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Firm Survival and Industry Evolution in Vertically Related Populations

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This paper examines how the density and governance of vertically related populations affect the life chances of organizations. We integrate the literatures on organizational ecology and vertical integration to develop a theory of how (1) specialized upstream industries affect downstream survival rates, (2) the prevalence of different governance forms among upstream and downstream organizations moderates this relationship, and (3) different forms of governance exert differential competitive pressures on focal organizations. We find evidence supporting our hypotheses in an empirical examination of the downstream laser printer industry and upstream laser engine industry.

Key words: organizational ecology; strategy; vertical integration; computer-electronic industries
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Introduction

A strong empirical regularity found across industries is the nonmonotonicity of firm density over time. In economics, sociology, strategy, and organizational behavior, researchers have documented in hundreds of studies that the number of firms in an industry increases from the birth of the industry to a peak and then declines to some roughly steady-state number. Sociologists, led by organizational ecologists, have attributed this trend to legitimation of organizational fields and subsequent competition (Hannan and Freeman 1989, Hannan et al. 2007). Economists have attributed this inverted-U-shaped pattern to differences in cost structures of firms, driven mainly by random differences in production efficiency or the discovery/adoption of innovations (Jovanovic 1982, Jovanovic and MacDonald 1994, Klepper 1996).

Although the theoretical mechanisms for explaining this empirical regularity differ substantially across sociological and economic approaches, both approaches have typically evaluated organizational dynamics within the context of a single, largely homogeneous population or industry. This focus on a single population allows for precise theoretical predictions and lean empirical testing of the theoretical models. Nevertheless, this focus comes at a cost: it limits our insight into the mechanisms by which one population may affect another (Astley 1985). Some scholars have addressed this concern by exploring interrelations across populations that experience "niche overlap"—that is, populations that compete only partially for resources (Baum and Singh 1994, Dobrev and Kim 2006). Others have investigated how populations pursuing competing production technologies in the same industry will affect each other's life chances (Barnett and Carroll 1987, Barnett 1990). Still others have launched a study of "community ecology" in which interdependent populations within a community of populations influence each others' evolution (Astley 1985, Lomi 1995, Ruef 2000). Yet thus far, the empirical efforts to flesh out the relationships between populations have focused almost entirely on horizontally related populations.

A nascent literature has begun to explore interactions between vertically related industries. Bonaccorsi and Giuri (2001) consider coevolution across vertically related industries, arguing that evolutionary dynamics of one industry are affected by dynamics of the other. Negro and Sorenson (2006) consider the effect of vertical integration on the competitive intensity generated by rivals. In this study we extend this literature by explicitly considering a broad set of connections between vertically related industries. We believe that this is a particularly fruitful area of study because it enables us to draw on the voluminous literature on vertical integration and vertical governance (e.g., Williamson 1985, Perry 1989). Specifically, we explore whether a downstream firm's exit rate is affected by the prevalence of upstream suppliers of a key component. In particular, we explore whether the densities of different governance forms in the upstream supplier industry—vertically integrated (VI) suppliers versus suppliers that sell on the open market—have differential effects on the life chances of downstream firms. We also explore whether different governance forms among downstream rivals affect a downstream firm's exit rate differently.

After developing predictions pertaining to the above relationships, we test them empirically in a study of the desktop laser printer industry from 1984 to 1996. Hewlett-Packard pioneered this industry in 1984, introducing a printer that relied on a laser printer engine produced by Canon. Both industries experienced rapid growth in number of firms until 1991; the printer industry then experienced a gradual decline in population through the end of our sample, whereas the engine industry has retained a stable number of firms since 1992. These industries are characterized by a variety of governance forms: fully integrated firms, partially integrated firms (tapered integration), and nonintegrated firms. We begin the empirical exercise by replicating the results commonly found in organizational ecology studies. Then, we bring our data to examine the theoretical predictions in the model presented. In particular, we extend the literature on organizational ecology to include the full populations of both upstream and downstream organizations from the birth of both industries in two related industries.

We find that the density of the upstream engine population affects survival rates for downstream printer firms in a nuanced way. Overall, the exit rate of printer firms declines with increases in the density of engine firms. But this effect is driven most heavily by density of nonintegrated engine firms; increases in density of vertically integrated firms (who "sell" some or all of their engine output in-house to a downstream printer division) have significantly less effect on printer firm exit rates. Focusing on downstream rivalry, we find that fully integrated laser printer firms exert substantially more competition on their downstream rivals than do nonintegrated firms, even after controlling for the density of arms-length upstream suppliers. Consistent with Negro and Sorenson (2006), we also find evidence of "asymmetries" in the above relationships. Integrated rivals generate more intense competitive pressure on nonintegrated firms than on other integrated firms, but experience less reciprocal pressure from nonintegrated rivals than from integrated rivals. And whereas the relationship between engine firm density and printer firm survival holds for nonintegrated printer firms, printer firms with in-house engine production are unaffected by engine firm density. In sum, we find that vertical populations are interdependent, and that these interdependencies vary with the nature and degree of vertical integration across them.

Theory: Vertical Relationships and Firm Survival Rates

How does the density of firms in a focal industry affect the life chances of a constituent firm? Sociologists have developed an ecological theory to explain the carrying capacity of an industry or population (Hannan and Freeman 1989; Hannan and Carroll 1992; Carroll and Hannan 1995, 2000). When new industries are born, organizational forms are not well understood, and consequently the purveyors of such forms face difficulties in overcoming the reluctance of key resource providers to transact with them. For example, the first automobile producers had to convince prospective suppliers, employees, buyers, financiers, and others that the automobile would be a viable product—that it actually served a useful purpose, it satisfied customer needs in a way that adds value, and it could generate a profit for manufacturers. In such an environmental context, firms find it difficult and costly to operate. When there are only a handful of such organizations, each organization is likely to be dismissed as lacking legitimacy. But as such organizations become more prevalent, the organizational form becomes more widely accepted as legitimate or taken for granted, and each organization in the population faces fewer difficulties in accessing resources. The downward-sloping portion of the U-shaped relationship between density and exit rates is attributable to these legitimating effects of density. However, further increases in density yield diminishing returns in terms of legitimacy, and eventually the competitive effects of density swamp legitimation effects. Competitive effects arise as an increasing number of firms compete for the finite pool of resources available.

The theory generates an organization failure rate equation that can be described through a hazard rate equation as follows:

$$\lambda(t) \propto \exp(\gamma_1 n_{it} + \gamma_2 n_{it}^2), \tag{1}$$

where $\lambda(t)$ is the hazard rate of a focal firm failing at time t, n_{it} is the density of organizations in population i at time t, and γ_1 and γ_2 are parameter coefficients (Carroll and Hannan 1989). Equation (1) indicates that the hazard rate is proportional to the exponential function raised to organizational density and density squared. In the traditional formulation of the organizational ecology model, $\gamma_1 < 0$ and $\gamma_2 > 0$. This results in a U-shaped curve of exit rates in time or, in the full formulation of the model, an inverted U-shaped density curve.

The basic model has been extended in many ways since its original formulation. Hannan et al. (1995) make a compelling argument that a multilevel model is, in many cases, a more appropriate formulation of density dependence and organizational evolution.

Using data on the European automobile industry, they argue that events across all of Europe affected legitimation of the automobile firms in a single country. However, because of political and trade barriers, competition was localized in each focal country. The theory generated from such a multilevel model argues

$$\lambda_t(t) \propto \exp(\gamma_1 N_t + \gamma_2 n_{it}^2), \tag{2}$$

where N_t is the density of organizations in all of the related horizontal populations that convey legitimation to the organizational form (in the Hannan et al. 1995 example, the number of automobile firms in all of Europe), and n_{it} is the density of organizations in population i in the focal country (such as France). This model also predicts $\gamma_1 < 0$ and $\gamma_2 > 0$.

The insight of this multilevel analysis has led to many variants on the theme of interdependence within and among populations, most focused on the niches within an organizational field. For example, the degree of overlap among niches in terms of needed resources has been shown to affect the degree of competition and mutualism exhibited across these niches (e.g., Baum and Singh 1994). More generally, the relationship between market segments or niches in terms of identity formation as well as resource demands affects the evolution of organizational populations (Dobrev and Kim 2006, Dobrev et al. 2006).[1]

Alternatively, the study of community ecology—wherein scholars study a "group of populations bound by ecological ties ... that consequently coevolve with each other" (Rao 2002, p. 541)—is another major stream of thinking on this issue. Studies of the interaction between rural banks and urban banks in Italy (Lomi 1995), between telephone companies relying on common-battery technology and those relying on magneto technology (Barnett 1990), or among different organizational forms within the healthcare industry (Ruef 2000) demonstrate mutualistic and competitive effects across niches. In this literature, as in the work of Hannan et al. (1995) and Bigelow et al. (1997), multilevel modeling of the founding and failure process allows researchers to understand how interdependent subpopulations affect each other. Generally, though, these studies have focused on interac tions among overlapping populations, or industry segments, competing for roughly similar resources and customers. In this sense, these papers examine horizontal interdependencies.

Yet, as Negro and Sorenson (2005, 2006) elaborated, some of these same insights concerning interdependence can be extended to vertically related populations. In particular, the survival of firms in an industry is not only intimately related to activities in the focal industry, but also to activities in other parts of the value chain such as suppliers of key components. Multiple suppliers to an industry offer many avenues for downstream firms to obtain components. Resources such as physical components and the knowledge embedded within them will be more widely available the more suppliers there are. Moreover, the cost of these resources will be lower than they would be under more concentrated upstream regimes because of upstream competition (de Fontenay and Gans 2005, Salinger 1988).

The density of upstream suppliers can also affect downstream firms in ways beyond these direct economic effects. Increased supplier density not only ensures that downstream manufacturers can obtain the supplies they need, perhaps from multiple sources, but can also increase the variety of upstream resources available, thus supporting greater variation (and consequently enhanced survival prospects) in the organizational population downstream. Moreover, increased variety can also promote greater innovation in the downstream industry as there is greater exposure to alternative approaches and ideas.

Which upstream supplier populations matter? Although commodity inputs may affect downstream survival through the simple mechanics of supply and demand—for example, a sharp increase in the price of jet fuel can affect the survival of airlines—the density of commodity suppliers typically will not affect downstream exit.[2] More generally, inputs that are so generic as to be useful in a wide range of industries are unlikely to offer the above-described advantages. In contrast, components that promote substantial variety in the downstream population and allow organizations in the downstream population to achieve either a higher differentiation or lower cost position relative to the competition are most likely to affect the differential survival rates of downstream firms. We call the providers of such components "core" upstream industries and populations. As noted in our discussion below of vertical integration, core industries are characterized by potential specialization or cospecialization of inputs or assets (Williamson 1985), where the downstream industry is either unilaterally dependent upon the upstream industry for specialized or specific inputs, or the downstream and upstream industries have made cospecialized specific investments. For example, bumpers, fasteners, and sun visors are unlikely to be core supplier industries to the automobile industry because they offer little in the way

[1] Recent research has shed further light on where and how such identities are formed (e.g., McKendrick et al. 2003).

[2] By definition, commodity inputs are priced at the marginal cost of the marginal competitor such that increased density of suppliers will not reduce margins, and commodity inputs do not offer variety.

of substantial differentiation or lower cost to a focal automobile manufacturer relative to other automobile manufacturers. In contrast, transmissions, engines, and onboard electronics all involve specific investments both upstream and downstream and are core component suppliers to the automobile industry that can have large impacts on the differentiation and cost position of the firm and impact firm survival substantially (Argyres and Bigelow 2007, Novak and Stern 2008). Overall, upstream providers of core components expand the definition of the resource space that organizations access. Thus, an increase in the density of upstream core firms enhances the carrying capacity of the downstream industry, but the reverse is not true through this theoretical mechanism. Formally:

$$\lambda(t) \propto \exp\left(\sum_{0}^{k} \gamma_{1k} n_{Ukt} + \gamma_2 n_{Dt} + \gamma_3 n_{Dt}^2\right), \qquad (3)$$

where n_{Ukt} is the population density of core upstream industry k at time t, and n_{Dt} is the downstream population density at time t. In the absence of vertical integration, then, we would expect organizational mortality rates of downstream firms to decline with increases in density of core upstream suppliers ($\gamma_{1k} < 0$ in Equation (3)).

Although this is a useful theoretical baseline, industries characterized by potential specialization of assets or inputs typically exhibit positive levels of vertical integration. We now turn our attention to the effect of integration in both the upstream and downstream industries on downstream survival rates.

Effect of Vertical Integration

The literature on vertical integration is vast and has been a favorite of economists and sociologists for decades. At the risk of oversimplification, theories of vertical integration can be grouped under three broad motivations: efficiency, market power, and reduction of uncertainty.[3] The first category proposes that firms integrate to operate more efficiently. Vertical integration can enhance efficiency if it reduces "double marginalization." Consider the case of an upstream firm that sells components to a downstream buyer at a price that gives it a supracompetitive profit margin—in other words, price above marginal cost. The downstream firm that buys these components in turn sells its end products to consumers at a price higher than marginal cost. In this case, the price of the final product will be inefficiently higher and quantity produced inefficiently lower than what a profit-maximizing integrated firm would produce. Vertical integration solves the double marginalization problem by internalizing incentives of the two firms, reducing prices of the end product, enhancing profits for the integrated firm, and increasing social welfare (Besanko et al. 2007).[4]

Vertical integration can also enhance efficiency by reducing the threat of hold-up and thus facilitating investment in specialized assets (Williamson 1985, Grossman and Hart 1986). When actors invest in transaction-specific investments, they often place themselves at risk of opportunistic behavior by their exchange partners. Although actors attempt to reduce this risk via detailed contractual arrangements, not all contingencies can be specified in a contract; hence, actors may refuse to make ex ante investments due to the fear of ex post opportunistic behavior at contract renegotiation. To solve this problem, under certain conditions firms will integrate. Such integration leads to more efficient investment and production.

The market power view of vertical integration argues that firms integrate to enhance their position relative to the competition. In the extreme, a downstream firm that integrates into upstream production of components will have an incentive to weaken its nonintegrated downstream rivals by refusing to sell components to them at all—in economic terms, it "vertically forecloses" its rivals (Ordover et al. 1990). In a somewhat more benign version of this theory, the vertically integrated producer will not foreclose the downstream competitor, but will charge its rivals a higher price for components in an attempt to raise rivals' costs (Salop and Scheffman 1983). This branch of study has spawned a large game-theoretic literature that demonstrates when vertical integration may be optimal to increase market power in oligopolistic markets (e.g., Salinger 1988, Rey and Tirole 2007).

The third approach to vertical integration focuses on organizations' dependence on resources and their desire to reduce uncertainty in the acquisition of these resources (Pfeffer and Salancik 1978). According to resource dependence theory, resources are dispersed throughout the economy, endowing some firms with better positions to access these resources than others. Those firms afflicted by poor access to resources will become dependent upon those that have privileged access and thus become exploited by the resource-rich firms. To solve this problem, firms may vertically integrate. More recent work on this question has focused not just on dyad-specific dependence on physical resources, but upon the entire social network,

[3] A fourth approach is institutional isomorphism, which predicts that firms will choose to integrate if other firms are integrated. However, it does not specify how the first firm becomes integrated; hence we omit it from this discussion.

[4] Double marginalization issues may be particularly acute in the face of economies of scale (Hortacsu and Syverson 2007) and severe asymmetric information about production processes.

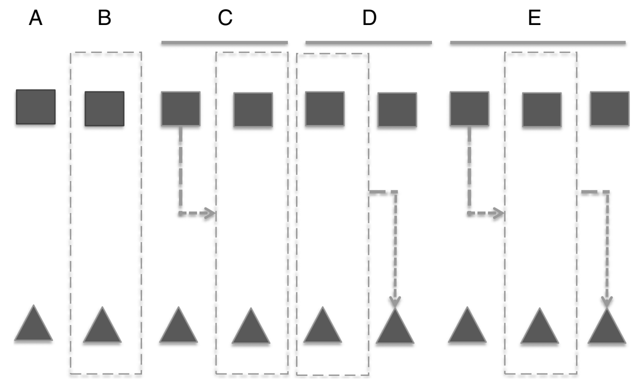
a firm's position within the network, and a broader set of resources such as information (e.g., Burt 1992).

Although these three lenses propose alternative motivations for vertical integration, they share four commonalities. First, each of the three lenses invokes some notion of firm or industry specialization to justify the integration decision.[5] Second, each implies that the benefits of resources generated by a vertically integrated upstream division accrue primarily or exclusively to its downstream division rather than to the downstream population at large. Third, each implies that if vertically integrated firms have specialized assets or positional advantages, then they are likely to generate more intense competition for rivals than nonintegrated firms, because of more efficient production or privileged access to key resources. Fourth, each relies on an equilibrium analysis of organizations and on strategic interactions of small numbers of firms, each of which has some market power; as such, they are somewhat divorced from ecological theory, which posits a more dynamic approach to industry evolution that encompasses populations consisting of dozens or hundreds of firms of which few actually exert market power (for an exception, see Nickerson and Silverman 2003).

We incorporate these ideas of specialization from the vertical integration literature into our theory to explain how integration of core industry suppliers will affect the failure rates for firms in the downstream industry. Going forward, we consider only core suppliers. For clarity, Figure 1 illustrates the five types of upstream vertical integration. Case A denotes an independent (or nonintegrated) set of upstream and downstream firms, characterized by arms-length vertical relationships. Case B denotes the classic fully integrated structure, where an upstream division transfers all of its output to its downstream division. Case C denotes a form of partial (or "tapered") integration in which the upstream division transfers all of its production to its downstream division, but the downstream division also purchases additional units from outside suppliers. In case D, the upstream division sells components to both its internal downstream division and on the open market. Finally, case E is a combination of cases C and D where the firm sources engines both internally and externally, and supplies engines both internally as well as to competitors. Thus, there are six types of firms (if we count the nonintegrated case as two separate firms—an upstream and a downstream firm).

[5] This is explicit in the transaction-cost, market-power, and resource-dependence literatures, where vertical integration decisions are triggered by the need to access resources whose provision via thick markets is problematic. It is also a crucial, if less explicit, aspect of the double-marginalization approach, because a supplier can charge a supracompetitive price only if competitors cannot provide a substitute on the open market.

Figure 1 Vertical Integration Structures



Earlier we argued that an increase in the density of core suppliers will lower failure rates for downstream firms. However, the resource effect is not likely to be the same for all core upstream suppliers. Fully integrated upstream firms—those vertically integrated suppliers that sell exclusively to downstream divisions—will not convey the same level of benefits regarding firm failure rates in the downstream industry as nonintegrated suppliers. In an ecological sense, the average downstream firm enjoys far more access to the resources provided by independent, nonintegrated upstream suppliers than it does to those provided by fully integrated suppliers. With fewer independent suppliers, downstream firms find themselves in competition for components—components for which they will likely have to pay higher prices because there are fewer suppliers to access. Moreover, the expertise and knowledge resources that reside in the captive suppliers are unlikely to be easily disseminated to downstream firms (de Figueiredo and Teece 1996).

For similar reasons, partially integrated suppliers—who sell some of their components on the open market and some to their downstream divisions—will have an intermediate effect on access to resources. Consequently, the density of partially integrated suppliers will reduce the exit rate of downstream firms more than that of fully integrated suppliers, but less than that of nonintegrated suppliers:

$$\lambda(t) \propto \exp\left(\sum_{0}^{k} \beta_{1k} n_{Ukt}^{VI} + \sum_{0}^{k} \beta_{2k} n_{Ukt}^{PI} + \sum_{0}^{k} \beta_{3k} n_{Ukt}^{NI} + \gamma_2 n_{Dt} + \gamma_3 n_{Dt}^2\right), \quad (4)$$

where the last two terms are identical to those in Equation (3), and n_{Ukt}^{VI}, n_{Ukt}^{PI}, and n_{Ukt}^{NI} are the density of the vertically integrated upstream firms, partially integrated upstream firms, and nonintegrated upstream firms in core industry k, respectively. This represents a decomposition of the n_{Ukt} in Equation (3) to reflect the distinct effect of each governance form among suppliers. The theory predicts that β_{1k}, β_{2k}, and β_{3k} should all have negative coefficients—lowering the hazard rates of downstream firms—and their relative effects should conform to $\beta_{3k} < \beta_{2k} < \beta_{1k} < 0$. In other words, independent suppliers have the strongest effect on decreasing downstream hazard rates, partially integrated suppliers have a moderate effect, and captive suppliers have the smallest effect on decreasing downstream hazard rates.

Hypothesis 1A (H1A). *Organizational mortality rates of downstream firms will decline more steeply with increases in the density of nonintegrated upstream suppliers in core supplier industries than with increases in the density of partially integrated suppliers in core supplier industries* ($\beta_{3k} < \beta_{2k} < 0$ *in Equation* (4)).

Hypothesis 1B (H1B). *Organizational mortality rates of downstream firms will decline more steeply with increases in the density of partially integrated upstream suppliers in core supplier industries than with increases in the density of fully integrated suppliers in core supplier industries* ($\beta_{2k} < \beta_{1k} < 0$ *in Equation* (4)).

Hypothesis 1C (H1C). *Organizational mortality rates of downstream firms will decline more steeply with increases in the density of nonintegrated upstream suppliers in core supplier industries than with increases in the density of fully integrated suppliers in core supplier industries* ($\beta_{3k} < \beta_{1k} < 0$ *in Equation* (4)).

We next examine how *downstream* firms that are vertically integrated into core supplier industries will affect downstream firm failure rates.[6] Generally, vertically integrated firms will enhance competition downstream and diminish life chance for all firms in the industry. First, as Negro and Sorenson (2006) note, vertically integrated firms can better coordinate and thus mitigate certain types of uncertainty by relying on internal rather than external resources. This absorption of internal resources means fewer external resources for all firms, and for nonintegrated firms in particular. If supply becomes tight upstream, then the downstream divisions that have captive suppliers will be first in line to receive the restricted supply. Second, a vertically integrated firm has made a revealed preference investment in upstream assets that are likely specific to the downstream provider (Williamson 1985). Because the assets are relationship specific and are likely to be accompanied with specialized capabilities to use these assets, the assets and techniques are unlikely to be valuable in second use (Klein et al. 1978). Thus the investments are largely sunk. This will raise the probability that a vertically integrated downstream firm will stay in the industry and compete fiercely when others would find it advantageous to exit. Said differently, the firm is more committed to the industry than nonintegrated firms (Ghemawat 1991). Overall, firms that are vertically integrated into core supplier industries are likely to gain an advantaged position in the competition for resources and are likely to fight to stay in the industry longer under adverse conditions.

Note that this does not mean that vertical integration is a superior form of organization relative to markets. Indeed, our paper does not theorize about the survival rates of vertically integrated firms.[7] Rather, we focus on the competitive effect that vertically integrated firms, partially integrated firms and nonintegrated firms exert on other firms in the industry. To the extent that vertical integration provides preferential access to resources and incurs high sunk costs through the mechanisms articulated above, vertically integrated firms will be more intense competitors than nonintegrated firms, and thus will decrease survival rates for all rivals more than will nonintegrated firms.

Partially integrated firms in core supplier industries will also exhibit similar effects on competitive pressure in the industry, although likely not as strong as those for fully integrated firms. Partially integrated firms will enjoy some of the coordination advantage and uncertainty mitigation that integrated firms have and will be a partial resource provider. Partially integrated firms will have the opportunity to be a dedicated supplier to their downstream division when components are in short supply; however, to maintain their downstream customers, they will likely allocate resources to downstream nonintegrated firms as well. And to supply nonintegrated customers as well as their own downstream divisions, their assets are unlikely to be as specialized as their fully integrated competitors (Williamson 1985). Consequently, such firms are less likely than fully integrated firms to persist in the industry under adverse circumstances. Overall, because they combine both preferential access to some resources and industry competition for the remaining components, partially integrated firms will not have the same level of resource access and sunk costs that fully integrated firms will possess, and thus will be intermediate in the level of competitive intensity they exert on competitors.[8] We formalize these

[6] To some extent, integration from the downstream view is the flip side of integration of the upstream view, because several of the mechanisms that make a captive supplier less beneficial to the average downstream firm also enhance the competitive intensity generated by the captive supplier's downstream division. However, some mechanisms differ, as described in this section.

[7] There is a robust literature on the advantages and disadvantages of vertical integration; e.g., Williamson (1985, 1996), Macher and Richman (2008).

[8] Again, in this paper we do not comment on whether partial integration is a superior form of organization. We focus only on the competitive pressures that these firms exert.

ideas by extending Equation (3) in a comparative static sense as follows:

$$\lambda(t) \propto \exp\Bigg(\sum_{1}^{k} \gamma_k n_{Ukt} + \varphi_1 n_{Dt}^{VI} + \varphi_2 (n_{Dt}^{VI})^2 + \varphi_3 n_{Dt}^{PI} + \varphi_4 (n_{Dt}^{PI})^2 + \varphi_5 n_{Dt}^{NI} + \varphi_6 (n_{Dt}^{NI})^2\Bigg), \quad (5)$$

where the first term is the same as in Equation (3), and the next six terms represent the density of different organization forms in the downstream industry; n_{Dt}^{VI}, n_{Dt}^{FI}, and n_{Dt}^{NI} are the densities of downstream firms that are vertically integrated, partially integrated, and nonintegrated in core supplier industries. These three variables, and their values raised to second power, are a decomposition of n_{Dt} term in Equation (3). We expect that the effects of integrated-rival density on firm failure will be stronger than those of density of less integrated rivals. For the reasons noted above, these more integrated firms compete more intensely for resources in the organizational field, making it more difficult for other firms to survive in the industry:

Hypothesis 2A (H2A). *Organizational mortality rates of downstream firms will increase more steeply with increases in the density of fully integrated (into core supplier industries) rivals than with increases in the density of partially integrated rivals (the combined effect of $\phi_1 + \phi_2 > \phi_3 + \phi_4$, in Equation (5)).*

Hypothesis 2B (H2B). *Organizational mortality rates of downstream firms will increase more steeply with increases in the density of partially integrated (into core supplier industries) rivals than with increases in the density of nonintegrated rivals (the combined effect of $\phi_3 + \phi_4 > \phi_5 + \phi_6$, in Equation (5)).*

Hypothesis 2C (H2C). *Organizational mortality rates of downstream firms will increase more steeply with increases in the density of fully integrated (into core supplier industries) rivals than with increases in the density of nonintegrated rivals (the combined effect of $\phi_1 + \phi_2 > \phi_5 + \phi_6$, in Equation (5)).*

If we integrate H1A–H1C and H2A–H2C into a single equation, we obtain Equation (6) for the fully specified econometric model:

$$\lambda(t) \propto \exp\Bigg(\sum_{0}^{k} \beta_{1k} n_{Ukt}^{VI} + \sum_{0}^{k} \beta_{2k} n_{Ukt}^{PI} + \sum_{0}^{k} \beta_{3k} n_{Ukt}^{NI} + \varphi_1 n_{Dt}^{VI} + \varphi_2 (n_{Dt}^{VI})^2 + \varphi_3 n_{Dt}^{PI} + \varphi_4 (n_{Dt}^{PI})^2 + \varphi_5 n_{Dt}^{NI} + \varphi_6 (n_{Dt}^{NI})^2\Bigg). \quad (6)$$

Finally, we explore asymmetric competition by adopting and extending the approach of Negro and Sorenson (2006). Per their argument, there is reason to expect that vertically integrated firms will generate greater competitive pressure on nonintegrated firms than on other integrated firms. To the extent that an integrated firm generates pressure by controlling access to a core input, this pressure will be felt more intensely by a firm that must rely on the market for its inputs than by a firm that has its own internal supply. At the same time, as Negro and Sorenson (2006) note, nonintegrated firms are likely to generate less competitive pressure on integrated firms than on other nonintegrated firms because of the privileged position the integrated firms enjoy in the competition for resources.

Extending this line of reasoning, there is reason to expect that the density of upstream suppliers will generate greater benefits for nonintegrated downstream firms than for integrated firms. To the extent that an integrated firm is buffered from market competition for access to a core input, such a firm should be relatively unaffected by the density of alternative suppliers. In contrast, a nonintegrated firm must depend upon the market to provide the input; consequently, the density of suppliers should strongly affect the fortunes of such a firm. Partially integrated suppliers, according to this logic, would have an intermediate effect.

Operationalizing this in the context of Equations (5) and (6) would involve separating the samples by organization type (integrated and nonintegrated) and running hazard rate models. When doing this, the theory would predict the following outcomes.

Hypothesis 3A (H3A). *The density of vertically integrated rivals (integrated into core supplier industries) will increase failure rates of nonintegrated firms more than failure rates of integrated firms.*

Hypothesis 3B (H3B). *The density of nonintegrated rivals (not integrated into core supplier industries) will increase failure rates of nonintegrated firms more than failure rates of integrated firms.*

Hypothesis 3C (H3C). *The density of upstream suppliers in core supplier industries will decrease failure rates of nonintegrated firms more than failure rates of integrated firms.*

Together, H1A–H1C, H2A–H2C, and H3A–H3C combine the vertical integration literature from the economics and management literature with the organizational ecology framework to make predictions about firm entry and survival. We bring data from the laser printer and laser engine industries to examine the validity the predictive power of these hypotheses.

Methods

Empirical Context

As the personal computer market expanded in the 1980s, so too did the market for desktop printers, which we define as printers that produce up to 24 pages per minute and have dimensions that allow placement on a table as opposed to the floor. Hewlett-Packard introduced the first desktop laser printer for the retail market in 1984. By the end of 1985, seven firms had introduced 10 models of printers. At its peak in 1991, the industry had 102 firms, but by 1996 the number of firms had fallen to 84.

A desktop laser printer is made, essentially, of three main components—a laser engine, a controller card (the electronics), and exterior features such as toner cartridge, feeder tray, and plastic outside box. To create a printed page, the paper passes from the feeder tray to the laser engine, where the page is electrically charged. Fine-grain toner of the opposite charge is attracted to the paper, heated, and fused to the page by the fuser assembly of the laser engine. The paper is then ejected to the exterior paper tray. The controller card governs the process and provides the many features that a given laser printer offers.

Of these components, the laser engine is the most expensive, is a key differentiating component of the laser printer in product space, is highly specialized to laser printers, and is subject to the most variation in organizational governance. Controller cards, the other potentially differentiating component, are made in-house by the vast majority of laser printer producers. Conversely, virtually all laser printer makers purchase exterior features, which are essentially commodity components, on the open market. For these reasons, we consider the laser engine a core component and focus on the laser engine–laser printer nexus in the remainder of this paper.

There is substantial variation in production of laser engines, with nearly 25% of laser printer firms making at least some of their engines in-house. From the perspective of the engine manufacturers, approximately 72% of laser engine producers sell at least some of their engines to other firms. Canon is the dominant engine supplier, with approximately a 60% market share throughout the sample period (including in-house shipments that comprise a small amount of market share). Thus, the laser engine is the upstream focus for this study. Figure 2 shows the entry and exit patterns of vertically integrated and vertically disintegrated laser printer firms, whereas Figure 3 shows these patterns for laser engine firms.

Data Construction

Following de Figueiredo and Kyle (2005, 2006), we compiled life histories of each product and firm in the desktop laser printer industry from its inception in 1984 through 1996. Our primary data source was Dataquest's annual *SpecCheck* report on page printers, which is the single most comprehensive public database on these printers. *SpecCheck* provides information on a variety of printer characteristics including name of printer manufacturer, name of engine manufacturer, initial ship date, and number of units shipped in the year. We supplemented this data source with information from *PC Magazine* and *PC World*. In addition, we obtained further quantity data from a separate, nonpublic Dataquest market research database and from a private consulting firm that had engaged in a long-term study of the laser printer industry. Finally, we filled in missing data on the identity of engine manufacturer for nearly 500 printer models via extensive searches of websites dedicated to laser printer

Figure 2 Density of Laser Printer Firms, 1984–1996

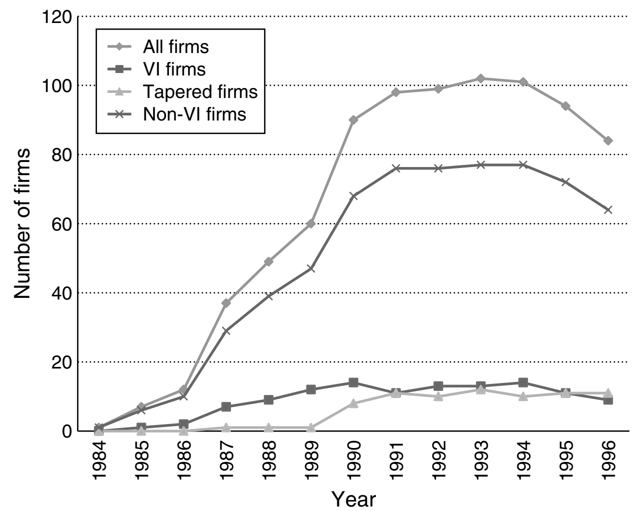
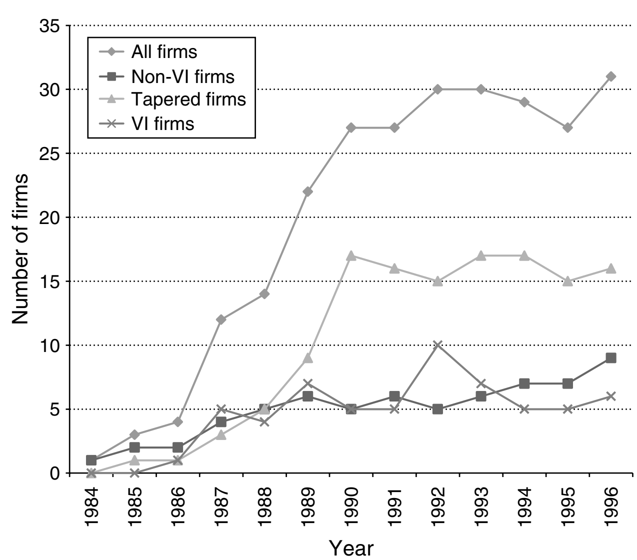


Figure 3 Density of Laser Engine Firms, 1984–1996



maintenance.[9] We believe that the resulting data set is the most comprehensive available for the laser printer and laser engine industries. Over the 13-year period, we record 4,317 printer-year observations that aggregate up to 917 firm-year observations; 703 of these observations are for nonintegrated firms, 136 are for fully integrated firms, and 78 are for partially integrated firms. We observe 41 exits of laser printer firms in the data (and three exits of laser engine firms).

To test our hypotheses, we analyze organizational exit from the laser printer industry. Consequently, we construct a dependent variable identifying instances of exit.

$Exit_{jt}$ is a categorical variable set equal to 1 if printer firm j exits the laser printer industry during year t, and 0 otherwise. Printer firm j exits the laser printer industry when it ceases to ship all products in the industry. Note that retailers may continue to have inventory even after the producer ceases shipments. If firm j withdraws one or more products but continues to sell at least one other product in the industry, then it does not exit the industry. If firm j is acquired by another firm, this is not coded as an exit but rather as a right-censored observation.

Our hypotheses focus on the effects of integrated versus nonintegrated engine firm density and integrated versus nonintegrated printer firm density on the exit rate of a focal printer firm j. We construct density measures as follows.

$EngineDensity_t$ is a count of the number of laser engine firms operating at the beginning of year t. This includes independent laser engine firms that sell all of their products on the open market, fully vertically integrated producers, and partially integrated firms that both sell on the market and sell to a downstream division. Although we do not formally test a hypothesis using *EngineDensity*, we have a baseline expectation that the coefficient for *EngineDensity* will be negative.

$EngineSellSomeDensity_t$ is a count of the number of laser engine firms that sell *at least some* of their engines on the open market at the beginning of year t, and $EngineUseAllDensity_t$ is a count of the number of laser engine firms whose engine production is entirely consumed by a downstream laser printer division. To further distinguish levels of integration, we disaggregate *EngineSellSomeDensity* into *EngineSellAllDensity* and *EngineSell&UseDensity*, which are counts of the number of laser engine firms that sell only on the open market and that both use engines in-house and sell on the open market, respectively.

$PrinterDensity_t$ is a count of the number of laser printer firms operating at the beginning of year t, and $PrinterDensity_t^2$ is the square of $PrinterDensity_t$. A long literature in organizational ecology finds that the density of firms has a U-shaped effect on the exit rate of a focal firm in that industry (see Hannan et al. 2007 for a review). Consequently, we expect that the coefficient on *PrinterDensity* will be negative and the coefficient on $PrinterDensity^2$ will be positive, at least in our baseline estimation.

$PrinterMakeSomeDensity_t$ is a count of the number of laser printer firms that make *at least some* of their own laser engines at the beginning of year t, $PrinterMakeSomeDensity_t^2$ is the square of $PrinterMakeSomeDensity_t$, $PrinterBuyDensity_t$ is a count of the number of laser printer firms that buy all of their laser engines at the beginning of year t, and $PrinterBuyDensity_t^2$ is the square of $PrinterBuyDensity_t$. To further distinguish levels of integration, we also disaggregate *PrinterMakeSomeDensity* into *PrinterMakeAllDensity* and *PrinterMake&BuyDensity*, which are counts of the number of laser printer firms that use only in-house engines and that use both in-house and purchased engines, respectively.

In the above formulation, a vertically integrated firm adds 1 to both an engine density and a printer density measure.[10]

[9] For example, see http://www.fixyourowncomputer.com. We identified the engine supplier for all but six printer models, produced by one of two printer firms. Each of these firms relied on a single engine supplier for all of its other printers. We assume that the same engine supplier was used for these models. Our results are unaffected by dropping these models.

[10] There is no consensus in the literature regarding the construction of densities for vertically integrated firms. We construct measures in which a vertically integrated firm contributes fully to each stage in which it is present. An alternative approach might borrow from research on "fuzzy density," in which a firm's contribution to population density is weighted by a parameter between 0 and 1 that approximates the degree of identification between firm and category (Hannan et al. 2007). In the context of vertical integration, this implies that each firm might have an aggregate density contribution of 1, distributed across relevant density categories through a weighting scheme; a fully integrated firm might add 1/2 to *EngineUseAllDensity* and 1/2 to *PrinterMakeAllDensity*. There are a number of challenges to applying this approach to our context. First, fuzzy density is largely concerned with legitimation effects, where identification with a category is paramount. This study focuses on competition, specifically the effect of different types of engine firms and printer firms on competition. The weighted-density approach used in fuzzy density research thus addresses a qualitatively different problem. Second, given our focus on competition, a weighted-density measure will likely quantitatively misattribute the competitive effects of vertical integration. Consider a nonintegrated printer firm that acquires a nonintegrated engine firm. Before the acquisition, each firm counts as 1 toward a density in its stage of production. It is theoretically counterintuitive and empirically problematic to reduce the contribution of these firms to 1/2 toward the density in each stage, simply as a function of the acquisition. Despite these issues with the partial counting approach to density, in unreported models we use weighted densities based on a firm's unit sales of engines and printers. These results are generally similar, albeit slightly weaker, than the results reported herein. We wish to thank Glenn Carroll for his insights on this matter.

We also include several control variables in our estimation. A firm's size is frequently found to have a positive effect on its survival chances. Furthermore, one might anticipate that vertical integration is positively associated with firm size. We therefore include ln$UnitSales_{jt}$, measured as the natural log of unit sales of laser printers by firm j in year t. Although firm sales can be a problematic measure because it may conflate other key aspects of the firm's performance with its size—i.e., more successful firms have higher sales and also are not likely to exit—our interest is not in the size effect per se, but rather in controlling for size-related relationships, which reduces concern about this measure. Relatedly, prior research demonstrates that firms with broader scope are less likely to exit an industry (de Figueiredo and Silverman 2007). We therefore include ln$Models_{jt}$, measured as the natural log of the count of printer models that firm j ships in year t. As prior research suggests that a firm's level of vertical integration may affect its survival, we include $AllBuy_{jt}$, which is set equal to 1 if firm j buys all of its engines (i.e., does not produce any engines in-house) during year t and 0 otherwise. Finally, a firm's age is often found to have an effect on its survival rate. We address this by breaking a firm's age within the laser printer industry into time pieces and using piecewise hazard rate modeling. In unreported results we estimate exponential models and include $FirmAge_{jt}$, measured as the number of years that firm j has participated in the laser printer industry as of year t. This specification does not significantly change the coefficients of any variables in the model.

Regarding population-level factors, we control for population density at time of founding with $DensityDelay_j$, measured as *PrinterDensity* for the year in which firm j entered. We also include ln$PCUnitSales_t$, measured as the natural log of U.S. personal computer units sold in year t. Because printers are typically bought to support personal computers, this variable proxies for the level of latent demand enjoyed by printers. In alternative models we replaced ln$PCUnitSales_t$ with ln$PCInstalledBase_t$, measured as the natural log of the installed base of personal computers in the United States, which is an alternative measure of the latent demand for laser printers. The results are essentially identical.[11]

[11] Although standards frequently affect competition in technology-based industries, in the laser printer industry different standards required only modest changes to the controller card, and the standards were freely available (with the exception of Postscript before 1990, which required a license fee). There were four major standards: HPPCL, Postscript, Diablo, and Epson. Only one-quarter of our observations describe firms whose printers are based on a single standard. More than 40% describe firms whose printers are based on three or more standards.

Table 1 displays the descriptive statistics for our variables. The average firm is 4.4 years old, ships slightly more than 26,000 units per year, and offers five printer models. Approximately 25% of laser printer firms make at least some of their engines, and approximately 28% of laser engine firms are entirely captive to downstream laser printer producers. The correlation matrix indicates medium to high correlations between some variables—notably, between printer firm density and engine firm density. We conduct several tests to determine the extent of multicollinearity, described below, which lead us to conclude that multicollinearity is a moderate but not fatal concern for this study.

Results

To test our hypotheses, we estimate piecewise exponential hazard rate models of the probability that firm j exits the laser printer industry in year t.[12] Table 2 presents results from our tests of H1A–H1C concerning the effect of density in the upstream engine industry—distinguished between integrated and nonintegrated engine firms—on exit rates in the downstream printer industry. Models 1 and 2 estimate traditional baseline models from the prior literature. Models 3 and 4 extend Models 1 and 2 by including a measure of engine firm density corresponding with Equation (3) above. Models 5 and 6 introduce the governance-based measures of engine density.

Governance Structures Upstream

Two observations before turning to an assessment of H1A–H1C. First, the coefficients on the conventional density measures in the baseline models are consistent with prior ecological research. In Model 2, the coefficients on *PrinterDensity* and $PrinterDensity^2$ are negative and positive, reflecting the conventional U-shaped effect of density on a printer firm's exit rate. The combined effect turns positive at a density of 49 firms, well within the observed range of data. Because we are able to replicate the core empirical finding in the organizational ecology literature, we have some confidence that our subsequent results are not an artifact of idiosyncratic data. Second, the coefficients on the control variables are consistent across all six estimations, with ln*UnitSales* always negative, *AllBuy* always positive, and the other variables almost always insignificant. Greater sales are associated with lower exit rate for a printer firm—a standard-deviation increase in unit sales decreases a firm's exit rate by 73%—whereas a printer firm that

[12] The results are robust to alternative pieces and to alternative hazard rate specifications. Note that the piecewise method "costs" one observation per firm, so that our N for the estimations is 793 rather than 917.

Table 1 **Descriptive Statistics ($N = 917$ Firm-Year Observations)**

	Mean	Std dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1 *ExitYear*	0.05	0.22	0	1	1.000															
2 *PrinterDensity*	85.59	21.94	0	102	0.067	1.000														
3 *PrinterMakeSomeDensity*	20.01	5.61	0	25	0.074	0.993	1.000													
4 *PrinterMakeAllDensity*	12.63	2.81	0	15	0.083	0.770	0.758	1.000												
5 *PrinterMake&BuyDensity*	7.38	3.93	0	11	0.047	0.866	0.884	0.367	1.000											
6 *PrinterBuyAllDensity*	65.58	16.38	0	77	0.064	0.999	0.987	0.772	0.857	1.000										
7 *EngineDensity*	26.57	6.35	0	31	0.034	0.933	0.937	0.689	0.844	0.929	1.000									
8 *EngineSellSomeDensity*	20.61	5.51	0	25	0.037	0.927	0.937	0.618	0.895	0.921	0.959	1.000								
9 *EngineSellAllDensity*	6.60	1.32	0	9	−0.037	0.603	0.595	0.250	0.671	0.603	0.765	0.799	1.000							
10 *EngineSell&UseDensity*	14.01	4.52	0	17	0.056	0.953	0.967	0.679	0.895	0.945	0.945	0.984	0.682	1.000						
11 *EngineUseAllDensity*	5.96	1.89	0	10	0.005	0.434	0.418	0.516	0.228	0.438	0.566	0.310	0.242	0.307	1.000					
12 *Models*[a]	4.97	6.38	1	69	−0.137	0.282	0.289	0.134	0.317	0.279	0.294	0.317	0.280	0.304	0.064	1.000				
13 *UnitSales* (thousands)[a]	26.4	149.8	0	1,952.5	−0.123	0.150	0.146	0.255	0.026	0.150	0.102	0.098	−0.038	0.130	0.058	0.510	1.000			
14 *FirmAge*	4.41	2.63	1	12	−0.010	0.408	0.417	0.054	0.556	0.403	0.455	0.484	0.542	0.432	0.119	0.528	0.139	1.000		
15 *AllBuy*	0.770	0.421	0	1	0.085	−0.028	−0.026	−0.030	−0.019	−0.028	−0.031	−0.027	−0.032	−0.025	−0.029	−0.184	−0.157	−0.095	1.000	
16 *PCUnitSales* (million)[a]	13.79	6.21	6.0	26.5	0.031	0.473	0.495	0.093	0.699	0.465	0.532	0.589	0.689	0.527	0.134	0.329	0.061	0.691	−0.027	1.000

[a]The natural log of *Models* (ln*Models*), *UnitSales* (ln*UnitSales*), and *PCUnitSales* (ln*PCUnitSales*) are used in the estimations.

produces no engines in-house is significantly more likely to exit than one that produces at least some of its own engines. We now turn to H1A–H1C.

In Models 3–6 we include our various measures of upstream engine density. Models 3 and 4 include *EngineDensity*,[13] which does not distinguish different levels of integration among engine firms. Model 5 replaces this with *EngineSellSomeDensity* and *EngineUseAllDensity*. Model 6 replaces these with our most fine-grained measures of integration, *EngineSellAllDensity*, *EngineSell&UseDensity*, and *EngineUseAllDensity*. Because the results are generally similar across models, and because Model 6 offers the most direct test of H1A–H1C, we focus our attention on Model 6. The likelihood-ratio test indicates that Model 6 offers significantly greater explanatory power than the baseline ecological Model 2 ($\chi^2(3) = 9.88$, $p < 0.05$). In this model, the point estimates for the coefficients on all three engine density variables are negative as predicted; the coefficients for *EngineSellAllDensity* and *EngineUseAllDensity* are negative and statistically different from zero at the 99% and 95% levels of confidence, whereas the coefficient for *EngineSell&UseDensity* is negative but does not rise above the 90% level of confidence. H1A–H1C laid out specific predictions for the relative magnitude of the coefficients on these three variables. Holding all other variables at their mean, a standard-deviation increase in *EngineSellAllDensity*, *EngineSell&UseDensity*, and *EngineUseAllDensity* decreases the exit rate of printer firms by 87%, 60%, and 38%, respectively. This pattern is broadly consistent with the predictions.

A more stringent test is to examine whether the magnitudes of the coefficients are statistically different from one another. To do this, we conduct a χ^2 test for equality across the coefficients. Consistent with H1A and H1C, we find that the coefficient on *EngineSellAllDensity* is significantly greater (in absolute value) than those for either of the other engine density measures at the 95% level of confidence. However, the coefficients on the other two measures are not significantly different from each other, inconsistent with H1B. Overall, then, a printer firm's exit rate is reduced more by increases in density of engine makers that sell all engines that they produce than by increases in the density of partially or fully captive engine makers.

[13] To explore whether *EngineDensity* has a nonlinear effect on printer firm survival, we conducted a grid search in which we replaced *EngineDensity* with $EngineDensity^x$, where $x \in (0.25, 0.26, \ldots, 1.99, 2.00)$. Although the log-pseudolikelihood indicates that the best fit occurs at $x = 1.28$, the results with $EngineDensity^{1.28}$ are identical to those with $EngineDensity^{1.00}$. The estimations in this paper rely on $EngineDensity^{1.00}$ for convenience.

Table 2 Effect of (Upstream) Engine Firm Population on Exit Rate for (Downstream) Laser Printer Firms

	(1)	(2)	(3)	(4)	(5)	(6)
Age < 10 *years*[a]	−3.829***	−0.869	−2.607**	−0.786	−0.742	−0.133
	(1.325)	(0.867)	(1.227)	(0.945)	(1.043)	(0.988)
Age ≥ 10 *years*[a]	−14.473***	−9.785***	−10.791***	−9.813***	−10.353***	−7.828***
	(1.596)	(1.440)	(1.695)	(1.568)	(1.691)	(1.867)
PrinterDensity	0.029**	−0.083**	0.093***	0.002	0.028	0.101
	(0.013)	(0.032)	(0.018)	(0.050)	(0.051)	(0.067)
PrinterDensity^2/1,000		0.848***		0.607*	0.574*	0.110
		(0.284)		(0.314)	(0.300)	(0.370)
EngineDensity			−0.251***	−0.203**		
			(0.074)	(0.088)		
EngineSellSomeDensity					−0.312**	
					(0.124)	
EngineSellAllDensity						−1.258***
						(0.357)
EngineSell&UseDensity						−0.171
						(0.170)
EngineUseAllDensity					−0.179**	−0.230**
					(0.088)	(0.111)
ln*UnitSales*	−0.333***	−0.382***	−0.417***	−0.434***	−0.469***	−0.411***
	(0.076)	(0.085)	(0.089)	(0.094)	(0.105)	(0.105)
ln*Models*	−0.416	−0.354	−0.317	−0.298	−0.255	−0.321
	(0.273)	(0.273)	(0.278)	(0.277)	(0.282)	(0.292)
DensityDelay	−0.008	−0.007	−0.007	−0.007	−0.007	−0.008
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
ln*PCUnitSales*	−0.003	0.006	0.012	0.013	0.025	0.080**
	(0.022)	(0.027)	(0.024)	(0.027)	(0.031)	(0.036)
AllBuy	1.093**	1.070**	1.053**	1.043**	1.038**	1.049**
	(0.548)	(0.527)	(0.540)	(0.527)	(0.525)	(0.525)
N	793	793	793	793	793	793
Wald	830.4***	729.6***	721.1***	769.2***	810.7***	798.0***
Log-pseudolikelihood	−94.13	−90.89	−90.50	−89.07	−88.53	−85.95

Note. Piecewise exponential hazard rate estimation is shown; robust standard errors are in parentheses.
[a]In unreported models we use alternative age pieces (e.g., 0–3 years, 4–9 years, 10+ years) that fit the data almost as well as the two pieces in the above models. The results for our other variables are unchanged.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

One pattern in the results is that the inclusion of engine density measures in Models 3–6 reduces the main effect of *PrinterDensity* to insignificance, whereas *PrinterDensity*^{2} generally retains its positive coefficient. As noted above, there appears to be correlation between the *PrinterDensity* and *EngineDensity* variables. Although the standard errors remain relatively consistent with the addition of *EngineDensity*, it is possible that multicollinearity influences the loss of significance for the negative coefficient on *PrinterDensity*. We pursued three avenues to assess this potential issue. Following Sorenson and Waguespack (2006) and Jensen (2006), we first calculated the condition number for Model 3 (the results are similar, but more complicated to describe, for Model 6). Condition numbers above 30 and 100 indicate moderate and strong collinearity, respectively (Belsley et al. 1980). The condition number for Model 3 is 60, indicating moderate concern for multicollinearity. We note, however, that the bulk of multicollinearity appears to stem from *PrinterDensity* and *PrinterDensity*^{2}; the condition number of Model 2 is 34. We next calculated variance inflation factors (VIFs) for all coefficients in these models. The VIF for *EngineDensity* is 15.7 in Model 3, at the edge of the commonly used thresholds of 10–15, above which one begins to worry about multicollinearity. As with condition numbers, VIFs for *PrinterDensity* and *PrinterDensity*^{2} in Model 2 are significantly higher than those for *EngineDensity*, whose value is above 24. Third, following Sine et al. (2005), we orthogonalized *PrinterDensity*, *PrinterDensity*^{2}, and *EngineDensity* using the ORTHOG command in STATA and reestimated our models. Our results—notably the competitive effect for printer firm density and the negative coefficient on engine firm density—were generally the same or stronger in all reestimations. We conclude that multicollinearity introduced by *EngineDensity* is a moderate concern, but that the results are sufficiently robust to measures that address collinearity to allow reasonable interpretation of estimated coefficients.[14]

Governance Structures in the Focal Population

In Table 3 we distinguish between the density of vertically integrated and nonintegrated laser printer firms. Models 7–10 estimate predictions from Equation (5), and Models 11–13 reflect Equation (6). Models 7–8 replicate Models 3–4 from Table 2, except that *PrinterDensity* is replaced by *MakeSomePrinterDensity* and *BuyPrinterDensity*. Models 9 and 10 do the same, except that they use our most fine-grained measures of printer-firm integration, *PrinterMakeAllDensity*, *PrinterMake&BuyDensity*, and *PrinterBuyAllDensity*. Because the results are generally similar across models, and because Models 9 and 10 offer the most direct test of H2A–H2C, we focus our attention on Models 9 and 10.

In Model 9, both *PrinterMakeAllDensity* and *PrinterMake&BuyDensity* have positive coefficients, with the coefficient on the former approximately one-third larger than the coefficient on the latter. In contrast, the coefficient on *PrinterBuyAllDensity* is not statistically significant, and the point estimate is close to zero. A standard-deviation decrease in *PrinterMakeAllDensity* or *PrinterMake&BuyDensity* is associated with a decrease in exit rate of 93% or 90%, respectively. This pattern of coefficients and multiplier effects is consistent with H2A–H2C. We next conduct the more stringent χ^2 test of equality across all three printer density coefficients. This test indicates that *PrinterMakeAllDensity* and *PrinterMake&BuyDensity* generate significantly greater competition for a focal firm than does *PrinterBuyAllDensity*, consistent with H2B and H2C. However, the difference between fully and partially integrated firm density is not significant, inconsistent with H2A.

Model 10 includes square terms for the printer density measures. This model offers a modest improvement in explanatory power over Model 9 ($\chi^2(3) = 4.84, p < 0.10$). Although several of the printer density effects are insignificant in this model, two observations stand out. First, the coefficients on *PrinterBuyAllDensity* and *PrinterBuyAllDensity*^{2} are negative and positive, respectively, suggesting that nonintegrated printer firms generate a conventional U-shaped effect on a focal firm's exit rate. In contrast, the coefficient on the main effect *PrinterMakeAllDensity* is positive while the coefficient on the square term is insignificant, implying that the density of fully integrated rivals has a purely competitive effect on a focal firm. The coefficients on *PrinterMake&BuyDensity* and its square term are both statistically insignificant. At first glance, this ordering of results appears consistent with the prediction that fully integrated printer firms will generate the most competition for a focal firm, followed by partially integrated firms, followed by nonintegrated firms. Second, although these point estimates are not statistically significant, if we take them as unbiased estimates, then the results are corroborated. The combined effect of the coefficients on *PrinterMakeAllDensity* and its square term increases with increased density until the population includes 18 fully integrated firms, after which the effect becomes negative. The maximum number of fully integrated firms in the data is 15. Hence, fully integrated printer firms generate a purely competitive effect throughout the observed range of data. Similarly, the combined effect of the coefficients on *PrinterMake&BuyDensity* and its square term increases until 13 firms; the maximum number of partially integrated firms in the data is 11. In contrast, the combined effect of the coefficients on *PrinterBuyAllDensity* and its square term decreases with density until 68 firms. The maximum number of nonintegrated printer firms is 77; the density of nonintegrated printer firms equals or exceeds 68 in more than one-third of the years in our data. Again, this ordering of results appears consistent with the predictions of H2A–H2C: fully integrated printer firms will generate the most competition for a focal firm, followed by partially integrated firms, followed by nonintegrated firms.

In Models 11–13, we replicate Models 7–9 except that we replace *EngineDensity* with the appropriate governance-based measures of engine firm density.[15] Again, because results are generally consistent across models, we focus on the most direct test of our predictions, Model 13. The ordering and significance of the coefficients on the three measures of printer density remain identical to those in Model 10; fully and partially integrated rivals generate more competition than do nonintegrated rivals. The χ^2 test of equality of coefficients again finds that the coefficients on *PrinterMakeAllDensity* and

[14] Regressions that are affected by multicollinearity generate unbiased estimates of the coefficients, but with inflated standard errors. We note that the inclusion of *EngineDensity* does not change the standard errors of other variables substantially. Furthermore, Tables 2 and 3 indicate that our results are robust to the addition and exclusion of a range of other variables, whereas models afflicted by multicollinearity tend to be unstable in the face of such alterations.

[15] Ideally, we would also replicate Model 10 but replace *EngineDensity* with *EngineSellAllDensity*, *EngineSell&UseDensity*, and *EngineUseAllDensity*. Despite our best efforts, this model does not converge to a stable result.

Table 3 Effect of Fully vs. Partially vs. Nonintegrated Printer Firm Density on Printer Firm Exit Rate

	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Age < 10 *years*	−1.442	−1.040	−2.360	−0.616	−0.529	1.065	1.237
	(1.167)	(1.251)	(1.697)	(1.315)	(1.226)	(1.875)	(2.212)
Age ≥ 10 *years*	−10.890***	−9.396***	−9.932***	−7.727***	−6.067**	−4.353	0.132
	(1.884)	(1.819)	(2.175)	(2.078)	(2.998)	(4.717)	(7.200)
PrinterMakeSomeDensity	0.644***	0.072			1.093***	2.434	
	(0.199)	(1.035)			(0.300)	(1.779)	
PrinterMakeSomeDensity^2		0.011				−0.025	
		(0.022)				(0.032)	
PrinterMakeAllDensity			0.723***	2.717*			1.467**
			(0.208)	(1.457)			(0.624)
PrinterMakeAllDensity^2				−0.077			
				(0.056)			
PrinterMake&BuyDensity			0.554**	1.048			1.320**
			(0.234)	(0.700)			(0.609)
PrinterMake&BuyDensity^2				−0.041			
				(0.045)			
PrinterBuyAllDensity	−0.037	0.071	−0.038	−0.686*	−0.015	−0.370	0.063
	(0.049)	(0.310)	(0.057)	(0.414)	(0.060)	(0.424)	(0.104)
PrinterBuyAllDensity^2/1,000		−0.519		4.707*		2.482	
		(2.038)		(2.688)		(2.831)	
EngineDensity	−0.392***	−0.339**	−0.384***	−0.169			
	(0.117)	(0.132)	(0.112)	(0.196)			
EngineSellSomeDensity					−0.904***	−1.136**	
					(0.302)	(0.550)	
EngineSellAllDensity							−2.193**
							(1.033)
EngineSell&UseDensity							−1.219*
							(0.628)
EngineUseAllDensity					−0.501**	−0.623*	−0.797*
					(0.211)	(0.336)	(0.420)
ln*UnitSales*	−0.367***	−0.396***	−0.358***	−0.407***	−0.448***	−0.443***	−0.420***
	(0.085)	(0.094)	(0.084)	(0.100)	(0.108)	(0.110)	(0.106)
ln*Models*	−0.373	−0.337	−0.387	−0.318	−0.265	−0.271	−0.302
	(0.281)	(0.278)	(0.282)	(0.282)	(0.286)	(0.286)	(0.287)
DensityDelay	−0.007	−0.007	−0.008	−0.007	−0.007	−0.007	−0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
ln*PCUnitSales*	−0.003	−0.004	0.023	0.064	−0.017	−0.033	0.011
	(0.026)	(0.029)	(0.036)	(0.050)	(0.041)	(0.054)	(0.079)
AllBuy	1.055**	1.048**	1.063**	1.055**	1.041**	1.040*	1.054**
	(0.532)	(0.523)	(0.533)	(0.519)	(0.522)	(0.522)	(0.517)
N	793	793	793	793	793	793	793
Wald	836.4***	774.9***	741.4***	751.9***	729.0***	803.9***	759.5***
Log pseudolikelihood	−87.20	−86.72	−86.60	−84.18	−84.59	−84.26	−82.90

Note. Piecewise exponential hazard rate estimation is shown; robust standard errors are in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

PrinterMake&BuyDensity are significantly larger than that on *PrinterBuyAllDensity*. These results are consistent with Model 10 and with H2B and H2C.

As for the effect of the different types of engine density, Model 13 actually generates stronger support for H1B than did Model 6. The coefficients on the three measures of engine density are all negative. Whereas the coefficient on *EngineSell&UseDensity* was insignificant and did not lie between the coefficients on *EngineSellAllDensity* and *EngineUseAllDensity* in Model 6 of Table 2, in Model 13 the coefficient is both statistically significant at $p < 0.10$ and between the coefficients on the polar forms of engine governance, consistent with H1B. A χ^2 test of equality of coefficients now finds that *Engine-UseAllDensity* > *EngineSell&UseDensity* ($2.78, p < 0.10$), *EngineSell&UseDensity* > *EngineSellAllDensity* ($2.70, p < 0.10$), and *EngineUseAllDensity* > *Engine-SellAllDensity* (4.19, $p < 0.05$). We interpret this as additional, and in fact less equivocal, support for H1A–H1C.

Asymmetric Competition

H3A–H3C predict that printer firm densities will affect a focal firm differently depending on its own level of integration. One way to test this is to run identical models separately on different subsamples of focal firms, based on their levels of integration (Negro and Sorenson 2006). In Table 4 we estimate such models. Three caveats loom over these tests. First, there are no exits among the 11 partially integrated firms in our sample, and only three exits among the 15 fully integrated firms. As a result, we cannot estimate models for partially integrated firms, and instead we compare nonintegrated firms to firms with any positive level of integration. Second, because of the limited number of exits among integrated firms, the fully specified models do not converge in the statistical algorithm. However, we can achieve convergence by omitting two control variables that are consistently statistically insignificant in Tables 2 and 3, *DensityDelay* and ln*PCUnitSales*. In some models we also must omit *EngineDensity* to achieve convergence. Third, we cannot obtain convergence when including all square terms for printer density in the same model, and instead introduce them one at a time. Recognizing these limitations, we hope to gain some insights into H3A and H3B by observing patterns of results across multiple partially specified models.

Throughout Table 4, the "a" models estimate effects for nonintegrated focal firms, whereas the "b" models estimate effects for integrated focal firms. Models 14a–15b include *PrinterMakeSomeDensity* and *PrinterBuyDensity*, with *PrinterBuyDensity*^{2} introduced in Models 14a and 14b and *PrinterMakeSomeDensity*^{2} introduced in Models 15a and 15b. Models 16a–17b replace *PrinterMakeSomeDensity* with *PrinterMakeAllDensity* and *PrinterMake&BuyDensity*. In both Models 14a and 15a, the density of integrated rivals is positively related to the exit rate of nonintegrated firms. In contrast, in Models 14b and 15b, the density of integrated rivals is not significantly related to the exit

Table 4 Asymmetric Effects of Competition

	(14a) Noninteg. subsample	(14b) Integrated subsample	(15a) Noninteg. subsample	(15b) Integrated subsample	(16a) Noninteg. subsample	(16b) Integrated subsample	(17a) Noninteg. subsample	(17b) Integrated subsample	(18a) Noninteg. subsample	(18b) Integrated subsample
Time pieces	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
PrinterMakeSomeDensity	0.300*	0.670	−0.308	29.443						
	(0.166)	(0.466)	(0.284)	(33.668)						
PrinterMakeSomeDensity^2			0.013***	−0.619						
			(0.004)	(0.698)						
PrinterMakeAllDensity					0.511***	0.650***	−0.222	−1.315		
					(0.196)	(0.201)	(0.410)	(6.887)		
PrinterMakeAllDensity^2							0.025*	0.050		
							(0.014)	(0.278)		
PrinterMake&BuyDensity					0.236	0.664*	0.204	0.189*		
					(0.174)	(0.380)	(0.184)	(0.105)		
PrinterMake&BuyDensity^2										
PrinterBuyAllDensity	−0.196***	17.840	−0.005	−0.053	−0.269***	17.546	−0.050	0.173		
	(0.066)	(19.815)	(0.065)	(0.163)	(0.077)	(15.687)	(0.065)	(0.223)		
PrinterBuyAllDensity^2/1,000	0.001***	−0.122			0.001***	−0.120				
	(0.000)	(0.137)			(0.000)	(0.108)				
PrinterDensity									0.113***	0.262***
									(0.036)	(0.102)
EngineSellAllDensity									−1.021***	2.105
									(0.274)	(1.316)
EngineSell&UseDensity									−0.216	−0.498
									(0.146)	(1.346)
EngineUseAllDensity									−0.233**	−4.794
									(0.110)	(3.662)
ln*UnitSales*	−0.342***	−0.230	−0.359***	−0.168	−0.351***	−0.228	−0.296***	−0.150	−0.390***	−0.294
	(0.089)	(0.296)	(0.092)	(0.132)	(0.090)	(0.277)	(0.082)	(0.097)	(0.103)	(0.205)
ln*Models*	−0.289	−1.405***	−0.268	−1.171**	−0.236	−1.411***	−0.319	−1.377***	−0.175	−1.184**
	(0.282)	(0.502)	(0.281)	(0.532)	(0.297)	(0.449)	(0.295)	(0.357)	(0.307)	(0.571)
N	601	192	601	192	601	192	601	192	601	192
Wald	701.7***	56.4***	692.7***	164.7***	700.8***	76.4***	793.7***	62.8***	708.4***	911.2***
Log pseudolikelihood	−83.70	−6.05	−83.31	−6.10	−81.50	−6.06	−83.91	−6.47	−81.29	−3.91

Note. Piecewise exponential hazard rate estimation is shown; robust standard errors are in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

rate of integrated firms. This is consistent with H3A, which predicted that the competitive effect of integrated rivals would be more intense for nonintegrated than for integrated focal firms. This result is slightly qualified in Models 16a–17b, in that the density of fully integrated rivals is positively related to the exit rate of integrated firms in Model 16b (although this effect becomes insignificant in 17b), and the density of partially integrated rivals has a stronger effect on integrated firms than on nonintegrated firms. Overall, there is a slight preponderance of evidence consistent with H3A, but this is at best indicative rather than conclusive.

In Models 14a and 16a, *PrinterBuyAllDensity* exhibits a U-shaped relationship with the exit rate of nonintegrated firms, with the inflection point within the range of observed data albeit close to the maximum level of *PrinterBuyAllDensity*. In contrast, there is no significant relationship between *PrinterBuyAllDensity* and the exit rate of integrated firms. These results—notably the positive coefficient on *PrinterBuyAllDensity*^{2} in Models 14a and 16a versus the insignificant coefficient on *PrinterBuyAllDensity*^{2} in Models 14b and 16b—are technically consistent with H3B, which predicted that the competitive effect of nonintegrated rivals would have a stronger impact on the exit rates of nonintegrated than of integrated firms. That said, the sizeable negative coefficient on *PrinterAllBuyDensity* in Models 14a and 16a actually makes the combined effect of *PrinterAllBuyDensity* and *PrinterAllBuyDensity*^{2} negative for most of the observed range of data.

Models 18a and 18b explore the asymmetric effect of engine density on integrated versus nonintegrated printer firms. In Model 18a, the coefficients on the various types of engine firms are generally consistent with those in models of the full sample: increases in density of both nonintegrated and fully integrated engine firms are negatively related to the exit rate of nonintegrated printer firms, but increases in the density of nonintegrated engine firms have a significantly greater impact. As Model 18b shows, the density of engine firms is not significantly associated with exit rates of integrated printer firms, who have their own in-house engine production capacity. This is consistent with H3C.

Finally, the control variables demonstrate remarkable consistency across all models. In every "a" model, ln*UnitSales* is negatively related to exit rates, and ln*Models* has no effect, whereas in every "b" model, ln*Models* is negatively related to exit rates, and ln*UnitSales* has no effect. Put differently, economies of scale appear to matter for nonintegrated firms (average annual unit sales, 5,241; average number of models, 3.8), whereas economies of scope appear to matter for integrated firms (average annual unit sales, 26,401; average number of models, 6.4). One reason for this may be that integrated firms are, on average, larger than nonintegrated firms and thus may already have achieved scale economies; the next margin on which they maximize is scope economies. Nonintegrated firms, on average, have not achieved scale, so scale economies matter more to these firms on the margin.

Conclusion

This paper was motivated by an opportunity in the existing literature on industry evolution: to integrate robust economic theories with highly developed ecological approaches to understand how the density of a vertically related population affects the exit rate of a focal population. We predicted that density in the population of upstream suppliers of a core specialized input would negatively affect the exit rate within a focal (downstream) population—in particular, that this survival-enhancing relationship would be strongest for the density of nonintegrated upstream suppliers and weakest for the density of fully integrated "captive" suppliers. Turning our attention to the downstream industry, we predicted that vertically integrated rivals would generate more intense competition against a focal firm than would nonintegrated rivals in the industry. Finally, we predicted that the above effects would be particularly intense for nonintegrated focal firms—that is, integrated printer firms would generate asymmetrically strong competition for nonintegrated printer firms, and the presence of upstream engine firms (especially nonintegrated firms that sell to all comers) would be particularly beneficial to nonintegrated printer firms.

We tested these predictions with data describing the U.S. laser printer and laser engine industries from their births in 1984 through 1996. Our analyses generally supported the predictions. In particular, our results suggest that a laser printer firm's survival depends on the density of laser engine suppliers and on the degree to which these engine suppliers sell their products on the open market. Increases in the density of nonintegrated laser engine suppliers enhance survival rates for laser printer firms to a significantly greater degree than comparable increases in the density of integrated suppliers. These impacts are economically significant: a standard-deviation increase in the density of nonintegrated engine suppliers from the mean level is associated with an 87% decrease in the exit rate of printer firms (based on Model 6 in Table 2), whereas a comparable increase in the density of fully integrated engine suppliers is associated with a 38% decrease in the exit rate.[16] These effects represent

[16] Alternatively, one can look at the marginal effect of an additional engine firm. At the mean level of densities of nonintegrated and

a significant influence on firm survival, particularly given the underemphasis on vertically related populations in the extant literature. By way of contrast, a standard-deviation decrease in printer firm density is associated with an 89% decrease in exit rates (in Model 5), and an analogous increase in a focal firm's size is associated with a 48% decrease in printer firm exit rate.

We also find that the competition generated by vertically integrated rivals is more intense than that generated by nonintegrated rivals; whereas a standard-deviation decrease from the mean in density of integrated rivals is associated with a 90%–93% decrease in the exit rate of printer firms, a comparable decrease in nonintegrated-rival density has a negligible impact on exit rates.

Our results concerning asymmetric competition are mixed. The results lean toward an interpretation that nonintegrated firms are subject to competition from vertically integrated rivals, whereas vertically integrated firms are buffered from nonintegrated-rival competition. Similarly, the results imply that the density of engine producers affects the life chances of nonintegrated printer firms but not those of integrated printer firms. However, these results are generated from only partially specified models and are not extremely robust.

When interpreting the results of this study, one should keep in mind three significant limitations. First, we have analyzed the survival-affecting impact of vertically related industries, and of integration, only on the laser printer industry. As noted above, the lack of exits among laser engine firms precluded us from exploring reciprocal effects on the laser engine industry. Moreover, our theory examines only the unidirectional effects of suppliers on buyers. Second, we lack information on alliances or other hybrid governance arrangements between engine firms and printer firms, and therefore can not assess the effect of such hybrid forms on firms' life chances. Third, we study only the first 13 years of the industries' lives, and therefore cannot explore the very long-term effect of vertical integration on competitive dynamics. Barnett (1990) proposed that large firms generate weaker competition as they age because they are buffered from selection processes. To the extent that vertical integration similarly buffers firms, we might expect that the strong competitive intensity of vertically integrated rivals found in this study could decline in the very long term. These limitations notwithstanding, this study contributes to the literature on industry evolution by explicitly extending insights from community ecology to those from literatures on vertically related industries, thus enhancing our understanding of the features that influence firm survival and exit in evolving industries. This study thus joins a handful of other studies that have explored how governance choices that are made for organizational efficiency reasons also generate competitive effects for their rivals (Silverman and Baum 2002, Negro and Sorenson 2006, Oxley et al. 2009).

These results suggest two lines of future research. First, although there has long been a call for studies of "community ecology," most of this research has focused on horizontally related populations. Our study demonstrates that there is value in exploring a broader range of interdependencies among populations. Future studies of vertical relationships in other industries would provide evidence of the generality, or lack thereof, of this study's findings. Studies of other forms of interdependent populations, such as between complementary industries (i.e., computer hardware producers and software producers), would further shed light on such community processes. Second, such studies can both benefit from prior research in economics and sociology on vertical or complementary relationships and help to inform this prior research. For example, to the extent that economic models of vertical integration offer predictions about behavior under different market structures, economics can contribute to future ecological research that generates more refined predictions of population dynamics. Conversely, to the extent that studies of population dynamics can shed light on these equilibrium-based economic models, the greater the opportunity for ecological models to elucidate dynamic paths that are relevant for economic models.

Finally, although this paper has devoted primary attention to the influence of an upstream industry on the life chances of firms in a downstream industry, it is likely that industries coevolve. The industry evolution literature has tended to focus on the evolution of single industries, but rarely considers such coevolution. This paper begins to make headway in understanding the ways in which vertically related industries coevolve. Further research along these lines could ultimately generate a more comprehensive understanding of coevolution that, in turn, will shed further light on industry evolution and population dynamics.

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fully integrated suppliers, an increase by one supplier is associated with decreases in printer firms' exit rates of 66% and 22%, respectively.

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