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Dynamic capabilities and firm performance

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ABSTRACT

This paper juxtaposes conflicting claims about the relationship between codified dynamic capabilities and firm performance at different levels of environmental dynamism. Furthermore, it argues that the contradictory propositions and findings in prior research are due to said relationship being contingent on key, yet thus far overlooked and unaccounted for, factors internal to the firm such as dynamism exposure and asset base complexity. Empirical tests in the context of the mutual funds industry provide evidence that the performance contribution of codified dynamic capabilities does decline as environmental dynamism increases, yet for any given level of environmental dynamism the magnitude and even the sign of the performance contribution of codified dynamic capabilities are significantly influenced by firms' dynamism exposure and asset base complexity. Going beyond received wisdom, this study advances a more nuanced contingency approach to dynamic capabilities which contributes to a better understanding of how the value of dynamic capabilities is shaped by a complex interplay of environmental and internal factors.

Introduction

Since the publication of Teece, Pisano and Shuen's (1997) (TPS from here onwards) pioneering work on dynamic capabilities, dynamic capabilities research has become one of the most active areas of inquiry in the field of strategic management. Indeed, hundreds, if not thousands, of research papers, workshops, and conference sessions around the world have been dedicated to advancing our understanding of dynamic capabilities. Yet, in spite of the ample scholarly and practitioner interest and the high intensity of the research effort, substantial conceptual concerns and disagreements remain about core elements of the construct such as the very nature and performance consequences of dynamic capabilities (Barreto, 2010; Di Stefano et al., 2014; Helfat et al., 2007; Peteraf et al., 2013).

Recent work by Di Stefano, Peteraf and Verona (2014, 2013) has documented that the dynamic capabilities research domain has developed under the strong influence of two seminal papers – TPS and Eisenhardt and Martin (2000) (EM from here onwards) – that, while complementary in many respects, "represent not only differing but contradictory views of dynamic capabilities" (Peteraf et al., 2013: 1389). They concluded that the "differences between the two papers are such that, in essence, they represent two mutually exclusive approaches for framing dynamic capabilities" (Peteraf et al., 2013: 1389) with

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the differences being "starkest and most divergent in high-velocity environments" (Di Stefano et al., 2014: 317). The relationship between dynamic capabilities and firm performance in dynamic markets is an area where the conflict between the TPS and EM conceptions is particularly striking. While TPS portray dynamic capabilities as organizational routines which embody "learned organizational skill" (TPS: 521) supported by codification (TPS: 525) providing firms with the "ability to … address rapidly changing environments" (TPS: 516), EM reject that view arguing instead that dynamic capabilities in the form of codified, analytic organizational routines will put firms at a disadvantage in high-velocity environments where the rapid creation of new situation specific knowledge through "simple, experiential, unstable processes" (EM: 1106) will be called for rather than the efficient application of codified knowledge accumulated from prior experience.

Given the stark contradiction in the literature, I juxtapose the opposing propositions of TPS and EM, and of subsequent research associated with the two perspectives, on the relationship between the performance contribution of codified dynamic capabilities and environmental dynamism. Furthermore, I argue that the mixed and contradictory findings and conclusions in extant research may be due to the above relationship being contingent (Burns and Stalker, 1961; Thompson, 1967) on thus far overlooked and unaccounted for heterogeneity in factors internal to the firm, specifically firms' dynamism exposure and asset base complexity. My empirical examination of the above propositions on a large sample of U.S. equity mutual funds over the period 1999 to 2009 provides evidence that the performance contribution of codified dynamic capabilities does decline as environmental dynamism increases, yet for any given level of environmental dynamism the magnitude and even the sign of the performance effect of codified dynamic capabilities are contingent on firms' dynamism exposure and asset base complexity.

This study contributes to research on dynamic capabilities in several ways. For one, extant research tends to be predominantly theoretical in nature or perform empirical analyses that do not address the fundamental contradictions between the TPS and EM conceptions of dynamic capabilities. This paper offers a direct empirical test of their contradictory propositions regarding the value of codified dynamic capabilities under environmental dynamism. Furthermore, I theorize and provide novel empirical evidence that this contested relationship is contingent on firm heterogeneity in dynamism exposure and asset base complexity, theoretically and empirically unaccounted for by prior research, which has a major influence on the magnitude and even direction of the performance effect of codified dynamic capabilities. This paper, thus, contributes a novel explanation for the mixed and contradictory findings reported in prior literature. It brings to the fore the significance of exploring how the value of codified dynamic capabilities is determined by a complex interplay of environmental and internal factors. In so doing, it answers the call of Peteraf et al. (2013) for contingency-based studies that help bridge the theoretical divide between TPS and EM and help further the theoretical integration of the field.

Theory and hypotheses

The influential recent work of Di Stefano, Peteraf and Verona (2014, 2013) has exposed a fundamental split in the literature on dynamic capabilities. Peteraf et al. (2013) first provided evidence that the dynamic capabilities research domain has developed under the strong influence of two fundamental papers (EM and TPS), far surpassing any other articles in terms of their influence and recognition, that, while complementary in many respects, "represent not only differing but contradictory views of dynamic capabilities" (Peteraf et al., 2013: 1389). They concluded that the "differences between the two papers are such that, in essence, they represent two mutually exclusive approaches for framing dynamic capabilities" (Peteraf et al., 2013: 1389) with the differences between the conceptualization of dynamic capabilities in TPS and EM being "starkest and most divergent in high-velocity environments" (Di Stefano et al., 2014: 317). The impact of dynamic capabilities in the form of codified organizational routines on firm performance in high-velocity environments is an area of particularly stark disagreement and divergence between the TPS and EM conceptions of dynamic capabilities.

The seminal paper of TPS originated the construct of dynamic capabilities to answer the question of how firms achieve and maintain competitive advantage "*in regimes of rapid change*" (TPS: 509). TPS portrayed dynamic capabilities as involving "complex routines" that provide a firm with the "ability to … address rapidly changing environments" (TPS: 516). TPS argued that this "capacity to reconfigure and transform is itself a learned organizational skill" (TPS: 521) supported by "deep process understanding" and "codification" (TPS: 525). Subsequent research by other authors in the cluster of scholarship related to TPS's framing of dynamic capabilities (cf. Peteraf et al., 2013) has likewise pointed out the performance benefits of dynamic capabilities based on articulated, codified routines (e.g., Zollo and Winter, 2002; Zollo and Singh, 2004; Kale and Singh, 2007). Codification of experience helps firms see through the fog of causal ambiguity that surrounds complex activities by facilitating the identification of the cause-and-effect relationships that govern performance outcomes (Heimeriks et al., 2012; Nelson and Winter, 1982; Zollo and Winter, 2002). Furthermore, codification allows for the externalization of important, often tacit, knowledge and insights, thus improving firms' ability to retain and consistently replicate the lessons learned from past experience (Cowan and Foray, 1997; Nelson and Winter, 1982; Winter, 1987; Zollo and Winter, 2002). Routine codification also contributes to firm performance by instilling discipline, reducing the likelihood of impulsive and biased individual action, and improving the speed, coordination, and accuracy of firm responses in dynamic environments (Nelson and Winter, 1982; Postrel and Rumelt, 1992).

Empirical work associated with TPS's framing of dynamic capabilities as complex, codified routines has provided evidence of a positive relationship between codified dynamic capabilities and firm performance. For example, in the context of acquisitions, Zollo and Singh (2004) find a strong positive relationship between the degree of codification of acquisition experience and acquisition outcomes as knowledge codification gives rise to dynamic capabilities that strongly and positively influence firms' acquisition performance. Likewise, in the context of strategic alliances, firms that develop codified alliance routines by codifying their alliance management knowledge as well as their alliance learning processes have been found to experience greater alliance performance and success rates (Kale et al., 2001, 2002; Kale and Singh, 2007). Furthermore, in the context of semiconductor manufacturing, Macher and Mowery's (2009) study on the dynamic capabilities of firms to introduce new process technologies finds that the introduction of new process technologies is more effective the greater the codification (particularly through IT) of the routines by which new technologies are deployed. In sum, TPS and the cluster of work around their conceptualization of dynamic capabilities suggest that:

Hypothesis 1a. The higher the level of environmental dynamism, the higher the contribution of codified dynamic capabilities to firm performance.

EM reconceptualized and reoriented work on dynamic capabilities, challenging the constructs and relationships in the TPS framework and delineating boundary conditions. In contrast to TPS, EM claim that the nature and performance consequences of dynamic capabilities will be radically different depending on the dynamism of the environment – "effective patterns of dynamic capabilities vary with market dynamism" (EM: 1106). In particular, they argue that TPS's depiction of dynamic capabilities may hold true in relatively stable ("moderately dynamic") environments where dynamic capabilities may indeed take the form of detailed, analytic, codified organizational routines that rely extensively on existing knowledge. In contrast, EM argue that in highly dynamic ("high velocity") environments, where the strategic imperatives are flexibility and the rapid creation of new knowledge specific to the situation at hand, rather than the efficient reuse of existing knowledge, "dynamic capabilities take on a different character" (EM: 1106). In the latter environments, EM posit that dynamic capabilities are not codified, detailed, analytic routines (EM: 1115) but rather "simple, experiential, unstable processes" (EM: 1106) that rely on rapidly created new knowledge and iterative refinement and execution to produce rapid adaptive responses to unpredictable environmental changes. They suggest that while dynamic capabilities as codified routines will have a positive effect on firm performance in stable and moderately dynamic environments (EM: 1113), codified dynamic capabilities will have a negative effect on firm performance in high-velocity environments where the optimal degree of codification and structure will be substantially lower (EM: 1103, see also Davis et al., 2009 for an elaboration of that argument).

Subsequent work by Eisenhardt and colleagues (Bingham and Eisenhardt, 2011; Bingham et al., 2007; Davis et al., 2009; Eisenhardt and Sull, 2001) and other authors in the EM cluster of scholarship has reaffirmed that opposing view. For example, Benner and Tushman (2003) argue that environmental dynamism places a boundary condition on the effectiveness of dynamic capabilities as codified organizational routines, predicting that the increased inertia that ensues from codification will "severely stunt a firm's dynamic capabilities" in dynamic environments, while it will positively contribute to performance in stable environments. Likewise, Heimeriks et al. (2012) argue that it is surprising that only the beneficial effects of knowledge codification have been the focus of much of the TPS-inspired work on dynamic capabilities. As they point out, "nearly a century of research unequivocally suggests that codification has both beneficial and harmful effects" (Heimeriks et al., 2012: 707). Thus, dynamic capability development through knowledge codification can also entail significant negative effects as it gives rise to inertial forces that may render a firm insufficiently flexible to effectively customize its behavior to the specific situation at hand (Heimeriks et al., 2012). Moreover, efforts by firms to codify the lessons of experience usually entail focusing on a limited set of properties and causal links (Zollo, 2009) which increases the risks of competency traps (Lampel et al., 2009; Leonard-Barton, 1992; Levinthal and March, 1993; Levitt and March, 1988; Zollo, 2009). In sum, EM and subsequent work related to their line of argumentation suggest that:

Hypothesis 1b. The higher the level of environmental dynamism, the lower the contribution of codified dynamic capabilities to firm performance.

The moderating effect of dynamism exposure

The recent work by Di Stefano, Peteraf and Verona (2014, 2013) has made the case for the adoption of a contingency approach (Burns and Stalker, 1961; Thompson, 1967) in future research on dynamic capabilities as a way to reconcile the seemingly mutually exclusive views of TPS and EM and develop paths toward the integration of dynamic capabilities research. Building on Di Stefano, Peteraf and Verona (2014, 2013), I suggest that a contingency approach that takes into account heterogeneity in both environmental (dynamism) and internal firm factors can help reconcile the two contradictory perspectives. In particular, I argue that firms' dynamism exposure is an essential, yet thus far overlooked, internal factor moderating the relationship between the performance contribution of codified dynamic capabilities and environmental dynamism. Prior literature suggests that exposure to environmental dynamism is a key dimension of firm heterogeneity (Miller, 1992, 1998; Miller and Waller, 2003) that governs the sensitivity of a firm to environmental changes affecting firm performance (Miller, 1992). While environmental dynamism may be common to all competitors in an industry and arise from exogenous sources, eliminating or controlling a firm's dynamism exposure can provide an alternative to flexibility as a strategic response to uncertain, unpredictable environmental conditions (cf. Miller, 1992). Thus, I posit that a firm's dynamism exposure provides a mechanism that can help overcome the "dark side" of codified dynamic capabilities, i.e. the inertial misapplication of potentially obsolete codified routines (also referred to as "negative experience transfer" (Ellis, 1965; Gick and Holyoak, 1987)), as well as augment the "bright side" of codified dynamic capabilities by reducing the likelihood and cost of dealing with unfamiliar, unknown environmental change and/or increasing the firm's ability to capitalize on changes it has already learned how to deal with. In sum, the judicious management of dynamism exposure could be viewed as a "countervailing process" (Schreyögg and Kliesch-Eberl, 2007) that can counteract the risk of negative experience transfer as well as amplify the learning and efficiency benefits of codified dynamic capabilities.

EM's prediction that dynamic capabilities in the form of codified organizational routines will have a negative impact on firm performance in high velocity environments characterized by rapid, unpredictable change hinges on the assumption that a firm's existing knowledge embodied in codified routines will be rendered obsolete and/or misapplied. Yet, the extent to which this assumption holds, i.e., the extent to which codified dynamic capabilities produce such obsolescence and misapplication effects, will vary across firms depending on their dynamism exposure. Thus, for example, Berkshire Hathaway's resource allocation dynamic capabilities characterized by an emphasis on investing in assets with predictable characteristics and maintaining a large "margin of safety" have retained their value over decades even under high levels of environmental dynamism (Hagstrom, 1997). Likewise, dynamism exposure will affect the extent to which firms can capitalize on the learning and efficiency benefits of codified dynamic capabilities emphasized by TPS. Therefore, I posit that in highly dynamic environments in which the likelihood of encountering novel, unpredictable challenges the firm has not yet learned how to solve is high, the negative effects of inertia and loss of flexibility brought about by codified dynamic capabilities will be magnified (reduced) by high (low) dynamism exposure. Conversely, in less dynamic environments in which the likelihood of encountering familiar, predictable challenges the firm has already learned how to solve is high, the positive effect of codification's learning and efficiency gains will be magnified (reduced) by high (low) dynamism exposure.

Hypothesis 2. The relationship between the performance contribution of codified dynamic capabilities and environmental dynamism will be moderated by a firm's dynamism exposure.

The moderating effect of asset base complexity

Di Stefano, Peteraf and Verona's (2014; 2013) recent work on dynamic capabilities has, furthermore, proposed that dynamic capabilities in the form of complex, codified routines (as envisioned by TPS) may contribute to competitive advantage and firm performance even in high velocity environments as part of a "dynamic bundle". As they put it, "although EM have placed the emphasis on the role of simple rules and routines *in high-velocity markets, more complex routines such as those for* product development, alliancing, knowledge brokering, and *resource allocation also play a role*." (Peteraf et al., 2013: 1405, emphasis added). Leveraging the example of Cisco System's acquisition process, they argue "even Eisenhardt and Brown (1999, p. 76, emphasis added) acknowledged that 'Cisco's pattern for adding businesses includes *routines* for selecting acquisition targets. . . For mobilizing special integration teams, for handling stock options, and for tracking employee retention rates.' Clearly, these comprise a complex set of routines performed at the organizational level rather than simple routines in the form of simple rules, as described by EM." (Di Stefano et al., 2014: 320). Thus, Peteraf et al. (2013: 1405) conclude that, if EM (1107) define dynamic capabilities as "the firm's processes that use resources—specifically the processes to integrate, reconfigure, gain, and release resources—to match and even create market change," then dynamic capabilities include not only simple rules but also complex, codified routines with the latter playing a role not only in stable but also in high velocity environments.

Taking the above arguments by Di Stefano, Peteraf and Verona (2014, 2013) as my point of departure, I herewith propose that the complexity of a firm's asset base is a second key internal factor that moderates the relationship between the performance contribution of codified dynamic capabilities and environmental dynamism. The codification of experience helps firms "see through the fog" of causal ambiguity that surrounds complex activities by facilitating the identification of the cause-effect relationships governing performance outcomes (Galbraith, 1977; Mintzberg, 1979). Thus, one would predict that the value of codified dynamic capabilities would be higher, the higher the complexity of the resource/asset base reconfiguration or integration activities supported by a firm's dynamic capabilities. Indeed, extant research on dynamic capabilities has argued and provided evidence that the contribution of codified dynamic capabilities to firm performance is positively and significantly related to the complexity of the asset base reconfiguration processes they support (e.g., Zollo and Singh, 2004; Zollo and Winter, 2002) as codification helps counteract the steeper barriers to the understanding of cause–effect relationships. Therefore, ceteris paribus, a firm with a more complex asset base should be expected to benefit more from the use of codified dynamic capabilities.

Importantly, the use of codified knowledge, refined and tested by prior experience, reduces the need for and alters the nature of trial and error experimentation in rapidly changing environments (Simon and Newell, 1972). By leveraging codified dynamic capabilities to perform complex asset reconfiguration and integration tasks, firms can reduce the demands placed on scarce managerial attention (Cyert and March, 1963). Thus, firms can use codified dynamic capabilities to free up managerial attention for the very nonroutine tasks and explorative search (March, 2006; Simon, 1997), e.g., the rapid creation of new situation specific knowledge, that EM emphasize as essential in high velocity environments. Given that managerial attention is a scarce, capacity-constrained resource (Levinthal and Wu, 2010; Ocasio, 1997, 2011) and that the demands on managerial attention are highest in rapidly changing environments (Eisenhardt et al., 2010; Teece, 2007), the value of using codified dynamic capabilities in higher velocity, rapidly changing environments should be greater for firms with a more complex asset base than for firms with a less complex asset base. Thus, I hypothesize:

Hypothesis 3. The relationship between the performance contribution of codified dynamic capabilities and environmental dynamism will be moderated by the complexity of a firm's asset base.

Empirical design

Data

The empirical setting for this study is mutual funds. Mutual funds pool capital contributed by their shareholders for the purpose of investing in a diversified portfolio of assets which may be stocks, bonds, money market instruments or other securities and investable assets. Each individual mutual fund has a separate legal existence under the Investment Company Act of 1940. It has its own capital, shareholders, board of directors, and investment policy described in the fund's prospectus. The management of a fund's portfolio of assets is usually contracted out to investment management companies, such as Fidelity, Vanguard, or Putnam. The set of mutual funds a given investment management company provides investment management services to is typically referred to as a fund family. Each mutual fund has one or more designated investment professionals (fund managers) responsible for the day-to-day management of their fund's portfolio of assets and all corresponding investment decisions.

Mutual funds have a number of features that make them a particularly suitable setting for studying dynamic capabilities. First, mutual funds exhibit observable differences in the extent to which they leverage codified dynamic capabilities in the form of articulated, codified organizational routines when reconfiguring and reallocating their asset portfolios, i.e. when making decisions on what assets to acquire, keep, or dispose of. Second, mutual funds are an excellent example of an industry where environmental dynamism can vary substantially over time as funds need to deal with varying levels of change and unpredictability regarding potential investment opportunities and threats and how those may affect a focal fund's portfolio. Furthermore, mutual funds provide a setting of high economic significance and substantive interest being one of the world's largest financial intermediaries with over $15 trillion of assets under management in the U.S. alone (Investment Company Institute, 2014). Thus, this is not an unusual context but one where one would expect dynamic capabilities to develop and have substantial value (cf. Arend and Bromiley, 2009). Finally, mutual funds offer a setting in which extensive, survival-bias-free, longitudinal data on fund characteristics, codified dynamic capabilities, environmental dynamism, and fund performance is available and accessible for research purposes. In sum, mutual funds in many ways offer a natural laboratory for the empirical examination of propositions about the nature and performance consequences of dynamic capabilities.

The main source of data for this study is the Survivor-Bias-Free U.S. Mutual Fund Database maintained by the Center for Research in Security Prices (CRSP) at the Booth Graduate School of Business of the University of Chicago. The CRSP Mutual Fund Database covers all (living and dead) equity, bond, and money market mutual funds since December 1961. For each fund, it provides a comprehensive historical record, including monthly data on its name, identifying information, launch and termination dates, net asset values, investment category, fees, assets under management, returns, fund family, etc. The CRSP mutual fund data were supplemented with data on environmental dynamism obtained from the Chicago Board Options Exchange, data on fund's dynamism exposure developed by Petajisto and colleagues (Cremers and Petajisto, 2009; Petajisto, 2013), and codification data obtained from the U.S. SEC EDGAR mutual funds database (further details provided in the descriptions of our variables below). The final sample used in this study contains all actively managed U.S. diversified equity mutual funds[1] for which data on all variables were available, tracked on a monthly basis from January 1999 to December 2009. The resulting final sample contains 138,680 fund-month observations on 2119 mutual funds.

Dependent variable

The outcome of interest is firm (i.e., fund) performance operationalized as a focal fund's investment return. Investment return, r_{it}, is measured as the return achieved by fund i in time period (month) t, including reinvested dividends and net of operating expenses, as calculated and provided by the Center for Research in Security Prices at the Chicago Booth School of Business. For ease of interpretation, returns are expressed in percentage terms in all analyses.

Independent variables

Codified dynamic capabilities (Codified DCs): measured by a dummy variable which takes a value of one if a mutual fund uses a codified, quantitative process for reconfiguring its asset portfolio and zero otherwise. Quantitative funds make asset allocation decisions and reconfigure the fund's portfolio in response to changing market conditions by virtue of executing fully articulated and codified algorithms. Fund managers' responsibility is limited to the development and periodic update of their fund's codified investment routines based on historical patterns seen in past data, uncovered through a routinized, analytical search process.

The resource allocation capabilities of funds that use a quantitative investment process are inherently dynamic as they are directed toward continuously changing a fund's asset base (Helfat and Winter, 2011) with the aim of finding new ways to increase or forestall the decrease in the returns to the fund's assets. Notably, both EM and TPS identify resource allocation routines as a quintessential example of dynamic capabilities given their focus on the reconfiguration of assets and capabilities

[1] Funds classified by Lipper as domestic equity funds belonging to one of twelve equity mutual fund style categories defined along the dimensions of market capitalization (Large, Mid-Cap, Small, Multi-Cap) and growth-vs-value (Growth, Core, Value).

within firms. Indeed, capabilities that enable firms to modify/reconfigure their asset base by definition qualify as dynamic capabilities even if they "support existing businesses or seemingly non-radical change" (Helfat and Winter, 2011: 1247). Discovering and allocating resources to attractive new investment opportunities and away from unattractive ones on a repeated basis enables mutual funds to repeatedly modify their asset portfolios in the pursuit of superior returns. Mutual funds which use a quantitative investment process justify their preference for codified dynamic capabilities by pointing to the types of benefits emphasized by the TPS view of dynamic capabilities (and acknowledged by EM as pertinent in more stable environments), e.g. reducing causal ambiguity and organizational forgetting through systematic knowledge articulation and codification as well as disciplined and efficient execution by limiting the influence of emotions and bounded rationality in resource allocation decisions (Acadian Asset Management, 2002; Burton, 2006; Heingartner, 2006).

Data on mutual funds that use a quantitative investment process were acquired through searches of the U.S. Securities and Exchange Commission's EDGAR mutual funds database for the terms "quantitative", "quant", "disciplined", "computer", "algorithm", and "model". The prospectuses and history of all mutual funds uncovered through these searches were examined to determine the extent to and time during which they adhered to a quantitative investment process and only those funds whose prospectuses for a given time period explicitly indicated that the fund's investment decisions are made by quantitative algorithms were coded as funds with codified dynamic capabilities.

Environmental dynamism: I use the average monthly value[2] of the Chicago Board Options Exchange VIX volatility index to measure environmental dynamism. The VIX index measures investor expectations of equity market turbulence and uncertainty as implied by S&P 500 stock index option prices (cf. Chicago Board Options Exchange, 2009). It is considered a premier measure of equity market uncertainty/dynamism by equity investors and analysts around the world and has been very extensively used as such in academic research (e.g., Baker et al., 2016; Connolly et al., 2005). The variable is mean-centered to reduce collinearity between it and its interaction terms (Aiken and West, 1991).

Dynamism exposure: I operationalize a focal fund's dynamism exposure by its active share. A fund can attempt to outperform (and expose itself to the risk of underperforming) its benchmark only by taking positions that are different from its benchmark index, i.e. the index the fund's performance is evaluated relative to. Active share measures the distance between a fund's portfolio holdings and its benchmark index holdings (Cremers and Petajisto, 2009; Petajisto, 2013). It can be interpreted as the "fraction of the portfolio that is different from the benchmark index." (Cremers and Petajisto, 2009: 3330). It is available for U.S. equity mutual funds over the time period 1980–2009 (http://www.petajisto.net/data.html). The measure ranges from zero, when a fund's portfolio is identical to its benchmark index, to one, when there is no overlap in holdings between the benchmark index and the fund's portfolio. The variable is mean-centered to reduce collinearity between it and its interaction terms (Aiken and West, 1991).

Asset base complexity: I operationalize asset base complexity as the natural logarithm of the number of different holdings (i.e., stocks) in a focal fund's portfolio in a given time period using the Thomson Financial CDA/Spectrum Mutual Funds holdings database which provides the industry standard mutual funds holdings data (e.g., Chen et al., 2004). The greater the number of different holdings, the greater the number of decisions that need to be made and implemented regarding the fund's asset base and, thus, the greater the complexity of its reconfiguration (March and Simon, 1958; Simon, 1962; Thompson, 1967). The variable is mean-centered to reduce collinearity between it and its interaction terms (Aiken and West, 1991). All independent variables are lagged by one period (month).

Control variables

I control for the effect of variables that might influence fund performance and correlate with the independent variables. Larger mutual funds may find it more difficult to sustain high returns due to the limited availability of superior investment opportunities or due to the price impact of their trades (Chen et al., 2004). Thus, to control for this effect all models contain a control for mutual fund size through a variable (Fund Size) measuring the logarithm of monthly fund assets under management (AUM) in millions of U.S. dollars. The size of the fund family, e.g., Vanguard, Putnam, Fidelity, etc., a fund is affiliated with is also controlled for to control for the possibility that funds related to fund families of a given size may be more or less likely to investment in codified dynamic capabilities. To account for this, all models control for fund family size through a variable (Family Size) measuring the logarithm of the total assets a focal fund's family had under management in a given month (in millions of U.S. dollars).

Third, I control for the effect of fund age on fund performance. This is in line with the possibility that learning from experience can have an impact on performance (cf. Argote, 1999; Levin, 2000). For example, older funds have been found to be systematically more likely to receive higher average performance ratings than younger funds (Morey, 2002). To account for the effect of fund age on performance, all models include a control variable measuring the logarithm of fund age in months (Fund Age). Since family age may have an effect on fund performance over and above the effect of fund age due to generalized learning from the competitive experience of other funds related to the same family, all models also include a control variable measuring the logarithm of the focal fund's family age in months (Family Age[3]).

[2] Based on daily closing values.

[3] Family age is measured by the age of the oldest fund in the focal fund's family.

Following prior research, all models also control for differences in funds' expenses, portfolio turnover, and capacity status (e.g., Chevalier and Ellison, 1999). To control for fund expense differences, I use the corresponding variable in the CRSP U.S. Mutual Fund Database measuring the (logarithm of the) percentage of a fund's assets paid to cover the fund's operating expenses (Expenses), including management fees. Differences in funds' portfolio turnover are controlled for by including a variable measuring the annual turnover ratio of the securities held in a fund's portfolio (Turnover). I use the corresponding variable in the CRSP U.S. Mutual Fund Database which measures the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month total net assets of the fund. The variable is expressed in percentage terms and logarithmically transformed. The possibility that fund returns may be affected by a fund's capacity status is also controlled for. It is not uncommon for fund managers to close a fund to new investment if they decide that the fund has grown too large to be managed effectively. To control for these differences, all models include the corresponding variable in the CRSP U.S. Mutual Fund Database which is a dummy variable taking a value of one when a fund is open for new investments and zero otherwise (Open).

Furthermore, to account for the possible effect of competition on fund performance, a variable measuring (the logarithm of) the count of the number of funds in a focal fund's category in a given month (Funds in Category) is constructed and included in all models. To control for unobserved effects on fund performance related to a fund's investment category[4] and prevailing market conditions, such as the level of risk of a given investment category, differences in investment opportunities, etc., all models include dummy variables for each investment category-month combination. All control variables, excluding the category-month dummies, are lagged by one period (month).

Analytical procedure

Taking advantage of the longitudinal nature of the data the empirical estimation was performed using fixed-effects OLS panel regression models using the xtreg, fe (fixed fund effects) routine in STATA 14.1. In order to account for potential heteroscedasticity of error terms, all models were estimated using heteroscedasticity-robust estimates of the standard errors (White, 1980). Descriptive statistics and a correlation matrix for the variables used in the empirical analyses are reported in Table 1.

Table 1
Descriptive statistics and correlations[a].

	Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Return	0.25	5.52	1.00												
2	Codified DCs	0.03	0.17	−0.01	1.00											
3	Environmental dynamism	0.00	9.48	−0.03	0.01	1.00										
4	Dynamism exposure	0.00	0.16	0.03	−0.11	−0.05	1.00									
5	Asset base complexity	0.00	0.70	0.00	0.17	0.00	−0.34	1.00								
6	Fund size	5.56	1.71	−0.03	0.00	−0.04	−0.17	0.23	1.00							
7	Family size	9.21	2.44	−0.02	0.05	−0.01	−0.23	0.34	0.54	1.00						
8	Fund age	4.67	0.94	−0.01	−0.06	0.02	−0.09	0.01	0.48	0.15	1.00					
9	Family age	5.82	0.86	−0.01	0.00	0.00	−0.13	0.19	0.36	0.68	0.35	1.00				
10	Expenses	0.81	0.19	0.01	−0.10	−0.04	0.29	−0.16	−0.30	−0.22	−0.15	−0.04	1.00			
11	Turnover	0.56	0.34	−0.01	0.08	0.05	0.06	0.09	−0.15	0.05	−0.08	0.01	0.20	1.00		
12	Open	0.94	0.24	0.00	−0.01	0.03	−0.14	−0.05	−0.14	−0.09	−0.09	−0.06	0.04	0.04	1.00	
13	Funds in category	6.22	0.56	−0.04	−0.01	0.03	−0.22	−0.10	0.04	0.04	0.01	0.04	−0.09	−0.05	0.12	1.00

[a] N = 138,680. Correlations greater than 0.01 (in absolute value) are significant at the $p < 0.01$ level.

Results

Table 2 presents the results of fixed-effects OLS panel regressions with heteroscedasticity-robust standard errors.

All models include the full set of control variables. Hypothesis 1a (TPS) suggested that the contribution of codified dynamic capabilities (Codified DCs) to firm performance will be higher, the higher the level of environmental dynamism. In contrast, the competing hypothesis H1b (EM) suggested that the contribution of codified dynamic capabilities to firm performance will be lower, the higher the level of environmental dynamism. Model 3 provides an empirical test of hypotheses 1a and 1b. The estimated interaction effect of codified dynamic capabilities and environmental dynamism is negative and highly statistically significant. The estimation results provide empirical support for Hypotheses 1b and, correspondingly, no support for Hypothesis 1a. Hypothesis 2 suggested that the relationship between environmental dynamism and the contribution of codified dynamic capabilities to firm performance will be moderated by a firm's dynamism exposure. Model 4 reports the results of the empirical test of Hypothesis 2. The estimated coefficient on the interaction of codified dynamic capabilities, environmental dynamism, and dynamism exposure is negative and statistically significant. The estimation results, thus,

[4] Lipper's twelve domestic equity fund class categories defined by the intersection of the dimensions of market capitalization (Large, Mid-Cap, Small, Multi-Cap) and growth-vs-value (Growth, Core, Value) of the equities a fund invests in (cf. http://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/lipper-us-fund-classification-methodology.pdf).

Table 2
Results of fixed-effects OLS panel regression.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent Variable	Return	Return	Return	Return	Return
Codified DCs		−0.16 (0.38)	−0.18 (0.38)	−0.23 (0.38)	−0.23 (0.38)
Environmental dynamism			−0.02*** (0.00)	−0.02*** (0.00)	−0.02*** (0.00)
Codified DCs x Environmental dynamism (H1ab)			−0.01*** (0.00)	−0.02*** (0.00)	−0.01*** (0.00)
Dynamism exposure				−0.16 (0.12)	
Codified DCs x Environmental dynamism x Dynamism exposure (H2)				−0.04* (0.02)	
Codified DCs x Dynamism exposure				−0.26 (0.57)	
Environmental dynamism x Dynamism exposure				−0.00 (0.01)	
Asset base complexity					0.07** (0.03)
Codified DCs x Environmental dynamism x Asset base complexity (H3)					0.01** (0.00)
Codified DCs x Asset base complexity					0.31** (0.15)
Environmental dynamism x Asset base complexity					−0.00*** (0.00)
Fund size	−0.34*** (0.01)	−0.34*** (0.01)	−0.35*** (0.01)	−0.35*** (0.01)	−0.35*** (0.01)
Family size	−0.06*** (0.01)	−0.06*** (0.01)	−0.06*** (0.01)	−0.06*** (0.01)	−0.06*** (0.01)
Fund age	0.11*** (0.03)	0.11*** (0.03)	0.12*** (0.03)	0.12*** (0.03)	0.11*** (0.03)
Family age	0.05 (0.03)	0.05 (0.03)	0.05 (0.03)	0.05 (0.03)	0.05 (0.03)
Expenses	0.10 (0.10)	0.10 (0.10)	0.07 (0.10)	0.07 (0.10)	0.07 (0.10)
Turnover	−0.11*** (0.04)	−0.11*** (0.04)	−0.10** (0.04)	−0.10** (0.04)	−0.11*** (0.04)
Open	0.06 (0.05)	0.06 (0.05)	0.05 (0.05)	0.05 (0.05)	0.06 (0.05)
Funds in category	−0.70*** (0.07)	−0.70*** (0.07)	−0.65*** (0.07)	−0.65*** (0.07)	−0.66*** (0.07)
Constant	6.14*** (0.45)	6.14*** (0.45)	5.94*** (0.45)	5.93*** (0.45)	6.00*** (0.45)
Category-month dummies	Included	Included	Included	Included	Included
R-squared (overall)	0.7794	0.7795	0.7796	0.7798	0.7799
Number of funds	2119	2119	2119	2119	2119
Observations	138,680	138,680	138,680	138,680	138,680

Note: Robust standard errors in parentheses beneath coefficients; ***p < 0.01, **p < 0.05, *p < 0.1.

provide empirical support for Hypothesis 2. Hypothesis 3 predicted that the relationship between environmental dynamism and the contribution of codified dynamic capabilities to firm performance will be moderated by the complexity of a firm's asset base. Model 5 reports the results of our empirical test of Hypothesis 3. The estimated coefficient on the three-way interaction of codified dynamic capabilities, environmental dynamism, and asset base complexity is positive and statistically significant, providing empirical support for Hypothesis 3.

In all models, and consistent with previous findings (cf. Chen et al., 2004), fund size has a significant negative effect on returns. The relation between fund family size and fund returns is also negative and statistically significant. One would expect fund age to be positively related to returns, if funds learn from experience. The estimated effect of fund age is indeed positive, large, and highly statistically significant. The estimated effect of family age is not statistically different from zero. Likewise, a fund's management fees and expenses (*Expenses*) are also not significantly related to its returns. The level of turnover of the securities in a focal fund's investment portfolio is negatively related to its returns. A fund's capacity status (open vs. closed to new investors) is not significantly related to its returns. Fund managers often claim that they close funds to protect investor returns.[5] Yet, consistent with our finding of no significance of capacity status, recent research by Bris et al. (2007) has found that mutual funds that close do not earn superior returns after they close. In line with expectation, the number of funds in the focal fund's investment category has a negative and highly statistically significant effect on returns.

Given that mutual funds are the world's largest financial intermediary with over $15 trillion of assets under management in the U.S. alone (Investment Company Institute, 2014), it is important to also discuss the economic significance of the results. Admittedly, as shown in Table 2, the explanatory power of the models (the R-squared values) improves only marginally once each independent variable and its interactions are added to the base control variables specification. However, it is important to remember two things. First, the dollar value of investments in these funds is massive and, thus, even the smallest percentage improvement in returns can have a very large financial impact. For example, the investment return achieved by a fund with codified dynamic capabilities will, other things being equal, be more than 1.1% higher (on an annual basis) when environmental dynamism is one standard deviation below the mean. It is important to note that this translates into $15 million in value added from the use of codified dynamic capabilities for the average fund (the average fund has ca. $1.36 billion of assets under management) and into $2.2 *billion* of potential annual value added for the largest fund in the sample.

[5] For example, Bill McVail, portfolio manager of the Turner Small-Cap Growth Fund, recently closed it to new investors and was quoted in the Wall Street Journal as saying “we want to make sure we can perform for our clients. If we left it open, it would have compromised our ability to provide value.” (See Talley, K., 2005, “Sorry, This Small-Cap Fund Is Full – More Managers Close Door to Potential New Investors, Citing the Stocks' Illiquidity,” Wall Street Journal, August 22, 2005: p. C13.).

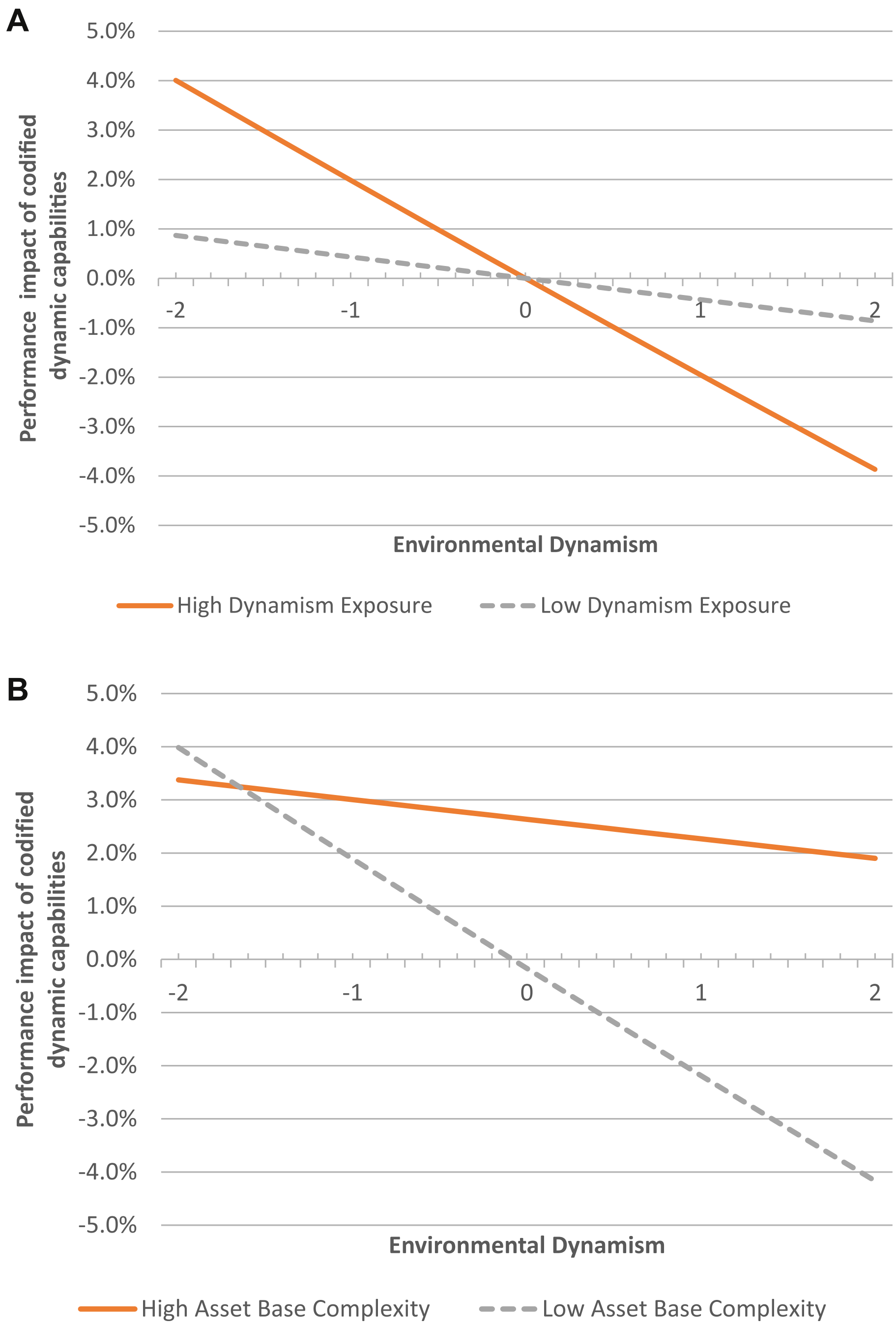

Fig. 1. (A) Performance impact of codified dynamic capabilities at different levels of environmental dynamism and dynamism exposure. Note: High (low) dynamism exposure corresponds to one standard deviation above (below) the sample mean. Environmental dynamism is standardized - values correspond to the number of standard deviations below/above the sample mean. Performance measured as the difference in annual return relative to firms without codified dynamic capabilities, holding all else equal. (B) Performance impact of codified dynamic capabilities at different levels of environmental dynamism and asset base complexity. Note: High (low) asset base complexity corresponds to one standard deviation above (below) the sample mean. Environmental dynamism is standardized - values correspond to the number of standard deviations below/above the sample mean. Performance measured as the difference in annual return relative to firms without codified dynamic capabilities, holding all else equal.

Moreover, the interplay of environmental dynamism, dynamism exposure and asset base complexity gives rise to non-obvious, economically significant implications for firm performance, e.g., when environmental dynamism is high (one standard deviation above the mean) the annual return of funds with codified dynamic capabilities is, on average, 1.1% lower than those without, yet a full 2% lower if their dynamism exposure is high and 2.3% *higher* if their asset base complexity is high (see Fig. 1A and B). Second, the very limited explanatory power of fund-level variables when it comes to mutual fund investment returns is entirely consistent with extant research on mutual funds and is due to mutual funds being subject to an extremely high degree of external scrutiny, disclosure requirements and competition. Any observed performance differences in spite of external scrutiny, transparency and competition exist against significant odds, namely the suggestions of the Efficient Markets Hypothesis (cf. Fama, 1970), as potential fund advantages should generally be competed away with publicly available information and vigorous competition. That the effects reported in this study are economically and statistically significant in spite of the above significant hurdles posed by the empirical setting is a testament to the ability of the theory developed here to withstand a very stringent test.

Discussion

In this paper I juxtapose and subject to an empirical test the conflicting claims of EM and TPS, and their associated clusters of scholarship, on the relationship between the performance contribution of codified dynamic capabilities and environmental dynamism. What is more, I argue that their contradictory propositions and findings may be due to said relationship being contingent on key, yet thus far overlooked and unaccounted for, differences in factors internal to the firm – specifically, on heterogeneity in firms' dynamism exposure and asset base complexity. Empirical tests in the context of the mutual funds industry provide evidence that the value of codified dynamic capabilities does decline as environmental dynamism increases, yet at any given level of environmental dynamism the magnitude and even the *sign* of the performance contribution of codified dynamic capabilities are significantly influenced by a firm's dynamism exposure and asset base complexity. Going beyond received wisdom, this paper thereby moves the debate on the nature and performance consequences of dynamic capabilities away from the simple environmental dynamism determinism of TPS and EM toward a more nuanced contingency approach that considers the complex interplay between environmental and internal firm factors.

This study contributes to the literature on dynamic capabilities in multiple ways. For one, extant research tends to be predominantly theoretical in nature or perform empirical analyses that do not address the fundamental contradictions between the TPS and EM conceptions of dynamic capabilities. This paper offers a direct empirical test of their opposing propositions regarding the value of codified dynamic capabilities at different levels of environmental dynamism. Second, going beyond the empirical testing of existing theory, I develop new theory arguing that said relationship is significantly moderated by firm heterogeneity in dynamism exposure and asset base complexity. Third, I contribute a large-sample empirical examination of the above propositions, providing new evidence that for any level of environmental dynamism the magnitude and even the *sign* of the performance contribution of codified dynamic capabilities are strongly influenced by differences in firms' dynamism exposure and asset base complexity. This study, thus, contributes a novel explanation for the mixed and contradictory findings and propositions in prior literature on the relationship between the performance contribution of codified dynamic capabilities and environmental dynamism.

This paper has numerous implications for extant research. It provides an answer to the call of Peteraf et al. (2013) for contingency-based studies that can help sort out and reconcile the seemingly mutually exclusive views of TPS and EM and, thus, facilitate a greater theoretical integration of the field. Moreover, this study's propositions and findings suggest that codified dynamic capabilities can positively contribute to firm performance even in high-velocity environments – consistent with TPS and contrary to EM – if the complexity of a firm's asset base is high. This study, thus, is consistent with the argument that dynamic capabilities in the form of simple rules, as depicted by EM, may not be sufficient for competitive advantage in high-velocity environments and may need to be complemented by stable, complex, codified routines as part of a “dynamic bundle” (Di Stefano et al., 2014; Peteraf et al., 2013). Our arguments and evidence suggest that this is particularly likely to be the case when firms face the challenge of reconfiguring a highly complex asset base. Future research can help build deeper understanding of the ways in which firms combine simple rules (EM) and codified organizational routines (TPS) within dynamic bundles (Peteraf et al., 2013) as well as of the performance consequences of dynamic bundles in different environments.

This study naturally has its limitations future research can address. The empirical analysis is performed in the context of a single, if highly economically significant, industry. While the theoretical perspectives I examine and the theory I develop do not rely on idiosyncratic industry characteristics, future studies in other empirical contexts could help improve understanding of the generalizability of the results. Furthermore, I employ a dichotomous, binary measure of codified dynamic capabilities and the findings should be interpreted accordingly. Future studies could shed more light on the relationship between the extent of codification of dynamic capabilities and firm performance by developing and utilizing continuous measures. Overall, further research is needed to improve understanding of the conditions under which, even in high-velocity environments, the positive learning and efficiency effects of codified dynamic capabilities can outweigh codification's negative experience transfer (inertia/rigidity) effects. For example, future studies could elucidate what additional contingencies, other than dynamism exposure and asset base complexity, affect the performance contribution of codified dynamic capabilities in different markets/environments. Such research can move us significantly closer to a theoretical integration of the field by improving our understanding of the exact environmental and internal conditions under which firms gain or lose from leveraging dynamic capabilities in the form of complex, codified routines (TPS) versus simple rules (EM).

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