large and small formal firms and the informal sector. The Polynomial is estimated using sampling weights.

In this case, the distortions act as a tax on relatively productive firms, thereby constraining them from growing to their potential optimal size while promoting the growth of less productive firms beyond their optimal size. The consequence is an accentuated reduction in aggregate TFP.

Looking at Panel (A) of Figure 2, we find a strong positive correlation between TFPR and productivity, as shown by the local polynomial regression. Further, the scatter plots in the figure illustrate a positive association for both the formal and informal sector firms (see also the positive correlation coefficients presented in Table 2), but in most cases the scatter plots for informal firms are above those of formal firms and lie in the positive TFPR territory (above the zero line). In Panel (B), separate local polynomial regressions are presented for informal firms, small formal firms and large formal firms. We need to be cautious about comparing the firms at the end ranges of the TFPQ spectrum, as the number and overlap of observations across size categories drop off rapidly. Looking over the mid-range of TFPQ, where the bulk of firms in each category are situated, positive slopes are found for all firm categories, with a stacking of regression lines where informal firms are at the top and large formal firms are at the bottom. This stacking further suggests that informal sector firms face more restrictive distortions compared to formal sector firms. However, in all cases relatively productive firms are taxed, an outcome that Cirera et al. (2020) refer to as 'taxing the good'.

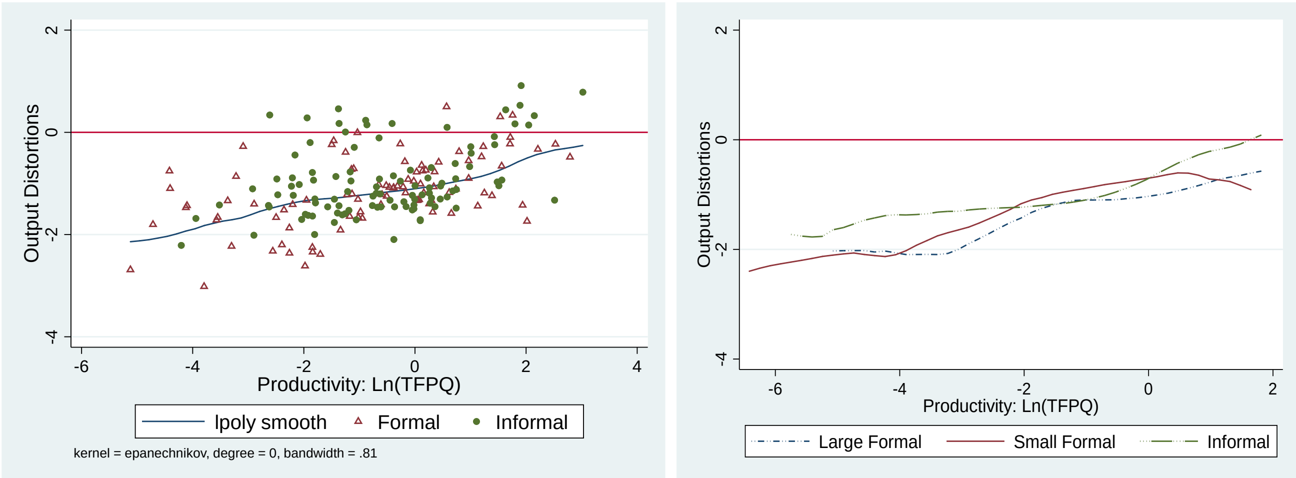
Output and capital distortions vs. productivity

To understand the sources and nature of distortions further, we separately analyse the relationship between productivity and capital distortions $ln(1+\tau_{ksi})$, and output distortions $ln\left(\frac{1}{1-\tau_{ysi}}\right)$.[15] Figure 3 and Figure 4 present the relationships. We find that both capital and output market distortions are higher for relatively productive firms, as is shown by the positive slopes. Further, on average, firms in

[15] Following Hsieh & Klenow (2009), the first-order condition from profit maximisation can be used to derive firm output and capital distortions respectively as; $1-\tau_{ysi}=\frac{\sigma}{1-\sigma}\frac{wL_{si}}{(1-\alpha_s)P_{si}Y_{si}}$ and $1+\tau_{ksi}=\frac{\alpha_s}{1-\alpha_s}\frac{wL_{si}}{RK_i}$.

both the formal and informal sectors have negative values of output distortions (see points below the zero line), implying that output distortions are at times large and are in general acting as a tax on firm output. However, in contrast to the earlier results, there are no substantial differences in the level and slope of the curves for output distortions across formal and informal firms – see the intermingled scatter plots in Panel (A) of Figure 3. While relatively productive firms face higher distortions reducing their output from the optimal level, the impact is experienced equally across all firm categories.

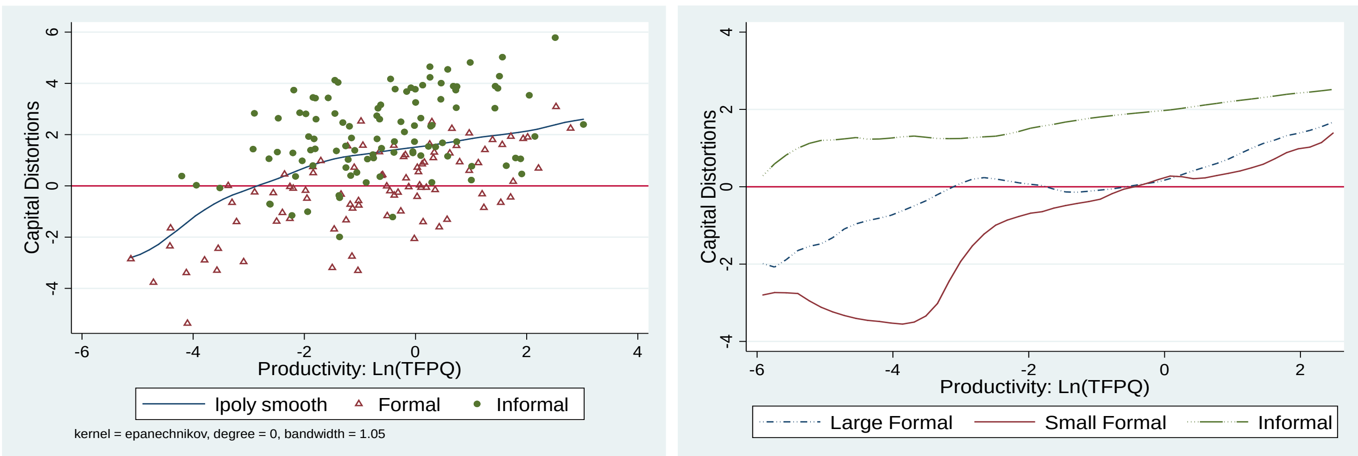
Figure 3. Output distortions against firm productivity



Panel (A) Panel (B)

Notes: The plots show the relationship between productivity TFPQ measured as $(\ln(\mathrm{TFPQ}_{si}/\overline{\mathrm{TFPQ}_{s}}))$ and output distortions, ln $\left(\frac{1}{1-\tau_{ysi}}\right)$. Panel (A) shows for the aggregate manufacturing sector. Panel (B) shows a comparison between the large and small formal firms and the informal sector. The Polynomial is estimated using sampling weights.

Figure 4. Capital distortions against firm productivity



Panel (A) Panel (B)

Notes: The plots show the relationship between TFPQ, $\ln(\mathrm{TFPQ}_{si}/\overline{\mathrm{TFPQ}_{s}})$ and capital distortions, ln $(1+\tau_{ksi})$. Panel (A) shows for the aggregate manufacturing sector. Panel (B) shows a comparison between the large and small formal firms and the informal sector. The Polynomial is estimated using sampling weights.

Contrast to this outcome, are the relationships shown in Figure 4 for capital market distortions. Here the curve for informal firms (Panel B) lies above that of small and large formal firms, whose curves broadly overlap with each other. Informal firms, therefore, face higher capital market distortions compared to their formal sector peers irrespective of their productivity level. The key implication of this finding is that the higher degree of misallocation found for informal firms can largely be attributed to challenges they face in accessing capital (relative to labour).

Sources of misallocation

To explore the possible factors that are associated with misallocation of resources in Zimbabwe, we use ordinary least squares (OLS) to regress different measures of distortion on surveyed firm characteristics and operational obstacles as follows:

$$\ln\,(D_{is}) = \beta_0 + \beta_1 TFPQ_{is} + \beta_2 Inf_{is} + X_{is}{}'\delta + Z_{is}{}'\delta + \varepsilon_{is} \qquad (4)$$

where $\ln\,(D_{is})$ represents the measures of misallocation (TFPR, capital distortions and output distortions, in log form), $TFPQ_{is}$ is firm physical productivity, Inf_{is} is a dummy variable for informality (coded 1 if a firm is in the informal sector and 0 otherwise), X_{is} is a vector of firm distortions that causes resource misallocation (lack of finance, shortage of electricity, and import competition), Z_{is} are firm characterises such as firms size (measured by the number of employees), firm age, firm industry and location, and ε_{is} is a white noise error term. It is key to note that these regressions only reveal the associations between distortions and indicators of misallocation and are not necessarily causal in nature. Table 3 presents the regression results.

We first look at the association between firm TFPQ and the indicators of misallocation and distortions. Theoretically, as argued by Restuccia & Rogerson (2008) the losses in aggregate TFP due to misallocation are compounded if there is a positive correlation between firm productivity and the indicators of misallocation. The results in Table 3 confirm such a relationship and are consistent with our earlier findings in the preceding sections.

We then test whether informal sector firms have higher misallocation relative to formal firms. The results indicate that informality is positively and significantly correlated with TFPR and capital, but negatively and weakly associated with output distortions. On average firms in the informal sector faces higher distortions, particularly capital distortions, that constrain access to resources compared to those in the formal sector. The result is that informal manufacturing firms are too small given their levels of productivity. These results indicate that formal and informal sector firms operate in different environments that are more hostile to informal firms.

Looking at potential obstacles that may fuel misallocation, the TFPR and capital distortion results show a positive and significant coefficient on financial access constraints. This result corroborates other empirical research (Cirera et al., 2020; Dias et al., 2016; Restuccia and Rogerson, 2008) where financial market frictions are found to impede the flow of credit to relatively efficient firms. Access to finance is particularly constrained in Zimbabwe. The survey responses reveal that 78% of informal firms and 57% of formal firms identify access to finance as a major constraint to their operations. This is a considerably higher share than the average for manufacturing firms in the sub-Saharan Africa (SSA) region, which equals 39% according to 2016 World Bank Enterprise data (World Bank, 2016). The World Bank Enterprise data also indicates that Zimbabwean manufacturing firms are less likely to have access to a bank loan/line of credit (10.5% vs. 21.9% for SSA), are more likely to have had recent loan applications rejected (69% vs. 16%), and when they do obtain a loan, are more often required to provide collateral (94% vs. 85%).

Table 3. Correlation between obstacles and indicators of misallocation

	(1)	(2)	(3)
VARIABLES	TFPR	Capital distortion	Output Distortions
TFPQ	0.66***	0.59***	0.41***
	(0.02)	(0.09)	(0.03)
Informality	0.65***	2.22***	-0.27*
	(0.09)	(0.39)	(0.15)
Financial Inaccessibility	0.70***	0.57**	0.28*
	(0.18)	(0.22)	(0.14)
Shortage of Power	-0.16	-0.54**	0.16
	(0.23)	(0.26)	(0.17)
Raw materials Inaccessibility	-0.20	-0.18	0.09
	(0.21)	(0.38)	(0.18)
Unfair Import Competition	0.16	-0.43*	0.34**
	(0.16)	(0.23)	(0.14)
Firm size (ln employment)	0.20**	0.56***	0.05
	(0.08)	(0.13)	(0.06)
Firm age	0.00	0.01*	-0.01
	(0.01)	(0.01)	(0.01)
Constant	-1.02***	-2.70***	1.80***
	(0.37)	(0.64)	(0.29)
Observations	197	197	197
R-squared	0.44	0.46	0.21
Location control	Yes	Yes	Yes
Industry control	Yes	Yes	Yes

Notes: The dependent variables are measures of misallocation, namely ln(TFRPsi) in column 1, ln $(1-\tau_{ksi})$ in column 2, and ln $\left(\frac{1}{1-\tau_{ysi}}\right)$. in column 3. In the regressions we did not use demeaned values of dependent. We control for industry FE. What we are interested on is the correlation between measures of distortions and indicators of misallocation. The key obstacle variables are Financial Inaccessibility, Shortage of Power, Raw materials Inaccessibility, and Unfair Imports Competition. These are binary variables that take value of one if the firm reports that is suffers from such constraints and zero otherwise. Firms were directly asked if they suffer from such constraints. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Access to electricity is also identified as a constraint by firms. Our data indicate that 15 % of formal firms and 18% of informal firms reported being constrained by electricity. Counterintuitively, the regression results show that firms that face a severe shortage of power are also those with relatively low capital market constraints as indicated by the negative coefficient on Shortage of power in column 2. A possible explanation is that with power shortages, firms resort to employing less capital than they would otherwise. This means that lack of electricity is a disincentive for firms to invest in capital equipment and hence use less capital relative to labour than in situations where there are no power shortages.

Unfair competition from imported products is identified by 73% of formal firms and 50% of informal firms as a key obstacle to their operations. The results in Table 3 indicate that unfair import competition is positive and significantly associated with output distortions, and negatively and weakly associated

(10% level) with capital distortions. The result for output distortions is consistent with the effect of reductions in demand and thus revenue associated with import competition.
Looking at other firm-specific characteristics, Table 3 indicates that firm size is positively and significantly correlated with TFPR and capital distortions. Controlling for other explanatory factors, this result indicates that large firms, on average face high misallocation. Firm age is positive, but only weakly significant.

Productivity gains

To what extent does this misallocation reduce aggregate TFP? To calculate aggregate productivity gains that can be realised if misallocation is corrected, HK used the ratio of actual TFP to the efficient level of TFP as shown in equation (5). [16]

$$\%Productivity\ Gain = \left(\frac{\mathrm{TFP_s}^{\mathrm{efficient}}}{\mathrm{TFP_s}^{\mathrm{actual}}} - 1\right) * 100 \qquad (5)$$

The calculations reveal that by efficiently allocating resources, aggregate TFP can be boosted by 126.7% for the entire manufacturing sector comprising of a 128.5% improvement in the formal sector and a 125.9% improvement in the informal sector.

These results place Zimbabwe amongst the top-end of countries experiencing losses in aggregate manufacturing TFP in response to misallocation. For example, Cirera et al. (2020) calculate that without misallocation, aggregate manufacturing productivity would have been higher by at least 31 % in Côte d'Ivoire, 67% in Ethiopia, 76% in Ghana, and 162% in Kenya. Gains in aggregate manufacturing TFP, for 9 of the 10 Latin American countries studied by Busso et al. (2013) where gains mostly range from 50 – 60%. The exception is Mexico where gains of 127%, similar to that of Zimbabwe, can be achieved. Fossati et al. (2021) found average TFP gains of 30.1% in Latin American countries and 76.9% for African countries. Interestingly, they found TFP gains of 120.91% for Zimbabwe, which is comparable to our results.

Robustness check

In this section, we conclude our analysis by assessing the sensitivity of our findings to the use of alternative calculations and measures of misallocation. First, we adjust for the underutilisation of capital reported by many firms in the survey. Second, we use the OP covariance measure as an alternative indicator of misallocation. Lastly, we construct alternative measures of misallocation based on Wu (2018) approach.

Adjusting for capital utilisation margin

The standard models of misallocation assume that the firm makes full use of all available production resources in the production process. However, in many instances firms may find it difficult to downsize, leading to underutilisation and idleness of capital. Idle capital may have critical implications for the

[16] Firm level productivity gains summed up to the industry level and then aggregated using the Cobb-Douglas aggregator $\frac{TFP^{actual}}{TFP^{efficient}} = \prod_{s=1}^{s}\left[\sum_{i=1}^{Ms}\left(\frac{A_{si}\overline{TFPR_s}}{\bar{A}_s TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{\theta s}{\sigma-1}}$, where θs denotes the industry share in value added.

measurement of misallocation as the utilisation of resources may influence productivity measures (Lanteri & Medina, 2017). Firms with low capacity utilisation are expected to have a low marginal product of (idle) capital.[17] Thus, failing to account for the idleness of capital may bias measures misallocation (Hang, 2022; Gorodnichenko et al., 2018).

This is an issue of considerable relevance for Zimbabwean manufacturing where many firms report very low utilisation of capital. For example, our data showed that the mean value of capital utilisation is 43% for formal firms and 55% for informal. We, therefore, re-calculate the indicators of misallocation using 'effectively' used capital obtained by adjusting actual capital stock by capacity utilisation. Adjusting for capital utilisation reduces the dispersion of misallocation indicators across firms as indicated by results in Table A2, in the appendix. For example, the dispersion of TFPR decreases from 1.04 to 0.98 while of capital distortions reduce from 1.89 to 1.74. This suggests that failure of surplus capital in the formal sector to re-allocate to firms in the informal sector is a key factor driving the overall misallocation of resources between the formal and informal sectors.

An alternative measure of misallocation: The OP Covariance

An alternative indicator of misallocation, as used by Bartelsman et al. (2013) is that of Olley and Pakes (1996) (OP) who decompose aggregate labour productivity (A_t) into mean firm productivity and the covariance between market share and firm productivity as follows:

$$A_t = \sum_{k=1}^{K} \theta_{it}\, A_{it} = \bar{A}_t + \sum_{k=1}^{K} (\theta_{it} - \bar{\theta}_t)\,(A_{it} - \bar{A}_t)$$

where A_{it} denotes labour productivity and θ_{it} the employment share of firm *i* at time *t*. A bar over a variable denotes the arithmetic mean of that particular variable. The final term on the right measures the covariance between market share and firm productivity. Although the underlying assumptions of the OP model are different from the HK model, the intuition of the two models are the same: in efficient markets, relatively productive firms within an industry should control higher shares of productive resources. In the Olley and Pakes (1996) framework, this outcome is represented by a positive covariance term. The OP indicator, however, is less restrictive than the HK measure as it is not subject to restrictive assumptions regarding the production function and constant returns to scale.

We test the robustness of our results using the OP approach in two ways. First, we calculate the OP covariance using two measures of productivity, namely value added per worker, and value-added per capital. Secondly, we decompose the total covariance into the within and between formal and informal sector contributions.[18] We do this to highlight the relative contribution to overall misallocation of distortions to resource re-allocation between the formal and informal sector.

Table 4 presents the results for the OP covariance. The results differ starkly according to whether productivity is measured in terms of value-added per labour or per capita. The OP covariance for labour productivity is positive, albeit low, with both the between and within components contributing positively towards allocative efficiency. While employment in the informal sector is lower than in the formal sector, so too is its labour productivity (66% lower according to the survey data) – hence the

[17] Firms operating at maximum capacity are expected to have high MRPK and MRPL as all machinery and labor are used to the fullest extent and there is demand for more (Greenwood et al, 1988).
[18] Cov(X,Y)=E[Cov(X,Y|Z)] +Cov[E(X|Z),E(Y|Z)], where the first term is the within group covariance, and the second term is the between group covariance.

positive between components. In contrast, capital appears to be misallocated across firms both within and between the formal and informal sector. The OP covariance term is negative, irrespective of whether capital is adjusted for capacity utilisation (-2.4) or not (-2.8). More than half (55-59%) of the negative covariance can be explained by the misallocation of capital between formal and informal firms. The share of capital used by informal sector firms is far lower than their output per capital merits. This result corroborates our earlier finding of relatively high levels of misallocation in Zimbabwean manufacturing that is strongly associated with capital market rigidities.

Table 4. Sectorial and Industry OP Covariance

	Value added per worker	Value added per capital	Value added per used capital
Within	0.4	-1.1	-1.1
Between	0.3	-1.7	-1.3
Total	0.7	-2.8	-2.4

Notes: Results for the covariance between capital and labour allocation and firm productivity. We use value-added per worker and value-added per capital as measures of firm productivity. The final column uses capital stock adjusted for capacity utilisation. Firm size is measured by either the number of employees, or the value of capital. All firms are included in the calculations.

An alternative measure of capital misallocation: The Wu (2008) approach.

As a final robustness check, we use an alternative measure of capital misallocation based on the marginal revenue product of capital ($MRPK_{i,t}$) proposed by Wu (2018).[19] Wu (2018) obtains an estimate of $\ln(MRPK_{i,t})$ as the residuals from the following regression model:

$$\ln\,(ARPK_{i,t}) = \beta_0 + \beta_1 \ln\,(\frac{\pi_{i,t}}{R_{i,t}}) + \beta_2 \frac{R_{i,t}}{\pi_{i,t}} + \beta_3 industry_{i,t} + \beta_4 location_{i,t} + \zeta_{i,t} \quad (8)$$

where $\ln\,(ARPK_{i,t})$ is the natural log of revenue-capital ratio, $\ln\,(\frac{\pi_{i,t}}{R_{i,t}})$ is the natural log of profit-to-revenue ratio, $\frac{R_{i,t}}{\pi_{i,t}}$ is a revenue-to-profit ratio, and $industry_{i,t}$ and $location_{i,t}$ are dummies for industry and location respectively.

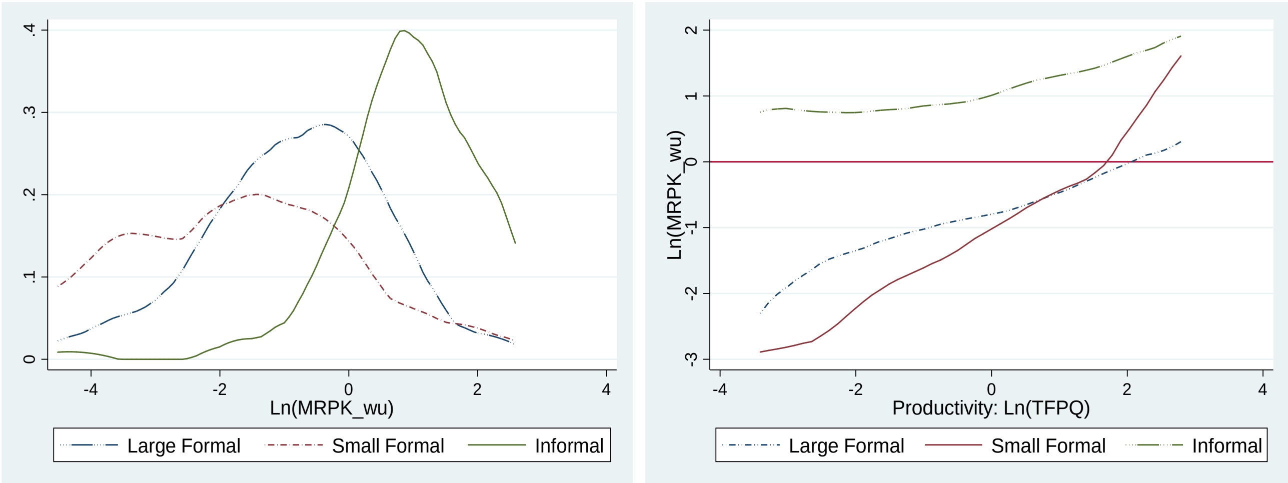
The advantages of using the Wu (2018) measure of MRPK over the HK is that, first, it takes into account heterogeneities in production functions and market power as compared to other measures in literature and it only displays the cost of capital. Second, the measure being a residual has a sample mean of zero and some interesting economic interpretation (Wu, 2018). For example, if $\ln\,(MRPK_{i,t})$ = 0.15 then the MRPK for that particular firm is 15% higher than the average MRPK in the economy.

Figure 5 presents the distribution of the $MRPK_{i,t}$ for the formal and informal sector firms. The wide

[19] For more details on this theory, see Wu (2018).

dispersion of MRPK results corroborate our HK-based findings of widespread and large misallocation of capital in the Zimbabwe manufacturing sector. Similarly, as found earlier, the positive relationship between MRPK and firm productivity implies an accentuation of the negative impact of misallocation on aggregate productivity. Finally, using the WU (2018) approach, results also reveal that capital misallocation is particularly high for informal sector firms – as shown by the relatively high $MRPK_{i,t}$ compared to formal sector firms.

Figure 5. The distribution of MRPK according to Wu (2018) approach



Panel (A) Panel (B)

Notes: *Ln(MRPK_wu)* is the indicator of misallocation obtained as a residual in equation 8. The left panel plots the distribution of MRPK while the right panel shows the correlation between MRPK and firm productivity.

Productivity

This paper assesses the extent of resource misallocation between and within the formal and informal manufacturing sector in Zimbabwe. The study applies the widely used Hsieh & Klenow (2009) approach to measuring resource misallocation using firm-level data for formal and informal sector manufacturing firms collected in 2015. A key contribution of the study is the inclusion of the informal manufacturing sector in the resource misallocation analysis. The informal manufacturing sector in Zimbabwe is large and contributes significantly towards employment and GDP. We measure misallocation using the dispersion of TFPR, capital distortions and output distortions.

The results reveal the widespread presence of idiosyncratic distortions to both output and factor markets in the formal and the informal sector in Zimbabwe, as indicated by the wide dispersion of different measures of misallocation. In both the formal and informal sectors, distortions act as a tax on more efficient firms, thus exacerbating the aggregate TFP losses due to misallocation. Market frictions, mainly in the capital market, are found to be particularly detrimental to production by informal sector firms. The implication is that misallocation of capital between the formal and informal sector is a major contributor towards aggregate misallocation in the economy. The study reveals that by efficiently allocating resources, aggregate TFP can be boosted by about 126.7%.

Overall, the findings suggest that product and factor market frictions are high in Zimbabwe and distort the efficient allocation of resources across manufacturing firms. Formal and informal sector firms compete in an integrated economic system, but the growth of productive informal firms is constrained by relatively high distortions restricting their access to capital. Reducing these distortions will boost aggregate productivity growth through improved resource allocation and raise the contribution of the informal sector to economic growth.

Conclusion

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Appendix

Data description and sampling procedure

This paper draws on the matched employer-employee dataset of Zimbabwean manufacturing firms under the "Matched Employee-Employer Data for Labour Market Analysis in Zimbabwe" project. The data was collected for firms in the formal and informal manufacturing sector.[20]

Data description and sampling procedure

The survey data collection for the formal manufacturing sector was carried out in 2015 and 2016. A stratified sampling procedure was used with firms selected according to firm size (5-19, 20-99, 100+ employees), industry (food, beverages and tobacco; wood and furniture; metal, machinery and equipment; textile and leather; chemical, and rubber) and location (Harare, Bulawayo, Mutare and Gweru). The desired sample size for the survey was set at 240 manufacturing firms, but given firm closures, a total of 195 firms were finally interviewed. Table A1 presents the distribution of firms surveyed by firm size and location.

Table A1. Number of formal firms by firm size and location

	5-19	20-99	100+	Total
Bulawayo	17	23	11	51
Harare & surrounds	33	50	36	119
Manicaland (Mutare)	2	6	2	10
Midlands (Gweru/Kwekwe/Redcliff)	9	4	2	15
Total	61	83	51	195

Data description and sampling procedure

One of the challenges when administering informal sector surveys was the lack of a register of informal firms as there is no Census of firms in the informal sector in Zimbabwe. Some insights can be obtained from the FinScope 2012 MSME survey, as well as the 2014/15 Business Register, which includes information on the number of small firms by industry (less than 5 workers). Neither of these provides reliable numbers on the current population of informal manufacturing firms by industry. The following approach was therefore adopted.

A two-stage sampling process was followed in selecting informal manufacturing firms. The sample was divided into the following set of industries: textiles, clothing and leather products; wood products,

[20] For full details of the survey and access to the data, see https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/702/study-description.

including furniture; metal fabrication; and others. This process was made easier by several characteristics of informal markets in Zimbabwe where manufacturing takes place. Firstly, informal manufacturing industries are largely clustered in distinct geographical areas (clusters). Secondly, in some areas (e.g. Mbare Magaba area in Harare), firms are clustered within specific complexes (e.g. a defined area such as a building, shed, etc.). Thirdly, firms within informal markets/areas tend to be clustered by industry and geographic location. For example, in Harare, the metal industry is clustered in the Mbare Magaba complex, the wood industry in Glenview area 8 complex while the textile is clustered in the central business district (CBD) downtown area.

Our sampling approach was as follows: In the first stage, the two main (or main areas where informal production is located in a single area) informal areas for each of the industry strata were selected. Where it is possible or sensible these areas were then divided into blocks (enumerating areas) with roughly equal numbers of firms based on spatial area or building complex. Blocks were then randomly selected. In the second stage, firms within each of these randomly selected blocks were listed. A random sample of firms was then selected for interviewing purposes from the listed firms in each randomly chosen block. In Harare, the interviews were conducted at Mbare Magaba and Gazaland complex for the metal industry, Glenview complex and Mbare Magaba for the wood industry, and Highfield and CBD for the textile industry. The following areas were selected for sampling in Bulawayo: Renkin and Kelvin North for wood and metal, CBD for textile and Nguboyenja for wood.

Table A2. Dispersion of TFPQ, TFPR and other misallocation indicators: adjusted vs adjusted capital

	ln (TFPQ)	**ln (TFPR)**	**ln (MRPK)**	**ln (1+ τ_k)**	**ln (1- τ_y)**
		Unadjusted Capital			
sd	1.47	1.04	1.95	1.89	0.72
N	197	197	197	197	197
		Adjusted Capital			
sd	1.42	0.98	1.77	1.74	0.72
N	197	197	197	197	197

Notes: For each firm i, in industry s TFPRsi=$\frac{P_{si}Y_{si}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$, TFPQsi =$\frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$, $1+\tau_{ksi} = \frac{a_s}{1-a_s}\frac{wL_{si}}{RK_{si}}$ and $1-\tau_{ysi} = \frac{\sigma}{1-\sigma}\frac{wL_{si}}{(1-a_s)P_{si}Y_{si}}$. The statistics for ln(TFPQ) and ln(TFPR) are deviations from respective industry means. sd is the standard deviation and N is the number of firms. Capital is adjusted for capital utilisation.