# The Industry Life Cycle, Acquisitions and Investment: Does Firm Organization Matter?

VOJISLAV MAKSIMOVIC and GORDON PHILLIPS<sup>\*</sup>

#### ABSTRACT

We examine the effect of industry life-cycle stages on within-industry acquisitions and capital expenditures by conglomerates and single-segment firms controlling for endogeneity of organizational form. We find greater differences in acquisitions than in capital expenditures, which are similar across organizational types. In particular, 36% of the growth recorded by conglomerate segments in growth industries comes from acquisitions, versus 9% for single-segment firms. In growth industries, the effect of financial dependence on acquisitions and plant openings is mitigated for conglomerate firms. Plants acquired by conglomerate firms increase in productivity. The results suggest that organizational forms' comparative advantages differ across industry conditions.

AN INFLUENTIAL BODY OF RESEARCH ARGUES that industries go through life-cycle stages and that these stages are characterized by marked differences in investment and restructuring activity (Gort and Klepper (1982), Jovanovic (1982), Klepper and Grady (1990), Klepper (1996)). The evidence suggests that changes in the number of firms in an industry occur at times of transition in an industry's life cycle, that is, when the producers' competitive advantages are changing. However, it is not known whether and how firm organization is associated with firm performance for industries that experience changes in exogenous long-run conditions.

In this paper we examine whether long-term changes in industry conditions affect investment by single-industry firms and divisions of conglomerate (multisegment) firms differently. We control for the endogeneity of organizational form and financial dependence. We focus on two factors that the literature identifies as giving multidivision firms an advantage in some competitive environments: (i) access to internal capital markets, and (ii) the ability to restructure,

\*Maksimovic is with University of Maryland and Phillips is with University of Maryland and NBER. This research was supported by National Science Foundation grant 0218045. We would like to thank Mike Lemmon, Harold Mulherin, Sheri Tice, Bernie Yeung, the referee, Center for Economic Studies staff, and seminar participants at the American Finance Association meetings, Duke-UNC corporate finance conference, Financial Economics and Accounting conference at USC, 2005 Frontiers in Finance Conference, George Washington, HKUST, Minnesota, NYU, Oxford, Pittsburgh, Rice, Tanaka School, Texas, UBC, UCLA, and Wharton. The research in this paper was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau at the Center for Economic Studies. Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Census Bureau. This paper has been screened to ensure that no confidential data are revealed.

which stems from a greater propensity to participate in the market for mergers and acquisitions. Specifically, we ask

- Does firm organization affect capital expenditures, intra-industry acquisitions, plant births, and plant deaths?
- Does the effect of organizational structure on firms' investment decisions depend on long-run industry conditions?
- Do differences in firm organization and industry conditions affect the extent to which firms' investment decisions depend on shortfalls in cash flows from operations?

In studying firm organization, we distinguish between single-segment firms and conglomerate firms that operate in multiple industries. These two types of firms are likely to have different access to financial resources (public markets and internal capital markets) and different types of monitoring (within-firm hierarchies vs. monitoring by external providers of capital). Moreover, this categorization builds on previous research that establishes the importance of a division's position within its firm for its investment policy, efficiency, extent of internal monitoring, and access to internal capital markets.<sup>1</sup>

We classify industries into four different long-run categories. (1) Growth industries—In Growth industries long-run industry shipments and the long-run number of firms are increasing, and changes for each of these factors are above the median industry change. (2) Consolidating industries—In Consolidating industries the change in long-run shipments is above the median industry change but the change in the number of firms is below the median. (3) Technological Change industries—In Technological Change industries, the change in long-run demand is below the median industry change but the change in the number of firms is above the median. (4) Declining industries—In Declining industries, the change in long-run demand and the change in long-run number of firms are both below the median industry change. The industry categories differ in the amount of restructuring (closings and acquisitions of business segments) and growth opportunities.

We find that the within-industry acquisition behavior of conglomerate segments differs sharply from that of single-segment firms, even after controlling for productivity, public firm status, purchaser size, and the endogeneity of conglomerate firm status. Segments of conglomerate firms are two to three times more likely to acquire plants within their existing industries than are single-segment firms. In particular, 36% of within-industry growth by conglomerate firms in growth industries comes from intra-industry acquisitions compared to 9% for single-segment firms. Acquisition rates also significantly differ across long-run industry conditions. Within-industry acquisitions by conglomerate segments in Growth industries represent a much higher percentage (10 percentage points higher) of total firm growth than acquisitions in Declining industries. In contrast to these findings, capital expenditures, which are

 $^{1}$  Early authors include Lang and Stulz (1994) and Berger and Ofek (1995). We discuss the other papers in this literature that are related to this paper in Section I.

typically the focus of prior research on conglomerates, vary less across organizational types and industry conditions.

We next examine whether the differences in within-industry acquisition rates and investment by different types of firm organizations are related to financial dependence, where we define as financially dependent those business segments (single-segment firms or segments of conglomerates) that spend more than their cash flow from operations on capital expenditures.<sup>2</sup> We control for the endogeneity of organizational form and financial dependence. To control for the endogeneity of firms choosing to be conglomerates, we predict whether an industry segment will belong to a conglomerate firm based on industry characteristics and segment productivity. Further, to control for the potential endogeneity between capital expenditures and realized cash flow from operations, in our empirical tests we examine how segments respond to predicted financial dependence rather than observed financial dependence.

We find that financially dependent segments tend to fall into two categories, namely, segments that are less productive compared to other segments in their industries, and very productive segments in high growth industries.<sup>3</sup> We have three major findings that show how financial dependence and organizational form affect firm acquisition and investment over different long-run industry conditions.

First, we show that predicted financial dependence affects plant acquisitions and investment by conglomerate segments and single-segment firms differently. Financial dependence has a negative effect on capital expenditures and the probability of within-industry acquisitions. In Growth and Consolidating industries, conglomerate firms have a positive offsetting effect on acquisitions.<sup>4</sup>

Second, we show that the effects of firm organization on reducing financial dependence in Growth industries are concentrated in conglomerate firms' most productive segments. For conglomerate firms' most productive segments, financial dependence has only a limited effect on within-industry acquisitions. Moreover, segments of a conglomerate in Growth industries have a significantly higher probability of acquiring plants within their industries if the conglomerate also has a less-productive main division in a declining industry. We also find that plants acquired by conglomerate firms—in particular, in Growth industries—significantly increase in productivity post-acquisition. Thus, the positive benefit of internal capital markets is the highest for conglomerate firms in Growth industries, where the value of reallocating assets is likely to be the

 $^{2}$  Thus, a segment that has an internal financial deficit in a given year must rely on cash flows from outside the segment or on the liquidation of its assets to fund capital expenditures at the plants it owns.

<sup>3</sup>The term "productive" is defined below and refers to the ability of firms to produce revenue from inputs at the segment level. It does not necessarily mean that conglomerate firms sell at a premium or discount in the market relative to single-segment firms.

<sup>4</sup> Results in an earlier working paper version of this paper also show that the effect of conglomerate firm status holds whether or not the firm is publicly traded. Public firm status does have an additional positive effect on mitigating the effect of financial dependence on acquisitions by public firms in Growth industries. However, this effect is much smaller in magnitude than the effect of conglomerate firm status. highest. These results are consistent with models that stress the benefits of the conglomerate form for the firms that adopt it, such as the model of the benefits of internal capital markets in Stein (1997), and the predictions about the efficient reallocations of assets within conglomerate firms in Maksimovic and Phillips (2002). These results are not consistent with models that predict subsidization of poorly performing divisions or divisions with poor growth prospects. The results are also not consistent with agency or empire building models that predict inefficient expansion.

Third, we find large differences in the effect of organizational form on plant birth and exit across industry categories. In Growth industries, a predicted financial deficit reduces the probability that a single-segment firm will open a new plant, while this effect is mitigated for conglomerate firms. Similar effects on plant births in declining industries do not obtain.

We find that plant exits differ across industry categories. Conglomerate firms are the least likely to close plants when their current segment is predicted to have a financial deficit in Declining industries. In Growth industries the relation between predicted financial dependence and plant exit is similar for conglomerate and single-segment firms, in contrast to the positive effect of conglomerate firms on acquisitions and plant births.

There are several key differences between our approach and the existing literature on investment and internal capital markets. First, we relate the firm's investment and financing needs to long-run changes in industry conditions. We show that long-run industry conditions are of primary importance to understanding the impact of organizational form on acquisitions and plant opening decisions. Second, with the exception of Maksimovic and Phillips (2001), Khanna and Tice (2001), and Schoar (2002), the existing literature examines the relation between capital expenditures and firm organization. By defining investment more generally than the existing literature to encompass acquisitions of plants and assets, we can examine whether firm organization affects investment through acquisition and plant openings differently from regular investment. Since acquisitions require extensive organizational skill in integrating operations while capital expenditures represent decisions with respect to existing operations, we examine whether the effects of organizational form are greater for acquisitions than capital expenditures at existing plants.<sup>5</sup> Third, we are able to obtain direct estimates of the productivity of each business unit, irrespective of whether it is independent or part of a larger firm. Thus, we can determine whether the relation between firms' investment and their organizational structure depends on their productivity and we can examine ex-post changes in the underlying productivity of transacted assets.

We conduct the above analysis using data from the Longitudinal Research Database (LRD), which is maintained by the Center for Economic Studies at the Bureau of the Census. The LRD database contains detailed plant-level data for manufacturing plants. There are several advantages to this database. First,

<sup>5</sup> GE, for example, has an extensive staff whose job responsibility is to evaluate acquisitions.

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 fourdigit 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. The database contains a plant-level code that identifies when plants change ownership. These features are key to our study as they allow us to identify plants that have changed hands from one year to the next.

The rest of the paper is organized as follows. Section I describes the prior literature and discusses why firm organization may have a differential impact over the industry life cycle. Section II introduces our methodology and Section III describes the data. The results are discussed in Section IV. Section V concludes.

#### I. Industry Conditions and Firm Organization

Studies of industry evolution by Gort and Klepper (1992) and Klepper and Grady (1990), among others, show that many industries go through life-cycle stages. These stages are characterized by differences in the growth rate of the industry and by dramatic changes in the number of producers in the industry. Many industries undergo periods of intense competition and Consolidating when many, perhaps the majority, of the producers are weeded out. However, firm strategies that work in times of expansion, such as preemptively acquiring large capital intensive plants, may lead to a competitive disadvantage in decline (Ghemawat (1984), Ghemawat and Nalebuff (1985)). These articles therefore emphasize the importance of industry conditions on firms' survival, and by extension on their capital budgeting decisions.

To examine the relation between the number of producers and industry growth, we first present exploratory evidence on long-run industry conditions using Census Bureau data.<sup>6</sup> We classify industries using Census Bureau data for the years 1972 and 1997. These years are used because they span 25 years of industry experience and are Census years that cover all firms. In Figure 1, we classify industries according to the growth in the real value of shipments.<sup>7</sup> Long-run changes in demand are calculated using the change in the real value (1982 dollars) of shipments of industries, classified using three-digit SIC codes. We split industries by the highest and lowest quartiles of real firm shipment growth and graph the long-run changes in the number of firms. In our subsequent tests, we further split these industries by the long-run change in the number of producers into "Declining" and "Technological Change" industries for contracting industries and "Growth" and "Consolidating" industries for growing industries.

 $<sup>^{6}</sup>$  Maksmovic and Phillips (1998) explore the asset sale decisions of bankrupt and nonbankrupt firms in industries experiencing different long-run shipment growth. However, they do not analyze changes in the number of producers or control for organizational form.

<sup>&</sup>lt;sup>7</sup> We later discuss results using classifications based on 10-year intervals.



Figure 1. Long Run Change in the Number of Firms by Industry Classification.

The histograms in Figure 1 show that among growing industries, while it is not uncommon to see a net increase of 30% in the number of producers, some industries exhibit a decline in the number of producers over the sample period. In contracting industries, a net decrease of 30% is common.

The fact that the number of firms can decrease even in a growing industry suggests that some firms may not possess the resources and/or skills necessary to survive. The resources and skills necessary for a firm to prosper are likely to differ across industries. In a growing industry, new producers are entering at high rates. Given that entrants are often high cost producers (Jovanovic (1982)), established firms in the industry are less likely to face hard competition. Success in this type of industry is likely to depend on the ability to marshal resources to take advantage of growth opportunities. In a consolidating industry, shipments are also growing rapidly but the competitive pressure is likely to be stronger. In these industries new producers are less likely to be entering and some existing producers might be forced out. We would expect that competitive advantages from belonging to a larger organization are likely to be most valuable in a fast-growing consolidating industry.

Numerous studies suggest that the firm's organizational structure affects the way it invests, grows, and sells assets. Conglomerates have internal capital markets that can transfer capital across industries and may have better access to external capital markets than would be available to their constituent divisions if they had remained independent (Bolton and Scharfstein (1990), Khanna and Tice (2001), Stein (1997)). In particular, Stein (1997) models how conglomerate firms can efficiently transfer resources from unprofitable to profitable projects. Moreover, as Peyer (2001) shows empirically, conglomerates have superior ability to obtain external financing, giving divisions of conglomerates a competitive advantage when internally generated funds are not sufficient to finance the desired level of investment. Thus, we would expect the investment by segments of conglomerates to be less affected by the level of internal financing than equivalent single-segment firms.

Note that the effect of conglomerate structure on investment need not be benign. One strand of the literature posits that 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 this policy for their private benefit (see Jensen and Meckling (1976) and Jensen (1986)). Thus, managers may obtain a private benefit, for example, from investment in capacity (Jensen (1986) and Matsusaka and Nanda (2001)). Opportunistic behavior by agents may also cause the firms to misallocate resources across industry segments. These possibilities are suggested by Lamont (1997), Shin and Stulz (1998), Rajan, Servaes, and Zingales (2000), and Scharfstein and Stein (2000).

More generally, organizational form may be endogenously determined by a firm's expertise and its ability to exploit opportunities (Campa and Kedia 2002, Maksimovic and Phillips 2002, Villalonga 2004). Maksimovic and Phillips (2002) argue that conglomerates differ from single-segment firms because their organizational skills are not industry specific and thus they find it optimal to operate in several industries. In their model, firm size and scope of operations adjust to economize on the firms' organizational talent. According to this view, as industries experience demand and technology shocks, firms' comparative advantage shifts. Conglomerates and single-industry firms adjust by building, acquiring, or closing plants to maximize value.<sup>8</sup> Because their model predicts a positive correlation between conglomerates' division size and productivity, the adjustments to shocks may depend on the relative size of a division within the conglomerate.

The tasks performed by a head office of a conglomerate are likely to differ across industry types. In Growth industries the head office of a multisegment firm is faced with managing and providing resources for increases in capacity. In Declining industries the focus is likely to be on optimally shrinking operations and reallocating resources to other segments. In Technological Change industries firms have to adapt to increasing competition from new entrants in industries with slowly growing or declining shipments, while in Consolidating industries the decision is whether to remain in the industry. Since the nature of these decisions involves a different mixture of monitoring, winner picking, and financing, the comparative advantage of internal capital markets relative to public markets may differ across these long-run industry conditions.

In our tests we first examine the extent to which conglomerates mitigate the effects of resource constraints across these types of industries. The above discussion suggests that the effects of conglomerate status should be stronger in growing industries. Consider a growth industry in which firms encounter repeated expansion opportunities. Much of the value of such firms consists of unexploited, and therefore intangible, growth opportunities. Corporate finance theory suggests that such firms are most likely to incur agency and asymmetric information costs when obtaining external finance (e.g., Myers (1977), Myers and Majluf (1984)). Internal capital markets are therefore most likely to

<sup>&</sup>lt;sup>8</sup>While not focusing on the industry life cycle, Bernardo and Chowdhry (2002) model how differential skills and opportunities over the firm's life endogenously cause a conglomerate discount given that the firm exercises its growth options as it matures.

be of value in segments in growing industries.<sup>9</sup> Thus, the first hypothesis we investigate is as follows:

H1: The effects of conglomerate status on mitigating the effects of financial dependence are greater in growing industries.

Maksimovic and Phillips (2002) show that conglomerate segments reallocate resources from less-productive divisions to more-productive divisions when positive demand shocks are realized. Investment decisions by conglomerate firms in one industry may create opportunity costs for investments in other industries in which they operate. Thus, segments' investment decisions depend on the relative demand growth across industries. In our context, we hypothesize that conglomerate segments are more likely to exploit investment opportunities in growth industries if their other segments are in declining industries. This prediction is summarized in the following hypothesis:

H2: The effects of conglomerate status on mitigating the effects of financial dependence are greater in growing industries when conglomerate firms have productive segments in growing industries and other large divisions in declining industries.

Conglomerates operating across multiple industries have experience in allocating resources and integrating operations. Since acquisitions require extensive organizational skill in integrating operations, while capital expenditures typically represent incremental additions to existing operations, we would expect that differences in organizational form affect acquisitions more than capital expenditures at existing plants. In particular, conglomerates' ability to integrate different business units and allocate capital can increase the payoff to providing capital for acquisitions to segments of conglomerate firms compared to single-segment firms, while capital expenditures may involve similar decisions and skills for both conglomerate and single-segment firms. We therefore test the following hypothesis:

H3: The effects of organizational form and financial dependence are greater for acquisitions than for capital expenditures.

The effect of financial dependence on conglomerate segments and singlesegment firms may differ because conglomerates efficiently provide resources to segments with insufficient internal resources that permit them to make value increasing acquisitions. However, it is also possible that conglomerate segments overinvest in acquisitions, perhaps due to agency reasons. While we cannot measure the private value created by acquisitions, which depends on the price paid, we can examine the subsequent changes in the acquired assets' productivity. Increases in productivity are consistent with the hypothesis that the acquisitions are economically efficient. We would expect these effects to be particularly important in growing industries. We formalize these predictions in the following hypothesis:

<sup>&</sup>lt;sup>9</sup> See, for example, Fluck and Lynch (1999).

H4: Acquisitions by conglomerate firms result in increases in productivity of acquired segments. The increases in productivity are greatest in growth industries.

Organizational form and financial dependence may also affect other capital budgeting decisions. Accordingly, we also examine how firms' decisions to build or close plants are affected by financial dependence and organizational form across industry conditions.

## II. Data, Long-Run Industry Conditions, and Variable Construction

In this section we describe the data, our classification of long-run industry conditions, and the method we use to calculate the variables employed in the tests of our hypotheses. The primary dependent variables we investigate are a firm's within-industry acquisitions of plants and its segment-level capital expenditures. We also examine plant births and exits. Our first dependent variable, within-industry acquisition, takes the value of one at the segment level if the conglomerate segment or stand-alone firm purchases one or more plants in that existing industry, and the value of zero otherwise. Our second measure, capital expenditures, measures plant-level capital expenditures at the plants owned by each firm at the beginning of each year and not sold during the year.

The primary independent variables we use are segment and plant productivity, the long-run change in aggregate industry conditions, and predicted financial dependence and organizational structure.

## A. Data

We use data from the Longitudinal Research Database (LRD), which is maintained by the Center for Economic Studies at the Bureau of the Census. 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.<sup>10</sup>

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 year to complete a rotating 5-year panel. Note that while the annual data are called the ASM, reporting is not voluntary for large plants and is not voluntary once a smaller firm is selected to participate. All data must be reported to the government by law and fines are levied for misreporting.

The data we use cover the period 1974 to 2000. To be included in our sample, firms are required to have manufacturing operations that produce goods in SIC codes 2000–3999. Since we construct measures of productivity (described in Section II) using 5 years of data, our regressions cover the 1979 to 2000 period. We require each plant to have a minimum of 3 years of data. For each

<sup>10</sup> For a more detailed description of the Longitudinal Research Database (LRD) see McGuckin and Pascoe (1988) and Kovenock and Phillips (1997).

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 1982 dollars.

For changes in ownership, we rely on LRD's identification of plants that change ownership, which is available for all years except 1978 (for an unknown reason coverage codes do not identify ownership changes for this year). Plant births and deaths are identified by John Haltiwanger using payroll records from the Longitudinal Business Database.<sup>11</sup>

To obtain a measure of organizational structure, we aggregate each firm's plant-level data into firm industry segments at the three-digit SIC code level. We refer to these firm-industry portfolios of plants as "segments." Thus, segments defined in this way capture all the plant-level operations of a firm in an industry.<sup>12</sup> We classify firms as single-segment or multisegment firms based on the three-digit SIC code. We classify a firm as a multisegment firm if it produces more than 10% of its sales in a second SIC code outside its principal three-digit SIC code. Using the 10% cutoff facilitates comparison with previous studies as 10% is the cutoff that public firms report. 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% of the firm's total shipments. Given we calculate growth rates and also divide capital expenditures by lagged capital stock, we lose the initial year a firm or firm segment enters the database. We also lose observations that are noncontiguous.

We include a firm's lagged size and the lagged number of plants in the segment as control variables. We also include an industry's capital intensity, calculated as the sum of all capital expenditures divided by the sum of all industry shipments. Finally, we adjust for industry and year effects for all capital expenditure and productivity data, subtracting out the industry-year averages.

## B. Long-Run Industry Conditions

We classify industries on the basis of exogenous shifts in their operating environments. Such shifts may require different financial and organizational capabilities of firms, and may therefore enable us to identify the advantages of different organizational forms.

Given the differences in industry conditions previously depicted in Figure 1, we capture the stages in an industry life cycle by classifying threedigit SIC manufacturing industries into four categories using both growth in shipments and changes in the number of firms producing in the United States. The first classification divides industries into those in which the growth of the

<sup>11</sup> We thank John Haltiwanger for providing us these linkages.

<sup>12</sup> The segments we construct do not correspond to those reported by COMPUSTAT. However, segment data reported by COMPUSTAT are 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. Hyland (1999) finds that only 72% of the firms that report under the FASB standards that go from one segment to more than one segment actually increase their number of industries in which they produce.

real value of shipments during our sample period, 1972 to 1997, exceeds the median growth of all manufacturing industries and those in which the growth of shipments is below the median. Many industries in the latter category experience an actual decline in shipments. Our second classification divides industries into those in which the growth of the number of producers exceeds the median growth in the number of producers for a manufacturing industry and those in which the number of producers is lower than the median, again for the 1972 to 1997 period.<sup>13</sup> We label these four industry categories as follows:

- 1. *Growth industries*—the change in long-run industry shipments and the change in the long-run number of firms are each above the median industry change.
- 2. *Consolidating industries*—the change in the long-run shipments is above and the change in the number of firms is below the median industry.
- 3. *Technological Change industries*—the change in long-run demand is below and the change in the number of firms is above the median industry.
- 4. *Declining industries*—the change in long-run demand and the long-run number of firms are both below the median industry change.

We also classify industries using 10-year floating windows, thereby allowing an industry to switch between life-cycle classifications over time (for example, from Growth to Declining). We use Census year data for these industry classifications because an accurate count of the number of firms is available in the Census years, which in our sample are every 5 years beginning with 1972. To classify an industry in a particular year using floating windows, we use the Census year following a particular year and calculate the change to that Census year from the Census 10 years prior. Thus, for 1993 we would calculate the change in the real value of shipments from 1987 to 1997. We also examine subperiods, specifically the 1980s and 1990s, and find no material differences versus the 10-year analysis that we report.

Table I presents summary statistics by industry category. The table shows that the industries in our four categories differ significantly. Over the 1972 to 1997 period, real shipments increase by an average of 43% in Growth industries and decrease by 42% in Declining industries. Real shipments in Consolidating industries change little (a 2% increase). Shipments fall by 28% in Technological Change industries. As expected, the number of producers increases (+83.6%) in Growth industries and decreases (-34.6%) in Declining industries. Technological Change and Consolidating industries present a contrast. Despite a large drop in real output, the number of producers in the former increases by 45%. In the latter, despite a stationary output level, there is a drop of 10.2% in the number of producers.

In each category, we also present long-run statistics for the five industries surrounding the average change to give a more detailed description of which

<sup>&</sup>lt;sup>13</sup> Our classifications are based on changes to firms producing in the United States (including private and foreign firms producing in the United States). We do not determine the causes of these changes. However, we note that many Declining production industries are industries that have been subject to increasing import competition. We believe the exact attribution of what drives industries to decline and grow over the long run is an important topic for future research.

## Table I Long-Run Industry Conditions

The table presents summary statistics by long-run industry changes and organization over 25 years. Declining (Technological Change, Consolidating, Growth) industries are industries whose long-run change in the real value (PPI deflated) of industry shipments over 1972 to 1997 is in the lowest (lowest, highest, highest) 50th percentile and whose long-run change in the number of firms is in the lowest (highest, lowest, highest) 50th percentile. All average changes are significantly different across industry categories.

	Long-run (25 year) change in:		
Industry classification/SIC code	Industry shipments	Number of firms	
All Declining Industries—Average Change	-41.95%	-34.64%	
Industries surrounding the average change in shipments			
332 Iron and Steel Foundaries	-52.56%	-25.79%	
302 Rubber and Plastics Footwear	-47.35%	-37.25%	
311 Leather Tanning and Finishing	-47.15%	-47.88%	
271 Newspapers: Publishing and Printing	-41.88%	-40.48%	
341 Metal Cans and Shipping Containers	-37.22%	1.42%	
All Technological Change Industries—Average Change	-28.41%	44.96%	
Industries surrounding the average change in shipments			
281 Industrial Inorganic Chemicals	-30.53%	54.09%	
329 Abrasive, Asbestos, and Miscellaneous	-28.59%	41.46%	
354 Metalworking Machinery and Equipment	-25.92%	44.60%	
342 Cutlery, Hand Tools, and General Hardware	-22.55%	28.93%	
356 General Industrial Machinery and Equipment	-17.73%	54.00%	
All Consolidating Industries—Average Change	1.75%	-10.22%	
Industries surrounding the average change in shipments			
228 Yarn and Thread Mills	-2.20%	-28.23%	
203 Canned, Frozen, and Preserved Fruits, Vegetables	-0.87%	-8.45%	
201 Meat Products	4.90%	-26.62%	
262 Paper Mills	6.88%	-23.46%	
227 Carpets and Rugs	15.97%	-15.72%	
All Growth Industries—Average Change	42.99%	83.55%	
Industries surrounding the average change in shipments			
282 Plastics Materials and Synthetic Resins	17.24%	61.43%	
381 Search, Detection, Navigation, Guidance	36.39%	198.89%	
283 Drugs	61.89%	123.85%	
308 Plastic Products	129.45%	161.42%	
366 Communications Equipment	202.02%	90.84%	

industries are in each category. Declining industries include iron and steel foundries, rubber, and plastics footwear. Technological Change industries include metalworking machinery and equipment. Consolidating industries include paper mills and carpet and rugs. Growth industries include plastics, drugs, and communications equipment.

In a Declining industry both the number of firms and real shipments are growing more slowly than in a median industry. In many such industries the number of producers is falling and firms face the task of managing decline or optimally exiting. Cash flow may be low or negative and firms belonging to a conglomerate may be able to use its resources to obtain a competitive advantage. By examining differences in the investment and acquisition activity of conglomerates and single-segment firms in these industries, we can determine whether conglomerates shift resources away from industries with declining shipments.

Real shipments are also declining or growing slowly in Technological Change industries. However, the high rate of growth of new producers in these industries implies that there exist growth opportunities. Thus, by comparing the differences in investment patterns of conglomerates and single-segment firms in Declining and Technological Change industries, we can examine whether conglomerate firms' response to decline in shipments depends on the existence of growth opportunities in an industry.

#### C. Variable Construction: Financial Dependence and Productivity

## C.1. Financial Dependence

We define a segment to be financially dependent (independent) in a particular year if the sum of the capital expenditures reported by all its plants exceeds (is less than) the total cash flow reported by these same plants. Cash flow is defined as the gross margin adjusted for inventory changes. A conglomerate segment or stand-alone firm that is financially independent is able to fund its plant-level capital expenditures directly from cash flow without obtaining resources from the head office, other divisions, or the financial markets.

To control for endogeneity in our subsequent regressions that examine acquisitions and investment, we first predict financial dependence and use the predicted financial dependence in our regressions. In any given year t, segment i is defined to be financially dependent if its capital expenditure is greater than its internal cash flow in period t ( $y_{it} = 1$ ), and zero otherwise. We estimate the probability of financial dependence by regressing  $y_{it}$  on industry- and segmentlevel variables that capture a segment's anticipated need for additional financing that exceeds that segment's internal cash flow. Thus, for a given segment iin year t, we estimate

$$pr(y_{it}|x_{it-1}\alpha, z_{it}\beta, v_i), \tag{1}$$

where  $x_{it-1}$  is a vector of lagged characteristics of segment  $i, z_{it}$  is a vector of industry characteristics in which the segment operates,  $v_i$  is a segment random effect, and  $\alpha$  and  $\beta$  are parameter vectors. We estimate these probabilities using a panel logit specification forming the log-likelihood for all observations.

We present the results of estimating financial dependence for all segments as a function of industry and segment-specific variables in Table III (see Section III) and then use the estimated coefficients  $(\alpha, \beta)$  and individual segment characteristics  $(x_{it-1}, z_{it})$  to predict the probability a segment will be financially dependent in period t. In the regression estimated to predict financial dependence, our choice of independent variables is motivated by the summary statistics presented later in Table II of Section III. To begin, we include firm size and lagged segment productivity (discussed in the next section). We also include squared values of these variables to allow for nonlinearities and the possibility that highly productive firms invest more than their cash flows. The summary statistics presented in the next section also show that a segment's cash flow depends on industry characteristics, in particular, on shipment growth. To capture industry-level differences we therefore include several control variables. To control for potential growth in the industry we use the change in industry shipments. To capture the amount of internal cash available to a segment in a particular industry, we use industry value added, measured as the difference between gross sales of the industry and the cost of materials, labor, and energy used in production, divided by industry sales. To control for industry-specific use of large amounts of fixed assets, we use industry capital intensity, measured as the sum of industry capital expenditures divided by industry sales. The industry value added and industry capital intensity measures are computed annually. All segment- and industry-level variables are at the three-digit SIC code level.

Our measure of predicted financial dependence is thus the *predicted* probability a segment will have investment greater than the segment's internal cash flow controlling for industry-level growth, internal cash flows and capital intensity, and firm-level productivity and size. This predicted financial dependence is then used to examine how the relation between investment and predicted financial dependence is affected by its ownership status (conglomerate or stand-alone), size, productivity, and industry type.<sup>14</sup>

## C.2. Productivity of Industry Segments

We calculate productivity for all firm segments at the plant level and aggregate this data into segments using weighted averages. Our primary measure of performance is total factor productivity (TFP). TFP takes the actual amount of output a plant produces with a given amount of inputs and compares it to a predicted amount of output, where "predicted output" is what the plant is expected to have produced given the amount of inputs it used. A plant that produces more than the predicted amount of output has greater-than-average productivity. This measure 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 operating margin differs from a typical cash flow number because our plantlevel data do not measure indirect segment-level costs such as advertising and research and development

To calculate a plant's predicted output, we assume that the plants in each industry have a translog production function. This functional form is a seconddegree approximation to any arbitrary production function, and therefore takes into account interactions among inputs. In estimating the production function

 $^{14}$  In the working paper version of this paper (available on SSRN), we investigate the effect of listing status on predicted dependence.

we use the last 5 years of data for each plant, thus the first year for which we calculate productivity is 1979. For each industry we estimate this production function using an unbalanced panel with plant-level fixed effects. To estimate productivity, we take the translog production function and run a regression of the log of the total value of shipments on the log of inputs, including cross-product and squared terms

$$\ln Q_{it} = A + f_i + \sum_{j=1}^{N} c_j \ln L_{jit} + \sum_{j=1}^{N} \sum_{k=j}^{N} c_{jk} \ln L_{jit} \ln L_{kit},$$
(2)

where  $Q_{it}$  represents year t output of plant i and  $L_{jit}$  is the year t quantity of input j used in production for plant i. The parameter 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. We deflate for industry price at the four-digit level.

We obtain two measures of plant-level TFP from equation (2). First, we obtain a firm-industry segment fixed effect,  $f_i$ , which we use in the regression to predict segment financial dependence. The segment fixed effect captures persistent productivity effects, such as those arising from managerial quality (Griliches 1957; Mundlak 1961, 1978). It also captures a segment's ability to price higher than the industry average. Second, we obtain a firm-plant residual that we aggregate into segments using predicted output to construct a segment-weighted productivity measure that we use in our regressions examining acquisitions, investment, and plant birth.

In each case we standardize plant-level TFP by subtracting out industry average TFP in each year and dividing by the standard deviation of TFP for each industry. We standardize to control for differences in precision with which productivity is estimated within industries. 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.<sup>15</sup> In computing the segment-level productivity in our regressions we construct a weighted average of the individual plant productivities, with weights equal to the predicted output of each plant.

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 investment. We include the log of firm size and the number of plants operating in an industry segment at the beginning of the year. We define firm size as the total deflated (using industry price deflators) value of shipments in 1982 dollars.

In estimating the TFPs in our sample, we use data for over 1,000,000 plant years, and for approximately 50,000 plants each year. In the productivity regression for each industry, we include three different types of inputs, namely,

<sup>15</sup> 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.

capital, labor, and materials, as explanatory variables. All these data exist at the plant level. Our productivity calculations do not capture any headquarters or divisional-level costs that are not reported at the plant level (i.e., overhead, research and development). The ASM also does not state the actual quantity shipped by each plant, but shows only the value of shipments. We thus deflate the value of shipments by 1982 price deflators to get a real value of shipments. For all inputs and outputs measured in dollars, we adjust for inflation by using four-digit SIC deflator data from the Bartelsman and Gray (1994) database. Each input has to have a nonzero reported value. Kovenock and Phillips (1997) describe these inputs and the method for accounting for inflation and depreciation of capital stock in more detail.

## **III. Results**

#### A. Summary Statistics

We first present summary statistics by both industry classification and organization type. In particular, we examine the relation between industry type and three variables of interest, namely, cash flows, capital expenditures, and plant acquisition.

Table II shows that the number of single-segment firms is far greater than the number of conglomerate firms. However, the number of segments operated by conglomerate firms and the percent of industry output produced by conglomerate firms is greater, with the exception of Growth industries, than that produced by single-segment firms. Interestingly, in Growth industries conglomerate firms operate 38% of the industry segments but produce a far greater percentage, 63.2%, of industry output. Segment size of conglomerate firms relative to single-segment firms is the largest in Growth industries.

The second panel of Table II shows that for segments as a whole the ratio of average annual cash flow to sales is positively related to the real rate of growth of shipments. The ratio is highest in Growth industries at 7.30% and lowest in Declining industries at 4.13%. The difference in these two ratios is statistically significant at the 5% level. Examining the cash flow statistics by organizational type, Table II shows that plants of conglomerate segments consistently realize substantially higher cash flows than those of stand-alone firms for all industry categories. Segment size and organizational type affect the differences in cash flows between segments of single- and multiple-segment firms. Large segments consistently realize substantially higher cash flows than small segments. The difference is approximately 5–7 percentage points, and is particularly striking in Declining industries, where small segments are barely breaking even at the segment level.<sup>16</sup> When we focus on large segments only and vary the organizational form, the table shows that conglomerate segments consistently realize cash flows that are 1.5–3 percentage points higher than single-segment firms.

<sup>16</sup> This suggests that models that predict early exit of larger producers in declining industries may be missing an important empirical difference between small and large segments.

#### Table II

#### **Investment, Acquisitions and Industry Conditions**

The table presents investment and acquisition statistics by long-run industry changes and organization over 25 years. Declining (Technological Change, Consolidating, Growth) industries are industries that have long-run change in the real value (PPI deflated) of industry shipments over 1972—1987 in the lowest (lowest, highest, highest) 50th percentile and the long-run change in the number of firms in the lowest (highest, lowest, highest) 50th percentile. \* and \*\* denote that the difference between Declining and Growth industries is significantly different from zero at the 1% and 5% level, respectively.

	Industry classifications				
	Technological				
	Declining	Change	Consolidating	Growth	
Summary statistics by organizational form					
Number of firms:	0.701	0.070	0.055	11 000	
Single-segment firms	3,731	3,378	2,855	11,322	
Multiple-segment firms	675	867	577	1,463	
Average number of segments for multiple firm segment firm	6.53	6.17	5.62	4.81	
Percent of total segments of multiple-segment firms	54.16%	61.29%	53.18%	38.33%	
Percent of industry output produced by multiple-segment firms	64.70%	69.18%	67.18%	63.18%	
Average annual plant-level cash flow/sales					
Plants of: All firms	4.13%	4.96%	6.72%	$7.30\%^{*}$	
Single-segment firms	3.65%	3.11%	5.54%	$5.61\%^{*}$	
Multiple-segment firms	5.35%	7.87%	9.76%	$10.43\%^{*}$	
Small firms	0.53%	1.76%	2.60%	$3.71\%^{*}$	
Large firms	7.69%	8.13%	10.82%	$10.87\%^{*}$	
Large single-segment firms	7.48%	6.59%	9.90%	9.26%*	
Large multi-segment firms	8.02%	9.49%	12.17%	$12.56\%^{*}$	
Average annual plant-level capital expenditu	res/lagged ca	pital stock			
Plants of: All firms	16.93%	17.31%	17.59%	$19.39\%^{*}$	
Single-segment firms	17.24%	18.10%	18.02%	$20.09\%^{*}$	
Multiple-segment firms	16.17%	16.10%	16.49%	$18.14\%^{*}$	
Small firms	16.14%	17.33%	16.45%	$18.88\%^{*}$	
Large firms	17.29%	17.30%	18.03%	$19.63\%^{*}$	
Percent of total shipment's growth accounted	for by acquis	sitions			
Single-segment firms	5.31%	7.42%	8.85%	9.05%**	
Multiple-segment firms	26.07%	30.17%	30.71%	$36.08\%^{*}$	
Small firms	15.95%	21.25%	20.30%	$24.61\%^{*}$	
Large firms	20.08%	24.56%	24.43%	$28.52\%^{*}$	

Next, we examine the ratio of average annual plant-level capital expenditures to lagged capital stock. This ratio is highest in Growth industries and lowest in Declining industries. The single-segment firms' capital expenditure to lagged capital stock ratio exceeds that of the mean segment of multisegment firms in all industry categories. However, overall, the capital expenditure rates are similar across organizational forms. The last block of numbers in Table II shows the percentage of total segment growth accounted for by within-segment acquisitions. The results show that the proportion of firm growth accounted for by acquisitions is substantially higher for multiple-segment firms than for single-segment firms. In Declining industries, within-industry growth by acquisitions for multiple-segment firms is 26.07%, whereas it is only 5.31% of firm growth for single-segment firms. In Growth industries the difference is even larger. In Growth industries the within-industry growth via acquisitions by multiple-segment firms is 36.08%, 25 percentage points more than the proportion of growth of single-segment firms accounted for by acquisitions. Across industry categories, we see that within-industry growth via acquisitions for multiple-segment firms in Growth industries is also 10 percentage points higher than the corresponding number for multiple-segment firms in Declining industries.<sup>17</sup>

These summary statistics show that differences in acquisition rates between multiple- and single-segment firms are substantial. Capital expenditure rates are fairly stable across industries, segment size, and firm organization, while acquisition rates vary sharply across different firm sizes and organizational forms. The literature on the relation between conglomerate cash flow and investment has focused on whether conglomerates' capital expenditures are efficient or whether they are too high as a result of unresolved agency conflicts. Although the data sources are not directly comparable because most previous studies use COMPUSTAT data, these initial results show that capital expenditures are not very different for single- and multiple-segment firms, and are, if anything, a bit higher for single-segment firms. However, these summary statistics show that plant acquisitions are sensitive to industry conditions, and segment size, and are significantly greater for multiple-segment firms. The finding that the effect of organizational form is greater for acquisitions than capital expenditures at existing plants is consistent with Hypothesis 3.

We next investigate segments' capital expenditures and plant acquisitions in a multivariate framework and examine how financial dependence of industry segments impacts acquisitions and investment.

#### B. Financial Dependence and Firm Organizational Status

We begin our analysis of financial dependence in Table III. Our goal is to analyze how financial dependence and industry factors affect a firm's investment and acquisition decisions. However, given that a firm segment's financial deficit may be endogenous, we begin by running a first-stage regression where we predict the financial dependence of a firm's segment at the three-digit SIC code. We use predicted dependence in our later regressions that examine investment and acquisitions.

<sup>&</sup>lt;sup>17</sup> When we calculate the importance of acquisition using the number of plants purchased, we also find that conglomerate firms' acquisition rate in terms of number of plants purchased divided by the number of existing plants is also two to three times greater than that of single-segment firms. In particular, the rate of acquisition by conglomerate firms in Consolidating and Growth industries is, respectively, 3.1 and 2.6 times the rate of single-segment firms.

### Table III Financial Dependence

The table presents results of panel logit regressions examining the probability that a division of a firm will invest more than its divisional cash flow. Annual change in industry shipments is the change in industry shipments at the three-digit SIC code level deflated by industry price deflators to give the real change in industry shipments. Industry capital intensity is capital expenditures divided by industry sales at the three-digit SIC code level. Firm-industry productivity is a firm-industry fixed effect from a production equation estimated using 5 years of lagged data. Relative-odds ratio is the change in the relative likelihood of financial dependence from a one-unit increase in the variable. All regressions contain industry and year fixed effects. Robust standard errors that correct for autocorrelation within segments are in parentheses. \* and \*\* denote significantly different from zero at the 1% and 5% level, respectively. Dependent Variable: Dependence = 1 if Divisional Investment > Divisional Cash Flow.

		Change in long	run shipments
	All industries	Declining (-)	$Growing\left(+\right)$
Variables:			
Long-run (25-year) change in industry shipments	$-0.202^{*}$	$-0.221^{*}$	0.112
standard error	(0.054)	(0.076)	(0.081)
relative-odds ratio	0.798	0.802	1.119
Annual (short-run) change in industry shipments	$-0.699^{*}$	$-1.014^{*}$	$-0.458^{**}$
standard error	(0.158)	(0.238)	(0.213)
relative-odds ratio	5.896	0.363	0.633
Lagged industry profitability (value added/shipments)	$2.115^{*}$	$5.614^{*}$	0.819**
standard error	(0.350)	(0.395)	(0.412)
relative-odds ratio	5.896	274.239	2.268
Industry capital intensity	$-0.779^{*}$	$-0.772^{*}$	$-0.789^{*}$
standard error	(0.005)	(0.007)	(0.006)
relative-odds ratio	0.459	0.462	0.454
Firm-industry productivity: Fixed effect (lagged)	$0.044^{*}$	0.005	$0.071^{*}$
standard error	(0.003)	(0.005)	(0.003)
relative-odds ratio	1.044	1.005	1.074
$(Firm-industry productivity)^2$ (lagged)	$-0.577^{*}$	$-0.582^{*}$	$-0.576^{*}$
standard error	(0.013)	(0.022)	(0.017)
relative-odds ratio	0.562	0.559	0.562
log(firm size) (lagged)	$0.022^{*}$	$0.022^{*}$	$0.022^{*}$
standard error	(0.001)	(0.001)	(0.001)
relative-odds ratio	0.562	1.001	1.001
Number of observations	409,815	159,382	250,433
Pseudo R-squared	0.14	0.133	0.13

In Table III, we use a panel logit specification to estimate the probability that a segment is financially dependent. A segment is classified as financially dependent, with financial dependence equal to one, when its capital expenditures exceed the segment's cash flow, and zero otherwise. We regress financial dependence on lagged firm- and industry-level variables that capture the segment's need for external (to the segment) financial capital. Column 1 of Table III shows that a segment in a fast-growing industry is less likely to be financially dependent than a segment in a slow-growing industry. The table's results show that segments in capital intensive industries are more likely to be financially dependent. The relation between the probability of financial deficit and a segment's productivity is convex as there is a negative coefficient on productivity and a positive coefficient on productivity squared. Very high productivity therefore increases the likelihood of financial dependence. This convexity causes a firm to be financially dependent at the 87th percentile of productivity, holding other characteristics at their median values. Lastly, segments of large firms are less likely to be financially dependent.

In Table II, Columns 2 and 3, we estimate this specification on two subsamples: segments in industries with above median and below median change in real shipments over the long-run 25-year period considered. The subsample results are similar to those for the whole sample with several exceptions. The coefficient on the change in industry shipments changes from negative to positive (albeit insignificant) in growing industries. Second, the coefficient of lagged industry profitability is approximately one-third smaller in high growth industries than in low growth industries. Thus, while growing industries are more profitable, they demand even more capital to meet industry growth as profitability has a smaller impact on financial dependence in these industries. Third, the squared productivity term remains positive and highly significant in high growth industries but is basically zero for slow-growth industries. Thus, in slow-growth industries there is no partial offsetting effect that makes highly productive segments more likely to be financially dependent. In these industries, productive segments are less likely to be financially dependent than in high-growth industries. These results are consistent with highly productive firm segments demanding more capital to invest in growing industries, thereby increasing their likelihood of financial dependence.

To control for endogeneity of organizational status, we conduct a similar analysis to examine the predicted decision to become a conglomerate. We use the predicted firm status in our subsequent regressions.<sup>18</sup> In Table IV we examine whether individual segments are more likely to be part of conglomerate firms. We undertake this analysis for two reasons. First, we recognize that firm status is endogenous and thus wish to use predicted firm status in subsequent regressions that examine investment and acquisitions. Second, the influence of industry factors on whether segments belong to conglomerate firms is of independent interest.

We estimate a logistic regression where the dependent variable is equal to one if the segment is part of a conglomerate firm in Column 1 of Table IV. Because we are exploring the role of financial dependence on the decision to be a conglomerate segment, our specification is similar to the one predicting

<sup>&</sup>lt;sup>18</sup> In a previous draft, available from the authors, we use actual firm status in the regressions. The coefficients on the actual firm status indicator variables (not instrumented) are more significant for acquisitions and are significant for plant exits. The significance of key interaction variables is similar in all cases. Thus, we view the results reported here as more conservative.

## Table IV Firm Organization Status

The table presents results of panel logit regressions examining the probability that a segment of a firm will be part of a conglomerate firm. Long-run change in industry shipments is the change in industry shipments at the three-digit level over 1972 to 1997 divided by industry price deflators to give the real change. Annual change in industry shipments is the annual change in industry shipments. Industry capital intensity is capital expenditures divided by industry sales at the three-digit SIC code level, calculated in each year. Firm-industry productivity is a firm-industry fixed effect from a production equation estimated using 5 years of lagged data. Relative-odds ratio is the change in the relative likelihood of financial dependence from a one-unit increase in the variable. All regressions contain industry and year fixed effects. Robust standard errors that correct for autocorrelation within segments are in parentheses. \* denotes significantly different from zero at the 1% level.

	$egin{array}{c} { m Dependent\ variable}\ { m conglomerate}\ { m firm}=1 \end{array}$
Variables:	
Long-run (25-year) change in industry shipments	$0.243^{*}$
standard error	(0.019)
relative-odds ratio	1.275
Annual (short-run) change in industry shipments	$-0.619^{*}$
standard error	(0.085)
relative-odds ratio	0.538
Lagged industry profitability (value added/shipments)	$5.175^{*}$
standard error	(0.546)
relative-odds ratio	176.797
Industry capital intensity	$-0.119^{*}$
standard error	(0.018)
relative-odds ratio	0.888
Firm-industry productivity: Fixed effect (lagged)	$0.158^{*}$
standard error	(0.019)
relative-odds ratio	1.171
(Firm-industry productivity) <sup>2</sup> (lagged)	$3.024^{*}$
standard error	(0.042)
relative-odds ratio	20.573
log(firm size) (lagged)	$-0.074^{*}$
standard error	(0.002)
relative-odds ratio	0.929
Number of Observations	409,815
Pseudo R-squared	0.57

financial dependence in Table III. However, since our hypotheses predict that conglomerate segments have advantages in some industry categories, we include long-run changes in industry shipments as a predictor. Since we do not split the sample by long-run changes in industry shipments, the inclusion of this variable is permitted.

The results show that in industries with high long-run growth industry shipments, segments are more likely to be part of a conglomerate firm. Short-run (annual) changes do not increase the probability that a segment belongs to a conglomerate firm. Industry capital intensity is a particularly important predictor of whether a segment belongs to a conglomerate firm, with a relativeodds ratio of 176. Thus, a 10% increase in industry capital intensity increases the likelihood of a segment belonging to a conglomerate 17.6 times. Productivity also has a significant impact on the status of a firm segment. Segments with low productivity and segments that are highly productive are relatively more likely to be part of a conglomerate firm, yielding a U-shaped relation between productivity and conglomerate status.

#### C. Plant Acquisitions

## C.1. Financial Dependence and Acquisitions

This section analyzes the effect of predicted financial dependence and firm organization on within-industry plant acquisitions. Table V examines the effect of our different long-run industry categories using both 10- and 25-year windows. The 25-year window captures long-run trends in the industry. The 10-year window allows an industry to switch categories over time. For any given year, the industry category for the 10-year window is calculated using the change in the real value of industry shipments from surrounding Census years.<sup>19</sup>

We estimate the predicted financial dependence of segments using the second and third specifications of Table III. We use the second (third) specification for predicted dependence in the first and second (third and fourth) quadrants. We estimate the predicted probability of conglomerate status using the specification of Table IV. As a measure of segment productivity we construct a weighted average of each plant's productivity, with weights equal to plant-predicted shipments. We include the lagged number of firm plants in each segment as a control variable.<sup>20</sup>

In order to examine whether the effects are statistically different from each other for different industry categories, we form a triple-interaction variable. To form this variable we interact the predicted probability that a segment is part of a conglomerate with its predicted dependence and with the quadrant indicator variable.<sup>21</sup>

Table V reveals several patterns. First, for all industry categories except Declining industries in the 10-year window, single-segment firms that are predicted to be financially dependent have a lower probability of acquiring

<sup>19</sup> We also estimate this specification using continuous measures of the changes in industry conditions—instead of the four separate quadrant indicators used here. We include the change in the number of firms and the change in industry shipments in separate specifications, over both 10-and 25-year periods to examine the effect of each of these long-run changes separately. The results are very similar and are available in a previous version of the paper.

 $^{20}$  We also verify whether the results are robust to including firm size as a substitute for the number of firm plants. The results are similar and the conclusions are unaffected by this change.

<sup>21</sup> We also construct a similar interaction variable for public firm status. The version of this paper available on SSRN shows that public firm status also offsets part of the negative effect of predicted dependence in Growth industries. The public variable interacted with predicted dependence is positive and significant in Growth industries for the 25-year period. However, this effect is much smaller than that for conglomerate firms, thus here we focus on organizational form.

## Table V Plant Acquisition

The regressions examine the relation between plant acquisition, predicted financial dependence, and firm organization. Predicted dependence is the predicted probability of financial dependence using the specifications of Table III. We use the second (third) specification for predicted dependence in the first and second (third and fourth) quadrants. The growth (Consolidating, Technological Change, Declining) quadrant corresponds to industries where the change in real value of shipments is in the upper (upper, lower, lower) 50th percentile and the change in the number of firms is in the upper (lower, upper, lower) 50th percentile of industries over 10- and 25-year periods. Conglomerate firm status is the predicted probability using the specifications of Table IV. Productivity of segment is the weighted average of plant-specific productivity for that segment. All right-hand-side variables represent values prior to the year of acquisition. Relative-odds ratios, which represent a change in the relative odds of acquisition, can be obtained by taking the natural exponent of reported coefficients. All regressions contain industry and year fixed effects. Robust standard errors correct for autocorrelation within segments. \* and \*\* denote significantly different from zero at the 1% and 5% level, respectively.

	Length of time used to determine life-cycle quadrants				
Dependent variable: plant acquisition	10-yea	r window	25-yea	25-year window	
Variables:	coefficient	standard error	coefficient	standard error	
Predicted financial dependence					
Quadrant 1 indicator: Declining	0.334	0.244	0.179	0.162	
Quadrant 2 indicator: Tech. Change	$-0.278^{**}$	0.131	$-0.250^{*}$	0.113	
Quadrant 3 indicator: Consolidating	$-0.355^{**}$	0.156	-0.214	0.198	
Quadrant 4 indicator: Growth	$-1.066^{**}$	0.485	$-1.037^{**}$	0.456	
Conglomerate multi-industry indicator (predicted)	$3.135^{*}$	0.070	3.110*	0.080	
Segment rank within firm $(1 = largest)$	$-0.070^{*}$	0.005	$-0.069^{*}$	0.005	
Conglomerate×dependence×Quadrant 1 indicator	-0.042	0.244	0.085	0.203	
Quadrant 2 indicator: Tech. Change	$0.512^{*}$	0.177	$0.330^{*}$	0.120	
Quadrant 3 indicator: Consolidating	$0.555^{*}$	0.152	0.779*	0.230	
Quadrant 4 indicator: Growth	$1.319^{*}$	0.440	$1.420^{*}$	0.412	
Average plant-level productivity of segment (lagged)	0.021	0.083	0.022	0.083	
Diversity: Standard deviation of growth across segments	-0.129	0.120	-0.047	0.068	
Number of Plants in Segment (lagged)	$0.028^{*}$	0.002	$0.028^{*}$	0.002	
Quadrant 2 indicator: Tech. Change	0.020	0.150	0.387	0.714	
Quadrant 3 indicator: Consolidating	0.171	0.116	$2.786^{*}$	1.015	
Quadrant 4 indicator: Growth	0.089	0.115	-0.186	1.426	
Constant	$-4.785^{*}$	0.155	$-7.434^{*}$	1.012	
Number of segment-years	408,430			408,430	
Pseudo R-squared	14.96%			15.05%	

plants in their industry from other firms. Second, in all categories except for Declining industries, this negative effect of financial dependence on acquisitions is offset for conglomerate firms. This offsetting effect is shown by the positive coefficient on the interaction of predicted financial dependence with conglomerate firm status and the quadrant indicator variable. The interaction effect is greatest in growing industries (Growth and Consolidating). The coefficient of the interaction variable for Growth industries is statistically greater than

## Table VI Plant Acquisition in Growth Industries

The regressions examine the relation between plant acquisition, predicted financial dependence, and firm organization. Predicted dependence is the predicted probability of financial dependence using the third specification of Table III for growing industries. Conglomerate firm status is the predicted probability using the specifications of Table IV. Productivity of segment is the weighted average of plant-specific productivity residuals for that segment. All independent variables represent values prior to the year of the acquisition. Relative odds ratios, which represent a change in the relative odds of acquisition, can be obtained by taking the natural exponent of reported coefficients. All regressions contain industry and year fixed effects. Robust standard errors that correct for autocorrelation within segments are in parentheses. \*,\*\*, and \*\*\* denote significantly different from zero at the 1%, 5%, and 10% level, respectively.

				Productiv	ity split
Dependent variable: plant acquisition	Grov	wth industr	ries	Bottom 50%	Top 50%
Predicted financial dependence	$-0.272^{*}$	$-0.661^{*}$	$-0.664^{*}$	$-0.460^{*}$	$-0.915^{*}$
_	(0.080)	(0.129)	(0.129)	(0.177)	(0.190)
Conglomerate multi-industry indicator	$3.689^{*}$	$3.504^{*}$	$3.507^{*}$	$3.626^{*}$	$3.398^{*}$
(predicted)	(0.063)	(0.080)	(0.081)	(0.116)	(0.113)
Segment rank within firm $(1 = largest)$	$0.044^{*}$	$0.044^{*}$	$0.044^{*}$	$0.044^{*}$	$0.043^{*}$
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Conglomerate×predicted dependence		$0.545^{*}$	$0.547^{*}$	0.237	$0.898^{*}$
		(0.138)	(0.138)	(0.186)	(0.208)
Relative productivity versus declining			$0.145^{**}$	* -0.022	$0.352^{*}$
division			(0.081)	(0.107)	(0.117)
Average plant-level productivity of	0.090**	0.093**	0.044	0.064	0.061
segment (lagged)	(0.045)	(0.045)	(0.050)	(0.096)	(0.088)
Lagged number of plants	-0.0004	-0.0001	-0.0002	-0.0079	0.0041
	(0.004)	(0.005)	(0.004)	(0.007)	(0.005)
Number of segment-years	185,281	185,281	185,281	92,106	93,175
Pseudo R-squared	21.8%	21.8%	21.8%	21.7%	22.3%

for the other industry categories for the 10-year window, and for all industry categories except Consolidating industries for the 25-year window (chi-squared tests not reported). Thus, these results support the prediction in Hypothesis 1 that the mitigating effects of organizational form on financial dependence are greatest in growing industries.

Lastly, given Lamont and Polk's (2002) finding that the diversity of a conglomerate's operations across industries affects its value, we include a variable capturing a firm's diversity of opportunities. We include the standard deviation of industry growth across a conglomerate firm's segments. The regressions show that this variable is unrelated to the probability of a firm making an acquisition.<sup>22</sup>

 $^{22}$  Using the input-output matrix we also examine whether these results vary by whether or not the conglomerate's divisions are in related versus unrelated industries. We find that the results for financial dependence are not affected much by whether the conglomerate segments are unrelated or related.

Table VI further investigates the effects of organizational form in Growth industries. We examine Growth industries in detail because our previous results indicate that organizational form has a particularly large effect in these industries. Column 1 of this table examines the effect of conglomerate firm status by itself when the interaction term between conglomerate status and predicted dependence is not included. In the third column we include a variable that measures the relative productivity of the firm's division in the growth industry relative to that of main divisions, if any, that the firm has in declining industries. This variable is calculated as the simple difference in productivity between these divisions. If a firm has no division in a declining industry, this variable is set equal to zero. We use this variable to examine whether productive conglomerate segments in growth industries grow faster if the conglomerate has a less-productive division in a declining industry, as predicted by Hypothesis 2. Finally, Columns 4 and 5 split the segments into high- and low-productivity subsamples. This enables us to determine whether high- and low-productivity segments of conglomerates in growth industries have different acquisition patterns.

Column 1 of Table VI shows that conglomerate firm status is positively related to the rate of acquisitions. As the second column shows, the coefficient on the interaction variable between predicted conglomerate status and the predicted financing dependence is also positive and significant. Columns 3 and 5 in Table VIa show that conglomerate segments in Growth industries have a significantly higher probability of acquiring plants if the conglomerate also has a less-productive main division in a declining industry. These results show that multisegment firms acquire plants in their productive segments in growth industries and that they mitigate the effects of financial dependence for these segments. As predicted by Hypothesis 2, this effect is greater when conglomerate firms also have a division in a declining industry.

## C.2. Economic Significance of Our Results

To investigate the economic significance of these effects, we compute the probability that a segment belonging to different subsamples of single-segment and multisegment firms acquires a plant. For each subsample we use the median value of each variable and then vary the predicted probability that a segment is financially dependent from the 10th to the 90th percentile. We report the predicted probability of within-industry acquisitions for conglomerate and singlesegment firms using the specification in Table VI, Column 2 and the coefficients from Table VI, Column 5 for the predicted probability for high-productivity segments. Each of the coefficients in Column 2 are multiplied by the sample medians except for predicted financial dependence, which is varied from the 10th to the 90th percentile. For example, for the 50th percentile in the "Multisegment firms" row in Table VII, we set all right-hand side variables equal to their medians in the subsample of all the multisegment firms in our sample. Using these data medians from the subsample of multisegment firms, the coefficients from Table VII, and the unreported year and industry fixed effects, we compute the predicted probability of an acquisition using the logit specification. We also

## Table VII Economic Significance

The table presents predicted probabilities of within-segment acquisition, varying the predicted probability of financial dependence from the 10th to the 90th percentile. All other variables are held at the sample medians for the respective subset of data (multi- and single-segment). Predicted probabilities are calculated using coefficients from Table VI, Column 2 for Growth industries and a similar specification for Declining industries. High (low) productivity segments are segments above (below) the industry-year median. Predicted probabilities for high-productivity segments use coefficients from Table VI, Column 5. The last row for each quadrant uses the medians of the data from the multisegment firm subset but assumes the firm is single segment, thus setting the multisegment firm indicator equal to zero.

Predicted financial dependence at the following percentiles:	10th	25th	50th	75th	90th
Panel A: Declining Industries: Q	uadrant	t 1			
Multisegment firms	4.38%	3.88%	3.52%	3.96%	4.54%
Single-segment	0.66%	0.41%	0.18%	0.10%	0.10%
Single-segment using medians of data from multisegment firms	3.49%	2.34%	1.11%	0.40%	0.19%
Panel B: Growth Industries: Qu	adrant	4			
Multisegment firms	6.08%	5.94%	6.26%	6.58%	7.30%
Multisegment firms: High-productivity segments	6.32%	6.15%	6.52%	7.07%	7.97%
Single-segment	0.69%	0.64%	0.57%	0.50%	0.44%
Single-segment firms: High-productivity segments	0.65%	0.62%	0.57%	0.52%	0.49%
Single-segment using medians of data from multisegment firms	5.46%	4.95%	4.55%	4.10%	3.28%

report economic effects for the Declining industry quadrant using a similar specification for comparability.

Table VII reports the economic significance of our results. The table shows that multisegment firms have substantially higher probabilities of making an acquisition than single-segment firms. Thus, for example, in Growth industries a conglomerate segment with median levels of all variables for the subsample of conglomerate segments has a 6.26% probability of making an acquisition in any given year, whereas the single-segment firm has a 0.57% probability of making an acquisition at the median levels of the variables for the subsample of single-segment firms. As the probability of being financially constrained increases from the 10th percentile to the 90th percentile, the probability of acquisitions increases for multisegment firms but decreases for single-segment firms. Thus, financially dependent single-segment firms are less likely to acquire plants, whereas financially dependent conglomerate segments are more likely to acquire plants. Given that financial dependence occurs when a segment's investment is high relative to its cash flow, this suggests that segments of conglomerate firms acquire plants when capital expenditures exceed segment cash flow, while single-segment firms have difficulty in making acquisitions when capital expenditures exceed cash flow.

To investigate the causes of these differences in acquisition probabilities between single-segment firms and conglomerate segments we recompute the probability of acquisition for single-segment firms using the median values of the data from conglomerate segments and the coefficient estimates for singlesegment firms. The estimates show that a substantial proportion of the difference in estimated probabilities is explained by differences in characteristics of single-segment and conglomerate firms. Thus, in Growth Industries, the median single-segment firm would have had 4.55% probability of making an acquisition if it had the data corresponding to the median of the subsample of multisegment firms (as opposed to the actual median single-segment firm, which has a 0.57% probability of acquisition). The difference between the median conglomerate segment's 6.26% estimated probability of making an acquisition and the 4.55% probability the single-segment firm would have had if it had the median values of conglomerate firm can be attributed to differences in organizational form. The results show that organizational form makes a larger difference for segments predicted to be financially dependent than for segments not predicted to be financially dependent. Comparing the first and last rows for Declining and Growth industries (comparing conglomerate segments to singlesegment firms with the data from conglomerate segments), it is striking that organizational form makes a larger difference (almost twice as large) in Growth industries than in Declining industries.

In the third and fourth panels, we also split the data into high- and lowproductivity segments and compute the predicted probability of an acquisition using the specifications in Columns 5 and 6 of Table VII. The results show that the previous effects of organizational form are higher for more-productive segments of conglomerate firms. As the third panel shows, the probability of a within-industry acquisition for multisegment firms increases to 7.97% when predicted financial dependence is at the 90th percentile. This evidence is consistent with conglomerate firms helping acquire plants in productive business segments.

These results show that within-industry acquisition probabilities depend on firm organizational form in several ways. First, conglomerate firms acquire more within their industries than single-segment firms overall. Second, particularly in Growth industries, acquisition probabilities increase with predicted financial dependence for conglomerate firms' productivity segments, while they decrease with financial dependence for single-segment firms. This finding is consistent with conglomerate firms providing resources to segments with growth opportunities. Third, the acquisition probability of a conglomerate firm's most-productive segments in growth industries increases when it has a division in a declining industry—a result that is consistent with the theoretical prediction in Stein (1997) and Maksimovic and Phillips (2002) and also with Boston Consulting Group's prescription for nongrowth industries to help fund "shining stars." The results are not consistent with theories that predict that conglomerate firms subsidize their less-efficient divisions because of influence costs.

## C.3. Post-acquisition Changes in Productivity

To examine whether these acquisitions are associated with value creation, Table VIII presents the ex-post changes in productivity for the acquired plants.

# Table VIII Productivity Changes Post Acquisition

The table presents changes in plant productivity post-acquisition. Productivity is the sum of a firm fixed effect plus the residual from an estimated industry production function. Changes in productivity are industry and year adjusted. Declining (Technological Change, Consolidating, Growth) industries are industries that have long-run change in industry shipments over 1972 to 1987 in the lowest (lowest, highest, highest) 50th percentile and the long-run change in the number of firms in the lowest (highest, lowest, highest) 50th percentile. Standard errors of the means are in parentheses. \*,\*\*, and \*\*\* denote significantly different from zero at the 1%, 5%, and 10% level, respectively.

Industry Category	Years —1 to 1	Years -1 to 2	Years -1 to 3	Years -1 to 4
Declining Industries				
Plants purchased by conglomerate firms				
Average productivity change	0.007	0.009	0.029	$0.052^{**}$
Standard error	(0.020)	(0.023)	(0.025)	(0.027)
Number of plants	1,365	1,146	1,011	888
Plants purchased by single-segment firms				
Average productivity change	0.028	0.022	0.007	0.001
Standard error	(0.021)	(0.024)	(0.029)	(0.034)
Number of plants	1,057	882	690	552
Technological Change Industries				
Plants purchased by conglomerate firms				
Average productivity change	$0.034^{*}$	$0.045^{*}$	$0.039^{*}$	0.032
Standard error	(0.012)	(0.013)	(0.012)	(0.016)
Number of plants	3,681	3,305	2,980	2,626
Plants purchased by single-segment firms	,	,	,	<i>,</i>
Average productivity change	-0.012	-0.029	$-0.042^{***}$	-0.042
Standard error	(0.018)	(0.021)	(0.024)	(0.027)
Number of plants	1,554	1,289	1,004	822
Consolidating Industries				
Plants purchased by conglomerate firms				
Average productivity change	0.010	0.016	0.017	0.022
Standard error	(0.012)	(0.014)	(0.015)	(0.016)
Number of plants	3,400	3,006	2,710	2,454
Plants purchased by single-segment firms				
Average productivity change	0.004	0.002	-0.012	-0.007
Standard error	(0.017)	(0.020)	(0.024)	(0.025)
Number of plants	1,829	1,458	1,167	941
Growth Industries				
Plants purchased by conglomerate firms				
Average productivity change	0.041*	$0.053^{*}$	$0.048^{*}$	$0.046^{*}$
Standard error	(0.008)	(0.009)	(0.010)	(0.011)
Number of plants	8,016	6,922	6,068	5,191
Plants purchased by single-segment firms	*	,	,	,
Average productivity change	0.005	$-0.025^{**}$	-0.018	0.007
Standard error	(0.011)	(0.012)	(0.015)	(0.017)
Number of plants	4,600	3,720	2,820	2,186

We compute the changes in productivity over a 4-year window. These changes in productivity are industry and year adjusted.

Table VIII shows that productivity changes for conglomerate acquisitions are significantly greater than zero in Technological Change industries and, in particular, in Growth industries. In all windows, -1 to +1, +2, +3, and +4 we find that industry-adjusted productivity significantly increases. In contrast, plants purchased by single-segment firms in these industries either show no significant increase or a slight decrease in productivity.

In sum, growth by acquisition is greater for segments of firms that are organized as conglomerates. Predicted financial dependence reduces the probability that a single-segment firm grows by acquisition, but has a considerably smaller, if any, effect on conglomerate segments. Consistent with Hypothesis 4, plants acquired by conglomerate firms in Technological Change and Growth industries experience significant increases in productivity post-acquisition. These results are not consistent with agency theories that predict that conglomerates overexpand into industries without good growth prospects and in which they have little expertise.

Overall, the analysis suggests that acquisition activity of conglomerates is consistent with Stein's (1997) model of the benefits of internal capital markets and with Maksimovic and Phillips's (2002) predictions about the efficient reallocation of assets within conglomerate firms. These results contradict models that predict subsidization of poorly performing divisions or divisions with poor growth prospects. The results are also not consistent with agency or empire building models that predict expansion into industries without considering the ex-post prospects and productivity in these industries.

## D. Capital Expenditures

We next examine the impact of predicted financial dependence and organizational form on capital expenditures. To test the effect of financial dependence and organizational form on capital expenditures, we interact predicted conglomerate firm status with predicted financial dependence. In Table IX, we estimate our capital expenditures regression for the four different industry categories separately. Alternative specifications using industry interaction variables, as in Table V, yield similar results.

Table IX shows that the effects of financial dependence and conglomerate structure depend on industry categories. Predicted financial dependence negatively affects capital expenditures in all categories. However, the negative effect of financial dependence is greater for single-segment firms than for conglomerate segments, as the interaction term, conglomerate status times predicted dependence, is positive and significant for all categories. We find that this interaction term is significantly higher for Consolidating and Growth industries versus Declining and Technological Change categories.

Finally, the weighted average plant-level productivity of a segment is significantly related to investment in all industry categories. This finding contrasts with the case of acquisitions, where the effect is only present in Growth

## Table IX Capital Expenditures

The table presents the results of logistic regressions examining the relation between firm organization, predicted financial dependence, and firm segment-level investment. Predicted dependence is the predicted probability of financial dependence using the specifications of Table III. We use the second (third) specification for predicted dependence in the first and second (third and fourth) quadrants. Conglomerate firm status is the predicted probability using the specifications of Table IV. Productivity of plant is the plant-specific productivity. Declining (Technological Change, Consolidating, Growth) industries are industries that have long-run change in industry shipments over 1972 to 1997 in the lowest (lowest, highest, highest) 50th percentile and the long-run change in the number of firms in the lowest (highest, lowest, highest) 50th percentile. All regressions contain industry and year fixed effects. Robust standard errors that correct for autocorrelation within segments are in parentheses. \*,\*\*, and \*\*\* denote significantly different from zero at the 1%, 5%, and 10% level, respectively. Dependent Variable: Capital expenditures/Lagged capital stock (Industry-year adjusted)

Industry category	Declining	Tech. change	Consolidating	Growth
Variables:				
Predicted financial dependence	-0.038	$-0.038^{**}$	$-0.066^{**}$	$-0.071^{*}$
-	(0.057)	(0.018)	(0.028)	(0.028)
Conglomerate multi-industry indicator	0.014	0.002	0.006	0.003
(predicted)	(0.012)	(0.002)	(0.006)	(0.003)
Conglomerate×predicted dependence	0.019	0.020*	$0.092^{*}$	$0.119^{*}$
	(0.013)	(0.004)	(0.015)	(0.013)
Segment rank within firm $(1 = largest)$	-0.001***	$-0.002^{*}$	0.0010*	$0.002^{*}$
	(0.0004)	(0.0005)	(0.0003)	(0.0003)
Average plant-level productivity of	$0.025^{*}$	$0.012^{*}$	0.038*	$0.062^{*}$
segment (lagged)	(0.006)	(0.002)	(0.012)	(0.011)
Number of industry plants (lagged)	$-0.003^{*}$	$-0.0002^{b}$	-0.0001	$-0.0020^{*}$
	(0.0003)	(0.0001)	(0.0003)	(0.0003)
Constant	$0.301^{*}$	$0.382^{*}$	0.291**	$0.352^{*}$
	(0.021)	(0.024)	(0.029)	(0.029)
Number of observations	92,282	74,472	68,869	195,266
Number of firm-industry segments	18,091	14,235	14,289	39,672
Adj. <i>R</i> -squared	0.20	0.19	0.21	0.26

industries. The relation between a segment's productivity and its capital expenditures is more robust than the relation between its productivity and the probability of within-industry acquisitions.

As a robustness test, we also check whether the same results hold when we consider only major investments by firms. We rerun the regressions taking as our dependent variable an indicator variable that takes the value one if the ratio of capital expenditures over lagged capital stock employed by the segment exceeds the 90th percentile of this variable, industry adjusted. These regressions are more likely to pick up major investments by smaller segments because large segments with many plants are more likely to be able to smooth their investment flows across time. These unreported regressions show that our results are robust across all industry categories. We also continue to find that

## Table X Plant Openings

The table presents the results of logistic regressions examining the relation between firm organization, predicted financial dependence, and new plant openings. Predicted dependence is the predicted probability of financial dependence using the specifications of Table III. We use the second (third) specification for predicted dependence in the first and second (third and fourth) quadrants. Conglomerate is the predicted probability that the firm produces in at least two different three-digit industries using the specification of Table IV. Productivity of plant is the plant-specific productivity. Declining (Technological Change, Consolidating, Growth) industries are industries that have long-run change in industry shipments over 1972 to 1997 in the lowest (lowest, highest, highest) 50th percentile and the long-run change in the number of firms in the lowest (highest, lowest, highest) 50th percentile. Odds ratio is the change in the relative likelihood of plant exit from a one unit increase in the variable. All regressions contain industry and year fixed effects. Robust standard errors that correct for autocorrelation within segments are in parentheses. \*,\*\*, and \*\*\* denote significantly different from zero at the 1%, 5%, and 10% level, respectively. Dependent Variable: New Plant Opening

Industry category	Declining	Tech. change Consolidating		Growth
Variables:				
Predicted financial dependence	0.023	0.119	$-0.557^{*}$	$-0.461^{*}$
standard error	(0.128)	(0.137)	(0.158)	(0.101)
relative odds ratio	1.023	1.126	0.573	0.631
Conglomerate multi-industry indicator (predicted)	2.032*	$2.084^{*}$	2.203*	1.818*
standard error	(0.094)	(0.105)	(0.122)	(0.075)
relative odds ratio	7.629	8.037	9.052	6.160
Conglomerate * predicted dependence	-0.240	0.367	$1.248^{**}$	$0.780^{*}$
standard error	(0.255)	(0.294)	(0.252)	(0.146)
relative odds ratio	0.787	1.443	3.483	2.181
Segment rank within firm $(1 = largest)$	$-0.066^{*}$	$-0.068^{*}$	$-0.107^{*}$	$-0.084^{*}$
standard error	(0.012)	(0.107)	(0.020)	(0.007)
relative odds ratio	0.936	0.934	0.899	0.920
Average plant-level productivity of segment (lagged)	0.153***	0.118	0.130	0.062
standard error	(0.088)	(0.092)	(0.097)	(0.056)
relative odds ratio	1.165	1.125	1.139	1.064
Number of plants in segment (lagged)	$0.052^{*}$	$0.078^{*}$	$0.046^{*}$	$0.096^{*}$
standard error	(0.004)	(0.009)	(0.004)	(0.005)
relative odds ratio	1.053	1.081	1.047	1.101
Number of segment-years	86,968	71,358	66,875	189,221
Number of firm-industry segments	18,210	14,322	14,473	39,891
Pseudo R-squared	0.124	0.130	0.144	0.125

in every industry category the more-productive firms have a higher probability of a major investment than the less-productive firms.

Comparing these results for capital expenditures with the results for acquisitions (Tables V and VI), we find evidence consistent with Hypothesis 3, which predicts that the effect of conglomerate organization on acquisitions is stronger than it is on capital expenditures. This evidence is of interest since it suggests that capital expenditures have received disproportionate attention in previous research.

#### E. New Plant Openings and Exits

We next examine the effect of predicted financial dependence and firm organization on new plant openings and exits across our industry categories. For new plant openings, we aggregate a firm's plants into three-digit industries to examine whether a particular firm-segment acquires an additional plant.

Table X shows that in Growth and Consolidating industries, predicted financial dependence has a significantly negative effect on plant openings for singlesegment firms. Conglomerate firms mitigate the effects of predicted financial dependence on new plant openings for their segments in Growth industries. Table X shows that the key conglomerate interaction variable only affects plant births in Growth industries and Consolidating industries.<sup>23</sup> As expected, we also find that segments with a higher number of plants are more likely to open plants in all industry categories.

Table XI examines plant exits across the different industry categories. We run these regressions at the plant level and assign the dependent variable equal to one if the plant exits in a given year and zero otherwise. Table XI shows that the effect of predicted financial dependence on plant exits is insignificant in all categories except for Growth industries. The effect of conglomerate firm status is limited. Plants of conglomerate firms that belong to segments predicted to be financially dependent are less likely to close in Declining industries as shown by the interaction variable *conglomerate* × *predicted dependence*. In other industry categories this effect is insignificant. More efficient plants are also less likely to be closed down. Finally, segment size affects closure in two ways. As the number of plants in a segment increases, closure probabilities increase. However, plants in bigger segments are less likely to be closed down, as shown by the coefficient on segment rank.<sup>24</sup>

Overall, the results for plant openings and plant exits differ over our longrun industry categories. Plant openings and exits depend on firm organizational form in several different ways. First, in growth industries, conglomerate firms that are predicted to be financially dependent have a significantly higher probability of new plant openings compared to dependent single-segment firms. Second, the probability of new plant openings by private, single-segment firms is the most adversely affected by predicted financial dependence. Third, there is a more limited effect of conglomerate organizational form and financial dependence on plant exits. In Declining industries, conglomerate firms are less likely to close plants of segments predicted to be financially dependent. However, this effect is insignificant in other industry categories. These results suggest that organizational form affects plant exits and plant openings differently, most likely because plant openings require significant resources, including the ability to integrate the new plant into existing operations, while plant exits do not. The

<sup>&</sup>lt;sup>23</sup> Results in the working paper version of this paper available on SSRN show that this effect is robust to including a public firm status variable.

<sup>&</sup>lt;sup>24</sup> Unreported regressions show that public firms are more likely to close plants, significantly so in Consolidating and Growth industries. However, the interaction effect of predicted public status with financial dependence is insignificant for all industry categories.

## Table XI Plant Exit

The table presents the results of plant-level logit regressions examining the relation between firm organization, predicted financial dependence, and plant closing. Predicted dependence is the predicted probability of financial dependence using the specifications of Table III. We use the second (third) specification for predicted dependence in the first and second (third and fourth) quadrants. Conglomerate is the predicted probability that the firm produces in at least two different three-digit industries using the specification of Table IV. Productivity of plant is the plant-specific productivity. Declining (Technological Change, Consolidating, Growth) industries are industries that have long-run change in industry shipments over 1972 to 1997 in the lowest (lowest, highest, highest) 50th percentile and the long-run change in the number of firms in the lowest (highest, lowest, highest) 50th percentile. Odds ratios are the change in the relative likelihood of plant exit from a one unit increase in the variable. All regressions contain industry and year fixed effects. Robust standard errors that correct for autocorrelation within segments are in parentheses. \* denotes significantly different from zero at the 1% level.

Dependent variable: Plant Exit

Industry category	Declining	Tech. change	Consolidating	Growth
Variables:				
Predicted financial dependence	0.187	0.031	-0.041	-0.200
standard error	(0.166)	(0.232)	(0.174)	(0.123)
relative odds ratio	1.206	1.031	0.960	0.819
Conglomerate multi-industry indicator (predicted)	-0.080	-0.125	$-0.428^{*}$	$-0.509^{*}$
standard error	(0.139)	(0.166)	(0.139)	(0.090)
relative odds ratio	0.923	0.882	0.652	0.601
Conglomerate×predicted dependence	$-1.255^{a}$	-0.345	-0.363	-0.120
standard error	(0.325)	(0.358)	(0.371)	(0.215)
relative odds ratio	0.285	0.708	0.696	0.887
Segment rank within firm $(1 = largest)$	$0.044^{*}$	0.030*	$0.044^{*}$	$0.031^{*}$
standard error	(0.004)	(0.005)	(0.005)	(0.003)
relative odds ratio	1.045	1.030	1.045	1.031
Average plant-level productivity of segment (lagged)	$-0.369^{*}$	$-0.441^{*}$	$-0.386^{*}$	-0.444
standard error	(0.015)	(0.016)	(0.016)	(0.011)
relative odds ratio	0.691	0.643	0.680	0.641
Number of plants in segment (lagged)	0.009*	0.008*	$0.004^{*}$	$0.015^{*}$
standard error	(0.001)	(0.001)	(0.001)	(0.002)
relative odds ratio	1.009	1.008	1.004	1.015
Number of plant-years	$151,\!247$	115,495	128,401	$276,\!658$
Number of firm-industry segments	18,209	14,322	14,472	38,891
Pseudo R-squared	0.03	0.04	0.04	0.04

results are consistent with Hypotheses 2 and 4, which posit that conglomerate firms have skills in integrating new acquisitions and providing resources that affect large decisions such as acquisitions and plant openings in productive industry segments.

# **IV.** Conclusions

A growing literature in corporate finance examines how multi-industry firms allocate investment across divisions. This literature tacitly assumes that industries do not differ much and that the relevant differences can be summarized by simple measures of investment opportunities. We argue that the competitive environment of an industry depends on changes in long-run industry conditions. Industries in different stages of their life cycle differ in the opportunities for profitable restructuring and in exploitable growth opportunities. These differences in the competitive environment have the potential to alter the comparative advantage of conglomerate multi-industry firms relative to single-industry firms. A comparative analysis of investment by segments of conglomerates and single-industry firms has to take these differences into account. Toward this end, we classify U.S. manufacturing industries into four different long-run industry categories based on both the growth rates of real shipments and changes in the number of producers.

We find evidence that the effects of firm organization, both actual organizational form and controlling for the endogeneity of organizational form, vary across these long-run industry changes. We have four major results that show the importance of long-run industry conditions:

- (1) In industries in which shipments are growing, within-industry acquisitions and new plant openings are significantly affected by firm organizational form. Conglomerates' segments are much more likely to purchase a plant, adding to their existing segments, than are single-industry firms. By contrast, capital expenditure rates are fairly stable across industries, segment size, and firm organization.
- (2) Examining acquired plants post-acquisition, we find that plants acquired by conglomerate firms in Technological Change industries and, in particular, in Growth industries significantly increase in productivity postacquisition.
- (3) We find evidence that within-industry acquisition rates are higher for highproductivity segments of conglomerates in Growth industries than for their business segments in Declining industries. Since the conglomerate effect on acquisitions is stronger for high-productivity segments, there does not appear to be subsidization of a conglomerate's less-efficient segments.
- (4) For new plant openings, we find that there is a significant positive effect of belonging to a conglomerate in Growth industries. Conglomerate firms offset the effects of predicted financial dependence on new plant openings in Growth industries. The effects on plant exit are more limited.

These findings are consistent with the existence of benefits of internal capital markets as argued by Stein (1997) and examined empirically by Khanna and Tice (2001) and Peyer (2001). The finding that the probability of an acquisition in growth industries increases for conglomerate firms that have highproductivity segments in growing industries and substantial other segments in declining industries is consistent with the theoretical prediction in Maksimovic and Phillips (2002). These results contradict models that predict subsidization of poorly performing divisions or divisions with poor growth prospects. The results are also not consistent with agency or empire building models that predict inefficient expansion into industries. These findings have important implications for the literature on conglomerates' allocation of investment. This literature uses capital expenditures as a proxy for segment-level investment. Thus, it does not take into account plant acquisition, which is an important component of conglomerate firms' investment but is not an important component of single-industry firms' investment. We document large effects of organizational form on financial dependence and in turn on acquisitions and plant openings. The differences in these effects of firm organization are largest in growing industries. The acquisition effect of organizational form on financial dependence has not been previously identified and is even stronger than the usually studied relation between conglomerate status and capital expenditures.

Overall, these findings document important effects of firm organization that vary over long-run industry life-cycle stages. The findings are consistent with conglomerates in growth industries providing resources that help business segments reduce or break the link between a segment's predicted financial dependence and its growth via acquisitions and plant opening decisions.

#### REFERENCES

- Bartelsman, Eric, and Wayne Gray, 1994, The NBER manufacturing productivity database, NBER Technical Working Papers 0205, National Bureau of Economic Research, Inc.
- Berger, Philip, and Eli Ofek, 1995, Diversification's effect on firm value, Journal of Financial Economics 37, 39-66.
- Bernardo, Antonio, and Bhagwan Chowdhry, 2002, Resources, real options and corporate strategy, Journal of Financial Economics 63, 211–234.
- Bolton, Patrick, and David Scharfstein, 1990, A theory of predation based on agency problems in financial contracting, *The American Economic Review* 80, 93–106.
- Campa, Jose, and Simi Kedia, 2003, Explaining the diversification discount, *Journal of Finance* 57, 1731–1762.
- Fluck, Z., and A. Lynch, 1999, Why firms merge and then divest: A theory of financial synergy, Journal of Business 72, 319–346.
- Ghemawat, Pankaj, 1984, Capacity expansion in the titanium dioxide industry, *Journal of Industrial Economics* 33, 145–163.
- Ghemawat, Pankaj, and Barry Nalebuff, 1985, Exit, The Rand Journal of Economics 16, 184-194.
- Gort, Michael, and Steven Klepper, 1982, Time paths in the diffusion of product innovations, *Economic Journal* 92, 630–653.
- Griliches, Zvi, 1957, Hybrid corn: An exploration in the economics of technological change, *Econometrica* 25, 501–522.
- Hayes, Rachel M, and Russell Lundholm, 1996, Segment reporting to the capital market in the presence of a competitor, *Journal of Accounting Research* 34, 261–279.
- Hyland, David, C., 1997, Why firms diversify, An empirical examination, unpublished doctoral dissertation, Ohio State University, Columbus, Ohio.
- Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance, and takeovers, *American Economic Review* 76, 323–329.
- Jensen, Michael C., and William Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Finance and Economics* 3, 305–360.
- Jovanovic, Boyan, 1982, Selection and the evolution of industry, Econometrica 50, 649-670.
- Khanna, Naveen, and Sheri Tice, 2001, The bright side of internal capital markets, *Journal of Finance* 56, 1489–1528.

- Klepper, Steven, 1996, Entry, exit, growth, and innovation over the product life cycle, American Economic Review 86, 562–583.
- Klepper, Steven, and Elizabeth Grady, 1990, The evolution of new industries and the determinants of market structure. *Rand Journal of Economics* 21, 24–44.
- Kovenock, Dan, and Gordon Phillips, 1997, Capital structure and product market behavior: An examination of plant exit and investment decisions, *Review of Financial Studies* 10, 767–803.
- Lamont, Owen, 1997, Cash flow and investment: Evidence from internal capital markets, *Journal* of Finance 52, 83–109.
- Lamont, Owen, and Christopher Polk, 2002, Does diversification destroy value? Evidence from industry shocks, *Journal of Financial Economics* 63, 51–77.
- Lang, L., and R. Stulz, 1994, Tobin's q, corporate diversification, and firm performance, Journal of Political Economy 102, 1248–1280.
- Maksimovic, Vojislav, and Gordon Phillips, 1998, Asset efficiency and the reallocation decisions of bankrupt firms, *Journal of Finance* 53, 1495–1532.
- Maksimovic, Vojislav, and Gordon Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there gains?, *Journal of Finance* 56, 2019–2065.
- Maksimovic, Vojislav, and Gordon Phillips, 2002, Do conglomerate firms allocate resources inefficiently across industries? *Journal of Finance* 57, 721–767.
- Matsusaka, John G., and Vikram Nanda, 2001, Internal capital markets and corporate refocusing, Journal of Financial Intermediation 11, 176–211.
- McGuckin, Robert, and George Pascoe, 1988, The Longitudinal Research Database (LRD): Status and research possibilities, Survey of Current Business 68, 31–37.
- Meyer, Bruce, 1990, Unemployment insurance and unemployment spells, *Econometrica* 58, 757–782.
- Mundlak, Yair, 1961, Empirical production function free of management bias, Journal of Farm Economics 43, 44–56.
- Mundlak, Yair, 1978, On the pooling of time series and cross section data, *Econometrica* 46, 69–85.
- Myers, Stewart C., 1977, Determinants of corporate borrowing, *Journal of Financial Economics* 5, 147–175.
- Myers, Stewart, and Nicholas Majluf, 1984, Corporate finance and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187–221.
- Pacter, Philip, 1993, Reporting disaggregated data, Financial Accounting Standards Board Research Report.
- Peyer, Urs, 2001, Internal and external capital markets, Mimeo, University of North Carolina.
- Rajan, Raghuram G., Henri Servaes, and Luigi Zingales, 2000, The cost of diversity: The diversification discount and inefficient investment, *Journal of Finance* 55, 35–80.
- Scharfstein, David S., and Jeremy C. Stein, 2000, The dark side of internal capital markets: Divisional rent-seeking and inefficient investment, *Journal of Finance* 55, 2537–2564.
- Schoar, Antoinette, 2002, Effects of corporate diversification on productivity, *Journal of Finance* 57, 2379–2403.
- Shin, Hyun-Han, and Rene Stulz, 1998, Are internal capital markets efficient? *Quarterly Journal* of Economics 113, 531–552.
- Stein, Jeremy, 1997, Internal capital markets and the competition for corporate resources, *Journal* of Finance 52, 111–133.
- Villalonga, Belen, 2004, Diversification discount or premium? New evidence from BITS establishment-level data, *Journal of Finance* 59, 479–506.