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Abstract

Are diversified firms mere collections of independent assets, or is there anything that glues together different businesses? We explore this question by looking at segment level growth of multi-segment (i.e., producing in several 6-digit industries at the same time) manufacturing firms in Japan. We find substantial co-movement between such segments and show that it can be driven by plant-wide but not firm-wide shocks. Our findings suggest that inputs that are shared firm-wide, such as brand and organizational routines, are not too important for production.

Keywords: Multi-segment firms, Growth of segments

JEL classification: L11, L23

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[1]This study is conducted as a part of the Project "Policy history and policy assessment" undertaken at Research Institute of Economy, Trade and Industry(RIETI). This study utilizes the micro data of the questionnaire information based on "Census of Manufactures" which is conducted by the Ministry of Economy, Trade and Industry (METI), and the Census of Manufactures converter, which is provided by the Research Institute of Economy, Trade and Industry (RIETI). The author is grateful for helpful comments and suggestions by Discussion Paper seminar participants at RIETI.

1 Introduction

Much economic activity happens in multi-segment firms—firms that operate in multiple industries at the same time (Bernard et al., 2010). Moreover, reallocation across products within multi-segment firms has been cited as a mechanism for productivity gains after a competition shock, such as trade liberalization (Bernard et al., 2011; Mayer et al., 2014). But is the distinction between single- and multi-segment firms a conceptual or technical one? Are multi-segment firms mere collections of independent production assets, or what glues different segments together?

A variety of candidate mechanisms have been proposed in the economics, finance, and business literatures, ranging from internal capital markets (Stein, 1997) to management (Lucas, 1978) and tacit knowledge (Teece, 1982). The nature of the linkages between segments is fundamental to the theory of the firm boundaries. Neoclassical theory imagines a first-best world of efficient resource allocation unaffected by integration decisions, whereas modern theories stress how redrawing the boundaries may have real consequences (Hart, 1995). Intra-firm linkages are also important for our understanding of what determines productivity and firm growth. For example, is the quality of the top management, who oversee operations of the entire firm, a key factor of production, or are plant managers generally more important because of decentralization of decisions? From the macroeconomic perspective, do large multi-segment firms make the economy "more correlated," in a similar way as global firms can increase co-movement of business cycles (Kleinert et al., 2015; Cravino and Levchenko, 2015)? Finally, empirical research which uses economy-wide datasets, e.g. in the international trade literature, has to take a stand on how to treat and model multi-segment firms. What is the simplest model of them that can fit the data?

This papers starts with the observation that different views on multi-segment firms have differential implications for the interdependencies between segments' growth trajectories. We focus on interdependencies of two types: first, whether there are shocks that affect all firm segments simultaneously, and second, whether a shock to an individual segment affects growth of other segments of the same firm. The former is a variance decomposition question, whereas the latter is causal. We discuss predictions by different models later but for one, if the value of the brand is an important determinant of firm profits, then any shock to the brand, e.g. from a public scandal, affects sales in all segments at the same time. Furthermore, when a segment wants to scale up due to a positive demand shock, the firm may invest in improving its brand, which leads to expansion of other segments, too.

This mechanism works for any shared resource that is non-rival within the firm, at least partially. The opposite prediction holds in models with inputs constrained at the firm-level, at least in the short run.

Careful analysis of multi-segment firms is often hampered by data availability: most firm-level datasets do not decompose activity of the firm by industry (e.g. Dun & Bradstreet's WorldBase, cf. Alfaro and Charlton, 2007), and many of them only specify the primary industry of each firm.[1] To circumvent such problems, we employ the Japanese Census of Manufactures which disaggregates firm sales by establishment (plant) and detailed 6-digit industries, enabling us to track segment growth over the period of 1992-2006.

Trajectories of firm segments appear to co-move substantially: the correlation between growth of two random segments in a firm is around 14%. This is equivalent to 14% of the variance in segment growth explained by firm dummies,[2] compared to under 5% explained by the industry and mere 1% by the aggregate business cycle.

However, we show that interpreting this correlation as reflecting firm-wide shocks is misleading. We first contrast plant-wide and firm-wide shocks. We establish that co-movement of segments is much stronger within a plant than across plants, while any firm-wide changes (e.g. replacement of a CEO) should affect all segments, whether or not they belong to the same establishment. The gap between the within- and across-plant correlations is not driven by compositional effects. Interestingly, co-movement of sales in the *same* industry across plants is strong (12%), consistently with the existence of shocks to the entire firm's production of a given product.

Moreover, for firms which went through a non-horizontal merger, we find that co-movement between their plants already exists *before* the deal. This evidence is inconsistent with shocks to brand or top management as an explanation for the across-plant co-movement. It suggests that preexisting similarity may be driving co-movement, although it is also consistent with contractual relationship between to-be-merged firms. Overall, our results on co-movement favor neoclassical theory of the firm over theories based on informational frictions (e.g., internal capital markets) or management and authority.

We then move on to measure transmission of segment-level shocks across segments. For a firm f which produces in industries i and j, we use the average growth of standalone

[1] One of the few exceptions, the Compustat Business Segment file, has raised many quality concerns, especially until the segment reporting rule SFAS 131 was introduced in in 1997 (cf. Villalonga, 2004; Berger and Hann, 2002).

[2] We show the equivalence of these two interpretations in Appendix A.

(single-segment) firms in j as a shock to the jf segment and look at how it impacts segment if, controlling for the shock to its own industry i. We find a positive, statistically significant, and sizable effect, which is consistent with the theories based on non-rival shared inputs. However, the strength of this effect is invariant to the relative size of the segments, which is a puzzle for all our theories.

Our findings overall suggest that quantitatively important linkages happen mostly within plants. This conclusion should not be confused with a claim that internal capital markets, CEO skills, or brand value are always irrelevant—a lot of research has shown otherwise (cf. Stein 2003; Bertrand and Schoar 2003). However, our findings suggest that plant-level shared resources, such as plant manager's skill or indivisible machines, are more important for segment productivity in multi-segment firms.

In Section 2, we discuss theoretical predictions about inter-segment linkages. Section 3 introduces the data. Then, in Sections 4 and 5 we explain the methodology and show the empirical results on firm-wide shocks and inter-segment transmission of shocks, respectively. Section 6 locates our results in the literature, and Section 7 concludes.

2 Conceptual Framework

2.1 Co-Movement between Segments

Why can one expect different segments in the firm to co-move, and how can we distinguish between different potential explanations? The simplest answer is that firms tend to produce in related industries, which can be subject to correlated shocks. For example, both computers and tablets require a processor, so technological progress in processors will reduce both MacBook and iPad production costs, as well as costs of their competitors. Similarly, firms cluster geographically, so same location shocks will relatively more often affect segments of the same firm. We are not interested in these types of clustering, so we will control for it by looking at the segments' performance *relative to* their industry or location.

Our candidate explanation for the remaining co-movement is based on firm's shared resources. Panzar and Willig (1981) pose that "when there are economies of scope, there exists some input [...] which is shared by two or more product lines without complete congestion." Shock to these resources will influence various firm's segments at once. Some of them, such as the CEO skills, brand value, organizational routines, or cash, are shared at the corporate level. Therefore, shocks to them, such as a change of the CEO or to firm-specific cost of capital should affect segments in the same plant or in different plants alike. Other resources are shared only by segments within a plant. Some of these relate to technological synergies, for example a flexible machine that can be used in different production lines. Changes in plant management in decentralized organizations can also lead to co-movement.

The distinction between firm- and plant-wide co-movement is important from the theory of the firm point of view. The neoclassical theory of the firm is based on operational synergies and therefore allows only for plant shared resources. Modern theories, on the other hand, emphasize informational frictions, agency frictions, and the role of authority, mostly predict firm-wide co-movement.The importance of plant management is an important exception.

2.2 Intra-Firm Transmission of Shocks

In the previous section we described what can explain co-movement between segments. But another set of, arguably more subtle, predictions by various theories is on how shocks to one segment affect others.

Obviously, if production is simple neoclassical whereby inputs are acquired in competitive markets and combined to produce outputs, a demand shock to one segment should have no effect on production or sales of others. More interestingly, there would be no transmission of shocks between segments if there are shared resources but they are unaffected by segment shocks. For example, all segments' productivity may depend on the CEO's health but to the extent that demand shocks do not influence health, this does not create any transmission of shocks. The model by Bernard et al. (2011) follows that approach by imagining a firm that is trying to enter all possible industries at the same time. But then the firm learns its "core productivity" (possibly driven by exogenous shared resources) and productivity shifters in each industry, and starts actual production only in the industries it is sufficiently good at, as in Melitz (2003). In a model like this, shocks to individual segments affect production of those segments only, although there may also exist shocks which affect the entire firm simultaneously.

However, exogeneity of all shared resources is in most cases an unrealistic assumption: firm can adjust their holdings of various resources in a similar way as they optimize capital and labor. When this is the case, the effect of a segment shock on other segments depends crucially on the type of the resource: whether it is non-rival or constrained. Non-rival resources have public good properties within the firm (but not across firms due to some contractual problems). Tacit knowledge is a typical example emphasized by Teece (1982)—this could be technological knowledge, organizational routines, or management practices. Firm brand, as well as indivisible plant capital are other examples. After a positive shock to one segment, the firm will be willing to invest more in the shared resource, which benefits other segments. We develop a simple model based on this argument in Appendix B.

There are, however, other inputs which are rival, not specific to an industry, and impossible to buy freely, at least in the short term. The firm has some pool of this constrained resource and has to allocate it between the segments. Internal capital market is a case in point: due to informational frictions and limited collateral, the firm can borrow only a fixed amount of money. (In a weaker version, interest rates increase with the amount borrowed by the firm.) Stein (1997) theoretically shows how merging the pools of cash can be efficiency improving, and therefore potentially lead to integration.

This mechanism creates negative transmission of shocks. When one segment becomes more attractive for investment, for example due to a permanent demand increase, the firm has to shrink investment in other segments, so their growth is retarded. Giroud and Mueller (2014) find corresponding evidence by analyzing a supply-side plant shock stemming from the introduction of a direct flight route between the headquarter of the firm and the focal plant. The model in Appendix B accommodates this effect, too.[3]

Certain inputs have both non-rival and constrained aspects to them. For example, the CEO's skill is non-rival (cf. Lucas, 1978), and so after a positive shock the firm can hire a better CEO or improve the compensation contract for the existing one to elicit more effort. At the same time, CEO's time is limited, so if one segment becomes more important and deserves more attention, others segments will be run less well.[4]

Another interesting combination of the two mechanisms is found in an important paper by Lamont (1997). He finds that oil price shocks lead to increased investment in other segments of diversified oil firms, e.g. in chemicals and railroads. The theory he proposes is based on internal capital markets but it is a positive transmission mechanism, not a negative one. Specifically, when oil prices go up, firm profit goes up, expanding the pool

[3]Nocke and Yeaple's (2014) notion of organizational capital is a generic name for a constrained resource. Their model, however, assumes homogenous productivity of all segments and therefore is not suitable to study the transmission of segment shocks.

[4]It might be, however, that if one segment performs well, it requires less attention. Similarly, it is not obvious whether a positive demand shock will imply more or less advertising, which improves the brand reputation.

of available cash, which is then split between all segments, whether efficiently or due to "corporate socialism".

All of the channels we discuss operate on the supply side, but there may also be demand-side interdependencies between segments, due to complementarities or substitutabilities between firm's products. If a MacBook and an iPhone work together particularly well, increased consumption of one of them due to a shock to production costs or tastes will raise demand for the other. Conversely, one firm's product might cannibalize demand for others, leading to the opposite effect. Hottman et al. (2014) model this cannibalization within a product group with a nested CES structure of preferences whereby the inner nest combines products of the same firm, and the outer nest aggregates across firms. Interestingly, it generates exactly the same interdependency between segment growth trajectories as our supply-side model outlines in Appendix B.

3 Data

We use the micro data from the Japanese Census of Manufactures prepared by the Ministry of Economy, Trade and Industry of the country (METI). The data cover all manufacturing establishments ("plants") with at least four permanent employees, and are available for the period of 1993-2007.[5] Bernard and Okubo (2015) describe the details of the data, in particular how establishments are grouped into firms, and how firms are linked across years, using concordances from METI.

We leverage the unusual feature of this dataset that the value of the establishment output is reported by detailed 6-digit industries, which we also call products. There are 1,624 six-digit manufacturing industries; plasma television receivers is a typical one (see Table 1 for more details). Industry codes are based on the Japan Standard Industry Classification, harmonized over time using the methodology of Pierce and Schott (2012).

Firms can have multiple plants, and each of them can produce multiple products at the same time. We will call the plant's production in a certain industry a *plant segment*, and the entire firm's production in this industry a *firm segment*; Figure 1 provides an illustration. Table 2 shows industry pairs that appear most frequently in the same plant or in different plants of the same firm—separately for industries in the same 4-digit group, in the same 2-digit but not 4-digit class, and in different 2-digit classes.

[5] In 2008, there was a major revision of the definition of output, which makes the data inconsistent. See Bernard and Okubo (2015).

Table 1: The Industry Classification

# digits	Example	# industries
2	Information and communication electronic equipment (30)	24
3	Communication equipment and related products (301)	148
4	Radio and television set receivers (3014)	464
6	Plasma television receivers (301412)	1,624

Figure 1: Firms, Plants, Industries, and Segments

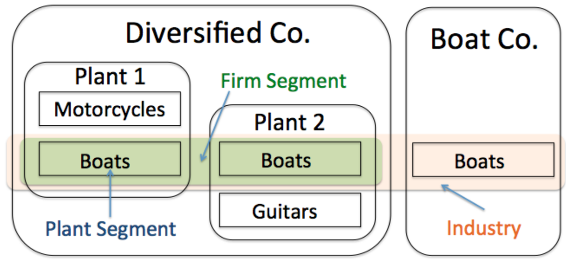


Table 2: Industries Most Frequently Combined in Firms

In...	... plants	Industry 1	Industry 2
Same 4d	Within	Lumbers less than 7.5cm depth	Squares 7.5cm or more depth
Same 2d	Within	Corrugated board (sheet)	Corrugated board boxes
Diff 2d	Within	Plastic products for electrical machinery and apparatus	Molds for plastics
Same 4d	Across	Concrete blocks for construction	Concrete products for roads
Same 2d	Across	Offset printing for paper	Relief printing
Diff 2d	Across	Wooden desks, tables and chairs	Aluminum sashes for housing

Table 3: Structure of Firms

	Share of sample, %	
Firm type	Unweighted	Sales-weighted
Simple	61.93	25.55
Single-plant	30.19	16.83
Horizontal	1.21	5.00
Diagonal	1.41	5.34
Complex	5.27	47.27

We measure output in fixed 2000 prices, with the deflator prepared by METI at the 4-digit industry code.[6] We then exclude plant segments with annual sales under 5 million yen (around 40,000 USD), and "miscellaneous" industries which combine activities that are not classified elsewhere.[7] More importantly, we focus on gradual growth or contraction of firms, so we exclude jumps: plant segment-year observations where output grows or shrinks at least 1.5 times compared to the previous year. This leaves us 3.73mln observations covering around 204 thousand firms in an average year. We will also use the "balanced" subsample where the entire firm-year is removed if any plant segment was added, dropped, or had a jump that year.

The structure of the firm is crucial for the analysis, so Table 3 divides firms into five types: simple ones which have one plant and produce one product; single-plant ones which produce multiple products; horizontally integrated which produce one product in several plants; diagonal which have several plants each producing one product; and complex which have multiple plants some of which are also multi-product. It is evident that although multi-product and especially multi-plant firms constitute the minority of observations in the sample, they form the core of the economic activity in Japan, consistently with prior evidence (Bernard et al., 2010; Bernard and Okubo, 2015).

We denote the output of firm f in plant p, industry i and year t by R_{ipft}, often suppressing the t subscript for brevity. The main variable of our interest is the growth of output between years t and $t+1$, $r_{ipft} = \ln(R_{ipf,t+1}) - \ln(R_{ipft})$, whenever it exists. We will similarly denote the growth of the firm segment, plant, and firm by r_{ift}, r_{pft}, and r_{ft}, respectively. We also denote the output share of the firm segment i in firm f by $s_{i|ft} = R_{ift}/R_{ft}$, and other shares in a similar fashion.

Years 1992 through 2006 are part of the long recession that the Japanese economy ex-

[6]The results are largely unaffected if nominal values are used instead.

[7]These are product codes in which the sixth digit is 9.

perienced after the asset prices bubble burst in early 1992, and is often called the "Lost Decades". Manufacturing sector was contracting in output and employment, and mass production and labor-intensive production were shifting to other Asian countries, particularly to China, through foreign direct investment. One of the biggest economic policy issues in the stagnant Japanese economy is to promote productivity-improving entry, exit, and mergers. It is not surprising therefore that the unweighted average annual segment growth is -1.3% (with the standard deviation is 16.0 percentage points).[8] However, as Bernard and Okubo (2015) demonstrate, this shrinkage was concentrated in single-establishment firms. Plant segments of multi-plant firms were contracting, too, but only by 0.3% per year in our sample.

4 Are There Firm-Level Shocks?

4.1 Methodology

Our main question in this section is whether being in the same firm leads segments to share important shocks and therefore co-move. For a first take on the question, we put aside endogeneity issues and ask if firm segments, which are observed to be in the same firm, co-move. The typical way to answer such question in the literature is by means of a variance decomposition: what share of variation in r_{if} can be explained by firm dummies? The statistical model underlying this approach is the one-way random effects model:

$$r_{if} = \lambda_f + \varepsilon_{if}$$

where λ_f and ε_{if} reflect firm-wide idiosyncratic segments shocks, and they are independently and identically distributed. ANOVA provides an unbiased estimate in that model.

We propose a different estimator, which is the weighted correlation between growth of two randomly picked different segments belonging to the same firm in the same year. Because for a firm with K_f segments there are $K_f(K_f - 1)$ pairs,[9] each pair is weighted by $1/(K_f - 1)$, so that the total weight of the firm is K_f. In Appendix A we prove that when K_f is the same for all firms, our weighted correlation (henceforth correlation) numerically coincides with the ANOVA estimate. Moreover, when the number of segments varies across firms, the correlation is a heteroscedasticity-robust version of ANOVA.

[8]The range of the distribution is $[-\ln 1.5, \ln 1.5]$ because of the excluded jumps.

[9]We distinguish between pairs (if, jf) and the symmetric one.

Since the variances of r_{if} and r_{jf} are the same by construction, the correlation also equals the slope coefficient in a regression of r_{if} on r_{jf} with the same weighting scheme. This regression approaches offers several advantages. It allows us to leverage the econometrics apparatus, for instance for computing standard errors for the estimator clustered at the firm level. Perhaps more importantly, it lets us decompose co-movement into parts defined by any characteristic of the pair of segments. For example, we can check whether co-movement is stronger between segments in similar industries than in very different ones. If weights are held fixed, the regression slope estimated from the entire set of segment pairs equals the average of the slopes computer for each part of the set.

In the previous discussion we ignored the fact that firms may have several segments in the same industry but in different plants. With the regression approach, we simply exclude all pairs of plant segments which belong to the same industry. We finally note that the random effects model assumes that firm-wide shocks hit all segments by the same amount. When this is not the case, the degree of co-movement between different segments will be downward biased. However, we argue in Appendix A that this bias is quite small.

4.2 Do Segments Co-move?

We are now ready to apply this methodology to measure the intra-firm co-movement. However, what magnitude can be called large or small? A natural benchmark, in our view, is the degree of co-movement within other relevant groups of segments, in particular:

- all segments—to measure the importance of aggregate business cycles;
- same industry—any industry-wide demand or supply shocks should create such co-movement;
- same location (one of 390 Japanese cities or 47 prefectures);
- same industry and prefecture.[10]

We additionally include the analogous statistic for correlation between growth of the same plant segment but across years, as a measure of persistence of growth.

Column 1 of Table 4 presents the results. Within-firm correlation is 14.4%, which is several times larger than all the benchmarks. For example, two randomly selected segments

[10]Note that only the main within-firm correlation requires a correction for having the same product in different firm's plants.

Table 4: Variance Decompositions

	Weighted correlation, %					
Within...	(1)	(2)	(3)	(4)	(5)	(6)
Year	1.11	0.88	1.57	2.25	1.07	1.34
Industry-year	4.54	3.49	6.60	10.09	4.36	7.05
City-year	1.30	1.06	1.77	2.57	1.25	1.68
Prefecture-year	1.37	1.10	1.92	2.71	1.30	1.65
Pref.-Ind.-year	5.48	4.21	8.10	11.65	5.22	9.47
Plant segment	1.27	0.78	2.99	4.12	1.70	2.63
Firm-year	14.35	16.23	12.68	11.92	14.35	8.47
Filter	—	Small	Large	Huge	Seg>1	Plt>1
Obs., mln	3.73	2.13	1.60	0.34	1.37	0.25

Notes: Obs. = number of plant segment-years.

in the same industry have growth trajectories correlated only at 4.5%. Aggregate business cycles explain only 1.1% of the variation, and geography does not add much.

The following columns show an important dimension of heterogeneity of the data. Columns 2, 3, and 4 limit the original sample to *small*, *large*, and *huge* segments—with plant segment sales under 100mln yen (equivalent of 80,000 USD), over 100mln and 1bln yen, respectively.[11] Larger segments exhibit much more co-movement within industries and mildly less of it within firms. The within-firm correlation is still stronger than the within-industry one but the difference is minor. Results in column 5 for multi-segment firms only are consistent with column 1. Finally, column 6 focuses on multi-plant (non-horizontal) firms. These are large firms, so within-industry correlation is relatively large. But the within-firm correlation is particularly small in this sample, only 8.5%; we will return to this finding in footnote 12.

In Table 4 we performed variance decompositions for firms and industries separately. However, industry factors can confound the within-firm correlation if multi-segment firms are likely to produce similar products (cf. Lemelin, 1982; Silverman, 1999 for evidence supporting this), and at the same time similar products are hit by correlated shocks. Our question therefore is whether segments of the same firm have similar performance relative to the industries they belong to. To account for that, we run a regression where on the left hand side we subtract from r_{if} the average growth of all standalone firms in that industry $\bar{r}_i^{SA}$, but keep r_{jf} on the right hand side. The statistical model behind this approach is

[11] Note that our calculations are not weighted by segment size because granularity of production (Gabaix, 2011) makes the estimates noisier.

Table 5: Within-Firm Correlations beyond Industry and Location Effects

	Within-firm correlation, %			
Controls	All	Small	Large	Huge
Panel A: Industry and Location Effects				
None	14.35	16.23	12.68	11.92
Year	13.64	15.48	11.77	10.66
City-year	13.54	15.39	11.68	10.58
Prefecture-year	13.43	15.29	11.54	10.37
Industry-year	11.71	13.90	9.20	6.92
Panel B: Industry Aggregation				
2-digit	12.23	14.22	10.09	8.74
3-digit	11.92	14.00	9.59	7.88
4-digit	11.75	13.91	9.25	7.30
Obs.	1.37m	624k	471k	140k

Notes: Obs. = number of plant segment-years in multi-segment firms.

$r_{if} = \lambda_f + \psi_i + \varepsilon_{if}$ where ψ_i may have arbitrary correlation structure across industries, and we are interested in $Var(\lambda_f)/Var(r_{if})$. Effectively, we subtract a placebo correlation between a random segment in i and the focal segment jf, to capture the impact of ψ_i.

In an analogous way we can remove the influence of aggregate business cycles, location or industry-location shocks on the within-firm correlation. Panel A of Table 5 presents the results. Expectedly, year and location controls do not change much. Removing industry shocks reduces the within-firm correlation to 11.7%, which is still strong compared to our benchmarks. Industry shocks matter more for huge segments, and the within-firm correlation drops from 11.9% to 6.9% when they are accounted for.

4.3 Within and Across Plants

We are now asking whether within-firm correlation can be driven by shocks, which affect all segments in the entire firm simultaneously. The statistical model behind this is a nested random effects model $r_{ipf} = \lambda_f + \upsilon_p + \varepsilon_{ipf}$. Of course, firm- and plant-wide components of growth can be only distinguished in multi-plant firms. Columns of Table 6 present the correlation separately for pairs of segments that belong to a single-plant firm, within a plant of a multi-plant firm, and in different plants of a firm. Rows correspond to how similar industries of these two segments are, e.g. whether they are in the same 4-digit but different 6-digit industries. Econometrically, we simply run the regression of Table 5 for various

Table 6: Correlations Within and Across Plants

	Within plant		Across plants	
Correlation, %	1-plant	Multi-plant	All	Same city
Different 6d (average)	12.35	9.06	3.95	4.54
Same 4d not 6d	17.87	11.46	4.61	6.50
Same 2d not 4d	10.14	8.04	3.74	4.50
Different 2d	7.94	8.18	3.82	3.90
Same 6d industry	—	—	11.70	20.04

subsamples of segment pairs, keeping $r_{ipf} - \bar{r}_i^{SA}$ as the left hand side variable to control for industry shocks.

Several patterns emerge. The within-plant correlation is larger between industries in more similar industries. This is not a consequence of correlated industry-level shocks, which have been removed, so it is likely to indicate stronger technological ties. Next, the within-plant correlation is slightly bigger in single-plant than multi-plant firms, which is consistent with a larger size of multi-plant firms.

The key observation for us is that the correlation across plants is less than a half of that within plants of multi-plant firms. In fact, what can be potentially attributed to firm-wide shocks is as low as 4%.[12] Consistent with the view that most types of firm-wide shocks—due to top management, brand, or cash—are not technological, the level of correlation is almost homogenous with respect to the distance between industries.

The strong contrast between within- and across-plant correlations is quite robust. The last column of Table 6 verifies that it is not driven by geography: when the two different plants are in the same city, the correlation is just mildly higher. Similary, Supplementary Table 9 compares large firms (over ¥1 billion of sales) to smaller ones. It finds that correlations within and across plants are (a) independent of the firm size for multi-plant firms, and (b) for single-plant firms, the only notable difference is for the same 4-digit industries. Finally, it could potentially be that segments combined within the same plant belong, on average, to more similar industries. Supplementary Table 10 rules out such compositional effects. Furthermore, the table considers firms which produce products i and j in some plant and also produce i in another plant, and confirms that the correlation is much larger within the plant than across plants, even holding *firm* and industry-pair fixed.

[12]This may explain why in Table 4 within-firm correlation is particularly low for multi-plant firms.

The last row of Table 6 demonstrates that while firm-wide shocks cannot play a big role, shocks to the firm's output of a given product in all plants may. We find an 11.7% correlation between trajectories of different plants when they are producing the exact same thing, and even 20.0% when they are in the same city. To sum up, our evidence so far is consistent with plant-wide and firm segment-wide shocks both happening a lot. But shocks which affect all plants and all products at the same time are bounded at 4% of the variance in growth.

4.4 Unobserved Similarity and Mergers

While the within- and across-plant correlations presented above can reflect shocks coming from firm and plant factors, there is an obvious alternative explanation. Specifically, although we observe detailed 6-digit industry codes, there is still a lot of residual heterogeneity of products within those industries. In a given pair of 6-digit industries, products in some subindustries may be particularly similar. These products may have more common shocks, while at the same time they are more likely to be produced by the same firm. We will then observe spurious within-firm correlation that would not go away even if the segments split.

We address this possibility in two ways. First, while we do not have finer industries, we can move to the opposite direction and suppose for a moment that we observed only coarser 2-, 3- or 4-digit codes. How much spurious within-firm co-movement would we get, compared to knowing all 6 digits? To answer this question, recall that we controlled for industry effects in Table 5's Panel A by regressing $r_{ifp} - \bar{r}_i^{SA}$ on r_{jf}, where $\bar{r}_i^{SA}$ is the average growth of standalone firms in the industry. In Panel B of Table 5 we repeat this exercise using coarse industries to compute the average. Naturally, the surviving within-firm correlation are between 14.4% without industry control and 11.7% with full controls. Notably, however, controlling for 2-digit industries does much of the job, and controlling for 4-digit codes is almost indistinguishable from using all 6 digits. So if the degree of disaggregation is similar at each step of the industry classification, we might speculate that further disaggregation will not change much. This is a very weak claim, of course.

A much better test is based on mergers and acquisitions. Suppose that if after a merger two plants still produce in the same industries as they did before, their product have not changed differently than they would without the merger.[13] In that case, firm-wide shocks

[13]There is evidence that mergers lead to a change in the product mix of the plants towards each other

Table 7: Mergers and Within-Firm Correlation

		Correlation, %			
		(1)		(2)	
	Plant segment pairs	Within firm	(se)	Comparison group	(se)
(A)	Across plants	3.94	(0.26)	—	
(B)	After and before merger	3.66	(1.06)	1.93	(1.82)
(C)	After and 3 years before merger	3.15	(1.33)	4.90	(1.91)
(D)	Before and after spinoffs	2.00	(1.00)	-0.31	(2.20)

should manifest themselves as increased correlation of growth trajectories after the merger. While standalone firms in the industry may not be a great comparison group, the same segment pre-merger is probably a better one to remove confounding unobserved similarity.

Table 7 implements this test. Row B shows that in the subsample of segment pairs which belong to two plants in the same firm that merged at some point earlier (i.e. existed before but inside different firms), the correlation is 3.7%, is similar to the overall across-plant correlation of 3.9%.[14] However, the correlation between them before they merged is already half of that, 1.9% (column 2). The pre-existing co-movement indicates unobserved similarity driving part of the result, although the statistical power of this test is quite weak[15]. One may worry of reverse causality: plants can start moving towards each other in preparation to the merger. Row C addresses this concern by comparing observations from three or more years before the merger as a comparison group.[16] There, too, we find significant correlation before the merger, which is even larger than the treated group correlation, although standard errors are large. Finally, row D repeats the same exercise for spinoffs, comparing plants that are in the same firm to future observations when they split for any reason. We do not find co-movement after the spinoff but before-spinoff correlation is also very weak, only 2.0%.[17]

We have shown earlier that much of the within-firm co-movement cannot reflect firm-

(Atalay et al., 2014). Bias in that direction would only strengthen our findings.

[14] As before, all correlations are net of the industry effects.

[15] The statistical power is weak because the correlations are low, and we observe only 3,662 merging pairs of plants.

[16] The treated group changes slightly because we remove all mergers where we do not have observations three or more years in advance.

[17] Supplementary Table 11 repeats this analysis for horizontal mergers, where two firms working in the same industry merge. While less aligned with our main question, this exercise has superior statistical power because correlations between firm segments in the same industry is quite large (see Table 6). Again, we find strong correlations exist prior to the merger that are close or even larger than after mergers.

wide shocks, except possibly for 4%. Mergers provide complementary evidence that even these 4% are partially due to unobserved similarity of products than rather to firm-wide shocks.

5 Are Shocks Transmitted Across Segments?

5.1 Methodology

The previous section explored the nature of the shocks which hit multiple segments of firms at the same time. Here we study the complementary question of how a shock to an individual segment affects growth of the others. Because we study the whole economy, we cannot use very specific shocks, such as oil price fluctuations in Lamont (1997). Instead, our shock to firm segment jf is the growth of output by standalone firms in industry j, $\bar{r}_j^{SA}$, as a proxy for industry-wide shocks ψ_j. Imagining for now a two-segment firm, we will be looking at how this shock affects growth of other segment if, controlling for the shock in its industry, $\bar{r}_i^{SA}$.

This approach has several caveats. First, Table 4 showed that industry shocks are not very prevalent, which limits our statistical power. However, the large sample size makes this problem less critical. Second, both $\bar{r}_i^{SA}$ and $\bar{r}_j^{SA}$ are estimated from data. Noise leads to attenuation bias but also, if the true transmission effect is nil, the coefficient at $\bar{r}_j^{SA}$ might not be zero because industry effects are correlated and so $\bar{r}_j^{SA}$ provides some signal about ψ_i even conditional on $\bar{r}_i^{SA}$. We believe this problem should not be sizable because a median segment of a multi-segment firm has $\bar{r}_j^{SA}$ estimated from as many as 179 firms. Additionally, we exclude all firms where at least one of the segments belongs to an industry which has less than 25 standalone firms in that year.

Third, if firm f produces robots (j) and vacuum cleaners (i), chances are that its vacuums are very hi-tech. Then, scientific progress than makes robots cheaper will also make this firm's vacuums cheaper compared to a random vacuum on the market. So higher sales in j will be spuriously predictive of if performance. We cannot rule out the possibility but want to contrast it with two similar stories that do not create problems for us. Any correlation between product-level shocks that we cared about in Section 4.3, is fine here because $\bar{r}_i^{SA}$ and $\bar{r}_j^{SA}$ are included at the same time. Moreover, idiosyncratic factors that only affect multi-segment firms (only firm f or other firms too) create classical measurement error in the left hand side variable, which is not a problem.

One might expect that with any plausible mechanism, e.g. based on non-rival or constrained inputs, the impact of ψ_i on r_{jf} will depend on the relative size of the segments within the firm. Therefore, we allow the effects of $\bar{r}_i^{SA}$ and $\bar{r}_j^{SA}$ to depend on $s_{i|f}$,the previous year output share of the focal segment. Also, a typical multi-segment has more than two segments. We deal with it by measuring for the focal segment i the average shock to all other industries:

$$\bar{r}_{-i,f}^{SA} = \frac{\sum_{j \neq i} s_{j|f} \bar{r}_j^{SA}}{1 - s_{i|f}}.$$

So the regression we run is

$$r_{ift} = g_1 \left(s_{i|ft} \right) \bar{r}_{it}^{SA} + g_2 \left(s_{i|ft} \right) \bar{r}_{-i,ft}^{SA} + \text{noise}, \tag{1}$$

for the balanced subsample, and cluster standard errors at the firm level. To estimate g_1 and g_2, we use linear functions in tables and step functions $\sum_{l=1}^{10} \gamma_l \cdot 1 \left[\frac{l-1}{10} < s_{i|f} \leq \frac{l}{10} \right]$ in graphs.

Given that $0 < s_{i|f} < 1$, we impose without loss of generality that $g_1(1) = 1$ and $g_2(0) = 0$, so that (1) fits standalone firms, too. Most theories predict that g_1 and g_2 are continuous at $s = 1$: tiny production in some other industries should not causally change the behavior of the focal segment. If, however, having some j in the product mix signals something about the segment if, this continuity may not hold, and that is testable.

Appendix B works out a toy model where production requires labor, a non-rival shared input that the firm buys at a constant per-unit price, and a constrained input. The firm decides on all the inputs after after observing all shocks. We show that this model implies

$$r_{ift} = \left(1 - \gamma \left(1 - s_{i|f} \right) \right) \psi_i + \gamma \left(1 - s_{i|f} \right) \bar{\psi}_{-i|f} + \text{noise}, \tag{2}$$

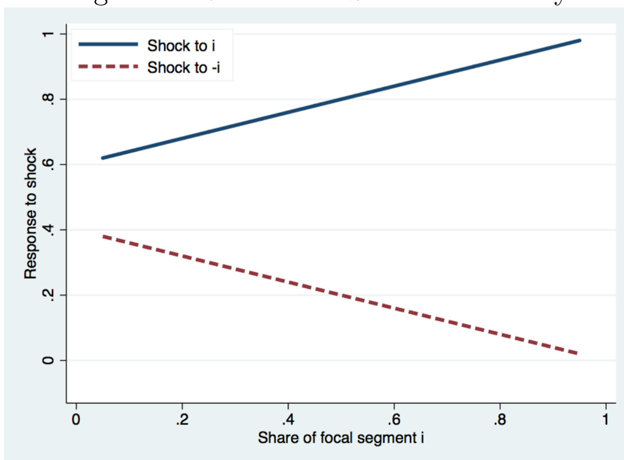
where $1 - \gamma = (1 - \alpha) / (1 - \beta)$, and α and β measure the important of non-rival and constrained inputs, respectively.[18]

Evidently, (2) is a special case of (1) with linear functions g_1 and g_2 that have opposite slopes. The case of $\gamma = 0.4$ is illustrated in Figure 2.

Notably, in both cases the overall firm growth, $r_f \equiv \sum_i s_{i|f} r_{if}$, does not depend on γ, i.e. intra-firm linkages affect where the shock will "land" in the firm but. The model predicts

[18] Note that our model does not nest Lamont's (1997) theory which presumes that oil prices determine the stock of cash—a constrained resources split among all segments, both oil and non-oil. We allow for shocks to the constrained resource but they should not be correlated with the industry shocks.

Figure 2: Reaction to Shocks in Theory



transmission of the shock but not a spillover in terms of the aggregates. To see intuition, imagine that all segments are hit by shocks of the same magnitude. These shocks will be magnified by endogenous actions (e.g., investment in a shared resource) but this magnification will be the same in single- and multi-segment firms. In the estimating equation (1), however, we leave the possibility of spillovers open by not imposing $g_1(\cdot) + g_2(\cdot) = 1$.

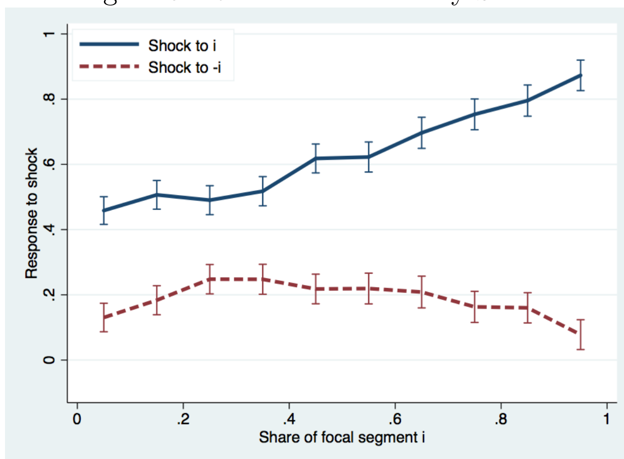
5.2 Results

Figure 3 shows the estimated g_1 and g_2 functions form equation (2), i.e. the response of r_{if} to a shock to industry i and the average shock to other industries in which the firm is producing, with 95% confidence bands. The estimate of $g_1(\cdot)$ is strongly upward sloping: the shock to i matters twice as strong for the growth of segment if when this segment constitutes most of the firm's sales than when it is only a small part of it. If this evidence is not driven by selection (i.e., endogenous firm structure), it is consistent with a strong impact of non-rival inputs.

However, the very flat shape of $g_2(\cdot)$ is inconsistent with that story. If interpreted causally, it suggests that a 10% positive shock to other segments corresponds to an increased growth of the focal one by around 2% regardless of the relative size of these segments. Even robots is a tiny part of vacuum firm production, when robots are doing well, this firm's vacuums have substantially increased growth.

This might suggest that selection of the sort described previously could be driving the

Figure 3: Reaction to Industry Shocks



estimate of g_2: no matter how much of robots you produce, your vacuums are hi-tech, so shocks will be spuriously correlated. However, if that was the case, we would expect g_1 to be flat as well. If vacuum producers with 10% and 90% robots are similar to each other, they should react to the shocks to vacuum cleaners industry equally, too. We do not currently have an explanation that would be consistnent with both curves.

Table 8 checks robustness of the finding in Figure 3 using linear (affine) functional form for g_1 and g_2. Column 1 is the baseline regression using the entire balanced subsample. Column 2 excludes unusal segments that are under 10% or over 90% of their firm. Column 3 rules out biases from industry composition by adding industry dummies interacted with s_{if}.

Because firms often integrate in similar industries, one may worry that strong correlation between $\bar{r}_i^{SA}$ and $\bar{r}_{-i,f}^{SA}$ makes the results unstable. Addressing this issue, columns 4 and 5 exclude a segment when its firm has another segment in the same 3- or 2-digit industry, respectively. Another way to decrease the degree of multi-collinearity is to only consider firms that integrate in weakly correlated industries.[19] For simplicity, we focus on two-segment firms. Column 6 present the baseline result for them, whereas column 7 only includes firms, the two segments of which are in industries with correlation between -0.5 and 0.5. Column 8 uses a stricter threshold of 0.3. Finally, column 9 applies filters from columns 4 and 7 simultaneously.

[19]More precisely, we measure, for each pair of industries, the time-series correlation between (unweighted) averages of growth of standalone firms belonging to them.

Table 8: Reaction to Industry Shocks: Robustness

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
g_1	$\bar{r}_i^{SA}$	0.412^a	0.398^a	—	0.475^a	0.496^a	0.416^a	0.381^a	0.406^a	0.448^a
	$s_{i\|f}\bar{r}_i^{SA}$	0.451^a	0.452^a	—	0.450^a	0.424^a	0.445^a	0.483^a	0.476^a	0.440^a
g_2	$\bar{r}_{-i.f}^{SA}$	0.206^a	0.232^a	0.125^a	0.134^a	0.117^a	0.164^a	0.165^a	0.217^a	0.120^a
	$s_{if}\bar{r}_{-i,f}^{SA}$	-0.037	-0.058	-0.053	-0.013	0.000	-0.001	-0.061	-0.146^a	-0.007
	Obs.	576k	473k	576k	191k	115k	398k	147k	87k	75k
	R^2, %	3.7	3.7	7.0	4.4	4.6	3.6	3.3	3.4	3.8
	Firms	M-seg	M-seg	M-seg	M-seg	M-seg	2-seg	2-seg	2-seg	2-seg
	Filters	—	Share	FE	3d	2d	—	$\|\rho\| < .5$	$\|\rho\| < .3$	(4)+(7)

Notes: [a] p-value<1%.

We find that the results are very robust: the slope of g_1 is always close to 0.45, whereas g_2 is flat with the average between 0.1 and 0.2. The only exception is column 8 where g_2 slopes down but that effect is driven only by segments with $s_{if} > 0.9$.

6 Related Literature

The question of our paper is quite close to Lamont's (1997) study of 26 oil firms. Our economy-wide results agree with his main finding that a positive shock to one segment benefits others. However, our further evidence is not consistent with his theory based on internal capital markets, both because we do not find firm-wide shocks, and because we demonstrate that the response to a shock in another segment is independent of the segment shares.

Our result, therefore, is closer to the critique of Lamont by Chevalier (2004), who finds evidence on the Lamont-type transmission before mergers. Our complementary analysis of mergers shows that within-firm correlation exists beforehand. Our data is advantageous, however, as we observe segment's behavior both before and after the merger, and we have a detailed industry classification. Her segment-level data is available only before the merger and for 2-digits industry codes.

When we compare within-firm and within-industry correlations, as well as other benchmarks, to find the source of shocks, our analysis resembles the literature in the field of corporate strategy on the determinants of segment profitability (e.g. Mcgahan and Porter, 1997). We believe that output growth as an outcome variable is more reliable at the segment level because it is less prone to accounting manipulations, but we view our findings as complementary to theirs. Methodologically, we also show that decompositions of variance into firm- and idiosyncratic parts may be misleading because of unobserved similarity and endogenous selection of segments in the firm.

Our paper also parallels a growing literature on how multinational firms transmit shocks between countries, and whether this contributes to the co-movement of business cycles in different countries (Kleinert et al., 2015; Cravino and Levchenko, 2015). While these papers study firms' behavior in the space of countries they operate in, our firms live in the product space.

7 Conclusion

In this paper we have shown that firm-wide shocks do not appear to be important for growth trajectories of Japanese multi-segment firms. In particular, the co-movement between growth of segments located in different plants of the firm is quite small and does not change much around mergers. This suggests that theories of the firm based on top management decisions or internal capital markets are unlikely to explain much of the data. We are certainly not arguing that these theories are wrong—prior research have found evidence consistent with them in multiple settings. Our argument, however, is that these theories do not seem to be quantitatively important drivers of firm growth, that has to be considered by economy-wide studies in macroeconomics or international trade. In that sense, empirical researchers can be satisfied if they observe plant-level statistics and do not know which plants belong to the same firm.

At the same time, we find evidence that there might be sizable plant-wide shocks. While they are consistent with technological synergies driving the existence of multi-segment firms, strong decentralization of decisions to the plant level is an interesting alternative, which may be particularly relevant in the Japanese environment, exemplified by the famous "Toyota way" of management.

We also uncovered a puzzle on how firm segments react to shocks in other segments. We have found, consistently with Lamont (1997) but in a much broader context, that there is positive transmission of shocks. However, more detailed analysis of how this reaction depends on the relative size of different segments reveals that the result is not consistent with our theory based on non-rival shared inputs, nor with Lamont's theory related to internal capital markets.

An important question that remains for further analysis is external validity of our findings: how well they can be extrapolated to other settings or periods of the Japanese economy. Japan's conglomerates may be quite different from the U.S. ones: for example, manufacturing firms are more often integrated with banks, which helps to smooth out shocks related to availability of financing (Hoshi et al., 1991). Moreover, the "lost decades" of the Japanese economy are characterized by a particularly low level of systematic shocks, so it is possible that in "normal times" there would be more interdependencies between firm segments even in Japan.

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Appendix A Econometric Appendix

A.1 Weighted Correlation

Suppose that a random sample of groups of size F is available, and for each group f, the outcome variable r_{if} is observed for all units $i = 1, \ldots, K_f$. For example, f can be a firm-year, and i is a segment. The total number of observations is $N = \sum_{f=1}^{F} K_f$. To simplify notation, we will assume that the sample average of r_{if} is zero.

The ANOVA estimate for the share of explained variance is

$$\hat{R}^2_A = 1 - \frac{\frac{1}{N-F}\sum_{f,i}(r_{if} - \bar{r}_f)^2}{\frac{1}{N}\sum_{f,i} r_{if}^2}$$

where $\bar{r}_f = \frac{1}{K_f}\sum_{i=1}^{K_f} r_{if}$. It also equals the adjusted R-squared in the regression of r_{if} on group dummies.

We propose a different estimator, and we prove its desirable properties in what follows. Our estimator equals the correlation between the two outcomes in a random pair of units $i \neq j$ in the same group, weighted by $1/(K_f - 1)$, that is:

$$\begin{aligned}
\hat{R}_C^2 &= \frac{\frac{1}{F}\sum_f \frac{1}{K_f-1}\sum_{i\neq j} r_{if}r_{jf}}{\frac{1}{F}\sum_f \frac{1}{K_f-1}\sum_{i\neq j} r_{jf}^2} \\
&= \frac{\frac{1}{F}\sum_f \frac{1}{K_f-1}\sum_{i\neq j} r_{if}r_{jf}}{\frac{1}{F}\sum_{f,i} r_{if}^2}
\end{aligned}$$

where the first equality uses the fact that variances of r_{if} and r_{jf} are the same, and the second one collapses all terms with the same jf but different $i \in \{1, \ldots, K_f\} \setminus \{i\}$.

Lemma 1. *If $K_f = K$ for all groups, $\hat{R}_A^2 = \hat{R}_C^2$.*

Proof. If $K_f = K$,

$$\begin{aligned}
\hat{R}_A^2 \cdot \sum_{f,i} r_{if}^2 &= \sum_{f,i} r_{if}^2 - \frac{K}{K-1}\sum_{f,i}(r_{if} - \bar{r}_f)^2 \\
&= \sum_{f,i} r_{if}^2 - \frac{K}{K-1}\left(\sum_{f,i} r_{if}^2 - \sum_f K\bar{r}_f^2\right) \\
&= -\frac{1}{K-1}\sum_{f,i} r_{if}^2 + \frac{K^2}{K-1}\left(\frac{1}{K}\sum_{f,i} r_{if}^2 + \frac{1}{K^2}\sum_f\sum_{i\neq j} r_{if}r_{jf}\right) \\
&= \sum_f \frac{1}{K-1}\sum_{i\neq j} r_{if}r_{jf} \\
&= \hat{R}_C^2 \cdot \sum_{f,i} r_{if}^2.
\end{aligned}$$

□

The following lemma shows that under the random effects model, $\hat{R}_C^2$ provides an estimate to the share of variance of r_{if} explained by the group factors. The result is robust to heterogeneity of K_f and heteroscedasticity of r_{if} across groups.

Lemma 2. *Assume that the random effects model with heteroscedasticity holds, i.e.*

$$r_{if} = \lambda_f + \varepsilon_{if}$$

where λ is distributed with mean 0 and variance σ_λ^2, and ε_{if} are independent across segments and distributed with mean 0 and variance σ_f^2. K_f and σ_f^2 are drawn from some joint distribution. Then, $\hat{R}_C^2$ converges in probability to the weighted average group-specific $R_f^2 = \sigma_\lambda^2 / \left(\sigma_\lambda^2 + \sigma_f^2\right)$,

$$R_C^2 \triangleq \operatorname{plim}_{F\to\infty} \hat{R}_C^2 = \frac{\mathbb{E}\left[K_f \sigma_\lambda^2\right]}{\mathbb{E}\left[K_f \left(\sigma_\lambda^2 + \sigma_f^2\right)\right]},$$

where the denominator is the probability limit of the sample variance of r_{if}, so $\hat{R}_C^2$ provides a proper variance decomposition.

Proof.

$$\begin{aligned}
\mathbb{E}\left[\frac{1}{K_f - 1}\sum_{i\neq j} r_{if} r_{jf}\right] &= \mathbb{E}\left[\frac{1}{K_f - 1}\sum_{i\neq j} \left(\lambda_f + \varepsilon_{if}\right)\left(\lambda_f + \varepsilon_{jf}\right)\right] \\
&= \mathbb{E}\left[K_f \lambda_f^2 + \frac{1}{K_f - 1}\sum_{i\neq j} \varepsilon_{if}\varepsilon_{jf}\right] \\
&= \mathbb{E}\left[K_f \sigma_\lambda^2\right].
\end{aligned}$$

Similarly,

$$\begin{aligned}
\mathbb{E}\left[\sum_i r_{if}^2\right] &= \mathbb{E}\left[K_f \lambda_f^2 + \sum_i \varepsilon_{if}^2 + \sum_{i\neq j} \varepsilon_{if}\varepsilon_{jf}\right] \\
&= \mathbb{E}\left[K_f \left(\sigma_\lambda^2 + \sigma_f^2\right)\right].
\end{aligned}$$

Then, as $F \to \infty$,

$$\begin{aligned}
\frac{1}{F}\sum_f \frac{1}{K_f - 1}\sum_{i\neq j} r_{if} r_{jf} &\to^p \mathbb{E}\left[K_f \sigma_\lambda^2\right], \\
\frac{1}{F}\sum_{f,i} r_{if}^2 &\to^p \mathbb{E}\left[K_f \left(\sigma_\lambda^2 + \sigma_f^2\right)\right],
\end{aligned}$$

and the Slutsky theorem implies convergence of $\hat{R}_C^2$. $\square$

A similar argument can be applied to $\hat{R}_A^2$:

Lemma 3. *Under the assumptions of Lemma 2,*

$$R_A^2 \triangleq \text{plim}_{F\to\infty} \hat{R}_A^2 = 1 - \frac{\mathbb{E}\left[(K_f - 1)\,\sigma_f^2\right]/\mathbb{E}\left[K_f - 1\right]}{\mathbb{E}\left[K_f\left(\sigma_\lambda^2 + \sigma_f^2\right)\right]/\mathbb{E}\left[K_f\right]}.$$

It is evident that in general, $R_A^2 \neq R_C^2$, unless K_f is independent from σ_f^2. ANOVA applies wrong weighting to the numerator, which binds when K_f and σ_f^2 are heterogeneous and dependent with each other—for example, growth is more volatile in firms with fewer segments. In fact, R_A^2 is not even guaranteed to be non-negative.

A.2 Heterogeneous Response to Shocks

The random effects model $r_{if} = \lambda_f + \varepsilon_{if}$ assumes that the group-level shock affects all units by the same amount. Here we justify the claim that we made towards the end of Section 4.1 that our results are not substantially biased if that assumption is violated.

Suppose the true model is

$$r_{if} = \mu_{if}\lambda_f + \varepsilon_{if}$$

where $\mu_{if} > 0$ is iid across units and independent of λ_f and ε_{if}. To isolate the effect of μ, assume $K_f \equiv K$, homogenous $\sigma_f^2 \equiv \sigma_\varepsilon^2$, and a log-normal distribution of μ_{if} with mean 1, i.e.

$$\log \mu_{if} \sim \mathcal{N}\left(-\frac{\sigma_\mu^2}{2}, \sigma_\mu^2\right).$$

Then the following lemma holds:

Lemma 4. *In the model with heterogenous response to group-wide shocks,*

$$R_C^2 = \frac{\sigma_\lambda^2}{\exp\left(\sigma_\mu^2\right)\cdot\sigma_\lambda^2 + \sigma_\varepsilon^2}.$$

Proof. For $i \neq j$,

$$\mathbb{E}\left[r_{if}r_{jf}\right] = \mathbb{E}\left[\lambda_f^2\mu_{if}\mu_{jf}\right] = \mathbb{E}\left[\lambda_f^2\right] = \sigma_\lambda^2$$

and

$$
\begin{aligned}
\mathbb{E}\left[r_{if}^2\right] &= \mathbb{E}\left[\lambda_f^2 \mu_{if}^2 + \varepsilon_{if}^2\right] \\
&= \left(1 + Var\left(\mu_{if}\right)\right) \sigma_\lambda^2 + \sigma_\varepsilon^2 \\
&= \exp\left(\sigma_\mu^2\right) \cdot \sigma_\lambda^2 + \sigma_\varepsilon^2.
\end{aligned}
$$

$R_C^2 = \mathbb{E}\left[r_{if} r_{jf}\right] / \mathbb{E}\left[r_{if}^2\right]$, which establishes the result. □

The lemma implies that R_C^2 is smaller than $R_{C,0}^2 = \sigma_\lambda^2 / \left(\sigma_\lambda^2 + \sigma_\varepsilon^2\right)$ that it would be equal with $\mu_{if} \equiv 1$. More precisely,

$$
R_{C,0}^2 = \frac{1}{1/R_C^2 - \left(\exp\left(\sigma_\mu^2\right) - 1\right)}.
$$

To get a sense of the difference between R_C^2 and $R_{C,0}^2$, suppose that in 95% cases, the response of an individual segment is between 1/4 and 4 of the average response. This corresponds to $\sigma_\mu^2 = (\ln 4/1.96)^2 \approx 0.5$ and $\exp\left(\sigma_\mu^2\right) - 1 \approx 0.65$. When $R_C^2 \approx 14\%$, as we observe in the data, $\hat{R}_{C,0}^2 \approx 15.4\%$, so the bias is tiny.

Appendix B A Model of Intra-Firm Linkages

Here we develop a toy model of two opposite mechanisms for transmission of shocks between segments: endogenous investment in non-rival shared resources and optimal reallocation of constrained resources. We use the model by Bernard et al. (2011) as the foundation for our analysis but focus on the intensive margin—how much each segment produces—rather than the extensive margin, i.e. which industries the firm enters. Because our empirical analysis is at the segment level, we assume a given finite set of industries.

B.1 Demand

Consider a closed static economy that consists of N industries indexed i or j. Representative consumer has the CES utility function over the composite products of these industries with elasticity of substitution σ:

$$
X = \left(\sum_i B_i X_i^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)}.
$$

Each industry has a large number of differentiated varieties produced by a *fixed* set of firms f, with one variety per firm. The composite good is the CES aggregate of these varieties:

$$X_i = \left(\sum_f X_{if}^{(\varepsilon-1)/\varepsilon} \right)^{\varepsilon/(\varepsilon-1)}$$

where the within-industry elasticity of substitution $\varepsilon \geq \sigma$. Notice that this demand system assumes away demand-side complementarities or cannibalization between firm's products.

The standard Dixit-Stiglitz result is that firm's demand and revenue are given by

$$X_{if} = \xi A_i P_{if}^{-\varepsilon}, \tag{3}$$

$$R_{if} = \xi A_i P_{if}^{1-\varepsilon} \tag{4}$$

where ξ is a constant that can be different every time it enters, and A_i is related to B_i and the industry's ideal price index. We will not look at the general equilibrium effects, so A_i will just be an industry-level demand shifter.

B.2 Shared Resources and Firm's Problem

Consider a firm f which produces in a given (exogenous) set of industries $\mathcal{I}_f$. Firms are heterogeneous in their productivity, although a model with demand-side heterogeneity would be isomorphic. To produce a unit of good i the firm has to employ C_{if} units of labor a constant unit cost, where

$$C_{if}^{1-\varepsilon} = \xi \Gamma_{if} Z_f^{\alpha} T_{if}^{\beta}. \tag{5}$$

Here $1 - \varepsilon < 0$ is a convenient normalization, and Γ_{if} is the exogenous productivity term that can be correlated between different firm segments, as in Bernard et al. (2011).

Z_f and T_{if} terms are the novel ones in my model. Here Z_f is the amount of non-rival shared resource that the firm can acquire at a constant per unit price ξ—for example, the value of brand.[20] Similarly, T_{if} is the amount of the constrained shared resource, e.g. CEO's time, allocated to segment i. We impose a hard constraint $\sum_i T_{if} = \bar{T}$, although softer constraints (convex costs of acquiring $\bar{T}$) produce the same qualitative result. Non-negative

[20] The constant unit price of Z_f is not a very restrictive assumption. If the total cost is instead ξZ_f^{θ} with $\theta > 0$, one can simply redefine $\tilde{Z}_f = Z_f^{\theta}$ and replace α with α/θ.

constants α and β measure the elasticity of segment revenue (and profit) with respect to these resources, respectively.

Since the firm's demand is CES and there are no cannibalization effects, it will set a constant markup, $P_{if} = \xi C_{if}$, so segment i's revenue is

$$R_{if} = \xi M_{if} Z_f^{\alpha} T_{if}^{\beta}$$

where $M_{if} = A_i \Gamma_{if}$ is the firm's market potential in the industry. Segment's profit is proportionate to the revenue. Then, firm's profit maximization problem is

$$\max_{Z_f, \{T_{if}\}} \xi \sum_i \left(M_{if} T_{if}^{\beta} \right) Z_f^{\alpha} - \xi Z_f \qquad \text{s.t.} \ \sum_i T_{if} = \bar{T}.$$

Maximizing first over T_{if}, we obtain

$$M_{if} T_{if}^{\beta - 1} = \xi,$$

so

$$T_{if} = \xi M_{if}^{1/(1-\beta)} = \bar{T} \frac{M_{if}^{1/(1-\beta)}}{M_f^{1/(1-\beta)}}$$

where

$$M_f \triangleq \left(\sum_j M_{jf}^{1/(1-\beta)} \right)^{1-\beta}, \tag{6}$$

and the last equality uses $\sum_i T_{if} = \bar{T}$.

Now plug in T_{if} to the maximization problem

$$\max_{Z_f} \xi \sum_i M_{if}^{1/(1-\beta)} M_f^{-\beta/(1-\beta)} Z_f^{\alpha} - \xi Z_f,$$

and simplify further to

$$\max_{Z_f} \xi M_f Z_f^{\alpha} - \xi Z_f.$$

At the optimum,

$$Z_f = \xi M_f^{1/(1-\alpha)},$$

so

$$\begin{aligned} R_{if} &= \xi M_{if} \cdot M_f^{\alpha/(1-\alpha)} \cdot \left(\frac{M_{if}}{M_f}\right)^{\beta/(1-\beta)} \\ &= \xi M_{if}^{1/(1-\beta)} M_f^{\frac{\alpha}{1-\alpha}-\frac{\beta}{1-\beta}}. \end{aligned} \tag{7}$$

This equation implies that a positive shock to the market potential M_j of another segment j is good for segment i if and only if $\alpha > \beta$, i.e. non-rival resources are more important for production than the constrained ones.

B.3 Firm Reaction to Shocks

Suppose that the economy is hit by two types of small shocks: to the industry-level demand A_i, as well firm-specific shocks to Γ_{if} with arbitrary correlations across segments within the firm. Lower-case letters will denote year-to-year log changes of the corresponding upper-case variables. Log-linearizing (6) and (7) and using that

$$\frac{M_{if}^{1/(1-\beta)}}{M_f^{1/(1-\beta)}} = \frac{R_{if}}{R_f} = s_{i|f},$$

we obtain:

$$\begin{aligned} m_f &= \sum_j s_{j|f} m_{jf}, \\ r_{if} &= \frac{1}{1-\beta} m_{if} + \left(\frac{\alpha}{1-\alpha} - \frac{\beta}{1-\beta}\right) m_f. \end{aligned} \tag{8}$$

In our empirical work in Section 5, we use the average growth of standalone firms $\bar{r}_i^{SA}$ as the industry shock. Provided there are sufficiently many of them for the law of large numbers to wash out all firm-level shocks,

$$\bar{r}_i^{SA} = \frac{1}{1-\beta} a_i + \left(\frac{\alpha}{1-\alpha} - \frac{\beta}{1-\beta}\right) a_i = \frac{1}{1-\alpha} a_i.$$

Table 9: Co-movement Within and Across Plants, by Firm Size

	Huge firms			Other firms		
	1-plant	Multi-plant		1-plant	Multi-plant	
Correlation, %	Within	Within	Across	Within	Within	Across
Different 6d (average)	9.82	9.11	3.87	13.07	9.71	4.45
Same 4d not 6d	12.13	11.21	4.69	18.98	14.52	4.25
Same 2d not 4d	9.36	8.07	3.81	10.47	7.48	1.76
Different 2d	8.23	8.53	3.56	8.24	6.84	6.37
Same 6d industry	—	—	11.32	—	—	16.76

Table 10: Co-movement Within and Across Plants, Compositional Effects

	Excess correlation within plants, %		
Industries	(1)	(2)	(3)
Different 6d (avg)	8.32	6.53	7.17
Same 4d not 6d	13.10	8.19	8.03
Same 2d not 4d	6.46	6.23	6.16
Different 2d	4.17	4.75	7.37
Controls	t	ijt	$ijft$

Notes: Each cell of the table reports coefficient β from the regression $r_{ipft} = \beta r_{jp'ft} \cdot 1\left[p = p'\right] + r_{jf} \cdot \lambda_c +$ noise, where $1\left[p = p'\right]$ indicates that two segments are within the same plant, and λ_c reflects the set of year dummies in column (1), industry-pair $\times$ year in column (2), and industry-pair $\times$ firm $\times$ year in column (3). The sample of plant segment pairs is restricted in each row based on the distance between i and j. Standard weighting applies.

Therefore, 8 can be rewritten as

$$\begin{aligned} r_{if} &= (1-\gamma)\,\bar{r}_i^{SA} + \gamma \sum_j s_{j|f} \bar{r}_j^{SA} + \eta_{if} \\ &= \left(1 - \gamma s_{-i|f}\right) \bar{r}_i^{SA} + \gamma s_{-i|f} \bar{r}_{-i,f}^{SA} + \eta_{if}, \end{aligned}$$

where $1 - \gamma = (1-\alpha) / (1-\beta)$, and η_{if} reflects all firm-specific shocks and is independent across firms.

Appendix C Supplementary Tables and Figures

Table 11: Mergers and Within-Firm Correlation, Within Industry

		Correlation, %			
		(1)		(2)	
	Plant segment pairs	Within firm	(se)	Comparison group	(se)
(A)	Across plants	11.67	(0.61)	—	
(B)	After and before merger	8.98	(2.18)	16.05	(3.65)
(C)	After and 3 years before merger	10.98	(2.71)	10.03	(3.70)
(D)	Before and after spinoffs	7.30	(3.12)	8.57	(9.04)