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Do Conglomerate Firms Allocate Resources Inefficiently Across Industries? Theory and Evidence

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ABSTRACT

We develop a profit-maximizing neoclassical model of optimal firm size and growth across different industries based on differences in industry fundamentals and firm productivity. In the model, a conglomerate discount is consistent with profit maximization. The model predicts how conglomerate firms will allocate resources across divisions over the business cycle and how their responses to industry shocks will differ from those of single-segment firms. Using plant level data, we find that growth and investment of conglomerate and single-segment firms is related to fundamental industry factors and individual segment level productivity. The majority of conglomerate firms exhibit growth across industry segments that is consistent with optimal behavior.

SEVERAL RECENT ACADEMIC PAPERS and the business press claim that conglomerate firms destroy value and do a poor job of investing across business segments.[1] Explanations for this underperformance share the idea that there is an imperfection either in firm governance (agency theory) or in financial markets (incorrect valuation of firm industry segments). These studies implicitly assume that the conglomerates and single-industry firms possess similar ability to compete, and that they differ mainly in that conglomerates

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[1] Lang and Stulz (1994), Berger and Ofek (1995), and Comment and Jarrell (1995) document a conglomerate discount in the stock market and low returns to conglomerate firms. Rajan, Servaes, and Zingales (2000) and Scharfstein (1997) examine conglomerate investment across different business segments. Lamont (1997) and Shin and Stulz (1997) examine the relation of investment to cash flow for conglomerate industry segments. For an example from the business press see Deutsch (1998).

have chosen to operate in more than one industry. However, firms do differ in their ability to exploit market opportunities.[2] In the absence of a benchmark model of how these differences affect firms' returns from investing in different segments, it is not clear whether earlier studies' results are driven by the underlying comparative advantages of different types of firms or by one or more of the postulated explanations.

In this paper, we analyze size and growth across industries in the absence of market imperfections, using a neoclassical model based on Lucas (1978).[3] In our model, a conglomerate discount caused by differences in underlying firm organizational or managerial ability can arise endogenously. We obtain predictions on how firms should allocate resources optimally across industries in the absence of agency problems. These predictions differ from those arising from models predicting inefficient investment. We test these predictions by using plant-level data from the U.S. census for the period 1974 to 1992 to examine the growth and productivity of over 50,000 firms. For each year, we classify each firm's plants into segments by SIC code, thereby constructing a profile of each firm's operations across industries.[4] By using this plant-level data, we can determine how the growth of a multiple-segment firm depends on the productivity of its plants in each industry (segment productivity for short) and relative demand in those industries.

We make three central empirical contributions. First, our empirical analysis shows that conglomerate firms are less productive than single-segment firms of a similar size, for all but the smallest firms. This finding is consistent with the finding of a conglomerate discount by Lang and Stulz (1994), Berger and Ofek (1995), and Denis and Thothadri (1999).[5] The finding raises the possibility that single-segment and diversified firms operating in the same industry do not have the same investment opportunities.

Second, we also show that the productivity pattern within a conglomerate firm's segments is consistent with our simple value-maximizing model. The model predicts, and we find empirically, that plants in the larger segments of conglomerate firms are more efficient than plants in smaller segments. The plants in the largest segments of conglomerates with a large number of segments are particularly efficient.

[2] Peters and Waterman (1982), Schmalensee (1985), and many other authors, have noted that firms differ even within the same markets. Lang and Stulz (1994) note that firms that become conglomerates may differ from those that stay within one industry.

[3] Firm growth has been examined in other contexts by Evans (1987) and Hall (1987). They test whether the relationship between firm growth and firm size is constant for different types of firms, as predicted by Gibrat's Law.

[4] Note that neither this profile nor the common approach of using COMPUSTAT segment data ensures that the segments match a firms' actual operating divisions. Hyland (1999) documents differences in the case of COMPUSTAT data. One advantage of this data is that it does not depend on how a firm uses its discretion in reporting its divisional structure to investors.

[5] It is also consistent with recent evidence by Campa and Kedia (1999) and Villalonga (1999), which documents that the conglomerate discount may arise endogenously.

Third, we also examine the growth and investment of conglomerate firms across the industries in which they operate. We find that conglomerate resource allocation is generally consistent with our model of efficient allocation of resources across firms' segments. Conglomerate firms grow more in industries in which their plants are productive when that industry receives a positive demand shock and when their other segment receives a negative shock.

Our model shows that firms with a comparative advantage, arising from firm skill in producing within an industry, have higher growth and attain a larger size in that industry. As a firm's returns to growing within an industry diminish, the firm limits its growth within the industry and moves into other industries. The optimal number and size of industry segments a firm operates depends on its comparative advantage across industries. Firms that are very productive in a specific industry have higher opportunity costs of diversifying. Thus, in equilibrium, if a high level of firm organizational skill is industry specific, single-segment firms are more productive than conglomerates of the same total size. Comparative advantage also implies that the larger segments of conglomerates are relatively more productive than their smaller segments.[6]

The model also predicts that the effect of demand shocks on the growth of a conglomerate's segment depends on the segment's productivity. The same positive shock that causes firms that are more productive than their industry to increase their market share also can cause less productive firms to sell capacity and decrease their size. Thus, less productive and more productive firms should invest differently when industry conditions change. This result implies that empirical tests of how conglomerates invest in response to changes in industry prospects could be misspecified if they do not control for the productivity of the firm's individual segments.

A key prediction of the model is that demand shocks faced by a segment of a conglomerate firm affect the growth rates of other segments, and do so even in the absence of agency costs and financial market imperfections. If a firm's segment is more (less) productive than its other segments, a positive demand shock for that segment decreases (increases) the growth rates of other segments. Because models that postulate inefficient internal capital markets imply a different relation, this prediction can be used to distinguish empirically between these models and our neoclassical model.

[6] Our model analyzes how comparative advantage in the product market may lead some firms to become conglomerates. Models that predict that firms become conglomerates to benefit from more efficient capital allocation include Matsusaka and Nanda (2002), Stein (1997), and Fluck and Lynch (1999). Hubbard and Palia (1998) present evidence from the 1960s that is consistent with these models. Hadlock, Ryngaert, and Thomas (1998) provide more recent evidence consistent with a capital allocation benefit of conglomerates. Our approach is closest to the model of Matsusaka (2001), where conglomerate firms have a firm-specific organizational ability that has different value in different industries. In Matsusaka, firms have to experiment to find out if their organizational ability has value in a specific industry. Experimentation has dynamic value although it may produce static inefficiency.

Our finding that larger segments have higher average plant productivity than smaller segments is consistent with maximizing behavior when firms expand until marginal returns are equal across segments. The differences in productivity across segments also suggest that, for most firms, organizational talent has an industry-specific component. However, when segments within a conglomerate are ranked by size, and compared with equally ranked segments of other conglomerates, we find a positive relation between the segment's productivity and the number of industries in which the conglomerate operates. This suggests that those conglomerates that operate in many segments have a higher level of general ability than conglomerates that operate in a few segments.

While these comparisons of the productivities within conglomerate firms are consistent with a neoclassical model, they might also occur if conglomerates suboptimally expand into industries in which they have a low level of specific skill. To discriminate between these two possibilities, we examine how conglomerates grow in different industries. We test whether the growth rate of a segment is related to the productivity of the conglomerate's segments and how growth changes in response to industry shocks.

The empirical tests show that the growth of both more- and less-productive firm segments is related to productivity and fundamental industry factors, both in recession and expansion periods. Segments of conglomerates grow more slowly if the conglomerate's other segments are more productive in their industries, and faster if their other segments are less productive. We also find similar results for investment. Investment is higher if the plants in a conglomerate's segments are more productive.[7]

We do find some evidence to indicate that some conglomerates may have agency problems. We examine conglomerates that experience significant restructuring.[8] We find that the growth of these broken-up conglomerates is not consistent with our model of optimal growth. However, even for these firms, we find no evidence that conglomerates subsidize the growth of unproductive segments. We also find that the growth rates of firms that remain conglomerates, which are the majority of conglomerates, are strongly sensitive to industry variables and productivity. These findings are consistent with optimal behavior. The results indicate that the surviving conglomerates grow efficiently across industries in which they operate.

Our work follows prior papers by Lang and Stulz (1994) and Berger and Ofek (1995), who show that conglomerate firms have a discount in the stock market relative to single-segment firms. Comment and Jarrell (1995) document that stock market returns to conglomerate firms are lower. Berger and Ofek (1995) and Comment and Jarrell (1995) explain their findings by ap-

[7] Our evidence on investment and growth is also consistent with the recent evidence by Khanna and Tice (2001), who examine incumbent firms' investment in response to Wal-Mart's entry into markets.

[8] See Lang, Poulsen, and Stulz (1995), Comment and Jarrell (1995), and Berger and Ofek (1999) for an analysis of the recent increases in firm restructuring.

pealing to agency theories that predict a misallocation of capital as firms allocate capital to segments that are underperforming. Lang and Stulz (1994) note that poorly performing firms may choose to become conglomerates. However, they find only limited evidence for this hypothesis, and their data do not permit them to examine how productivity varies by segment. Lamont (1997) and Shin and Stulz (1998) examine how investment is related to industry Tobin's q and cash flow. Scharfstein (1997) finds that conglomerate firms invest more in low-q industries if managerial ownership is low. Rajan, Servaes, and Zingales (2000) find that the extent of firm investment in segments in low-q industries is related to the diversity of investment opportunities across segments. However, there is one large limitation to these studies. These studies proxy for investment opportunities for conglomerate firms using an industry Tobin's q, calculated from single-segment firms. Using an industry Tobin's q implicitly assumes that all firms, conglomerates and single-segment firms, have similar investment opportunities within an industry and should increase investment when the industry single-segment q increases.[9]

The paper is organized as follows. Our framework is discussed in Section I. We discuss data and our methodology in Section II. Section III presents our results on growth and segment productivity for multiple-segment conglomerate and single-industry firms. We discuss the relationship of our work to other research in Section IV. Section V concludes.

I. Optimal Firm Size and Growth

We analyze a simple model that illustrates the trade-offs that determine the extent of firm diversification when firms maximize profits. The model yields testable predictions on how optimal growth in different industries is affected both by the comparative advantage of the firm in each industry and by changes in industry conditions. In subsequent sections, we take the predictions of our model to data and show how it can be used to provide a profit-maximizing benchmark for the level of firm growth and investment across industries.

To capture differences in organizational or managerial talent, we assume that in each industry, some firms operate plants more productively than other firms. As in Lucas (1978), firms differ because managerial and organizational talent varies across firms.[10] In each industry, firms with higher ability or skill can produce more output with the same amount of input, and thus have higher productivity, than firms with lower organizational ability

[9] Using industry q to proxy for marginal investment returns also increases measurement error associated with measuring true q, and biases the coefficient on q toward zero, as shown by Whited (2001).

[10] We interpret managerial talent broadly, including the ability to manage a large organization. Our definition of managerial talent thus includes firm-specific organizational capital or assets. Therefore, we also refer to this talent as firm ability.

or talent. Thus, differences in talent have greater economic significance when output prices are high. The productivity with which any given firm operates plants can differ across industries in which it operates.

We also assume that any given manager will do a better job of managing a small firm than a large firm. This follows Coase (1937) and Lucas (1978) in assuming diseconomies of scale within firms. Firms use the variables input, labor, and capacity units to produce output. Firms exhibit neoclassical decreasing returns-to-scale, so that their marginal costs increase with output.[11]

In our model, firms produce in industries in which they have a comparative advantage. This yields predictions about how the equilibrium diversification across industries of conglomerates depends on the organizational talent and the correlation of abilities across industries. Second, the model yields testable predictions on how optimal growth in different industries is affected both by the comparative advantage of the firm in each industry, and by changes in industry conditions. The predictions of our model differ from those of models that focus on the role of free cash flow. As a result, our model can be used to distinguish empirically between neoclassical and theories that focus on inefficient internal capital markets of conglomerate firms.

A. The First–Best Equilibrium with Conglomerate Firms

For concreteness, consider a population of firms that can operate in a maximum of two industries, which we denote as industry A and industry B, respectively. All firms are assumed to be price-takers, to produce a homogeneous output, and to be endowed with industry-specific homogeneous production capacity. Firms use two inputs: capital capacity k and labor l. For tractability, we assume that each unit of capacity produces one unit of output. For each firm j, the profit function is

$$d_{Aj} p_A k_{Aj} + d_{Bj} p_B k_{Bj} - r_A k_{Aj} - r_B k_{Aj} - u l_{Aj}^2 - u l_{Bj}^2 - w (l_{Aj} + l_{Bj})^2, \qquad (1)$$

where p_i and r_i are the prices of output and capacity in industry $i = A$ or B, u and w are cost parameters, and k_{ij} is the output of firm j in industry i. We model differential productivity by d_{ij}. Firms that have a higher productivity, d_{ij}, produce more output for a given level of inputs. The profit function embodies the assumption of neoclassical diminishing returns within each industry (the terms ul_{Aj}^2 and ul_{Bj}^2) and the assumption that when organizational talent is a scarce resource, costs depend on the firm's total size (the

[11] We focus on decreasing returns in each industry in the formal modeling. However, similar results may be obtained if variable costs within each industry are constant but investment projects in each industry are not homogeneous, so that firms invest in the highest return projects in the industry first. Alternatively, if output markets are imperfectly competitive in the Cournot sense, the return on marginal investment will be lower as capacity increases.

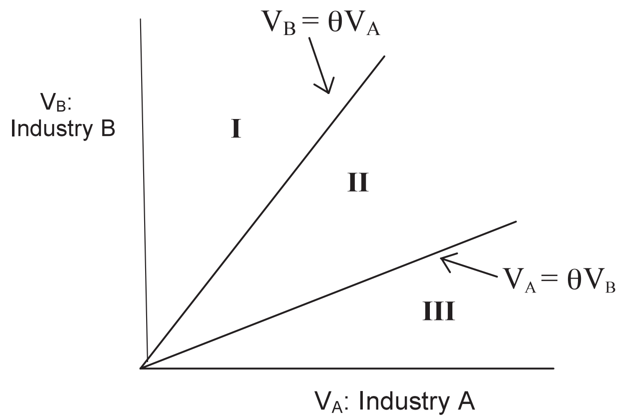

Figure 1. Optimal production with differing ability across industries.

term $w(l_{Aj} + l_{Bj})^2$).[12] For simplicity, we assume that the production technology requires one unit of labor per unit of capacity. Initially, we analyze the firm's output decision taking p_i and r_i as exogenous. When we consider the effects of demand shocks, we allow p_i and r_i to adjust endogenously.

Optimal outputs by the firms in each industry can be obtained by direct optimization. Dropping the firm subscripts and defining $v_i = d_i p_i - r_i$, it is easily shown that the optimum output for a firm, assuming conglomerate production, is given by

$$k_A = \frac{(u + w)(d_A p_A - r_A) - w(d_B p_B - r_B)}{2u(u + 2w)} = \frac{(u + w)v_A - wv_B}{2u(u + 2w)} \tag{2}$$

$$k_B = \frac{(u + w)(d_B p_B - r_B) - w(d_A p_A - r_A)}{2u(u + 2w)} = \frac{(u + w)v_B - wv_A}{2u(u + 2w)} \tag{3}$$

for $v_B > wv_A/(u + w)$ and $v_B < (u + w)v_A/w$. For values of v_A, v_B outside of this range, a firm will choose to be a single-segment firm.

Figure 1 illustrates which firms choose to be either conglomerates or single-segment firms. Letting $\theta = (u + w)/w$, we can rewrite the conditions under which a firm chooses to be a conglomerate as $v_B > v_A/\theta$ and $v_B < \theta v_A$. If $v_B > \theta v_A$, then the firm will produce only in industry B, so that $k_B(v_A, v_B) = v_B/2(u + w)$ and $k_A(v_A, v_B) = 0$. Similarly, if $v_A > \theta v_B$, then $k_A(v_A, v_B) = v_A/2(u + w)$ and $k_B(v_A, v_B) = 0$.

[12] The term $w(l_{Aj} + l_{Bj})^2$ captures the assumption that expansion in one segment affects costs in other segments. Alternatively, the term could be replaced by $wl_{Aj}l_{Bj}$. While this specification makes the assumption more transparent, it requires additional parameter restrictions to ensure that the profit function is well behaved. Either specification results in the same testable predictions.

Firms in region II optimally choose to be conglomerates, whereas firms in regions I and III choose to produce in a single segment. If industries A and B face the same output and productive capacity prices, then the firms' location in $v_A - v_B$ space depends only on their relative talent, d_A and d_B. By inspection we can see the following proposition.

PROPOSITION 1: *Diversification is optimal if* $\theta v_B > v_A$ and $\theta v_A > v_B$.

Specialization is optimal if the firm is much more productive in one industry than the other; diversification is optimal if the productivities are similar. Thus, the decision to diversify depends in part on the firm's comparative productivity in the two industries. An implication of this result is that, all else being equal, a conglomerate's large segment is more productive than its small segment.

In the absence of financial market imperfections and agency costs, one might observe diversified firms of differential productivity, as well as focused firms with very unproductive small peripheral segments in other industries. Furthermore, segments of conglomerate firms and single-segment firms in the same industry may differ in productivity and size. Thus, the empirical tests in the corporate finance literature, which, for the most part, implicitly assume that the investment opportunities of conglomerates' segments and single-segment firms are similar, are likely to be misspecified.

The relation between productivity and focus in a population of firms depends both on the distribution of ability within these firms and on the distribution of ability across firms. If organizational talent (productivity in our context) is industry-specific, firms that are highly productive in one industry are likely to be less productive in the other industry. Firms whose managers are not as highly skilled in any one industry are less focused. By contrast, if organizational talent is not industry specific, so that $d_A = d_B$, all firms divide their production equally between the industries. In this case, there is no relation between productivity and focus, and there are no differences in productivity across segments. Larger firms, however, are more productive than smaller firms across all segments.

A generalization of the model shows that this pattern persists across multiple industries. We illustrate the effects across multiple industries using two numerical examples that show how differences in organizational talent across industries causes firms to choose to operate segments of different sizes and different observed productivities. The generalization provides testable predictions about the relation between diversification and relative productivity.

In each example, we take the number of industries to be 10. We assume there are 25,000 potential firms, each of which is assigned firm-specific ability for each of the 10 industries. In terms of the previous discussion and the empirical work, high ability is the same as high productivity. We draw the ability assignment d from a normal distribution with a mean ability of 1 and a standard deviation of 0.5. The output and input prices and the cost parameters in all industries are held constant (in this case $p = 200$, $r = 200$,

$u = 5, w = 2$). In the first example, firm ability is industry specific. Firms' ability to manage in one industry is independent of their ability to manage in the other industries. Thus, the draws are independent and identically distributed both within firms and across firms. In the second example, there is a firm-specific effect: The draws within a firm for each of the 10 industries are correlated. We draw the common ability from a normal distribution with a mean equal to 0 and standard deviation equal to 0.25. We add this common ability to the random industry ability drawn earlier. Thus, part of a firm's ability can be applied equally to all industries. In each case, we determine the industries in which it is optimal for each firm to produce and also the amount of each firm's production in each industry, given the price of output and the prices of inputs. We keep track separately of firms that choose to produce in one industry only, two industries only, and so on, up to firms that choose to produce in all the industries (if such firms exist). Thus, we have simulated data on one-segment firms, two-segment firms, and so on. For all firms with a given number of segments, we rank the segments by size, and we compute the mean firm ability d for that segment.

Figure 2, Panel A, illustrates the case in which the assignment of firm ability is independent across industries in which the firm produces. Each row contains the average of productivity by segment number for firms with a given number of segments. The figure shows how average firm talent in the economy varies by the number of segments in which a firm operates and by segment rank. As predicted, the figure shows that within firms, the main segments of conglomerates are better managed than peripheral segments. As we go across the number of segments in which a firm operates, equally ranked segments at first become more productive and then less productive. The drop-off in productivity occurs because it is very unlikely that any single firm is productive in all 10 industries. Thus, firms that choose to produce in many industries are likely to have mediocre ability in all of them. In this example, no firms in the sample produce in all the industries. A simple OLS regression on the simulated data shows that firms' mean productivity is positively and significantly related to their focus, measured by the Herfindahl index, and size. Empirically, this may be observed as a conglomerate discount in the stock market.

In Figure 2, Panel B, we allow firm ability in each segment to have a firm-specific component. We still see that the main segments are more productive than the peripherals. However, now equally ranked segments are more productive in firms that operate in more segments. Firms that choose to operate in many segments are more productive in general. Interestingly, a simple OLS regression shows that firms' mean productivity is again positively and significantly related to their focus, measured by the Herfindahl index, and size, albeit less so than with no common firm talent.

These examples show that while the model makes predictions about the distribution of firms' production, this distribution of production across industries depends on the distribution of ability. As we show below, they are consistent with empirical data. The model outcomes are also consistent

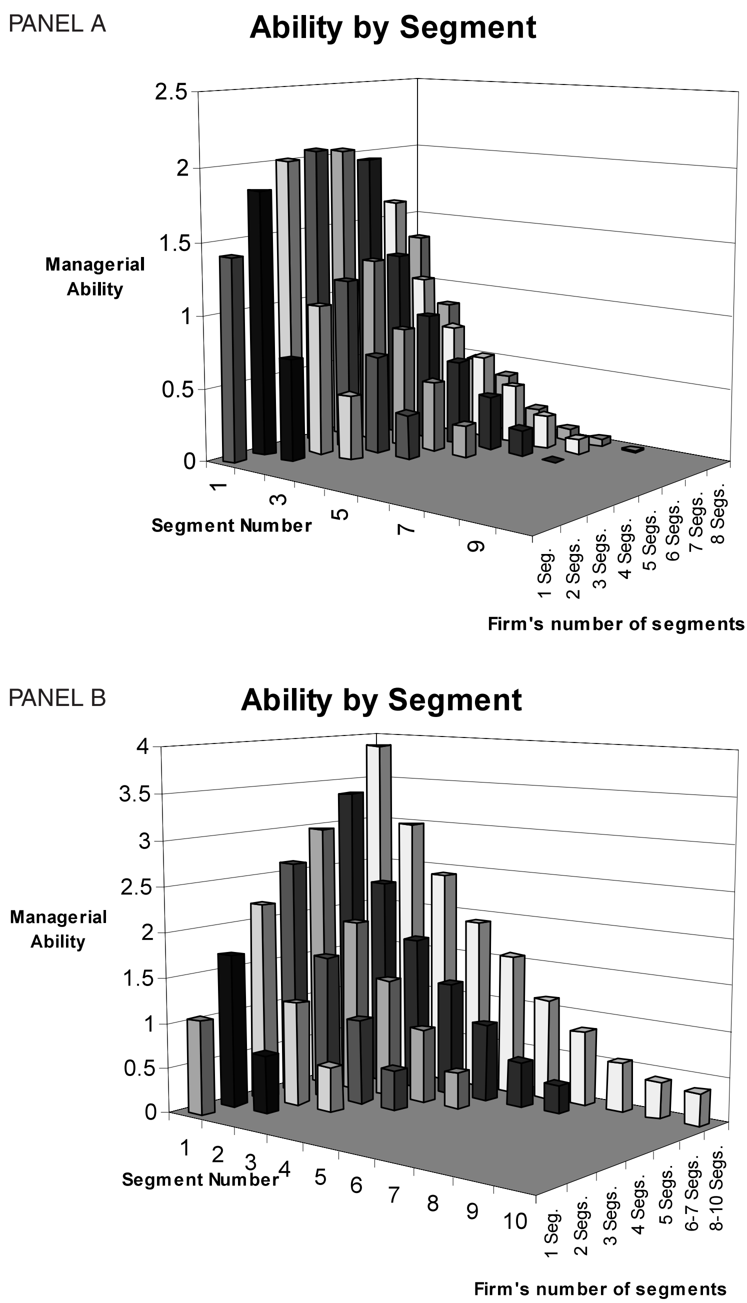

Figure 2. Model with no common managerial ability across industries (Panel A) and with managerial ability applicable across industries (Panel B).

with the existence of a conglomerate discount. Thus, they do not help differentiate the model from other models, such as empire-building models, which predict that firms inefficiently expand into industries outside their core competence. To help differentiate the inefficient internal capital markets and the neoclassical views, we extend the model to yield predictions on how conglomerates respond to demand shocks in industries in which they operate.

B. Shocks and Growth of Conglomerate Firms

To analyze the effect of price shocks on firm size more formally, we describe how the markets for capacity work. Assume that there is one period and two dates: $t = 1, 2$. At time $t = 1$, the firms learn the actual realization of a price shock Δp_A in the next period's output level in industry A. A market for industry A capacity opens in which firms can purchase or sell capacity units at a price r_A. Following an output price shock, there is an adjustment in the price of capacity Δr_A, so that supply again equals demand for capacity. Firms can choose to use all their capacity to produce, to sell some capacity to other firms that value capacity more after the shock and use the remainder to produce themselves, or to buy more capacity and produce. Firms may also choose to buy or sell capacity in industry B at price r_B in response to the new market prices in industry A. These transactions may cause the price of capacity in industry B, r_B and the price output p_B to adjust. In both industries, capacity may be purchased from and sold to other firms operating in the same industry, or from the suppliers of new capacity. We assume that the supply of capacity is not perfectly elastic, reflecting the addition of new capacity (for high levels of r_A) and sales for scrap (for low levels of r_A). Finally, at time $t = 2$, the firm realizes the cash flows. For simplicity, we assume that capacity has no salvage value at $t = 2$.

The model can be solved as follows: For each firm and each industry, we derive the demand for capacity as a function of the market prices for the output good p_i, $i = A$, B, which are given exogenously, and the prices of capacity r_i, which are endogenous. Then we sum up these demands and equate the total demand for capacity to the supply of capacity in each industry, which may itself depend on r_i. This allows us to solve for the equilibrium price of capacity r_i. Given r_i, we can then, in principle, find out the sizes of all the producers in each industry. Then following an output price shock we can solve for a new r_i and the new sizes of firms.[13] The sales and purchases can then, in principle, be determined by comparing the new and the old sizes of all firms.

We begin by analyzing how a conglomerate's segment's production responds to demand shocks in other segments and in its own segment. Since we are only interested in characterizing how the sizes of different types of

[13] This is similar to the way one might solve for optimal portfolios in a simple asset pricing model following a shock to the expected cash flow from the assets.

firms change after a price shock, we do not solve for the sales explicitly. Instead, we adopt a partial equilibrium approach and show how industry characteristics of interest affect a firm's size relative to other firms following a shock. For simplicity, we also assume that the effect of demand shocks in industry A only affect prices in that industry and that price effects in the other industry are of a second order.[14]

Following a price shock in industry A, the growth of a firm's output is positively related to $d_A \times \Delta p_A - \Delta r_A$.[15] The initial price shock in industry A and the corresponding change in the price of capacity have opposite effects on the firm's optimal output. Their net effect depends on the firm's ability d_A. First, consider highly productive firms. For such firms, the marginal positive effect of a price rise, $d_A \times \Delta p_A$, outweighs the effect of an increase in the cost of capacity Δr_A. As a result, such firms increase their output in industry A. To increase output, they either purchase new capacity or acquire existing capacity from other firms. The higher the ability d_A, the more capacity a firm adds in response to an increase in p_A. As the conglomerate firm adds capacity in industry A in response to a positive demand shock, the opportunity cost of its organizational talent increases. This makes it optimal to reduce the firm's output in industry B below what it would otherwise have been. Thus, following a positive price shock in industry A, the firm will refocus its operations out of industry B. This magnitude of effect is positively related to d_A.

The effect of a price shock in industry A on the marginal producers is more ambiguous. The expansion by the productive firms in industry A may bid up the price of capacity in the industry. If this effect is minor, then the marginal firms also expand in industry A. However, if the price of capacity is bid up sufficiently high so that Δr_A is larger than $d_A \times \Delta p_A$ for some firms, then these marginal producers in A find it optimal to sell out to more productive producers and focus instead in industry B. These firms' operations in industry A decline not only relative to those of more productive firms, but in absolute size as well. Thus, for example, a conglomerate whose core operations are in B may decide to sell a marginally productive unit in industry A when industry A receives a positive price shock and that peripheral's capacity becomes more valuable.

We show this more formally in Proposition 2.

PROPOSITION 2 (DEMAND SHOCKS AND FOCUS): *A positive price shock in industry A provides incentives for conglomerates that are productive in industry A to focus in that industry. If the supply of capacity in industry A is sufficiently inelastic, conglomerates that were marginal producers in industry A have an incentive to focus in industry B.*

[14] The working paper version of this paper solves an equilibrium model in which those prices, p_B and r_B, also adjust. The generalization does not affect the insights that we focus on here.

[15] These effects are obtained directly from equation (2).

Proof: From equations (2) and (3), the ratio of outputs of a conglomerate in industry A and industry B is

$$\frac{k_A}{k_B} = \frac{(u + w)(d_A p_A - r_A) - w(d_B p_B - r_B)}{(u + w)(d_B p_B - r_B) - w(d_A p_A - r_A)}.$$

The effect of a price shock in industry A is given by the following expression:

$$\frac{d\,\dfrac{k_A}{k_B}}{dp_A} = \frac{(u + 2w)u(d_B p_B - r_B)\left(d_A - \dfrac{dr_A}{dp_A}\right)}{((u + w)(d_B p_B - r_B) - w(d_A p_A - r_A))^2}. \tag{4}$$

A necessary condition for the firm to be a conglomerate is that $(d_B p_B - r_B) > 0$. Therefore the sign of this expression depends on the relative magnitude of d_A and dr_A/dp_A. We expect that $dr_A/dp_A \geq 0$. If the firm is very productive, then $d_A > dr_A/dp_A$, even for $dr_A/dp_A > 0$. For less productive firms, it may be that $d_A < dr_A/dp_A$, so that the firm refocuses in industry B. Q.E.D.

Since the size of a firm's operations in industry A is positively related to d_A, expression (4) directly yields a prediction about the effect of demand shocks in an industry on the firm's operations.

COROLLARY 1: *The greater the productivity of a conglomerate's operations in an industry, the greater the effect of price shocks in that industry on the optimal size of operations of the conglomerate in other industries.*

We thus would expect that shocks in a conglomerate's main segment (which, all else being equal, has a higher relative productivity) would produce greater effects on the industries in which it has its peripheral segments than if the opposite were true.

In the previous proposition, we focus on the effect of shocks on the relative size of the conglomerate's operations in each industry. Some of our empirical tests will compare the growth *rates* of segments within the same industry belonging to different conglomerates. The underlying intuition carries over to that case. In particular, the following result will be exploited in our empirical tests.

PROPOSITION 3 (DEMAND SHOCKS AND GROWTH): *Given a positive price shock in industry A, a conglomerate that is more productive in industry A will grow more slowly in industry B than an otherwise similar conglomerate that is less productive in industry A. Given a negative price shock in industry A, the relative growth rates of the two conglomerates in industry B are reversed.*

Proof: Consider two conglomerates, where conglomerate i has productivities of (d_A^i, d_B^i) and conglomerate j has productivity (d_A^j, d_B^j), where

$d_A^i > d_A^j$. The ratio of the outputs of conglomerate i to that of conglomerate j in industry B is given by

$$\frac{k_B^i}{k_B^j} = \frac{Z - w(d_A^i p_A - r_A)}{Z - w(d_A^j p_A - r_A)},$$

where $Z = (u + w)(d_B p_B - r_B) > 0$. In response to a shock to p_A, the change in the ratio of outputs in industry B is given by

$$\frac{d\,\dfrac{k_B^i}{k_B^j}}{dp_A} = \frac{Z + r_A w\left(1 + \dfrac{p_A}{r_A}\dfrac{\partial r_A}{\partial p_A}\right)}{(Z - w(d_A^j p_A - r_A))^2} \times (d_A^j - d_A^i).$$

The sign of the expression depends on the sign of $d_A^j - d_A^i$. Q.E.D.

Note that we do not predict this pattern of growth across conglomerates' business units because of agency problems within a conglomerate or because of the workings of conglomerate firms' internal capital markets. Rather, they result from the comparative advantage of conglomerates main and peripheral segments over different ranges of demand.

In measuring empirically the effects of price shocks in one segment on growth rates of other segments that we analyze above, we also need to control for the effect of own-industry shocks on the growth rates of producers. It is straightforward to show that a more productive producer adds more capacity than a less productive producer when its industry receives a positive demand shock. However, this does not necessarily imply that the growth *rate* of a producer following a positive demand shock is positively related to its productivity.

The key determinant of relative growth rates of firms within an industry following a demand shock is the extent to which the price of capacity changes relative to the price of output. When the price of output increases, more productive producers are willing to bid up the price of capacity higher than less productive producers. If the supply of capacity responds slowly to increases in demand, then the price of capacity may increase at a faster rate than the price of output. As a result, the more productive firms outbid the less productive firms, and the latter either invest more slowly, or maximize value by becoming sellers of capacity to more productive firms.[16] More productive firms not only add more capacity than less productive firms, as discussed earlier, but also become relatively larger. Conversely, if the supply of

[16] See the earlier version of this paper for a proof of this proposition. Maksimovic and Phillips (2001) provide support for this proposition testing an empirical model of capacity sales by firms in response to price shocks.

capacity is sufficiently elastic, then capacity becomes cheaper relative to the price of output following a positive demand shock, and less productive firms will grow faster relative to more productive firms.

In general we expect that the supply of new capacity is inelastic, especially when the economy is producing at capacity. Given the result of Proposition 1—that the main units of a conglomerate are more efficient than its peripheral units—we would expect that main units grow faster than peripherals when the industry receives a *positive* shock. In recessions, the opportunity cost of capacity may be its salvage value so that the supply of capacity is elastic, and we would expect main units to be cut less than peripherals when the industry receives a *negative* demand shock.[17] We examine this prediction in the empirical work below.

C. Relation of Our Model to the Agency Literature

An alternative view of the firm posits that the firms do not maximize profits. According to this view, the firm's investment policy is driven by opportunistic agents (usually the managers or the owners of a subset of the firm's securities), who attempt to distort the policy for their private benefit (see Jensen and Meckling (1976) and Jensen (1986)). We next discuss whether the comparative-static predictions derived above are also consistent with the agency view.

To the extent that the agents' opportunistic behavior is fully controlled by the firms' owners, the agency model is observationally equivalent to the profit maximizing model presented here. If opportunistic behavior is not fully checked, then the firm's investment policy may deviate from the profit-maximizing policy. Whether the opportunistic behavior leads to different predictions depends on the type of investment deviation. We consider three cases.

First, the agents may invest optimally, but divert a portion of the proceeds for their own benefits as higher overhead at the firm level or as overpayments for acquisitions. Our tests cannot necessarily detect this type of divergence as the firm's growth policy might still be very similar to that of the profit-maximizing firms. However, the diversion may involve higher payments to some factor of production (investment, labor, or materials). In that case, the link between measured productivity and investment would be broken, and the comparative-static predictions of the profit-maximizing model may be rejected.

Second, the agents may have a private benefit from investment in capacity (Jensen (1986) and Matsusaka and Nanda (2002)). In that case, firms invest more than is predicted by the profit-maximizing model developed above, but still allocate resources to the segment with the highest marginal return. Jensen (1986) and the subsequent literature on free cash flow do not model

[17] Maksimovic and Phillips (1998) examine how negative industry demand shocks affect the frequency and productivity of firms that are in Chapter 11 and Chapter 7 bankruptcy.

differences in the productivity of firms, so the predictions of those models about responses to demand shocks differ from those derived in Proposition 2 above. However, the profit-maximizing model above can be extended to allow for the private benefit to the agents that control the firm. Firms in the extended model overinvest, but the comparative statics of the model with respect to demand shocks and differences in technology are similar to those of the profit-maximizing model.[18] As a result, tests based on these comparative statics cannot reject the existence of private benefits of investment. However, by the same token, the hypothesis that such benefits are significant is not necessary to derive these predictions.

Third, opportunistic behavior by agents may cause firms to misallocate resources across segments. The misallocations may occur either because of internal conflicts within the firm or because firms diversify into industries in which they have insufficient expertise. These possibilities are suggested by prior work by Lamont (1997), Shin and Stulz (1998), Rajan et al. (2000), and Scharfstein and Stein (2000). Lamont (1997) contends that peripherals of firms in the oil industry are subsidized by the oil segments when the oil segment receives a positive price shock. Shin and Stulz (1998) find that investment of conglomerates' segments is affected by cash flows in other segments. The model by Scharfstein and Stein (2000) implies that weaker segments get subsidized by stronger ones. Rajan et al. (2000) argue that the investment by conglomerates with diverse opportunities depends on internal conflicts, so that they do not predict that such conglomerates will concentrate their growth in their relatively most productive segments. To the extent that such misallocation is material, our predictions developed above will be rejected by the data.

In sum, the comparative static predictions developed above allow us to test the hypothesis that firms allocate resources efficiently across segments. They do not directly test the hypothesis that there are private benefits of control. However, to the extent that the predictions are not rejected by the data, they suggest that resource allocation within conglomerates is consistent with profit maximization. Finally, we do not address the question of whether firms allocate resources efficiently across segments, but subsequently waste the cash flows through higher overhead.

II. Empirical Analysis: Firm Growth and Investment

We examine how industry demand, and firm-specific productivity affect the investment and growth of firm segments. Our null hypothesis is that the growth and investment decisions of conglomerate firms are consistent with profit maximizing behavior derived in Section I.

[18] If all firms overinvest, the price of output falls and the price of capacity may increase, reducing the desired output. As a result, once industry equilibrium is taken into account, the net increase in firm size is likely to be smaller than suggested by partial-equilibrium analysis.

We use three approaches to testing the predictions of our model. First, we calculate the productivities of conglomerates (main and peripheral industry segments) and of single-segment firms, and examine whether they are in accord with the patterns suggested by Proposition 1. While this test could reject our model, it does not allow us to differentiate between the model and other models which posit that conglomerates invest in peripheral segments for non-profit-maximizing reasons.

Second, to differentiate between our model and models that predict inefficient growth, we examine and test the growth patterns of conglomerates and compare them to growth patterns of single-segment firms. We also examine the investment decisions of conglomerate firms. One of our model's key predictions is that firms invest differently across industries based on comparative advantage in productivity. Specifically, we test the prediction of Proposition 3 that conglomerates will grow less in a particular segment (constructured by aggregating plant-level data into industries) if their other segment(s) is (are) more productive and if their other segment(s) experiences a larger positive demand shock. Models which posit inefficient cross-subsidization do not predict this relation. Rather, they suggest that positive shocks in other segments provide additional resources for the expansion of peripherals.

Finally, as a robustness check, we identify a subsample of "failed" conglomerates that were split up or have had substantial declines in the number of segments they operate over our sample period. If market forces are important in breaking up those conglomerates that have agency problems, then the failed conglomerates will be less likely to follow optimal policies than will the complementary subsample of conglomerates that survive. Thus, by comparing the fit of our model in the two subsamples, we can check whether our regressions are detecting optimal resource allocation.

A. Data

We examine both multiple-segment conglomerate firms and single-segment firms by using an unbalanced panel for the period 1975 to 1992. To be in our sample, firms must have manufacturing operations producing products in SIC codes 2000–3999. We require firms to meet these criteria because of the unique nature of the microlevel data that we use to calculate plant-level productivity and industry growth.

We use data from the Longitudinal Research Database (LRD), maintained by the Center for Economic Studies at the Bureau of the Census.[19] The LRD database contains detailed plant-level data on the value of shipments produced by each plant, investments broken down by equipment and buildings, and the number of employees.

The LRD tracks approximately 50,000 manufacturing plants every year in the Annual Survey of Manufactures (ASM). The ASM covers all plants with more than 250 employees. Smaller plants are randomly selected every fifth

[19] For a more detailed description of the LRD, see McGuckin and Pascoe (1988).

year to complete a rotating five-year panel. Note that while the annual data is called the Annual Survey of Manufactures, reporting is not voluntary for large plants and is not voluntary once a smaller firm is selected to participate. All data has to be reported to the government by law and fines are levied for misreporting.

We confine our analysis to 1974 through 1992. Given we construct measures of productivity (described in the next section) using five years of data, our regressions cover the period 1979 to 1992. We require each plant to have two years of data. For each firm, we also exclude all its plants in an industry (at the three-digit SIC code) if the firm's total value of shipments in the industry is less than $1 million in real dollars. After these requirements, we are able to construct productivity measures for 767,098 plant-year observations.

We aggregate each firm's plant-level data into firm industry units at the three-digit SIC code, giving us 374,339 segment-year observations. We call these industry-firm-level portfolios of plants "segments." Segments, defined this way, capture all the plant-level operations of a firm in an industry. However, these segments may not correspond to the true divisional structure of firms and we do not capture any headquarters or divisional level costs that are not reported at the plant-level (i.e., overhead, research and development). These constructed segments do not correspond to those reported by COMPUSTAT. The COMPUSTAT reported segments, however, as shown by Pacter (1993) and Hyland (1999), differ from actual operating segments. One advantage of the data we use is that these constructed segments actually do represent the industries in which a firm operates.

We classify firms as single segment or multiple segment, based on the three-digit SIC code. We use two cutoffs for classifying a firm as a conglomerate, 2.5 percent and 10 percent. We classify a firm as a multi-segment firm if it produces more than 2.5 percent (10 percent) of its sales outside its principal three-digit SIC code. To facilitate comparison with prior research, we report regression results (except for Table IV where we report results for both cutoffs) using the 10 percent cutoff.[20] For multiple-segment firms, we also classify each segment as either a main segment or a peripheral segment. Main segments are segments whose value of shipments is at least 25 percent of the firm's total shipments. Given we calculate growth rates and also divide capital expenditures by lagged capital stock, we also lose the initial year of firms that enter the database or a new segment, in years after 1978. This primarily affects smaller firms as new firms are likely to begin operation smaller. We also lose observations that are noncontiguous. These criteria cause our observations to fall to 279,200. Of these observations lost, 76 percent are single-segment firm-years. Our final data screen is we exclude segments that have continuously compounded annual growth rates greater than 100 percent in absolute value. Again, this requirement is more

[20] An earlier draft of this paper used the 2.5 percent cutoff for all regressions and found similar results.

likely to affect single-segment firms. Seventy percent of these final observations lost are years for single-segment firms. Imposing this last requirement leaves us with 266,103 segment-year observations.[21]

There are several advantages to this database: First, it covers both public and private firms in manufacturing industries. Second, coverage is at the plant level, and output is assigned by plants at the four-digit SIC code level. Thus, firms that produce under multiple SIC codes are not assigned to just one industry. Third, plant-level coverage means that we can track plants even as they change owners. One of the biggest advantages for this study is that the coverage accurately represents in which industries a multi-segment firm operates. As discussed earlier, segment data reported by COMPUSTAT is subject to reporting biases. Firms have considerable flexibility in how they report segments as shown by Pacter (1993). Firms may also have strategic reasons for the specific segments they choose or choose not to report, as Hayes and Lundholm (1996) show. In addition, Hyland (1999) finds that only 72 percent of firms that report under the FASB standards that they go from one segment to more than one segment actually increase their number of segments.

However, there are limitations to our data and the conclusions that can be reached from this study. The data base only covers manufacturing industries. We cannot track transfer pricing, and this may affect some of the cost measures, especially for vertically integrated firms. As noted earlier, we only have plant-level cost data, so that our data does not cover overhead or research and development at the corporate or divisional levels. Thus, our tests and conclusions pertain to the resource allocation between plants aggregated into industries. In addition, since our data does not distinguish between private and public firms, we cannot pick up the extent to which that privately traded conglomerates allocate resources efficiently while public ones do not.

B. Variable Selection

In this section, we describe the variables used to test our model and how we calculate these variables. The two primary dependent variables we investigate are a firm's segment growth and investment. The primary independent variables we use to test the predictions of our model are segment productivity and the change in aggregate industry shipments. We include a segment's lagged size and the lagged number of plants in the segment as control variables. We subtract out the industry average in each year from all segment level variables, except for the number of plants. In addition to these variables, we examine how growth is related to segment operating margin and value added per worker.

[21] We have also run tests using a cutoff of $10 million in real value of shipments as well as with growth rates of 500 percent and less and obtained similar results.

B.1. Productivity of Industry Segments

Our primary measure of performance is total factor productivity (TFP). We calculate productivity for all firm segments at the plant level. TFP takes the actual amount of output produced for a given amount of inputs and compares it to a predicted amount of output. "Predicted output" is what the plant should have produced, given the amount of inputs it used. A plant that produces more than the predicted amount of output has a greater-than-average productivity. This measure is more flexible than a cash flow measure, and does not impose the restrictions of constant returns to scale and constant elasticity of scale that a "dollar in, dollar out" cash flow measure requires. For robustness and comparability with prior studies, we also explore how segment growth is related to segment operating margin, both of the segment in question and of the conglomerates other segments. However, this measure is different from a typical cash flow number as we do not have cost measures for indirect segmental level costs, such as advertising and research and development, since our data is at the plant level.

In calculating the predicted output of each plant, we assume that for each industry there exists a production function that defines the relation between a plant's inputs and outputs. Then, for each industry, we estimate this production function using an unbalanced panel with plant-level fixed effects, using all plants in the industry within our 1974 to 1992 time frame. In estimating the production function, we use the last five years of data for each plant—thus, the first year of our data for which we have calculated productivity is 1979.[22]

To calculate a plant's productivity, we assume that the plants in each industry have a translog production function. This functional form is a second-degree approximation to any arbitrary production function, and therefore takes into account interactions between inputs. To estimate predicted outputs, we take the translog production function and run a regression of log of the total value of shipments on the log of inputs, including cross-product and squared terms:

$$\ln Q_{it} = A + f_i + \sum_{j=1}^{N} c_j \ln L_{jit} + \sum_{j=1}^{N} \sum_{k=j}^{N} c_{jk} \ln L_{jit} \ln L_{kit}, \tag{5}$$

where Q_{it} represents output of plant i in year t, and L_{jit} is the quantity of input j used in production for plant i for time period t. A is a technology shift parameter, assumed to be constant by industry, f_i is a plant-firm specific fixed effect (if a plant changes owners a new fixed effect is estimated. We leave off the firm subscript for tractability), and $c_j = \sum_{i=1}^{N} c_{ji}$ indexes returns to scale.

[22] A previous version estimated the production function using all years of data and found similar results.

Our measure of plant-level productivity is the residual from equation (5) plus the fixed effect, f_i. Using a fixed effect is important to capture higher persistent productivity arising from managerial ability, as the earliest studies by Griliches (1957) and Mundlak (1961, 1978) emphasize.[23] In terms of the model, TFP is $p * (d - predicted\ d)$, where d is output. TFP thus captures two effects. First, it captures the ability to produce at a higher level for a given amount of inputs. Second, as measured, it also captures the ability to price higher than the industry average, as we deflate for industry price at the four-digit level and also subtract out industry average TFP in each year. Thus, d in the model can be equated with these two factors. We standardize plant-level TFP by dividing by the standard deviation of TFP for each industry.[24] We standardize in this method so that when we include a segment's productivity, we control for the fact that in some industries we are able to estimate productivity more precisely. This correction is analogous to a simple measurement error correction and is similar to the procedure used to produce standardized cumulative excess returns in event studies. Our comparisons of plants' TFP will thus not be driven by differences in the dispersion of productivity within each industry. Finally, we compute a segment-level productivity at the three-digit SIC code by constructing a weighted average of the individual plant productivities, with weights equal to the predicted output of each plant. Alternative weighting schemes using the total value of inputs gave similar results in regressions. The variable for the productivity of the firm's other segments is the weighted average of all of the firm's other plants outside of the segment in question. The weights are the predicted plant-level value of shipments.

We also include other firm- and segment-level variables in our regressions to provide additional control for unmeasured productivity differences and other factors, such as size, that can influence firm growth. We include the log of firm size and the number of plants operated by a firm at the beginning of the year. We define firm size as the total value of shipments.

In estimating the TFPs in our sample, we use data for over 500,000 plant years, and for approximately 50,000 plants each year. In the productivity regression for each industry, we include three different types of inputs—capital, labor, and materials—as explanatory variables. All these data exist at the plant level. However, the ASM does not state the actual quantity shipped by each plant, but shows only the value of shipments. As a result, we take the difference between actual and predicted value of shipments as

[23] In addition to this specification for plant productivity, we also estimate two other related specifications. First, we just use the average of the plant fixed effects for the firm's division as a measure of firm ability in that segment (omitting the residual). Second, we estimate the above regression at the three-digit industry segment level, again using a firm-industry fixed effect plus the residual as a measure of firm ability in that segment. These alternative specifications still find a similar significant relationship between productivity and growth. Other variables also had the same signs and significance levels.

[24] This standardization does not affect the results we report. The results have similar levels of significance when we do not standardize productivity in this manner.

our measure of TFP. For all inputs and outputs measured in dollars, we adjust for inflation by using four-digit SIC code data from the Bartelsman and Gray (1994) database. Each input has to have a nonzero reported value. We also require that each plant have at least two years of data. As earlier noted, we then aggregate the plant-level TFP data into firm business-segment units at the three-digit SIC code from the individual plant-level data.

The production function approach also assumes that inputs into the production function are measured accurately. For most inputs (cost of materials, energy, workers), the assumption that the reported data are accurate appears reasonable. The data are required by law to be reported to the government and are cross-checked by the Bureau of the Census. However, for capital stock there are potential problems in using the reported values in each year. These values could be potentially misstated because of changes in reported values due to acquisitions. Thus, to obtain our capital stock measure we use a perpetual accounting method, beginning the plant's capital stock at its first reported level and use industry level depreciation rates from the Bureau of Economic Analysis to adjust the value of the capital stock in each year. Expenditures on buildings and equipment are added to the last year's value, adjusted for depreciation. We use data from the Bureau of Economic Analysis to make depreciation adjustments at the two-digit level. This method is similar to the method used to construct the value of capital used to construct Tobin's q. In addition, to capture vintage effects of capital, we include plant age in our productivity calculations. Plant age is the first year in which the plant appeared in the database, or 1972 (the first census year of the database we have), whichever is earlier. Kovenock and Phillips (1997) describe these inputs and the method for accounting for inflation and depreciation of capital stock in more detail.

As a robustness check, we also report alternative specifications where we use value added per worker and segment operating margin as our measure of skill or ability. While these productivity measures have potential limitations, checking the consistency of our results across the specifications provides a way of testing robustness of the results we report.

B.2. Industry Variables

To get a measure of industry demand, we use industry shipments at the four-digit SIC code level deflated using a 1982 industry price deflator from the Bartelsman and Gray (1994) database. We aggregate this data into the three-digit SIC code level. We detrend this data by regressing the actual value on a yearly time trend and take as our measure of an industry shock the difference between the actual and predicted value. We focus on detrended real industry shipments for two reasons. First, the value of capital and of allocating resources to growth in an industry depends on industry growth. Second, firms' cash constraints can depend on industry conditions. If firms in high-growth industries are less cash constrained than those in declining industries, then firms might have different growth rates.

To determine whether the level of industry demand alters the relation between the productivity and segment growth, we also classify years as recession or expansion years. We determine recession and expansion years by using aggregate and aggregate-detrended industrial production. We define detrended industrial production as the actual less predicted industrial production, where we calculate predicted industrial production from a regression of industrial production on a time trend. Recession years are years in which both real and detrended industrial production decline relative to the previous year. We classify years as expansion years when both real and detrended industrial production increase relative to the previous year.

This procedure gives us similar results as the NBER recession dating procedure, which NBER does quarterly. It also allows us to classify a year such as 1980, which, according to NBER, had a recession of less than six months. Using this procedure, we classify 1981 to 1982 and 1990 to 1991 as recession years and 1976 to 1978 and 1984 to 1988 as expansion years. Given that actual and detrended industrial production did not move in the same direction, 1979–1980, 1983, 1989, and 1992 are indeterminate years.

We also investigate the effect of industry cash flow on segment growth. We calculate industry cash flow by aggregating all plant-level costs and plant-level value of shipments to the three-digit SIC code. Thus, this measure is different from a typical cash flow number, as we do not have cost data for indirect segmental-level overhead costs, since our data is at the plant level. The results using industry cash flow are not presented. They are similar to the results presented and are available from the authors.

III. Results

A. Sample Summary Characteristics

Table I presents summary statistics for the firms in our data set. We break out the statistics by single- and multiple-segment firms. We present both real-growth rates and the proportion of total real-dollar value of shipments by industry segments. We calculate real-growth rates by using individual plant-level shipments deflated by four-digit SIC code deflators from the NBER productivity database.

Table I shows that from 1980 to 1990, the proportion of output produced by single-segment firms in the U.S. manufacturing sector increased by five percentage points. This increase occurred because of a substantial increase in the number of new single-segment firms and because multiple-segment firms decreased production in their peripheral segments. We also see that multiple-segment firms' main segments show almost a zero growth rate in recessions, and that single-segment firms and peripheral segments of multiple-segment firms register negative growth. Finally, the table shows that for both conglomerates and single-industry firms, more productive firms grow at substantially higher rates. Table I also shows that average segments of single-segment firms are more productive than those of conglomerate firms

Table I

Sample Characteristics: Single-segment and Multiple-segment firms

Sample characteristics of firms' industry operating segments. We calculate statistics from plant-level data aggregated into three-digit SIC codes for each firm. We classify single-segment versus multiple-segment firms based on three-digit SIC codes. For multiple-segment firms, main segments are segments that represent at least 25 percent of the firm's total shipments. We base size classifications on the previous year's real value of industry shipments relative to each industry's median value of shipments. We determine recession and expansion years using aggregate detrended industrial production. Recession years are years in which both real and detrended industrial production decline relative to the previous year. We classify years as expansion years when both real and detrended industrial production increase relative to the previous year.

	Sample of Firms		
		Multiple-segment Firms	
Statistics by Industry Segments	Single-segment Firms	Main Segments	Peripheral Segments
Number of segments—beginning of decade: 1980	13,298	4,880	2,582
Number of segments—end of decade: 1990	17,321	4,745	3,090
Proportion of value of shipments (all manufacturing industries)			
Beginning of decade: 1980	21.71%	50.75%	27.53%
End of decade: 1990	26.72%	49.65%	23.63%
		Multiple-segment Firms	
Productivity by segment size (average over years in panel)[a]			
\$1–\$10 million in value of shipments, (1982 \$)	−0.417	−0.331	
\$10–\$25 million in value of shipments, (1982 \$)	0.148	0.109	
\$25–\$50 million in value of shipments, (1982 \$)	0.322	0.317	
\$50–\$100 million in value of shipments, (1982 \$)	0.404	0.383	
Segments > \$100 million (1982 \$)	0.487	0.449	
		Main Segments	Peripheral Segments
Average annual industry segment growth rate			
Recession years (1981–1982, 1990–1991)			
All industry segments	−5.15%	−0.01%	−5.48%
Firms' most productive segments (top 50th percentile of TFP by industry)	−3.54%	1.57%	−4.06%
Expansion years (1976–1978, 1984–1988)			
All industry segments	2.46%	7.30%	2.60%
Firms' most productive segments (top 50th percentile of TFP by industry)	5.99%	9.66%	4.35%

[a] Productivity is total factor productivity (TFP) and is a relative measure of productivity. TFPs are standardized by dividing each TFP by the standard deviation of the industry's TFP at the three-digit level.

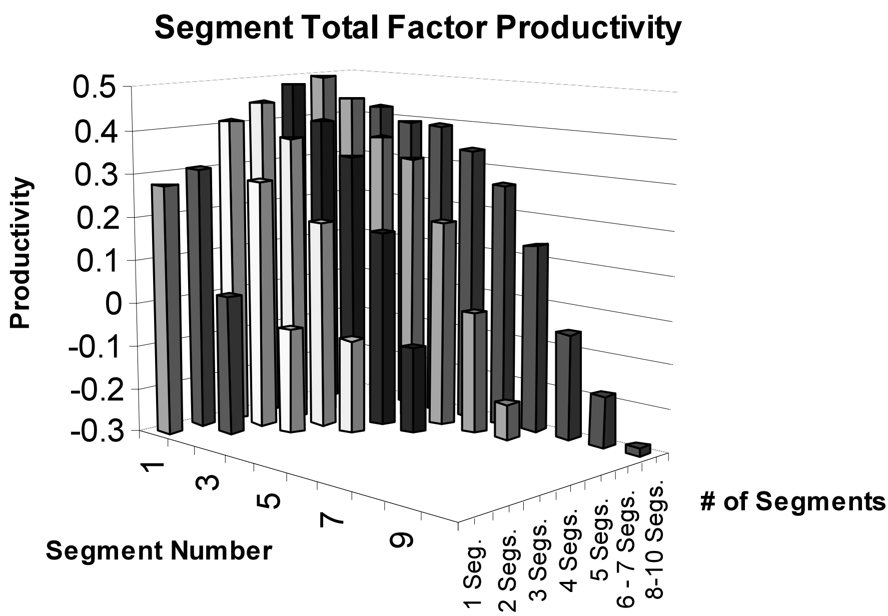

Figure 3. Productivity ordered by segment size.

for all size categories, except for the smallest size segments. The smallest size category, 1–10 million real dollars, comprise only 3.3 percent of the total conglomerate segments. The table also shows that size is significantly related to productivity. This finding is consistent with our model.

In Figure 3 we examine how the productivity of conglomerates' segments varies with the size ranking of the segment within the conglomerate, and with the total number of segments. We include the average productivity of each of the segment ranks for firms with a particular number of segments. There are a large number of single-segment firms with total sales less than 10 million dollars, while only a few conglomerate firms are less than this size. Given Table I shows that size is a critical variable, for comparability between single- and multiple-segment firms we only include firms with 10 million dollars in real value of shipments in this graph. If we include single-segment firms with total shipments less than 10 million dollars in this graph, average single-segment productivity falls to −0.05, while conglomerate segment productivity is relatively unaffected.[25] Figure 3 shows that there is a

[25] Only 3.3 percent of conglomerate segments are affected by this higher size cutoff and it has little effect on productivity. For example, if we include these smaller segments for conglomerate firms, productivity of the main segment of a conglomerate with two segments falls to 0.268 from 0.286, for a conglomerate with three segments productivity is slightly higher, 0.407 versus 0.394. By comparison, 37 percent of single-segment firms are between 1 and 10 million 1982 dollars. In our regressions, we do include these smaller segments as we control explicitly for size by including a size variable.

strong negative relation between the segment's rank and its productivity. This is consistent with the neoclassical hypothesis that conglomerates are larger in the segment on which they have a comparative advantage. This within-conglomerate drop-off in productivity in smaller segments suggests that organizational talent has an industry-specific component. One would expect such a drop-off in productivity in smaller segments if there is an industry-specific component to organizational talent.

Figure 3 also shows how the productivity of segments that are equally ranked by size within the conglomerate varies as the number of segments increases. Holding the within-conglomerate rank of a segment constant, its productivity increases as the total number of segments increases. Thus, for example, the mean productivity of the largest segment of a two-segment conglomerate is lower than its industry average, whereas the mean productivity of the largest segment of a conglomerate with more than 10 segments is higher. Figure 3 shows that conglomerates with 8 to 10 segments are more productive than their industry average in their first 7 segments. This is consistent with the hypothesis that there are a number of large conglomerates whose firm organizational talent is portable across several industries.

The comparison of equally ranked segments for conglomerates of different sizes suggests that firms choose whether or not to become conglomerates depending on their initial productivities. Some firms may move into a second industry because they have attained their optimal size in their main segment. Given decreasing returns in their main industry, their opportunities would be better in a second industry. Other firms may have higher ability in their main industry and will expand more in that industry. We would expect the latter to be highly valued by the stock market and the former to have a low valuation. As a result, conglomerate discounts may not necessarily be evidence of agency problems. Instead, conglomerate discounts and premia may reflect the underlying distribution of firm organizational or managerial ability and the extent to which it is industry specific.

B. Growth and Productivity over the Business Cycle

We first show how the average real growth and productivity of segments of single-segment and conglomerate firms can vary by size. Since our model predicts a different relation between productivity, size, and growth in response to positive and negative industry shocks, we report the results separately for expansion and recession years in the U.S. economy. These results appear in Table II. In this table, we define the size of each segment as the ratio of the size of the segment to the size of the median segment in the same industry, both measured at the beginning of the year. We only report three of five size classifications in the interest of space. The unreported size classifications for classifications two and four were presented in an earlier version and support similar conclusions as those from size classifications three and five.

Table II

Growth and Productivity over the Business Cycle

Sample characteristics of firms' industry operating segments in expansion and recession years. Statistics are calculated from plant-level data aggregated into three-digit SIC codes for each firm. Single-segment versus multiple-segment firms are based on three-digit SIC codes. For multiple-segment firms, main segments are segments which are at least 25 percent of the firm's total shipments. Size classifications are based on previous years real value of industry shipments and are relative to each industry's median value of shipments. Number of segments is for the beginning of the period. Expansion (recession) years are years in which both real and detrended aggregate industrial production increase (decrease) relative to the previous year.

	Sample of Firms		
		Multiple-segment Firms	
	Single-segment Firms	Main Segments	Peripheral Segments
Panel A: Characteristics of Firm Operating Segments in Expansion Years (Average over 1976–1978, 1984–1988)			
Size Group 1: one-quarter to one-half of the industry median			
Real growth of firm segment	5.10%	9.44%	2.97%
Growth of efficient segments (top 50% of TFP)[a]	13.70%	17.20%	11.40%
Productivity (TFP) of firm segment[a]	−0.200	−0.121	−0.391[b]
Number of firm segments	2025	213	65
Size Group 3: one to two times the industry median			
Real growth of firm segment	2.13%	9.08%	2.30%
Growth of efficient segments (top 50% of TFP)[a]	7.27%	13.56%	7.32%
Productivity (TFP) of firm segment[a]	0.197[c]	0.120	−0.173[b]
Number of firm segments	1195	412	274
Size Group 5: greater than five times the industry median			
Real growth of firm segment	1.10%	6.15%	4.23%
Growth of efficient segments (top 50% of TFP)[a]	2.67%	7.49%	6.70%
Productivity (TFP) of firm segment[a]	0.422[c]	0.375	0.154[b]
Number of firm segments	171	731	3241
Panel B: Characteristics of Firm Operating Segments in Recession Years (1981–1982, 1990–1991 Averages)			
Size Group 1: segment one-quarter to one-half of the industry median			
Real growth of firm segment	−1.50%	2.16%	−2.30%
Growth of efficient segments (top 50% of TFP)	7.57%	7.31%	4.79%
Productivity (TFP) of firm segment	−0.272	−0.169	−0.582[b]
Number of firm segments	3380	116	31
Size Group 3: segment one to two times the industry median			
Real growth of firm segment	−5.10%	−0.75%	−8.10%
Growth of efficient segments (top 50% of TFP)	−0.03%	4.77%	−3.11%
Productivity (TFP) of firm segment	0.173[c]	0.061	−0.198[b]
Number of firm segments	2495	341	130
Size Group 5: segment greater than five times the industry median			
Real growth of firm segment	−6.20%	−0.84%	−4.20%
Growth of efficient segments (top 50% of TFP)	−3.16%	0.60%	−0.78%
Productivity (TFP) of firm segment	0.379[c]	0.373	0.175[b]
Number of firm segments	1226	1305	3967

[a] Productivity is Total Factor Productivity (TFP) and is a relative measure of productivity. TFPs are standardized by dividing each TFP by the standard deviation of the industry's TFP at the three-digit level.

[b] Significant difference between main and peripheral segments at less than the five percent level using a two-tailed test for a difference from zero.

[c] Significantly different from multiple-segment firms at less than the five percent level using a two-tailed test for a significant difference from zero.

Table II examines three predictions of our model. First, we test whether single-segment firms are more productive than conglomerate firms of a similar size. Second, we test whether the main segments of conglomerate firms are more productive than peripheral segments. Third, we examine how the relation between growth and productivity during expansions and recessions differs for conglomerate firms' main and peripheral segments.

Panel A of Table II shows that single-segment firms have significantly higher productivity than conglomerate firms in two of the table's reported three size classes. We also find this result in the unreported second and fourth size classifications. The final column shows that conglomerate main segments are significantly more productive than peripheral segments for all size classes.

The third finding in Panel A is that there is a strong positive association between growth and productivity in expansions, and that size is very important to this relation. Firms that are large at the beginning of the year tend to be more productive, but grow at a slower rate than smaller firms. This finding seems to indicate that smaller firms grow much faster than large, productive ones. However, small firms tend to have a wider range in productivity. If we look at the most productive 50 percent of firms for each size class, we find that growth rates do increase with productivity. Finally, the table shows that conglomerates grow their productive main segments at a much faster rate than their less productive peripheral segments.

These results show that a relation exists between productivity and segment type, and that it is consistent with our model. As a result of this relation, the main and peripheral segments of conglomerates should not be investing similarly when there is a positive industry shock to demand.

In recessions, we find the following: First, for each size class, firm growth increases with productivity for single-segment firms and for segments of conglomerates. Second, conglomerate firms cut growth much more in their peripheral segments than in their main segments. Sales in their peripheral segments decrease sharply, although for some size classes, the main segments actually grow in real terms in the recession years. Finally, single-segment firms are more affected by recessions than main segments of conglomerate firms, but nevertheless show higher growth rates than do the peripheral segments of the conglomerate firms.

We also explore the average annual growth rates for single-segment and multiple-segment firms during recession and expansion years for segments of different levels of productivity. Our model predicts that the difference between the growth rates of high and low productivity firms should be lower during recessions than expansions. Thus, we compare the industry-adjusted annual growth rates of the most productive quartile of firm segments with the quartile of least productive segments. We find that the difference in annual growth rates between the most- and least-productive quartiles of industry segments was 2 to 2.5 percentage points higher in expansion years than in recession years.

Specifically, the difference in the growth rates between the main segments of conglomerate firms in the highest productivity quartile and the main segments in the lowest productivity quartile is 2 percentage points more during expansion years than during recession years. For single-segment firms and peripheral segments, the difference in growth rates between segments in the highest and lowest productivity quartiles is 2.5 percentage points higher in expansions than in recessions.

Before we examine the regression results, we can draw three conclusions. First, during both expansions and recessions, growth increases with productivity for nearly all size-based classifications. Second, productive firms grow faster in expansion years than during recession years. This finding supports the prediction of our model that positive shocks effect more productive firms differently. Third, peripheral segments experience the worst real growth declines in recession years. This may imply that conglomerate firms use their peripheral segments to subsidize main segments. Alternatively, as predicted by the neoclassical model, conglomerates could be cutting back on low productivity segments in response to large negative industry shocks when the supply of capacity is elastic, which is more likely to be the case in a recession.

We also examined whether the disparity in the performance of conglomerate firms' main segments and their peripheral segments can be explained by industry differences. It could be that peripheral segments are in low-growth industries and main segments are in high-growth industries. To control for industry growth, we examined high and low growth quartiles of all industries based on a 12-year real-growth rate of shipments described in the earlier section. Results available from the authors show that separate long-run analyses of high- and low-growth industries do not substantively change the previous results. The sharp differences between the main and peripheral segments of conglomerates remain. Peripheral segments grow at a much slower rate and are less productive both in high- and low-growth industries.

C. Growth and Relative Productivity with Industry Shocks

Table III examines the effect of productivity and industry fundamentals on the real-growth rates of conglomerate and single-segment firms in multivariate regressions. We measure the dependent variable, industry-adjusted segment growth, in real 1982 dollars, subtracting out the industry average for each year. Productivity and segment size are industry adjusted and represent absolute deviations from industry averages in each year.

Our empirical specification is motivated by equation (2). Our model predicts that the growth of a segment depends on the interaction between the segment's productivity and the sign of the demand shock in the industry. For positive (negative) shocks, growth is predicted to vary positively (negatively) with productivity. To test for this interaction, we include a variable that interacts the change in industry demand with the segment's productivity.

Table III

Segment Growth

Regressions test the effects of plant-level productivity and industry-level demand on firm industry segment sales growth for single-segment and multiple-segment firms. The dependent variable, segment growth is industry adjusted in each year. Segment size and productivity are industry adjusted in each year. Real industry shipments is detrended by regressing industry shipments (in 1987 dollars) on a yearly time trend. In column two (three) multiple-segment firms are firms with at least two segments each with 2.5 percent (10 percent) of their total shipments. Data are aggregated into firm three-digit SIC codes for industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conducted using heteroskedasticity-consistent standard errors following Huber–White. Data are yearly from 1979 to 1992. Observations are included for growth rates less than 100 percent and for firms whose real value of shipments is greater than one million dollars. (p-values are in parentheses.)

Dependent Variable: Segment Growth				
		Multiple-segment Firms		Test for Significant Diff.: Multiple-segment Interaction Variable (p-value)[d] Column 3–Column 1
Variable	Single-segment Firms	(2.5 percent cutoff)	(10 percent cutoff)	
Constant	0.024	−0.004	−0.005	
	(0.000)[a]	(0.004)[a]	(0.003)[a]	(0.000)[a]
Real industry shipments (detrended)	0.009	0.002	0.005	
	(0.186)	(0.717)	(0.462)	(0.715)
Firm segment productivity (TFP)[e]	0.069	0.054	0.054	
	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]
Industry shipments (detrended) ∗ TFP	0.013	0.022	0.019	
	(0.021)[b]	(0.002)[c]	(0.013)[b]	(0.106)
ln(lagged firm segment size)	−0.047	−0.002	−0.002	
	(0.002)	(0.339)	(0.376)	(0.242)
Number of plants owned by firm	−1.371	−0.028	−0.028	
(beginning of year, coeff ∗ 100)	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]
Firm multiple-segment variables				
Other segment's weighted TFP[f]		−0.008	−0.007	
		(0.000)[a]	(0.000)[a]	
Relative demand ∗ other segments		−0.003	−0.004	
weighted TFP[g]		(0.051)[b]	(0.035)[b]	
Total industry-segment years	171,126	94,977	87,915	
Chi-squared statistic	8871.14	2417.17	2111.30	
Significance level (p-value)	<1%	<1%	<1%	

[a,b,c] Significantly different from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively, using a two-tailed test.

[d] Significance test for a multiple-segment dummy variable interacted with each independent variable in a regression with all firm segments.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity is a weighted average of the firm's other segment(s) weighted by the segment(s) predicted output.

[g] Relative industry demand is interacted with other segments' productivity and equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

Proposition 3 of our model also predicts that the growth of a conglomerate firm's segment depends on the relative productivity and demand conditions facing the firm's other segments. Specifically, we consider how a segment of a given productivity will grow faster (slower) if the firm's other, more productive segments receive negative (positive) shocks and other, less productive segments receive positive (negative) shocks.

In our regressions, we use two variables to measure how the growth of a conglomerate firm's segment is affected by the firm's other segments. First, we measure the productivity of the other segments by weighting the TFP of each segment by its predicted sales. Second, we test for the interaction between the segment's shock and the shocks in other segments by interacting the segment's relative industry demand with the other segments' weighted productivity. We measure relative industry demand by a variable that equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment. Our model predicts that this variable will have a negative coefficient.

For each segment, we control for the segment's productivity (TFP), the total number of plants owned by the firm to which the segment belongs, and the log of firm size. The last two variables are lagged to represent values at the beginning of the year. Thus, for every segment, the regressions control for both the segment's own productivity, and for firm and industry characteristics.

We estimate the regression for both single- and multiple-segment firms. For multiple-segment firms, we present two different cutoffs for sales percentage a firm has to have in two segments to be classified as a multiple-segment firm, both 2.5 percent and 10 percent. All subsequent tables are presented using the 10 percent cutoff for comparability with previous samples of firms using COMPUSTAT. We estimate the regressions using unbalanced panel techniques, with random effects at the segment level and allow for correlated residuals within panel units. Standard errors are corrected for heteroskedasticity.[26]

The regression results in Table III show that both single- and multiple-segment firms' growth rates are significantly and positively related to segment productivity. The sensitivity is significantly greater for single-segment firms than it is for multiple-segment firms. However, the economic effects which follow in Table V show that this difference is not economically very large when we compare single-segment firms to the main segments of multiple-segment firms.[27] The number of plants is also negatively related to firm growth, which suggests that there are additional decreasing returns to expansion.

[26] Moulton (1987) shows that random effects have better consistency properties if the regressors are subject to measurement error, while fixed effects are preferred if the regressors are endogenous. Since our TFP measure may be subject to measurement error, we present results using random effects. In addition, we estimate this specification using productivity measured using just a fixed effect (omitting the residual) at the segment level. Again, we find similar results for the sign and significance of coefficients.

[27] This result is sensitive to how productivity is measured. When productivity is calculated over the whole period, versus just using data from the prior five years, we find growth of conglomerates is more sensitive to productivity than single-segment firms.

The evidence on the interaction effects is consistent with the predictions of our model. The own-segment interaction variable, real change in industry shipments times segment productivity, is positive and significant. Firms increase more in size when they receive a positive shock to a segment in which they have high productivity.

When we look at the interaction effects for conglomerate firms' other segments, we find evidence that the segment's growth rate is affected by the prospects of the firm's other segments. As predicted by our model, the segment's growth rate is negatively related to the interaction variable for a conglomerate's other segments, relative demand times the other segments' relative productivity. Thus, segment growth is lower when the other segments are more efficient and receive a positive demand shock. The influence of the other segments' relative productivity without controlling for demand is insignificant.

To test for robustness across estimation techniques, we ran the regression for conglomerates in Table III as a cross section for each year in the sample, as in Fama and MacBeth (1973). We averaged these coefficients over the individual years. For productivity (TFP), the average of the yearly coefficients was 0.047 and was highly significant, similar to the results for the entire panel we present. For change in industry shipments times TFP, the average of the yearly coefficients was 0.0265, with a t-statistic, based on the standard error of the mean, of 2.08, not as high a level of significance as the regression reported but still significant. This coefficient is also bit higher than the reported coefficient of 0.019 that we report in Table III. For the coefficient on "Relative demand times other segments weighted TFP," the average of the yearly coefficients was -0.0048, which again compares favorably with the reported coefficient, -0.004, for the whole panel in Table III. This average coefficient had a t-statistic of -2.71, which is more significant than the reported p-value for the panel of 0.035. Finally, the average coefficient on "Other segment's weighted TFP" was -0.008, which compares favorably with the panel coefficient of -0.007. The t-statistic based on the standard error on the mean of the yearly coefficients is -3.18, still highly significant.[28]

These results show that firms grow faster in segments that are more productive and that firms take into account the prospects of their other segments in a way that is consistent with the neoclassical maximizing firms in our model. While we do not have a precise benchmark for the optimal level of growth, the fact that conglomerate industry-adjusted and year-adjusted growth rates are highly sensitive to segment productivity across their segments is consistent with conglomerates making efficient resource allocation decisions.[29]

[28] In addition, we estimated the regressions in Table III using segment size relative to the industry as a proxy for productivity. The direct prediction of our model is that firms are bigger in their best segments. Size is thus a direct proxy for firm ability in a segment under the assumptions of our model. We found similar results as those reported in Table III.

[29] It is also consistent with an equal level of agency problems for both conglomerate and single-segment firms.

D. Growth of Conglomerates' Main and Peripheral Segments

Table IV estimates the same regressions as Table III, but breaks the conglomerate multiple-segment firms into their main and peripheral segments. In the last column, we test for significant differences in coefficients between main and peripheral segments of conglomerates.

The results in Table IV show that both main and peripheral segments' growth rates have positive sensitivity to relative productivity. The results also show that the peripheral segments are more sensitive to productivity than the main segments. We also find that, consistent with the neoclassical model, the interaction variable, relative demand times other segments' TFP, is significantly negative for peripheral segments. For main segments, our results are weaker. We find the same predicted negative relationship between growth and the other segments' productivity interacted with relative demand for main segments, but it is not significant. Corollary 1 predicts that a segment's growth is more sensitive to the other segments' prospects (measured by productivity interacted with relative demand) when the other segments are large. We test for this difference by comparing the coefficients of other segments' productivity interacted with relative demand for main divisions and peripherals. We find that they are not significantly different (the *p*-value for this test is at the 18 percent level), given the large standard error in the coefficient in the main divisions' equation.

Table V examines the economic significance of our regression results using the estimated coefficients from the regressions in Tables III and IV. We calculate predicted real-growth rates of conglomerate and single-segment firms, as productivity and change in shipments varies from the 25th to the 75th percentiles. In computing these predicted growth rates, we hold all variables, except productivity, at their sample medians.

The results in Table V show that both single-segment and conglomerate firms are very sensitive to their productivity relative to their industry competitors. Comparing the results for single-segment firms and conglomerate firms' main segments, we find that there is little economic difference in the predicted growth rates. There is an even smaller difference in predicted growth rates when we predict growth rates holding constant the underlying data across regressions. This result can be seen when we predict growth for the single-segment firms using the data from the main segments combined with the coefficients from the single-segment firms.

E. Segment Capital Expenditures

Table VI examines the investment of single segment and conglomerate firms' main and peripheral segments. In the last column, we test for significant differences in coefficients across conglomerates' main and peripheral

Table IV

Segment Growth

Regressions test the effects of plant-level productivity and industry-level demand on firm industry segment sales growth for main and peripheral segment of multiple-segment firms. The dependent variable, firm segment growth is industry adjusted in each year. Segment size and productivity are industry adjusted in each year. Real industry shipments is detrended by regressing industry shipments (in 1987 dollars) on a yearly time trend. Multiple-segment firms are firms with at least two segments each with 10 percent of their total shipments. Data are aggregated into firm three-digit SIC codes for industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conducted using heteroskedasticity-consistent standard errors following Huber–White. Data are yearly from 1979 to 1992. Observations are included for growth rates less than 100 percent. (p-values are in parentheses.)

Dependent Variable: Segment Growth			
	Multiple-segment Firms		Test for Significant Diff.: Multiple-segment Interaction Variable (p-value)[d]
Variable	Main Segments	Peripheral Segments	
Constant	0.010	−0.016	
	(0.000)[a]	(0.000)[a]	(0.000)[a]
Real industry shipments (detrended)	−0.009	0.010	
	(0.408)	(0.271)	(0.155)
Firm segment productivity (TFP)[e]	0.046	0.058	
	(0.000)[a]	(0.000)[a]	(0.000)[a]
Industry shipments (detrended) ∗ TFP	0.014	0.022	
	(0.292)	(0.019)[b]	(0.556)
ln(lagged firm segment size)	−0.012	−0.001	
	(0.149)	(0.511)	(0.178)
Number of plants owned by firm	−0.418	−0.182	
(beginning of year, coeff ∗ 1000)	(0.001)[a]	(0.000)[a]	(0.933)
Firm multiple-segment variables			
Other segment's weighted TFP[f]	−0.006	−0.005	
	(0.030)[b]	(0.089)[c]	(0.928)
Relative demand ∗ other segments	−0.001	−0.006	
weighted TFP[g]	(0.605)	(0.014)[b]	(0.178)
Total industry-segment years	32,517	55,398	
Chi-squared statistic	559.55	1474.38	
Significance level (p-value)	0.010	<1%	

[a,b,c] Significantly different from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively, using a two-tailed test.

[d] Significance test for a multiple-segment dummy variable interacted with each independent variable in a regression with all firm segments.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity is a weighted average of the firm's other segment(s) weighted by the segment(s) predicted output.

[g] Relative industry demand is interacted with other segments' productivity and equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

Table V

Economic Significance of Regression Results

Predicted real growth rates of conglomerate and single-segment firms as productivity and change in shipments * size varies from the 25th to the 75th percentiles. We compute these predicted growth rates holding all variables except productivity and change in industry shipments * size at their sample medians. Predicted real growth rates using coefficient estimates from Tables III and IV: Variables taken at the respective sample medians.

	Growth Rate at the		
Varying Total Factor Productivity	25th Percentile	50th Percentile	75th Percentile
Single-segment firms (own productivity data):	−2.69%	0.92%	4.39%
Data from conglomerates' main segments	−2.17%	1.05%	4.36%
(Both use coefficients from Table IV, column 1)			
Conglomerate firms			
All segments (using coefficients from Table IV, column 2)	−2.34%	0.28%	2.97%
Main segments (using coefficients from Table V, column 1)	−0.26%	1.88%	4.19%
Peripheral segments (own productivity data)	−3.70%	−0.85%	2.05%
Productivity data from conglomerates' main segments	−2.66%	0.10%	2.93%
(Both use coefficients from Table V, column 2)			

segments. In this table, we exclude all observations where the absolute value of capital expenditures divided by lagged capital stock is greater than 100 percent at the segment level.[30]

The results in Table VI show that both conglomerate and single-segment firms' investment is sensitive to the productivity and fundamental industry factors. Especially interesting is the fact that the interaction of productivity with industry shipments is significant both for peripheral firms and for main segments. These findings reinforce the conclusion that there is no evidence that conglomerate firms insulate their peripheral segments. We also find that interaction of relative demand and the firm's other segments' productivity is negative and significant as predicted by our model. We do not find evidence of investment patterns consistent with cross-subsidization.

Overall, the results suggest that conglomerate firms take into account the prospects of other segments when allocating resources. The consistency of these findings (for both capital expenditures and shipments growth) shows the robustness of our results. We find that the growth rate of both main and peripheral segments responds positively to segment productivity and industry variables that capture the fundamental prospects for that segment.

[30] This criterion affects 1.8 percent of the segment-year observations. The number of observations remaining is approximately 3 percent higher than the regressions in Table III that excluded observations based on the shipments growth rate. The reason for this fact is that a firm is less likely to double its capital stock than to double its shipments. This criterion also affects the number of single-segment firms more significantly. For these regressions, 73 percent of the segment-year observations excluded based on this criterion were for single-segment firms.

Table VI

Segment Capital Expenditures

Regressions test the effects of plant-level productivity and industry-level demand on a firm's capital expenditures in a segment for single-segment and multiple-segment firms. The dependent variable, segment capital expenditures, is divided by the beginning of period capital stock and is industry adjusted in each year. Productivity and segment size are also industry adjusted in each year. Real industry shipments is detrended by regressing industry shipments (in 1982 dollars) on a yearly time trend. Data are aggregated into firm three-digit SIC codes for industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conducted using heteroskedasticity-consistent standard errors following Huber–White. Data are yearly from 1979 to 1992. Observations are included for firms whose real value of shipments exceeds one million dollars and when observations are less than 100 percent in absolute value. (p-values are in parentheses.)

Dependent Variable: Segment Capital Expenditures				Test for Significant Diff.: Across Conglomerates
		Multiple-Segment Firms		
Variable	Single-segment Firms	Main Segments	Peripheral Segments	Column 2–3 (p-value)[d]
Constant	−0.033	0.001	−0.044	
	(0.000)[a]	(0.682)	(0.000)[a]	(0.000)[a]
Real industry shipments (detrended)	−0.001	−0.003	−0.001	
	(0.788)	(0.774)	(0.908)	(0.880)
Firm segment productivity (TFP)[e]	0.160	0.111	0.095	
(coefficient ∗ 10)	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.054)[c]
Industry shipments (detrended) ∗ TFP	0.016	0.033	0.013	
	(0.000)[a]	(0.018)[b]	(0.019)[b]	(0.725)
ln(lagged firm segment size)	−0.005	−0.001	−0.001	
	(0.000)[a]	(0.324)	(0.136)	(0.816)
Number of plants owned by firm	0.003	0.002	0.000	
(beginning of year, coeff ∗ 10)	(0.227)	(0.265)	(0.092)[c]	(0.749)
Firm multiple-segment variables				
Other segments weighted TFP[f]		−0.001	−0.001	
		(0.220)	(0.229)	(0.554)
Relative demand ∗ other segments		−0.004	−0.003	
weighted TFP[g]		(0.094)[c]	(0.038)[b]	(0.724)
Total industry-segment years	176,689	36,806	60,772	
Chi-squared statistic	810.49	37.62	134.88	
Significance level (p-value)	<1%	<1%	<1%	

[a,b,c] Significantly different from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively, using a two-tailed test.

[d] Significance test for a multiple-segment dummy variable interacted with each independent variable in a regression with all firm segments.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity is a weighted average of the firm's other segment(s) weighted by the segment(s) predicted output.

[g] Relative industry demand is interacted with other segments' productivity and equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

F. Robustness Tests

F.1. Alternative Measures of Efficiency

To make sure that our results are not dependent on our measurement of productivity, Table VII examines the growth of multiple-segment firms using two different measures of efficiency. We construct segment value added per worker and segment operating margin. Value added per worker is sales less materials divided by the number of workers. Operating margin is sales less materials cost of goods sold, employee costs, and capital expenditures divided by sales. Both value-added per worker and operating margin are also industry adjusted in each year.

The results in Table VII show that multiple-segment resource allocation remains sensitive to the efficiency measure and the interaction of industry shipments with this measure. Firms allocate more resources to their best segments in good times. We also find that interaction of relative demand and the firm's other segments' efficiency are negative, as predicted by our model. We do not find evidence of cross-subsidization.

F.2. Does the Extent of Diversification Matter?

We now examine whether the extent of diversification affects conglomerate firms' growth and investment. Table VIII examines both growth and investment for conglomerates when we interact productivity with a firm's segment Herfindahl.[31] The Herfindahl computes a firm's dispersion across the segments it operates by summing the squared shares of total firm sales for each segment. We measure a firm's segment Herfindahl both at the two- and three-digit SIC code level.

The significance of the results for investment in Table VIII depend on whether the Herfindahl is measured at the two- or three-digit SIC code. At the two-digit level, Herfindahl interacted with productivity is insignificant for segment growth and investment. Other results are similar to those reported in previous tables. For the capital expenditure regression in the last column, at the three-digit level, one of the two Herfindahl interaction variables is significant. We find that the sensitivity of investment increases with a firm's segment Herfindahl. Two potential interpretations can be made from this findings. One interpretation, consistent with our model, is that the three-digit level Herfindahl proxies for productivity. Segments at the three-digit level are more related and firms that choose to produce in closely related segments may have higher skill overall, which is not picked up by an individual segment's productivity measure. However, another interpretation, consistent with the literature on inefficient allocation, is that an increase in firm focus has benefits in increasing its sensitivity to productivity. We do still find that the other variables that our model predicts are impor-

[31] The Herfindahl is not significant when we include it by itself.

Table VII

Growth and Alternative Measures of Efficiency

Regressions test the effects of plant-level value added per worker and cash flow on firm industry segment sales growth for multiple-segment firms. The dependent variable, firm segment growth, is industry adjusted in each year. Value added per worker and operating margin are also industry adjusted in each year. Value added is sales less materials cost of good sold divided by the number of workers. Operating margin is sales less materials cost of goods sold, employee costs, and capital expenditures divided by sales. Real industry shipments is detrended by regressing industry shipments (in 1982 dollars) on a yearly time trend. Multiple-segment firms are firms with at least two segments each with 10 percent of their total shipments. Data are aggregated into firm three-digit SIC codes for industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for fixed effects and correlated residuals within panel units. Significance tests are conducted using heteroskedasticity-consistent standard errors. Data are yearly from 1979 to 1992. Observations are included for growth rates less than 100 percent. (p-values are in parentheses.)

Dependent Variable: Segment Growth

	Multiple-segment Firms	
Variable	Main Segments	Peripheral Segments
Constant	0.008	−0.018
	(0.000)[a]	(0.046)[a]
Real industry shipments (detrended)	0.005	0.009
	(0.614)	(0.261)
Efficiency measure		
Value added per worker	0.180	
	(0.000)[a]	
Operating margin		0.147
		(0.000)[a]
Industry shipments (detrended) * Efficiency measure	0.002	0.467
	(0.032)[b]	(0.000)[b]
ln(lagged firm segment size)	−0.006	−0.007
	(0.137)	(0.065)[c]
Number of plants owned by firm (beginning of year, coeff * 1000)	−0.693	−0.669
	(0.000)[a]	(0.000)[a]
Firm multiple-segment variables		
Other segment's weighted efficiency[d]	0.009	−0.015
	(0.323)	(0.213)
Relative demand * other segments weighted efficiency[e]	−0.010	−0.073
	(0.034)[b]	(0.000)[a]
Total industry-segment years	87,915	87,915
Chi-squared statistic	187.18	46.52
Significance level (p-value)	<1%	<1%

[a,b,c] Significantly different from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively, using a two-tailed test.

[d] Other segments' efficiency is a weighted average of the firm's other segment(s) weighted by the segment(s) predicted output.

[e] Relative industry demand is interacted with other segments' efficiency and equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

Table VIII

Extent of Conglomerate Diversification

Regressions test whether the extent of diversification influences segment resource allocation for multiple-segment firms. The extent of diversification is captured by a firm "Herfindahl." This Herfindahl is the sum of squared segment sales divided by total firm sales. The dependent variable in column one is firm segment growth while the dependent variable in column two is segment capital expenditures scaled by beginning of period capital stock. Real industry shipments is detrended by regressing industry shipments (in 1982 dollars) on a yearly time trend. Industry averages are subtracted in each year for both dependent variables. Segment size and productivity are also industry adjusted in each year. Data are aggregated into firm three-digit SIC codes for industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conducted using heteroskedasticity-consistent standard errors. Observations are included for growth rates less than 100 percent and capital expenditures less than the beginning of period capital stock. Regressions are limited to firms whose real value of shipments is greater than 10 million dollars. Data are yearly from 1979 to 1992. (p-values are in parentheses.)

Dependent Variable: Segment Growth and Capital Expenditures				
	All Divisions of Multiple-Segment Firms with Herfindahl Measured at the			
	2-Digit SIC Code		3-Digit SIC Code	
Variable	Segment Growth	Capital Expenditures	Segment Growth	Capital Expenditures
Constant	−0.004	−0.038	−0.004	−0.038
	(0.018)[b]	(0.000)[a]	(0.014)[b]	(0.000)[a]
Firm segment productivity (TFP)[d]	0.055	0.007	0.050	0.005
	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.001)[a]
Herfindahl * TFP	−0.003	0.003	0.007	0.009
	(0.603)	(0.293)	(0.220)	(0.013)[b]
Industry shipments (detrended)	0.003	−0.006	0.003	−0.006
	(0.629)	(0.137)	(0.615)	(0.130)
Industry shipments * TFP	0.020	0.011	0.020	0.011
	(0.008)[a]	(0.022)[b]	(0.008)[a]	(0.022)[b]
ln(lagged firm segment size) (coefficient * 100)	−0.002	−0.184	−0.002	−0.184
	(0.387)	(0.000)[a]	(0.379)	(0.000)[a]
Number of plants owned by firm (beginning of year, coeff * 1000)	−0.285	0.025	−0.284	0.028
	(0.000)[a]	(0.305)	(0.000)[a]	(0.247)
Firm Multiple-Segment Variables				
Other segment's weighted TFP[e]	−0.008	0.005	0.004	0.003
	(0.163)	(0.203)	(0.433)	(0.349)
Herfindahl * other segments TFP	0.001	−0.003	−0.006	−0.002
	(0.909)	(0.537)	(0.572)	(0.791)
Relative demand * other segments weighted TFP[f]	−0.004	−0.002	−0.004	−0.002
	(0.013)[b]	(0.077)[c]	(0.013)[b]	(0.077)[c]
Total industry-segment years	86,812	89,939	86,812	89,939
Chi-squared statistic	2042.74	164.09	2044.23	168.82
Significance level (p-value)	<1%	<1%	<1%	<1%

[a,b,c] Significantly different from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively, using a two-tailed test.

[d] Total Factor Productivity (TFP) is calculated using a translog production function.

[e] Other segments' productivity is a weighted average of the firm's other segment(s) weighted by the segment(s) predicted output.

[f] Relative industry demand is interacted with other segments' productivity and equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

tant for resource allocation, industry shipments * TFP and relative demand * other segments weighted TFP, remain significant with the predicted signs.

F.3. Conglomerates Which Restructure

The preceding tables examine resource allocation, taking the organizational form of firms as given. We now test whether the relation between growth and productivity for conglomerates that are broken up differs from that for conglomerates that still remain conglomerates at the end of our sample. Our hypothesis is that our model will hold better for these surviving conglomerates. To test this hypothesis, we identify conglomerates that experience significant restructuring, including those that become single-segment firms. We define significant restructuring as a 25 percent or greater decrease in the number of segments a conglomerate operates by 1992, the last year of our data. In addition, we split conglomerates that begin the period with two and three segments and those conglomerates that begin with more than three segments. We make this split to investigate whether it is just conglomerates with few segments that experiment with diversification and fail that are driving our results.

The results in Table IX show that our model does not hold in the period prior to the restructuring for conglomerates that experience significant restructuring. We find that there is an insignificant relation between growth and the interaction of change in shipments and own segment TFP and also an insignificant relation between growth and the interaction of relative demand and other segments' weighted TFP. This is true for both conglomerates that begin with only two to three segments and those with more than three segments. We also find no effect on growth for other segments' weighted TFP for these conglomerates that are broken up.

In contrast, both of these interaction variables are significant for conglomerates that are not broken up. We find a positive significant relation between growth and the interaction between TFP and change in shipments and also a negative, significant relation between growth and the interaction between other segments' TFP and relative demand. We also find a negative, significant effect on segment growth of other segment relative productivity for the conglomerates that are not broken up. This evidence suggests that there is a subset of conglomerates that behave inefficiently, perhaps as a result of agency problems, and are therefore broken up.

Thus, we do find some evidence consistent with agency problems in conglomerate firms. However, even for these firms, we do not find a significant positive coefficient between other segments' relative productivity and growth. Thus, we find no evidence that these conglomerates significantly subsidize the growth of inefficient segments. For conglomerates that survive, we find evidence of behavior consistent with our model. The results suggest that over our sample period, surviving conglomerates, which comprise the majority of conglomerates, grow efficiently across industries in which they operate.

Table IX

Conglomerate Firms that Restructure

Regressions test the effects of plant-level productivity and industry-level demand on firm industry segment sales growth. We separate out firms that have had major restructuring over the period. Firms are classified as having undergone major restructuring if they decrease the number of segments they operate by more than 25 percent by the last year they are in the database. The dependent variable, firm segment growth, is industry adjusted in each year. Real industry shipments is detrended by regressing industry shipments (in 1982 dollars) on a yearly time trend. Segment size and productivity are also industry adjusted in each year. Data are aggregated into three-digit SIC codes for industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conducted using heteroskedasticity-consistent standard errors following Huber–White. Data are yearly from 1979 to 1992. Observations are included for growth rates less than 100 percent and for firms whose real value of shipments is greater than one million dollars. (p-values are in parentheses.)

Dependent Variable: Firm Industry Segment Growth			
	Conglomerate Firms that had Major Restructuring		Conglomerate Firms with No or Limited Restructuring
	With 2–3 Segments	With >3 Segments	
Variable	(Years Before Restructuring)		(All Years)
Constant	0.010	−0.020	−0.001
	(0.174)	(0.000)[a]	(0.505)
Real industry shipments (detrended)	0.056	0.015	−0.001
	(0.028)[b]	(0.343)	(0.943)
Firm segment productivity (TFP)[d]	0.064	0.064	0.052
	(0.000)[a]	(0.000)[a]	(0.000)[a]
Industry shipments (detrended) * TFP	−0.048	−0.017	0.026
	(0.115)	(0.411)	(0.003)[a]
ln(lagged firm segment size)	0.015	−0.013	−0.001
	(0.834)	(0.215)	(0.741)
Number of plants owned by firm (beginning of year, coeff * 1000)	−4.939	−0.073	−0.346
	(0.000)[a]	(0.238)	(0.000)[a]
Firm Multiple-Segment Variables			
Other segment's weighted TFP[e]	−0.005	−0.002	−0.008
	(0.370)	(0.764)	(0.001)[a]
Relative demand * other segments weighted TFP[f]	0.003	0.005	−0.005
	(0.553)	(0.393)	(0.012)[b]
Total industry segment years	6,259	10,648	70,787
Total firms	1,075	510	3,629
Chi-squared statistic	231.93	341.96	1605.62
Significance level (p-value)	<1%	<1%	<1%

[a,b,c] Significantly different from 0 at the 1 percent, 5 percent, and 10 percent levels, respectively, using a two-tailed test.
[d] Total Factor Productivity (TFP) is calculated using a translog production function.
[e] Other segments' productivity is a weighted average of the firm's other segment(s) weighted by the segment(s) predicted output.
[f] Relative industry demand is interacted with other segments' productivity and equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

An alternative indicator of industry prospects is industry q. Our model predicts that the sign will be negative when q is interacted with the other segments' segment-level relative productivity. We proxy for industry prospects using an industry Tobin's q constructed by weighting individual single-segment firm q's from COMPUSTAT, where firm q is the market value of equity plus the book value of preferred stock, divided by the market value of equity plus the book value of preferred stock and debt. Note that we are using this variable to capture industry demand prospects—not to measure individual segment skill. To attempt the latter would confound two effects in our model: an individual firm's relative skill (versus a single-segment firm) in an industry and also the demand prospects in that industry. One other problem arose. In many industries, COMPUSTAT does not have data for a sufficient number of single-segment firms (our requirement was a minimum of four firms) to construct a benchmark for many of the three-digit SIC codes in our data.

For the subset of data with sufficient competitors, the results of the estimation for conglomerate firms had similar significance and signs as those of our earlier results. Given space considerations, we do not report these results. We find a negative relation between a segment's growth and other segments' weighted Tobin's q interacted with our segment-level productivity variable.

IV. Comparability of Our Results with Other Research

Prior studies have used industry q measured using single-segment firms to proxy for investment opportunities for conglomerate firms. This assumption requires that firms have homogeneous investment opportunities. Our approach explicitly allows for difference in organizational ability, which causes different types of firms to have differences in measured productivity. Empirically, we show that conglomerates have systematically different productivity. Except for the smallest size firms, conglomerates have lower productivity than single-segment firms of similar sizes.[32]

Our finding of lower productivity is consistent with a conglomerate discount documented by Lang and Stulz (1994) and Berger and Ofek (1995). However, our interpretation is that the discount arises even when firms are maximizing value, so that firm's decisions to diversify may be optimal even when there is a discount.

[32] A recent study by Schoar (1999) finds that plants of conglomerate firms have higher productivity. However, our measure of productivity includes a fixed effect (from the estimation of the production function) and the samples are different. Schoar uses a sample of conglomerates matched to COMPUSTAT that exist in 1987, while we have conglomerates throughout the period including those that are broken up prior to 1987. Our evidence on bustups shows that the least productive conglomerates are busted up. Also firms that are more likely to have been matched are the larger conglomerate firms, which we do find are very productive. On our larger sample, we ran a regression of TFP on one minus the Herfindahl and found a U-shaped relationship.

Differences in productivity have also been shown to impact merger and acquisition decisions. Maksimovic and Phillips (2001) show that the productivity of the purchased and sold assets, in conjunction with relative demand shocks, predict the probability of sale and the subsequent productivity gain.[33] Schlingemann, Stulz, and Walking (2000) show that conglomerates are more likely to sell peripheral segments that are poorly performing. Consistent with our evidence, they also find that the extent of diversification is not, by itself, significant in explaining disinvestment decisions. Several other recent studies also show that conglomerates acquire and sell assets that are different than the median single-segment firm and these differences may cause a conglomerate discount. Chevalier (1999) shows that target firms that choose to merge across SIC codes invested before their merger differently from firms that remain single segment. Graham, Lemmon, and Wolf (1999) show that conglomerate firms purchase firms that have a lower value than the acquisitions' single-segment counterparts.

We also show that conditional on differential productivity, the growth and investment decisions of conglomerates are consistent with efficient allocation of resources. Firms grow their more productive segments when those segments experience a positive demand shock and shrink these segments when other segments are more productive and they experience positive relative demand shocks. It thus differs in spirit from recent research on investment allocation in conglomerates, for example, by Shin and Stulz (1998) and Scharfstein (1997). They find that segments in conglomerates invest more than their stand-alone industry peers in bad industries and invest less than their stand-alone peers in high industries. The differences may arise because we control for productivity at the industry level, aggregated from underlying plant-level data, whereas these papers rely on industry q. Other explanations include the fact that our productivity measures do not capture headquarters- or divisional-level costs. Our findings may still be consistent with the prior results *if conglomerates are less productive* on average than single-segment firms in industries with high growth potential.

Our finding of high sensitivity of peripheral segments to productivity is also consistent with the predictions of Stein (1997) and Matsusaka (2001) in which conglomerates allocate resources across segments to their best segments. Our results hold both at the three-digit SIC code level reported in this paper and also at the two- and four-digit levels (not reported). We find that peripheral units of conglomerates are less productive than the main units, but that there is little evidence that peripheral growth is inefficient. This pattern is consistent with our neoclassical model of firms' comparative advantage. However, this finding of negative relative productivity of conglomerates' peripheral segments is also consistent with conglomerates having lower fixed costs of entry and lower costs of evaluating new ventures than do single-segment firms.

[33] Schoar also finds the result that acquisitions by conglomerate firms improve in productivity subsequent to their purchase.

Rajan, Servaes, and Zingales (2000) argue that distortion of investment increases with the diversification of the conglomerate when dispersion in q's across firm segments is higher. We also find some more limited evidence for a diversification effect: As the Herfindahl of the segment shares increases at the three-digit level, the sensitivity of investment to relative productivity also increases. However, we do not find evidence that the sensitivity of firm investment to other segments' relative productivity is affected by focus.

V. Conclusions

Our paper explores how fundamental industry conditions and productivity influence segment growth for both single industry and multiple-segment conglomerate firms. We test hypotheses derived from a neoclassical model of firm activity in multiple markets with decreasing returns to scale from organizational ability. The model yields predictions about firm-size distributions and investment and growth decisions of focused single-industry and multiple-segment firms as a function of firms' comparative advantage and industry demand shocks. The model predictions are also consistent with the existence of a conglomerate discount.

We have three key empirical findings. First, we find that plants of conglomerate firms are less productive than are plants of single-segment firms of a similar size, except for firms of the smallest size. This difference is mainly driven by smaller peripheral segments of the conglomerate, which show significantly lower productivity than do main segments.

Second, we find that the productivity pattern within a conglomerate firm's segments is consistent with our simple value-maximizing model. Plants of the largest segments of conglomerates with multiple segments are particularly efficient. This evidence supports the hypothesis that firms invest in industries in which they have a comparative advantage. This is consistent with optimal resource allocation decisions by conglomerates *and* also with the conglomerate discount being endogenous. The evidence is consistent with conglomerates having a discount because of lower productivity, not necessarily because of agency problems. Less-productive firms can exist in equilibrium because of decreasing returns to scale.

Third, using plant-level data aggregated into industry segments, we examine growth of these industry segments. We find that the growth of productive and unproductive segments (both for single-segment firms and conglomerate firms) is consistent with the model of efficient growth across industries. Segment growth is strongly related to fundamental industry factors and individual segment productivity. Conglomerate firms grow less in a particular industry if their other plants in their other industry(ies) are more productive and if their other industry(ies) experiences a larger positive demand shock. The differential pattern of productivity and conglomerate growth across conglomerates' industries, as well as a conglomerate discount, are consistent with a neoclassical model.

Our evidence is not consistent with conglomerates subsidizing less productive segments at the manufacturing plant level using resources from other segments. Instead, peripheral segments are often marginal segments whose growth declines when they have productivity below the industry average.

We do find some evidence that is consistent with some conglomerates having agency problems. We identify a subset of conglomerate firms whose growth decisions are, a priori, less likely to be consistent with our model of optimizing behavior. This subset comprises conglomerates that were broken up during the 1980s. We find that the growth of these broken-up conglomerates is not consistent with our model of optimal growth. However, even for these firms, we find no evidence that conglomerates significantly subsidize the growth of inefficient segments. As noted earlier, there may still be inefficiencies from higher overhead and other dissipative measures. Our evidence shows that the majority of conglomerate firms exhibit growth across industries that is consistent with optimal behavior.

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