Innovation, Modularity, and Vertical Deintegration: Evidence from the Early U.S. Auto Industry

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Although vertical integration choices have been found to significantly affect firm performance, there has been little empirical study of how such choices are affected by the stage of industry evolution in which firms find themselves. We empirically investigate two possible impacts of increasing modularity on a firm’s vertical integration choices. First, we hypothesize that increasing modularity is associated with vertical deintegration because of the high-level standardization of components that dominant designs tend to promote. Second, we posit that firms selling in higher market segments, because they are attempting to differentiate their products by incorporating unique components with less-modular interfaces with other components, will tend to be more vertically integrated than their lower-price rivals. We find evidence for both of these effects in data from the early U.S. auto industry.

Key words: innovation; modularity; vertical integration

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Scholars of technology and innovation management have recently focused attention on how technological change in the competitive environment impacts firms’ vertical integration strategies, with the idea that such strategies significantly affect a firm’s innovative performance as new technology emerges (e.g., Teece 1996, Afuah 2001, Macher 2006). An important strand of this literature has been concerned in particular with whether and how the increasing modularity of product architectures impacts firms’ vertical boundaries (e.g., Langlois 1988, Sanchez and Mahoney 1996, Baldwin and Clark 2000, Schilling 2000, Brusoni et al. 2001, Jacobides and Winter 2005, Baldwin 2007, Wolter and Veloso 2008). Scholars have perceived that in many technology-driven industries, there has been a tendency for the architectures of innovative, complex products to become more modular as they develop. They have been interested in whether firms capitalize on this increasing modularity by vertically deintegrating production, and whether firms differ in the degree to which they deintegrate in response to increasing modularity (e.g., Christensen et al. 2002). This paper empirically examines the relationship between modularization and vertical deintegration in the early U.S. auto industry.

Although the technology and innovation management literature has developed numerous important insights into the relationship between technological modularity and firm boundary choices, a major barrier to further progress has been the lack of large sample data on vertical integration and technological modularity. Most studies of the impact of modularity on vertical integration have been conceptual contributions relying on anecdotal and case study evidence. This approach is the natural first step for addressing new research questions about phenomena for which large sample data are scarce. An important next step, however, is to search for more systematic evidence on the phenomenon. This is where the current paper aims to contribute.

We begin by developing our hypotheses based on the technology management and transaction cost literatures. We then explain how our hypotheses apply in the context of the early U.S. auto industry. We then present our empirical approach and results. We conclude with implications for the modularity and transaction cost literatures.

Hypotheses

Modularity Effect

Product architectures are said to be modular if the engineering interfaces defining the ways in which product components interact are standardized (e.g., Sanchez and Mahoney 1996, p. 66). Standardized interfaces allow some variance in the design details of individual product components. This facilitates “modular innovation” (Henderson and Clark 1990): innovation in product components that does not significantly affect the
design of other components. This kind of innovation allows firms to produce families of products based on the same overall product architecture, thereby helping them to address heterogeneity in customer demand (e.g., Langlois and Robertson 1992). Product architectures built around idiosyncratic interfaces, on the other hand, place more constraints on component designs. This hinders component-level innovation, often requiring more difficult “architectural innovation” (Henderson and Clark 1990) for demand heterogeneity to be addressed.

Scholars have emphasized that in a range of technology-based industries such as personal computers, stereo systems, automobiles, aircraft, household appliances, power tools, software, and others, product architectures have tended to become more modular as they developed from their initial invention (e.g., Sanchez and Mahoney 1996). Complex systems products that are new to the world are often “built from scratch” using idiosyncratic components and other “patches” (Siggelkow 2002), some of which are designed to overcome impediments and technological glitches that were not anticipated at the beginning of the innovation process. Over time, as product designers improve their understanding of the ways in which product components interact, as well as their understanding of demand variety (Adner and Levinthal 2001), they often push toward standardized interfaces to lower costs. In these cases, higher component interdependence gradually gives way to lower component interdependence.

Lower component interdependence in turn implies that less of the engineering effort required to design a component is irrecoverable were the component to be developed for a different company’s product instead (Williamson 1975, 1985; Monteverde and Teece 1982). This is accomplished because standardized interfaces serve to structure the technical dialogue between component design engineers, thereby reducing the need for unstructured technical dialogue and reducing the total amount of product-specific dialogue (Monteverde 1995, Argyres 1999). Such architectures thus facilitate a reduction in asset specificity. By reducing the level of required communication, modular architectures also mitigate the hazard that proprietary information will be inadvertently leaked to another component designer (Teece 1996).

As transaction cost economics has long hypothesized, and as many empirical studies have confirmed, reductions in asset specificity and leakage concerns lead to the substitution of market-based for hierarchical forms of governance (Williamson 1985, 1991; Shelanski and Klein 1995). The reason is that hierarchical governance offers mechanisms for preventing holdups, reducing the transaction costs involved in haggling, and facilitating adaptation that market-based governance does not. These mechanisms are ultimately rooted in forbearance by the courts and of managerial fiat as a last resort (Williamson 1985, 1991). Therefore, by reducing various types of asset specificity, increasing modularity of product architecture leads to greater use of market-based mechanisms for governing the transactions between component designers, at the expense of vertical integration.

Hypothesis 1 (H1). Increasing modularity of product architecture is associated with less vertical integration of component production.

This hypothesis extends the “mirroring” hypothesis in the modularity literature to firms’ vertical boundary choices. The mirroring hypothesis states that organizational design tends to reflect product design, so that increasing modularity is associated with organizational decentralization (Henderson and Clark 1990, Sanchez and Mahoney 1996).

Differentiation Effect

As noted above, in the early stages of the development of a complex, new-to-the-world product, firms develop product architectures that are idiosyncratic to the firm and that feature customized and highly interdependent components. At this early stage of industry development, firms compete on the cost and/or differentiating features of their overall product architectures, with many firms earning a price premium based on the uniqueness of their product’s overall design (Klepper 1996). Because components are idiosyncratic, component production tends to be vertically integrated.

With increasing modularity, the innovation process shifts from emphasis on innovation in overall design to emphasis on innovation in components (e.g., Christensen et al. 1998). New market niches appear, to which component-level innovation is targeted (Lawless and Anderson 1996). Firms aiming at higher tiers of the market emphasize product differentiation generated by components that incorporate new functionality or aesthetics. Firms aiming at lower tiers of the market emphasize component innovation that reduces overall product cost. Still other firms may pursue a combination of cost- and differentiation-based competition.

As modularity increases and firms identify their competitive positioning strategies, firms’ vertical integration profiles begin to diverge. In particular, firms emphasizing differentiation will show greater degrees of vertical integration than firms emphasizing cost reduction. This is because the properties and requirements of components that bring a product closer to the technological frontier in terms of functionality are less well understood than other components, and therefore require more unstructured technical dialogue (Christensen et al. 2002) and efforts at systems integration (Brusoni et al. 2001). This in turn implies greater product-specific engineering effort, as well as greater leakage concerns. Moreover, in higher segments of the market, a firm’s reputation with consumers for the quality of its products is highly
sensitive to the performance of the product’s differentiating components. Because quality shading by external suppliers is often difficult to detect, relying on external suppliers for differentiating components can put the buyer’s reputation at risk (e.g., Barzel 1982). Finally, vertical integration of a critical differentiating component may be necessary to prevent its incorporation in rivals’ products, thereby preserving the firm’s differentiation (e.g., Schiling 2000).

Firms aiming to compete primarily on cost, on the other hand, will seek to standardize components to take advantage of economies of scale reachable by suppliers serving multiple buyers. Such standardization by definition reduces asset specificity and leakage hazards, thereby reducing the sum of production and transaction costs (Riordan and Williamson 1985). In addition, reputation concerns are less salient because buyers’ expectations for product performance are less demanding, and adoption of standard parts by competitors is less consequential. Thus, firms’ positioning strategies influence their choice of vertical integration profile (Ghosh and John 1999, Nickerson et al. 2001).

**Hypothesis 2 (H2).** As modularity of product architecture emerges in an industry, differentiated products are produced with higher levels of component integration than are less-differentiated products.

The logic underlying H1 and H2 also carries implications for the impacts of vertical integration choices on firm performance, and perhaps even firm survival. In particular, the logic underlying H1 implies that firms will tend to underperform their rivals if they are slower to vertically disintegrate the production of those components that the dominant design has rendered generic. Vertically integrated firms can face organizational constraints on their ability to quickly disintegrate vertically to achieve efficiency after an environmental change (Argyres and Liebeskind 1999, Nickerson and Silverman 2003). We might expect, then, that firms remaining more vertically integrated after the dominant design becomes established face a greater risk of mortality. Moreover, H2 would imply that the firms at the greatest such risk are the cost-based competitors. Differentiated producers can efficiently remain somewhat more vertically integrated than cost producers for the transaction cost reasons discussed above. Therefore, we predict the following:

**Hypothesis 3 (H3).** As modularity of product architecture increases, integration of component production has a larger positive effect on firm mortality for less-differentiated competitors.

### The U.S. Auto Industry Context

Increasing modularity of automobile product architecture was an important trend in the 1920s U.S. auto industry. As the early auto industry developed, automobiles became increasingly homogeneous in their overall design, and components became more standardized. Abernathy (1978) described this trend in terms of the emergence of a dominant design. In the early part of the 20th century, cars varied in terms of their locomotion, with some using steam engines, others electric engines, and still others internal combustion engines. Power train configurations varied, with engines placed in front in some vehicles, and in back in others. Steering controls differed from car to car, with some using levers of various kinds and others using steering wheels. Some cars featured pedal transmissions, whereas others used shafts. There were major differences in gearing across car models as well. Ignition and systems were heterogeneous, with some electric and others magnetic. Engine cooling systems also varied. Some car bodies were closed, others open.

By the mid to late 1920s, however, this variety had essentially disappeared. Virtually all engines were internal combustion and were placed at the front. Steering wheels replaced other kinds of steering controls, and by 1918 all mass-produced cars featured a steering wheel on the left side. Shaft transmissions increasingly became the standard. Electric ignitions replaced mechanical and magnetic starters. Whereas many car bodies were open during the early period of the industry, by 1926 over 70% of all cars sold in the United States featured all-steel closed bodies (Abernathy 1978). Abernathy (1978) suggests that by 1923 the dominant design was clearly emerging, and that by the mid-1920s it had become established.

The establishment of the dominant design implied a significant increase in the modularity of automobiles. This is because the broad engineering constraints that the dominant design imposed on component designs helped make component interfaces more standard, at least at a high level. For example, requiring the engine be placed in front helped determine the interface between engine and drivetrain, and engine and transmission. The all-steel closed body placed constraints on the design of the frame and engine. Electric ignitions imposed constraints on the design of the electrical system. Importantly, it is not that the automobile became entirely modular during the 1920s. After all, the dominant design did not specify the details of component interfaces. However, the dominant design did increase the degree of modularity relative to the earlier period in which various companies’ car (and therefore component) designs were idiosyncratic to the company. Although customers could not “mix and match” components on their own to create a customized product the way that stereo or computer users can (Langlois and Robertson 1992), the establishment of a dominant design in autos did stimulate the development of something analogous: the aftermarket...
for auto parts. Once a set of broad component standards were set (steering wheel on left, engine in front, shaft transmission, electric ignition, etc.) investments by external parts suppliers in component design became less model specific, and therefore less buyer specific, than earlier. By reducing unstructured technical dialogue and associated human and other forms of asset specificity, broad standards encouraged such investments by external suppliers. With contractual hazards falling, vertical deintegration could proceed.

The assumption that the emergence of a dominant design implied greater component standardization and therefore modularity in design is consistent with the timing of key historical events. For example, beginning in the early 1920s, General Motors (GM) began publishing a Book of Standard Parts, “containing 196 pages descriptive of standard parts, 100 pages on materials, and about 50 pages of miscellaneous information” (Baird 1923, p. 336). According to Baird (1923, p. 336), GM was “very generous in giving out copies of the volume to all who requested it, so that there [were] some 2,000 copies in existence.” In addition, it was during this period that the Society of Automotive Engineers (SAE) began promulgating parts standards through publication of its SAE Handbook (Sinsabaugh 1940). The Handbook provided detailed engineering specifications regarding size and other parts characteristics. Publication of parts specifications by GM and the SAE was clearly aimed at encouraging the development of competitive parts markets to facilitate vertical deintegration (Kuhn 1986). Engineers expressed concern that, in the absence of such industrywide standardization of “carburetors and ignition apparatus,” for example, “major alternations in engine construction were required to change sources of supply in these accessories” (Bachman 1921, p. 356).

One can point to a number of historical examples from the Standard Catalogue of American Cars 1805–1942 that suggest the plausibility of H2 (Kimes and Clark 1989). Each of these sources represents the culmination of many years of research by historians, journalists, collectors, and others. Parts of the database have been analyzed by Carroll and colleagues (e.g., Carroll et al. 1996, Dobrev et al. 2002). Our final sample consists of 444 car model year observations over the period 1920–1931.

The information we use for the current analysis includes yearly data on which of nine major automobile components were made or bought for a given car model in a given year. The components are rear axle, clutch, carburetor, transmission, body, frame, engine, steering, and ignition. These data were available for 31% of the car model years in the larger database in the period 1920–1931. We relied especially on Lester-Steele (1960) for these data. We used these data to construct a measure of vertical integration (vertical integration) as follows. If a given component was produced internally, we coded a 1 for that component in the car model year in question; otherwise, we coded a zero. In those few cases in which some units of a component were made and some were bought for a given car model year, we coded a value of 0.5. We created the vertical integration measure for each car model year by summing these make–buy values across the nine components for that car model year, so that the measure ranges from 0 to 8. The unit of analysis in our empirical analysis is thus the car model year.

We used two different proxy variables to measure product differentiation. Our first proxy is car price, which represents the list price charged for each car model year in the sample. Our assumption is that higher-priced car models tend to feature more differentiation.
in individual car components such as quality of interior, safety features, transmission performance, ignition performance, etc., than lower-priced models. Our data include information on automobile prices for 68% of the car model years listed in Kimes and Clark (1989), the definitive reference thought to capture information on every auto company that has operated in the United States. Auto prices come from Lester-Steele (1960), and were gathered for the same period. Our variable aveprice is the average price charged by a firm in a given year, where the average is taken across the firm’s models in that year.

Our second measure of product differentiation is engine size as reflected in horsepower (horsepower). Cars with larger, more powerful engines tend to be more differentiated in other components as well, with the largest engine sizes being found in highly differentiated luxury and sports car models, and the smallest engines being found in the most basic economy cars (trucks were excluded). We included this alternate measure of product differentiation because car price might be a noisy measure of product differentiation if, for example, there are very different levels of competition within different car categories. Population ecologists working with a variant of our data set have used engine size as a proxy for market segmentation in the auto industry (e.g., Dobrev et al. 2002). We also included the square of horsepower to once again account for possible nonlinearities in the effect of production differentiation on vertical integration.

For our survival analysis, we use several variables from our database that have been shown by Carroll et al. (1996) to be associated with firm survival in the auto industry during 1885–1981, namely, log of firm revenue (size), firm age (age), pre-entry experience (if entered from a related de alio = 1, otherwise 0), annual industry production (industry production), and number of car models produced by the firm in the given year (no. of models).

**Empirical Specifications and Estimations**

We estimated regression models featuring our measure of degree of *vertical integration* associated with a given car model year as the dependent variable. Our first independent variable of interest in these regressions was *time*. The literature on dominant designs has emphasized that the dominant design in automobiles emerged and became established during the 1920s. It is difficult to know exactly when the dominant design became “dominant” in the auto industry, and when design modularity began to affect vertical integration decisions. Abernathy (1978) suggests that the dominant design was clearly emerging by 1923, and notes that by 1926 over 70% of U.S. autos featured an all-steel closed body, the final dimension of the dominant design.

We began by using the midpoint of our sample period (1920–1931) as our threshold by specifying a dummy variable, “post-1925,” that takes the value of 1 for the years 1925–1931 and zero otherwise. In addition to its empirical convenience as the midpoint of our period, we expected that industrywide vertical disintegration would not be observable until the dominant design had actually become well established in the industry. This is because firms would not vertically disintegrate in advance of actually adopting the dominant design. In a separate, preferred specification, we replaced the post-1925 dummy with dummies for each year from 1920 to 1931. This specification is more precise than using the post-1925 dummy because it allows us to assess the year-by-year changes in vertical integration levels for the average car model year relative to the first year in the period.

Hypothesis H1 led us to expect a negative and significant coefficient estimate for the post-1925 variable, for the dummies representing the years after the mid-1920s. Our theory does not specify a precise date by which we might expect to see effects of the increasing modularity on vertical integration, and there are reasons to expect some lags in the process by which firms vertically disintegrate. For example, Argyres and Liebeskind (1999) argue that “governance inseparability constraints” can delay a firm’s attempts to vertically disintegrate in a way consistent with economizing on transaction costs. In their study of vertical deintegration as a response to U.S. trucking deregulation in the 1980s, Nickerson and Silverman (2003) found evidence consistent with the operation of such constraints.

H2 predicts a positive and significant sign on the coefficient estimate for *car price* because, as we argued based on industry lifecycle and transaction cost theories, greater component-level differentiation requires more model-specific components, which implies greater vertical integration. In a separate specification, we added *car price*\(^2\) with the idea that the effects of price on vertical integration may not appear until a firm moves higher up the quality ladder, or at least may be more important beyond some threshold price level. This is because autos in the lower and middle price ranges may not be sufficiently differentiated relative to basic car models to justify significant differences in component vertical integration patterns. We might therefore expect a positive and significant sign on the coefficient estimate for *car price*\(^2\).

As noted above, our data consist of information on car model years over the period 1920–1931, which corresponds to the shakeout stage of the auto industry lifecycle (see Figure 1). Our data are thus in panel form, and the panel is unbalanced. The unbalanced nature of the panel is caused by firm entries and exits over the period, and also by missing data for certain car model years.
Ordinary least squares (OLS) regression is usually inappropriate for estimation of unbalanced panels because of unobserved heterogeneity. If independent variables that affect the dependent variable are omitted because they are unobserved, OLS coefficient estimates will be biased. In our case, the relevant unobserved explanatory variables are most likely to be firm effects, that is, firm characteristics that one might expect to affect the vertical integration associated with a given car model year. For example, one might expect that firms that have accumulated superior production capabilities relative to suppliers might vertically integrate to a greater extent to exploit those capabilities (e.g., Langlois and Robertson 1989, Kogut and Zander 1992). Firms producing multiple car models that share components might be able to capture economies of scale in production of those components, economies that are large enough to lead them to integrate backward (e.g., Riordan and Williamson 1985, Lyons 1995). To control for these kinds of impacts in our unbalanced panel, we follow the standard practice of using fixed effects regression (e.g., Greene 2003).

Fixed effects regression involves entering dummy variables for each of the potential sources of unobserved heterogeneity as independent variables. In our case, these dummy variables represent each of the 130 firms in our panel. Our firm fixed effects model therefore automatically controls for all those firm characteristics that one might expect would affect the degree of vertical integration of a given car model year (e.g., firm production capabilities, firm scale, and scope, etc.). In addition to addressing the problem of unobserved heterogeneity, fixed effects regression also relieves the problem of selection, that is, the problem that firms may appear and disappear from the panel because of particular characteristics they possess, and therefore the sample may not represent a random sample from the population of auto firms in any given year. Firm fixed effects control for all those firm characteristics that are associated with firm entry into or exit from the industry, and therefore with their presence or absence from the panel in a particular year. They also control for those firm characteristics that are associated with the absence of firms from the panel in a particular year, even if those firms were active in the industry in that year (e.g., Wooldridge 2002).

Table 1 contains information on and correlations between our dependent and independent variables. Table 2 shows the models and estimated coefficients. Our first model included firm fixed effects along with car price and post-1925 as the independent variables of interest. Our second model added car price^2 into this regression. Our third and fourth models replaced the post-1925 dummy in the first and second models with year dummies, respectively. Our fifth, sixth, and seventh models replaced car price and car price^2 with horsepower and horsepower^2, respectively. Cars with larger, more powerful engines tend to be more differentiated in other components as well, with the largest engine sizes being found in highly differentiated luxury and sports car models, and the smallest engines being found in the most basic economy cars (trucks were excluded). We included this alternate measure of product differentiation because car price might be a noisy measure of product differentiation if, for example, there are very different levels of competition within different car categories. Population ecologists working with a variant of our data set have used engine size as a proxy for market segmentation in the auto industry (e.g., Dobrev et al. 2002). We included the square of horsepower to once again account for possible nonlinearities in the effect of production differentiation on vertical integration.

We tested the third and fourth models for serial correlation of the error terms using “pantest2,” a program

Table 1 Descriptive Statistics and Intercorrelations

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<th>Variable</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
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<tbody>
<tr>
<td>1. Vertical integration</td>
<td>2.68</td>
<td>2.29</td>
<td>0</td>
<td>8</td>
<td>1</td>
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<td>2. Car price</td>
<td>2.327</td>
<td>1.483</td>
<td>290</td>
<td>10,900</td>
<td>0.1646</td>
<td>1</td>
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<td>3. Horsepower</td>
<td>27.95</td>
<td>7.16</td>
<td>9.8</td>
<td>48.6</td>
<td>0.1145</td>
<td>0.5410</td>
<td>1</td>
<td></td>
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<tr>
<td>4. Age</td>
<td>11.88</td>
<td>7.82</td>
<td>0</td>
<td>29.5</td>
<td>0.3923</td>
<td>0.0037</td>
<td>0.3858</td>
<td>1</td>
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<td>5. Size (log)</td>
<td>7.36</td>
<td>2.99</td>
<td>0</td>
<td>1</td>
<td>0.4371</td>
<td>−0.3654</td>
<td>−0.0053</td>
<td>0.5130</td>
<td>1</td>
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<td>6. De alio</td>
<td>0.538</td>
<td>0.499</td>
<td>0</td>
<td>1</td>
<td>−0.0198</td>
<td>0.1341</td>
<td>0.1888</td>
<td>0.2301</td>
<td>−0.1267</td>
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<td>7. No. of models</td>
<td>1.81</td>
<td>1.54</td>
<td>0</td>
<td>11</td>
<td>0.1320</td>
<td>−0.1928</td>
<td>0.0460</td>
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<td>0.5047</td>
<td>−0.1208</td>
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<td>8. Industry production</td>
<td>2,297,515</td>
<td>972,120</td>
<td>943,436</td>
<td>0.0605</td>
<td>−0.1520</td>
<td>0.2288</td>
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<td>0.3704</td>
<td>0.0380</td>
<td>0.4033</td>
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### Table 2  Fixed Effects Estimation of Vertical Integration Models

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<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Model 4&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Model 8&lt;sup&gt;a&lt;/sup&gt;</th>
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<tbody>
<tr>
<td><strong>Car price</strong></td>
<td>0.0001</td>
<td>-0.0002</td>
<td>0.0002**</td>
<td>0.0004</td>
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<td></td>
<td>(0.00008)</td>
<td>(0.002)</td>
<td>(0.00009)</td>
<td>(0.0002)</td>
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<td><strong>Car price</strong>&lt;sup&gt;2&lt;/sup&gt;</td>
<td>3.5e-8</td>
<td>1.5e-8</td>
<td>0.004</td>
<td>-0.097</td>
<td>0.029**</td>
<td>-0.121</td>
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<td></td>
<td>(2.6e-8)</td>
<td>(2.6e-8)</td>
<td>(0.015)</td>
<td>(0.080)</td>
<td>(0.016)</td>
<td>(0.080)</td>
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<td><strong>Horsepower</strong></td>
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<td><strong>Horsepower</strong>&lt;sup&gt;2&lt;/sup&gt;</td>
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<tr>
<td><strong>Post-1925</strong></td>
<td>-0.839***</td>
<td>-0.801***</td>
<td>-0.831***</td>
<td>-0.811***</td>
<td></td>
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<td></td>
<td>(0.114)</td>
<td>(0.111)</td>
<td>(0.120)</td>
<td>(0.121)</td>
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<td><strong>1921</strong></td>
<td>0.051</td>
<td>0.060</td>
<td>0.078</td>
<td>0.108</td>
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<tr>
<td></td>
<td>(0.157)</td>
<td>(0.158)</td>
<td>(0.156)</td>
<td>(0.156)</td>
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<tr>
<td><strong>1922</strong></td>
<td>0.227</td>
<td>0.222</td>
<td>0.171</td>
<td>0.210</td>
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<td></td>
<td>(0.156)</td>
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<td>(0.156)</td>
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<td><strong>1923</strong></td>
<td>0.267</td>
<td>0.250</td>
<td>0.136</td>
<td>0.188</td>
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<td>(0.171)</td>
<td>(0.173)</td>
<td>(0.166)</td>
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<td><strong>1924</strong></td>
<td>0.426</td>
<td>0.409</td>
<td>0.328</td>
<td>0.356</td>
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<td></td>
<td>(0.294)</td>
<td>(0.296)</td>
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<td><strong>1925</strong></td>
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<td>-0.205</td>
<td>-0.367***</td>
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<td></td>
<td>(0.225)</td>
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<td><strong>1926</strong></td>
<td>-0.344</td>
<td>-0.354</td>
<td>-0.502**</td>
<td>-0.393*</td>
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<td>(0.242)</td>
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<td>(0.238)</td>
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<td><strong>1927</strong></td>
<td>-0.485***</td>
<td>-0.488**</td>
<td>-0.646***</td>
<td>-0.584***</td>
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<td>(0.220)</td>
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<td><strong>1928</strong></td>
<td>-0.618***</td>
<td>-0.622***</td>
<td>-0.817***</td>
<td>-0.759***</td>
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<td>(0.236)</td>
<td>(0.237)</td>
<td>(0.248)</td>
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<td><strong>1929</strong></td>
<td>-0.768***</td>
<td>-0.767***</td>
<td>-0.989***</td>
<td>-0.918***</td>
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<td></td>
<td>(0.293)</td>
<td>(0.293)</td>
<td>(0.271)</td>
<td>(0.272)</td>
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<tr>
<td><strong>1930</strong></td>
<td>-1.38***</td>
<td>-1.38***</td>
<td>-1.62***</td>
<td>-1.58***</td>
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<td></td>
<td>(0.263)</td>
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<td><strong>1931</strong></td>
<td>-1.08***</td>
<td>-1.08***</td>
<td>-1.34***</td>
<td>-1.29***</td>
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<td>(0.258)</td>
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<td>(0.280)</td>
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</table>

| **Constant**   | 2.62***| 3.21***| 2.35***| 2.55***| 2.81***| 4.18***| 4.04***| 4.03***|
|                | (0.204)| (0.368)| (0.264)| (0.433)| (0.402)| (1.14) | (0.430)| (1.13) |
| **No. of obs.**| 444   | 444    | 444    | 444    | 444    | 444    | 444    | 444    |
| **p**          | 0.8720| 0.8693 | 0.8764 | 0.8742 | 0.8753 | 0.8687 | 0.8799 | 0.8712 |
| **Within-group R²** | 0.1559| 0.1580 | 0.2221 | 0.2230 | 0.1520 | 0.1564 | 0.2215 | 0.2308 |
| **Prob. > F**  | 0.0000| 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

<sup>a</sup>Omitted year dummy is 1920.  
<sup>*p < 0.1; **p < 0.05; ***p < 0.01; one-tailed test.</sup>
ysis at the level of the firm, rather than at the level of the car model as we did in our fixed effects regressions. Because our vertical integration data were calculated for each car model, to obtain a vertical integration value for each multimodel firm we computed the average vertical integration value across each firm’s models in each year. Our main independent variable for use in testing H3 is the interaction between the firm-level vertical integration measure and the time period dummy representing the post-1925 years in our data (vertical integration × post-1925). Recall that our hypothesis is that vertical integration will have a greater effect on firm mortality as the dominant design emerges over time, so that we expect a positive sign on the coefficient estimate for this interaction term. Recall that vertical disintegration in our sample began in 1925, and accelerated in 1927.5

Our specification of controls is similar to that in Carroll et al. (1996). Firm size is thought to proxy for firm production capabilities, and therefore production efficiency (Klepper 2004), whereas firm age has been found to covary negatively with hazard rates in many industries (e.g., Dunne et al. 1988). We therefore expect negative signs on the coefficient estimates for size and age. Including firm age helps control for left censoring (Tuma and Hannan 1984). Pre-entry experience (de alio) in a related industry has been found to improve survival chances in the full auto data set covering 1885–1981 (Carroll et al. 1996), as well as in other auto data (Klepper 2004). The no. of models variable controls for possible economies of scope across models that might improve efficiency and therefore survival chances. We also included the aveprice variable to control for possible effects from changes in the composition of demand on firm survival. Annual production helps control for macroeconomic impacts on firm survival, though the Gompertz specification includes a time variable that also helps control for such effects.6

Results

In Model 1, the coefficient estimate on the post-1925 dummy variable is negative and statistically significant, indicating that level of vertical integration for the average car model decreased once the dominant design became established in the auto industry. This finding is thus consistent with H1. The coefficient estimate on car price is positive but not significant in this regression, providing no support for H2. The results from the Model 2 estimation again show a negative and consistent significant coefficient on the post-1925 variable, consistent with H1. The coefficients on car price and car price² are not significant, again suggesting no support for H2.

Models 3 and 4 introduce the year dummies. The models show a positive and significant coefficient estimate for the car price variable, implying support for H2. The coefficient estimates for the year dummies in both of these models show positive and nonsignificant coefficients for the earlier years in our sample period, but negative and significant coefficients for the later years. The omitted year in these regressions is 1920. Therefore, these coefficient estimates show a significant decline in the degree of vertical integration for the average car model beginning in 1927. This finding is consistent with H1. Note that, based on the coefficient sizes, the decline proceeds on an annual basis through 1930. The 1931 level of vertical integration is significantly lower than the 1920 level, but the rate of decline by this point has tapered off.

Models 5–8 feature the same specification as Models 1–4, except that horsepower and horsepower² replace car price and car price², respectively. horsepower and horsepower² carry statistically nonsignificant coefficients in Models 5 and 6, providing no support for H2, but horsepower carries a positive and significant coefficient in model, providing support for H2. Model 8 suggests a nonlinear effect of horsepower, but it is only significant at the 10% level. Because Models 7 and 8 containing the year dummies are more precise in their measurement of time, we interpret this pattern of results as, on balance, offering support for H2. Again, the post-1925 dummies are negative and significant, as predicted in Models 5 and 6, supporting H1. Model 7 shows a negative and significant effect of the dominant design on vertical integration beginning in 1925, two years earlier than in Models 5 and 6. Model 8’s results in this regard are more similar to those of Models 5 and 6.

Note from Table 2 that the percentage variance explained by the firm fixed effects in our regressions is relatively large at 87%. This implies that the larger impacts on vertical integration at the car model level in these data were firm characteristics such as (likely) production capabilities, product line breadth, etc. The price and dominant design effects were smaller. It is important to keep in mind, however, that the theory on which we base H2 does not predict a large effect on a vertical integration scale of the kind we use in this paper. Instead, it predicts that firms aiming for differentiation will select vertically integrate just those key components that provide the effective differentiation they are seeking. Such firms will presumably vertically disintegrate the production of more standardized components, as low-cost competitors do. Therefore, even a difference in one key component integrated as a result of pursuing a differentiation strategy could well have strategic impact, even if the statistical impact on a scale measure is significant but not large in size.

Table 3 shows the coefficient estimates and other information from the survival analysis. Model 11 is aimed at testing H3. This model was estimated on only those firms who were cost-based competitors, defined as those firms whose average model price was less than...
the sample mean of $2,327. Note that in Model 11, the coefficient estimate on the independent variable of interest, vertical integration \times post-1925, is not positive, as expected, and is not statistically significant. This implies an absence of support for H3.\(^7\) Models 9 and 10 were estimated on all competitors for comparison’s sake, and again there were no positive and significant effects of vertical integration on mortality. Remaining relatively vertically integrated later in the period did not hurt the average cost-based competitors’ survival chances as our theory predicted, nor did it hurt the survival chances of the average firm in the sample. The size, age, and de alio variables in Model 3 behave as expected.\(^8\) The positive and significant coefficient estimate on industry production suggests the presence of oversupply in the period. The negative sign on the aveprice variable suggests a shift in demand during the period toward higher-priced models.

### Discussion and Conclusion

Our results suggest evidence for two kinds of determinants of vertical integration over the industry lifecycle. First, we found evidence for a modularity effect: on average, auto firms reduced their levels of vertical integration as automobile interfaces and components arguably became more standardized during the 1920s. Second, we found evidence for a differentiation effect; firms that charged higher prices or sold cars with more powerful engines, arguably indicative of differentiation, remained more vertically integrated than lower-price/smaller-engine firms.

These findings can be compared to those of two other studies in our research stream on vertical integration in the early U.S. auto industry. Bigelow and Argyres (2007) found that in the population of auto firms as a whole, vertical integration of engines was associated with their degree of asset specificity during 1917–1933, even though the population consisted of small, possibly capital-constrained firms. We also found that firms with longer industry experience tended to integrate engine production during the shakeout period in which cost competition heated up, presumably to exploit their superior capability for low-cost production. Argyres and Bigelow (2007) found that even if most firms in the population were following transaction cost prescriptions, many were misaligned. Those that were misaligned only experienced significantly worse survival chances during the shakeout period, however, not during the earlier period. In addition, larger misaligned firms showed better survival chances than smaller misaligned firms.

Taken together, although the three papers offer broad support for transaction cost prescriptions, beyond that they suggest that the stage of an industry’s technological evolution, firms’ competitive positioning choices during that evolution, and differential firm capabilities can affect transaction costs. Thus, the findings point to the need to endogenize transaction costs in a strategic theory of the firm, and provide some evidence for factors that can determine their level. As Argyres and Zenger (2009) argue, however, firm capabilities may themselves be determined by past transaction costs, suggesting the need to endogenize their development as well.

There may be a number of reasons why we did not find a positive and significant impact on firm mortality from vertical integration as modularity increased in the auto industry. A prominent possibility is that large firms, and older firms, were so advantaged in terms of survival that excess vertical integration was not enough to hurt their survival chances (Argyres and Bigelow 2007). Large firm advantages may have stemmed from superior production capabilities, organizational inertia, distribution channels, and/or market power. Such advantages may have overcome the losses in incentive intensity and other bureaucratic costs from excessive internalization of component production. Had we been able to measure the effects of vertical integration on profitability (rather than survival alone) during our period of dominant design establishment, we might have found results more in line with the predictions of our combination of industry lifecycle and transaction cost theories.

There is an alternative explanation for the modularity effect that is worth considering. In particular, it is possible that by the mid-1920s component suppliers had,
contra Klepper (2004), actually developed superior production capabilities to those possessed by auto firms, and therefore could produce at lower cost and/or higher quality. Such a tendency, if broad enough, could account for the vertical disintegration we observe. As Langlois and Robertson (1989) explain, however, suppliers had been prominent in the industry from its very beginning in the late 19th century, with many automakers organized as more or less pure assemblers. It would be quite coincidental if suppliers had happened to surpass auto firms in their component production capabilities just a few years after the dominant design became established for reasons totally independent of the establishment of that design.

A more subtle theoretical implication of our findings regards the relationship between changes in the firm’s technological environment and changes in the characteristics of the firm’s transactions. North (1990) argued that changes in the legal and regulatory structures within which firms operate has an important impact on the firm’s choice of its vertical boundaries. For example, new laws providing for stronger protection of intellectual property, by stimulating the market for inventions, reduce the incentive for vertical integration of research and development activities. Along these lines, it has been argued that policies aimed at reducing judicial corruption, by making contract enforcement by the courts less biased, can similarly cause firms to substitute markets for internalization of transactions (Mui 1999). Williamson (1991) suggested that such changes in the institutional environment tend to affect the governance of transactions by acting as “shift parameters”—i.e., changing the relative governance costs of one institutional arrangement (i.e., vertical integration or market governance) versus another.

Our findings here suggest that not only legal and regulatory changes may act as shift parameters in Williamson’s (1991) framework, but that technological evolution can act in such ways as well. In particular, there may be natural patterns of technological evolution—especially as new technologies emerge from firms’ innovation choices—that systematically impact the characteristics of firms’ transactions, and in turn cause temporal patterns in vertical integration behavior. Increasing modularity may be one example of this kind of technological evolution, but there may be others as well. For example, scholars have suggested that disruptive technologies, by introducing entirely new technological systems, can reduce modularity within an industry (e.g., Christensen 2002). This implies that successful firms in the new regime will be vertically integrated. To our knowledge, this hypothesis has not yet been directly tested on a large sample of firms.

Recognizing these kinds of possibilities and understanding the underlying impacts of technological and demand evolution on transaction features can help make transaction cost economics more useful as a strategic management theory. This is because by understanding the determinants of transaction characteristics (rather than simply taking transaction characteristics as given) and how those characteristics can change as an industry evolves, firms can better forecast future changes in governance that they might need to make. Note that such forecasting is not very important if we assume that shifting a governance structure to increase efficiency is costless and can be achieved instantaneously. This has been the traditional assumption in transaction cost economics. If, on the other hand, adjustment costs are significant and governance inseparability is strong, as Argyres and Liebeskind (1999) and Nickerson and Silverman (2003) have discussed, and if firms can make mistakes in matching governance forms to transaction characteristics (Masten 1993), then such adjustments may require significant time and cost, in which case the ability to forecast the need for governance changes could be extremely valuable. Future research should continue to explore the ways in which technological evolution might impact transaction characteristics, and thereby suggest the need for changes in governance.

Acknowledgments

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Endnotes

1 An exception is Hoetker (2006), whose large-sample study of the notebook computer industry found that product modularity was not associated with greater use of external suppliers, but was associated with more use of loosely coupled networks of internal suppliers.

2 Some firms, however, may choose to exploit their lower-cost production capability by integrating production of those components that account for a high proportion of total product cost. Bigelow and Argyres (2007) find evidence for this effect in a related data set.

3 The 1990s saw a new surge toward modularization in the world auto industry, with increasingly detailed component standards being adopted (Takeishi and Fujimoto 2001).

4 One concern with this kind of estimation approach is endogeneity. If firms choose their level of vertical integration with an eye toward their survival, then the vertical integration variable will be endogenous in the hazard rate model, and the resulting coefficient estimates will be biased. To examine this issue, we used a probit model to exploit the Smith-Blundell exogeneity test, using number of available engine suppliers as our instrumental variable. We could not reject the hypothesis of exogeneity of the vertical integration variable ($\chi^2 > 0.0006; p = 0.9806$).
In unreported regressions, we replaced our vertical integration \times post-1925 variable with a vertical integration \times post-1927 variable. Our results did not change in any significant way.

In unreported regressions, we included measures of density and density squared in the survival models using our data on the entire population of auto firms. Our results for the vertical integration \times post-1925 interaction term did not change significantly when these measures were included.

In unreported regressions, we replaced the vertical integration \times 1925 variable with vertical integration \times 1922. We did this because the positive and significant coefficient on the vertical integration coefficient in Models 2 and 3 might suggest that 1925 was too late to pick up the vertical integration effect on survival. (Figure 1 shows the shakeout beginning in 1921–1922). In the unreported regressions, the coefficient on the interaction term did not become significant, and the coefficient on vertical integration lost significance. We also eliminated the size variable because it is correlated with vertical integration at 0.44. Still, we found no significant effect of vertical integration on the hazard rate.

As Table 1 shows, size and age are correlated, but our results regarding the vertical integration \times 1925 variable do not change if we leave out one or the other covariate.

References


