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The dynamics of related diversification: Evidence from the health insurance industry following the affordable care act

Yue Maggie Zhou[1] | Weikun Yang[1] | Sendil Ethiraj[2]

[1]Ross School of Business, University of Michigan, Ann Arbor, Michigan, USA

[2]Department of Strategy, London Business School, London, UK

Correspondence
Yue Maggie Zhou, Ross School of Business, University of Michigan, 701 Tappan Street, Ann Arbor, MI 48109, USA.
Email: ymz@umich.edu

Abstract

Research Summary: We provide a theory of when relatedness will encourage both diversifying entry and post-entry exit. Our formal model reveals two channels through which resource sharing in combination with firm capabilities affects diversifying entry and post-entry exit. Facing business opportunities in a new segment, low capability firms from a more related segment expect to benefit from more synergies and are therefore more likely to enter than firms with similar capability but from less related segments. Post entry, unfavorable shocks in the new segment tighten the survival criteria and drive some more related but low capability firms out. These predictions are supported using data on U.S. health insurance firms' entry into and exit from the Affordable Care Act market from 2013 to 2017.

Managerial Summary: When would factors that favor related diversifiers' entry into a new business segment also encourage their exit post-entry? Using data on U.S. health insurance firms' entry into and exit from the Affordable Care Act (ACA) market from 2013 to 2017, we find that more related diversifiers (i.e., insurers offering Medicaid), especially the low capability ones, are more likely to enter ACA. However, facing cost shocks in the new segment, more related diversifiers, especially the low capability ones, are more likely to exit than less related diversifiers (i.e., insurers offering no Medicaid). This is consistent with our formal model that predicts a selection at entry that favors related diversifiers due to expected synergies and an adverse selection post-entry against low capability related diversifiers.

KEYWORDS

capability, diversifying entry, exit, healthcare, resources

1 | INTRODUCTION

A large body of strategy research is devoted to understanding the impact of relatedness on diversifying entry and post-entry performance including survival (Ahuja & Novelli, 2017). However, studies that jointly analyze diversifying entry and post-entry exit are rare. Such a joint study is theoretically uninteresting (and unnecessary) if the factors that encourage entry (e.g., synergies) also discourage exit, and factors that deter entry (e.g., coordination costs) also encourage exit. For example, Helfat and Lieberman (2002) predict that "the greater the similarity between pre-entry firm resources and the required resources in an industry, the greater the likelihood that a firm will enter that particular industry, and the greater the likelihood that the firm will survive and prosper" (p. 725). For the same reason, if the expected costs dominate expected benefits of related diversification, firms from a more related segment will be less likely to enter the new segment and more likely to exit conditional on entry. Studying diversifying entry and post-entry exit jointly becomes more interesting and important if the factors that encourage entry (exit) encourage rather than delay exit (entry). Following this intuition, we ask under what conditions a higher degree of relatedness will encourage *both* diversifying entry and post-entry exit.

The literature frequently cites three drivers for diversifying entry from a firm's existing (old) business segment into a target (new) segment: (a) inter-temporal economies of scope that arise from *resource redeployment* and reduce sunk costs in the *new* segment (Helfat & Eisenhardt, 2004), (b) intra-temporal economies of scope that arise from contemporaneous *resource sharing* and reduce operating costs in both the *old and new* segments (Helfat & Eisenhardt, 2004), and (c) firm-specific *capabilities* that can be applied to the new segment to reduce costs in the *new* segment (subject to fungibility; Leiblein & Miller, 2003; Jovanovic, 1982). These different drivers have different implications for diversifying entry and post-entry exit.

A few recent studies have focused on resource redeployment as the main factor that encourages both entry into and exit from the same industry (including but not limited to Lieberman, Lee, & Folta, 2017). While these studies advance our understanding of entry and exit patterns conditioned by redeployment of non-scale free resources, they are less suited to explain the entry and exit patterns of firms whose relatedness is rooted in resources that are not constrained by scale. Several recent examples fit this pattern. For instance, Microsoft entered the smartphone industry (via acquisition of Nokia) in 2014 and exited in 2017. The related resource is the operating system which is a scale-free resource, that is, its use in smartphones does not necessitate its redeployment from computers. Similarly, Uber entered the food delivery business in India, the Czech Republic, and Egypt and exited within a short period of time even while it was entering this business in other countries. Once again, the relatedness is rooted in the (scale free) platform-specific resources that connect buyers and sellers, and the diversifying entry does not entail significant redeployment of resources from its ride-sharing business.

We see an opportunity to complement recent studies and sketch a theory of when relatedness will encourage both diversifying entry and post-entry exit in situations where little resource needs to be redeployed, that is, a theory rooted in resource sharing rather than redeployment. Our formal model reveals two channels through which resource sharing in combination with firm capabilities affects diversifying entry and post-entry exit. The first channel is a selection effect at entry: economies of scope arising from resource sharing lower expected operating costs in both the old and the new segment and increase the expected joint profits. Higher expected joint profits lower the threshold of firm capability for entry by more related diversifiers, thereby increasing their likelihood of entering the new segment relative to less related diversifiers of similar capability.

The second channel is what we dub a "reverse" selection effect when, post-entry, firms face an unfavorable cost shock in the new segment. The shock tightens the survival threshold and forces some low capability firms to exit. Among firms that entered the new segment, those with a higher level of relatedness are more likely to have a lower average capability (because of the favorable selection effect at entry) than those with a lower level of relatedness. Thus, more related diversifiers are more likely to exit the new segment post-shock.

We test these predictions using data from the U.S. health insurance industry from 2013 to 2017, when the Affordable Care Act (ACA) was introduced and reached full implementation. The ACA required all providers of individual major-medical health insurance (Individual insurance hereafter) to offer ACA-compatible plans. For non-Individual insurance providers, ACA created an opportunity to generate additional revenues from providing coverage to millions of uninsured Americans (ValuePenguin, 2014), with little requirement for additional investment. However, the initial profit projection of the ACA market turned out to be overly optimistic (Laszewski, 2015). After entry, providers of ACA plans discovered that their costs were unexpectedly high, and they suffered abnormal losses (Singhal, Coe, & Finn, 2020). As a result, as much as 46% of the entrants exited the ACA market between 2014 and 2016 (Garthwaite & Graves, 2017).

We compare entries and exits in the ACA market by non-Individual insurers that diversified from a more related segment—Medicaid, which shares significant resources with the ACA market—with entries and exits by non-Individual insurers from less related segments—such as providers of employer-based group plans and non-Medicaid government plans. The results support our predictions. Insurance firms with operations in the highly related Medicaid segment were more likely to enter the ACA market than firms from other segments, and such difference was more salient for low capability firms than for high capability firms. In addition, firms from the Medicaid segment were also more likely to exit the ACA market when facing post-entry cost shocks, especially among low capability firms.

The paper makes several contributions. First, it examines an underexplored theoretical possibility that factors encouraging diversifying entry based on intra-temporal economies of scope could also encourage rather than discourage exit. Our model sheds light on the interdependence between firm capability and resource relatedness in influencing expected and realized profitability and consequently firms' decision about diversifying entry and post-entry exit. Second, we extend recent efforts on the choice of both entry and exit by related diversifiers. Among these efforts, Lieberman et al. (2017) examine diversifying entry through resource redeployment. We provide an alternative theory that focuses on resource sharing. In contrast to their paper which focuses on sunk cost affected by redeployability, we study savings in operating costs driven by resource sharing and capability application across businesses. Finally, this article relates to one of the most important and controversial policy debates in U.S. history. While prior studies have investigated the impact of ACA on individuals (Blumenthal, Collins, & Fowler, 2020) and healthcare providers (Ercia, 2021), ours is the first study of insurance providers that we are aware of, especially the sustainability of their business model.

2 | RELATED LITERATURE

2.1 | Economies of scope and related diversification

The literature on diversification dates back to the seminal contributions of Rumelt (1974) and Penrose (1959). Central to theories of diversification is the notion of economies of scope. The classic notion of economies of scope refers to reduction in unit costs when multiple products are produced jointly rather than separately, due to sharing of productive, operational, distributional, or human capital resources between these products (e.g., Bailey & Friedlaender, 1982; Montgomery, 1994). The concept has been widely cited in the strategy literature as a major benefit of related diversification. More recent papers distinguish between two types of economies of scope: *intra-temporal economies of scope* and *inter-temporal economies of scope* (Helfat & Eisenhardt, 2004). *Intra-temporal economies of scope* arise from the contemporaneous *sharing* of resources between multiple segments. An example of diversification based on such resource sharing might be a passenger airline using excess capacity in landing gates at an airport to diversify into the air cargo business. *Inter-temporal economies of scope*, in contrast, arises from *redeploying* resources from one segment to another. An example of diversification based on such resource redeployment might be a grocery store redeploying some of its parking space (the resource) to diversify into gasoline retailing.

There are some characteristics of resources that enable their sharing or redeployment, respectively. Resource redeployment is typically associated with the use of non-scale free resources, that is, the use of resources in one setting precludes their use in other settings (Levinthal & Wu, 2010). Resource sharing is typically associated with the use of scale-free resources (e.g., brand names, patents) or non-scale-free resources with excess capacity.

2.2 | The role of capability in diversification

While economies of scope arising from resource sharing or redeployment have been well studied, another factor, firm-specific capabilities, is also implicated in diversification. Firm-specific capabilities are characterized by labels such as combinative capabilities (Kogut & Zander, 1992), competencies (Henderson & Cockburn, 1994), or operational capabilities (Helfat & Winter, 2011). They are fungible across a variety of products, markets, or industries. The benefits of capability accrue from its *being leveraged* in a new business rather than from resource sharing or redeployment (Leiblein & Miller, 2003). One example may be the superior capability of Honda to produce high quality engines at low cost, which may allow it to diversify into a variety of industries where engines are a core component of a product (e.g., automobiles, lawn mowers, motorcycles, motorboats; example cited in Prahalad & Hamel, 1997).

The distinction between resources and capabilities is subject to much debate in the literature (see e.g., Makadok, 2001). To clarify, resources are defined as factors, assets, or inputs that the firm owns or controls on a semi-permanent basis; in contrast, capabilities are defined as the ability to deploy resources, through organizational routines and processes, to produce a given amount of output, perform a set of coordinated tasks or effect a desired end (Ethiraj, Kale, Krishnan, & Singh, 2005; Helfat & Peteraf, 2003; Nelson & Winter, 1982). In this sense, "capabilities act upon resources in routine fashion" (Helfat & Lieberman, 2002, p. 725). This concept of capability as a firm's ability to use resources more efficiently is reflected in related literatures, such as managerial or entrepreneurial technology that allows firms to produce more output for a given level of input (Maksimovic & Phillips, 2002), or organizational efficiency that allows firms to incur a smaller cost for a given level of output (Jovanovic, 1982).

The distinction between resources and capabilities presents important implications for diversification. First, resources and capabilities set different limits for diversification. While the exhaustion of resources, especially the non-scale free ones, sets a limit to diversification based on resource sharing (Levinthal & Wu, 2010), capabilities can generally support multiple products or businesses within the same time period (Helfat & Raubitschek, 2000) absent limits to coordination capacity (Zhou, 2011). Second, resources and capabilities provide different bases for consecutive diversification moves. Resource-based diversification involves either contemporaneous resource sharing between an old and a new segment or partial/complete exit from an old segment before entering and redeploying the resources to a new segment (Helfat & Eisenhardt, 2004). In contrast, capability-based diversification involves leveraging capability across multiple segments (subject to fungibility).

Having clarified the meaning of resource sharing, resource redeployment, and capability, we now turn to a brief review of how these concepts might account for the dynamics of diversification, that is, the pattern of entries into and exits from industries.

2.3 | Dynamics of diversification: Patterns of entry and exit[1]

Historically, strategy scholars tended to treat firms' diversification and divestment choices as separate decisions. Recent work has begun to examine how interplays among resource sharing and resource deployment influence the value of diversified firms (see e.g., Sakhartov & Folta, 2014). These influences can potentially affect both entry and exit decisions. Consistent with such logic, Miller and Yang (2016) find that high-tech firms tend to implement a simultaneous entry and exit strategy to release constrained resources from old segments and redeploy these resources to new segments of higher growth potential.

In a related vein, eschewing the focus on exit from an old industry in preparation for entry into a new industry, Lieberman et al. (2017) explore diversifying entry into a new industry conditioned on the expected cost of future exit from the same industry. They present descriptive statistics on product market exit from a panel of 163 firms in the telecommunications and internet sector and show that exit rates are higher for more related than for less related diversifying entrants. The authors conceive of related diversification as an experiment wherein firms

[1]We use the term dynamic to describe real-time adjustments to emerging changes (Bohren, Imas, & Rosenberg, 2019), rather than a completely forward-looking process in the strict decision-theoretic sense.

attempt a diversification move and reverse it if the post-entry profit turns out to be unfavorable (see Jovanovic, 1982 for a more general model of such passive learning). Related diversification facilitates such experimentation because the cost of reversal (i.e., redeploying resources back to the old segment) is lower than that of unrelated diversification.

The small number of existing studies on both entry and exit have focused mostly on the redeployment of non-scale free resources and have largely ignored firm-specific capabilities. One important exception is Chang (1996) (recently replicated in Miller & Yang, 2016), who develops a theory of sequential search for and selection of new business segments by firms. According to Chang, at any given point in time, a firm will diversify into (enter) new segments with similar capability (knowledge) requirements to its knowledge in existing segments and divest (exit from) existing segments with less similar knowledge requirements to the rest of its portfolio. Chang (1996) conceptualizes knowledge as "operational knowledge…embedded in its routines" (p. 589), which can be interpreted as a capability to continuously learn from prior experience (Ethiraj et al., 2005).

There are three important differences between our model and the theory in Chang (1996). First, Chang takes an evolutionary perspective on diversification: Firms acquire additional knowledge in sequential diversification moves such that the core knowledge of the firm can evolve over time. As a result, diversification entries will be more positively correlated with recent diversification moves rather than those far in the past, and divestments or exits are less positively correlated with recent diversification moves. In other words, as the core knowledge of the firm evolves, businesses that a firm diversified into in the distant past may no longer be a good fit with current diversification moves and trigger exit. At any given point in time, the business segments that firms exit are different from those that they recently entered. In contrast, our theory is about firms entering and exiting the same segment. Second, Chang predicts that factors (i.e., knowledge relatedness) that encourage entry also discourage exit. In contrast, we examine factors that encourage both entry and exit. Finally, Chang focuses on the development and evolution of firm capabilities (knowledge) over time through diversification, whereas we examine how firms apply a relatively stable set of capabilities to a new segment and are selected by market conditions in the new segment.

3 | A MODEL OF RELATED ENTRY AND EXIT

There are potentially two channels for a firm-specific capability to affect both entry and exit. One channel is that firms learn about their capability only after entry, and they exit the new industry if such learned capability is lower than their expectation (both relative to their peers, as in Jovanovic, 1982; Lippman & Rumelt, 1982). A second channel is that firms know about their individual capability (relative to their peers) before entry but face an exogenous (i.e., unanticipated) unfavorable cost shock post-entry. Even if the cost shock is randomly distributed and affects all firms with equal likelihood, those with lower capability are more likely to exit due to tighter selection criteria. Our model explores this second channel.

3.1 | Setup

Our model includes three key ingredients. First, diversifying firms share resources between their old and new segments to obtain intra-temporal economies of scope, and the potential for resource sharing is greater between more related segments than between less related segments. Second, capabilities are independent of resources and differ between firms within the same industry. Third, firms experience a cost shock post-entry that is randomly drawn from a distribution common to all firms (Jovanovic, 1982). We model intra-temporal economies of scope arising from resource sharing as a reduction in operating costs in both the old and new segments (Pires & Catalão-Lopes, 2013). We model firm capability as an absolute cost advantage (Jovanovic, 1982).[2]

To make the model more tractable, we make a few simplifying assumptions. Model extensions with more complicated assumptions, including a more complicated demand function, a market-wide fixed amount of cost shock, an expectation of uncertainty, and capability fungibility, generate similar results. They are included in the Appendix S1 (Section 1) and explained in Section 3.4.

Our first simplifying assumption is that all firms face a baseline unit operating cost c in all segments. Each firm's actual unit operating cost c_i will depend on its capability and economies of scope. Second, firms are price takers in their old segment (as modeled in Jovanovic, 1982; Maksimovic & Phillips, 2002) and earn a profit of $\pi_{\text{old segment}} = p_1 - c_i$, where p_1 is the market price in the old segment. Third, firms' old segments are homogenous in terms of market structure and average cost (so that we can focus on relatedness and capability). Fourth, we assume that the production set is {0,1} in the old segment, and a diversifying firm will always produce one unit of output in its old segment. That is, the old segment remains profitable by itself (so that we can focus on conditions in the new segment).

Now let a new segment with profit opportunities emerge. Firms in the new segment are also price takers[3] and earn a profit of $\pi_{\text{new segment}} = p_2 - c_i$, where p_2 is the market price in the new segment. For simplicity, we assume that the production set is {0,1} in the new segment. That is, the firm can choose to produce either one unit of output or nothing at all. Firms will compare profits from different combinations of output choices (i.e., always one unit in the old segment and zero vs. one unit in the new segment) to make their entry and exit decision.

Diversifying entrants differ in the degree of relatedness, $r \in [0,1]$, or potential for resource sharing, between their old and new segments: $c_i = (1-r)c$ when firm i operates in both segments.

3.2 | Entry decision

We first model firms with homogeneous capabilities to isolate the effect of relatedness. If a firm enters the new segment, it will make a joint profit of $\pi' = p_1 - (1-r)c + p_2 - (1-r)c$. The net

[2]The literature typically identifies two types of capabilities (Helfat & Peteraf, 2003, p. 999): Operational capabilities that "involves performing an activity, such as manufacturing a particular product, using a collection of routines to execute and coordinate the variety of tasks required to perform the activity," as well as dynamic capabilities that "build, integrate, or reconfigure operational capabilities." Because dynamic capability is a second order capability that "must act upon other (operational) capabilities in order to change them," we focus on operational capabilities in our model for simplicity and leave dynamic capabilities for future study.

[3]This assumption is consistent with our empirical context. The ACA market is heavily regulated. In each plan category, firms can set premiums only within a narrow range conditioned on the customer's age, location, tobacco use, and individual vis-à-vis family enrollment (Healthcare.gov, n.d.). The government provides consumers with subsidies only up to the price of the second-cheapest silver plan (Norris, 2022). This sets an upper bound on firms' pricing power and forces them to compete on cost.

benefit of diversifying into the new segment will be $\Delta\pi = \pi' - \pi_1 = p_2 - (1-r)c + rc$. Because $\frac{\partial \Delta\pi}{\partial r} = 2c > 0$, the benefit of entering the new segment is monotonically increasing in the degree of relatedness, r. We therefore propose the following:

Baseline Hypothesis. *Firms from a more related segment will be more likely to enter a new segment than firms from a less related segment.*

Next, we introduce heterogeneity in firm capability, θ: $c_i = (1-\theta)c$ for firm i operating in either the old or the new segment, where c is the baseline cost in either segment. $\theta \in [0, 1]$ is drawn from a uniform distribution. Therefore, a firm operating only in its old segment will make a profit of $\pi_1 = p_1 - (1-\theta)c$. If it diversifies into the new segment, it will make a joint profit of $\pi' = p_1 - (1-r)(1-\theta)c + p_2 - (1-r)(1-\theta)c$. The net benefit of diversifying into the new segment will be $\Delta\pi = \pi' - \pi_1 = (p_1 - (1-\theta)c(1-r)) + (p_2 - (1-\theta)c(1-r)) - (p_1 - (1-\theta)c)$ $= p_2 + c(1-\theta) - 2c(1-r)(1-\theta)$. Solving the zero-marginal-profit condition $\Delta\pi = 0$ yields the threshold capability for diversifying entrants:

$$\theta^*(r) = \begin{cases} \dfrac{2cr - c + p_2}{2cr - c}, \text{ if } r < r^* = 0.5 - \dfrac{p_2}{2c}. \\ 0, \text{ if } r \geq r^* = 0.5 - \dfrac{p_2}{2c} \end{cases} \tag{1}$$

That is, firms will diversify into the new segment if and only if their capability $\theta \in [\theta^*(r), 1]$. Given that we have assumed a uniform distribution of $\theta \in [0, 1]$,[4] the probability that $\theta \in [\theta^*(r), 1]$ is $1 - \theta^*(r)$. We can derive from Equation (1) that $\frac{\partial}{\partial r}\mathrm{P}(entry)(r) = \frac{\partial}{\partial r}(1 - \theta^*(r)) = \frac{2p_2}{c(1-2r)^2} \geq 0$. That is, diversifying entrants from a more related segment are more likely to enter the new segment, confirming the baseline hypothesis.

The entry threshold, however, only applies to low capability firms. Firms with sufficiently high capability could be above the threshold ($\bar{\theta} = \frac{c - p_2}{c}$) regardless of relatedness. For those high capability firms, they will enter the new segment even if their relatedness is 0. That is, relatedness will not have any effect on their entry decision.

Hypothesis (H1). *The effect predicted in the baseline hypothesis is more salient for low capability firms than for high capability firms: Firms from a more related segment with lower capability will be more likely to enter a new segment than firms from a less related segment with similar capability.*

3.3 | Exit decision

Assume that post entry, firms experience an unexpected cost shock, d, which is uniformly distributed between zero and some $d^u > 0$: $d \in [0, d^u]$.[5] The post-shock unit cost becomes $(1-r)(1-\theta)(c+d)$.[6] The firm's profit is $\pi'' = p_1 - (1-r)(1-\theta)c + p_2 - (1-r)(1-\theta)(c+d)$ if it stays

[4]The distribution of capabilities can be relaxed to more general distributions. So long as the density of capabilities has a constant slope, is nonincreasing, and has support [0,1], our results hold.

[5]The distribution of d can be relaxed to any distribution with support being a bounded subset of R^+.

[6]The post-shock unit cost can be rewritten as $(1-r)(1-\theta)c + (1-r)(1-\theta)d$. So the effective increase in unit cost, $(1-r)(1-\theta)d$, is smaller for more related and/or more capable diversifiers.

and $\pi_1 = p_1 - (1-\theta)c$ if it exits. Accordingly, the net benefit of staying in the new segment is $\Delta\pi' = \pi'' - \pi_1 = (p_1 - (1-\theta)c(1-r)) + (p_2 - (1-\theta)(c+d)(1-r)) - (p_1 - (1-\theta)c) = p_2 + \mathrm{c}(1-\theta)r - (\mathrm{c}+\mathrm{d})(1-\mathrm{r})(1-\theta)$.

Solving the zero-marginal-profit condition $\Delta\pi' = 0$ generates the exit threshold capability $\theta'(r, d)$.[7]

$$\theta'(r, d) = \begin{cases} \dfrac{-c-d+p_2+2cr+dr}{-c-d+2cr+dr}, \text{ if } r < r' = \dfrac{d+c-p_2}{2c+d} \\ 0, \text{ if } r \geq r' = \dfrac{d+c-p_2}{2c+d} \end{cases}.$$

That is, firms with $\theta \leq \theta'(r, d)$ will exit the new segment. Note that only firms with capability $\theta \geq \theta^*(r)$ in Equation (1) would have entered the new segment. Therefore, the probability of exit conditional on entry is:

$$P(Exit) = \begin{cases} \dfrac{\int_0^{d^u} 1 - \dfrac{1-\theta'(r,\ d)}{1-\theta^*(r)}\, d(d)}{d^u}, \text{ if } r < r^* = 0.5 - \dfrac{p_2}{2c} \\ \dfrac{\int_0^{d^u} 1 - \dfrac{1-\theta'(r,\ d)}{1}\, d(d)}{d^u}, \ r^* < r < r' \\ 0, \ \ if\ r \geq r' = \dfrac{d+c-p_2}{2c+d} \end{cases}. \tag{2}$$

Equation (2) allows us to study the effect of relatedness. In particular,

$$\frac{\partial P(Exit)}{\partial r} = \begin{cases} \dfrac{1}{d^u}\displaystyle\int_0^{d^u} \dfrac{cd}{(d(r-1)+c(2r-1))^2} d(d) > 0, \text{ if } r < r^* = 0.5 - \dfrac{p_2}{2c} \\ \dfrac{1}{d^u}\displaystyle\int_0^{d^u} \dfrac{-(2c+d)p_2}{(d(r-1)+c(2r-1))^2} d(d) < 0, \ r^* < r < r' \\ 0, \ \ if\ r \geq r' = \dfrac{d+c-p_2}{2c+d} \end{cases}.$$

This suggests three interesting results. First, when relatedness r is within a certain range ($r^* < r < r'$), the conditional probability of exit decreases in r. That is, only within a medium range of relatedness we can obtain the results that have been assumed in the literature: Firms from the more related segment are both more likely to enter and more likely to stay post-entry. Second, when r is very high ($r > r'$), relatedness has a zero marginal effect on firms' entry or exit decision. Finally, unless r is sufficiently high ($r < r^* = 0.5 - \frac{p_2}{2c}$),[8] relatedness actually has a negative marginal effect on post-entry survival: More related diversifiers are more likely to exit facing a negative shock post-entry than less related diversifiers.

[7]Simple algebra shows that $r' > r*$.

[8]Numerically, r^* actually represents a fairly high level of intra-temporal economics of scope that should cover a wide range of realistic possibilities. For example, $r^* = 0.3$ means the firm is able to save 30% of operating costs via resource sharing. This value is comparable to the conceptualization of highly related diversifiers in other papers (e.g., Sakhartov & Folta, 2014).

A graphical and a numerical illustration of our theory are presented in the Appendix S1 (Sections 2 and 3). Intuitively, when the market condition in the new segment unfavorably deviates from expectation, it tightens the criteria for survival and drives out some low capability firms from the new segment. Given that the selection effect at entry results in a higher percentage of low capability firms in the new segment being from the more related segment, these firms are more likely to exit when operating costs increase. Therefore, on average, a higher percentage of exiting firms will be from the more related segments.

We therefore propose the following:

Hypothesis (H2). *Following a cost shock in the new segment, unless relatedness is sufficiently high, diversifying entrants from a more related segment will be more likely to exit than diversifying entrants from a less related segment.*

3.4 | Model extensions

We implement a number of alternative formulations of our main model to test its robustness. These extensions are provided in the Appendix S1 (Section 1), and they support our predictions. First, for simplicity, our main model assumes a fixed price level in each segment. As a robustness check, we allow firms to face a downward-sloping demand curve. Second, our main model follows existing studies in IO (Asplund & Nocke, 2006; Jovanovic, 1982) to assume that each firm obtains a random draw (d) from a cost distribution that is common to all firms. As a robustness check, we experiment with a simpler assumption of a market-wide fixed amount of cost shock that is common to all firms. Third, our main model assumes that firms have an expectation of their post-entry profit (conditioning on their capability and relatedness). It does not incorporate expected uncertainty in such profit that needs to be resolved after entry. A model that incorporates firms' expectation of uncertainty is more complicated but generates a similar result: Unless relatedness is sufficiently high, after a cost shock that is more severe than expected in the new segment, diversifying entrants from a more related segment will be more likely to exit than diversifying entrants from a less related segment. However, testing this slightly revised hypothesis would require us to measure both expected and realized cost shocks, which is infeasible with our data.

Finally, for simplicity, our main model assumes that capabilities are fully fungible between segments. As a robustness check, we allow the capability to have different degrees of fungibility between a firm's old and new segments. We model fungibility to be $f=\frac{r}{a}$, where $a \geq 1$ is a constant: Capability is more fungible between more related segments than between less related segments. As a result, the percentage of cost saving from capability in the new segment becomes $(1-\theta)(1-f)$: The greater the fungibility, the greater will be the cost saving. Note that the cost saving brought about by fungibility applies only to the new segment; costs in the old segment will not be affected by fungibility. This is different from economies of scope r, which benefit both the old and the new segment. This extension also generates all the predictions in our main model.

4 | EMPIRICAL CONTEXT

The health insurance industry in the United States is broadly categorized into three segments. About 56% of the population obtain health insurance from *employer-based (group) plans*, 43%

from *government plans* (e.g., Medicare, Medicaid, and Fed-employee-health plans), and about 16% from *individual plans* (Dickstein, Ho, & Mark, 2021).[9] Resource and capability differences between insurers operating in these three segments are critical to our empirical design as elaborated below.

The Affordable Care Act (ACA) is a comprehensive healthcare reform law that aimed to broaden affordable health insurance by providing government subsidies to households with income between 100% and 400% of the federal poverty level and by limiting pricing power and service discrimination by insurance providers. It was signed into law by President Obama in 2010, and enrollment policies written by health insurance companies first went into effect on January 1, 2014. By 2016, the uninsured share of the population had roughly halved, with approximately 20 million more people obtaining coverage (Tolbert, Orgera, & Damico, 2020).

ACA included two main provisions that aimed to create a win-win solution for U.S. households and the health insurance industry. First, the *Individual Mandate* required all but a few exempt groups of U.S. individuals to have a health insurance plan with basic coverage and pay a tax penalty otherwise (Patient Protection and Affordable Care Act of 2010, 2010, p. 145). This was designed to reduce adverse selection in the health insurance market. Second, the *No Preexisting Condition Exclusion* forbade insurers from pricing policies differently based on individuals' preexisting conditions or demographic status (except age) (Patient Protection and Affordable Care Act of 2010, 2010, pp. 45–46). This was designed to make health insurance more affordable for lower-income consumers. As required by ACA, almost all Individual insurers started to provide ACA plans. In addition, many non-Individual insurers, including providers of employer-based group plans and government plans, also entered the ACA market.

Examining diversifying entry by non-Individual insurers into the ACA market is appropriate for testing our predictions for a few reasons. First, business opportunities brought about by the Individual Mandate were highly visible to all firms. It was estimated that the Individual segment would experience a $90 billion increase in premium and a significant increase in profits (ValuePenguin, 2014). This publicity made the entry decision salient for all non-Individual insurers.

Second, firms faced significant shocks to operating costs after entering the ACA market, which resulted in subsequent exits. The initial profit projection of the ACA market by the health insurance industry turned out to be overly optimistic. One of the most commonly used cost indicators in the industry, the Medical Loss Ratio (MLR, or the portion of premium revenue insurers pay out in the form of healthcare claims), turned out to be unexpectedly high for many ACA insurers. For instance, the MLR for Blue Network's Individual business was 82% before it started to offer ACA plans but grew to 91% in 2014 and 99% in 2015 (Laszewski, 2015). Firms soon realized that much of the premium growth had been unprofitable, and they lost $2.7 billion in 2014 and 7.9 billion in 2015 (Singhal et al., 2020). As a result of the cost shock, a large number of firms exited the ACA market (Garthwaite & Graves, 2017).

Third, serving the ACA market does not require a large amount of incremental fixed investments for diversifying entrants from non-Individual segments. Rather, diversifying into the ACA market offers opportunities for resource sharing. In health insurance, the typical resources include IT systems, insurance plan designs, employees, business relationships with care providers (e.g., hospitals and pharmaceutical companies), and the customer base. This feature makes the redeployment of non-scale free resources less important for firms' diversification decisions than synergistic savings in operating costs arising from resource sharing.

[9]These shares sum to over 100% because households often receive coverage from more than one source in a year.

Among non-Individual segments, there is a clear distinction between more and less related ones for the ACA market. Employer-based group plans are less related to ACA in that they are subscribed to by employers on behalf of individual employees. Among the major government plans, Medicaid, like the ACA, covers low-income individuals who cannot get affordable healthcare insurance through the commercial market. In contrast, Medicare mainly covers the elderly (rich or poor), and Fed-employee plans are restricted to federal government employees or employees of certain tribes, tribal organizations, or Urban Indian organizations; they are therefore also less related to ACA than Medicaid.

Due to similarities in coverage, Medicaid and ACA have several channels for resource sharing. Medicaid enrollees often face unique challenges and require different resources than enrollees in commercial employee-based and other government plans. For example, many Medicaid enrollees live in rural areas that lack medical specialists, and they do not have means for long-distance transportation. Consequently, insurers have to invest in telemedicine technology to meet the needs of such patients (Livingston, 2019). Medicaid providers also employ proprietary IT systems that cater to customer service, data analysis, and risk management for the poor (Garfield, Orgera, & Damico, 2021). Such systems can be easily shared with ACA enrollees given the similarity in socio-economic circumstances. In addition, Medicaid and ACA programs use similar insurance plan designs, and employees with similar skills who design and/or manage these plans (Baumrucker & Fernandez, 2013). They, therefore, can share the cost of designing these plans and acquiring these employees. Furthermore, Medicaid providers have made relationship-specific investments in networks of providers (e.g., HMOs) and pharmacy benefit managers (PBMs) who are willing to charge lower fees in exchange for exclusive business. Diversifying into ACA enables Medicaid providers not only to share their existing networks between Medicaid and ACA, but also to negotiate new contracts jointly for Medicaid and ACA, potentially leveraging economies of scale and scope (Wengle, Curran, Courtot, Elmendorf, & Lucia, 2020). Finally, similar to ACA, Medicaid serves a unique customer base of lower-income individuals and families. Such a similar customer base allows the providers to keep their customers who may transition between Medicaid and ACA plans due to income fluctuations, and to provide coverage to the entire family as individual family members seek coverage through different government-sponsored insurance programs with the same network and delivery system (Wengle et al., 2020).

Because of these opportunities for resource sharing, the impact of ACA on Medicaid enrollment has been found to be positive (Garfield et al., 2021). For example, investments to modernize and simplify the ACA enrollment processes have also benefitted Medicaid enrollment. The "no wrong door" enrollment system makes it easier to enroll in and renew Medicaid coverage. ACA also spurred outreach and enrollment efforts to connect eligible people to coverage, either by ACA or Medicaid.

The last reason that examining diversifying entry by non-Individual insurers into the ACA market is appropriate to test our model is that in addition to the degree of resource sharing, diversifying entrants differ in their firm-specific capabilities that can help them gain a competitive advantage in the ACA market. The profit margin in the ACA segment is low. Insurance companies that have accumulated knowledge, experience, and processes for providing cost-effective care will be able to apply such capabilities to the ACA market. For example, in order to participate in Medicare and Medicaid, hospitals are required to have an effective utilization review program (CMS, 2015). Such a program is a key component of a value-based approach that intends to improve efficiency in healthcare, and insurance companies are often involved in the review to grant approval for tests or treatments. Insurance companies that have developed similar processes would be able to apply them to the ACA market, even if they had no prior experience in the Individual or Medicaid segment. For example, ConnectiCare, Humana, Innovation Health, PreferredOne, and UnitedHealthcare are all providers of Medicare and/or employer-based plans that had no operation in the Individual segment in some states before 2014. However, all of these companies had excellent utilization management routines, procedures, and structure for pre-service review and authorization, concurrent delivery monitoring (including internal clinic policies and inpatient hospital analysis), discharge planning, and retrospective review (Humana Behavioral Health, n.d.; Innovation Health Office, 2015; Frederick, 2012; Morse, 2020; ConnectiCare, 2015). These firms would be able to apply their capability in utilization management to the ACA market.

Another way to lower cost is through the value-based capitation model, where a care provider is paid a fixed amount for each patient per period of time depending on the patient's medical history, regardless of the actual services provided. This differs from the fee-for-service model, where a care provider receives a fee for each service it provides. ACA plans are based on capitation models (The Washington Post, n.d.). Insurers with knowledge and experience in managing the capitation model could apply such knowledge and experience to the ACA market, even if they had no prior experience in the Individual or Medicaid segment. For example, Humana and UnitedHealthcare had both adopted the capitation model and evidence-based clinical guidance before 2014 (Humana Behavioral Health, n.d.; Morse, 2020). They would be able to apply these capabilities to the ACA market.

5 | EMPIRICAL DESIGN

5.1 | Data and sample

We tested our hypotheses on a sample of U.S. health insurance firms from 2013 to 2017.[10] Because most firms in the Individual segment participated in the ACA market as required by ACA, we limited our sample of potential diversifiers to firms that had not offered Individual plans prior to the ACA implementation. We built a dataset of firms' operation in different healthcare segments, their financial performance, and entry and exit patterns with respect to the ACA market. Our data mainly came from the National Association of Insurance Commissioners, Health Insurance Exchange Compare, Kaiser Family Foundation, and the Bureau of Economic Analysis. We manually matched our data from these different sources using the company name and state.

We organized the data into two samples corresponding to the entry and exit analysis, respectively. In the sample for entry analysis, we collected information for all health insurers operating in any state between 2013 and 2017. Over 70% of ACA entries happened in states where entrants had already been operating a non-Individual business. Therefore, we included in the risk set for each firm only the states where the firm already had a non-Individual business to avoid the bias when estimating rare events.[11] For every firm-state pair, we kept the observations

[10] 2013 data was used to construct lagged explanatory variables. We excluded years after 2017 since policies under the Trump administration sharply changed the implementation of ACA.

[11] As a robustness check, we used logit and rare-event logit models on alternative risk sets that included (a) all states geographically adjacent to the firm's operating states, or (b) all states (even the states where the firm had no insurance business). Results are similar.

from 2013 until the year the focal firm entered the state's ACA market or until the end of the sample period, whichever was earlier. The entry sample contained 558 firms, 1707 firm-state pairs, and 5,160 firm-state-year observations.

In the sample for exit analysis, for every firm-state pair, we included observations from the year when the firm entered the state's ACA market until the year the firm exited or until the end of the sample period, whichever was earlier. The exit sample contained 65 firms, 77 firm-state pairs, and 163 firm-state-year observations.

5.2 | Variables

The dependent variables are entry and exit, respectively. We first identified from our data all non-Individual insurers in a given state and year. We then manually searched on the internet to identify those that offered ACA plans (i.e., Individual plans in the ACA marketplace) in the given state and year. Accordingly, *Entry* is a dummy variable that turns to 1 if the focal firm offered an ACA plan for the first time, and 0 otherwise. *Exit* is a dummy variable that turns to 1 if the focal firm stopped offering ACA plans, and 0 otherwise.

Our main independent variable is *Relatedness*, which is set to 1 if the focal firm had a Medicaid business in the focal state in the previous year, and 0 otherwise.

Our second independent variable is post-entry *Cost Shock*, measured based on a cost ratio (total medical reimbursement paid to the insured divided by premium revenue), which is similar to the industry standard measure of cost, Medical Loss Ratio (MLR).[12] We calculated *Cost Shock* by taking the difference between the diversifying entrant's lagged cost ratio (after entering the ACA market) and the average cost ratio across all health insurance firms in the target state in the year before the focal firm entered the ACA market (which should be observable to the focal firm to form an expectation of the baseline cost in the target state).

Because our model predicts an asymmetric selection effect that would apply mainly to low capability firms, we categorized the sample firms into those with low and high capability, respectively. Consistent with our model, we calculated a firm's capability using its unit cost, that is, total claims and medical expenses paid out by the firm to the insured divided by total enrollment across all insurance segments in a given state before ACA entry. We then compared the firm's average unit cost with the median unit cost of benchmark firms in the same state and over the same time period. If the focal firm's average pre-ACA unit cost was higher than that of the benchmark, the firm was categorized as a *Low Capability* firm; otherwise, it was categorized as a *High Capability* firm. For the entry sample, we included all firms in the focal state as benchmarks for the focal firm. For the exit sample, we included all firms that entered the ACA market in the focal state as benchmarks for the focal firm.

We included control variables at three levels. Our state-level controls included the state's political environment (a state was labeled a *Democratic State* if the state voted for a Democratic presidential candidate in the previous election cycle, and zero otherwise), Herfindahl–Hirschman Index (*HHI*) of market concentration based on enrollment in the state's Individual segment, and *Income* per capita (log-transformed). Our firm-level controls included *Total Assets* (log-transformed), *Return on Assets*, and *Liability Ratio* (Liability/Assets). At the firm-state level,

[12]MLR also accounts for quality improvements and other adjustments. Unfortunately, such information was not reported in our data source.

we controlled for the size of the firm's non-Individual and non-Medicaid businesses in the target state, using its *NonIndividualnonMedicaidEnrollment* (log-transformed).

In addition, we included a control variable in the exit analysis to account for the potential for resource *Redeployment* from the ACA market back to the old segment. As predicted by Lieberman et al. (2017), related diversifiers may be more likely to exit the new segment because their opportunity to redeploy resources back to the old segment is greater. As explained earlier, in our setting, diversifiers (including the more related Medicaid providers) do not need to deploy a large amount of resources to the ACA market and therefore do not need to redeploy resources back to their old business if they exit the ACA market. Nevertheless, to empirically account for the potential for resource redeployment, we followed Lieberman et al. (2017) and used the size (enrollment) of the focal firm's Medicaid business relative to its Individual business (log-transformed). A relatively larger Medicaid business will make it easier for the firm to find an opportunity to redeploy its ACA resources back to the Medicaid business.

Section 4 in the Appendix (S1) provides summary statistics and correlation coefficients for key variables. There was a significant difference between firms in the subsample for entry analysis (firms that had not entered the ACA market) and firms in the subsample for exit analysis (firms that had entered the ACA market). Six percent of the firms that had not entered the ACA market had operated in the more related segment (i.e., Medicaid), whereas 23% of the firms that had entered the ACA market had operated in Medicaid, suggesting that on average more related diversifiers were more likely to enter the ACA market. Firms that had entered a state's ACA market also had a lower *Return on Assets* than firms that had not entered the ACA market, suggesting that these firms might have viewed the ACA market as an opportunity to improve asset utilization (via resource sharing) and, consequently, profitability. Upon closer investigation, we found that firms that had not entered the ACA market (i.e., those in the entry sample) had an average Assets-to-enrollment ratio of around 1,600 dollars per member-year, whereas firms that had already entered the ACA market (i.e., those in the exit sample) had an average Assets-to-enrollment ratio of around 450 dollars per member-year, confirming our intuition.

5.3 | Specifications

We used the following specification to estimate the likelihood of entry:

$$E(Entry_{ist}=1)=\beta_0+\beta_1 Relatedness_{i,s,t-1}+\gamma_1 CV_{s,t-1}+\gamma_2 CV_{i,t-1}+\gamma_3 CV_{i,s,t-1}+\varepsilon_{i,s,t} \quad (3)$$

where $CV_{s,t-1}$,$CV_{i,t-1}$, and $CV_{i,s,t-1}$ are state-, firm-, and firm-state-level control variables, respectively. We lagged all explanatory variables to avoid simultaneity. We used the conditional logit model (with state being the matched group variable). The baseline hypothesis predicts $\beta_1>0$.

In addition to the full-sample analysis, we also estimated the impact of relatedness on the two subsamples of firms with low and high capability, respectively. As our model predicts, relatedness should positively influence the likelihood of entry only in the subsample of low capability firms but have no impact in the subsample of high capability firms. Thus, H1 predicts $\beta_1>0$ in the subsample of low capability firms.

We used the following specification to estimate the likelihood of exit:

$$E(Exit_{ist}=1)=\beta_0+\beta_1 Relatedness_{i,s,t-1}+\beta_2 CostShock_{i,s,t-1} * Relatedness_{i,s,t-1}+\beta_3 CostShock_{i,s,t-1}+\gamma_1 CV_{s,t-1}+\gamma_2 CV_{i,t-1}+\gamma_3 CV_{is,t-1}+\varepsilon_{i,s,t} \quad (4)$$

We used conditional logit models (with state being the matched group variable) in our main regressions. H2 predicts $\beta_2>0$.

6 | RESULTS

6.1 | Relatedness, capability, and diversifying entry

Table 1 presents the estimated effect of relatedness on firms' entry decisions. Column (1) starts with only the control variables. Columns (2)–(4) include our key independent variable, *Relatedness*. Columns (1) and (2) are estimated on the full sample, and Columns (3) and (4) are estimated on the two subsamples of low and high capability firms, respectively.

Looking across the columns, coefficients on the control variables are largely consistent with expectations. For example, firms with lower *Return on Assets* were more likely to enter a state's ACA market, probably to increase asset utilization through resource sharing. Column (2) shows that firms with more *Related* business (Medicaid) in the target state were more likely to enter its ACA market. The coefficient estimate suggests that firms with Medicaid business were three times more likely to enter the ACA market than firms with no Medicaid business. This is consistent with our baseline hypothesis.

Columns (3) and (4) examine the selection mechanism in our model on the two subsamples of low and high capability firms, respectively. The coefficients show that relatedness had no impact on high capability firms but favored entry for low capability firms: Low capability firms with a Medicaid business were seven times more likely to enter the ACA market than low capability firms with no Medicaid business.

6.2 | Relatedness, capability, and exit

Table 2 presents the estimated effect of relatedness on firms' exit decisions. Column (1) starts with only the control variables, Columns (2)–(6) add our key independent variables, *Relatedness* and *Cost Shock*. Columns (1) and (2) are estimated on the full sample; Columns (3)–(6) are estimated on the two subsamples of low and high capability firms, respectively.

Looking across the columns, coefficients of the control variables are largely consistent with expectations. For example, once entered, firms were less likely to exit a more concentrated state where they would have greater market power relative to later entrants. Column (2) shows that more related diversifiers in a state were more likely to exit its ACA market after experiencing a cost shock than less related diversifiers. The coefficient in Column (2) suggests that, if there were no cost shock in a state, firms with a Medicaid business would be 10% less likely to exit than firms with no Medicaid business. However, after experiencing a cost shock, firms with a Medicaid business in the state were 15% more likely to exit the state's ACA market than firms with no Medicaid business.

Columns (3) and (4) show that, after experiencing a cost shock in a state, having a Medicaid business did not affect high capability firms' exit decision, but low capability firms with a Medicaid business were 20% more likely to exit the state's ACA market than low capability firms with no Medicaid business. These results support the selection mechanism posited in our

TABLE 1 Estimation of the likelihood of entry

DV = entry (1,0)	(1) All firms	(2)	(3) Low capability firms	(4) High capability firms
Relatedness (1,0)		2.276	1.894	0.776
		[0.290]	[0.314]	[1.154]
		(.000)	(.000)	(.501)
Democratic state (1,0)	−0.465	−0.543	−0.590	0.752
	[0.419]	[0.452]	[0.539]	[0.930]
	(.267)	(.230)	(.273)	(.419)
HHI	1.001	0.885	0.583	1.355
	[0.966]	[0.955]	[0.852]	[4.763]
	(.300)	(.354)	(.493)	(.776)
Log (income per capita)	0.597	1.579	0.007	31.580
	[2.700]	[2.613]	[2.283]	[15.590]
	(.825)	(.546)	(.997)	(.043)
Log (Total assets)	−0.023	−0.095	−0.407	−0.140
	[0.049]	[0.053]	[0.079]	[0.105]
	(.635)	(.075)	(.000)	(.181)
Return on assets	−1.061	−0.887	−0.250	1.933
	[0.420]	[0.503]	[0.493]	[0.816]
	(.012)	(.078)	(.612)	(.018)
Liability ratio	−0.853	−0.641	−2.539	0.556
	[0.943]	[0.988]	[1.228]	[2.521]
	(.366)	(.517)	(.039)	(.825)
NonIndividualnonMedicaid Enrollment	0.011	0.118	0.402	0.018
	[0.045]	[0.039]	[0.063]	[0.106]
	(.807)	(.002)	(.000)	(.864)
Observations	5,160	5,160	1,729	1,584
Log-likelihood	−560.0	−520.4	−310.3	−91.61

Note: Robust standard errors in brackets, followed by *p* values in parentheses. The number of observations drops in Columns (3) and (4) due to the loss of within-group variation in subsamples. Re-estimating Columns (1) and (2) using the observations kept in Columns (3) and (4) generates similar results. All models use State as the matched group variable.

model. As a robustness check, Columns (5) and (6) replace the firm-level measure of *Cost Shock* with a state-level measure. The results are consistent.

6.2.1 | Alternative explanations

While we controlled for the potential for resource redeployment from ACA back to the old segment in our regressions, we performed additional investigations that would help to separate the

TABLE 2 Estimation of the likelihood of exit

DV = exit(1,0)	(1) All firms	(2)	(3) Low capability firms	(4) High capability firms	(5) Low capability firms	(6) High capability firms
Relatedness (1,0)		2.075	−11.930	−2.830	−233.811	0.939
		[1.815]	[10.520]	[7.718]	[13.670]	[4.254]
		(.253)	(.257)	(.714)	(.000)	(.825)
Cost shock		2.193	15.550	3.303		
		[0.897]	[12.510]	[7.744]		
		(.015)	(.214)	(.670)		
Relatedness (1,0) * cost shock		14.773	289.766	39.486		
		[5.640]	[20.867]	[44.113]		
		(.008)	(.000)	(.371)		
Cost shock (state)					−0.250	−0.003
					[0.042]	[0.049]
					(.000)	(.945)
Relatedness (1,0) * cost shock (state)					11.112	−0.170
					[0.502]	[0.215]
					(.000)	(.429)
Democratic state (1,0)	0.473	1.358	43.456	−18.491	29.464	−19.445
	[1.032]	[1.170]	[5.193]	[1.654]	[1.360]	[1.301]
	(.647)	(.246)	(.000)	(.000)	(.000)	(.000)
HHI	−6.031	−1.739	−121.091	−77.848	−232.100	−51.735
	[6.971]	[9.016]	[15.770]	[65.667]	[30.126]	[26.127]
	(.387)	(.847)	(.000)	(.236)	(.000)	(.048)
Log (income per capita)	66.410	84.480	14.483	−6.790	7.041	−14.416
	[26.760]	[30.659]	[2.199]	[7.922]	[0.882]	[1.951]

TABLE 2 (Continued)

DV = exit(1,0)	(1) All firms	(2)	(3) Low capability firms	(4) High capability firms	(5) Low capability firms	(6) High capability firms
	(.013)	(.006)	(.000)	(.391)	(.000)	(.000)
Log (Total assets)	−0.210	−0.404	−2.724	−0.502	−0.918	−1.159
	[0.159]	[0.209]	[3.059]	[0.483]	[0.657]	[1.492]
	(.187)	(.053)	(.373)	(.299)	(.163)	(.437)
Return on assets	−1.235	1.114	15.921	−4.303	−2.465	−2.772
	[1.348]	[2.001]	[15.461]	[17.060]	[1.919]	[11.320]
	(.360)	(.578)	(.303)	(.801)	(.199)	(.807)
Liability ratio	−0.715	−1.477	−6.418	71.990	−3.536	46.416
	[0.768]	[1.014]	[3.245]	[55.490]	[2.371]	[19.025]
	(.352)	(.145)	(.048)	(.194)	(.136)	(.015)
NonIndividualnonMedicaidEnrollment	0.060	0.138	0.801	2.344	−0.100	1.815
	[0.179]	[0.208]	[1.953]	[1.590]	[0.213]	[0.568]
	(.736)	(.508)	(.682)	(.140)	(.639)	(.001)
Redeployment	0.226	−0.112	−1.669	0.778	−0.070	0.583
	[0.110]	[0.180]	[1.235]	[0.438]	[0.322]	[0.353]
	(.040)	(.533)	(.177)	(.076)	(.829)	(.098)
Observations	163	163	71	62	71	62
Log-likelihood	−36.47	−29.15	−3.781	−4.870	−8.467	−5.481

Note: Robust standard errors in brackets, followed by p values in parentheses. The number of observations drops in Columns (3/5) and (4/6) due to the loss of within-group variation in subsamples. Re-estimating Columns (1) and (2) using the observations kept in Columns (3/5) and (4/6) generates similar results. All models use State as the matched group variable.

mechanisms of resource redeployment and resource sharing. If the resource redeployment effect dominates, we would observe a substitution effect between the size of operations in the old and the new segment. Otherwise, if resource sharing dominates, we would observe a complementary effect. This is because when a more related diversifier exits the ACA market, (a) it will stop sharing resources between Medicaid and ACA, which will remove economies of scope and restore its cost to the pre-ACA level, thereby reducing the optimal level of its Medicaid business, or (b) it can redeploy resources from the ACA business to the Medicaid business,

TABLE 3 Presence in the ACA market and Medicaid enrollment

DV = Medicaid enrollment	(1)	(2)
In ACA (1,0)	277,606	
	[49,122]	
	(.000)	
In ACA (1,0; lagged)		252,915
		[52,077]
		(.000)
Democratic state (1,0)	−53,068	−61,155
	[23,761]	[25,073]
	(.026)	(.015)
HHI	7,527	7,281
	[24,801]	[26,910]
	(.762)	(.787)
Log (Total assets)	48,719	49,518
	[7,064]	[7,874]
	(.000)	(.000)
Return on assets	38,530	55,109
	[24,354]	[25,884]
	(.114)	(.033)
Liability ratio	6,748	7,445
	[2,228]	[2,442]
	(.002)	(.002)
NonIndividualnonMedicaidEnrollment	−25,596	−57,342
	[86,730]	[107,275]
	(.768)	(.593)
Constant	−803,371	−787,882
	[154,169]	[174,486]
	(.000)	(.000)
Observations	10,677	9,301
Adjusted R^2	0.854	0.857

Note: Robust standard errors in brackets, followed by p values in parentheses. All models include firm-, state-, and year-fixed effects.

which will increase its business volume in Medicaid. As we explained in Section 4, various industry studies have reported a complementary effect, that the impact of ACA on Medicaid was positive rather than negative.

To provide statistical evidence, we compared in Table 3 firms' Medicaid enrollment when they were present in versus when they were absent from the ACA market. The independent variable *In ACA* is a dummy variable that is set to 1 for the year when the firm operated in the ACA market and 0 otherwise. With firm fixed effects, the coefficient on the lagged *In ACA* variable demonstrates the change in Medicaid enrollment a year after a firm entered or exited the ACA market. Table 3 shows a complementary effect: the firm's Medicaid enrollment increased the year after it entered the ACA market and decreased the year after it exited the ACA market. Column (1) uses current *In ACA* and Column (2) uses lagged *In ACA*. The results are similar.

6.3 | Robustness check

We provided a number of additional tests in the Appendix S1 (Section 5) using different specifications and measures to assess robustness. First, in the entry analysis, we included in the risk set for each firm only the states where the firm already had a non-Individual business. As a robustness check, we used alternative risk sets that included (a) all states geographically adjacent to the firm's operating states, or (b) all states (even the states where the firm had no insurance business). Results are similar. However, these alternative risk sets are large and make entry a rare event. In order to mitigate bias when estimating rare events with a standard logit model (Tomz, King, & Zeng, 2003), we also re-estimated entries using rare-event logit models. The results are similar. Second, we used a survival model to account for right-censoring. Our results also hold.

7 | DISCUSSION AND CONCLUSIONS

The starting point for this article was addressing a gap in theories of diversification that typically examined entry or exit decisions separately. We sought to complement the contribution in Lieberman et al. (2017), who offered a model of both entry and exit. In their model, it is the potential to engage in reversible experimentation (via redeployment of assets from one business to another) that induces firms to engage in both higher levels of related diversification and exits. While this model provides a simple and intuitive explanation for diversification involving sunk costs of entry, it does not explain cases where similar levels of entry and exit occur even when sunk costs of entry are not salient. Our paper aimed to fill this gap in theory and leverage a dataset on insurance firms' entry into and exit from the ACA market. The paper offers three principal contributions to the broader strategy and diversification literatures.

Our first contribution is the simple model of entry and exit that unites two distinct theories of diversification—one based on sharing resources and one based on leveraging firm capabilities. Using this simple model, first, we show that more related diversifiers with lower capabilities are more likely to enter a new segment as compared with firms with lower relatedness but similar capabilities. Second, we show that following a cost shock, such related diversifiers with lower capability are also more likely to exit the new segment as compared with firms that entered with less relatedness advantages. In other words, relatedness favors entry by lowering the entry threshold for capability. However, upon facing an unfavorable cost shock post-entry, the same firms face a reverse selection effect that prompts exit. Thus, we are able to explain why related diversifiers might both enter and exit industries at higher rates even when sunk costs of entry are not salient. The model itself follows the tradition of passive learning models in both the strategy (Lippman & Rumelt, 1982) and IO literatures (Jovanovic, 1982), where the key ingredient generating ex-post heterogeneity is a stochastic post-entry profit or cost draw that determines whether a firm stays in the industry or exits. To these models of selection, we add capability differences to generate a richer set of predictions that help explain empirical patterns of related diversification and exits.

Second, there is increasing empirical evidence that positive demand shocks (e.g., opening up of a market to international trade or changing regulations facilitating new market opportunities) are associated with heightened levels of simultaneous entries and exits of firms (Melitz & Redding, 2012). The dominant explanation for such a pattern is that a larger market in the wake of a demand shock triggers the entry of larger and more productive firms that ignored the market when it was small. The entry of the larger and more efficient firms squeezes the less efficient firms out of the market resulting in the reallocation of resources from less productive to more productive firms. While this is certainly possible, our model and empirical evidence suggest that the source of heterogeneity may not lie only in the differences between more productive entrants and less productive incumbents. Our model opens up heterogeneity between entrants themselves. Firms that are less efficient but enjoy relatedness benefits are more likely to enter following a demand shock as compared with their equally efficient counterparts that do not possess any relatedness advantages. However, in the wake of unexpected cost shocks, the higher capability (but lower relatedness) entrants are better able to survive. This offers an alternative explanation for the observed cleansing effect of positive demand shocks where the productivity of industries rises.

Finally, the paper leverages a new dataset on insurance firms' entry into and exits from the ACA exchanges following the implementation of the ACA. The health insurance industry is a critically important industry accounting for over 24% of government spending, and health insurance is the largest component of nonwage compensation (Nunn, Parsons, & Shambaugh, 2020). The passing of the ACA resulted in the largest reduction in the uninsured population in the US in over a generation while simultaneously posing many policy questions around the stability and feasibility of serving this group of customers. Our study joins a small part of this debate in showing that the churn of entry and exit in the ACA market could be an expected process of related diversifiers aggressively entering the market, learning about the profit potential and exiting if it doesn't actually meet their profitability standards.

The paper also offers an interesting implication for a longstanding assertion in the diversification literature, that "firms diversifying into unrelated businesses usually had lower profits but also lower risk" (Amit & Livnat, 1989, p. 879). The lower risk for unrelated or less related diversification is believed to be due to lower covariance in cash flows. This will be beneficial to firms when solvency risks such as bankruptcy are a concern (Amit & Livnat, 1988). Our model suggests a different and more nuanced mechanism for this conclusion: More related diversifiers, especially the low capability ones, might experience higher risks not only because of more correlated industry-specific cashflows but also because of the greater rates of entry and exit as compared with less related diversifiers that face a disadvantage at entry due to lack of expected synergies. Unrelated or less related diversifiers face a higher capability threshold at entry which allows them to better cope with unexpected cost shocks and thus also mitigate their exit risk.

This conjecture, while plausible, might appear to contradict survival-based measure of relatedness, such as those developed by Bryce and Winter (2009) and Teece, Rumelt, Dosi, and

Winter (1994). The logic behind the survival-based measure of relatedness is that "surviving firms are repositories for knowledge, skills, and resources" and their activities across industries are revelatory of the resource relatedness across industries (p. 1571). Our speculation that firms with less relatedness are more likely to be stable in their diversification patterns presents a point of discord. We believe the apparent discord can be explained in two ways. First, our model only predicts a less stable portfolio composition for more related but *low capability* firms. Portfolio compositions of high capability firms do not differ in our model and may be explained by other factors offered in the literature, such as synergies, agency, or risk. Second, our model only predicts post-entry exits facing negative shocks. When post-entry shocks are nonexistent or positive, survival might be screened based on competition rather than zero profit margin, and more related diversifiers may have a higher conditional and unconventional probability of staying in the new segment. To the extent that post-entry shocks can be negative, nil, or positive, it is not surprising that the empirical relationships between relatedness and exit are inconclusive (Lieberman et al., 2017). Therefore, the applicability of a survival-based measure of relatedness depends on the capability distribution and industry dynamics of the empirical setting. We leave this as an opportunity for future study.

This article has a few limitations that provide additional opportunities for future research. First, our paper focuses on the joint selection effect of capability and economies of scope arising from resource sharing. We do not model resource redeployment as in Lieberman et al. (2017). Whether the theory of resource redeployment or our theory prevails depends on the specific empirical context and the type of applicable resources. The question about a potential complementary versus substitutive relationship between resource sharing and resource redeployment, as posed by Folta, Helfat, and Karim (2016), is an intriguing one. We are not able to study this relationship in this particular paper as our empirical context requires little resource redeployment. Therefore, we leave the joint effect of resource sharing, resource redeployment, and capability on diversifying entry and post-entry exit for future study when clear measures of resource sharing vs. resource redeployment become available.

In addition, our empirical context is the healthcare industry, where all diversifiers are somehow related, even though our formal model can be generalized to diversification with a broad range of relatedness. Detailed empirical studies in alternative contexts with a larger variation in relatedness may shed additional light on the underlining mechanisms. Fourth, we did not construct risk-adjusted measures of cost for each segment. Future studies can use such measures when data becomes available. Finally, we did not study the ACA market under the Trump administration, which sharply changed the implementation of ACA in 2017 and generated a different shock with multidimensional effects (e.g., the elimination of the individual mandate, the work requirement for Medicaid, the reduction in healthcare cost-sharing, etc.). We decided to focus the current study on cost shocks rather than policy uncertainty. Future studies of the ACA market during more recent periods could incorporate policy uncertainty and provide additional insights on entry and exit decisions by more vis-à-vis less related diversifiers.

In sum, through both a formal model and empirical analyses using unique data, this article provides a more nuanced study of both entry and exit made by more versus less diversifiers. Despite its shortcomings, it incorporates intra-temporal economies of scope and firm capability to shed light on the underlying mechanisms driving diversifying entry and exit.

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DATA AVAILABILITY STATEMENT

Research data are not shared due to third party license restriction.

ORCID

Yue Maggie Zhou https://orcid.org/0000-0001-7102-6484
Weikun Yang https://orcid.org/0000-0001-7501-1116
Sendil Ethiraj https://orcid.org/0000-0002-2462-3435

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

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