Do Multi-plant Firms Reduce Misallocation? Evidence from Canadian Manufacturing*

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Abstract

Using Canadian plant-level data, this paper shows that, depending on the industry, the differences in the average plant-level productivity and cross-plant allocation of resources between multi-plant and single-plant firms account for 1 to 15 percent of the industry-level TFP. A large part of this contribution stems from more efficient cross-plant allocation of resources, measured by the covariance between plant size and productivity, in the pool of plants in multi-plant firms compared to the pool of plants in single-plant firms. There is less dispersion in the marginal products of the inputs, and thus less misallocation, in industries in which multi-plant firms account for a larger share of output. The patterns found in the cross-plant distribution of productivity and size are also consistent with better allocative efficiency among plants in multi-plant firms than among plants in single-plant firms.

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1 Introduction

Recent empirical literature documented substantial dispersion in the productivity and the marginal products of inputs across establishments in an industry (Banerjee, Munshi and Duflo, 2003; Syverson, 2004*b*; Hsieh and Klenow, 2009; Bartelsman, Haltiwanger and Scarpetta, 2013). Several authors interpreted this as evidence of misallocation of resources that can lead to non-negligible losses in aggregate total factor productivity (TFP). The misallocation may stem from various distortions, some of which are created by market imperfections (e.g., financial constraints); others are policy-induced (e.g., size-dependent policies).[1] These distortions typically directly influence input and output markets and thus the allocation of resources *among* firms. If a firm operates several productive establishments (plants), another round of allocation takes place *within* the firm. It is then natural to ask how multi-plant firms affect the efficiency of allocation of resources across plants in an industry (and thus the aggregate industry-level TFP).

On the one hand, within-firm allocation is to a certain degree insulated from external market distortions. As a result, within-firm allocation may improve the allocation of resources across plants in an industry. On the other hand, multi-plant firms tend to be large; they may be more subject to size-dependent policies (whether subsidies or restrictions), and they may distort market conditions, for example, through their market power. As a result, the very existence of large multi-plant firms may exacerbate the (mis)allocative effects of some external market distortions. Using data from the Canadian Annual Survey of Manufacturers, this paper empirically assesses the overall impact of multi-plant firms on industry-level allocative efficiency and TFP. Can we find evidence that multi-plant firms improve the allocation of resources across plants in an industry? If yes, how much this efficiency gain contributes to the industry-level TFP? The short answers are yes and 1 to 15 percent, depending on the

[1] For the role of financial constraints, see Jeong and Townsend (2007); Erosa and Hidalgo Cabrillana (2008); Castro, Clementi and MacDonald (2009); Amaral and Quintin (2010); Buera, Kaboski and Shin (2011); for the role of size-dependent policies, see Guner, Ventura and Xu (2008); Restuccia and Rogerson (2008).

industry.

I first document that in Canada, as in many other countries, multi-plant firms are not numerous, but they are large and account for a substantial part of economic activity. Multi-plant firms represent about 15 percent of plants but they create more than 75 percent of the overall value added in the Canadian manufacturing sector. I then calculate plant-level TFP as a residual from the logged Cobb-Douglas production function. I use the estimates of the plant-level TFP to assess the allocative effects of multi-plant firms through three alternative approaches. First, I provide a simple decomposition that isolates the contribution of the differences between multi-plant and single-plant firms to the industry-level TFP. The results suggest that multi-plant firms contribute in an important way to the aggregate industry-level TFP because their plants tend to be more productive on average but mainly because the allocation of production across the plants in the pool of multi-plant firms is more efficient compared to the pool of single-plant firms. Second, I show that there is less dispersion in the marginal products of the inputs, and thus less misallocation, in industries in which multi-plant firms account for a larger share of the output. Third, I verify that the plant-level productivity distribution in the data features the main cross-sectional patterns implied by better allocative efficiency among plants in multi-plant firms than among plants in single-plant firms.

In the first approach, I decompose the industry-level TFP index into the unweighted average productivity of plants within each group of firms (multi-plant and single-plant firms), the covariance of the output share and the productivity of the plants within each group, and the covariance of the average output share and the average productivity of the plants between the two groups. Because efficiency dictates more productive plants should produce more and account for a larger share of the industry output, the covariance terms are convenient summary measures of the allocative efficiency.[2] Comparing the *average productivity* terms according to the firm type reveals that the plants owned by multi-plant firms tend to be more productive than those owned by single-plant firms. However, since the plants in multi-plant firms are few, the differences in the unweighted average productivities contribute little (around 1 percent at the manufacturing sector level, -2 to 4 percent at the individual

[2]See, for example, Olley and Pakes (1996) and Bartelsman, Haltiwanger and Scarpetta (2013).

3-digit North American Industry Classification System (NAICS) industry level) to the aggregate industry-level TFP.[3] The *within-group covariance* term indicates whether inside a given group of firms plants with higher-than-average productivity account for a higher-than-average share of activity. My results show large differences in the within-group allocative efficiency. The differences in the within-group covariance term contribute roughly 7 percent of the aggregate manufacturing-sector TFP. At the level of individual 3-digit NAICS industries, the differences in the within-group covariance term contribute between 1 and 14 percent of the industry-level TFP.[4] Finally, the *between-group covariance* term indicates how much production is shifted to the group with higher average productivity (multi-plant firms). This term accounts for about 3 percent of the aggregate manufacturing-sector TFP and 0 to 10 percent of the aggregate TFP at the level of individual 3-digit NAICS industries. These magnitudes are roughly stable over the four years of the sample period.

My second approach focuses on the input side of the production process. I use the estimated Cobb-Douglas production functions and a simple static model of profit-maximizing plants to calculate a measure of the implied plant-specific prices of inputs along the lines of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Profit-maximization implies that plants equalize marginal product of each input to its implied plant-specific price. In the model, efficiency requires marginal products to be equalized across plants. It follows that dispersion in implied input prices across plants in an industry is a convenient measure of misallocation: Plants with higher implied prices face relatively worse input markets, have higher marginal products, and are operated at a scale that is too low. I show that the dispersion is lower (and thus the cross-plant allocation of inputs is better) in industries in which multi-plant firms account for a larger share of the output. I also explore how the level of implied input prices varies with the type of firm, plant productivity, and size. I show that allocative distortions tend to be correlated with plant size and TFP (larger, more productive plants face higher implied plant-specific prices), but the distortions are, on average, lower

[3] These numbers are relative to a counter-factual exercise. They indicate by how much the aggregate industry-level TFP index would decrease if plants in multi-plant firms had the same average TFP as plants in single-plant firms.

[4] These numbers indicate by how much the aggregate industry-level TFP index would decrease if the covariance between size and productivity in the group of plants in multi-plant firms was the same as in the group of plants in single-plant firms.

for plants in multi-plant firms than for plants in single-plant firms.

In the third alternative assessment of the allocative efficiency of multi-plant firms, I focus on two implications of a simple theory of efficient internal markets for the cross-sectional relationship between plants' operating size and TFP. First, when the selection of plants into multi-plant firms is endogenous (for example, through mergers, acquisitions, and corporate asset sales), plants with high TFP are more likely to join multi-plant firms. This selection arises because in the presence of external market imperfections, the gain from reallocating resources internally to highly productive plants is large, which makes these plants desirable targets for acquisition. Second, once a highly productive plant is part of a multi-plant firm, the plant is more likely to be operated at its optimal (large) size. The intuition here is that a multi-plant firm has a larger capacity to loosen the plant's resource constraint than a single-plant firm because the multi-plant firm can take resources away from the relatively less productive affiliated plants and supply these resources to the highly productive plant. In the cross section, this mechanism implies that small plants in multi-plant firms should have, on average, lower TFP than their counterparts in single-plant firms, but large plants in multi-plant firms should have, on average, higher TFP than their counterparts in single-plant firms. Interestingly, non-parametric estimates of the cross-plant TFP distribution from the data reveal precisely such a shift, providing further support for the higher allocative efficiency within the group of multi-plant firms.

1.1 Related Literature

This paper is related to two large strands of literature. First, the decomposition of the aggregate productivity index and the study of implied input prices follows the tradition, and to a large extent the methodology, of the literature on the effects of the allocation of resources on aggregate productivity (Banerjee, Munshi and Duflo, 2003; Alfaro, Charlton and Knaczuk, 2008; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Buera, Kaboski and Shin, 2011; Bartelsman, Haltiwanger and Scarpetta, 2013; Midrigan and Xu, 2014). In contrast to these studies, I take into account the organizational form of firms and the possibilities of internal reallocation within the firms. I provide a quantification of the contribution of these aspects, which were largely ignored by this literature. One feature that this study cannot take into account due to the limitations of the dataset are production chains and vertical integration. However, Atalay, Hortaçsu and Syverson (2014) showed that vertical integration does not appear to be primarily used to facilitate transfers of goods along the production chain, but to promote efficient intra-firm transfers of intangible inputs. This suggests that the internal reallocation mechanism should be relevant for vertically integrated firms as well.

Second, there is vast corporate finance literature devoted to the study of internal markets in conglomerates and corporate diversification. Maksimovic and Phillips (2001; 2002) provide empirical evidence on the efficient transfers of resources through asset sales and internal reallocation inside multi-unit firms. More recent empirical literature showed how conglomerates use internal markets to alleviate misallocation and financial constraints during episodes of industry economic distress or financial market distress (Kuppuswamy and Villalonga, Forthcoming; Gopalan and Xie, 2011; Matvos and Seru, 2014) and presented empirical evidence on the functioning of internal markets in environments with under-developed and distorted external markets (Masulis, Pham and Zein, 2011; Natividad, 2013). My paper shares with this literature the starting-point idea that multi-unit firms (conglomerates or multi-plant firms) run internal markets in which resources might be allocated to the most productive use within the firm more efficiently than through external markets.[5] The crucial difference is that I go beyond testing whether multi-plant firms allocate resources efficiently across the plants *within* the firm; I am interested in how the allocation at the aggregate level (i.e., across *all* plants in the industry) is affected by the existence of multi-plant firms. This enables me to quantify the contribution of plants in multi-plant firms to the aggregate industry-level productivity.

2 Data

I use data on manufacturing establishments from the Canadian Annual Survey of Manufacturers (ASM) and the Business Register (BR) maintained by Statistics Canada. Statistics Canada uses a four-level hierarchy of statistical entities for businesses: the enterprise, the

[5]For a formal theoretical treatment of this idea, see Gertner, Scharfstein and Stein (1994) and Stein (1997).

company, the establishment, and the location (Statistics Canada, 2015). The enterprise is defined as the organizational unit of a business that directs and controls the allocation of resources related to its domestic operations. The company is the organizational unit for which income and expenditure accounts and balance sheets are maintained from which operating profit can be derived. The establishment is defined as the smallest level at which the data on principal inputs, revenues, salaries, and wages are available. Finally, the location is defined as a producing unit at a single geographic location and for which, at a minimum, employment data are available. The ASM collects financial and commodity data at the establishment level. In the manufacturing sector, this level usually represents a plant, and in the rest of the paper, I use the term *plants* to refer to the establishment-level observations. The BR provides data at the enterprise level. In the rest of the paper, I use the term *firms* to refer to the enterprise-level observations.

The ASM gathers detailed information on the production inputs and revenues of manufacturing plants from three principal types of sources: questionnaires sent to survey participants, administrative tax records, and imputation from aggregate or industry records.[6] My sample covers four years from 2000 to 2003. These years were selected because they provide almost exhaustive coverage of the population of manufacturing plants in Canada.[7] From the initial 244,250 plant-year observations, I exclude 12,374 observations that were imputed from aggregate or industry records. I further exclude the observations for which the yearly value added is lower than 50,000 Canadian dollars. This leaves me with a sample of 190,493 plant-year observations.

The BR provides information on all activities of Canadian firms, particularly the NAICS codes of industries in which a firm operates as well as sales and employment in each industry. However, the BR was designed as a sampling frame for various business surveys, and not all records in the BR are regularly updated and suitable for research purposes. Using the firm identifier and the reporting year in the ASM as matching variables, I obtained accurate firm-level information from the BR records for 168,054 plant-year observations in the ASM. I had to delete a further 531 observations associated with firms for which the BR reports

[6]Responding to ASM questionnaires is mandatory, and firms can be fined for non-compliance.

[7]See Appendix A for more details.

activities in manufacturing industries that are not reported in the ASM.[8] After this final cut, I have a sample of 167,523 plant-year observations spanning the period 2000 to 2003, with at least 40,799 plant observations per year.

Notice that the ASM data are limited by their concentration on manufacturing industries. If a firm is diversified outside the manufacturing sector, the non-manufacturing operations are not recorded. As a result, a firm might be wrongly classified as single-plant although it operates other establishments outside the manufacturing sector. This issue occurs in all studies of corporate diversification that use detailed plant-level manufacturing data.[9] One advantage of my data set is that it combines information on production output and inputs at the plant level from the ASM with the firm-level BR records, which allows me to properly control for firms' extra-manufacturing activities.[10]

2.1 Multi-plant Firms in Canadian Manufacturing

Table 1 reveals that the proportion of plants that operate under multi-plant firms averages between 14 and 15 percent over the sample period. The proportion of firms that are classified as multi-plant is around 5 percent. Over the sample period, multi-plant firms accounted for roughly 77 percent of production (measured by the value added) and 60 percent of employment in the manufacturing sector. These statistics suggest that multi-plant firms operate a relatively small number of plants in the Canadian manufacturing sector, but these plants are large and account for a large part of production and employment.

The industries in which multi-plant firms produced the largest fraction of output are Beverage and tobacco manufacturing (NAICS 312) and Petroleum and coal product manufacturing (NAICS 324). The industries with the lowest concentration of production in multi-plant firms were Clothing manufacturing (NAICS 315) and Miscellaneous manufac-

[8]This is a consistency requirement. Since the ASM file is updated regularly and provides more accurate information on manufacturing industries than the BR, I use the ASM data whenever BR records on manufacturing are not consistent with the ASM file. I make the implied assumption that the ASM reports truthfully all manufacturing activities of the firm.

[9]Schoar (2002) addressed this problem by matching the observations from the Longitudinal Research Database of the U.S. Bureau of Census to the Compustat Segment data. Although this might have partially solved the difficulty of controlling for diversification outside manufacturing, it came at the great cost of limiting the sample to the firms included in the Compustat files. Given the known issues with the Compustat data (see Villalonga, 2004), this sample selection could introduce bias to the analysis.

[10]I am indebted to Robert Gibson for retrieving and cleaning the firm-level data from the BR.

Table 1: Prevalence of multi-plant firms

	Percentage accounted for by multi-plant firms			
Year	Plants	Firms	Value added	Employment
2000	14.5	5.4	77.8	61.2
2001	14.2	5.1	74.9	59.0
2002	14.4	5.3	77.3	59.9
2003	14.9	5.7	76.4	61.7
All years	14.5	5.4	76.6	60.5

Table 2: Plant size summary statistics

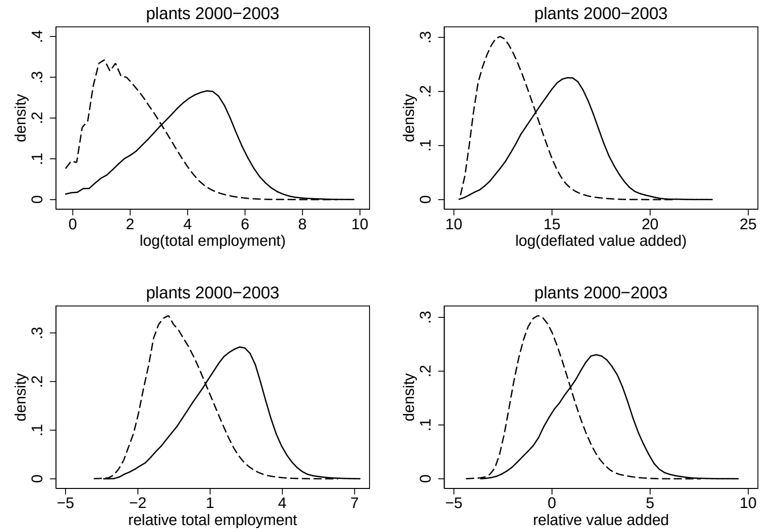
	Multi-plant			Single-plant		
	N. obs.	Mean	S.d.	N. obs.	Mean	S.d.
log(Value added)	24,301	15.4	1.7	143,222	12.8	1.3
Employment	24,301	143.7	354.6	143,222	16.0	50.8

turing (NAICS 339).

2.2 Establishment Size and Multi-plant Conglomeration

Table 2 gives the summary statistics of the plant size measured by the deflated value added and the total number of workers at the plant. Plants in multi-plant firms are larger, and there is more size dispersion across these plants. This is confirmed in Figure 1 by the non-parametric kernel density estimates of plant size distributions, which have the advantage of conveying information on the shape of the entire distribution instead of only few of its moments. The top two panels in Figure 1 show the size distributions in terms of the logarithm of employment and the logarithm of the value added. The estimates indicate that, in both cases, the mass of the distribution of plants in multi-plant firms is shifted toward larger sizes. The Kolmogorov-Smirnov test strongly rejects (p-value=0.0) the hypothesis of the equality of the density estimates.

Comparisons based on simple size measures, such as the value added or employment, are convenient, but they do not take into account the possible selection of multi-plant firms into specific industries. As a result, several concerns may arise. First, the differences in the value added include the effects of variation in the prices of the output and the materials across industries. Second, the differences in the number of employees include the effects of variation in labor intensity across industries. Third, both comparisons include the effects of



Epanechnikov kernel, bandwidth = 0.25. Solid line - multi-plant. Dashed line - single-plant.

Figure 1: Size distributions

other industry-specific differences, such as returns to scale and the minimum efficient size of the operation. If multi-plant firms are predominant in a few specific industries, then the difference between the size distributions might arise solely because of this composition effect, and in some contexts, the comparisons provided by the top panels of Figure 1 may seem inappropriate. It is therefore interesting to consider an approach that would control for industry-specific characteristics and allow us to compare the size of these establishments in more relative terms. To do so, I construct relative size measures, defined as the residual from a regression of the logarithm of the plant's size on a full set of industry-year dummies and their interactions. The relative size measure is a log (that is, percentage) difference in a given size variable between the plant and the average computed at the level of the industry-year fixed effect. The bottom panels of Figure 1 show that the observed differences in the size distributions remain significant even when relative size is considered. Multi-plant firms operate plants that are large even compared to other plants within the same industry; the differences in the size distributions are not induced solely by industry-specific effects and selection.

2.3 Estimating Plant-level Productivity

In order to examine the efficiency of the allocation of resources to plants, I first need to measure the productivity of each plant. I construct the plant-level TFP indices as residuals from logged Cobb-Douglas production functions. I assume a plant-level log-linearized production function of the form

$$y_{i,j,t} = \alpha_{j,t} k_{i,j,t} + \beta_{j,t} l_{i,j,t} + \epsilon_{i,j,t}, \tag{1}$$

where $y_{i,j,t}$ is the logarithm of the output of plant i that produces in industry j in year t, $k_{i,j,t}$ and $l_{i,j,t}$ are the logarithms of the inputs of capital services and labor, and $\epsilon_{i,j,t}$ is the (logarithm of) plant-level TFP.

The elasticities $\alpha_{j,t}$ and $\beta_{j,t}$ are calibrated to match the input cost shares calculated from industry-level data from the CANSIM database. This requires assuming constant returns to scale. In practice, I follow the Statistics Canada approach that considers land a third, fixed factor. As a result, there are decreasing returns to with respect to capital and labor (the calibrated $\alpha_{j,t} + \beta_{j,t} < 1$), but constant returns to overall scale.[11] The capital costs are calculated as the sum of the reported cost of the capital input for building structures, engineering structures, information and communication technologies (ICT) machinery and equipment, and non-ICT machinery and equipment (CANSIM Table 383-025). The reported labor compensation (CANSIM Table 383-0032) is used to calculate the labor cost share.

I consider two variants of this calibration. First, in order to provide an idea of the importance of multi-plant firms for the aggregate TFP at the level of the entire manufacturing sector, I assume the same production function for all manufacturing plants and calibrate $\alpha_{j,t}$ and $\beta_{j,t}$ to match the cost shares calculated at the whole manufacturing sector level. Second, in order to take into account the specificities of individual industries, I calibrate $\alpha_{j,t}$ and $\beta_{j,t}$ to match the cost shares calculated at the 3-digit NAICS industry level. This is the finest level at which the information on the cost of capital is readily available.

The measures of the output and inputs are obtained directly from the ASM data. I use value added deflated by the respective 4-digit NAICS industry price indices from CANSIM database for measuring output. Thus, $\epsilon_{i,j,t}$ is a revenue-based measure of the TFP and

[11] If, for example, in a given year for an industry cost shares according to Statistics Canada are 60% for labor, 30% for capital, and 10% for land, the calibrated parameters $\alpha_{j,t} = 0.6$ and $\beta_{j,t} = 0.3$.

includes possible variations in output prices across the plants.[12] One caveat that must be mentioned is that my data set does not allow me to separately identify intra-firm sales of goods in vertically integrated firms. If the intra-firm sales are important and the transfer prices differ substantially from the market prices, the plant's value-added and the revenue-based TFP measure will be affected. For instance, if plants in multi-plant firms charge lower transfer prices than the market price, my TFP measure is likely to underestimate the plants' productivity. However, recent work by Atalay, Hortaçsu and Syverson (2014) documented that internal shipments account for small shares of plants' output in vertically integrated firms, suggesting that this problem should not be severe.

The labor input is the total number of workers at the plant. Unfortunately, the Canadian ASM does not provide information on capital stocks or investments. To overcome this difficulty, I follow Burnside, Eichenbaum and Rebelo (1995) in using data on energy expenditures to proxy for capital utilization. In particular, I assume that capital services vary in proportion to energy use, $k_{i,j,t} = \log \lambda_j + e_{i,j,t}$, where λ_j is a factor of proportionality and $e_{i,j,t}$ is the logarithm of deflated energy expenditures at plant i in year t.[13] In the TFP calculation, I simply replace the input of capital services with the plant-level energy expenditures deflated by the industrial energy price index from CANSIM database. As a result, my plant-level productivity measure includes an industry-specific term that depends on the factor of proportionality λ_j and is not directly comparable to the usual TFP measure in the literature. In the end, I am able to recover the estimated plant-level TFP for 154,412 plant-year observations for which I have information on all necessary output and input variables.

3 Aggregate TFP Decomposition

In this section, I introduce a simple decomposition that allows me to quantify the contribution of plants in multi-plant firms to the aggregate industry-level TFP. The decomposition also informs us about the sources of this contribution.

[12] See Syverson (2004*a*) and Foster, Haltiwanger and Syverson (2008) for a discussion of the revenue-based productivity and physical productivity measures.

[13] This imposes the assumption that the elasticity of capital services with respect to energy use is one.

3.1 Methodology

Define an aggregate productivity index for an industry as the weighted average of plants' productivity

$$TFP_t \equiv \sum_{i=1}^{N} s_{i,t}\epsilon_{i,t}, \tag{2}$$

where I dropped the industry index j for better readability and where $s_{i,t} = \frac{y_{i,t}}{\sum_i y_{i,t}}$ is the share of plant i in the total industry output and $\epsilon_{i,t}$ is the residual from the log-linearized production function (1). Following Olley and Pakes (1996), this index can be decomposed as

$$\begin{aligned}
TFP_t &= \bar{\epsilon}_t + \sum_{i=1}^{N_t} \left(s_{i,t} - \bar{s}_t\right)\left(\epsilon_{i,t} - \bar{\epsilon}_t\right) \\
&= \bar{\epsilon}_t + N_t \frac{\sum_{i=1}^{N_t} \left(s_{i,t} - \bar{s}_t\right)\left(\epsilon_{i,t} - \bar{\epsilon}_t\right)}{N_t} \\
&= \bar{\epsilon}_t + N_t cov\left(s_{i,t}, \epsilon_{i,t}\right),
\end{aligned} \tag{3}$$

where $\bar{\epsilon}_t$ and $\bar{s}_t$ are the unweighted averages of the plant-level productivity and output shares and N_t is the number of plants in the industry in year t. The *average productivity term* in equation (3) contains information about plant selection. The *covariance term* informs us about whether the plants with above-average productivity are allocated an above-average share of the output. Thus, the covariance term provides a convenient measure of the contribution of allocative efficiency of production among the existing plants to the aggregate sectoral TFP. The larger this term, the better the allocation of the output (and inputs) across plants.

I further decompose each of the two terms in order to isolate and highlight the contribution of multi-plant firms to the aggregate sectoral TFP. Let M_t and S_t denote the sets of plants in multi-plant and single-plant firms, and let N_t^M and N_t^S be the number of plants in each set, respectively. For the average productivity term, we have:

$$\begin{aligned}\bar{\epsilon}_t &= \frac{\sum_{i\in M_t}\epsilon_{i,t} + \sum_{i\in S_t}\epsilon_{i,t}}{N_t^M + N_t^S} \\ &= N_t^M \frac{\bar{\epsilon}_t^M}{N_t^M + N_t^S} + N_t^S \frac{\bar{\epsilon}_t^S}{N_t^C + N_t^S},\end{aligned} \tag{4}$$

where $\bar{\epsilon}_t^M$ and $\bar{\epsilon}_t^S$ are the unweighted average productivities within each set of plants. The term $\bar{\epsilon}_t^M / \left(N_t^M + N_t^S\right)$ in equation (4) is the average contribution of a plant in a multi-plant firm to the unweighted average productivity in the industry.

For the covariance term, we have:

$$\begin{aligned}N_t cov\left(s_{i,t}, \epsilon_{i,t}\right) = &\underbrace{\sum_{i\in M_t}\left(s_{i,t} - \bar{s}_t - \bar{s}_t^M + \bar{s}_t^M\right)\left(\epsilon_{i,t} - \bar{\epsilon}_t - \bar{\epsilon}_t^M + \bar{\epsilon}_t^M\right)}_{A_t^M} + \\ &\underbrace{\sum_{i\in S_t}\left(s_{i,t} - \bar{s}_t - \bar{s}_t^S + \bar{s}_t^S\right)\left(\epsilon_{i,t} - \bar{\epsilon}_t - \bar{\epsilon}_t^S + \bar{\epsilon}_t^S\right)}_{A_t^S},\end{aligned}$$

where $\bar{s}_t^M$ and $\bar{s}_t^S$ are the average shares of a plant in a multi-plant firm and of a plant in a single-plant firm in the aggregate manufacturing output, respectively. Developing and rearranging the A_t^M and A_t^S terms, we can show that the aggregate covariance term can be written as[14]

$$N_t cov\left(s_{i,t}, \epsilon_{i,t}\right) = \underbrace{N_t^M cov^M\left(s_{i,t}, \epsilon_{i,t}\right)}_{\text{efficiency within } M_t} + \underbrace{N_t^S cov^S\left(s_{i,t}, \epsilon_{i,t}\right)}_{\text{efficiency within } S_t} + \underbrace{N_t cov\left(\bar{s}_t^g, \bar{\epsilon}_t^g\right)}_{\text{efficiency between groups}}, \tag{5}$$

where the notation $cov^g\left(s_{i,t}, \epsilon_{i,t}\right) \equiv {}^1/_{N_t^g} \sum_{i\in g_t}\left(s_{i,t} - \bar{s}_t^g\right)\left(\epsilon_{i,t} - \bar{\epsilon}_t^g\right)$ is the covariance of the output shares and productivity *within* the set of plants g and $cov\left(\bar{s}_t^g, \bar{\epsilon}_t^g\right) \equiv {}^1/_{N_t} \sum_g N_t^g\left(\bar{s}_t^g - \bar{s}_t\right)\left(\bar{\epsilon}_t^g - \bar{\epsilon}\right)$ is the covariance of the average output shares and the average productivities across the two sets of plants. The first term in equation (5) informs us about the allocative efficiency within the set of plants in multi-plant firms, the second term informs us about the allocative effi-

[14] See Appendix B for a detailed description of the algebra manipulations.

ciency within the set of plants in single-plant firms, and the third term indicates whether the production is more or less efficiently allocated between the two sets of plants.

The main question I ask is how much the *differences* between the plants in multi-plant firms and the plants in single-plant firms contribute to the industry-level TFP. Combining equations (3), (4), and (5) and rearranging the terms, I obtain the following decompositon, which answers this question[15]:

$$\begin{aligned} TFP_t = \; & \bar{\epsilon}_t^S + N_t cov^S \left(s_{i,t}, \epsilon_{i,t} \right) \\ & + \frac{N_t^M}{N_t} \left(\bar{\epsilon}_t^M - \bar{\epsilon}_t^S \right) + N_t^M \left[cov^M \left(s_{i,t}, \epsilon_{i,t} \right) - cov^S \left(s_{i,t}, \epsilon_{i,t} \right) \right] + N_t cov \left(\bar{s}_t^g, \bar{\epsilon}_t^g \right). \end{aligned} \quad (6)$$

Equation (6) highlights the differences with respect to a counter-factual scenario in which the pool of plants in multi-plant firms has the same characteristics as the pool of plants in single-plant firms. More precisely, the third term in equation (6) tells us by how much the industry-level TFP would decrease if the plants in multi-plant firms had the same average productivity as the plants in single-plant firms. The fourth term tells us by how much the industry-level TFP would decrease if the covariance between plant size and productivity in the group of plants in multi-plant firms was the same as in the group of plants in single-plant firms. I will use equation (6) to quantify by how much plants in multi-plant firms improve industry-level TFP. The notion of "improve" here is relative to the counter-factual scenario in which there would be no differences in terms of average productivity and covariance between size and productivity across the two groups of plants.

3.2 Results - Whole Manufacturing Sector

In this section, I use the plant-level estimates of TFP obtained from assuming a unique Cobb-Douglas production function for all plants in the manufacturing sector, where the input elasticities were calibrated to match the year-specific input cost shares calculated from the aggregate data at the manufacturing sector level. Although this approach has the weakness of ignoring the finer industry differences, I believe it illustrates quite well how important

[15]I would like to thank an anonymous referee for suggesting this rewriting of the decomposition.

Table 3: Sectoral TFP decomposition

	Percentage of aggregate TFP					
		$N_t \times$	$N_t^M/N_t \times$	$N_t^M \times$	$N_t \times$	
Year (t)	$\bar{\epsilon}_t^S$	$cov^S\left(s_{i,t}, \epsilon_{i,t}\right)$	$\left(\bar{\epsilon}_t^M - \bar{\epsilon}_t^S\right)$	$\left[cov^M\left(s_{i,t}, \epsilon_{i,t}\right) - cov^S\left(s_{i,t}, \epsilon_{i,t}\right)\right]$	$cov\left(\bar{s}_t^g, \bar{\epsilon}_t^g\right)$	TFP_t
2000	86.9	1.6	0.7	8.0	2.8	100
2001	88.2	1.8	0.6	6.7	2.6	100
2002	88.9	1.3	0.5	7.1	2.2	100
2003	88.7	1.6	0.8	5.7	3.2	100

TFP_t is the total factor productivity index for the entire manufacturing sector constructed as the output-weighted average of the plants' estimated (logged) total factor productivities. Plant-level total factor productivity is obtained as the residual from the logged Cobb-Douglas production function using input cost shares calculated at the whole manufacturing sector level to calibrate the input elasticities.

multi-plant firms are from the aggregate "macroeconomic" point of view.

Table 3 provides the results from the decomposition according to equation (6). The differences in average plant productivity between the two groups of plants account for around 0.7 percent of the aggregate sectoral TFP, whereas the differences in the within-group covariance terms account for around 6.9 percent of the aggregate sectoral TFP. In other words, there is evidence that the existence of multi-plant firms increases the aggregate TFP, mostly by helping allocate production and inputs more efficiently across plants in the industry. If the pool of plants in multi-plant firms had the same characteristics (average productivity and within-group covariance between plant size and productivity) as the pool of plants in single-plant firms, the sectoral TFP index would decrease by roughly 10.3 percent (this includes the between-group covariance term, which would be zero in the counter-factual scenario). These magnitudes are roughly stable over the years of the sample period and show that multi-plant firms contribute in a non-negligible fashion to the aggregate TFP in the Canadian manufacturing sector.

3.3 Results - Individual Industries

The decomposition applied at the level of the whole manufacturing sector provided a broad picture of the importance of multi-plant firms for manufacturing sector productivity. However, it rests on the estimates of plant-level TFP obtained under the assumption of the same production function across all manufacturing industries in a given year. In this section, I strive to better control for industry differences by letting the input elasticities of the production function vary to match the industry-year-specific input cost shares calculated from the aggregate data at the 3-digit NAICS level. I then apply the decompositions separately for each 3-digit NAICS industry and year. In order to increase readability of the results, I report the average effects over the four years of the sample period.

Table 4 contains several interesting results. First, consistently with the results obtained in the decomposition for the whole manufacturing sector, for most industries the higher average productivity of plants in multi-plant firms improves the industry-level TFP relatively little (see column 3 of Table 4).[16]

Second, in all industries, the difference between the within-group covariance in the pool of plants in multi-plant firms and the within-group covariance in the pool of plants in single-plant firms is always positive (see column 4 of Table 4). This indicates that multi-plant firms help improve allocative efficiency across the plants in all industries. However, there are large differences in the magnitude of this effect across industries. In the first group of industries (NAICS 315, 316, 322, 323, 326, 332, and 337), the contribution of the covariance difference term is small—between 1 and 2 percent of the industry-level TFP. Thus, in these industries the allocative efficiency would not be very different without multi-plant firms. Of course, this set of industries includes some in which multi-plant firms are not important overall, but interestingly, it includes industries such as NAICS 315 - Clothing manufacturing and NAICS 337 - Furniture and related products manufacturing in which multi-plant firms are very present and account for, respectively, 64 and 54 percent of the yearly industry value added on average over the sample period. In the second group of industries (NAICS 311, 31A, 321, 325, 327, 331, 333, 334, and 335), the contribution of the covariance difference term is between 3 and 7 percent. In these industries, the presence of multi-plant firms has a non-negligible impact on the industry-wide allocative efficiency. Finally, in three industries (NAICS 312, 324, and 336), the contribution of the covariance difference term is more than 10 percent, indicating a substantial positive impact of multi-plant firms on the allocation of resources.

[16] For NAICS 324 - Petroleum and coal product manufacturing, the plants in multi-plant firms are less productive than the plants in single-plant firms, thus the negative number.

Table 4: 3-digit NAICS industry TFP decomposition

Industry	Percentage of aggregate TFP (averages over 2000-2003)				
	$\bar{\epsilon}_t^S$	$N_t \times$ $cov^S(s_{i,t}, \epsilon_{i,t})$	$N_t^M/N_t \times$ $(\bar{\epsilon}_t^M - \bar{\epsilon}_t^S)$	$N_t^M \left[cov^M(s_{i,t}, \epsilon_{i,t}) \right.$ $\left. - cov^S(s_{i,t}, \epsilon_{i,t})\right]$	$N_t \times$ $cov(\bar{s}_t^g, \bar{\epsilon}_t^g)$
311 - Food	86.0	1.7	1.8	5.8	4.7
312 - Beverage, tobacco	74.7	0.4	3.9	11.4	9.8
31A - Textile and textile products	92.8	1.8	0.4	3.0	2.0
315 - Clothing	92.2	4.0	0.3	1.7	1.8
316 - Leather and allied products	96.4	1.9	0.1	1.3	0.4
321 - Wood products	91.7	1.8	0.9	3.1	2.6
322 - Paper	97.9	0.7	0.2	1.0	0.2
323 - Printing	95.6	1.4	0.3	1.0	1.6
324 - Petroleum, coal products	87.4	0.6	−1.7	14.2	−0.4
325 - Chemicals	89.4	1.6	1.3	6.0	1.7
326 - Plastics, rubber products	93.8	1.7	0.8	2.0	1.6
327 - Non-metallic mineral products	93.4	1.6	0.7	3.0	1.2
331 - Primary metal	91.8	1.4	1.6	3.2	2.0
332 - Fabricated metal products	94.3	1.9	0.3	2.0	1.6
333 - Machinery	90.8	2.9	0.5	3.8	1.9
334 - Computer, electronic products	88.9	1.5	0.4	6.6	2.6
335 - Electrical equipment, appliances	91.0	1.3	1.2	3.0	3.4
336 - Transportation equipment	81.3	1.3	1.4	11.7	4.2
337 - Furniture and related products	92.8	2.9	0.3	1.7	2.4
339 - Miscellaneous	92.5	3.9	0.2	2.1	1.3

Columns may not add up to 100 due to rounding. The aggregate total factor productivity index for each industry is constructed as the output-weighted average of the plants' estimated (logged) total factor productivities. Plant-level total factor productivity is obtained as the residual from the logged Cobb-Douglas production function using the input cost shares calculated at the 3-digit NAICS industry level to calibrate the input elasticities.

3.3.1 Robustness

One issue that the reader might be worried about is the dependence of covariance on the dispersion of the entering variables. The above results might be driven by the fact that there is more dispersion in plants' output shares and productivities within the pool of plants in multi-plant firms than within the pool of plants in single-plant firms. In a sense, the covariance may obscure a bit the effects on allocation with the effects of selection. An easy way to verify the robustness of the previous results is to look at the correlation coefficients instead of covariances.[17]

For each industry and year, I calculate the ratio of the correlation between the plants' output shares and productivities within the pool of multi-plant firms to that correlation within the pool of single-plant firms. In Figure 2, I plot the averages of this ratio over the sample period for each industry. For 19 of the 20 industries, the average ratio is greater than 1, in line with the result of the better allocation of resources within the pool of multi-plant firms than within the pool of single-plant firms.

For each industry and year, I also test whether the correlation coefficients are statistically different across the two pools of plants. More formally, the null hypothesis is H0: $corr^M(s_{i,t}, \epsilon_{i,t}) = corr^S(s_{i,t}, \epsilon_{i,t})$ and the alternative is H1: $corr^M(s_{i,t}, \epsilon_{i,t}) > corr^S(s_{i,t}, \epsilon_{i,t})$. I use the inverse hyperbolic tangent transformation (Fisher's z transformation) to map the correlation coefficients into variables that span the entire real line and ensure approximate normality of the test statistic.[18] The test statistic is

$$z_t = \frac{\operatorname{atanh}\left[corr^M(s_{i,t}, \epsilon_{i,t})\right] - \operatorname{atanh}\left[corr^S(s_{i,t}, \epsilon_{i,t})\right]}{\sqrt{1/\left(N_t^M - 3\right) + 1/\left(N_t^S - 3\right)}}. \tag{7}$$

The shading of the bars in Figure 2 indicates for each industry the number of sample years for which the null hypothesis is rejected at the 5 percent level. I am not able to reject the null hypothesis for all years and all industries, mainly due to a low number of observations in the pool of multi-plant firms in some industries.[19] Notwithstanding, the main results

[17] I opted for not to rewrite the whole decompositions in terms of the correlation coefficients in order to keep the terms simple and in line with the decompositions used in previous studies (Olley and Pakes, 1996; Bartelsman, Haltiwanger and Scarpetta, 2013).

[18] For more details on Fisher's z transformation and its implementation in STATA see Cox (2008).

[19] As explained in Section 2 and Appendix A my sample ensures a very good coverage of the population

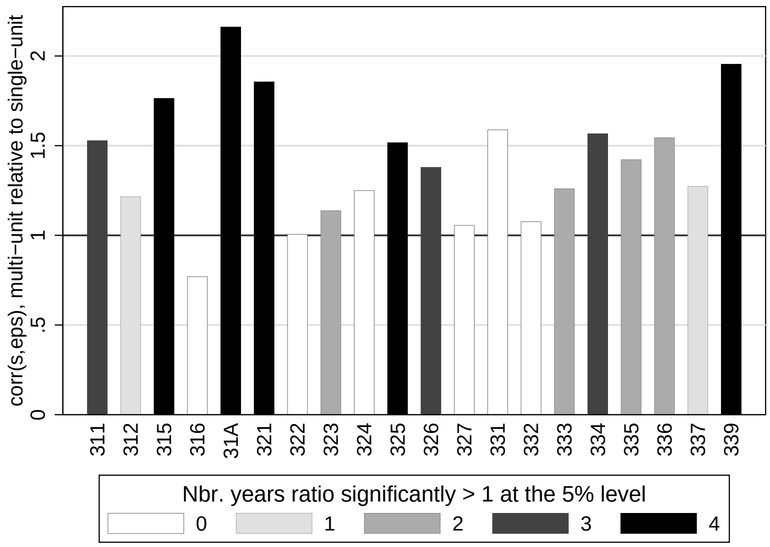


Figure 2: Ratio of correlation coefficients

seem reasonably robust to measuring the efficiency of allocation by correlation instead of covariance between plant size and productivity.

4 Implied Input Prices and Misallocation

In the second approach, I attempt to directly measure misallocation (proxied by the dispersion in the marginal products of inputs across plants) in each industry and year, and then test whether the misallocation is significantly lower in industry-years in which multi-plant firms account for a larger share of the economic activity. This approach is related to the large literature on dispersion in the marginal products of inputs across productive establishments (see e.g. Banerjee, Munshi and Duflo, 2003; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). The main idea is that if marginal products of inputs are not equalized across establishment, the aggregate output can be increased by simply reshuffling the existing inputs across plants. In other words, dispersion in marginal products results in misallocation: Some establishments with relatively high marginal products are operated at a scale that is too small, whereas other establishments with relatively low marginal prod-

of plants in the Canadian manufacturing sector in the selected sample years. Thus, the small number of plants in the pool of multi-plant firms in some industries is not likely due to sample limitations. It is rather a feature of the population of plants in those industries.

ucts are operated at a scale that is too large with respect to their optimal size that would maximize the aggregate output.

My strategy for quantifying this misallocation is to use a simple model of profit-maximizing plants to back out a measure of unobserved plant-specific input prices from plants' TFP-to-value-added ratios. The model implies that these implied input prices are equal to the marginal products of inputs. I then calculate the standard deviation of the implied input prices across plants in each industry and year and use it as a proxy for measuring misallocation.

To see how we can obtain a measure implied input prices from the data on value added and production inputs, consider a standard static profit maximization problem of plant i in industry j and year t that faces price of capital services $R_{i,j,t}$ and wage rate $W_{i,j,t}$. Solving for the unconditional input demands and replacing these input demands back in the production function we obtain

$$Y_{i,j,t} = \left[\exp\left(\epsilon_{i,j,t}\right) \left(\frac{\alpha_{j,t}}{R_{i,j,t}} \right)^{\alpha_{j,t}} \left(\frac{\beta_{j,t}}{W_{i,j,t}} \right)^{\beta_{j,t}} \right]^{\frac{1}{1-\alpha_{j,t}-\beta_{j,t}}}, \tag{8}$$

where $Y_{i,j,t}$ is the value added. Prices $R_{i,j,t}$ and $W_{i,j,t}$ are plant-year-specific and profit maximization implies they are equal to the marginal products of the respective inputs at plant i in year t. Taking the log of both sides of equation (8), we obtain a linear relationship between the (logged) output $y_{i,j,t}$ and (logged) TFP $\epsilon_{i,j,t}$

$$y_{i,j,t} = \frac{1}{1-\alpha_{j,t}-\beta_{j,t}} \left[\epsilon_{i,j,t} + \alpha_{j,t} \log \alpha_{j,t} + \beta_{j,t} \log \beta_{j,t} - \alpha_{j,t} \log R_{i,j,t} - \beta_{j,t} \log W_{i,j,t} \right]. \tag{9}$$

In my data, prices $R_{i,j,t}$ and $W_{i,j,t}$ are unobserved. However, equation (9) provides a way to back out a summary measure of these implied input prices using the estimated plant-level TFP $\epsilon_{i,j,t}$ and the calibrated input elasticities $\alpha_{j,t}$ and $\beta_{j,t}$ from Section 2.3 as

$$\begin{aligned} p_{i,j,t} &\equiv \alpha_{j,t} \log R_{i,j,t} + \beta_{j,t} \log W_{i,j,t} \\ &= \epsilon_{i,j,t} - \left(1-\alpha_{j,t}-\beta_{j,t}\right) y_{i,j,t} + \alpha_{j,t} \log \alpha_{j,t} + \beta_{j,t} \log \beta_{j,t}. \end{aligned} \tag{10}$$

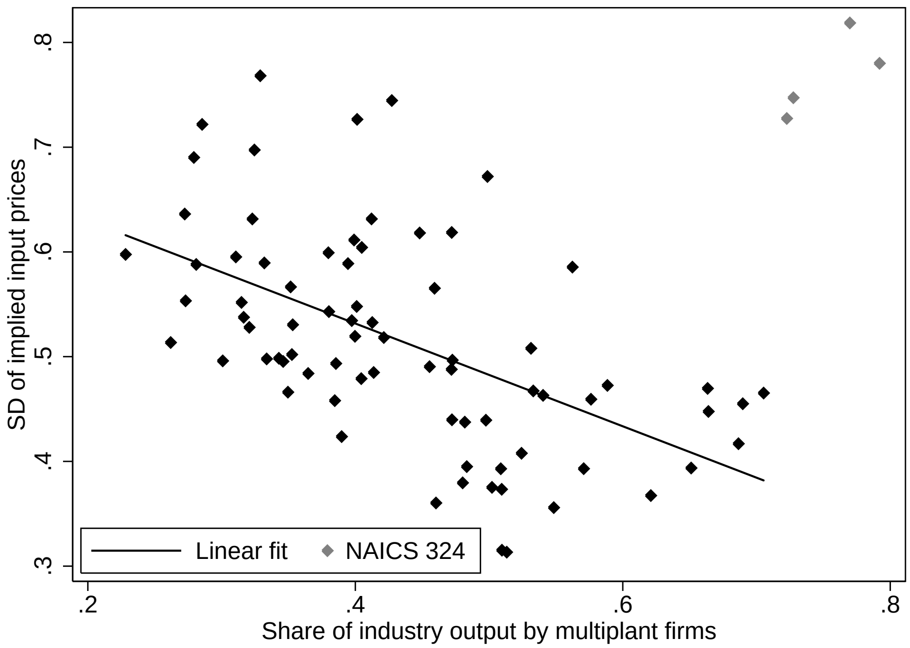


Figure 3: Dispersion in the implied input prices and the prevalence of multi-plant firms

Equation (10) shows that the cross-plant variation in the implied input prices will be inferred from the variation in plants' TFP-to-value-added ratios. For plants with a high ratio, the model interprets their relatively small size as reflecting the fact that they face high implied input prices. Similarly, through the lense of the model, plants with a low ratio are large not so much because they have high productivity, but because they face low implied input prices and as a result buy a lot of inputs.

I measure the dispersion in the implied input prices by calculating the standard deviation of $p_{i,j,t}$ in the cross section of plants in each 3-digit NAICS industry and year. If multi-plant firms help improve the allocation of resources, industry-years in which multi-plant firms account for a larger share of the output should display lower dispersion in the implied input prices. Figure 3 shows this statistically significant negative relationship. When calculating the regression line, I excluded NAICS 324 - Petroleum and coal product manufacturing, which is a clear outlier. The relationship remains negative and significant even when the analysis is repeated year by year (see Appendix C for figures).

An important caveat when interpreting my results is that the notion of misallocation employed here is relative to the setting in which plants have equalized marginal products. This would obtain, for example, if all plants were buying their inputs in an industry-wide perfectly competitive market and faced no distortions or additional costs limiting adjustments in their size. In reality marginal products can differ across plants for a number of reasons. Some of this variation comes from idiosyncratic distortions that create wedges between the marginal product of an input and its market price. These distortions can be created, for example, by credit constraints or size-dependent policies. Another part of the variation in the marginal products is due to the fact that the actual input prices may vary across producers. For example, labor or capital markets can be to some extent local, some plants may have some market power on the input markets, or there may be unobserved differences in input quality. Finally, non-convex size adjustment costs, such as inventory adjustment fixed costs or partial investment irreversibility, will also result in dispersion in the marginal products across plants. However, notice that although there are various possible sources of dispersion in marginal products, eliminating them and equalizing the marginal products would increase the industry-level output and TFP.

While implied price dispersion enables us to measure misallocation, studying the levels of implied prices provides hints on the sources and features of the misallocation. In Table 5, I pool the observations from all industries and years, and I regress $p_{i,j,t}$ on a dummy variable that is equal to one if the plant belongs to a multi-plant firm, a full set of industry and year dummies and their interactions, and plant size or productivity. The negative coefficient on the multi-plant dummy reveals that, depending on the regression specification, plants in multi-plant firms have, on average, the summary measure of implied input prices 14 to 20 percent lower than plants in single-plant firms.[20] In other words, plants in multi-plant firms seem to face substantially better input markets than plants in single-segment firms.

Another interesting result is that the coefficients on value added or TFP are always positive and statistically and economically significant.[21] On the one hand, the positive relationship between implied input prices and plant size or TFP may suggests that the idiosyncratic distortions that drive wedges between the marginal products and competitive

[20]The 14 and 20 percent correspond to 1-exp(coefficient of the multi-plant dummy).

[21]An increase of 1 percent in the value added is associated with an increase of $100 \times (\exp(0.126) - 1) = 13.4$ percent in the implied input prices. Similarly, an increase of 1 percent in a plant's TFP is associated with 128 percent increase in the implied input prices.

Table 5: Regressions of the measure of implied input prices

	(1)	(2)
Multi-plant dummy	$-0.151^{\star}$	$-0.218^{\star}$
	(0.009)	(0.002)
Log(value added)	$0.126^{\star}$	
	(0.001)	
Log(plant TFP)		$0.828^{\star}$
		(0.001)
Industry × year dummies	yes	yes
R^2	0.773	0.980
Nbr. observations	154,412	154,412

The dependent variable is the summary measure of the implied plant-specific input prices $p_{i,j,t}$ calculated from equation (10). Log(TFP) is the residual $\epsilon_{i,j,t}$ in the log-linearized Cobb-Douglas production function where the input elasticities were calibrated to the industry-year input cost shares. The multi-plant dummy is equal to one if the plant belongs to a firm that has more than one plant. Industry dummies are constructed on the 3-digit NAICS level. Robust standard errors corrected for clustering at the firm-year level are in parentheses; $\star$ indicates statistical significance at the 1 percent level.

input prices are *correlated*: Larger plants and plants with higher TFP face larger distortions. As shown by several studies (Restuccia and Rogerson, 2008; Guner, Ventura and Xu, 2008; Bartelsman, Haltiwanger and Scarpetta, 2013), this type of distortion has the potential to generate larger misallocation than uncorrelated distortions, and can have sizeable negative effects on aggregate TFP. In this light, my results suggest that firms with highly productive plants might use the conglomeration of several plants as an additional margin along which they adjust in order to mitigate the effects of the correlated distortions. On the other hand, recent studies in industrial organization literature note that the standard measures of implied input prices may still reflect demand or cost shocks even in a frictionless market, which could explain the positive correlation between the implied input prices and size or TFP (Foster, Haltiwanger and Syverson, 2016; Foster et al., Forthcoming).

Finally, I provide a quantification of the impact of the dispersion in marginal products on the aggregate industry-level TFP. I consider the experiment of reallocating production

Table 6: Decomposition of TFP loss implied by marginal products dispersion

	% TFP loss (averages over 2000-2003)			
Industry	$N_t \times$ $cov^S(s_{i,t}, \epsilon_{i,t})$	$N_t^M \left[cov^M(s_{i,t}, \epsilon_{i,t}) - cov^S(s_{i,t}, \epsilon_{i,t})\right]$	$N_t \times$ $cov(\bar{s}_t^g, \bar{\epsilon}_t^g)$	Total TFP
311 - Food	4.1	16.6	0.3	12.1
312 - Beverage, tobacco	−0.4	13.4	0.4	13.4
31A - Textile and textile products	17.7	−1.2	−1.3	15.1
315 - Clothing	7.4	6.8	0.6	14.8
316 - Leather and allied products	13.0	−2.1	−0.5	10.5
321 - Wood products	21.2	−0.3	−1.9	19.0
322 - Paper	27.4	−7.4	0.4	20.3
323 - Printing	12.0	5.9	0.1	18.0
324 - Petroleum, coal products	25.0	−10.5	0.1	14.6
325 - Chemicals	−0.7	19.4	0.4	19.0
326 - Plastics, rubber products	13.9	4.6	−0.3	18.2
327 - Non-metallic mineral products	19.6	−1.4	−1.0	17.3
331 - Primary metal	19.8	0.2	−1.5	18.6
332 - Fabricated metal products	25.1	−3.6	−1.5	20.0
333 - Machinery	21.3	1.3	−0.9	21.6
334 - Computer, electronic products	13.7	−1.1	−1.0	11.6
335 - Electrical equipment, appliances	3.4	7.0	0.2	10.6
336 - Transportation equipment	23.2	−5.2	−2.5	15.5
337 - Furniture and related products	20.0	1.7	−1.0	20.7
339 - Miscellaneous	7.8	10.2	1.0	19.0

The first three columns may not add up to the Total TFP loss in column four due to rounding.

Entries are $(x_{efficient} - x_{actual})/TFP_{efficient}$, where x is the particular quantity corresponding to each column of the table.

inputs across plants so that marginal products are equalized while keeping the aggregate quantity of each input and the plant-level productivities on their observed level. I calculate the hypothetical industry output and output shares of each plant in this scenario. From these quantities I obtain the value of the aggregate TFP index implied by equalization of marginal products, $TFP_{efficient}$. I then decompose $TFP_{efficient}$ according to equation (6) as in Section 3. I perform this experiment for each year and industry, calculating the gap between the values of the components of the actual and counter-factual industry-level TFP. I report in Table 6 the averages over the sample period of this gap expressed as percentages of the counter-factual TFP. The overall losses vary between 10 and 22 percent, and for a majority of industries they come mostly from too low covariance between plant output share and productivity among the single-plant firms (column 1 of Table 6).[22]

5 Cross-plant TFP Distribution and Internal Markets

In this section, I identify three basic testable implications of a standard efficient internal markets theory along the lines of Stein (1997) and Jovanovic and Rousseau (2002) for the relationship between plant-level productivity and size and check whether they are verified in the data. The plant productivity–size implications can be derived as a result of a basic selection mechanism present in any framework that shares two key elements: first, more efficient internal markets for resources inside multi-plant firms than external markets and, second, endogenous selection of plants into multi-plant firms in the spirit of the Q theory of mergers (see Jovanovic and Rousseau, 2002). I now state the testable implications and provide the basic intuition behind each. An illustration of how we can derive these implications in a simple stylized model of business conglomeration is provided in Appendix D. If we look at the cross-sectional distribution of productivity, the three testable implications of multi-plant conglomeration with efficient internal markets are as follows:

Implication 1 *There should be a higher proportion of high-productivity plants in multi-plant firms than in single-plant firms.*

[22] There is no TFP loss on the average productivity terms ϵ^S and ϵ^M since in the counter-factual experiment I keep the plant-level productivities on their actual level.

Implication 2 *Among small plants, there should be a lower proportion of high-productivity plants in multi-plant firms than in single-plant firms.*

Implication 3 *Among large plants, there should be a higher proportion of high-productivity plants in multi-plant firms than in single-plant firms.*

Implication 1 is the result of the endogenous selection of plants into multi-plant firms. The intuition is that the gain from the internal reallocation of resources to high-productivity plants is more likely to be high, which makes them desirable partners for multi-plant conglomeration. Implications 2 and 3 result directly from more efficient transfers of resources to their most productive use inside multi-plant firms. As discussed in Section 3, if the allocation of resources across plants is more efficient in the group of plants in multi-plant firms than in the group of plants in single-plant firms, there will be a higher correlation between plant size and plant-level TFP within the group of plants in multi-plant firms. In particular, if a plant in a multi-plant firm is small, it should be relatively less productive compared to plants of similar size in single-plant firms. The same argument implies that if a plant in a multi-plant firm is large, it should be relatively more productive than plants of similar size in single-plant firms.

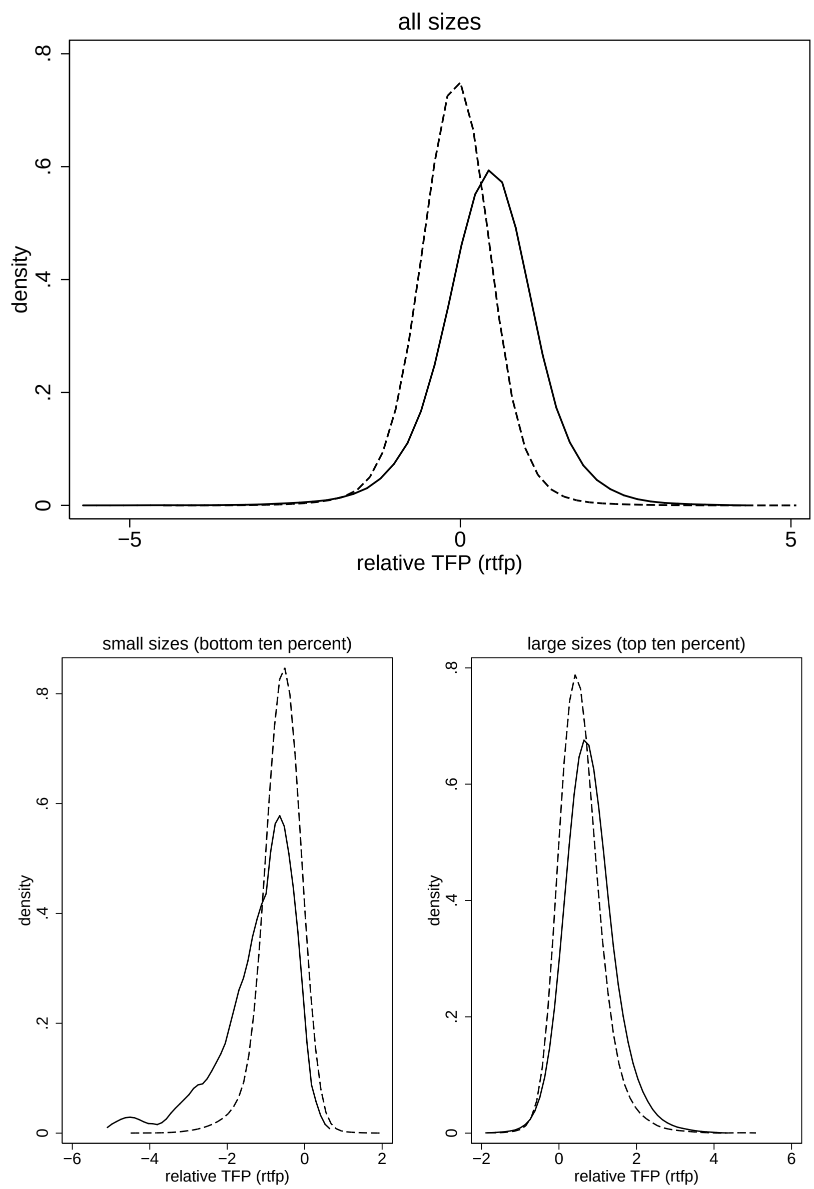
I examine the empirical TFP distribution to verify whether the data support the theory's predictions. In particular, I use non-parametric smoothing kernels to estimate and compare the plant-level TFP distributions for multi-plant and single-plant firms in different size categories. One concern with comparing plant-level TFP for multi- and single-plant firms is the endogenous selection of multi-plant firms into specific industries. Since I calculate $\epsilon_{i,j,t}$ as the residual from the Cobb-Douglas production function that is calibrated separately for each 3-digit NAICS industry-year, my measure of the plant-level TFP includes an industry-year-specific component. Thus, if multi-plant firms are more present in some industries than others, the TFP distributions for multi- and single-plant firms may not be directly comparable. In order to address this concern and meaningfully represent the TFP distribution across plants in different industries and years, I first construct a relative TFP measure as

$$rtfp_{i,j,t} \equiv \epsilon_{i,j,t} - \epsilon^{pred}_{i,j,t}, \tag{11}$$

where $\epsilon_{i,j,t}$ is the logged plant-level TFP recovered from the production function, and $\epsilon_{i,j,t}^{pred}$ is the adjusted linear prediction from the regression of $\epsilon_{i,j,t}$ on the multi-plant dummy, plant size (deflated value added), plant age, and the full set of industry and year dummies and their interactions. The prediction is adjusted by setting the values of the multi-plant dummy and the plant size to the sample averages of these variables. The $rtfp_{i,j,t}$ is the log (that is percent) difference in the TFP between plant i and the average TFP computed at the level of industry-year fixed effects conditional on the plant's age.

The top panel in Figure 4 presents the estimates of the distributions of $rtfp$ unconditional on the plant production size. Consistent with Implication 1, the unconditional distribution features a larger mass of high-productivity plants in multi-plant firms. The bottom panel in Figure 4 gives the estimates of the $rtfp$ distributions for small and large plants. The small class includes the plants in the bottom decile of the value added distribution in the plant's industry, whereas the large class includes the plants in the top decile of the value added distribution in the plant's industry. The estimates show exactly the composition effect predicted by Implications 2 and 3 of the theory of efficient internal markets. In the small class, there is a smaller mass of highly productive plants in multi-plant firms than in single-plant firms. In the large class, the mass of highly productive plants is larger in multi-plant firms than in single-plant firms.[23] The estimates of the plant TFP distributions indicate that all three testable implications of the efficient internal markets are verified in the data. I interpret this as an additional piece of evidence in support of the better allocation of resources inside the group of plants in multi-plant firms. These results are fairly robust. In particular, qualitatively similar figures and conclusions are obtained when different percentiles of the size distribution are used as the cut-offs for defining the small and large classes (see Appendix E for a top/bottom quartile cut) and definitions of the size classes that are not industry specific are used.

[23] In all panels of Figure 4, the Kolmogorov-Smirnov test rejects equality of the density functions at the 1 percent level.



Epanechnikov kernel, bandwidth = 0.25. Solid line - multi-plant firms. Dashed line - single-plant firms.

Figure 4: Relative TFP distribution in the data

6 Concluding Remarks

This paper provided new empirical evidence on the role of multi-plant firms for the allocation of production inputs and outcomes across plants in an industry and for the level of aggregate productivity. The main conclusion is that multi-plant firms account for a non-negligible part of the industry-level aggregate TFP and their contribution stems primarily from better cross-plant allocation of inputs and production.

This study provided the first look into the role of multi-plant firms for aggregate productivity, and I believe that there is much left to be done in this line of research. First, we need to understand in more detail the functioning of the internal allocation of resources inside firms. For example, how do internal markets influence production and investment dynamics? What is their role in dampening or amplifying of external shocks? These questions are crucial for evaluating eventual policy interventions and external market regulations. A promising step in this direction is the recent work of Kehrig and Vincent (2013). Second, although internal markets are a well-recognized feature of multi-plant firms, they are not the sole reason for business conglomeration. Other theories whose implications for allocative efficiency are worth examining empirically include vertical integration as a solution to hold-up problems and horizontal mergers as a means of realizing economies of scale or scope.

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A ASM Data Files History and Sample Period

The ASM started in 1985 as an exhaustive census of manufacturers. Later, it evolved into a survey with some records inferred from administrative tax data and some records imputed from industry-level aggregate data to ensure the representativeness of the file. All observation weights in the ASM are equal to 1. However, Statistics Canada analysts do not consider the quality of the imputed records sufficient for micro-data research purposes.

In 2000, the ASM became part of the Enterprise Survey Program, and it adopted the Business Register as its new sampling frame. As a result, the coverage and the representativeness of the ASM substantially improved, and a large number of additional, mostly smaller plants were included in the survey. During the years 2000-2003, the ASM covered almost exhaustively the universe of plants in the Canadian manufacturing sector, and the imputed records accounted only for a very small fraction of the data.

In 2004, due to the need to cut costs, Statistics Canada decided not to survey the bottom 10% of plants in each industry and province. These records were instead replaced by imputing from aggregate data. Therefore, in the years following 2003, there is a relatively lower number of smaller plants in the survey than in the actual distribution in Canadian manufacturing. This lead me to concentrate on the period 2000-2003, which ensures the best possible coverage and representativeness of the sample. I have verified that the results remain qualitatively unchanged when extending the sample period to 1997-2006.

B Decomposition of the Aggregate Covariance Term

Developing and rearranging the A_t^M term, we obtain[24]

$$A_t^M = \sum_{i \in M_t} \left(s_{i,t} - \bar{s}_t^M\right)\left(\epsilon_{i,t} - \bar{\epsilon}_t^M\right) + \left(\bar{s}_t^M - \bar{s}_t\right) \sum_{i \in M_t} \epsilon_{i,t} - \bar{\epsilon}_t \sum_{i \in M_t} s_{i,t} + N_t^M \bar{s}_t \bar{\epsilon}_t.$$

[24]This calculation uses the fact that $\sum_{i \in M_t} s_{i,t} - N_t^M \bar{s}_t^M = 0$.

Applying the same development for the A_t^S term and adding the two expressions, we obtain the following expression for the aggregate covariance term:

$$N_t cov\left(s_{i,t},\epsilon_{i,t}\right)=\sum_{i\in M_t}\left(s_{i,t}-\bar{s}_t^M\right)\left(\epsilon_{i,t}-\bar{\epsilon}_t^M\right)+\left(\bar{s}_t^M-\bar{s}_t\right)\sum_{i\in M_t}\epsilon_{i,t}+$$
$$\sum_{i\in S_t}\left(s_{i,t}-\bar{s}_t^S\right)\left(\epsilon_{i,t}-\bar{\epsilon}_t^S\right)+\left(\bar{s}_t^S-\bar{s}_t\right)\sum_{i\in S_t}\epsilon_{i,t}.$$

Dividing and pre-multiplying each term by the number of plants in each respective set of plants, we obtain:

$$N_t cov\left(s_{i,t},\epsilon_{i,t}\right)=N_t^M cov^M\left(s_{i,t},\epsilon_{i,t}\right)+N_t^S cov^S\left(s_{i,t},\epsilon_{i,t}\right)+$$
$$N_t^M\left(\bar{s}_t^M-\bar{s}_t\right)\bar{\epsilon}_t^M+N_t^S\left(\bar{s}_t^S-\bar{s}_t\right)\bar{\epsilon}_t^S, \quad (12)$$

where the notation $cov^g\left(s_{i,t},\epsilon_{i,t}\right)\equiv {}^1/_{N_t^g}\sum_{i\in g_t}\left(s_{i,t}-\bar{s}_t^g\right)\left(\epsilon_{i,t}-\bar{\epsilon}_t^g\right)$ is the covariance of the output shares and productivity *within* the set of plants g. Finally, notice that the last term in equation (12) can be rewritten as[25]

$$N_t^M\left(\bar{s}_t^M-\bar{s}_t\right)\bar{\epsilon}_t^M+N_t^S\left(\bar{s}_t^S-\bar{s}_t\right)\bar{\epsilon}_t^S=N_t^M\left(\bar{s}_t^M-\bar{s}_t\right)\left(\bar{\epsilon}_t^M-\bar{\epsilon}_t\right)+N_t^S\left(\bar{s}_t^S-\bar{s}_t\right)\left(\bar{\epsilon}_t^S-\bar{\epsilon}_t\right).$$

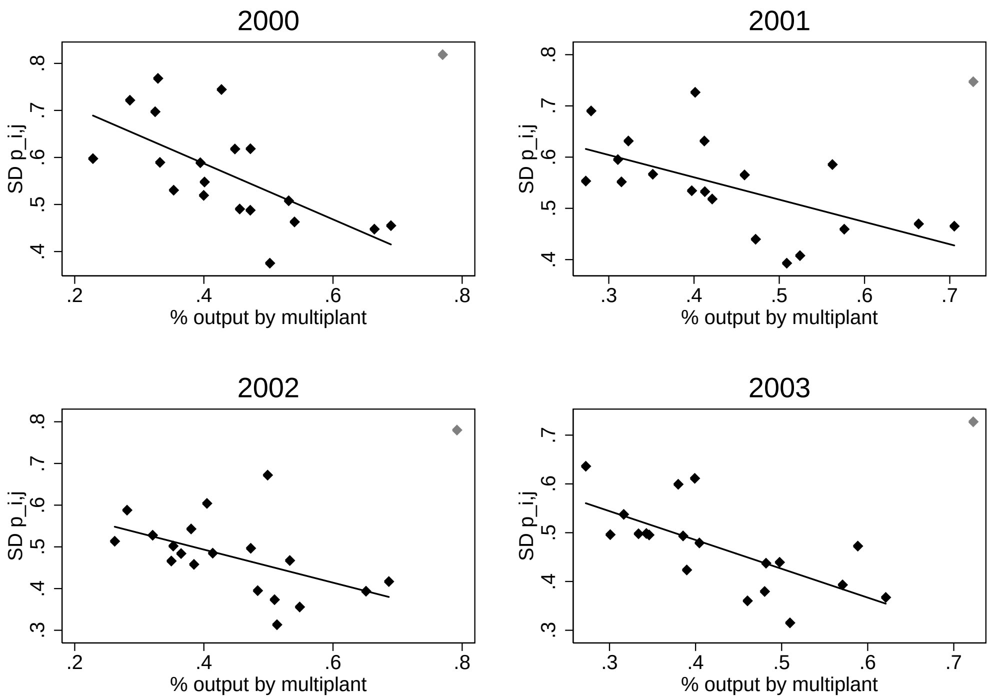
Thus, multiplying and dividing this last term by N_t, we can rewrite it as a function of the covariance of the average output shares and average productivities across the two sets of plants $cov\left(\bar{s}_t^g,\bar{\epsilon}_t^g\right)\equiv {}^1/_{N_t}\sum_g N_t^g\left(\bar{s}_t^g-\bar{s}_t\right)\left(\bar{\epsilon}_t^g-\bar{\epsilon}\right)$. The resulting final form for the decomposition of the covariance term is

$$N_t cov\left(s_{i,t},\epsilon_{i,t}\right)=\underbrace{N_t^M cov^M\left(s_{i,t},\epsilon_{i,t}\right)}_{\text{efficiency within } C}+\underbrace{N_t^S cov^S\left(s_{i,t},\epsilon_{i,t}\right)}_{\text{efficiency within } S}+\underbrace{N_t cov\left(\bar{s}_t^g,\bar{\epsilon}_t^g\right)}_{\text{efficiency between groups}}.$$

C Dispersion in implied Input Prices

Figure 5 shows the relationship between the dispersion in the implied input prices and the share of the industry output produced by multi-plant firms for each year in the sample.

[25] This calculation uses the fact that $-N_t^M\bar{s}_t^M\bar{\epsilon}_t+N_t^M\bar{s}_t\bar{\epsilon}_t-N_t^S\bar{s}_t^S\bar{\epsilon}_t+N_t^S\bar{s}_t\bar{\epsilon}_t=\left(N_t^M+N_t^{SA}\right)\bar{s}_t-N_t^M\bar{s}_t^M-N_t^S\bar{s}_t^S=0$.



NAICS 324 - Petroleum and coal product (grey point) is not included in the calculation of the regression line.

Figure 5: Dispersion in implict input prices and prevalence of multi-plant firms

D A Model of Efficient Internal Markets

This section illustrates the link between the cross-sectional relationship of plant size, productivity, and multi-plant conglomeration within a simple stylized model. Consider a continuum of measure one of plants, each characterized by a productivity parameter $z_i \in \{z_L, z_H\}$ and an endowment of $a_i \in \{1, 2, 3\}$ units of a resource that is used as the input in the production process. Suppose that $z_L < z_H < 2z_L$. In addition, z_i and a_i are independently and identically distributed across plants, and the plants of each (z_i, a_i) type represent an equal proportion $(\frac{1}{6})$ of the total plant population. The production function at the plant level features decreasing returns and is given by

$$y_i = \begin{cases} z_i k_i & \text{if } k_i < 2, \\ 2z_i & \text{if } k_i \geq 2, \end{cases} \tag{13}$$

where k_i is the amount of resources used as the production input at the plant.[26] In general, k_i may be different from a_i. Plants may be operated either as single-plant firms or as a part of multi-plant firms. I am interested in how the firms' organizational structure affects the allocation of the available aggregate resources to various plants.

As a benchmark, notice that, in order to maximize the aggregate output, a central planner would allocate two units of the resource to each plant. This is efficient allocation, leading to the maximum aggregate level of output $Y^P = z_H + z_L$. When individual plants maximize their profits, this allocation can be supported by an appropriate price in a frictionless market for the resource.[27]

In practice, various frictions, such as private information or limited enforcement of contracts, hinder the allocation of the resource through the external market. In particular, some "poor" plants may not be able to raise two units of the resource and may end up being operated on a smaller-than-optimal scale. At the same time, some "rich" plants may not be able to sell/lend their surplus resources, and consequently, a part of the resources may end up unexploited. Because the frictions are specific to the external market, they can be mitigated by trading in internal markets within multi-plant firms.

To illustrate the mechanism in the simplest way, I make a set of stark assumptions, all of which can be generalized without affecting the main qualitative predictions of the model. First, I assume that the frictions lead to a complete breakdown of the external market (as in Akerlof, 1970), but they do not affect transactions in the internal markets.[28] Second, the

[26] The setup is designed to have the minimum heterogeneity in the productivity and endowments across plants that will allow it to exhibit the main selection and sorting mechanism. Having three levels of endowment, together with the particular decreasing returns to scale technology, allows the model to feature not only efficient internal transfers from unconstrained low-productivity plants to constrained high-productivity plants but also efficient internal transfers from unconstrained high-productivity plants to severely constrained low-productivity plants. The extreme form of decreasing returns, as well as the uniform distribution of resource endowments and productivity, are assumed for simplicity. The main results go through in a more general setup, but the exposition would require numerical simulations. See Ševčík (2015) for a quantitative dynamic general equilibrium model in which the production function is a Cobb-Douglas combining capital and labor, and the factor prices and the distribution of the resources are endogenously determined in a stationary equilibrium.

[27] Any price in $(0, z_L]$ can support efficient allocation.

[28] The necessary condition for the mechanism to work is that the frictions that affect internal markets are less severe than those on the external market. As long as this condition is satisfied, the qualitative implications of the model go through, even if the external market does not break down completely and there are some frictions in the internal markets.

scope of internal markets is limited to two plants.[29] Finally, I assume the following specific method for creating the internal markets. Potential partners (i.e., owner-managers of the individual plants) meet randomly in pairs. Once the partners meet, they observe each other's productivity and resource endowments and decide whether they will form a multi-plant firm or operate their projects as two stand-alone single-plant firms.[30] The difference between the two arrangements is that plants in a multi-plant firm can pool their resources, whereas each single-plant firm must rely solely on the resources it owns. The objective of a multi-plant firm is to maximize the joint surplus, which is then shared between the partners according to some sharing rule.[31] The decision whether to stay together is therefore made by comparing the joint profits under the multi-plant firm to the sum of the profits that the two plants would obtain if they were operated as separate single-plant firms. As a tie-breaking rule, assume that if both arrangements yield the same joint profits, then separate single-plant firm operation is preferred.[32]

The maximization of the joint surplus implies that, inside a multi-plant firm, each unit of resources will be allocated to the plant in which its marginal product is the highest. As a result, there will be three basic types of multi-plant firms. First, there are multi-plant firms featuring plants with the same level of productivity and different resource endowments in which at least one plant would be more resource constrained if it were operated as a single-segment firm. These firms are characterized by (z_i, a_i, z_j, a_j) such that

$$z_i = z_j \text{ and } (a_i < 2 < a_j \text{ or } a_i > 2 > a_j). \tag{14}$$

These situations are depicted as the shaded regions in the left panel of Figure 6. The pattern of the shading shows the direction of the transfers in the internal markets.

Multi-plant firms of the second type feature plants with different productivities in which

[29] In principle, the model can be generalized to allow a larger scope of multi-plant firms.

[30] An alternative to random matching would be to consider a competitive mergers and acquisition market, as in Jovanovic and Rousseau (2002). Similar to the results obtained here, the competitive market would ensure that only the mergers in which the gains from reallocation of the resource are high enough would be realized.

[31] The exact form of the sharing rule is not important; it might be determined, for example, by a Nash bargain.

[32] This can be justified by considering some arbitrarily small fixed cost of creating a multi-plant firm.

the plant with higher productivity would be more resource-constrained if it were operated as a single-segment firm. These firms are characterized by (z_i, a_i, z_j, a_j) such that

$$z_i > z_j \text{ and } a_i < 2. \tag{15}$$

These situations are depicted as the horizontally shaded region in the right panel of Figure 6. Of course, in this case, the resources flow from the less productive plant j to the more productive plant i.

Finally, the third-type multi-plant firms feature plants with different productivities in which the plant with lower productivity would be more resource-constrained if it were operated as a single-plant firm, and due to this constraint, it has a higher marginal productivity. In the model, these firms are characterized by (z_i, a_i, z_j, a_j) such that

$$z_i > z_j \text{ and } a_i > 2 > a_j. \tag{16}$$

They are depicted as the vertically shaded region in the right panel of Figure 6.[33]

With the assumption of the discrete uniform distributions of the productivities and resource endowments, there are $(2 \times 3)^2 = 36$ possible quadruples (z_i, a_i, z_j, a_j), each describing the characteristics of a possible match and each occurring with the same probability $\frac{1}{36}$. Figure 7 shows the optimal organizational form and production size decisions for all of these possible outcomes of the partner matching. The first row and column give the types of potential partners, and each cell in the subsequent rows and columns corresponds to one possible match. The numbers in each cell indicate the optimal production size of each plant, given the optimal organizational form of the firm(s). The shading corresponds to the situations in which it is optimal to operate as a multi-plant firm. The cells that are not shaded correspond to situations in which the two plants are optimally operated as separate single-plant firms.

The assumption regarding the ordering of productivities, $z_L < z_H < 2z_L$, ensures the

[33]Notice that, although the exact inequalities characterizing each type of multi-plant firm are specific to the simple model with the linear production function, the same type of taxonomy for multi-plant firms would be obtained in a more general setting, provided that the technology has decreasing returns at the plant level and that internal markets are less affected by the frictions that hinder the allocation of the resource than the external market. For example, the taxonomy applies when the plant-level production function is a Cobb-Douglas and/or the scope of multi-plant firms is allowed to be any finite number of plants.

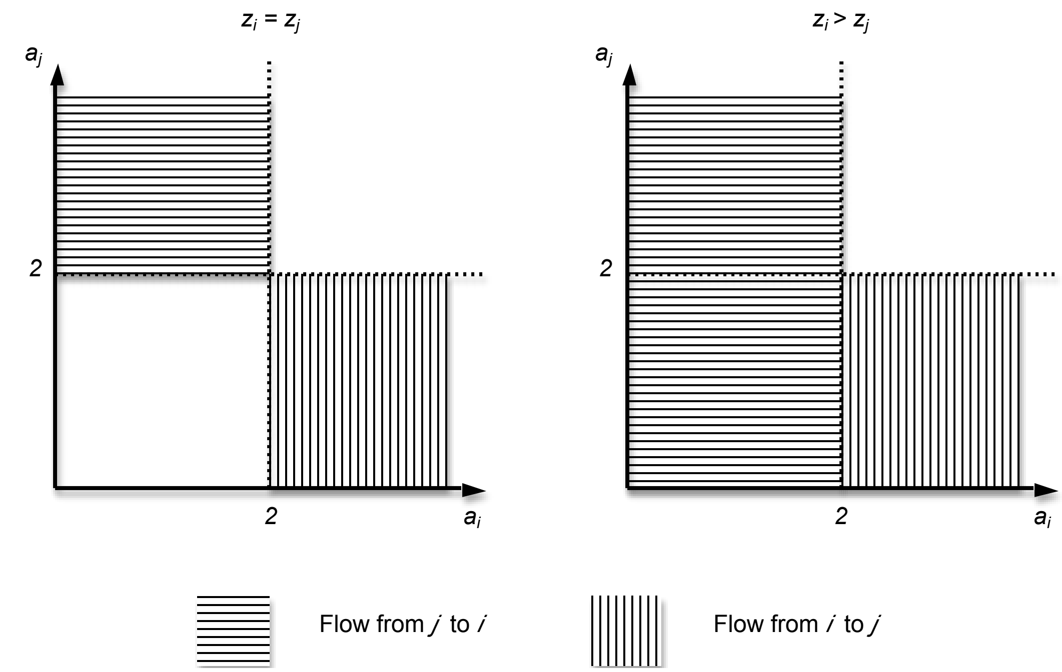


Figure 6: Conglomeration decision

	$(z_H, 1)$	$(z_H, 2)$	$(z_H, 3)$	$(z_L, 1)$	$(z_L, 2)$	$(z_L, 3)$
$(z_H, 1)$	z_H z_H	$2z_H$ z_H	$2z_H$ $2z_H$	0 $2z_H$	z_L $2z_H$	$2z_L$ $2z_H$
$(z_H, 2)$	z_H $2z_H$	$2z_H$ $2z_H$	$2z_H$ $2z_H$	z_L $2z_H$	$2z_L$ $2z_H$	$2z_L$ $2z_H$
$(z_H, 3)$	$2z_H$ $2z_H$	$2z_H$ $2z_H$	$2z_H$ $2z_H$	$2z_L$ $2z_H$	$2z_L$ $2z_H$	$2z_L$ $2z_H$
$(z_L, 1)$	$2z_H$ 0	$2z_H$ z_L	$2z_H$ $2z_L$	z_L z_L	$2z_L$ z_L	$2z_L$ $2z_L$
$(z_L, 2)$	$2z_H$ z_L	$2z_H$ $2z_L$	$2z_H$ $2z_L$	z_L $2z_L$	$2z_L$ $2z_L$	$2z_L$ $2z_L$
$(z_L, 3)$	$2z_H$ $2z_L$	$2z_H$ $2z_L$	$2z_H$ $2z_L$	$2z_L$ $2z_L$	$2z_L$ $2z_L$	$2z_L$ $2z_L$

Figure 7: Production size of plants in the model

following ordering of production sizes: $z_L < z_H < 2z_L < 2z_H$.[34] Given this, it is natural to consider two size classes: "small" sizes with $y_i < 2z_L$ and "large" sizes with $y_i \geq 2z_L$. In line with the empirical evidence, plants in multi-plant firms are more present in the large size category ($\frac{19}{22}$ of plants with output greater than zero in multi-plant firms are large, whereas in single-plant firms, this proportion is $\frac{19}{24}$).

Figure 8 depicts the distribution of productivity across plants, conditional on the firm's organizational structure. The top panel shows that among the plants in operation under multi-plant firms (conglomerates), a higher proportion ($\frac{10}{22}$) are of high productivity z_H than among the plants operated as single-plant firms (where this proportion is $\frac{19}{48}$). The intuition behind this result is that highly productive plants are more likely to select into multi-plant firms, because the gain from the internal reallocation of resources toward these plants is more likely to be high. Therefore, average plant productivity is higher in multi-plant firms than in single-plant firms.

The two bottom panels in Figure 8 show the productivity distributions conditional on the size category. One result particularly stands out: None of the small-sized plants in multi-plant firms is of the high-productivity type z_H. This is a consequence of internal reallocation within multi-plant firms: The appropriate amount of resources is always transferred internally so that the highly productive plant is exploited on an efficient (large) size. If we look at the cross-sectional distribution of productivity by size class, the two testable implications of such efficient internal transfers are the following:

1. In the small class, there is a lower proportion of high-productivity plants in multi-plant firms than in single-plant firms, and, conversely,

2. in the large class, there is a higher proportion of high-productivity plants in multi-plant firms than in single-plant firms.

[34]Some plants in the multi-plant firms will give all of their resources to their more productive partner and, therefore, will have production size equal to zero. I ignore these plants, since they will also be "invisible" in the empirical micro-data.

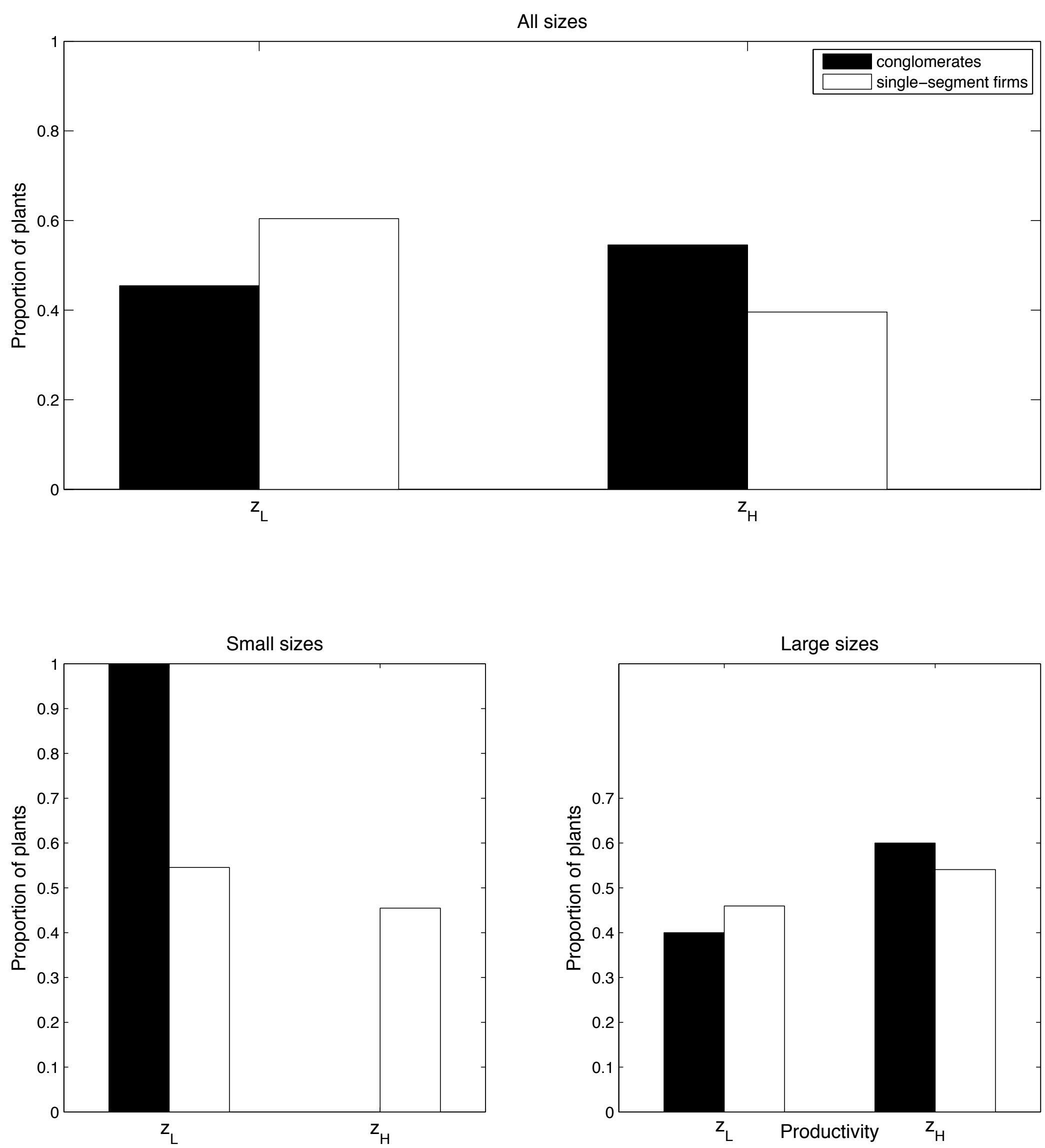
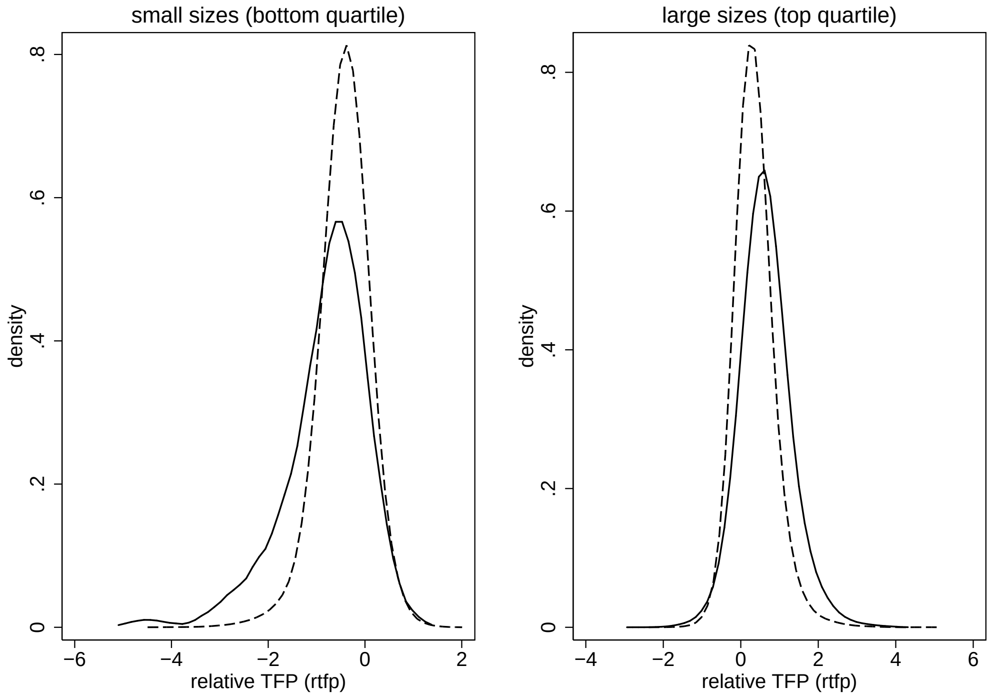


Figure 8: Productivity distribution in the model

E Relative TFP Distrubution - Robustness

Figure 9 shows the estimates of the distribution of the plant-level relative TFP when size classes' cut-offs are defined by the top and bottom quartiles of the value added distribution.



Epanechnikov kernel, bandwidth = 0.25. Solid line - multi-plant firms. Dashed line - single-plant firms.

Figure 9: Relative TFP distribution in the data