DOES EXPERIENCE IMPLY LEARNING?

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Research Summary

Research traditionally uses experiential learning arguments to explain the existence of a positive relationship between repetition of an activity and performance. We propose an additional interpretation of this relationship in the context of discrete corporate development activities. We argue that firms choose to repeat successful activities, thereby accumulating high experience with them. Data on 437 aircraft projects introduced through three governance modes show that the positive performance effect of the firm's experience with the focal mode becomes insignificant after accounting for experience endogeneity. We suggest that in a general case, experience with corporate development activities may be tinged with both learning as well as selection effects. Therefore, omitting to account for experience endogeneity may lead to incorrect conclusions from an "empirically observed" positive experience-performance relationship.

125 words

Managerial Summary

This paper emphasizes that firms generally choose to undertake the corporate development activities (new product introductions, diversification moves, international expansions, alliances, acquisitions, etc) with which they have been the most successful in the past and expect to be the most successful in the future. Hence, if a firm possesses certain capabilities, it will repeatedly engage in certain activities corresponding to those capabilities, thereby simultaneously achieving high levels of activity experience as well as superior activity performance. This view suggests that an "empirically observed" positive experience-performance relationship may not be due solely to learning-based enhanced capabilities but also driven by astute self-selection. Overall, we provide a new interpretation of the relationship between experience and performance in the context of infrequent, heterogeneous, and causally-ambiguous corporate development activities.

125 words

Key words: Corporate development activities, experience, learning, endogeneity, *make-ally-buy* choices.

The experience-performance relationship is fundamental to the strategic management literature. This relationship is generally operationalized as the association between the number of times a firm has conducted a particular activity and the resulting performance, and is interpreted consistent with the long-standing idea that practice enhances efficiency through learning processes (BCG, 1970). Drawing upon this idea of learning-by-doing[1], research has shown that experience is a key driver of performance in a wide range of operational processes such as good manufacturing and service delivery (for a review, see Argote, 1999). More recently, the study of the experience-performance relationship has been expanded to numerous corporate development activities (CDAs) including new product introductions, diversification moves, international expansions, alliances, and acquisitions (Shaver, Mitchell, and Yeung, 1997; Anand and Khanna, 2000; Hayward, 2002; Nerkar and Roberts, 2004; Sampson, 2005; Mulotte, 2014). These studies generally assume a positive relationship between experience and performance at least as a starting point and attribute it to experiential learning, consistent with the previous analyses of operational processes.

We argue that in the context of CDAs, while experience may allow for some experiential learning (as theorized in the previous literature), it also involves a strong self-selection effect in that firms are likely to have *chosen* to accumulate their experience. Different from operational processes in which experience is mainly accumulated through a routinized, semi-automatic pattern, experience with CDA-type decisions results from discrete choices. Further, relative to operational processes, CDA-type decisions involve lower levels of similarity and frequency as well as higher levels of causal ambiguity and outcome ambiguity (Reed and DeFillippi, 1990; Zollo and Singh, 2004; Zollo, 2009). As a result, given the complicated nature of decision making processes in CDA-type decisions, firms are likely to

[1] Throughout the paper, by 'learning' we mean learning-by-doing rather than other forms of learning (Levitt and March, 1988). By "experience", we only mean the repetition of a task and thus do not refer to any form of experiential learning, learning-by-doing, enhanced efficiency, or improved competency.

repeat and accumulate experience in their past successful activities with the expectation that doing so will enable them to achieve superior future performance. Consistent with this reasoning, we claim that experience accumulation in CDAs does not result from exogenous or random choices but rather from endogenous decisions driven by superior performance expectations. It follows that the positive performance impact of experience observed or otherwise assumed by research on CDAs may not solely be due to experiential learning, but also driven by the endogenous nature of the accumulation of experience.

We test this argument using data on 437 aircraft projects introduced by 159 firms during the 1944-2000 period through three governance modes, namely internal development, joint development, and licensing. We analyze the performance impact of the firms' experience with the same mode of new product introduction (NPI) as that used for the focal NPI. The results largely support our view. When we do not account for the endogeneity of the firms' NPI-mode experience, experience significantly enhances performance, consistent with previous findings (e.g., Nerkar and Roberts, 2004). However, once we account for experience endogeneity, the performance impact of experience becomes insignificant, albeit still positive. We do not mean to imply that learning effects are absent in CDAs; rather, we suggest that in a general case, experience with CDAs is tinged with both a learning effect and a selection effect. Moreover, even though firms will primarily self-select the CDAs for which they have the appropriate capabilities, they may improve these capabilities through experiential learning (Helfat, 2000), which will reinforce even further the selection effect in future endeavors.

Our research contributes to the stream of the strategy literature that examined experience effects in CDAs. On the theoretical side, we propose that CDA experience also has a self-selection facet that empirical researchers should take into account since omitting to do so might bring about incorrect conclusions from an "empirically observed" positive experience-performance relationship. Our findings also suggest that experience with CDA-type activities may reflect capabilities developed through a combination of selection and learning since firms would purposely gather experience with the activities for which they have the necessary capabilities while improving them through learning processes. On the empirical side, we use a rigorous procedure to address the endogeneity of the experience variable: we first model the firm's decision to engage in a certain CDA by identifying an "excluded" instrument that has no direct impact on performance, then use the *simulated* level of CDA experience derived from the first-stage model as another instrument for CDA experience. Such an approach differs from the well-known Instrumental Variables two-stage least-squares (IV-2SLS) procedure and is effective in addressing the endogeneity of categorical decision variables or their variants. Overall, we provide a new perspective to supplement the experiential learning interpretations in the extant organizational learning literature, and offer suggestions for future empirical analyses of experience-performance relationships in CDAs.

BACKGROUND

A longstanding theme of strategy research has been the relationship between experience and performance. As early as 1776, Adam Smith examined this relationship when he analyzed the benefits from the specialization of tasks. He asserted that task specialization enables workers to benefit from efficiency gains (referred to as "dexterity") as well as to avoid potential costs entailed by task selection processes.[2] Drawing upon this idea that experience leads to learning benefits, research has shown that experience greatly improves performance in a wide range of product manufacturing and service-based operational processes, including oil refining (Hirschmann, 1964), chemical processing (Lieberman, 1989), ship building (Argote, Beckman, and Epple, 1990; Thornton and Thompson, 2001), pizza delivery (Darr, Argote, and Epple,

[2] Adam Smith indicated that increased performance due to the division of labor "is owing to three different circumstances; first, to the increase of dexterity in every particular workman; secondly, to the saving of the time which is commonly lost in passing from one species of work to another; and lastly, to the invention of a great number of machines which facilitate and abridge labour" (1776: chapter 1).

1995), semiconductor manufacturing (Hatch and Mowery, 1998), and aircraft manufacturing (Wright, 1936; Argote, Beckman, and Epple, 1990; Benkard, 2000).

Organizational learning research has replicated this logic in the context of CDAs. Specifically, several scholars have examined the relationship between a firm's experience and the performance of new product introductions (Moorman and Miner, 1997; Nerkar and Roberts, 2004; Mulotte, 2014), diversification moves (Pennings, Barkema, and Douma, 1994; Barkema and Schijven, 2008), international expansion (Barkema, Bell, and Pennings, 1996; Delios and Beamish, 2001; Shaver *et al.*, 1997), strategic alliances (Anand and Khanna, 2000; Delios and Beamish, 2001; Gulati, 1995; Hoang and Rothaermel, 2005; Sampson, 2005) and corporate acquisitions (Barkema *et al.*, 1996; Vermeulen and Barkema, 2001). In general, such studies have proposed and observed a positive experience-performance relationship, and have attributed it to effective experiential learning, consistent with the framework applied for operational processes. When the results are not consistent with this framework, the explanation typically involves the lack of transferability of learning from one context to another (e.g., Haleblian and Finkelstein, 1999; Nadolska and Barkema, 2007); therefore, the explanation is, in either case, based on learning (or inappropriate learning).

While this aforementioned work sheds important light on the experience-performance relationship in the context of CDAs, it suffers from two key limitations. Firstly, it has underestimated the difference between operational and CDA-type activities. Firms are most likely to learn from accumulating experience with a particular activity when the activity is characterized by high levels of frequency (Cyert and March, 1963), when it is similar to what was done in the past (Cohen and Levinthal, 1990), and when it involves low levels of causal (Reed and DeFillippi, 1990) and outcome ambiguity (Zollo, 2009). However, relative to operational processes, CDA experiences generally involve higher levels of causal and outcome ambiguity as well as lower levels of frequency and similarity (Hayward, 2002; Zollo, 2009);

they are thus not well suited to experiential learning processes (Levitt and March, 1988). Secondly, this work has not taken into account the possibility that, in CDAs, firms *purposely* choose to gather their experience, which might not generally be the case in operational processes.

We argue that in the context of CDAs, a positive experience-performance relationship may not be only caused by enhanced efficiency resulting from experiential learning processes, but also driven by astute self-selection, in the sense that firms tend to choose to repeat the CDAs associated with the highest past performance. Extant research highlighted the endogenous nature of several CDA-type decisions, including the choice between different manufacturing modes (Leiblein *et al*., 2002), foreign entry modes (Shaver, 1998; Slangen and Hennart, 2008), alliance types (Sampson, 2004), alliance portfolio strategies (Vasuveda and Anand, 2011), and NPI modes (Castañer *et al*., 2014). We complement this literature by taking into account the possibility that firms make each of the CDA-type decisions included in their experience on the basis of superior performance expectations. Cyert and March (1963) emphasize that a strong performance increases a firm's likelihood of persisting with prior actions, whereas a poor performance promotes exploration of new strategies (see also Lant, Miliken and Batra, 1992; Greve, 1998). We thus argue that when firms consecutively undertake CDAs of the same type, they are likely to expect to maximize performance by repetitively doing what they have done in the past (Robertson and Gatignon, 1998; Haleblian, Kim, and Rajagopalan, 2006).

This view, however, poses empirical challenges in that some of the factors driving such repetition-based decision-making, which happen to be difficult or even impossible to observe or measure, may also have a pivotal impact on performance. For instance, a firm that owns the (unobservable) skills required to undertake a given CDA in a particular way will eventually enjoy high levels of activity experience as well as achieve superior activity performance. This means that experience with CDAs is tinged with endogeneity, for which empirical researchers of the performance impact of experience must decidedly account. Simply regressing performance on CDA experience would generate inconsistent and biased estimation of the experience effects (Greene, 1990); the coefficient for the experience variable could actually be higher, lower, or even of a different sign (Antonakis *et al*., 2010).

It is noteworthy that we do not mean to imply that learning effects are absent in CDAs; rather, we suggest that CDA experience may have both a learning facet and a selection facet. For example, start-up firms may base their CDA-type choices on their pre-founding experience, managerial inclinations, peer imitation, or even luck. If they are successful, they are likely to repeat this choice and accumulate experience with it. In doing so, they may develop certain skills with this specific CDA via learning processes, which will lead them to a virtuous cycle of persisting with this choice. On the other hand, if they are unsuccessful, they are likely to look for alternatives and may not accumulate experience in their initial choice, and also not benefit from experiential learning. In this way, the two mechanisms, both selection and learning, together may drive a positive relationship between experience and performance and even reinforce each other. Figure 1 depicts the causal relationships associated with the learning facet and the selection facet of experience accumulation processes.

-------------------------Include Fig. 1 about here -------------------------

Overall, the key implication of our view is that *the positive effect of experience on performance that extant corporate strategy research traditionally observes may not be due solely to experiential learning, but also driven by experience endogeneity*.

EMPIRICAL ANALYSIS

Empirical context and data

To demonstrate our view, we empirically examine New Product Introduction (NPI) processes. Building on the fact that firms may launch new products through internal development, joint development, or licensing (White, 2000), we examine the performance impact of the firm's experience with the same NPI mode as that used for the focal product (referred hereafter to as "same-NPI-mode experience"). Although firms are likely to self-select which CDA they undertake in many settings, NPI is a particularly good setting to examine the extent to which experience endogeneity affects the experience-performance relationship for the following reasons. First, extant research provided empirical evidence that the NPI-mode choice has significant implications on firm performance and survival (Brown and Eisenhardt, 1995; Danneels, 2002). At the same time, research found that both general NPI experience (Moorman and Miner, 1997; Nerkar and Roberts, 2004) and same-NPI-mode experience (Mulotte, 2014) are key drivers of NPI performance. This effect traditionally has been interpreted as evidence for productive experiential learning.

We test the relationship between same-NPI-mode experience and NPI performance on a proprietary dataset that comprises essentially all jet aircraft projects launched by Asian, European, and South and North American firms between 1944 and 2000 in four areas of business: fighter, turboprop, helicopter, and jet (including jet airliner, jet cargo, and business jet). Our sample consists of 437 new aircraft introductions undertaken by 159 firms. They include 189 fighters, 110 turboprops, 74 helicopters, and 64 jets. The number of NPIs per firm ranges from 1 to 13, with a mean of 2.75. Of the 159 firms in our sample, 41% appear once, 17% twice, 16% three times, 8% four times, 7% five times, and 11% six times or more.

Our main data source is the *Aerospace Systems Group Library* (FI/DMS, 2000), which consists of individual reports on each aircraft project commercialized since WWII. The reports provide technical characteristics (e.g., maximum payload, range and speed), the dates of maiden flight and initial deliveries, estimated unit price and total production, and when relevant, licensees and firms sharing prime contractorship. FI/DMS specifies the cumulative production up to 2000. It also provides the project's NPI mode, distinguishing between internal developments (e.g., the Boeing B-737), joint developments (e.g., the Aerospatiale/BAC Concorde), and licensing (e.g., the Canadair CF-116, which is a license-built version of the Northrop F-5). Overall, our data include 262 introductions of internally-developed aircraft, 72 introductions of jointly-developed aircraft, and 103 introductions of licensed aircraft. We verified the information available in the *Aerospace Systems Group Library* with the *All the World's Aircraft* yearbooks (Jane's, 1944-2000).

Variables and Measures

Our dependent variable *NPI Performance* is the aircraft's cumulative unit sales (FI/DMS, 2000). This is a traditional measure of product performance in the aircraft industry (Mulotte *et al*., 2013; Castañer *et al*., 2014; Mulotte, 2014). Overall, *NPI Performance* ranges from 3 to 14,896 with a mean of 245 in our dataset.[3] Because *NPI Performance* displays a lognormal distribution, we take a log transformation after dividing the sales figures by 1,000. Our independent variable *Mode Experience* is the number of times that firms have used the same NPI mode as that used for the focal product (internal development, joint development, or licensing) since their entry in the relevant area of business, consistent with prior studies of experience effects in NPI (Moorman and Miner, 1997; Nerkar and Roberts, 2004). *Mode Experience* ranges from 0 to 9, with an average of 1.15. In our dataset, 48% of the NPIs were undertaken by firms with no prior experience with the focal mode, 22% by firms with one prior experience, and 30% by firms with two or more.

As for the controls, *Firm Size* estimates the firm's revenues in the relevant area of business: fighter, turboprop, helicopters, and jet (Mulotte, 2014). We expect larger firms to enjoy greater sales on any new project. The dummy variable *State Owned* equals to one if the

[3] 115 aircraft projects included in our sample were still being produced in 2000. To avoid right-censoring bias, we estimate unit sales based on the average yearly cumulated production (by percentage) of those projects whose production was terminated in 2000. We find that, on average, aircraft projects reached 6% of their total production in the first year, 13% by the end of the second, 38% by the end of the fifth, 68% by the end of the tenth, and 86% by the end of the fifteenth, with production falling after that (Jane's, 1944-2000). Drawing upon those trends, we extrapolate the cumulative unit sales for aircraft projects still in production in 2000.

focal firm was owned by a national government. *Prior Firm Performance*, measured by the average sales performance of all prior products introduced by the same firm in the same area of business, controls for performance heterogeneity across firms and areas of business. The dummy variable *Incumbent* assesses whether the focal product is the firm's first product in the relevant area of business and the *Age in Market* variable captures the firm's number of operating years in the relevant area of business. The dummy variable *Military Design* equals to one if the focal aircraft was designed for military use. *Relative Technical Complexity* may impede sales (Kessler and Chakrabarti, 1996). We estimated an aircraft's technical complexity by the logarithm of its maximum speed, range, and takeoff weight (Frenken and Leydesdorff, 2000). We obtained *Relative Technical Complexity* by dividing the technical complexity of the focal aircraft by the technical complexity of the most complex aircraft introduced by the same firm in the same area of business. We also introduce a categorical variable *Area of Business,* which equals to 1 for the fighter area of business, 2 for helicopter, 3 for prop, and 4 for jet. NPI mode dummies capture whether the focal product is an *Internal Development* (omitted), a *Joint Development*, or a licensed product (*Licensing*). *Prior Mode Success* is the average sales performance of all prior products that the firm has launched with the focal mode in the same area of business. The *Number of Competitors* variable, which is the number of firms that operated in the area of business in the year prior to each introduction, controls for the level of competitive intensity. We measured the *Potential Market Size* with the GDP of firm's home country because national preference is an important factor in purchases of both military and commercial aircraft. We also estimated the *Economic Climate* with the GDP growth in the firm's home country, as aircraft sales may be driven by economic growth (Anand and Singh, 1997). The *Year* variable, which is the date for each project on which the first aircraft delivery took place, captures any trend effects.

Analytical Approaches

We first use the OLS specifications to show consistency with past work. Replicating the methodology used by past research, we use the following functional form:

$$PERF_{m,i,t} = \beta_0 + \beta_1 EXP_{m,i,t} + X_{m,i,t}\theta + \varepsilon_{m,i,t} \tag{1}$$

where $PERF_{m,i,t}$ is the performance of product i that firm m launched at year t, $EXP_{m,i,t}$ indicates the same-NPI-mode experience that firm m has accumulated prior to year t, θ is a coefficient vector, $X_{m,i,t}$ is a vector of control variables, and $\varepsilon_{m,i,t}$ is the error term. As a further refinement, we capture time-invariant firm heterogeneity with firm dummies.

As discussed earlier, the experience variable ($EXP_{m,i,t}$) might be endogenous because unobservable factors affecting NPI performance might also drive NPI experience, leaving $EXP_{m,i,t}$ to correlate with the error term $\varepsilon_{m,i,t}$. Although IV estimation is commonly used to overcome endogeneity biases (Bascle, 2008; Antonakis *et al.*, 2010), it is particularly challenging in our setting because we cannot directly apply the conventional IV-2SLS reasoning. The conventional IV-2SLS procedure is useful to address the endogeneity of a continuous variable; it estimates the first-stage equation by OLS, then substitutes the linear fitted value from the first stage for the endogenous variable in the second-stage main equation. Our potentially endogenous variable ($EXP_{m,i,t}$) is the sum of a categorical variable (i.e., using a given mode or not at a given year) over time, which research usually estimates via nonlinear models (e.g., multinomial logit) rather than OLS. When the first-stage model is nonlinear, the substitution practice in the second stage is not allowed because nonlinear models cannot guarantee to generate first-stage residuals that are uncorrelated with fitted values and exogenous controls (Angrist and Pischke, 2008). A solution to this problem is to use the nonlinear fitted values as instruments (Angrist, 2001) instead of directly replacing the endogenous variable in the second-stage equation with the first-stage fitted values (as done in the conventional IV-2SLS procedure).

We thus run a nonlinear model in the first stage to calculate the fitted values, which we then use as *an instrument* for the endogenous variable in the second-stage main equation. Specifically, we use a multinomial logit in the first stage to estimate the firm's likelihood to bring to market the focal product through *Internal Development*, *Joint Development*, or *Licensing*. We estimate the following mode-choice model:

$$Prob(Y = j) = \frac{e^{W_{m,i,t}\delta_j}}{\sum_{k=1}^{3} e^{W_{m,i,t}\delta_k}} \quad (2.1.1)$$

j ∈ {internal development, joint development, licensing}

where the dependent variable is *NPI Mode* (=1 for internal development, =2 for joint development, and =3 for licensing – benchmark case), and $W_{m,i,t}$ is a vector of exogenous characteristics for product *i* launched by firm *m* at year *t.* The vector $W_{m,i,t}$ includes the control variables used in the vector $X_{m,i,t}$ (Equation 1), except the dummy variables capturing the NPI-mode choice*,* which are now included in the dependent variable.

We construct the predicted mode choice for a given project ($\widehat{Mode_{m,i,t}}$) by selecting the NPI mode for which the multinomial logit produces the highest predicted probability among the three. We then use $\widehat{Mode_{m,i,t}}$ to count the frequency that firms are predicted to use the focal mode since their entry. This predicted frequency ($\widehat{EXP_{m,i,t}}$) is computed as follows:

$$\widehat{EXP_{m,i,t}} = \sum_{t=1}^{T} \widehat{Mode_{m,i,t}} \quad (2.1.2)$$

where $\widehat{Mode_{m,i,t}} = j \; if \; Prob(Y = j) > Prob(Y = -j)$

j ∈ {internal development, joint development, licensing}

We use $\widehat{EXP_{m,i,t}}$ as *an instrument* for the endogenous variable $EXP_{m,i,t}$ and then apply the conventional IV-2SLS procedure to estimate Equation (2.2), the equation of primary interest.[4]

$$PERF_{m,i,t} = \beta_{0IV} + \beta_{1IV} EXP_{m,i,t} + X_{m,i,t}\theta_{IV} + \varepsilon_{m,i,t} \quad (2.2)$$

Exclusion Restriction Requirement

[4] Instead of using the sum of the predicted modes ($\widehat{EXP_{m,i,t}}$) as the instrument, we also used the sum of the predicted probabilities from equation (2.1.1) as an instrument for the endogenous experience variable and applied IV-2SLS to estimate equation (2.2). All our results still hold with this alternative specification.

IV estimations require at least one "excluded" explanatory variable (also referred to as "excluded instrument") that influences the first-stage equation but not the second-stage equation (Angrist and Pischke, 2008: 116-117).[5] Our "excluded instrument" is *IPR Effectiveness,* which measures the effectiveness of the IPR protection in the focal firm's home country. We thus use the International Patent Protection Index (Ginarte and Park, 1997; Park, 2008). This index is available for 110 countries worldwide and is based on five elements of patent law: coverage; membership in international treaties; duration of protection; enforcement mechanisms; and restrictions. This index, which provides an indicator of the strength of patent protection, has been widely used in strategy research (e.g., Oxley, 1999; Sampson, 2004; Zhao, 2006; Reuer and Tong, 2005).

The effectiveness of the IPR protection regime has been identified as an important factor affecting the choices of innovation activities for a firm (Teece, 1986; Veugelers and Cassiman, 1999), especially in the aircraft manufacturing industry (Cohen, Nelson, and Walsh, 2000). If a country has good IPR protection, its firms will have a greater incentive to develop technology internally since they may reap more "rents" from the technology in the long term. On the other hand, in countries with weak IPR protection, firms are less likely to invest in internal development of technology and may be keener to in-license older existing forms of technology. At the same time, however, in an efficient market for technology under strong IPR protection, firms may buy technology on the external market, making in-licensing also an attractive option (see, for instance, Oxley, 1999). Although the impact of the IPR protection regime on the NPI-mode choice is not straightforward, it is certainly an important factor influencing the firm's choice. Nevertheless, there are no theoretical reasons to expect IPR

[5] This exclusion restriction "is not strictly required" in our case, because we use a nonlinear model in the first stage to generate the instrument (Ravallion, 2008: 3824). Although the nonlinearity of the first-stage model allows our second-stage equation to be technically identified, we prefer to avoid this sort of back-door identification (Angrist and Pischke, 2008) and still meet this exclusion restriction requirement. As a result of our efforts, the source of identification becomes clearer.

effectiveness to have any direct effect on aircraft unit sales over the years, which is a function of demand.

We also checked that *IPR Effectiveness* satisfies both statistical conditions that make it a reasonable "excluded instrument". First, we verified that *IPR Effectiveness* correlates sufficiently with the endogenous experience variable by checking its significant impact in the first-stage model (Cassiman and Veugelers, 2006; Moatti *et al.*, 2015). As Table 2 shows, the coefficient of *IPR Effectiveness* is positive and highly significant for *Internal Development* (β=0.571, p-value=0.009) and for *Joint Development* (β=0.645, p-value=0.020), suggesting that firms are more likely to depart from licensing when IPR protection is more effective. Second, we regressed *NPI Performance* on *IPR Effectiveness* and the set of exogenous controls used in vector $X_{m,i,t}$ (including firm dummies). As expected (and required), the coefficient of *IPR Effectiveness* is insignificant (β=0.148, p-value = 0.342).[6]

RESULTS

We provide descriptive statistics and a correlation matrix in Appendix 1. Table 1 reports the results of the analysis. Following the traditional research design, we estimate Equation (1) with OLS specifications (see Model 1). In Model 2, we add firm dummies to capture time-invariant firm heterogeneity. The overall pattern of our variables does not reveal a tendency toward multi-collinearity as individual VIF measures are inferior to the generally accepted threshold of 10, with a maximum mean at 2.33 without firm dummies and 5.33 with firm dummies. The *Mode Experience* variable is significant and positive in both models (β_1=0.148, p-value<0.05, Model 1; β_1=0.159, p-value<0.05, Model 2). Overall, these findings corroborate

[6] As a further analysis, we also regressed *NPI Performance* on *IPR Effectiveness*, *Mode Experience*, and the same set of exogenous controls. The coefficient of *IPR Effectiveness* becomes marginally significant (coefficient=0.497, p-value = 0.073) and the coefficient of *Mode Experience* remains positive and significant (coefficient=0.158, p-value = 0.036), suggesting that IPR effectiveness affects NPI performance only indirectly through mode experience. All the analysis results regarding the validity of our instrument are available from the authors upon request.

extant research: experience significantly enhances performance when we do not consider experience endogeneity.

Models 3 and 4 examine the performance impact of experience, while accounting for its endogeneity. We focus on Model 4 which includes firm dummies and present Model 3 for comparison purposes only. Prior to discussing the IV estimation results, we need to show that the first-stage multinomial logit model is a reliable procedure to generate our instrument (Table 2). An assumption of multinomial logit models is that outcome categories must have the property of independence of irrelevant alternatives (IIA).[7] We thus performed a suest-based Hausman test; the chi-squared test statistics are respectively 20.254 (p-value=0.162), 17.424 (p-value=0.294), and 7.379 (p-value=0.946) for *Internal Development*, *Joint Development,* and *Licensing*, which support the IIA assumption. The value added of our procedure to generate the instrument also depends on the predictive power of the multinomial logit. Our dataset includes 262 internal developments, 72 joint developments, and 103 licensing cases. Among them, 225 cases, 43 cases, and 92 cases are correctly classified, respectively. Thus, our model correctly predicts 82.4% of the cases, indicating its robust predictive power.

-------------------------Include Tables 1&2 about here-------------------------

We then validated our use of the IV approach by testing whether $EXP_{m,i,t}$ is indeed endogenous, as we theoretically suggest. In Model 4, the endogeneity test statistic is 4.433 (p-value < 0.05), which confirms the endogeneity of $EXP_{m,i,t}$ and suggests that OLS estimation results are inconsistent and biased. We also checked the relevance of the instrument $\widehat{EXP_{m,i,t}}$. The under-identification test statistic (i.e., the Anderson canonical correlations test) is 230.571 (p-value < 0.01), suggesting that the instrument is correlated sufficiently with the endogenous variable. The weak identification test (i.e., Cragg-Donald Wald F-test) statistic is greater than

[7] This assumption requires that the inclusion or exclusion of categories does not affect the relative risks associated with the independent variables in the remaining categories.

the 10% maximal IV size Stock-Yogo critical values, which further confirms the relevance of our instrument (Stock and Yogo, 2005).

Overall, Model 4 shows that the coefficient of *Mode Experience*, while still positive, is not significant anymore (β_{1IV}=0.038, *p*-value=0.645). This supports our view that the positive performance impact of experience we observed using OLS specifications may not be due solely to experience-based enhanced efficiency and associated learning but also driven by experience endogeneity. When we account for experience endogeneity, the positive impact of experience on performance may decrease or even be insignificant.

Several controls affect sales (Model 4). *Prior Firm Performance*, *Incumbent*, *Military Design*, and *Year* decrease sales while *Economic Climate* increases them. *Areas of Business* also exhibit significant differences. Further, collaborative products achieve higher sales than autonomous products and, in turn, autonomous products achieve higher sales than licensed products, possibly because aircraft licensing agreements often include contractual clauses enforcing territorial limitations and/or market restrictions on civil or military use.

Several results stand out from our first-stage model (Model 5). As mentioned above, *IPR Effectiveness* is significant: as *IPR Effectiveness* increases, the firm's likelihood to opt for licensing decreases. The coefficient of *Prior Mode Success* is positive and significant, substantiating the positive impact of past success on experience accumulation processes (Robertson and Gatignon, 1998). This result confirms our argument that in CDA-type decisions, firms are likely to choose an activity that they have been doing successfully in the past, what leads them to accumulate more experience in that particular activity. Also, *Firm Size*, *Number of Competitors,* and *Potential Market Size* increase the likelihood to prefer internal development over licensing while *State-ownership* decreases it. *Age in Market*, *Potential Market Size*, *Prior Mode Success, Economic Climate, Year* increase the firm's likelihood to prefer joint development over licensing while *Military Design* decreases it. *Areas of Business* also exhibit significant differences.

We conducted numerous sensitivity analyses. First, firms that used a unique mode may differ from firms that used different modes, in terms of both NPI-mode decisions and NPI performance. In our dataset, 113 out of the 159 firms used only one NPI mode (72 firms used only internal development, 11 firms only joint development, and 30 firms only licensing). We thus ran a subsample analysis on the firms that only used one mode: our main results remain supported. Second, our main analysis used extrapolated unit sales for the 115 NPIs that were still produced at the end of our study period (2000). We thus added a dummy variable that equals to 1 if an aircraft project's sales was extrapolated (0, otherwise): our results still hold.[8] Third, although a survivor bias is not severe in our dataset since it contains all firms in the industry, more successful firms might be different from firms that introduced only one product and quickly exited the industry (see Mitchell, 1991). We thus re-ran the analysis after having excluded the 51 firms that launched one project throughout the study period and ceased production before 2000. The results are consistent with those obtained from the full sample. Fourth, we dropped the mode dummies *Joint Development* and *Licensing*: our results still hold. Appendix 2 reports the OLS and IV estimation results of the aforementioned sensitivity analyses. Also, our results remain robust after discounting *Mode Experience* by the age of the project, dropping *Prior Mode Success* and *Incumbents* (which are correlated with *Prior Firm Performance* and *Age in Market,* respectively*)*, replacing *Area of Business* with *Fighter*,

[8] To further verify that extrapolation did not affect our findings, we conducted two more tests without extrapolated data: (1) we ran our analyses on a subsample that includes only projects for which we have at least 30 years of performance (i.e., only projects prior to 1970). Very few firms in this subsample need to be extrapolated because so much of the sales life has already occurred. (2) We included 11 cohort dummies for year of production (namely 1944-50, 1951-55, 1956-60, 1961-65, 1966-70, 1971-75, 1976-80, 1981-85, 1986-90, 1991-95, and 1996-2000). Inclusion of these cohort dummies controls for the time to realize sales for projects within the same cohort and removes the need for extrapolation. Our findings remain unchanged. We thank an anonymous reviewer for suggesting these additional tests.

Helicopter and *Prop* dummies; and replacing *Number of Competitors* with the number of competing products. Overall, these tests allow us to believe that our results are robust.

DISCUSSION AND CONCLUSIONS

The objective of our paper was to offer a fine-grained understanding of the relationship between experience and performance in the context of CDA-type decisions. We argued that most extant work on the experience-performance relationships in the context of CDAs overlooked the fact that CDAs involve high levels of causal and outcome ambiguity and low levels of frequency and similarity. Therefore, CDAs differ greatly from repetitive operational processes. Further, whereas operational processes are generally repeated unchanged regularly (Balasubramanian and Lieberman, 2010), CDAs are usually chosen based upon past performance. Since "experiences can become endogenous when outcomes of past learning determine what the organization experiences subsequently" (Schulz, 2002: 432), we further investigated the impact of experience on performance in the context of CDAs. We contended that firms are gathering experience with CDAs by repeatedly self-selecting the activities with which they have been the most successful in the past and expect to be the most successful in the future. It follows that firms' experience with CDAs may not result from exogenous or random choices but rather from endogenous decisions driven by superior performance expectations. It follows that scholars that analyze the experience-performance relationship in the context of CDAs must account for potential endogeneity in the accumulation of experience.

Empirical analyses using data on 437 aircraft projects introduced since WWII largely supports this idea. In specifications that do not account for experience endogeneity, NPI-mode experience positively affects NPI performance. When we accounted for the fact that astute self-selection drives NPI-mode experience, the positive impact of experience on performance is not significant anymore. We do not mean to imply, however, that the choice between various NPI modes *never* produces experiential benefits; rather, we propose that in a general case, NPI-mode experience is tinged with both a learning effect and a selection effect which are likely to be complementary and reinforcing in nature. Once a firm makes a choice, it is more likely to repeat it if it achieves success, and then this repetition opens the door to potential experiential learning. Symmetrically, once a firm has learned skills specific to a particular activity, it is more likely to select it again in the future.

Our study contributes to research in strategic management in several ways. Firstly, we offer an additional and novel causal mechanism to explain experience-performance relationships, distinct from learning-based arguments that past work has traditionally used. We showed that the experience gathered by firms with CDA-type decisions, which involve low levels of frequency and similarity as well as high levels of causal and outcome ambiguity, may also be driven by astute self-selection. Our perspective resonates with recent research by Hennart (2011: 135) who claims that "multi-nationality [i.e., a firm's international footprint] results from a firm's choice between coordinating internally the stages of its value chain and letting them be organized on the market and hence that there are no reasons to expect net gains from an increase or a decrease in multi-nationality." Our findings also support the idea according to which "there is also a serious problem of survivor bias in specifying the experiences themselves as the cause or origin of learning and behavior. That is, organizations which began particular activities early on and continue to repeat and accumulate the right activities inherently took initial, important steps which have nothing to do with number of experiences, but rather underlying factors which allowed them to have the experience in the first place" (Felin and Foss, 2011: 239).

Secondly, our view suggests that firms generally choose to gather experience with a given activity when they already possess the capabilities required to achieve success in that activity. We may thus surmise an additional causal chain between experience, capabilities, and performance. Extant research suggests that experience provides capabilities through learning processes, which in turn enhance performance. Conversely, we showed that capabilities allows for enhanced performance, which in turn increases experience. Our view thus suggests that, in CDAs, we can interpret a positive experience-performance link as an indication for some "practice-enhanced congenital capabilities" since firms would gather experience with the activity for which they have the necessary capabilities while continuously improving them.

We also contribute to the strategic management literature by developing a careful method derived from the IV model that can be used to examine experience-performance relationships in CDA-type settings, while accounting for experience endogeneity. Several studies in strategic management have used the Heckman selection model to account for the endogenous nature of binary decisions, primarily when studying the performance impact of two different governance modes (see, among others, Shaver, 1998; Leiblein *et al*., 2002; Mulotte *et al.*, 2013; Castañer *et al*., 2014). Two recent papers used an IV approach to address the endogeneity of more general categorical variables (Cassiman and Veugelers, 2006; Ren *et al*., 2011),[9] albeit neither used it to examine experience effects. Extending the logic used by these two recent studies, we exploited the cumulative nature of our NPI experience variable and developed a valid "technical" instrument ($\widehat{EXP_{m,\iota,t}}$) for our *continuous* experience variable that is a variant of categorical variables. Moreover, following the suggestions of Semadeni *et al.* (2013)[10], in addition to a theoretical justification, we have conducted numerous statistical tests to show that our two instruments (i.e., the "technical" one $\widehat{EXP_{m,\iota,t}}$ and the conventional

[9] In both studies, the endogenous variables are categorical variables, rather than continuous variables. Cassiman and Veugelers (2006) studied the impact of different innovation strategies (make, buy, make & buy, no-make & buy) on innovation performance in which they used a multinomial logit model as the first stage to generate the instrument. Ren *et al*. (2011) applied a probit model in the first stage to predict the probability of whether a rival chain opens a store or not in a local geographic market, then used the predicted probability as an instrument for the second-stage binary endogenous variable.

[10] Semadeni, Withers, and Certo (2013) have recently surveyed all empirical papers appearing in the *Strategic Management Journal* between 2005 and 2012 that used the IV approach to analyze continuous endogenous variables. Of the 24 articles they could identify, only 10 studies test for endogeneity, 3 studies test for instrument strength, and 5 studies test for instrument exogeneity.

"excluded" instrument *IPR Effectiveness*) are indeed strong and exogenous. Finally, we justified our use of the IV approach by providing endogeneity test statistics.

In future research, we need to better understand the contextual and organizational conditions under which selection or learning-based mechanisms are likely to dominate in driving experience-performance relationships. Note that some CDAs may be akin to operational processes. For instance, a firm that regularly launches marginally-improved products (e.g., video game producers focusing on series) needs to frequently undertake tasks that are fairly repetitive, involve lower levels of causal ambiguity, and whose performance outcomes may be historically compared. The firm is thus likely to be able to derive from its experience valuable inferences about factors driving the efficiency of the various processes used (Levitt and March, 1988). Experience therefore may allow for enhanced efficiency and improved performance. It is thus probable that learning is likely to be dominant when a firm frequently undertakes CDAs involving high levels of similarity and low levels of causal and outcome ambiguity (Zollo, 2009). However, even a firm that undertakes CDAs with such features is likely to self-select its strategic initiatives based on expected returns. Thus, its experience is also likely to be tinged with endogeneity. Future research could try to identify further the conditions under which the learning effect may dominate (or conversely be submerged by) the selection effect.

We also need to better understand the role of capabilities in the relationship between experience and performance in strategic settings (Bingham, Eisenhardt, and Furr, 2007; Helfat and Raubitschek, 2000). Our view suggests that firms would gather experience with the CDAs for which they have the necessary capabilities even though this experience also helps accumulate or retain these capabilities (Nelson and Winter, 1982). Future research should investigate further how firms develop the capabilities they use to undertake CDAs and where these capabilities originate in the initial stages of firm formation (Klepper and Simons, 2000;

Holbrook *et al.*, 2000). Future research should also examine how capabilities evolve over time and how this evolution affects experience accumulation processes and *vice versa*. Firms may choose activities for which they possess capabilities, and at the same time, the repetition of the activity helps retain the capability. Without such repetition, the capability may be lost or depreciate (Helfat, 2000). More strikingly, research should carefully examine how changes in the firms' capabilities can lead them to opt to cease to accumulate experience with a particular CDA and, in turn, how changes in capabilities can allow firms to undertake novel CDAs (Garud and Nayyar, 1994). Further, future research may investigate the role of serendipity in the accumulation of capabilities. This is all the more important that we argue that positive performance feedback from past choices may "trap" the firm in accumulating further experience, and not trying other, possibly more successful, alternatives.

Finally, as far as we are aware, no study within the stream of the strategic management literature that examined the relationship between experience and performance in CDA-type settings rigorously accounted for the endogenous nature of experience accumulated processes. There is thus an opportunity for empirical researchers to use our proposed IV-based method and to re-examine the performance impact of experience accounting for experience endogeneity in a variety of empirical settings. It is likely that some of results highlighted by extant research about the performance impact of experience in CDA-type settings would not hold any more –or at least would be much less significant– after accounting for the fact that experience accumulation in CDAs does not result from exogenous or random choices but rather from endogenous decisions driven by superior performance expectations (Antonakis *et al.*, 2010).

In summary, we demonstrated that experience with CDA-type activity results from endogenous choices based on superior performance expectations. If a firm possesses certain capabilities, it will engage in certain activities corresponding to those capabilities, thereby achieving superior performance. It follows that an "empirically observed" positive experience-performance relationship may not be due solely to learning-based enhanced capabilities but also driven by astute self-selection. Overall, we provide a new perspective to supplement the experiential learning interpretations in the extant organizational learning literature, and offer suggestions for future empirical analyses of experience-performance relationships in corporate development activities.

REFERENCES

Anand, B., Khanna, T. 2000. Do firms learn to create value? The case of alliances. *Strategic Management Journal* **21**(3): 295-315.

Anand, J., Singh, H. 1997. Asset redeployment, acquisitions, and corporate strategy in declining industries. *Strategic Management Journal* **18**(Special Issue): 99-118.

Angrist, J. 2001. Estimation of limited dependent variable models with dummy endogenous regressors. *Journal of Business & Economic Statistics* **19**(1): 2-16.

Angrist, J., Pischke J. 2008. *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Antonakis, J., Bendahan, S., Jacquart, P., Lalive, R. 2010. On making causal claims: A review and recommendations. *The Leadership Quarterly* **21**(6):1086-1120.

Argote, L. 1999. *Organizational learning: creating, retaining, and transferring knowledge.* Kluwer Academic: Boston, MA.

Argote, L., Beckman, S., Epple, D. 1990. The persistence and transfer of learning in industrial settings. *Management Science* **36**(2): 140-154.

Balasubramanian, N., Lieberman, M. 2010. Industry learning environments and the heterogeneity of firm performance. *Strategic Management Journal* **31**(4): 390-412.

Barkema, H., Bell, J., Pennings, J. 1996. Foreign entry, cultural barriers, and learning. *Strategic Management Journal* **17**(2): 151-166.

Barkema, H., Schijven, M. 2008. How do firms learn to make acquisitions? A review of past research and an agenda for the future. *Journal of Management* **34**(3): 594-634

Bascle, G. 2008. Controlling for endogeneity with instrumental variables in strategic management research. *Strategic Organization* **6**(3): 285-327.

BCG. 1970. *Perspectives on experience*. Boston, Mass.: Boston Consulting Group.

Benkard, L. 2000. Learning and forgetting: the dynamics of aircraft production. *American Economic Review* **90**(4): 1034-1054.

Bingham, C., Eisenhardt, K., Furr, N. 2007. What makes a process a capability? Heuristics, strategy, and effective capture of opportunities. *Strategic Entrepreneurship Journal* **1**(1/2): 27-47.

Brown, S., Eisenhardt, K. 1995. Product development: Past research, present findings, and future directions. *Academy of Management Review* **20**(2): 343-378.

Cassiman, B., Veugelers, R. 2006. In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition. *Management Science* **52**(1): 68-82.

Castañer, X., Mulotte, L., Garrette, B., Dussauge, P. 2014. Governance mode vs. governance fit: Performance implications of make-or-ally choices for product innovation in the worldwide aircraft industry, 1942–2000. *Strategic Management Journal* **35**(9): 1386-1397.

Cohen, W., Levinthal, D. 1990. Absorptive capacity: A new perspective on learning and innovation.
Administrative Science Quarterly **35**(1): 128-152.

Cohen, W., Nelson, R., Walsh, J. 2000. Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). *National Bureau of Economic Research*, No. w7552.

Cyert, R., March, J. 1963. *A Behavioral Theory of the Firm*. Englewoods NY: Prentice-Hall.

Danneels, E. 2002. The dynamics of product innovation and firm competences. *Strategic Management Journal* **23**(12): 1095-1121.

Darr, R., Argote, L., Epple, D. 1995. The acquisition, transfer, and depreciation of knowledge in service organizations: productivity in franchises. *Management Science* **41**(11): 1750-1762.

Delios, A., Beamish, P. 2001. Survival and profitability: the roles of experience and intangible assets in foreign subsidiary performance. *Academy of Management Journal* **44**(5): 1028-1038.

Felin, T., Foss, N. 2011. The endogenous origins of experience, routines, and organizational capabilities: the poverty of stimulus, *Journal of Institutional Economics* **7**(2): 231-256.

FI/DMS. 2000. *Aerospace Systems Group Library*. Newtown CN: FI/DMS.

Frenken, K., Leydesdorff, L. 2000. Scaling trajectories in civil aircraft (1913-1997). *Research Policy* **29**(3): 331-349.

Garud, R., Nayyar, P. 1994. Transformative capacity: Continual structuring by intertemporal technology transfer. *Strategic Management Journal* **15**(5): 365-385.

Ginarte, J., Park, W. 1997. Determinants of patent rights: A cross-national study. *Research Policy*, **26**: 283-301.

Greene, B. 1990. *Econometric Analysis*. Macmillan, New York.

Greve, H. 1998. Performance, aspirations, and risky organizational change. *Administrative Science Quarterly* **43**(1): 58-86.

Gulati, R. 1995. Does familiarity breed trust? The implications of repeated ties for contractual choices in alliances. *Academy of Management Journal*. 38(1): 85-112.

Haleblian, J., Finkelstein, S. 1999. Organizational acquisition experience on acquisition performance: a behavioral learning perspective. *Administrative Science Quarterly* **44**(1): 29-56.

Haleblian, J., Kim, J-Y., Rajagopalan, N. 2006. The influence of acquisition experience and performance on acquisition behavior: Evidence from the U.S. commercial banking industry. *Academy of Management Journal* **49**(2): 357-370.

Hatch, N., Mowery, D. 1998. Process innovation and learning by doing in semiconductor manufacturing. *Management Science* **44**(11): 1461-1477.

Hayward, M. 2002. When do firms learn from their acquisition experience? Evidence from 1990 to 1995. *Strategic Management Journal* **23**(1): 21-39.

Helfat, C. 2000. Guest editor's introduction to the special Issue: the evolution of firm capabilities. *Strategic Management Journal* **21** (Special Issue): 955–959.

Helfat, C., Raubitschek, R. 2000. Product sequencing: Co-evolution of knowledge, capabilities and products. *Strategic Management Journal* **21**(Special Issue): 961-979.

Hennart, J.-F. 2011. A theoretical assessment of the empirical literature on the impact of multinationality on performance *Global Strategy Journal* **1**(1):135-151.

Hirschmann, W. 1964. Profit from the learning curve. *Harvard Business Review* **42**(1): 135-139.

Hoang, H., Rothaermel, F. 2005. The effect of general and partner-specific alliance experience on joint R&D project performance. *Academy of Management Journal* **48**(2): 332-345.

Holbrook, D., Cohen, W., Hounschell, D., Klepper, S. 2000. The nature, sources, and consequences of firm differences in the early history of the semi-conductor industry. *Strategic Management Journal* **21**(Special Issue): 1017–1041.

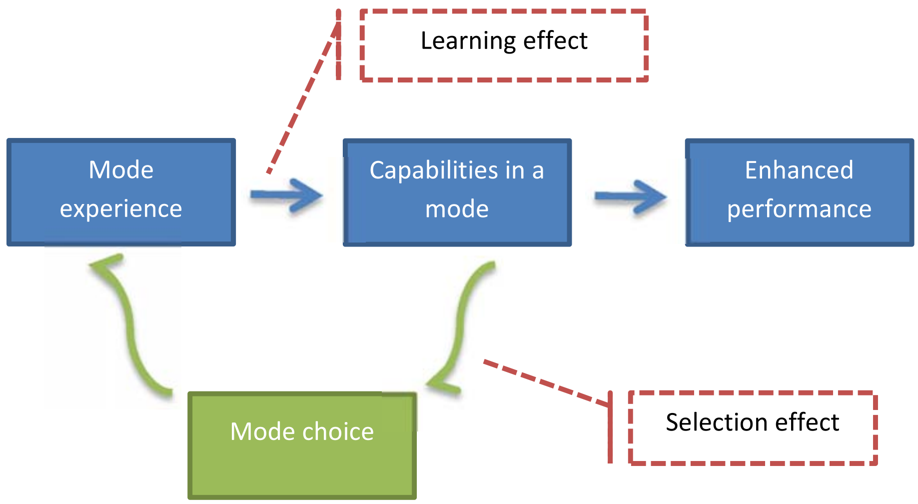
Jane's. 1944–2000. *All the World's Aircraft*. Jane's Publishing Company Ltd.: London, U.K.

Kessler, E., Chakrabarti, A. 1996. Innovation speed: a conceptual model of context, antecedents, and outcomes. *Academy of Management Review* **21**(4): 1143-1191.

Klepper, S., Simons, K. 2000. Dominance by birthright: Entry of prior radio producers and competitive ramifications in the US television receiver industry. *Strategic Management Journal*, **21**(Special Issue): 997-1016.
Lant, T., Milliken, F., Batra, B. 1992. The role of managerial learning and interpretation in strategic persistence and reorientation: an empirical exploration. *Strategic Management Journal* **13**(8): 585-608.
Leiblein, M., Reuer, J., Dalsace, F. 2002. Do make or buy decisions matter? The influence of organizational governance on technological performance. *Strategic Management Journal* **23**(9): 817-833.
Levitt, B., March, J. 1988. Organizational learning. *Annual Review of Sociology* **14**: 319-340.
Lieberman, M. 1989. The learning curve, technology barriers to entry, and competitive survival in the chemical processing industries. *Strategic Management Journal* **10**(5): 431-447.
Mitchell, W. 1991. Dual clocks: Entry order influences on incumbent and newcomer market share and survival when specialized assets retain their value. *Strategic Management Journal* **12**: 85-100.
Moatti, V., Ren, C., Anand, J., Dussauge, P. 2015. Disentangling the performance effects of efficiency and bargaining power in horizontal growth strategies: An empirical investigation in the global retail industry. *Strategic Management Journal* **36**(5):745-757.
Moorman, C., Miner, A., 1997. The impact of organizational memory on new product performance and creativity. *Journal of Marketing Research* **34**(1): 91-106.
Mulotte, L. 2014. Do experience effects vary across governance modes? *Organization Science*, **25**(3): 757-775.
Mulotte, L., Dussauge, P., Mitchell, W. 2013. Does pre-entry licensing undermine the performance of subsequent independent activities? *Strategic Management Journal* **34**(3): 358-372.
Nadolska, A., Barkema, H. 2007. Learning to internationalise: the pace and success of foreign acquisitions. *Journal of Internatational Business Studies* **38**(7): 1170-1186.
Nelson, R., Winter, S. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge, MA.
Nerkar, A., Roberts, P. 2004. Technological and product-market experience and the success of new product introductions in the pharmaceutical industry. *Strategic Management Journal* **25**(8/9): 779-799.
Oxley, J. E. 1999. Institutional environment and the mechanisms of governance: The impact of intellectual property protection on the structure of inter-firm alliances. *Journal of Economic Behavior and Organization*, **38**: 283-309.
Park, W. 2008. International Patent Protection: 1960–2005, *Research Policy*. **37**(4): 761-766.
Pennings, J., Barkema, H., Douma, S. 1994. Organizational learning and diversification. *Academy of Management Journal* **37**(3): 608-640.
Ravallion, M., 2008. Evaluating Anti-Poverty Programs. In *Handbook of Development Economics (Volume 4).* Ed. P. Schultz & J. Strauss. Elsevier, B.V.:3787-3845.
Reed, R., DeFillippi, R. 1990. Causal ambiguity, barriers to imitation, and sustainable competitive advantage *Academy of Management Review* **15**(1): 88-102.
Ren, C., Hu, Y., Hu, YJ, Hausman, J. 2011. Managing product variety and collocation in competitive environment: An empirical investigation of consumer electronics retailing *Management Science* **57**(6): 1009-1024.
Reuer, J. Tong, T. 2005. Real options in international joint ventures, *Journal of Management*, **31**(3): 403-423
Robertson, T., Gatignon, H. 1998. Technology development mode: transaction cost conceptualization. *Strategic Management Journal* **19**(6): 515-532.
Sampson, R. 2004. The cost of misaligned governance in R&D alliances. *Journal of Law, Economics and Organization* **20**(2): 484-526.
Sampson, R. 2005. Experience effects and collaborative returns in R&D alliances. *Strategic Management Journal* **26**(11): 1009-1031.

Schulz, M. 2002. Organizational Learning, in J. Baum (ed.) *Companion to Organizations*, Blackwell Publishers, Oxford, UK: 415-441.
Semadeni, M., Withers, M., Certo, T. 2013. The perils of endogeneity and instrumental variables in strategy research: Understanding through simulations. *Strategic Management Journal*, Article first published online: 25 June 2013
Shaver, M. 1998. Accounting for endogeneity when assessing strategy performance: Does entry mode choice affect FDI survival? *Management Science* **44**(4): 571-585.
Shaver, M., Mitchell, W., Yeung B. 1997. The effect of own-firm and other-firm experience on foreign direct investment survival in the United States (1987-92). *Strategic Management Journal* **18**(10): 811-824.
Slangen, A., Hennart, J.-F. 2008. Do foreign greenfields outperform foreign acquisitions or vice versa? An institutional perspective. *Journal of Management Studies* **45**(7): 1301-1328.
Smith, A., 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*. London: W. Stahan & T. Cadell.
Stock, J.H., Yogo, M. 2005. Testing for Weak Instruments in Linear IV Regression. In D.W.K. Andrews and J.H. Stock, eds. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*. Cambridge: Cambridge UP, 80-108.
Teece, D. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* **15**: 285-305.
Thornton, R., Thompson, P. 2001. Learning from experience and learning from others: An exploration of learning and spillovers in wartime shipbuilding. *American Economic Review* **91**(5): 1350-1368.
Vasudeva, G., Anand, J. 2011. Unpacking absorptive capacity: a study of knowledge utilization from alliance portfolios Academy of Management Journal, **54**(3): 611-623.
Vermeulen, F., Barkema, H. 2001. Learning through acquisitions. *Academy of Management Journal* **44**(3): 457-476.
Veugelers, R., Cassiman, B. 1999. Make and buy in innovation strategies: Evidence from Belgian manufacturing firms. *Research Policy* **28**: 63-80.
White, S. 2000. Competition capabilities and the make, buy, or ally decisions of Chinese state-owned firms. *Academy of Management Journal* **43**(3): 324-341.
Wright, T. 1936. Factors affecting the cost of airplanes. *Journal of Aeronautical Science* **3**(4): 122-128.
Zhao, M. 2006. Conducting R&D in countries with weak intellectual property rights protection. *Management Science* 52(8): 1185-1199
Zollo, M. 2009. Superstitious learning with rare strategic decisions: Theory and evidence from corporate acquisitions. *Organization Science* **20**(5): 894-908.
Zollo, M., Singh, H. 2004. Deliberate learning in corporate acquisitions: Post-acquisition strategies and integration capability in U.S. bank mergers. *Strategic Management Journal* **25**(13): 1233-1256.

Figure 1. Coexistence of Selection and Learning Effects in CDAs[11]



Notes:

Learning effect: Experience provides capabilities through learning processes, which in turn enhances performance.

Selection effect: Since capabilities may allow for enhanced performance, they drive mode choice, thereby increasing experience in that mode.

[11] We thank Dan Levinthal for his input in this figure.

Table 1. Regression Analysis of the Impact of Experience on NPI Performance (N=437) [a]

	Model 1	Model 2	Model 3	Model 4
Estimation Method	OLS	OLS	IV [b]	IV [b]
Mode Experience	0.148**	0.159**	0.051	0.039
	(0.061)	(0.074)	(0.078)	(0.084)
Firm Size	-0.014	-0.047	0.055	-0.002
	(0.144)	(0.172)	(0.146)	(0.144)
State Owned	-0.019	-0.307	-0.044	-0.379
	(0.157)	(0.284)	(0.155)	(0.237)
Prior Firm Performance	0.050	-0.443***	0.095	-0.433***
	(0.216)	(0.128)	(0.112)	(0.105)
Incumbent	-0.230	-0.682***	0.084	-0.674***
	(0.180)	(0.241)	(0.213)	(0.198)
Military Design	-0.209	-0.321	-0.237	-0.364**
	(0.179)	(0.207)	(0.176)	(0.172)
Relative Technical	-0.930*	-0.572	-0.869	-0.346
Complexity	(0.558)	(0.635)	(0.549)	(0.535)
Age in Market	0.001	0.014	0.008	0.023
	(0.010)	(0.019)	(0.011)	(0.016)
Area of Business	-0.157*	-1.387**	-0.166**	-3.207***
	(0.085)	(0.659)	(0.083)	(0.975)
Prior Mode Success	0.098	0.083	0.052	0.043
	(0.095)	(0.095)	(0.096)	(0.081)
Number of Competitors	-0.019**	-0.010	-0.019**	-0.007
	(0.008)	(0.013)	(0.008)	(0.011)
Potential Market Size	0.151**	-0.132	0.147**	-0.133
	(0.062)	(0.124)	(0.061)	(0.102)
Economic Climate	1.367	5.011	1.756	5.347*
	(3.037)	(3.400)	(2.992)	(2.806)
Year	-0.024***	-0.035*	-0.025***	-0.035**
	(0.007)	(0.018)	(0.007)	(0.015)
Joint Development	0.604***	0.697***	0.471**	0.497**
	(0.198)	(0.241)	(0.207)	(0.221)
Licensing	-0.603***	-0.383	-0.616***	-0.340*
	(0.170)	(0.237)	(0.167)	(0.196)
Constant	48.200***	71.622**	48.952***	76.507***
	(13.716)	(35.706)	(13.491)	(28.600)
Firm Dummies	Not included	Included	Not included	Included
F Statistics	F(16, 420) = 7.96***	F(172, 264) = 2.37***	F(16, 420) = 7.58***	F(172, 264) = 2.28***
R^2/Adjusted R^2	0.23/0.20	0.61/ 0.35	n/a	n/a
Underidentification test	n/a	n/a	261.528***	230.571***
Weak identification test [c]	n/a	n/a	625.977***	328.383***
Endogeneity test	n/a	n/a	χ^2=3.859**	χ^2=4.433**

Notes: Coefficients are significant at 1%***, 5%**, and 10%*. Standard deviations are in parentheses.

[a] The dependent variable of all models is *NPI Performance*. Model 1 estimates Equation (1) with an OLS analysis. Model 2 is the OLS analysis with firm dummies.

[b] As part of our IV approach, Model 3 estimates Equation (2.2) with the IV-2SLS method without firm dummies, Model 4 adds firm dummies. $\widehat{EXP_{m,\iota,t}}$ is used as an instrument for the *Mode Experience* variable. The first-stage analysis results of the IV-2SLS model (i.e., the model that regresses *Mode Experience* against the instrument and the exogenous control variables) are available from the authors upon request.

[c] Three asterisks (***) denote that the weak identification test result is greater than the 10% maximal IV size.

Table 2. Multinomial Logit Analysis of NPI Mode Choice (N=437) [a]

	Model 5-1 *Internal Development*	Model 5-2 *Joint Development*
Firm Size	3.278**	2.301
	(1.331)	(1.429)
State Owned	-0.769**	0.123
	(0.392)	(0.491)
Prior Firm Performance	-0.393	-0.427
	(0.339)	(0.405)
Incumbent	-0.325	-0.470
	(0.702)	(0.877)
Military Design	-0.151	-1.090*
	(0.525)	(0.615)
Relative Technical Complexity	-1.917	1.295
	(1.483)	(2.058)
Age in Market	0.006	0.068**
	(0.026)	(0.030)
Area of Business	0.957***	0.924***
	(0.235)	(0.276)
Prior Mode Success	0.537**	0.558**
	(0.224)	(0.263)
Number of Competitors	0.043**	0.042
	(0.021)	(0.029)
Potential Market Size	0.630***	0.401*
	(0.169)	(0.207)
Economic Climate	-5.727	38.640***
	(6.859)	(14.278)
Year	-0.016	0.041*
	(0.018)	(0.024)
IPR Effectiveness[b]	0.571***	0.645**
	(0.218)	(0.276)
Constant	31.934	-88.619*
	(34.393)	(46.222)

Notes: Coefficients are significant at 1%***, 5%**, and 10%*. Standard deviations are in parentheses.
Pseudo $R^2 = 0.33$, $\chi^2(28) = 268.56$***, log likelihood = -278.45.

[a] The dependent variable of the multinomial logit model is *NPI Mode* (=1 for internal development, =2 for joint development, =3 for licensing). Licensing is the benchmark outcome category.

[b] *IPR Effectiveness* is the "excluded" variable for the IV estimation: *IPR Effectiveness* is included in the multinomial logit model, but not in the main performance equation.

Appendix 1. Descriptive statistics and correlation matrix (N=437)

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. NPI Performance	-1.41	1.37	1.00																		
2. Mode Experience	1.15	1.56	0.12	1.00																	
3. Firm Size	0.25	0.57	0.20	0.43	1.00																
4. State Owned	0.29	0.45	-.19	-.11	-.12	1.00															
5. Prior Firm Performance	-.69	1.03	0.15	-.19	0.27	-.13	1.00														
6. Incumbent	0.63	0.48	0.06	0.56	0.33	0.01	-.51	1.00													
7. Military Design	0.68	0.47	-.06	0.04	0.04	0.08	-.07	0.01	1.00												
8. Relative Tech Complexity	0.89	0.12	-.18	-.04	-.18	-.08	-.01	-.11	-.06	1.00											
9. Age in Market	10.81	11.82	0.05	0.59	0.22	0.07	-.24	0.63	-.00	-.00	1.00										
10. Area of Business	2.11	1.22	-.02	-.14	-.13	-.07	-.01	-.05	-.69	0.12	-.06	1.00									
11. Prior Mode Success	-.58	1.08	0.13	-.30	0.21	-.07	0.79	-.41	-.04	-.02	-.24	-.02	1.00								
12. Internal Development	0.60	0.49	0.18	0.19	0.21	-.33	0.15	0.03	-.08	-.10	-.09	0.14	0.15	1.00							
13. Joint Development	0.16	0.37	0.09	-.14	-.06	0.11	-.11	0.13	-.19	0.10	0.33	0.17	-.08	-.54	1.00						
14. Licensing	0.24	0.42	-.29	-.10	-.19	0.29	-.09	-.15	0.26	0.03	-.18	-.31	-.11	-.68	-.25	1.00					
15. Number of Competitors	19.36	8.80	-.18	0.19	0.15	0.11	-.17	0.25	0.25	0.20	0.17	-.36	-.09	-.08	0.01	0.09	1.00				
16. Potential Market Size	-.37	1.26	0.25	0.21	0.26	-.36	0.12	0.21	-.26	-.03	0.31	0.27	0.09	0.33	0.11	-.47	-.17	1.00			
17. Economic Climate	0.04	0.02	0.02	-.04	0.02	-.01	-.04	-.00	0.04	0.02	-.19	0.04	-.02	-.04	-.01	0.06	0.03	-.12	1.00		
18. Year	1971	14.17	-.18	0.19	-.09	0.25	-.16	0.23	-.24	0.25	0.60	0.28	-.13	-.17	0.36	-.12	0.19	0.24	-.23	1.00	
19. IPR Effectiveness	3.13	1.00	0.24	0.24	0.22	-.36	0.16	0.19	-.21	0.01	0.42	0.18	0.08	0.22	0.19	-.42	-.11	0.67	-.17	0.36	1.00

Appendix 2. Selected Sensitivity Analyses on the Impact of Experience on NPI Performance [a]

	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Estimation Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Mode Experience	0.328**	0.094	0.117*	0.020	0.157**	0.026	0.104*	-0.010
	(0.162)	(0.140)	(0.066)	(0.077)	(0.075)	(0.090)	(0.062)	(0.072)
Firm Size	-0.331	0.125	-0.089	-0.048	-0.037	0.011	0.053	0.137
	(0.202)	(0.164)	(0.163)	(0.145)	(0.173)	(0.150)	(0.159)	(0.151)
State Owned	-0.136	-0.084	-0.064	-0.098	-0.379	-0.453*	0.049	0.006
	(0.541)	(0.401)	(0.207)	(0.184)	(0.290)	(0.251)	(0.178)	(0.166)
Prior Firm Performance	-0.272*	-0.310***	-0.172	-0.151	-0.428***	-0.419***	-0.047	-0.018
	(0.152)	(0.114)	(0.118)	(0.105)	(0.128)	(0.110)	(0.124)	(0.115)
Incumbent	-0.203	-0.220	-0.152	-0.119	-0.738***	-0.730***	-0.066	-0.016
	(0.347)	(0.260)	(0.221)	(0.196)	(0.243)	(0.209)	(0.234)	(0.218)
Military Design	-0.372	-0.377*	-0.151	-0.175	-0.251	-0.305	-0.354*	-0.370**
	(0.293)	(0.216)	(0.174)	(0.154)	(0.218)	(0.189)	(0.184)	(0.170)
Relative Technical	-2.450**	-2.061**	-1.020*	-0.897*	-0.468	-0.226	-1.272**	-1.180**
Complexity	(1.085)	(0.811)	(0.572)	(0.510)	(0.644)	(0.565)	(0.601)	(0.558)
Age in Market	-0.006	0.024	-0.012	-0.005	-0.009	-0.001	0.014	0.022*
	(0.032)	(0.025)	(0.013)	(0.012)	(0.022)	(0.019)	(0.012)	(0.011)
Area of Business	-1.648**	-3.097***	0.088	0.087	-0.291	0.627	-0.024	-0.040
	(0.765)	(0.961)	(0.151)	(0.133)	(0.628)	(0.508)	(0.102)	(0.095)
Prior Mode Success	--	--	0.052	0.013	0.073	0.030	0.129	0.078
			(0.091)	(0.083)	(0.095)	(0.084)	(0.099)	(0.094)
Joint Development	0.561	0.536	0.363*	0.225	0.684***	0.448*		
	(0.608)	(0.449)	(0.201)	(0.192)	(0.256)	(0.247)		
Licensing	-0.876	-1.273*	-0.396*	-0.381**	-0.428*	-0.379*		
	(0.987)	(0.737)	(0.212)	(0.188)	(0.239)	(0.207)		
Number of Competitors	-0.004	0.004	-0.006	-0.004	-0.010	-0.007	-0.020**	-0.019**
	(0.021)	(0.016)	(0.010)	(0.009)	(0.013)	(0.012)	(0.010)	(0.009)
Potential Market Size	-0.123	-0.062	0.162**	0.163**	-0.087	-0.079	0.154**	0.153**
	(0.163)	(0.120)	(0.080)	(0.070)	(0.141)	(0.121)	(0.073)	(0.068)
Economic Climate	0.217	0.464	4.716	4.992*	5.209	5.546*	5.969*	5.802*
	(5.049)	(3.734)	(3.201)	(2.832)	(3.411)	(2.936)	(3.406)	(3.158)

Year	-0.051** (0.025)	-.059*** (0.019)	-0.038*** (0.011)	-0.039*** (0.010)	-0.012 (0.021)	-0.011 (0.018)	-0.021** (0.009)	-0.023*** (0.008)
Extrapolation Dummy			1.492*** (0.177)	1.530*** (0.158)				
Constant	106.074** (51.344)	125.094*** (37.141)	72.801*** (22.077)	75.736*** (19.566)	24.424 (42.146)	17.904 (35.901)	41.037** (18.358)	44.296*** (17.059)
N	234	234	437	437	386	386	437	437
Firm Dummies	Included	Included	Included	Included	Included	Included	Included	Included
R^2/Adjusted R^2	0.69/0.35	n/a	0.65/0.42	n/a	0.54/0.34	n/a	0.59/0.33	n/a
F Statistics	F(123, 110) = 2.03***	F(123, 110) = 2.24***	F(173, 263) = 2.82***	F(173, 263) = 3.12***	F(121, 264) = 2.60***	F(121, 264) = 2.44***	F(170, 266) = 2.28***	F(170, 266) = 2.17***
Under-identification test	n/a	188.800***	n/a	252.319***	n/a	198.084***	n/a	279.129***
Weak identification test	n/a	543.002***	n/a	463.157***	n/a	297.260***	n/a	657.729***
Endogeneity test	n/a	χ^2= 5.386**	n/a	χ^2=3.796*	n/a	χ^2=4.406**	n/a	χ^2=7.044***

Notes: coefficients are significant at 1%***, 5%**, and 10%*. Standard deviations are in parentheses.
[a] The dependent variable of all models is *NPI Performance*.
[b] Three asterisks (***) denote that the weak identification test result is greater than the 10% maximal IV size.

Models 6-7 run the analyses in a subsample of firms that used only one mode throughout the period of our study. The variable *Prior Mode Success* is dropped because it measures the same thing as does the variable *Prior Firm Performance* for firms that used only one mode.
Models 8-9 add an *Extrapolation* dummy to control for the extrapolated cases.
Models 10-11 run the analyses in a subsample of more successful firms which excludes firms that introduced only one new product and ceased production before 2000.
Models 12-13 remove the dummies *Joint Development* and *Licensing*.