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Endogeneity in Strategy-Performance Analysis: An Application to Initial Human Capital Strategy and New Venture Performance

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Abstract

Managers engage in a variety of strategies, not randomly, but having in mind their performance implications. Therefore, strategic choices are endogenous in performance equations. Despite increasing efforts by various scholars in solving endogeneity bias, prior attempts have almost exclusively focused on single, one-sided, and discrete (binary) organizational decisions. Yet, in reality, managers often face multiple, simultaneous and inter-dependent decisions, possibly including a continuous choice set. These choices may further entail a two-sided process between managers and others, such as employees, strategic partners, customers, or investors, whose choices and preferences also affect the final decision. We discuss how endogeneity can plague the measurement of the performance effects of these two-sided strategic decisions – which are more complex, but more realistic, than prior representations of organizational decision making. We provide an empirical demonstration of possible methods to deal with three different sources of bias, by analyzing the performance effects of two human capital choices made by founders at startup: the size and average quality of the initial workforce.

Keywords: endogeneity, human capital choices, selection effects, simultaneous equations, strategy-performance effects

Managers do not make random decisions, but base them on strategic considerations, having in mind their (performance) implications. This is why organizational choices are endogenous in performance equations. These choices are multiple and complex, ranging from financing alternatives, changes in top management team, which type of (foreign) investments to undertake, whether and with whom to engage in partnerships and strategic alliances, business model design, product market strategies, to even more regular decisions pertaining to which employees to hire and/or promote (and when).

Scholars have paid considerable attention to measuring the effects of many of those strategic choices on performance (e.g., Agarwal & Audretsch, 2001; Campello, 2006; Geroski, Mata & Portugal, 2010; Goerzen, 2007; Klingebiel & Rammer, 2013; Zajac, 1990). More recently, the academic community has become increasingly concerned about the way in which these measurements have taken place, since these choices are deliberate decisions and often a function of expected performance outcomes (e.g., Cloughtery, Duso, & Muck, 2016), which implies that firm choices are indeed strategic, but also endogenous. Neglecting this fact is likely to lead to biased estimates of the effect of strategic choices on performance, and thus to erroneous conclusions regarding their "treatment effect" on firm outcomes. In this paper, we revisit these concerns and address endogeneity bias in strategy-performance analyses that can be more complex than previously described in the literature. We explain the different sources of endogeneity often present in these settings, and describe possible methods addressing these biases, together with an empirical demonstration of a study of the venture performance effects of entrepreneurs' human capital decisions at startup.

Endogeneity is often addressed by performing experiments, either in the laboratory or in the field. However, laboratory experiments are unlikely to capture the long-term effects of complex decision making in a realistic manner. Randomized field experiments may be an interesting alternative, but they are certainly unfeasible (not to say expensive and possibly unethical) in real contexts of complex and dynamic decision making, such as recruitment and investment strategies. Hence, researchers are dependent on observational data, and the possibility of making causal claims in this kind of strategy-performance analyses is therefore dependent on the researchers' awareness of the different sources of bias, as well as the techniques and data available to solve (or at least mitigate) them.

Several attempts to make researchers aware of endogeneity bias have been made in both micro- and macro-based research since Shaver (1998), with several techniques being proposed over the most recent years (see Antonakis, Bendahan, Jacquart, & Lalive, 2010; Cloughtery et al., 2016; Reeb, Sakakibara, & Mahmood, 2012; Semadeni, Withers, & Certo, 2014). In the domain of business studies, this attention has come mainly from studies in strategic management, but less from studies in the fields of organizational behavior and human resource management (Hamilton & Nickerson, 2003; Cloughtery et al., 2016). Furthermore, prior efforts have so far been mostly focused on single organizational decisions that are discrete (often binary) in nature. Examples of those choices could include whether to engage in Foreign Direct Investment (FDI), innovation, strategic partnerships, or CEO replacement.

Obviously, reality is sometimes more complex than this simplified representation. Managers and entrepreneurs often have more than two alternatives to choose from, and the number of choices can even be unlimited, i.e., the choice set can be continuous. Besides, managers are used to making multiple, often simultaneous and inter-dependent, strategic decisions. For instance, once a venture decides to internationalize, it has to choose where to, how (entry mode) and by how much (e.g., share of total production). Another example is about choosing financing options: firms often have to decide when, how much money to raise, and from whom (e.g., banks, several types of equity investors, the crowd, or a combination of different options). When launching their products (or services), firms have to make inter-related decisions regarding pricing strategies, distribution channels, and which customer segments to target. Also, when choosing whom to hire for their teams, firms have to decide how many employees to recruit and how skilled they should be. In all these examples, we can identify strategic choices that are simultaneous and inter-dependent, with a likely and intended impact on future performance. Besides, they often entail a two-sided matching process where firms (namely their founders or managers) need to coordinate with another side of the "market", such as employees, strategic partners, customers, or investors. The final realization of strategic choices is thus dependent on the latter accepting the "deal". This acceptance may depend on firms' or managers' own characteristics, such as their quality (which is rarely observed by the researcher). Therefore, addressing endogeneity to obtain unbiased measures of the effect of these more complex decisions on firm performance is not easy.

This paper addresses three specific complexities that, if neglected, are likely to produce erroneous conclusions in strategy-performance analyses. The first complexity involves dealing with omitted variables that are possibly correlated with firm strategies, but directly unobservable to the researcher. The second complexity is dealing with multiple and simultaneous strategic decisions that often involve a two-sided matching problem between the firm (or manager) and other elements in the market (e.g., employees or customers). The third complexity arises from the fact that strategies are indeed a *choice* that firms (or managers) select from multiple options, partly dependent on their own (unobserved) characteristics and other competitors' choices. By addressing these three sources of bias in more complex (and realistic) strategic management settings than prior representations in most strategy and management research (where strategies are often reduced to binary, one-sided, choices), we aim at increasing researchers' awareness of the empirical challenges in strategy-performance analyses, besides providing them with methodological approaches to deal with the different complexities in a variety of contexts, including organizational behavior and human resource management.

We provide an empirical demonstration of these methods in the field of entrepreneurship and human resource management by analyzing the performance effects of two simultaneous and inter-related choices founders make at early stages – size and average quality of the initial workforce – using rich matched employer-employee data for Portugal. Empirical research has suggested that larger initial size and stronger founder capabilities lead to better venture outcomes (e.g., Brüderl & Schussler, 1990; Cooper, Gimeno-Gascon, & Woo, 1994; Geroski et al., 2010; Koch, Späth, & Strotmann, 2013). However, prior research has treated a venture's human capital endowment as independent from other factors affecting venture performance or survival. This assumption seems invalid on several grounds. First, we agree with Agarwal, Campbell, Franco, and Ganco (2016) that a venture's initial human capital stocks are at least partly determined by the founder's quality and capabilities, as well as the (expected) quality (i.e., success) of the new venture.[1] Omitting (observed and unobserved) founder characteristics from the human capital-performance analysis is hence likely to bias the measured effects of initial workforce characteristics. Additionally, prior studies have found a positive association between founder quality and both firm size and workforce quality (Lucas, 1978; Baptista, Lima, & Preto, 2013; Dahl & Klepper, 2015). This is likely the result from a two-sided "market" process, where founders and employees choose to work with one another. Founder quality thus impacts both their own access to better quality employees, and the decision of these employees to join the founder (Agarwal et al., 2016). Moreover, and related to the above, initial human capital stocks

[1] Though we are not the first to recognize this (see also Colombo, Delmastro, & Grilli, 2004; Hvide & Møen, 2010; and Melillo, Folta, & Delmar, 2012), we are the first to show how it biases the human capital-performance relationship.

represent a fundamental choice of the founding entrepreneur(s), which means they are self-selected, rather than exogenously allocated to new ventures.

This paper contributes to prior efforts in highlighting the nature of endogeneity problems often present in organizational and strategic decision making, by extending our focus to strategy-performance analyses where multiple and inter-dependent two-sided organizational choices take place, which are more complex (and realistic) than most prior representations in both substantive and methodological articles. We highlight the nature of these endogeneity problems by focusing on the three aforementioned biases. We discuss proposed methods to address or mitigate these problems, using founders' human capital decisions as an illustration. We finally provide a more detailed empirical demonstration of these issues and empirical approaches, showing how conclusions change compared to the baseline case in which endogeneity is neglected. We conclude by revisiting some of the settings where our empirical approaches could be applicable, yet acknowledging some limitations, hoping to encourage researchers to embrace our (or other) approaches to address endogeneity in their future analyses.

Sources of Endogeneity Bias in the Strategy-Performance Relationship

It has often been argued that a firm's initial and subsequent strategic choices have enduring performance consequences (Stinchcombe, 1965). Empirical evidence from management, economics, organization, and strategy research tends to support this thesis. Shane and Stuart (2002) indicate that founding conditions might determine the success in venture capital funding and IPO, besides reducing failure rates, while Geroski et al. (2010) confirm that founding conditions may have quite persistent effects over the first 10 years of a new firm's life, since "*choices made* at inception … may not be easy to undo" (p. 511). Firms do make strategic choices not only at inception – for instance, regarding team composition (Agarwal, Campbell, Franco, & Ganco, 2016) – but continuously over their life cycle, either regarding team changes (Forbes, Borchert, Zellmer-Bruhn, & Sapienza, 2006), building or acquiring human capital (Lepak & Snell, 1999), CEO selection, replacement, and compensation (Zajac, 1990), internationalization (Shaver, 1998), innovation (Klingebiel & Rammer, 2013), strategic alliances and partnerships (Goerzen, 2007), or financing options (Campello, 2006) – just to name a few. Managers do not make these choices randomly, but based on strategic considerations pertaining to their expected outcomes. This is the essence of the endogeneity problem.

Despite extensive reviews and increasing awareness of the topic, most studies keep neglecting endogeneity in their strategy-performance analyses, possibly leading to biased results. According to Hamilton and Nickerson's (2003) survey of strategy research, only 27 out of 196 empirical articles on firm performance attempted to correct for endogeneity issues. Clougherty et al.'s (2016) follow-up survey of the most recent research documents that still less than half of the studies (45 percent) address endogeneity concerns.

The endogeneity issue is quite extensive and involves a number of sub-dimensions. In this section, we address three sub-dimensions or potential causes of endogeneity – omitted variables, simultaneity and self-selection – (a) by providing examples of how each may confound measures of how organizational choices influence venture outcomes; and (b) by explaining how we confront each challenge (together with the limitations pertaining to our approaches), using the illustrative example of founders' human capital choices and their effect on new venture performance.

Omitted Variables

One cause of endogeneity is model misspecification due to omitted variables that both affect the dependent variable and are correlated with one or more explanatory variables. As a consequence, included variables will correlate with the error term, violating the critical assumption that the error term is orthogonal to these explanatory variables. As an illustration, consider the following regression model:

$$Firm\ Performance_i = a_0 + a_1 x_1 + a_2 x_2 + \cdots + u_i \qquad (1)$$

and suppose that x_2 is omitted from the regression, either due to model mis-specification or because x_2 cannot be observed directly. Then the expected value of the coefficient estimate for x_1 would be

$$E(\bar{a}_1) = a_1 + a_2\delta_1 \qquad (2)$$

where a_2 is the (hypothetical) coefficient for x_2, and δ_1 is the hypothetical covariance between x_1 and x_2. The direction of the bias introduced by omitted variables depends on the relationship between a_2 and δ_1. Imagining that both coefficients are positive, we would expect that $\bar{a}_1$ overstates the effect of x_1 on firm performance.

Using the example of a founder's human capital choices, any model relating either startup size or initial workforce quality to firm performance would produce biased conclusions if the founder's quality is omitted from the performance regression – not only because the quality of the founding team is expected to improve performance (Cooper et al., 1994), but also because startup size and employees' quality are believed to be (positively) correlated with founder ability (Dahl & Klepper, 2015; Hvide & Møen, 2010).

As a correction for this potential source of bias, it is *a priori* not sufficient to *simply* add controls to the performance equation for the founders' ability, such as proxies for their human capital. *Observed* levels of individual skill heterogeneity imperfectly reflect their *true* heterogeneity (e.g., Abowd, Kramarz, & Margolis, 1999; Iranzo, Shivardi, & Tosetti, 2008). For instance, skills that are innate or obtained through informal experiences are likely to remain unobserved, being at the same time, influential on organizational decisions.

In order to mitigate concerns related to omitted abilities of the decision maker, we adopt a composite measure for the skill quality of founders inspired by the multi-dimensional skill index developed by Portela (2001). It incorporates two observed dimensions (i.e., education and experience) together with a third dimension capturing unobserved components of human capital quality based on their prior career earning histories in the labor market (see below).

Formally, and following Portela (2001), the skill index S of founder i in year t is computed as follows:

$$S_{i,t} = mschool_t * a_{i,t_{school}} * a_{i,t_{experience}} * a_{i,t_{unobservable}} \tag{3}$$

where, for year t, $mschool$ is the average number of years of education in the economy, and each of the remaining terms correspond to correction factors taking into account the actual position of individual i in the overall distributions of schooling, experience, and unobserved quality, respectively. Since the three human capital dimensions complement each other, these components enter the equation multiplicatively.

As an illustration, the factor correcting the schooling level of individual i is measured as

$$a_{i_{school}} = 0.5 + \frac{e^{(school_i - mschool)/sschool}}{1 + e^{(school_i - mschool)/sschool}} \tag{4}$$

where $school_i$ is the schooling level (in years) of individual i and $sschool$ represents the standard deviation of schooling in the population.[2] Bound between 0.5 and 1.5, this correction factor takes on values larger (smaller) than one when individuals are more (less) educated than average. A similar approach is used to generate $a_{i_{experience}}$.

[2] The use of the logistic distribution controls for the effect of outliers.

Regarding the individual's unobserved quality, $a_{i_{unobservable}}$, we use the individual fixed effect obtained from the estimation of a wage equation using individual labor market histories. This wage equation uses real hourly earnings (in logs) as a dependent variable, and controls for individual education, skill level, non-linear effects of age and tenure, calendar year effects, and controls for both individual and firm fixed effects (Abowd *et al.*, 1999) to obtain estimates of worker (and firm) quality unexplained by observable measures. The individual fixed effect approximates each individual's unobserved ability, which is an explanatory factor of their earnings premium over time. Hence, this measure of unobserved ability discriminates between two individuals with similar education and other background characteristics (including previous employers' quality), but who have had distinct income levels in the past.[3]

These steps enable the computation of the skill index for each individual i in firm j and year t. Since founders' and workers' skills are likely to be positively correlated, we use the exact same index to measure both workers' (i.e., non-founding employees') and founders' skill quality. We compute aggregate variables at the firm-level in order to measure the two key aspects of human capital quality for each venture: founder quality and initial workforce quality – or x_1 and x_2 in the hypothetical model (1).

The resulting standardized skill index S (equation 3) neatly summarizes the joint effect of different variables having different units of measurement in a single standardized measure of ability. By including several dimensions of human capital in a single index that can be used for

[3] Agarwal et al. (2016) also acknowledge the importance of accounting for founder quality in similar settings, and – like in several studies (see references therein) – use founder's pre-founding earnings as a reflective measure of individual's underlying attributes. The skill measure we use is an improvement over a measure solely based on earnings, since earnings are largely correlated with previous employer quality. By estimating a wage equation with both firm and worker fixed effects, we obtain a more refined measure of individual unobserved ability that is no longer confounded with previous employer quality.

both founders and employees, we hope to reduce omitted bias related to founder ability (as well as firm quality, since both are positively correlated). This comprehensive measure of quality for both founders and employees will also help address the complexities related to simultaneity, which we introduce next.

Furthermore, Portela's (2001) index can be applied in other settings, where measuring the (multi-dimensional) quality of either firms or decision makers is crucial – and possibly correlated with organizational decisions. The elements included in the skill index will certainly depend on the available data and the skill or quality dimensions considered relevant in each setting. Alternative proxies for individual unobserved skills could be ability test scores obtained through survey methods. The index can also be easily used to measure quality at an organizational level, see for instance Sá, Florax, & Rietveld (2004, 2012), who used an adapted version of Portela's (2001) skill index to quantify university quality, by taking into account different elements such as the quality ratings of teaching facilities, curriculum, and academic staff.

Simultaneity

A second cause of endogeneity is simultaneity, meaning that two (or more) variables simultaneously cause each other. Reverse causality is a form of simultaneity bias (see Antonakis et al., 2010). We are particularly concerned about another form of simultaneity bias, because reverse causality is less of an issue when we investigate how decisions made at founding impact future performance (i.e., when x precedes y temporally, as in our case). We are mostly concerned with the fact that multiple decisions are jointly made and simultaneously determined by unobserved factors, such as manager or firm quality. This is the case, for example, when managers (or founders, as in our illustration) make joint decisions regarding workforce size and quality, as in a variety of other domains such as innovation, financing, partnerships, business model design, market entry, or internationalization, where multiple inter-related decisions must be made at once.

A further complication may be that decisions are made based on a two-sided process – in our example involving founders and (prospective) employees – where sorting based on (unobserved) quality is likely to take place. Often times, positive sorting governs the dynamics between the two sides – i.e., more skilled workers are drawn to work for more able founders, and *vice versa*.[4] Recent efforts in highlighting endogeneity issues in strategic management research have remained silent on how to deal with these sources of bias in more complex settings (e.g., Cloughtery et al., 2016).

Our approach to deal with the simultaneity aspect of organizational decisions follows the logic of structural models and simultaneous-equation systems (see also Reeb et al., 2012, Roodman, 2011). In these systems, explicit equations describe individual or firm behavior and, subsequently, the organizational choices under investigation. In particular, we follow Roodman's (2011) methodological approach, which extends the logic of seemingly unrelated regression (SURE) models to systems of equations where (some) dependent variables may relate to each other, under a structural or recursive logic. This approach also has the advantage of enabling the estimation of a panoply of models (e.g., binary models, linear or truncated regressions) within the same system of equations, which may be useful to model multiple simultaneous decisions with different choice sets (i.e., either discrete or continuous).

[4] Another example where these two-sided processes are observed includes founder-CEO replacement decisions. CEO turnover is often dictated by mismatches between business quality and CEO ability. Therefore, CEO replacement decisions aim at improving the match between the two sides of the "market", sorting the best CEOs into the best firms (Chen & Thompson, 2015).

Using human capital choices of founders as an illustration, we simultaneously estimate the following system of equations, where mutual influences are allowed, in order to predict the key organizational decisions of interest, which we later label as firm-level "benchmarks" for human capital quantity and quality choices:

$$\begin{cases} Solo_{it} = \boldsymbol{FounderHC}'_{it}\boldsymbol{\beta_1} + \boldsymbol{FounderExp}'_{it}\boldsymbol{\lambda_1} + \theta_{11}Size_{jt} + \theta_{12}WQuality_{jt} + \boldsymbol{Z\varphi_1} + \varepsilon_{1it} \\ Founder\ Quality_{it} = \theta_{21}Size_{jt} + \theta_{22}WQuality_{jt} + \theta_{23}Founder\ Quality_{jt} + \theta_{24}Solo_{it} + \boldsymbol{Z\varphi_2} + \varepsilon_{2it} \\ WQuality_{it} = \boldsymbol{FounderExp}'_{it}\boldsymbol{\lambda_3} + \theta_{31}Size_{jt} + \theta_{32}WQuality_{jt} + \theta_{33}Solo_{it} + \theta_{34}FounderQuality_{it} + \boldsymbol{Z\varphi_3} + \varepsilon_{3it} \\ Size_{it} = \boldsymbol{FounderExp}'_{it}\boldsymbol{\lambda_4} + \theta_{41}Size_{jt} + \theta_{42}WQuality_{jt} + \theta_{43}Solo_{it} + \theta_{44}FounderQuality_{it} + \boldsymbol{Z\varphi_4} + \varepsilon_{4it} \end{cases} \tag{5}$$

Our intention is thus to jointly predict organizational decisions related to initial size and workforce quality based on pre-determined founding team information. The first equation in the system corresponds to the decision of running the business alone or in a team. We expect this choice to be closely related to the founder's general and specific human capital ($\boldsymbol{FounderHC}$ and $\boldsymbol{FounderExp}$), as well as to the size and quality of the workforce to be employed (which, in turn, is affected by the size of the founder team). However, these two last variables refer to endogenous choices in the system, and the equations must be designed recursively to guarantee identification. Thus, we use the average number and the average quality level of the workers employed by firms operating in the same 2-digit industry *j* and year *t* ($Size_{jt}$ and $WQuality_{jt}$, respectively) as exogenous proxies for the quantity and Portela's (2001) measure of quality of human resources to be hired by the firm.

This choice of running a business alone or with a co-founder may, in turn, affect the overall quality level of the founder (team): team members are strategically chosen (or left out) in order to benefit from (skill) complementarities (Forbes, Borchert, Zellmer-Bruhn, & Sapienza, 2006). The second equation thus estimates the (average) quality of the founder (team).

The final two equations in the system correspond to the key human capital choices of interest: the (Portela-indexed) quality and number of workers hired by each firm in each year. The equations include not only the entrepreneurs' quality, experience, and their business' quality, which are likely drivers of these two key human capital choices, but also the average choices of naturally comparable firms (competitors from the same industry). This captures the likely correlation between what our focal firms do and what their competitors do, based on industry characteristics, norms or (for that matter) competitive considerations.

All equations include a vector ***Z*** containing dummy variables for firm age, year, 2-digit industry, Nuts-III region, and dummies for necessity-driven (founders coming from a firm that suddenly closed down) and opportunity-driven entrepreneurs (founders coming from paid employment in an existing firm that keeps operating afterwards). ***FounderHC*** includes founder's age and education (years of schooling), while ***FounderExp*** controls for specific human capital of the founder(s), namely their experience as entrepreneurs, in the industry, and in management positions.

Besides including the sample of startups under analysis, we also use data on all incumbent firms with complete information in our dataset during the same period. Thus, we use a total sample of 194,357 firms observed during 1992-2007, out of which 5,341 are the startups in our main sample – as we describe in the next section. Including incumbent firms in the estimation of "benchmark" strategies (i.e., the average behavior of comparable competitors in the same industry) is relevant because incumbent firms may also compete with startups and thereby shape their choices at the time of entry.

The results from this simultaneous estimation (not reported, but available upon request) confirm the existence of a strong and positive association between worker and founder quality. More skilled and more experienced founders hire more skilled workers and larger workforces, on average. This provides evidence of a positive matching of entrepreneurs and employees based on their skill levels. Neglecting it may bias the estimation of the treatment effects of human capital on venture performance. Moreover, the number (quality) of workers hired over a firm's lifecycle is found to be significantly and positively associated with the average number (quality) of workers employed by competitors in the same industry. This further corroborates our concerns related to simultaneity bias.

The adoption of this methodological step would be relatively straightforward in other research settings. For instance, researchers interested in investigating the performance effects of venture capital, innovation strategies, particular business model elements, or adjustments in the management team, should rely on existing theories to redesign the equations to be included in this first-stage estimation, in order to capture the underlying dynamics of interest – e.g., eventual two-sided interactions between the focal firm and other elements in the market, such as investors, customers, or employees. Roodman (2011) provides further guidance for identification issues, depending on the type of system to be estimated (e.g., recursive or not).

Self-selection

Selection bias might be considered a form of omitted-variable bias, since the selection process represents an excluded variable that manifests in the error term and correlates with both the endogenous choice construct and the outcome variable [see Antonakis et al. (2010) and Clougherty et al. (2016) for a review and proposed solutions for this issue]. Our concern is focused on self-selection bias. In the more conventional binary treatment context (i.e., whether to engage in a particular strategy, such as CEO replacement, FDI, or entering a strategic alliance), self-selection implies that agents make choices regarding whether they join the “treatment” or the “control” group based on unobservable variables (e.g., motivations, cognitive biases, ability) that may correlate with both performance and observable predictors.

Matching methods dividing the sample into comparable groups engaging and not engaging in the “treatment” (strategy) of interest (treatment and controls groups, respectively) would be a partial solution (see Li, 2012, for a review and practice guide). However, matching is only a valid solution in case all the relevant differences between individuals in the treatment and control groups that determine differences in outcomes are observable. This is unlikely to be the case. Moreover, it requires the strategy under analysis to be dichotomous – and in many business situations the “treatment” is not *simply* a binary choice, but may instead have a continuous element to it (e.g., the extent to which a firm decides to internationalize, based on the share of total production exported or produced abroad; the gender or skill composition of the top management team, based on the share of members with certain characteristics). These decisions are not random, but influenced by certain factors, often unobserved to the researcher.

In the example of founders’ human capital choices, founder traits that are unobserved by the researcher may determine the selection into certain ranges of workforce size or quality, and also affect future performance. Thus, parameters estimates of the relationship between workforce size/quality and firm outcomes can be confounded with the selection process into certain ranges of workforce size/quality. Solving this type of endogeneity often entails estimating a so-called selection equation in a first stage, which explains the decision by organizations to engage in a certain strategy, using a standard Instrumental Variables approach (see Clougherty et al., 2016). However, this approach is more often used in case of a single (i.e., one “first stage”) strategic decision of interest and if at least one suitable identifying instrument is available – and they are often absent or hardly convincing.

Our approach to deal with selection of workforces of varied size and quality mimics the logic of matching methods, in the sense that we compare the different human capital decisions made by very similar founders and firms. This approach builds on the system of equations estimated before to address simultaneity bias. As is often the case in more traditional self-selection problems related to binary "treatments" (i.e., strategies), the first-stage estimation (now of a system, rather than a single equation) is crucial in addressing self-selection bias in this case. From this system of simultaneous equations, we predict the strategic choices of interest – in our example, quantity and quality of human capital to be employed at startup – based on all the observed characteristics that define the focal firm, and the unobserved quality of the founder (team) as far as we can capture this with the skill index. Next, we measure the deviation of each venture's observed decision (in this case, actual human capital choices) from their predicted "benchmark decisions":

$$\textit{Size Deviation} = \frac{\textit{Initial Venture Size} - \textit{Benchmark Size}}{\textit{Benchmark Size}} \qquad (6)$$

$$\textit{Worker Quality Deviation} = \frac{\textit{Initial Workforce Quality} - \textit{Benchmark Workforce Quality}}{\textit{Benchmark Workforce Quality}} \qquad (7)$$

The extent to which self-selection problems are solved by using firms' relative positions compared to a narrowly defined benchmark hinges on the validity of the assumption that deviations from the firm-specific benchmarks are not determined by the same factors that determine performance. In our example, entrepreneurs starting up with more or higher quality human capital than the average narrow set of comparable firms (i.e., startups with similar founder and firm characteristics) may do so out of ignorance, due to forecasting errors, over- optimism or confidence, or risk seeking (Camerer & Lovallo, 1999; Åstebro, Herz, Nanda, & Weber, 2014;

Hyytinen, Lahtonen, & Pajarinen, 2014). On the other hand, those who do not reach the size and/or quality thresholds are more likely to correspond to pessimistic or risk averse entrepreneurs. Other explanations for the existence of many startups entering at sub-optimal scales include the entrepreneurs' expectations of learning by doing (Jovanovic, 1982; Pakes & Ericson, 1998): entrepreneurs are often uncertain about their ability, so they may decide to enter at a very small scale, hoping that they will be able to correct entry choices later on, as they update their beliefs about their ability (Audretsch, Santarelly, & Vivarelly., 1999; Audretsch, Houweling, & Thurik, 2000). All these reasons to deviate from the estimated benchmark are unlikely to be direct determinants of performance. Therefore, we use these measures in the "second stage" (i.e., performance equations) as exogenous proxies for the initial size and quality of a venture's workforce, following the logic of more traditional Instrumental Variables approaches.

We acknowledge that some founders may deliberately deviate from the benchmark because they have private information about why doing so would benefit their companies. These unobserved factors cannot be addressed by our approach (or by matching methods) and may cause a remaining bias.[5] Researchers should therefore be critical about any remaining bias that could persist after applying all these methodological steps in other settings. Nevertheless, (i) the better one controls for unobserved factors that potentially affect firm performance, as well as strategic choices, and any associated two-sided matching, and (ii) the more comprehensive is the structural system estimated in the first stage, the smaller will be the remaining bias, and the closer will the researcher be to the "true" treatment effect of the organizational strategies under analysis.

[5] Avoiding any of this remaining bias would require experimental methods with random assignment of founders and workforces, which is not feasible.

Empirical Demonstration: Initial Human Capital and New Venture Performance

We demonstrate the application of the outlined approaches using the example of founders' initial human capital choices. Empirical evidence has indicated that founders' human capital (e.g., Eisenhardt & Schoonhoven, 1990) and startup size (Brüderl & Schüssler, 1990; Mata & Portugal, 1994; Audretsch, Santarelli, & Vivarelli, 1999; Agarwal & Audretsch, 2001) influence venture survival and performance. A relatively new, but important, topic is how venture survival and performance are influenced by the quality of the human resources beyond the founding team (Agarwal et al., 2016). There are compelling reasons to believe that initial workforce quality improves venture success, since more capable employees generally complete tasks and responsibilities more effectively and timely, enabling ventures to capture more opportunities. Prior research has, however, largely overlooked that these decisions are strategically made by founders based on their own characteristics (see, for instance, Baptista, Lima, & Preto, 2013; Dahl & Klepper, 2015) and the expected impact on future performance. This implies that analyses of the effects of human capital choices on firm performance cannot neglect the possible endogeneity of those organizational decisions in the performance equation.

Our illustration proceeds in four stages. First, founder and worker skill indices are estimated, as a basis for the measurement of initial workforce quality choices and reducing omitted variable bias related to founder (observed and unobserved) ability. Second, the system of equations for the founder's choice for solo (versus team) entrepreneurship, founder quality, and the key strategic choices of interest (workforce size and average quality) is estimated following Roodman (2011). Based on this, we can predict the average workforce size and quality at startup for a small *cosmos* of comparable founder-firm combinations ("benchmark choices"). Third, deviations from these benchmarks at entry are calculated, and their effects on venture success are finally estimated using multivariate regression techniques. The analysis of the relationship between human capital choices and future venture performance is presented in steps, addressing each of the different sources of endogeneity in turn, to be able to identify whether and how they affect the results.

Data and Sample

In the illustrative application of our empirical approach, we use data from *Quadros de Pessoal* (hereafter, QP), a large longitudinal linked employer-employee dataset collected by the Portuguese Ministry of Employment. QP dataset covers *all* private firms operating in Portugal employing at least one wage earner, which contrasts with data that may systematically ignore smaller ventures. Available information at the firm-level includes employment, sales, industry, ownership, location, among others. At the individual-level, QP reports information about each worker's age, education, gender, qualifications, wages, occupational category, tenure, number of hours worked, and type of contract. All firms, establishments and workers are identified with a unique identification number, so they can be followed and matched over time. We have access to original QP files for the period 1986-2009.

Firm entry is identified by the first year a firm is recorded in QP files, and founders are identified by their listing as "employers" (i.e., business owners hiring, at least, one employee). Our analysis is based on startups in manufacturing industries, whose founder(s) was (were) in paid employment in *t-1* or *t-2*. [6] We focus on manufacturing industries for two reasons. First, it consists of a more comparable sample of firms (despite the variety of industries included, which

[6] We exclude startups whose founder was unobserved in the files prior to founding, because we cannot ascertain whether their absence is correlated with their initial human capital choices. Possible reasons for their absence in the files include unemployment spells, periods outside the labor market (e.g., leave periods, emigration, investment in education), self-employment without employees, or employment in the public sector.

are controlled for via fixed effects) than if services were included.[7] Second, we believe that human capital choices may be more interesting in manufacturing industries, where there is a larger scope for developing specific skills (also because knowledge intensive services account for a very small share of the Services sector in Portugal). Meta-analyses of the impact of human capital on firm performance indeed suggest that effects may be stronger – and thus choices may be more strategic – when human capital becomes more specific, and thus less tradable, in the labor market (Crook, Todd, Combs, Woehr, & Ketchen, 2011).

Our final sample is composed of 5,341 startups entering manufacturing industries between 1992 and 2007 (excluding 2001), employing at least one wage earner in the first year, and whose founder(s) came from paid employment.[8] Data for the years 1986-1991 were only used to trace and characterize the labor market experiences of founders. Following earlier literature (e.g., Rocha, Carneiro, & Varum, 2018 and references therein), we first focus on firm survival, which captures more accurately the primary objective of new organizations. Yet we acknowledge that a firm's longer longevity does not necessarily imply better performance (Gimeno, Folta, Cooper, & Woo, 1997), so we complement our analysis by using labor productivity as a measure of venture success. We observe the outcomes of each firm annually until the end of the observation period or until the moment of an ownership change (depending on which of the options occurs first).[9] The analysis stops in 2007, the last year for which we can

[7] Estimations reported in the paper include industry fixed effects at the 2-digit level. Robustness checks with fixed effects at the 5-digit industry level provide qualitatively similar results, but would reduce the period of analysis due to changes in industry classifications.

[8] No individual-level data were collected in 2001, which does not allow us to accurately identify the founder(s) of firms created in this year. We therefore exclude startups founded in 2001 from our analysis.

[9] After ownership changes, the business identity may change, as the entrepreneur-firm quality match may also change. It is not our aim to study these processes of ownership change, neither their impacts. For this reason, we

accurately identify firm exits. Firm exit (and thus survival) is identified by the moment when a firm ceases to answer the survey.[10] Following previous studies using the QP dataset to study firm exit (e.g., Mata & Portugal, 2002; Geroski et al., 2010), we require an absence of the firm from the files for at least two years in order to identify its definite exit. For this reason, data for 2008 and 2009 are only used to check the presence or absence of firms in QP files. Variable definitions are provided in the Appendix.

Descriptive Analysis

Table 1 summarizes the descriptive statistics. On average, founders are more skilled and experienced than employees.[11] The correlations between founder capabilities (measured by education, entrepreneurial and managerial experience, and founders' skill index) and the number and quality of employees at startup are positive, as expected (see also Figures 1a and 1b). Apparently, a positive sorting process is occurring between workers and founders, further fueling concerns about the endogenous nature of initial human capital choices.

Figures 1c and 1d illustrate the effectiveness of our control for self-selection bias by showing the association between the founder skill index and firm deviations from size and quality benchmarks, obtained from the estimation of the system of equations in the first stage. In both

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censor the spells at the point of ownership change. Robustness checks using the complete spells of firms changing owners do not change the main conclusions from our analysis.

[10] We define exit as firm closure, since QP data do not allow the distinction between different modes of exit. Prior studies (Geroski et al., 2010) document that less than 1 percent of the liquidations in Portugal have been due to mergers or acquisitions, thus suggesting that our inability to identify exits due to M&As is unlikely to affect our results.

[11] In Portugal, up to six formal years of education corresponds to the International Standard Classification of Education (ISCED) 1, while seven to nine years of formal education correspond to ISCED 2 (OECD, 2014). The average employee (founder) in these startups has an education level within ISCED 1 (2), which is rather low compared to an international benchmark.

cases the association with founder skills is very weak, giving us confidence that these measures of initial human capital (quantity and quality) reduce selection bias driven by founder and business quality, being thus more exogenous than the previous measures.

Unconditional correlations between the two measures of startup performance and both size and quality of the initial workforce confirm the existence of strong associations. Both human capital quantity and quality have a negative association with firm hazard (pairwise correlations are -0.1029 and -0.1147, respectively), in line with prior literature (e.g., Mata & Portugal, 1994; Geroski et al., 2010). More skilled workforces at entry are also positively correlated with future levels of productivity, as expected (correlation = 0.1681). Startup size, in turn, has a negative association with firm productivity levels (correlation = -0.0650).[12] This negative finding may be consistent with lower flexibility and adaptation levels when starting up relatively large in an unknown environment (Cabral, 1995; Dhawan, 2001) and in a relatively rigid labor market, such as the Portuguese one (Martins, 2009; OECD, 2012).

[Table 1 and Figure 1 here]

Initial Human Capital Choices and Venture Hazard

We now test whether the relationships between initial workforce size and quality and new venture outcomes hold in a multivariate model estimated with a semi-parametric discrete time proportional hazard model.[13] An advantage of hazard rate models for the analysis of duration data is their capacity to deal with right-censored data, which is the case when firms

[12] This contrasts with the common result that large (incumbent) firms are more productive on average (Bartelsman & Doms, 2000). However, we study a different benchmark, i.e., larger startups. There is little comparative evidence on the association between startup size and productivity within the population of startups.

[13] Alternative estimations using Gamma-frailty models produce similar results.

continue to survive beyond the observation period (i.e., 2009). Table 2 presents our results. Positive coefficients reflect a positive association with the hazard of the firm. All models control for firm location, industry, firm age, necessity-driven (versus opportunity-driven) motivations, and calendar time (year) effects. All variables are z-standardized, to make coefficients comparable across models and size effects easy to interpret.

Models (1) and (2) replicate prior research by displaying the effects of founder quality and initial workforce size. Consistent with earlier studies (e.g., Bates, 1990; Delmar & Shane, 2006), founders with higher levels of education, and longer industry and management experiences have ventures with lower hazard rates. Also, founding a startup alone is associated with an increased exit risk relative to sharing ownership. Consistent with prior findings (e.g., Brüderl, Preisendörfer, & Ziegler, 1992; Mata & Portugal, 1994), starting larger ventures is associated with a reduced firm hazard. A one-standard deviation increase in startup size is associated with a decrease in firm hazard by 15 percent ($1 - exp(-0.1614)$). The consistency of this effect will be ascertained by addressing endogeneity bias due to omitted variables, simultaneity, and self-selection.

Model (3) includes observed measures of initial workforce quality: average workers' education level and age, but a Likelihood Ratio (LR) test shows that this model does not provide a significant contribution beyond model (2). If we were to stop here, without addressing any endogeneity bias in founders' human capital choices, we would conclude that initial workforce quality is unimportant in predicting venture survival.

Models (4) and (5) consider the first source of endogeneity bias by dealing with omitted variables concerning unobserved founding team quality and unobserved workforce quality. To this end, we add skill indices for founding members and for non-founding employees to the hazard equation. Both are significant improvements over the baseline models according to LR tests, indicating that unobserved skills pertaining to founding teams and workforces are also important determinants of firm survival. Noteworthy is the fact that the estimate for startup size is now slightly smaller (about 6 percent smaller), confirming that the positive correlation between founder quality and entry size might overestimate the performance bonus of entering at a larger scale. Similarly, the coefficient for the founder's skill index decreases by 19 percent (from -0.0736 to -0.0595) once the workers' skill index is included in the estimation, thereby accounting for workers' unobserved quality. Our example clearly shows the biases in the key estimates of interest when we omit variables that are correlated with each other and that influence firm outcomes (recall equations 1 and 2).

Column (6) addresses endogeneity issues tied to simultaneity, by including the system of equations in the first stage and adding predicted benchmarks (which reflect competitors' average choices) as additional regressors in the second stage. This helps addressing possible biases due to two-sided matching process between employees and employers and biases due to simultaneous decision making. While the key coefficients of interest (startup size and workforce quality) seem to be largely unaffected by this step, the coefficient of founder quality increases in magnitude once we acknowledge that human capital decisions involve a two-sided matching process between entrepreneurs and employees. The results confirm that founder human capital – and especially founder quality that is unobserved to the researcher – plays a crucial role in this matching process, and neglecting simultaneity bias risks underestimating the impact of founder quality on firm persistence. The results indicate that founder quality plays an important role for firm survival, which goes beyond its role in attracting high-skilled employees.

Model (7) addresses endogeneity concerns tied to self-selection into certain venture sizes and workforce quality compositions, which may also affect venture survival. Compared to model (6), *observed* startup size and workers' initial quality are replaced by the *deviation*, in percentage, *from their respective benchmarks*. The variation in these variables is now assured to be exogenous, as long as the estimated benchmarks for size and skills include the factors that drive decisions about workforce size and quality that are also related to venture success. Noteworthy is how variables of interest are affected by this additional control for self-selection. Though the coefficient for initial workforce size remains similar, the coefficient for initial workforce quality drops by 26 percent (from -0.1026 to -0.075). This suggests that part of the estimated effect of workforce quality was indeed attributed to founder's self-selection bias, which overestimates the true effect of initial human capital quality choices. Yet the significance of workforce quality remains strong and economically impactful: a one standard deviation increase in a venture's workforce quality will reduce its hazard by 7.3 percent.

In sum, our approach to dealing with three complex forms of endogeneity present in the relationship between initial human capital choices and firm performance provides the following insights. Endogeneity caused by omitted variables related to both founder and workforce unobserved quality would overstate the effects of some key variables (e.g., founders' education, accumulated experience, and startup size). Biases driven by the simultaneous two-sided matching between founders and employees would mostly underestimate the effect of founder (unobserved) quality. Finally, self-selection bias is found to be particularly dangerous when estimating the effect of workforce quality on venture survival. Our exercise suggests that about a quarter of the effect found with more "naïve" methods might be attributed to selection, rather than treatment effects.

[Table 2 here]

Initial Human Capital Choices and Firm Productivity

We acknowledge that survival may have some limitations as a performance measure in the context of startups (Gimeno et al., 1997; Rocha et al., 2018), so in this subsection we go beyond survival and illustrate how initial human capital choices are related to labor productivity, measured by the ratio between total sales (2005 constant prices) and total employment in $t + 1$, in logs. Since this outcome is only observed for firms surviving between t and $t + 1$, a two-equation Heckman model is estimated to account for attrition (survival) bias in every specification. Table 3 reports the results for the second stage. The sequence of models is identical to that presented in Table 2.

Like Table 2, Table 3 suggests that initial workforce quality has an important effect on venture success, and that endogeneity should not be neglected. Models (4) and (5) control for omitted variables tied to unobservable founder and workforce skills, and both coefficients are positive. A one standard deviation increase in founder skills raises labor productivity by 11.2 percent, and a one standard deviation increase in workforce skills raises labor productivity by 6.1 percent (model 5).

Correcting for simultaneity bias (column 6) lowers the estimates of all human capital coefficients, albeit to different degrees. The coefficient for initial workforce size is reduced by 31.5 percent, and the coefficient for initial workforce quality is reduced by 13.2 percent. Addressing self-selection bias in model (7) further reduces both coefficients, though not significantly from the estimates obtained in the previous model. Noteworthy is also that the founder's quality index has no effect on productivity once the two-sided simultaneous match is taken into account in column (6). This might indicate that a founder's unobserved quality affects labor productivity mainly through the attraction of better quality workers. In contrast, a founder's unobserved quality might still affect survival (and possibly other outcomes) through many other channels (e.g., attraction of funding). This suggests that the way in which we measure performance is not an entirely innocuous choice, especially if the focus would be on founder's human capital effects.

In general, the results in Table 3 confirm that more skilled workforces at entry boost the labor productivity of the firm over the lifecycle, while a larger initial workforce size has a detrimental effect on future productivity. According to our final model, a one-standard deviation increase in workers' initial quality increases labor productivity by about 4.9 percent, while a similar increase in startup size reduces labor productivity by 2.7 percent. Addressing the different sources of endogeneity leads to significantly lower estimates, especially in the case of workforce quality, in line with our previous findings for firm survival.

Table 4 provides a summary of the different sources of endogeneity, together with our proposed empirical strategy to deal with them and an overview of their effects, using the illustrative case of initial human capital choices.

[Tables 3 and 4 here]

Discussion and Conclusion

Empirical researchers in management, strategy, organization, and related fields often measure the effects of organizational decisions on a variety of outcomes, such as firm performance. Given the impossibility or difficulty of conducting experiments in these settings, scholars often use observational data, where some factors correlated with both the organizational decision under analysis and the outcome variable often remain unobserved, rendering coefficient estimates from standard regressions causally uninterpretable. The contribution of this paper is threefold. First, we highlight the nature of endogeneity problems often present in analyses of the effect of organizational decision making on performance. Second, we extend our focus to more complex settings than most representations in prior research, namely by acknowledging that managers often make multiple inter-related decisions, possibly continuous (rather than binary) in nature, which are furthermore not one-sided, but rather involve an interaction with other parties of varied (unobserved) quality (e.g., strategic partners, investors, customers, employees). Third, we complement prior research (e.g., Antonakis et al., 2010; Cloughtery et al., 2016; Reeb et al., 2012; Semadeni et al., 2014; Shaver, 1998), by outlining and illustrating possible methodological solutions to deal with multiple endogenous decisions in strategy-performance research.

We have illustrated how to deal with omitted variables, simultaneity, and self-selection issues in organizational decisions, using the simultaneous and inter-related choices of size and average quality of the workforce at founding as an example. The importance of human capital in venture success is entrenched in social sciences, yet most prior work has implicitly assumed that initial human capital decisions are independent from founder characteristics and the type of venture founded. This assumption implies that the founder has no role in formulating an initial strategy around human capital, which not only mischaracterizes organizational practices, but also may lead to mis-measurement of the performance effects of initial human capital choices.

Our empirical approach contends with the three sources of endogeneity mentioned above in a two-stage model. Initial human capital choices (quantity and quality) by entrepreneurs are compared to benchmark human capital choices of similar ventures and founders, which are jointly estimated in a first stage. In the second stage, these (benchmarked) human capital choices are related to firm performance in terms of survival and labor productivity. While we find that initial human capital choices embedded in the workforce have strong effects on venture success, our analysis demonstrates that using more naïve empirical approaches neglecting endogeneity issues may lead to overestimated effects of both workforce size and quality on venture outcomes. All three sources of bias are found to influence the key estimates of interest.

Our analysis can be viewed as an illustration of complex, two-sided, strategy-performance analyses where founders and/or managers of new and existing organizations engage in multiple strategic choices that are influenced by their own quality (or other unobserved characteristics), and that require a match with others, likewise of varying (unobserved) quality and/or preferences. These key elements – which are the main cause of simultaneity and self-selection bias – are indeed present in an array of contexts that have been under the radar of strategy, organization, human resources, and entrepreneurship researchers. Examples include decisions regarding strategic partnerships or alliance composition, adjustments (e.g., additions and/or replacements) and compensation in top management teams, and also financing options and exit decisions, where often managers' and investors' decisions align based on unobserved quality of the firm and/or team. The variety of choices related to business model (re)design – which every firm has to go through over its lifecycle – are other examples where managers often engage in multiple, inter-related, and two-sided decision making where endogeneity is certainly present. For instance, pricing strategies and choices pertaining to distribution channels involve a two-sided matching between firms and customers of different "qualities" (or preferences). Even the most core decisions of product market strategy, such as firms' dilemmas between cost and differentiation strategies, encompass similar challenges as we describe. Most choices related to the firm's core product and/or service are simultaneous and inter-dependent, besides being explained by the firm's (or top management's) quality and conditioned by the segments of customers a firm (and its rivals) is able to target. While all of these decisions are supposedly impactful for firm performance, they are also certainly endogenous. We therefore hope that our effort might encourage researchers in (human resource) management, strategy, organization, entrepreneurship, and related fields to embrace endogeneity concerns in their empirical analyses of strategy-performance relationships.

We acknowledge some limitations in our empirical approach and in our example in particular. We estimated the unobserved component of skills based on the fixed earnings *premia* of individuals in their past careers, as proposed by labor economists (e.g., Abowd et al., 1999; Iranzo *et al.*, 2008). While longitudinal matched employer-employee data enable using this measure, we are aware of the fact that longitudinal data are not always available, and that this measure might not capture all the skills that are possibly productive in the setting under study (startups). Likewise, we recognize that business quality not captured by founders' skill indices or by the distinction between necessity- and opportunity-driven entrepreneurs remains unaccounted for by our analysis. We therefore encourage researchers to find complementary proxies for the unobserved quality of managers and/or firms, for instance by adding surveys or cognitive tests at the individual-level to data gathering efforts.

The success in reducing omitted variable bias related to firm and/or manager quality is a crucial step in addressing endogeneity issues in organizational decisions. Equally important is the design of the system of equations used to deal with simultaneity and self-selection bias, which should be backed by relevant theories. Yet, we acknowledge that some endogeneity bias may still remain, depending on how successful researchers can be in these two steps. In our example, the deviations from benchmarks could reasonably be interpreted as exogenous shocks in the size and quality of the workforce, or so it seemed. However, this may not apply in other cases, for instance if (some) entrepreneurs deliberately deviate from a closely defined benchmark based on private information or unobserved constraints. Nevertheless, we can still safely claim that our approach mitigates important drawbacks imposed by omitted variables, simultaneity, and self-selection biases, leading to less biased estimates of the impact of the strategic decisions of interest. We show significant differences between estimates obtained using our approach and those obtained using more naïve methods.

Another limitation of our empirical exercise pertains to the sample, which only includes manufacturing firms in one country (Portugal). However, focusing on manufacturing firms provides a more homogeneous context, where strategic choices of human capital are likely to be highly relevant for firm performance, given the (relatively) high(er) extent to which individuals can develop specific skills (especially compared to (low-skill) Services). We acknowledge that Portugal is characterized by a very rigid labor market (Martins, 2009; OECD, 2012), which could lead to relatively large(r) estimates of human capital effects, since choices made at entry may be harder to reverse later and, thus, have more persistent effects on performance. Although our results appear (qualitatively) aligned with earlier results obtained with different data (and using different estimation methods) – e.g., Eisenhardt & Schoonhoven (1990), Geroski et al. (2010), Koch et al. (2013) – we encourage replication studies using our or alternative methods, in combination with data from different countries with more flexible labor markets and more comprehensive industries, given the practical relevance of this specific topic for strategy and management literature.

The richness of our dataset and this particular human capital example have enabled us to show how to combine new methods in an attempt to address multiple endogeneity concerns in more complex strategy-performance analyses. This has also allowed us to demonstrate how each step of the combined methods might alleviate endogeneity concerns and produce cleaner estimates of the "true" performance effects. For this purpose, we believe it is worthwhile to sacrifice some level of external validity in our study, to the benefit of its internal validity.

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TABLES

Table 1. Descriptive statistics and correlation matrix

				Correlation matrix									
		Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Founders’ average education	7.120	3.633	1.000									
(2)	Founders’ average age	35.65	8.560	-0.100	1.000								
(3)	Founders’ initial quality (skill index, in logs)	1.890	0.345	0.588	0.367	1.000							
(4)	Founders’ industry experience (years)	3.536	3.508	-0.093	0.104	0.092	1.000						
(5)	Founders’ entrepreneurial experience (years)	1.442	1.305	-0.026	0.265	0.134	0.170	1.000					
(6)	Founders’ management experience (years)	1.096	1.455	0.146	0.159	0.283	0.175	0.506	1.000				
(7)	Single founder (dummy)	0.630	0.483	0.116	-0.066	0.045	0.061	-0.172	-0.031	1.000			
(8)	Startup size (log)	1.665	0.797	0.078	0.110	0.099	0.079	0.170	0.094	-0.270	1.000		
(9)	Workers’ average education	5.968	2.577	0.373	0.012 [ns]	0.374	-0.030	-0.001 [ns]	0.117	0.058	-0.120	1.000	
(10)	Workers’ average age	31.67	8.372	0.042	0.143	0.086	0.077	0.044	0.109	0.025 [ns]	0.052	-0.193	1.000
(11)	Workers’ initial quality (skill index, in logs)	1.695	0.278	0.292	0.089	0.421	0.054	0.072	0.214	0.018	-0.042	0.560	0.394

Descriptive statistics (mean and standard deviations) refer to the year of startup. “ns” means not statistically significant correlation ($p > 0.10$). All the other correlations are statistically significant at the 5 percent or 1 percent level.

Table 2. Proportional hazard models estimating the hazard of firm closure

	Baseline models		Omitted variables			Simultaneity	Self-selection
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Founders' average education	-0.0940***	-0.0709***	-0.0604***	-0.0309	-0.0353*	-0.0372*	-0.0367*
	(0.0162)	(0.0165)	(0.0176)	(0.0195)	(0.0195)	(0.0195)	(0.0195)
Founders' average age	-0.0231	-0.0095	-0.0052	0.0232	0.0172	0.0147	0.0142
	(0.0167)	(0.0168)	(0.0172)	(0.0189)	(0.0190)	(0.0191)	(0.0191)
Founders' quality (skill index)				-0.0736***	-0.0595***	-0.2185**	-0.2110**
				(0.0210)	(0.0213)	(0.0855)	(0.0854)
Founders' industry experience	-0.0569***	-0.0508***	-0.0519***	-0.0481***	-0.0473***	-0.0604***	-0.0607***
	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0202)	(0.0202)
Founders' entrepreneurial experience	0.0022	0.0180	0.0179	0.0143	0.0144	-0.0013	0.0010
	(0.0214)	(0.0213)	(0.0213)	(0.0214)	(0.0214)	(0.0232)	(0.0233)
Founders' management experience	-0.0523**	-0.0450*	-0.0443*	-0.0387*	-0.0358	-0.0451*	-0.0442*
	(0.0235)	(0.0233)	(0.0233)	(0.0234)	(0.0234)	(0.0239)	(0.0239)
Single founder (vs team)	0.5174***	0.4726***	0.4725***	0.4760***	0.4743***	0.5299***	0.5129***
	(0.0185)	(0.0191)	(0.0191)	(0.0191)	(0.0191)	(0.0416)	(0.0417)
Startup initial size		-0.1614***	-0.1649***	-0.1557***	-0.1526***	-0.1540***	-0.1598***
		(0.0172)	(0.0173)	(0.0175)	(0.0175)	(0.0178)	(0.0174)
Workers' average education			-0.0282	-0.0135	0.0450*	0.0336*	0.0299
			(0.0176)	(0.0180)	(0.0229)	(0.0202)	(0.0200)
Workers' average age			-0.0132	-0.0117	0.0355*	0.0448*	0.0384*
			(0.0164)	(0.0164)	(0.0201)	(0.0229)	(0.0228)
Workers' quality (skill index)					-0.0993***	-0.1026***	-0.0755***
					(0.0245)	(0.0246)	(0.0203)
Benchmark startup size						0.0896	-0.0223
						(0.0597)	(0.0595)
Benchmark workers' initial quality						0.1949*	0.1297
						(0.1036)	(0.1034)
Year and industry dummies, firm age, and firm location	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	14,669	14,669	14,699	14,699	14,699	14,699	14,699
Log Likelihood	-7,908.1	-7,861.9	-7,860.5	-7,854.4	-7,846.3	-7,844.4	-7,840.2

*** p< 0.01; ** p<0.05; * p<0.10. The values reported are z-standardized coefficients of a complementary log-logistic regression, with cluster-robust (at the firm-level) standard errors (reported in parentheses). Note that model (7) replaces *observed* values of startup initial size and workers' quality by the *deviations from the predicted size and workforce quality* ("benchmarks"), obtained from the first-stage system of equations.

Table 3. Heckman model for labor productivity

	Baseline models		Omitted variables			Simultaneity	Self-selection
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Founders' average education	0.1346***	0.1401***	0.1160***	0.0692***	0.0715***	0.0673***	0.0672***
	(0.0097)	(0.0098)	(0.0105)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Founders' average age	0.0393***	0.0431***	0.0342***	-0.0087	-0.0046	-0.0107	-0.0105
	(0.0101)	(0.0102)	(0.0104)	(0.0112)	(0.0113)	(0.0112)	(0.0112)
Founders' quality (skill index)				0.1146***	0.1060***	0.0418	0.0417
				(0.0119)	(0.0121)	(0.0470)	(0.0469)
Founders' industry experience	0.0086	0.0099	0.0125	0.0063	0.0053	0.0384***	0.0383***
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0102)	(0.0115)	(0.0115)
Founders' entrepreneurial experience	0.0215*	0.0244**	0.0259**	0.0336***	0.0326***	0.0523***	0.0525***
	(0.0112)	(0.0112)	(0.0112)	(0.0111)	(0.0111)	(0.0146)	(0.0121)
Founders' management experience	0.0749***	0.0761***	0.0754***	0.0682***	0.0667***	0.0781***	0.0783***
	(0.0125)	(0.0125)	(0.0124)	(0.0124)	(0.0124)	(0.0127)	(0.0127)
Single founder (vs team)	-0.0416***	-0.0512***	-0.0508***	-0.0577***	-0.0569***	-0.1813***	-0.1848***
	(0.0094)	(0.0098)	(0.0097)	(0.0097)	(0.0097)	(0.0230)	(0.0231)
Startup initial size		-0.0356***	-0.0272***	-0.0427***	-0.0441***	-0.0302***	-0.0273***
		(0.0102)	(0.0103)	(0.0104)	(0.0104)	(0.0104)	(0.0098)
Workers' average education			0.0662***	0.0457***	0.0113	0.0063	0.0037
			(0.0104)	(0.0106)	(0.0135)	(0.0135)	(0.0135)
Workers' average age			0.0200**	0.0211**	-0.0071	-0.0144	-0.0169
			(0.0096)	(0.0096)	(0.0118)	(0.0118)	(0.0118)
Workers' quality (skill index)					0.0592***	0.0514***	0.0483***
					(0.0146)	(0.0146)	(0.0123)
Benchmark startup size						-0.2020***	-0.2249***
						(0.0341)	(0.0340)
Benchmark workers' initial quality						0.1450**	0.1805***
						(0.0569)	(0.0568)
Year and industry dummies, firm age, and firm location	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,935	9,935	9,935	9,935	9,935	9,935	9,935
Log Likelihood	-13,877.6	-13,871.5	-13,851.3	-13,805.5	-13,797.3	-13,756.7	-13,755.7

*** p< 0.01; ** p<0.05; * p<0.10. The values reported are z-standardized coefficients. Robust standard errors clustered at the firm-level in parentheses. Heckman two-step model, where 1st stage is survival. The survival equation includes all the variables considered in Table 2, in addition to some industry-level time-varying characteristics (namely industry concentration and entry rates) that are found to influence firm survival, but not firm-level labor productivity (exclusion restrictions). The dependent variable in the second stage is the ratio between Firm Total Sales (deflated according to the Consumer Price Index (2005 = 100)) and Firm Total Employment, both in *t+1*, in logs. Note that model (7) replaces *observed* values of startup initial size and workers' quality by the *deviations from the predicted size and workforce quality* ("benchmarks"), obtained from the first-stage system of equations.

Table 4. Endogeneity bias in strategy-performance relationships: description, proposed methodological approaches, and illustration

General Endogeneity Issues		Study-specific Applications	
Source of bias in strategy-performance relationship	**Description**	**Proposed strategy (with an illustration)**	**Effect on our results**
Omitted variables	Certain variables have been omitted from the performance equation that reflect unobserved quality (of the firm/founder) and that correlate with both performance (y variable) and key regressor(s) of interest (x variable(s)) – e.g., hiring choices, partnerships or alliances, business model type, pricing or product market strategies, internationalization decisions, or CEO turnover.	Improved measures of firm/founder quality, using a skill index that combines in a single measure different quality (e.g., human capital) dimensions, including a proxy for unobserved ability based on individuals' prior career and earnings history in the labor market. [Since the strategy under analysis relates to hiring and this involves a two-sided matching with employees, this skill index can also be used to measure the quality of the hires. This helps dealing with (other) omitted variables in the performance equation and to mitigate the bias related to simultaneity (see below).]	The overall estimated effect of founder quality on new venture performance is often biased (downwards) if unobserved measures of human capital are omitted. The negative effect of initial workforce size on hazard rate (productivity) is also slightly overestimated (underestimated) when founder's and initial workforce's skill index are omitted from performance equations.
Simultaneity	Multiple key strategies are simultaneously determined and jointly affect firm/founder (unobserved) quality and expected outcomes. Oftentimes, this simultaneity can be related to a two-sided matching process where firms (strategically) choose (and are chosen) by third parties (e.g., employees, investors, partners, customers), who also vary in quality.	System of simultaneous equations in the first stage, where the multiple strategy choices (size and quality of the initial workforce) are jointly estimated and related to founder/firm characteristics, in order to predict "benchmark strategies". Since there is more than one decision variable, and they may be continuous (rather than discrete – e.g., binary), a system of simultaneous equations is estimated following Roodman (2011). Ideally the system would include sources of exogenous variation (e.g., instruments) to improve identification. In our case, the system models additional strategies along with the key hiring strategies of interest, and all existing firms in the market are included in the estimation (besides the startups in our main sample) to improve identification of "benchmark strategies". Estimated benchmarks for the key strategies under analysis (here startup size and workforce quality) are then added as further controls in the performance equations.	The estimated effects of initial startup size and workforce quality are overestimated in productivity equations when simultaneity bias is neglected. In survival equations, this bias does not seem to affect the estimated effects of initial workforce characteristics, but does underestimate the effect of founder quality.
Self-selection	Firms/founders are not randomly allocated to strategies, but rather select strategies based on their (unobserved) characteristics. Part of the estimated effect of those strategies on performance can therefore be attributed to self-selection, rather than the strategy itself.	Since the strategy decisions under analysis are multiple and non-discrete, a traditional propensity score matching approach is not applicable. We instead compute deviations from the estimated "benchmark" strategies obtained in the first stage, and use them as exogenous proxies for the hiring strategies (size and average quality of initial workforce).	The effect of initial workforce quality is overestimated when self-selection is neglected (especially in hazard equations). The effect of initial workforce size is relatively less affected by self-selection bias.

Figures

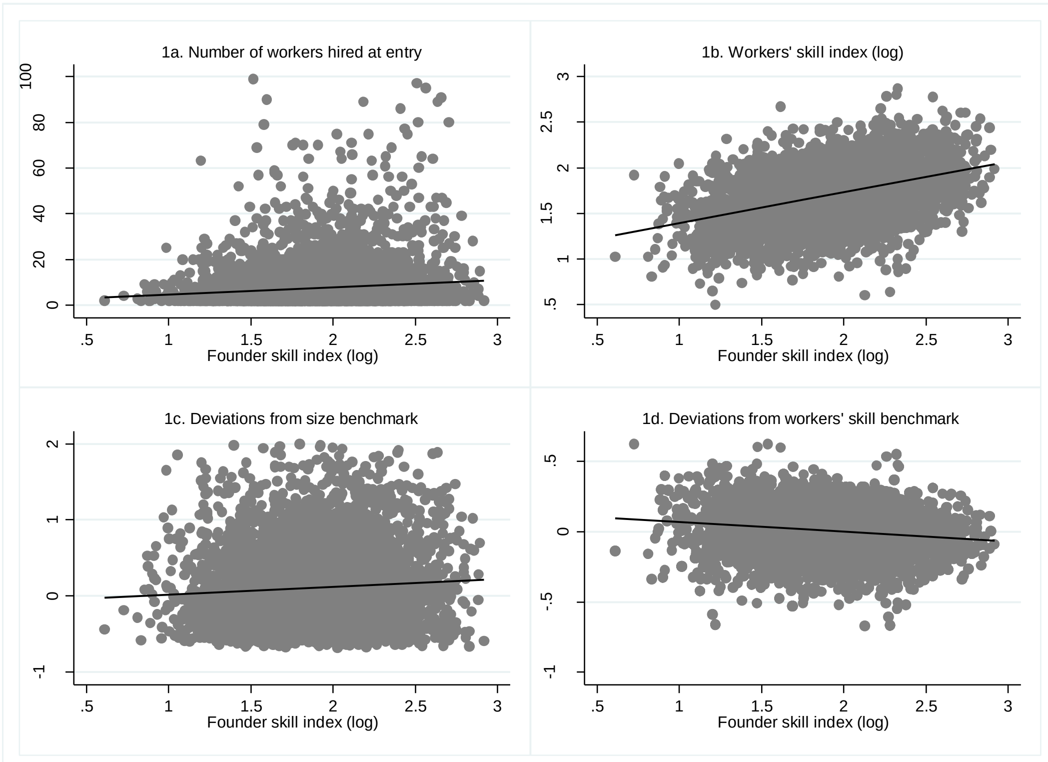

Figure 1. Correlation between founder quality and initial human capital endowments

Notes: Figures 1a and 1b display the correlation between founder quality (measured by the skill index) and the observed measures for initial human capital quantity (i.e., startup size) and quality (i.e., workers' average skill index at entry). Figures 1c and 1d display comparable correlations, but use deviations from benchmark startup size and workforce skill level as exogenous measures for the initial human capital quantity and quality, respectively. Deviations from the benchmarks are measured in percentages and are computed as follows: $\frac{(observed\ size\ or\ skills - predicted\ size\ or\ skills)}{predicted\ size\ or\ skills}$, as described in the text.

Appendix: Variable Definitions

Variable	Definition
Dependent variables	
Firm exit	Dummy variable taking the value 1 in the last year of activity of the firm, 0 if the firm remains active in the following year
Firm-level labor productivity	Log ratio between firm's sales in year *t+1* (2005 constant prices) and firm's total employment in year *t+1*
Independent variables	
Founders' average education	Total number of years of formal education completed
Founders' average age	Founders' age, in years
Founders' initial quality	Founder skill index (in logs), following Portela's (2001) skill index (described in the text)
Founders' industry experience	Years of accumulated experience in the same 2-digit industry of the venture
Founders' entrepreneurial experience	Years of accumulated experience in positions as business-owner/employer
Founders' management experience	Years of accumulated experience in management occupations
Single founder	Dummy variable taking the value 1 if there is no other co-founder (i.e., another individual classified as employer/business-owner) in the firm in the year of entry; 0 otherwise
Startup size	Log number of employees hired at entry, excluding the founder(s)
Workers' average education	Average number of years of formal education (since the first grade in primary school) completed by the workers hired at startup
Workers' average age	Average age of the workers hired at startup, in years
Workers' initial quality	Average skill index (in logs) of the workers hired at startup (further described in the text)

Note: Whenever the venture is founded by two or more founders, human capital variables related to the founder refer to the average human capital in the founding team (e.g., average age, average education or experience (in years)).