Digital “is” Strategy:
The Role of Digital Technology Adoption in Strategy Renewal

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Abstract

As digital technologies emerge and improve rapidly, firms face changing tradeoffs in terms of their technology infrastructure and strategic direction. Hence, many of them adopt new digital technology and develop new business models and strategies. The literature on strategic alignment of IT suggests that firms need to synchronize these different domains of choice. We therefore ask how far firms renew their strategy as they adopt new technologies. We study this question empirically by assessing if the adoption of new digital technologies is associated with, or even leads to, changes to firm strategy using a detailed survey-based dataset on firms’ strategy renewal and their adoption of digital technologies. We observe a strong positive association between the extent of strategy change and the stage of adoption of advanced digital technologies overall, suggesting a tight coupling between (technological) structure and strategy. Further, using instrumental variable regressions to disentangle the two effects, we find that the adoption of new technologies may lead to a large and robust effect on strategy change: the more extensive the adoption, the larger the change in strategy. This result is robust to various specifications and across industries. However, we notice substantial differences across technologies, potentially pointing at heterogeneity in their strategic nature or maturity level.

Keywords:

Digital transformation, Strategic Organization Design, Technology adoption, Strategic renewal, Digital strategy.

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1. Introduction

The emergence of new digital technologies in the last decades has coincided with a wave of strategic change initiatives by firms and an increase in the perceived stress from these widespread technological changes. While these trends may simply coexist, it seems likely that they are at least to some extent interdependent, not least because digital technologies enable certain forms of strategy change through the adoption of new technologies.

Yet, little is known to date about the interdependence and timing of technology adoption and strategy change (Kretschmer et al. 2012). Despite the well-established result that investments in IT require organizational adaptations (Caroli and Van Reenen 2001, Bresnahan et al. 2002, Bloom et al. 2012, Bloom et al. 2014), the channels through which the availability of new technologies affects firm strategy and organization have been studied in less detail. And although strategic renewal has received wide attention (Crossan and Berdrow 2003, Floyd and Lane 2000, Agarwal and Helfat 2009), how the concept applies to digitally-enabled renewal is still understudied. Hence, we ask how firms respond to the emerging reality of increased digitization and the rapid emergence and introduction of novel technologies. Do firms change their strategy to deal with the threat of digitization for their core business and/or to take advantage of the opportunities afforded by digital technologies, or are these technologies simply adopted without corresponding changes in firm strategy?

We propose a simple conceptual framework in which two complementary domains of strategic choice (Henderson and Venkatraman 1999), business strategy and digital technology, lead to different possible configurations with different costs and benefits. We argue that firms choose the most profitable configuration. In the long run, the two domains are kept in sync and co-evolve as the *"right foot follows the left"* (Mintzberg 1990). However, if one of the two domains experiences rapid changes in costs, possibilities or returns, the trade-offs for firms may change and adoption of one technology for instance may prescribe a new optimal configuration for the other domain (in this case strategy). The past decade has been such a period of rapid changes in the costs and capabilities of digital technologies. In such conditions, our conceptual framework suggests that firms adopting the new digital technologies are more likely to also renew their strategy. We further expect this synchronization to occur gradually.

We seek empirical evidence on these interdependences of corporate-level strategy change and within-firm digital technology adoption and diffusion. Our empirical analysis uses data from a unique survey led by McKinsey & Company in 2017. The survey looks at digitization (focusing on the adoption of new generations of technology) and how firms have adapted their strategy to the threats and opportunities created by these technologies. The sample covers a wide range of firms (in terms of size, ownership structures and geographies) and industries to give a broad view on the phenomenon.

Our results show that (a) digital technology adoption is positively associated with strategy renewal, (b) this association exists at the extensive (i.e. any strategic change) and the intensive (a greater degree of change) margin in that the more widespread a company has adopted a certain technology within the firm, the more likely it is to be engaged in more fundamental strategy change, (c) there are likely situations in which technology adoption inspires and drives strategy renewal, and (d) the strength of this association depends on the technology itself. These results are robust to a battery of robustness tests, including the inclusion of a control for the level of perceived stress from digitization, as well as to the use of instrumental variables. We replicated our analysis with a second survey-based dataset with a different sample of firms and a different set of digital technologies (this survey was exclusively focused on AI technologies) and obtained consistent results.

More generally, our results support the view that digital technology at large and specific technologies in particular are indeed strategic. They have implications for our understanding and the management of digitization and emphasize the close interdependence between strategic renewal processes and technology adoption. Thus, we contribute to the literature on strategic organization design, which posits that strategy and (technological) organization go hand in hand, specifically by documenting related strategic and technological adjustment processes in a period of rapid technological change.

2. Theoretical background and conceptual model

We conceptualize our strategic organization design (SOD) decision with the following simple formalization: Assume that an organization consists of different “domains of strategic actions” (Henderson and Venkatraman 1999) that are complementary to each other, i.e. the strategic actions taken in one domain affect the marginal benefit of the actions in the other domain. For simplicity, consider an organization with two strategic domains: Strategy (S) and Structure (T). Given our empirical setting and the goal of our study, we focus on (information) technology as part of the organizational structure (Melville et al., 2004).[1] The complementarity between the two suggests that there is one “best” configuration of S and T that maximizes an organization’s profits (net of the cost of implementing the two activities). These net profits can be firm-specific; for example, a firm with high absorptive capacity (Cohen and Levinthal 1990) or extensive IT support staff will face lower cost of running a state-of-the-art technological system, or smaller firms may expect lower benefits (at equal cost) of a process technology with fixed cost of implementation. On the strategy side, the cost of implementing a customer-oriented online sales strategy will differ between an already sales-driven organization and a former state-owned monopolist employing former civil servants. This has two implications: First, organizations will strive for a configuration that maximizes their profits and second, this optimal configuration may differ across organizations (Kearns and Sabherwal, 2006). In steady state therefore, we will likely observe outcomes with clusters of (sufficiently similar) firms choosing the same or similar configurations (Kretschmer et al. 2012).

Now suppose that one of the domains, T, experiences a shift in the cost of some actions in it, for example because a technology matures and its cost of implementing declines, or, by a similar logic, a new technology becomes available in the first place. This will have two immediate consequences: First, such a shift will lead to a new steady-state configuration for some organizations. These organizations found implementing T prohibitively costly prior to the shift such

[1] The technology used in a firm is part of the firm’s organizational design as it guides the way work is organized, delegated and monitored within the firm (Englmaier et al. 2018).

that they did not choose the bundle of S and T including the new technology, but they may now. The second consequence is that the firm may end up changing its strategy S in response to the cost shift in T. This is not because the benefits or costs of the actions in S have changed, but rather because the shift in costs of T has changed the optimal configuration of S and T for the organization.

Figure 1 illustrates this in a very simple numerical example:

*** FIGURE 1 HERE ***

In the "Pre" phase, the configuration S_1T_1 offers the highest net benefits (6 – 2 – 2 = 2). In the "Post" phase, technology T_2 gets cheaper (we could easily assume that it was not available before and thus had an infinite cost), which leads to the two changes we predicted: First, the new optimal configuration is S_2T_2, and second, the change in technology ($T_1 \rightarrow T_2$) triggered a change in strategy ($S_1 \rightarrow S_2$).

Based on the above, we can distinguish between two "states". The first is the steady state in which both elements S and T are closely aligned and affect each other "like each foot follows the other" (Mintzberg, 1990). In steady state therefore, the statements "structure follows strategy" (Chandler 1962) or "strategy follows structure" (Hall and Saias 1980) are not meaningful because a specific strategy would not have been chosen without the best structure in mind, and vice versa (Englmaier et al. 2018, Nadler and Tushman 1988, Galbraith 1974). The second state describes the transitional state in which one of the two domains has experienced a shock to its relative costs and thus triggers a causal chain: First, the domain in which a change in costs has occurred will change, selecting actions that have become comparably cheaper than the previously chosen one. This in turn will lead to an adjustment of the other domain to settle on the new optimal configuration. In this state, a shock to one activity domain can lead to a successive adjustment of other parts of the system.

In terms of the theory of strategic alignment, this conceptualization simply implies that the optimal configuration may change as a result of a shift in cost or benefit of one of the domains, i.e. that a new configuration may become optimal. The strategic organization design perspective deserves some qualification here: while the suggestion that Strategy and Structure are necessarily chosen jointly and with a view on the overall profits may be accurate in steady state, it may not hold in situations of flux and uneven shifts in the cost of some of the activities. Here, the “affected” activity may lead the “unaffected” one both chronologically, but also causally as unaffected activities will only be changed once the affected ones have been tried and tested. Finally, the transition from one aligned configuration to another may require that changes occur in a stepwise fashion, which has two advantages: First, the “misalignment” between Strategy and Structure at any one point of the transition is comparably small since the changes in each activity are small. Second, the transition can still be reversed at relatively moderate cost as the organization does not fully implement a new solution for one activity that would be hard to reverse, but rather performs a series of smaller commitments to avoid a costly failure (Chakravarthy 1982).

One important nuance, however, stems from the potential impact of each technology on businesses. Agarwal and Helfat (2009) proposed that a resource can be considered as strategic if it affects the long-term prospects of a firm. Our theoretical development inspires an empirical test for the strategic importance of a given resource: a resource that is not strategic in Agarwal and Helfat’s terms will not significantly affect the long-term benefits of the firm and so changes in the costs of adopting this resource (T) would not change the returns of possible strategies (S) for the firm. In contrast, a technology that does trigger strategic change is one that is affecting the future profits of the firm enough to encourage a different strategic configuration. A strong positive association between adoption of one specific technology and strategy renewal would therefore be empirical evidence of the strategic character of the focal technology.

Our theoretical logic is anecdotally illustrated by many recent cases in digital transformation occurring alongside strategy transformation. For instance, BBVA, Madrid-based financial conglomerate, built data analytics and data management tools that were so powerful and efficient that it was able to spin them off as a new subsidiary called BBVA Data & Analytics (Alfaro et al. 2018). Originally aimed at selling new data-based products externally (such as anonymized payment statistics), the subsidiary quickly turned into a powerful transformational force for the entire bank, guiding internal improvements to operations and inspiring new digital product features and experiences. From a limited-scope technology-driven initiative, the technology capabilities created ended up driving a much larger strategy renewal at the bank level.

In a very different industry, Netflix's business model was also dramatically reshaped by new technology. When its original business of DVD rental by post was no longer sustaining its growth, the company shifted to streaming technology as a new opportunity to distribute content. But the game changer came when big data technology and AI could lead to enhance user choice, which led Netflix to scale its strategy as a heavily customer-centric subscription model from US to worldwide.

The transformation of Ping An, the Chinese insurance conglomerate, was perhaps even more radical. Its early incursions into digital channels and mobile applications enabled it to add a classified ads digital platform to its P&C insurance products and start building an entire fintech ecosystem. Ping An's entire business scope got redefined as a consequence of the new technologies and capabilities acquired along the way.

The common element in these examples is the driving role of new digital technology to inspire changes of varying degrees in the firm's strategy. Here, digital technology is not simply an operand resource supporting the firm's business strategy, but an operant resource that triggers new business innovations and ultimately renewal (Lusch and Nambisan 2015, Xiao et al. 2019). In effect, the opportunities brought by new technologies open up avenues for new products or services and new business models. Of course (technology) structure and strategy inform one another, but more often than not in these examples, strategic renewal[2] was triggered by new technological capabilities.

These examples illustrate potential ways in which new technological possibilities may drive strategic renewal. One plausible mechanism underlying this ripple effect is the notion of learning or cognition. As shown by Kaplan (2008), senior management cognition is key to strategic responses to new technological

[2] Agarwal and Helfat (2009) define strategic renewal, the most extensive form of strategic change, as "includ[ing] the process, content and outcome of refreshment or replacement of attributes of an organization that have the potential to substantially affect its long-term prospects."

developments. Technology experimentation and adoption in local initiatives may well raise top management awareness and cognition about the technological possibilities. Anecdotally, the CEO of a multinational manufacturing company based in Belgium recently indicated that he had overlooked the potential of digitalization until he had seen some of its potentialities in the form of pilot new products and applications, opening the door to new delivery and service models.[3] Only after the pilot and proof of concept did he realize that digital technology could well be the catalyst for the strategic renewal he felt was necessary. In his own eyes, technology experimentation had been instrumental to cognition, which then led to strategy renewal.

Another underlying mechanism potentially at play is suggested by Lusch and Nambisan (2015). They suggest that new digital technologies may create new ways for other resources to be deployed and create value, or may create new operand resources themselves. Xiao et al. (2019) suggest for instance that "*the introduction of e-commerce platforms could trigger resource reconfiguration and process reengineering and eventually create innovations in business operations*".

3. Data and Empirical Approach

3.1. Estimation Model

To empirically investigate our theoretical considerations outlined above, we estimate the likelihood of a firm implementing a strategy change S_i as a function of its actual adoption of digital technologies (A_i, reflecting an attempt at identifying or seizing the upside), after controlling for the firm's perceived stress (E_i), firm characteristics (X_i) and industry and region effects (I_i), as in Equation 1:

$$S_i = c + \alpha A_i + \beta E_i + \delta X_i + \theta I_i + \varepsilon_i \quad (1)$$

This model only captures an aggregate effect of adoption on strategy change. It does not capture possible differences across firms in the degree of adoption and their differential links to different degrees of strategy change. Absent longitudinal data, we run our model along different margins of strategy change (from ad-hoc tactical changes to major strategy renewal) and/or different margins of digital

[3] Based on an interview with one of the authors in March 2018.

technology adoption (from experimentation to local adoption to large-scale diffusion). Assuming firms first experiment with a technology before adopting it in one specific (often localized) use case until they diffuse the technology at scale, we can for instance assess whether the different stages of adoption correlate differently with a specific margin of strategy change.

Intuitively, if structure and strategy influence each other, then more advanced stages of technology adoption should be correlated with higher degrees of strategy change. This is the main assertion we want to test empirically. If confirmed, it will support the view that these technologies are "strategic" in that they inform a different strategic configuration to maximize the future profits of the firm.

We use a probit model to estimate equation (1) and subsequently run a series of robustness tests using different specifications of dependent and independent variables, different sets of controls, and different specifications.[4] We also use instrumental variables regressions (explained in more detail in the following section) to assess potential bias due to unobserved heterogeneity. Our results are robust to all those changes.

3.2. Addressing omitted variable bias and endogeneity

Despite our large list of controls (including industry and geography dummies), our empirical strategy is not immune to potential omitted variable bias or reverse causality. One such concern in particular is that some firms might be prone to experimentation and that this propensity to explore the space of possibilities might drive a higher rate of experimentation and strategy change without implying any direct relationship between the two. Although this might hold true at lower margins of technology adoption and strategy change, it is unlikely to affect our core results at the technology diffusion and strategy change levels, which serve as our baseline estimates. A firm might indeed experiment with various technologies and make tactical changes to its course of action on a frequent basis, but strategy renewal as defined in our empirical setting could not happen

[4] All our estimates were also performed with a logit model. The results were not affected.

overnight or every other month since it is changing the long-term strategy of the firm. Most likely, this fickleness would also not be profitable for the firm.

Similarly, diffusing a new digital technology at scale within the organization requires a strong commitment and significant investments in complementary forms of capital (typically human and organizational) that take time to adjust. Because of that, unobserved heterogeneity in this case might drive a correlation between technology experimentation and low levels of strategy change but it is unlikely to drive a correlation between adoption at scale and strategy renewal.

Still, to mitigate the risk of omitted variable bias, we have included in equation 1 the level of stress from digitally-enabled disruptions perceived by the focal firm as a control. We do this to control for the importance of scaling versus experimenting, as stress may be a strong driver of strategy renewal (see e.g. Huff et al. 1992).

To mitigate the risk of reverse causality, we have further run instrumental variables regressions in which we endogenize our core measure of digital technology adoption. We make use of the widespread and more basic nature of two of the technologies in our survey (web applications and cloud-based services), which are excluded from our measures of adoption in our main estimates. Because they are highly generic, these technologies are likely to act as enabling or pre-required foundations for the successful adoption of the more advanced technologies that are otherwise considered in our survey (see e.g. Andrews et al. 2018, Bughin and van Zeebroeck 2018, Bughin 2017, Candel Haug et al. 2016). Given their widespread adoption and established character, their adoption is unlikely to be driven by current strategy renewal but might well predict adoption of new technologies. We statistically test and validate their exogeneity.

3.3. Data

We make use of a unique and novel dataset. The data form a cross-section of firms across a wide range of characteristics, industries and geographies and stem from a survey run by TNS Soffres on behalf of McKinsey in the first half of 2017 toward a list of CxOs. This list of CxOs forms a representative database of 12,000 C-level executives, cutting across a wide range of regions and industries. They represent organizations from all sectors (including non-profit) and firm sizes (from less than

10 employees to more than 10,000 employees), although the vast majority of respondents come from North America, Europe and Asia. Note that the database of C-level executives to which the survey is distributed has no connection with McKinsey, it is maintained exclusively by TNS Sofres for conducting business surveys like these.

To ensure the highest possible quality in the responses, questions and answer options are systematically randomized across respondents, and anonymity is guaranteed to minimize overstatements. Responses may include missing values, as respondents may skip questions where they do not have good knowledge of answers. More broadly, the survey procedure has been validated in multiple studies (see among others Bughin et al. 2017). Standard tests did not reveal any systematic common method bias.

The survey looks at digitization at large and contains 1619 responses, a 13.3% response rate. These data are remarkable as it is very rare to obtain information jointly on adoption of digital technology and new strategies among firms, especially with responses coming exclusively from C-level executives. The main downside of these data is the anonymity guarantee that prevents us access to the identities of the firms and exact values for their main characteristics. We are therefore limited to the categorical values provided to us.

Summary statistics are provided in Table 1, and correlations in Table 2. Due to missing values (responses were not mandatory in the survey, as a way to avoid "noise" in answers), our final analysis sample size is 956. Note that we have also run our analyses with a full sample, either imputing the missing values or omitting the control variables with missing values and the results hold.

*** TABLES 1 AND 2 HERE ***

For robustness purposes and to mitigate some of these limitations, we also ran our analysis on a second dataset, coming from another McKinsey-led survey, performed in the same year (2017). The sample here comes from a different database of CxO's maintained by McKinsey, although not necessarily McKinsey clients, with a response rate of about 15%. This alternative survey included the same strategy question as our main dataset, but adoption questions were asked on a narrower set of digital technologies belonging to the broad field of Artificial Intelligence (AI). This “AI” alternative dataset includes more observations (3,073 responses, of which 2,453 are complete and exploitable for our analysis) and offers a more granular control for firm size (albeit still in the form of a categorical variable). In turn, other firm controls (like diversification, ownership or incumbency) are not available in this alternative dataset. Summary statistics for our alternative dataset are reported in Table 1, next to the main dataset, and results are given in the Appendix.

Measuring strategy renewal. Our measure of strategy change is built from a unique question included in our survey: “*How, if at all, has your organization adapted its corporate strategy to address the digitization-related changes it has experienced in the past three years?*” Respondents were asked to pick their response among the following graduated list of options:

(1) *We have not yet responded.*

(2) *We have responded through ad hoc initiatives and actions.*

(3) *We have developed a coordinated plan to respond to the changes but have not changed our longer-term corporate strategy.*

(4) *We have changed our longer-term corporate strategy to address the changes.*

(5) *We initiated at least some of the changes in the industry.*

Note that, as formulated, the question explicitly refers to a *response* to digitalization, thereby inducing a causal chain of events from enabling digital technology to strategy renewal, which motivated the formulation of equation 1 with strategy renewal as a dependent variable, We code our dependent variable (strategy renewal) as a dummy equal to 1 if the focal firm has changed its long-term corporate strategy (i.e. levels 4 and 5 on the survey response scale) to address the changes, but we the sensitivity of our results to different margins of change, i.e. including response (3), having at least developed a coordinated plan, and response (2), ad-hoc initiatives and actions. Overall, 46% of the respondents have at least changed their corporate strategy and 67% have at least developed a coordinated plan. We also run our model on the original responses on a scale from

1 to 5 to test the linearity of our effects along the intensive margin (i.e. are experimentation, local adoption or diffusion associated with increasing levels of strategic change?).

Measuring adoption. Which technologies (among a set of prelisted ones) the responding firm has already experimented with, or adopted in at least one functional area, or deployed at scale throughout the organization is at the heart of the survey. These questions have been asked for a set of 10 broad families of digital technologies.[5] We constructed different measures of adoption, either as binary variables (at least one technology has been experimented with/adopted locally/diffused at scale), as count variables (number of technologies experimented/adopted/diffused) or relative count variables (difference between number of technologies experimented/adopted/diffused and in-sample median of the same). Table 3 reports adoption rates by technology for each of the three different margins of adoption.

*** TABLE 3 HERE ***

In our data, traditional web applications and cloud-based services stand out as very largely adopted. Barely 3% of the firms in our sample have not even experimented with Web applications (66% have it fully diffused at scale). For cloud-based services, these figures are 8% (no adoption whatsoever) and 44% (full-scale diffusion) respectively. Given their widespread adoption and diffusion, we exclude these two technologies from our independent variables.

These two technologies (web and cloud) are not just more widespread, they are also likely to be complementary to many of the other (more advanced) technologies in the survey (Andrews et al. 2018, Bughin and van Zeebroeck 2018, Bughin 2017, Candel Haug et al. 2016). We take advantage of this feature to use their adoption

[5] The categories are: Big data and big-data architecture (e.g., data lakes), Advanced neural machine-learning techniques (e.g., deep learning), Robotics (e.g., robotic process automation), Artificial-intelligence tools (e.g., virtual assistants, computer vision, voice recognition), Additive manufacturing (e.g., 3D printing), Mobile Internet technologies (i.e., devices that connect to the Internet and work individually, such as wearable technologies and Internet-enabled appliances), Cloud-based services, Traditional web technologies (e.g., social media, online meetings, video conferencing), Augmented-reality (AR) technologies, Internet of Things (i.e., devices that can communicate with each other as part of a network).

by the focal firm as an instrument for the focal firm's adoption of other technologies (see "Addressing endogeneity" below)

Controlling for perceived stress. One important potential confounding factor in our analysis could be the extent to which firms perceive threats in their environment due to digitalization of their competitors or new entrants (Huff et al. 1992, Leavy 1997, Zucchini et al. 2018). Such stress could indeed potentially drive both the adoption of digital technology and strategy renewal. We therefore need to control for firm perceived stress from digital technologies, which we capture through the following question: "*If your organization took no action in the future to digitize any elements of its business, how much of its current revenue do you think would be at risk of being lost or cannibalized within the next three years*?"[6] Answers to this question are recoded as a dummy variable indicating whether the focal firm has negative expectations about the impact of digital technologies, which we use as proxy for perceived stress.[7] 51% of firms report comparatively high stress (relative to their peers) for the baseline version and 29% for the more restrictive version (based on the third quartile).

Other firm controls. We are limited by our data in the number of firm observables we have and can therefore use as controls (the identities of our sample firms are unknown to us). In addition, the firm controls in our data are categorical variables. They enable us nonetheless to control somewhat for several key sources of heterogeneity at the firm level: region (at the country level), industry, size (proxied by a dummy variables indicating revenues in excess of or below $1 billion), age (proxied by a dummy distinguishing between incumbent (established) firms and new entrants) and ownership (whether the firm is publicly listed or not). We include all these controls as dummy variables in our model. We further exploit

[6] In the alternative (AI) dataset, the question reads as "which of the following statements best describes the impact you think AI will have in your industry in the next 3 years?" with response options ranging from "Major negative impact" to "Major positive impact". Our measure of stress is a dummy equal to 1 if the firm's response is negative (minor or major). In an alternative specification, it takes value 1 only for "Major negative impact".

[7] This dummy is equal to 1 if the share of revenue at risk is above the median (which is around 25% of the revenues at risk) and 0 otherwise, reflecting more negative expectations relative to other firms in our sample. Our results are robust to an alternative construct in which the stress variable is set to 1 when revenues at risk exceed the third quartile (roughly 50% of revenues at risk or more) instead of the median.

information about the degree of diversification of the focal firm (B2C v. B2B, Product v. Service, Mono-product v. Portfolio). This extensive set of controls – although categorical – is aimed at capturing as much heterogeneity at the firm level as possible. They are not as granular or detailed as one could hope, but if the latent variables they serve as proxy for were confounding factors, then their inclusion or exclusion would significantly affect the coefficient of our core explanatory variable, which they do not. Nonetheless, since they may not entirely rule out all sources of unobserved heterogeneity, we develop our strategy to mitigate endogeneity concerns further in the next section.

Addressing endogeneity. Establishing causality in a cross-section like ours is difficult. However, we exploit a feature of our data to mitigate potential omitted variable bias. Among the technologies whose adoption was surveyed, two are considerably more widespread and established than all others: "traditional web applications" and "cloud computing". Because they have been established for a longer period, the adoption of these technologies is unlikely to trigger strategic renewal today, but they contribute to the digital infrastructure that a firm needs in order to adopt newer technologies (see Andrews et al. 2018, Bughin and van Zeebroeck 2018, Bughin 2017, Candel Haug et al. 2016). We therefore use these as instrument for the adoption of more advanced technologies in our main equation with IV estimates. To gain further confidence in our IV estimates, we run several diagnostic tests for under-, weak- and over-identification and test our model with different sets of instruments (either one of the two or both) and models (linear probability model and probit). All those tests support the validity and the consistency of our IV estimates.

4. Results

We start by estimating Equation 1 on our sample, using the diffusion of at least one technology at scale within the firm (excluding web and cloud) as default measure of adoption. Results are reported in Table 4. Column 1 reports our baseline estimates of Equation 1 using a probit model (our default specification).

4.1. Control variables

Looking first at our control variables, Table 4 (column 1) shows that perceived stress is indeed strongly and positively associated with strategy renewal. Its marginal effect (computed at the means of all covariates) corresponds to a 11.9 percentage point increase in the likelihood of strategy renewal. With a baseline likelihood of 45% in our analysis sample, this corresponds to a 26% higher renewal likelihood for firms perceiving comparatively high stress. This coefficient is remarkably stable across our different specifications, except when the dependent variable is based on a lower level of strategy change (see below).

Among other controls, most coefficients are not significantly or consistently different from zero, except for three. The first is the "large firm" dummy, which indicates firms with over $1 billion in annual revenues. Large firms are positively associated with a higher likelihood of strategy renewal. While superficially at odds with the widespread assumption that large firms are more inert due to established processes and incentives, large firms may also possess superior management skills. In contrast but more expectedly, incumbent firms are associated with a lower likelihood of strategy renewal.

The second striking result among our controls is the significantly negative coefficient associated with mono-product and mono-service firms. This may be because diversified firms are more versatile, making pivots or shifts among product portfolios less costly than in highly specialized and less diversified firms.

4.2. Main effect of technology adoption

Turning now to our main explanatory variable, we first find that technology adoption is positively and significantly associated with strategy change. The estimated coefficient of the standalone term (in column 1) corresponds to a 19 percentage point higher incidence of strategy renewal among firms that have adopted at least one technology (marginal effects computed at sample means). Given a baseline incidence of strategy renewal of 46% (see Table 1), this marginal effect represents a 41% increase in strategy renewal from technology adoption.

*** TABLE 4 HERE ***

4.3. Instrumental variables regressions

We run our baseline estimates with instrumental variables (IV), using the diffusion at scale of web and cloud technologies within the focal firms as instruments for that same firm's adoption of the other (more advanced) technologies. The results of our 2-stage least squares estimates are reported in the second column of Table 4. First stage results are reported in column 3.

*** TABLE 7 HERE ***

The first stage results clearly support the enabling role of cloud and web technologies as they both strongly predict the adoption of other technologies. The second stage results are qualitatively consistent with our non-IV estimates: technology adoption is still strongly and positively associated with strategy change. Strikingly, the coefficient of technology adoption gets 3 to 4 times larger in IV compared with non-IV results.[8] This is partly due to the fact that most control variables are associated with technology adoption (as suggested by most probit models of adoption in the literature, sometimes referred to as "rank effects") and their effect on strategy renewal is therefore channelled through technology adoption itself.

Diagnostic tests of these IV estimates are reported at the bottom of Table 4. They do not reveal evidence of weak, under or over identification and therefore support the formal validity of our instruments. Interestingly, most our control variables are significant in the first-stage regression, but not in the second-stage IV regression. This suggests that some of the effects of our technology adoption variables are picked up by the control variables unless we run IV regressions.

In sum, these results are supportive evidence of a direct influence of technology adoption on strategy change.

4.4. Exploring gradual effects

In the subsequent columns of Table 4, we use the more fine-grained nature of our survey responses regarding our key independent and dependent variables. We run

[8] To avoid comparing apples and oranges, comparing column 1 of Table 4 with column 4 of Table 7 (IV Probit estimates) and Column 2 of Table 4 with the last column of Table 5 (2SLS).

regressions using the different extents of technology adoption first one by one (columns 4 and 5) and then jointly (column 6). In column 4, the core explanatory variable takes value one if the focal firm has experimented with at least one technology (and has gone beyond experimentation with no other) and zero otherwise. In column 5, it is similarly set to one if and only if the focal firm has adopted at least one technology locally (but has not diffused any). The coefficient for both variables is significant and negative, indicating that strategy renewal is less likely when a firm has only experimented with or started adopting locally one or more technologies. In column 6, it appears further that the coefficient increases with the stage of adoption. Conditional on having diffused at least one technology, being at experimentation or adoption stage with at least one other technology is positively associated with renewal, but the coefficient is not significant at conventional levels for experimentation and local adoption. The same pattern is observed in column 9, which uses a discrete version of the dependent variable reflecting the level of strategy change.[9]

These patterns suggest that firms who try out new or emerging digital technologies are likely to dip a toe in the water to see whether they should develop a strategy around it. Firms advanced in their adoption of technologies are significantly more likely to have engaged in a strategy change than those at the experimentation stage, suggesting that technology adoption and strategy change follow each other.

Columns 7 and 8 test our full specification against 2 alternative versions of the dependent variable. Column 7 corresponds to the lowest level of response (ad-hoc (tactical) initiatives only). Column 8 uses the intermediate level of reaction (having a coordinated plan but no effective change to the long-term strategy yet). Comparing these two columns with our baseline (strategy renewal, in column 6), we find that the lower levels of adoption (experimentation and adoption) correlate positively with the lowest level of response (ad-hoc initiatives, column 7). In contrast, the coefficient associated with the highest level of adoption (diffusion, our default) on the lowest level of reaction (ad-hoc initiatives) is negatively signed.

[9] From 1 = no change to 4 = renewal and 5 = disruption.

Although they are not significant at conventional levels, the coefficients of adoption stages on different degrees of strategic change are consistent with our core assumption that more advanced levels of adoption are associated with higher orders of strategy change.

4.5. Exploring robustness

Different robustness checks are reported in Tables 5 to 7. In column 2 of Table 5, we drop the "stress" variable from the controls. This lets us check the consistency of our core estimates when removing this potential source of heterogeneity. Our results hold (there is no statistically significant difference between the coefficients of our core explanatory variable between this specification and our baseline, repeated in column 1).[10] This is important as it indicates that stress perception does not mediate the technology-strategy relationship. In column 3, we introduce an alternative measure of stress, which is set to 1 when firms' perceived level of stress is in the top quartile of our in-sample distribution (instead of the default measure based on the median value). Our core results are unchanged. In columns 4 to 6 of Table 5, we check whether our results are robust to different sets of controls (or no controls at all). They are. Finally, column 7 reports the results of our baseline specification estimated with a linear probability model using OLS.

*** TABLE 5 HERE ***

We report further robustness tests in Table 6. They exploit different margins of technology diffusion. We first use two alternative measures of diffusion. In column 1, we use the nominal count of technologies diffused at scale within the focal firm (instead of a dummy indicating "at least one" as we do elsewhere), thereby testing the intensive margin. Again, we find a positive association with strategy renewal. In column 2, we use a dummy equal to 1 if the number of technologies the focal firm has already diffused at scale is equal to or larger than the median. Columns 3 and 4 use two alternative versions of our core diffusion measure, including the two technologies we had excluded given their widespread adoption (traditional web applications and cloud-based services). Both are included in the diffusion

[10] In this specification we recover a substantial number of observations that had missing stress information. All our results were tested with both samples (with and without stress test) and they are fully consistent.

variable in column 3 and only Web (the most widespread, with the highest rate of diffusion) is excluded in column 4. We also replicated all our estimates (Table 4) with these versions of the key explanatory variable and all our results hold.[11]

*** TABLE 6 HERE ***

Different specifications of our IV estimates are in Table 7. The first column reports our baseline IV estimates with both instruments. Columns 2 and 3 report estimates with only one instrument (web adoption in column 2, cloud adoption in column 3). Our results still hold. In column 4, we report IV estimates with both instruments using an IV probit model, rather than a linear 2SLS one. All results are robust to these changes.

*** TABLE 7 HERE ***

4.6. Exploring technology differences

We lastly turn to technology-specific effects. To this end, our baseline specification was tested with each technology-specific measure of adoption as explanatory variable. The results are reported in Table 8.

*** TABLE 8 HERE ***

These technology-specific estimates offer some contrast to our baseline results. For all 8 technologies, diffusion is positively associated with strategy renewal (except for additive manufacturing, where the coefficient is close to zero). However, the magnitude and significance of the coefficients varies widely, from a low of 0.04 percentage point increase (marginal effect computed at the means) associated with AI and not significantly different from zero) to a high of 26.0 percentage points increase for big data. Three technologies clearly stand out as most strongly associated with strategy renewal: Big data, mobile Internet and Internet of things. This is interesting as these technologies stand out in our set of surveyed technologies. First, compared to the other technologies in our sample, IoT, mobile Internet and Big data (fully diffused in 12%, 22% and 11% of firms, respectively) had already reached maturity and were diffused more widely than, say, additive manufacturing or artificial intelligence (2% and 6% full diffusion, respectively) in

[11] The results of these tests are available from the authors upon request.

our survey period (2017). This suggests that firms had more time and opportunity to experiment with and develop use cases for the technology that can then be utilized to initiate and implement a major strategic change. This is in line with our conceptual considerations that for a technology to truly play a key role in facilitating strategic change, firms need to be able to integrate it into their organization design, which takes time and experimentation. A second notable difference between IoT, mobile Internet and Big data and the other technologies surveyed is that they can potentially be applied to a much wider range of use cases.

The popular press and industry reports typically emphasize the general purpose nature of these technologies, pointing out that their application goes beyond a single industry or function within the firm (Cardona et al. 2013). In contrast, some other technologies like additive manufacturing or robotics are more limited to the manufacturing of physical goods of a certain type. While this can (and will) enable firms to redesign their production processes to become more efficient, the role these technologies play in realizing new business models and/or redesigning their organizational processes (beyond the manufacturing function) is limited. Hence, it is plausible that the three technologies most strongly associated with strategic change are the ones with the most general applicability, most resembling a general purpose technology. We therefore speculate that for a technology to be closely linked to firm-wide strategic change it has to be mature enough to permit sufficient experimentation and generic enough to support multiple use cases.

4.7. Exploring industry differences

Table 10 reports the results of our estimations of Equation 1 with industry subsamples. We organized industries in 5 clusters: Manufacturing, Financial services (including private equity), For profit services (including retail, transport and professional services), Public and non-profit services (including also healthcare and energy/utilities), and High-Tech (including media and telecom companies). The results do not reveal any strong differences across industries, suggesting that our results are not driven by one specific industry and use case.

*** TABLE 9 HERE ***

5. Discussion and conclusions

How do firms respond to the emerging reality of increased digitization and frequent and often unforeseen introduction of novel technologies? Do they change their strategy to circumvent the threat (in a "bold retreat" approach suggested by Adner and Kapoor (2016))? Do they simply digitize their core business without changing their corporate-level strategy? Or do they follow a combination of these two approaches? More generally, do the two processes – technology adoption and strategy change – occur in sequence or in parallel?

Our conceptual model suggests a distinction between a steady state situation in which technology structure and strategy – two interdependent domains of strategic choice – are well aligned, which means that they have been chosen to jointly ensure the highest possible payoff. In this long-run equilibrium, strategy follows technology as much as technology adoption follows strategy, and it is very hard to disentangle a causal relationship. Our conceptual model predicts that sudden changes in the cost of the options in one domain (e.g. new technologies) will create new trade-offs encouraging firms to experiment with new technologies, creating in turn new optimal configurations in the other domain (strategy). This implies that exogenous shocks in the availability or cost of new technologies as firms have been experiencing for a decade or so provides a particular situation where technology may push firms into unchartered territories and reassess their strategic options as they experiment with the technology.

This leads us to empirically test the extent to which gradual changes in the firm's technology are associated with gradual changes to their strategy, up to their potential renewal. This approach cogently offers an empirical test for the strategic nature of technologies, as evidence of a link between the adoption of a specific technology and firm renewal will suggest that the focal technology is affecting the long-term prospects of the firms enough to encourage a strategy renewal, and hence that it is a strategic resource (in Agarwal and Helfat (2009)'s terms).

Our empirical analysis, based on data from a large survey of executives cutting across different geographies and industries, supports our conceptual model as technology adoption and strategy renewal clearly occur in parallel and in close connection with each other. Moreover, we find evidence in the particular context of our study that suggests a direct impact of technology adoption on strategy renewal.

Given the cross-sectional nature of our data, our estimates rely on inter-firm variance in levels of technology adoption and in degrees of strategy change. We find a strong and robust positive association of the degree of strategy change with the level of technology adoption. Moreover, we find a strong and positive association between the extent of strategy change and the perceived stress from emerging digital technologies, suggesting that it is a potentially important source of motivation for a strategic renewal as predicted by the literature (Leavy 1997).

Overall, the main insight from our empirical analysis is that firms do not necessarily craft a new strategy simply by contemplating emerging technologies, but some redefine their strategy more gradually as they experiment with new technologies. We therefore uncover one possible channel through which technology reshapes strategy (Sambamurthy et al. 2003, Bharadwaj et al. 2013, Mithas et al. 2013). Although our results suggest that not all firms respond in the same way to the emergence of new digital technologies, times of technological change are likely to coincide with episodes of widespread changes in firm strategies.

The gradually strengthening association between degrees of technology adoption and degrees of strategy change support the view of a learning mechanism operating in this context. This speaks to the notion of cognition (see e.g. Kaplan 2008) as technology experimentation may reveal new strategic opportunities gradually and raise top management cognition gradually. More research would be welcome to further uncover these mechanisms, and the role of dynamic capabilities in those processes.

Our results speak to two main bodies of literature: Strategic Organization Design (Nadler and Tushman, 1988, Englmaier et al., 2018, Kretschmer and Khashabi, 2020) and IS Alignment (Tallon and Pinsonneault 2001, Wu et al. 2015, Liang et al. 2017)). To the former, our study shows that there exists a set of strategic renewal processes that may be driven by new technology experimentation and adoption. To the latter, our research backs up the view that adoption of digital technologies and strategy change are closely linked processes, thereby advocating for an integrated view of digitalization as a core embedded feature of the business rather than as a separate function that needs to be aligned with the core business (El Sawy et al. 2010, Bharadwaj et al. 2013).

Our work also has important managerial implications. Specifically, we stress the role of technology experimentation in devising strategic responses to digitalization. Our analysis suggests it is unrealistic for firms to build a new strategy based on a technology they have not yet experimented with. One may hypothesize that experimentation is needed as much to clarify the actual possibilities of a technology (cognition) as to start building the right skills and capabilities that would be needed to leverage the technology (creation of new operand resources). To paraphrase Mintzberg, strategy needs structure as much as structure needs strategy. Firms should therefore ensure close integration of their digital experimentation with their strategy function and processes to ensure they inform and reinforce each other.

Our study has some limitations. First, although our data offers a uniquely detailed insight into the experiences and attitudes of firms across a wide range of regions, industries and sizes, this level of detail comes at a cost. Fixed or random effects models based on panel data would certainly help achieve better identification of causal relationships and uncover the actual timing and event dynamics within the relationships we identify.

The current pandemic may also offer a unique natural experiment to validate our conceptual model. During the pandemic, firms have been forced to adopt digital technologies in a short period of time (e.g. to enable remote work). This is therefore a unique context where technology adoption has been exogenously imposed. It will be interesting to study its impact on strategy renewal in the years to come. We hope that this paper will help inspire some efforts in this direction.

References

Adner, R. & R. Kapoor. 2016. Innovation ecosystems and the pace of substitution: Re-examining technology S-curves, Strategic Management Journal, 37, 625–648.

Agarwal, R., & C.E. Helfat. 2009. Strategic renewal of organizations. Organization science, 20(2), 281-293.

Alfaro, E., J. Murillo, F. Girardin, B. Wixom and I. Someh. 2018. BBVA Fuels Digital Transformation Progress with a Data Science Center of Excellence. Case Study Report. Center for Information Systems Research, Massachusetts Institute of Technology (MIT).

Andrews, D., G. Nicoletti and C. Timiliotis. 2018. Digital technology diffusion. OECD library.

Bharadwaj, A. El-Sawy, O., Pavlou, P. & N. Venkatraman. 2013. Digital Business Strategy: Toward a next generation of insights. MIS Quarterly, 37(2), 471-482.

Bloom, N., L. Garicano, R., Sadun and J. Van Reenen. 2014. The distinct effects of information technology and communication technology on firm organization. Management Science, 60(12), 2859-2885.

Bloom, N., R. Sadun and J. Van Reenen. 2012. Americans do IT better: US multinationals and the productivity miracle. American Economic Review, 102(1), 167-201.

Bresnahan, T., E. Brynjolfsson and L. Hitt. 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. The Quarterly Journal of Economics, 117(1), 339-376.

Bughin, J. 2017. The Diffusion Pattern of Enterprise 2.0 Technologies: Worldwide Estimates of a Bass Co-diffusion Model for the Last 10 Years. Journal of Contemporary Management. Retrieved from http://www.bapress.ca/jcm/jcm-article/1929-0136-2017-02-31-12.pdf.

Bughin, J., L. LaBerge and A. Mellbye. 2017. The case for digital reinvention. McKinsey Quarterly, 2, 1-15.

Bughin, J. and N. van Zeebroeck. 2018. Artificial intelligence: Why a digital base is critical. The McKinsey Quarterly. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/artificial-intelligence-why-a-digital-base-is-critical.

Candel Haug, K., T. Kretschmer and T. Strobel. 2016. Cloud adaptiveness within industry sectors–Measurement and observations. Telecommunications policy, 40(4), 291-306.

Cardona, M., T. Kretschmer and T. Strobel. 2013. ICT and productivity: conclusions from the empirical literature. Information Economics and Policy, 25(3), 109-125.

Caroli, E. and J. Van Reenen. 2001. Skill-biased organizational change? Evidence from a panel of British and French establishments. The Quarterly Journal of Economics, 116(4), 1449-1492.

Chakravarty, B. 1982. Adaptation: A promising metaphor for strategic management. Academy of Management Review, 7(1), 35-44.

Chandler, A. D. 1962. Strategy and structure: Chapters in the history of the American enterprise. Cambridge, Massachusetts Institute of Technology, 125-137.

Cohen, W. and D. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative science quarterly, 128-152.

Crossan, M. M. & I. Berdrow. 2003. Organizational learning and strategic renewal. Strategic Management Journal, 24(11), 1087-1105.

El Sawy, O., A. Malhotra, Y. Park, Y. & P. Pavlou. 2010. Research commentary—seeking the configurations of digital ecodynamics: It takes three to tango. Information systems research, 21(4), 835-848.

Englmaier, F., N. Foss, T. Knudsen and T. Kretschmer. 2018. Organization design and firm heterogeneity: Towards an integrated research agenda for strategy. Organization Design (Advances in Strategic Management, Vol. 40), 229-252.

Floyd, S. & P. Lane. 2000. Strategizing throughout the organization: Managing role conflict in strategic renewal. Academy of Management Review, 25(1), 154-177.

Galbraith, J.R. 1974. Organization design: An information processing view. Interfaces, 4(3), pp.28-36.

Hall, D. J. & M. A. Saias. 1980. Strategy follows structure!. Strategic management journal, 1(2), 149-163.

Henderson, J. & H. Venkatraman. 1999. Strategic alignment: Leveraging information technology for transforming organizations, IBM systems journal, 32(1), 472-484.

Huff, J. O., A. S. Huff & H. Thomas. 1992. Strategic renewal and the interaction of cumulative stress and inertia. Strategic Management Journal, 13(1), 55-75.

Kaplan, S. 2008. Cognition, capabilities, and incentives: Assessing firm response to the fiber-optic revolution. Academy of Management Journal, 51(4), 672-695.

Kearns, G. & R. Sabherwal. 2006. Strategic alignment between business and information technology: a knowledge-based view of behaviors, outcome, and consequences. Journal of management information systems, 23(3), 129-162.

Kretschmer, T. & P. Khashabi. 2020. Digital Transformation and Organization Design – an Integrated Approach. California Management Review, 62(4), 86-104.

Kretschmer, T., E. Miravete & J. Pernías. 2012. Competitive Pressure and the Adoption of Complementary Technologies. American Economic Review. 2/104. 1540-1570

Leavy, B. 1997. Strategic renewal: Is disruptive revolution unavoidable?. Strategic Change, 6(5), 283-298.

Liang, H., N. Wang, Y. Xue & S. Ge. 2017. Unraveling the Alignment Paradox: How Does Business—IT Alignment Shape Organizational Agility?. Information Systems Research, 28(4), 863-879.

Lusch, R. and S. Nambisan. 2015.. Service innovation: A service-dominant logic perspective. MIS quarterly, 39(1), 155-176.

Melville, N., Kraemer, K. & V. Gurbaxani. 2004. Information Technology and Organizational Performance: An Integrative Model of IT Business Value. MIS Quarterly, 28(2), 283-322.

Mintzberg, H. 1990. The design school: Reconsidering the basic premises of strategic management. Strategic Management Journal, 11(3), 171-195.

Mithas, S., Tafti, A., & Mitchell, W. 2013. How a Firm's Competitive Environment and Digital Strategic Posture Influence Digital Business Strategy. MIS Quarterly, 37(2).

Nadler, D., & M. Tushman. Strategic Organization Design. Glenview, IL: Scott, Foresman and Company, 1988.

Sambamurthy, V., Bharadwaj, A., & Grover, V. 2003. Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. MIS quarterly, 237-263.

Tallon, P. and A. Pinsonneault. 2011. Competing perspectives on the link between strategic information technology alignment and organizational agility: insights from a mediation model. MIS Quarterly, 35(2), 463-486.

Wu, S., D. Straub and T. Liang. 2015. How information technology governance mechanisms and strategic alignment influence organizational performance: Insights from a matched survey of business and IT managers. MIS Quarterly, 39(2), 497-518.

Xiao, J., Y. Wu, K. Xie and Q. Hu. 2019. Managing the e-commerce disruption with IT-based innovations: Insights from strategic renewal perspectives. Information & Management, 56(1), 122-139.

Zucchini, L., S. Böhmer-Horländer and T. Kretschmer. 2018. Competitive pressure: competitive reactions at the group-level. Industry and Innovation, 1-24.

Tables and Figures

Figure 1: Numerical example of two-domain, two-action organization.

Benefits	T_1	T_2
S_1	6	3
S_2	2	8

Cost	Pre	Post
S_1	2	2
S_2	3	3
T_1	2	2
T_2	4	2

Table 1. Summary statistics

Variable	Main survey (Digital) Obs	Mean	StDev	Min	Max	Alternative survey (AI) Obs	Mean	StDev	Min	Max
Level of strategy change	956	3,22	1,16	1	5	2453	2,68	1,35	1	5
Strategy change: tactical only	956	0,28	0,45	0	1	2453	0,23	0,42	0	1
Strategy change: plan only	956	0,67	0,47	0	1	2453	0,51	0,50	0	1
Strategy change: renewal or disruption	956	0,46	0,50	0	1	2453	0,31	0,46	0	1
At least one technology diffused at scale (excl. Web & Cloud)	956	0,37	0,48	0	1	2453	0,26	0,44	0	1
At least one technology diffused at scale (excl. Web, incl. Cloud)	956	0,56	0,50	0	1					
At least one technology diffused at scale (incl. Web & Cloud)	956	0,76	0,43	0	1					
Highest technology stage is experimentation (excl. Web & Cloud)	956	0,22	0,41	0	1	2453	0,72	0,45	0	1
Highest technology stage is adoption (excl. Web & Cloud)	956	0,35	0,48	0	1	2453	0,53	0,50	0	1
Cloud computing technologies have been diffused at scale	946	0,44	0,50	0	1					
Traditional Web technologies have been diffused at scale	949	0,66	0,47	0	1					
Firm's perceived stress is high (relative to in-sample median)	956	0,51	0,50	0	1	2453	0,14	0,35	0	1
Firm's perceived stress is high (relative to in-sample 3rd quartile)	956	0,29	0,45	0	1	2453	0,09	0,29	0	1
Firm's business is primarily around products	956	0,65	0,48	0	1					
Firm's business is mono-product	956	0,18	0,39	0	1					
Firm's primary focus is on B2C	956	0,30	0,46	0	1					
Firm is publicly-listed	956	0,41	0,49	0	1					
Firm's revenues are larger than $1B	956	0,36	0,48	0	1					
Firm is an incumbent (not a new entrant)	956	0,87	0,33	0	1					
Number of employees:										
Less than 10						2453	0,21	0,31	0	1
Between 10 and 50						2453	0,13	0,34	0	1
Between 50 and 250						2453	0,12	0,32	0	1
Between 250 and 500						2453	0,11	0,31	0	1
Between 500 and 1,000						2453	0,12	0,33	0	1
Between 1,000 and 5,000						2453	0,17	0,38	0	1
Between 5,000 and 10,000						2453	0,07	0,25	0	1
More than 10,000						2453	0,08	0,26	0	1

Table 2. Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 Level of strategy change	1.0000																		
2 Strategy change: tactical only	-0.6156*	1.0000																	
3 Strategy change: plan only	0.8530*	-0.8463*	1.0000																
4 Strategy change: renewal or disruption	0.8765*	-0.5759*	0.6804*	1.0000															
5 At least one technology diffused at scale (excl. Web & Cloud)	0.1983*	-0.1312*	0.1990*	0.1828*	1.0000														
6 At least one technology diffused at scale (excl. Web, incl. Cloud)	0.2098*	-0.1247*	0.2114*	0.1962*	0.6631*	1.0000													
7 At least one technology diffused at scale (incl. Web & Cloud)	0.2070*	-0.1212*	0.2048*	0.1893*	0.4297*	0.6480*	1.0000												
8 Highest technology stage is experimentation (excl. Web & Cloud)	-0.0580	0.0834*	-0.0930*	-0.0545	-0.3817*	-0.3180*	-0.2520*	1.0000											
9 Highest technology stage is adoption (excl. Web & Cloud)	-0.0250	0.0508	-0.0114	-0.0591	-0.5511*	-0.2963*	-0.1211*	-0.3674*	1.0000										
10 Cloud computing technologies have been diffused at scale	0.1551*	-0.0963*	0.1560*	0.1570*	0.3329*	0.7827*	0.5085*	-0.1948*	-0.1154*	1.0000									
11 Traditional Web technologies have been diffused at scale	0.1677*	-0.1015*	0.1686*	0.1542*	0.2510*	0.4075*	0.7910*	-0.1696*	-0.0322	0.3954*	1.0000								
12 Firm's perceived stress is high (relative to in-sample median)	0.1324*	-0.0853*	0.1268*	0.1440*	0.1344*	0.1154*	0.0607	-0.0845*	-0.0303	0.1294*	0.0325	1.0000							
13 Firm's perceived stress is high (relative to in-sample 3rd quartile)	0.0823*	-0.0644	0.0768*	0.1086*	0.1085*	0.0954*	0.0697	-0.0800*	-0.0079	0.1202*	0.0507	0.6251*	1.0000						
14 Firm's business is primarily around products	0.0515	-0.0712*	0.0802*	0.0382	0.0322	0.0207	0.0448	-0.0572	0.0602	-0.0064	0.0222	-0.0350	-0.0113	1.0000					
15 Firm's business is mono-product	-0.1316*	0.0857*	-0.1493*	-0.0944*	-0.0930*	-0.0757*	-0.0852*	0.0246	-0.0134	-0.0609	-0.0689*	-0.0490	0.0089	-0.1406*	1.0000				
16 Firm's primary focus is on B2C	0.0870*	-0.0996*	0.1203*	0.0600	0.0342	-0.0158	0.0162	-0.0239	0.0059	-0.0762*	-0.0103	0.0246	0.0145	0.0788*	-0.0244	1.0000			
17 Firm is publicly-listed	0.0882*	-0.0712*	0.1304*	0.0482	0.0666	0.0398	0.1089*	-0.0285	0.0567	0.0197	0.1292*	-0.0290	-0.0426	0.2276*	-0.1620*	0.1383*	1.0000		
18 Firm's revenues are larger than $1B	0.0934*	-0.0834*	0.1314*	0.0666	0.0349	0.0352	0.1037*	-0.0194	0.0780*	0.0337	0.1394*	-0.0823*	-0.0883*	0.2162*	-0.1486*	0.1494*	0.6682*	1.0000	
19 Firm's revenues are larger than $1B	-0.1146*	0.0841*	-0.0908*	-0.1193*	-0.1113*	-0.1038*	-0.0481	0.0637	0.0567	-0.1197*	-0.0056	-0.1219*	-0.1870*	0.0799*	-0.0986*	0.0546	0.1720*	0.1668*	1.0000

** Correlation coefficient is significant at the 1% probability level*

Table 3. Adoption rates

Technology	Not at all	Experimentation	Adoption	Diffusion
Main Survey (Digital)				
Traditional Web	3%	9%	22%	66%
Cloud-based services	8%	18%	29%	44%
Mobile Internet	31%	23%	24%	22%
Big data	33%	33%	22%	12%
AI	43%	34%	16%	6%
IoT	48%	26%	16%	11%
Robotics & RPA	61%	20%	14%	6%
Deep learning	65%	24%	8%	3%
AR/VR	68%	22%	7%	3%
Additive manufacturing	77%	14%	7%	2%
Alternative Survey (AI)				
Speech Recognition	57%	16%	16%	11%
Image Recognition	63%	14%	12%	11%
Decision Management	65%	14%	11%	10%
Natural language processing (NLP)	69%	14%	9%	9%
Robotics Process Auto	70%	11%	10%	10%
Natural language generation (NLG)	70%	13%	8%	8%
Robotics	71%	12%	9%	9%
Machine Learning	71%	11%	9%	9%
Virtual Agents	71%	11%	9%	9%

Table 4. Estimates of equation 1

	Baseline	IV Second stage	IV First stage	Experimentation	Local adoption	All adoption levels	Reaction = Ad-hoc (tactical)	Reaction = Only having a plan	Reaction level (continuous) (OLS)
At least one technology diffused at scale (excl. Web & Cloud)	0.4705***	0.5974***				0.5653***	-0.0378	0.0683	0.6751***
	(0.0895)	(0.1041)				(0.1876)	(0.1992)	(0.2128)	(0.1863)
Highest technology stage is experimentation (excl. Web & Cloud)				-0.2591**		0.0528	0.4165**	0.0932	0.2494
				(0.1064)		(0.1968)	(0.2022)	(0.2198)	(0.1936)
Highest technology stage is adoption (excl. Web & Cloud)					-0.2143**	0.1326	0.3837*	0.1512	0.3132*
					(0.0891)	(0.1885)	(0.1974)	(0.2119)	(0.1863)
High perceived stress	0.2433***	0.0488	0.0534*	0.2641***	0.2782***	0.2384***	-0.1350	-0.0540	0.1914**
	(0.0883)	(0.0359)	(0.0306)	(0.0873)	(0.0873)	(0.0884)	(0.0944)	(0.0991)	(0.0752)
Firm is product-based	-0.0462	-0.0324	0.0337	-0.0454	-0.0174	-0.0521	-0.1346	0.2830**	0.0415
	(0.0987)	(0.0387)	(0.0342)	(0.0984)	(0.0981)	(0.0990)	(0.1036)	(0.1148)	(0.0815)
Firm is mono-product/service	-0.3177***	-0.0402	-0.1473***	-0.3644***	-0.3704***	-0.3123***	0.2992**	-0.0659	-0.3093***
	(0.1174)	(0.0463)	(0.0370)	(0.1164)	(0.1161)	(0.1179)	(0.1166)	(0.1316)	(0.1010)
Firm is mainly B2C	0.0142	-0.0141	0.0524	0.0244	0.0320	0.0140	-0.1877	0.1844	0.0512
	(0.1052)	(0.0411)	(0.0359)	(0.1052)	(0.1049)	(0.1052)	(0.1142)	(0.1157)	(0.0897)
Firm is public	-0.0842	-0.0736	0.0916**	-0.0397	-0.0446	-0.0884	-0.0000	0.1307	-0.0238
	(0.1185)	(0.0482)	(0.0422)	(0.1177)	(0.1176)	(0.1184)	(0.1264)	(0.1241)	(0.0976)
Firm is large (Rev>1b$)	0.1829	0.1071**	-0.1150***	0.1451	0.1666	0.1769	-0.3605***	0.1719	0.1633
	(0.1223)	(0.0496)	(0.0436)	(0.1210)	(0.1214)	(0.1222)	(0.1340)	(0.1275)	(0.1015)
Firm is an incumbent	-0.2844**	-0.0248	-0.1378***	-0.3348**	-0.3521***	-0.2766**	0.4468***	-0.0760	-0.2877**
	(0.1363)	(0.0586)	(0.0469)	(0.1337)	(0.1334)	(0.1365)	(0.1554)	(0.1490)	(0.1174)
Traditional Web technologies have been diffused at scale			0.1399***						
			(0.0337)						
Cloud computing technologies have been diffused at scale			0.2557***						
			(0.0349)						
Constant	0.7865	0.5615***	0.3455**	1.1072**	0.9559*	0.7168	-1.0056*	-1.4995***	3.5625***
	(0.5268)	(0.1868)	(0.1680)	(0.5193)	(0.5356)	(0.5560)	(0.5916)	(0.3943)	(0.5193)
Pseudo/Adjusted R^2	0.08	-0.07	0.14	0.06	0.06	0.08	0.09	0.05	0.09
Log likelihood	-607.14	-699.61	-560.93	-618.04	-618.11	-606.76	-519.24	-458.79	-1,436.75
N	956	945	945	956	956	956	960	954	960
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Underidentification test: LM statistic (P-value)		106.86 (0.00)							
Weak identification test: F statistic (Stock-Yogo 10% max relative bias)		63.19 (19.93)							
Overidentification test: Hansen J statistic (P-value)		1.45 (0.23)							

In columns 1, 2, 4, 5 and 6, the dependent variable is our baseline (binary) measure of strategy renewal. Columns 7 and 8 use a different margin of strategy change (tactical in column 7, plan only in column 8). Column 9 uses a discrete measure from 1 (no change) to 4 (renewal) and 5 (disruption). Standard Errors in parentheses. Coefficients significant at the * 10%, ** 5% or ***1% probability levels.

Table 5. Robustness to different specifications

	Baseline	No control for stress	Alternative measure of stress	No firm controls	No industry or region controls	No controls	Baseline (OLS)
At least one technology diffused at scale (excl. Web & Cloud)	0.4705***	0.4793***	0.4807***	0.4386***	0.4455***	0.4792***	0.1746***
	(0.0895)	(0.0785)	(0.0892)	(0.0793)	(0.0872)	(0.0671)	(0.0338)
High perceived stress	0.2433***			0.3056***	0.2718***		0.0883***
	(0.0883)			(0.0787)	(0.0841)		(0.0329)
Very high perceived stress (higher than the 75th percentile)			0.1330				
			(0.0967)				
Firm is product-based	-0.0462	-0.0263	-0.0501		0.0227		-0.0152
	(0.0987)	(0.0873)	(0.0986)		(0.0901)		(0.0363)
Firm is mono-product/service	-0.3177***	-0.2622***	-0.3301***		-0.2912***		-0.1080***
	(0.1174)	(0.0976)	(0.1166)		(0.1121)		(0.0413)
Firm is mainly B2C	0.0142	0.0838	0.0189		0.1018		0.0037
	(0.1052)	(0.0929)	(0.1047)		(0.0915)		(0.0395)
Firm is public	-0.0842	-0.0575	-0.0708		-0.0442		-0.0318
	(0.1185)	(0.1052)	(0.1178)		(0.1138)		(0.0444)
Firm is large (Rev>1b$)	0.1829	0.1446	0.1643		0.2076*		0.0677
	(0.1223)	(0.1086)	(0.1217)		(0.1175)		(0.0459)
Firm is an incumbent	-0.2844**	-0.4010***	-0.2875**		-0.3241**		-0.1039**
	(0.1363)	(0.1091)	(0.1369)		(0.1299)		(0.0505)
Constant	0.7865	0.6626	0.8038	-0.0630	-0.1664	-0.2991***	0.7676***
	(0.5268)	(0.4587)	(0.5251)	(0.5049)	(0.1510)	(0.0407)	(0.1755)
Pseudo/Adjusted R^2	0.08	0.08	0.08	0.06	0.05	0.02	0.08
Log likelihood	-607.14	-785.75	-609.99	-754.42	-631.43	-1,033.03	-638.92
N	956	1,240	956	1,163	964	1,538	960
Industry dummies	Y	Y	Y	Y	N	N	Y
Region Dummies	Y	Y	Y	Y	N	N	Y

Dependent variable is our baseline (binary) measure of strategy renewal. Standard Errors in parentheses. Coefficients significant at the * 10%, ** 5% or ***1% probability levels.

Table 6. Robustness to different measures of diffusion

	Diffusion count	Relative diffusion rate
Number of technologies diffused at scale (excl. Web & Cloud)	0.1391***	
	(0.0427)	
Firm is in top 50% of adopters at scale (excl. Web & Cloud)		0.3741***
		(0.1247)
High perceived stress	0.2504***	0.2555***
	(0.0878)	(0.0878)
Firm is product-based	-0.0523	-0.0408
	(0.0983)	(0.0984)
Firm is mono-product/service	-0.3484***	-0.3594***
	(0.1164)	(0.1159)
Firm is mainly B2C	0.0259	0.0226
	(0.1050)	(0.1054)
Firm is public	-0.0708	-0.0619
	(0.1176)	(0.1174)
Firm is large (Rev>1b$)	0.1638	0.1532
	(0.1214)	(0.1209)
Firm is an incumbent	-0.3124**	-0.3199**
	(0.1341)	(0.1339)
Constant	0.8272	0.8974*
	(0.5368)	(0.5321)
Pseudo-R^2	0.07	0.07
Log likelihood	-614.54	-616.31
N	956	956
Industry dummies	Y	Y
Region Dummies	Y	Y

Dependent variable is our baseline (binary) measure of strategy renewal. Standard Errors in parentheses. Coefficients significant at the * 10%, ** 5% or ***1% probability levels.

Table 7. Robustness of IV estimates (2nd stage)

	Both instruments (baseline)	Only web technologies	Only cloud computing	Both instruments IV Probit
At least one technology diffused at scale (excl. Web & Cloud)	0.5974***	0.7268***	0.5521***	1.9886***
	(0.1041)	(0.1538)	(0.1143)	(0.3943)
High perceived stress	0.0488	0.0389	0.0521	1.9886
	(0.0359)	(0.0385)	(0.0359)	0.3943
Firm is product-based	-0.0324	-0.0374	-0.0269	0.1366
	(0.0387)	(0.0408)	(0.0381)	0.1009
Firm is mono-product/service	-0.0402	-0.0210	-0.0491	-0.0399
	(0.0463)	(0.0513)	(0.0462)	0.1027
Firm is mainly B2C	-0.0141	-0.0119	-0.0190	-0.1499
	(0.0411)	(0.0433)	(0.0406)	0.1303
Firm is public	-0.0736	-0.0785	-0.0721	0.0119
	(0.0482)	(0.0518)	(0.0478)	0.0819
Firm is large (Rev>1b$)	0.1071**	0.1106**	0.0982**	-0.1049
	(0.0496)	(0.0528)	(0.0490)	0.0926
Firm is an incumbent	-0.0248	-0.0028	-0.0337	0.1709
	(0.0586)	(0.0658)	(0.0579)	0.1054
Constant	0.5615***	0.5090**	0.5872***	-0.0694
	(0.1868)	(0.2064)	(0.1843)	0.1552
Adjusted R^2	-0.07	-0.19	-0.05	0.0915
Log likelihood	-699.61	-756.36	-691.09	
N	945	953	950	1,156
Industry dummies	Y	Y	Y	Y
Region Dummies	Y	Y	Y	Y

Dependent variable is our baseline (binary) measure of strategy renewal. Standard Errors in parentheses. Coefficients significant at the * 10%, ** 5% or ***1% probability levels.

Table 8. Exploring technology differences

	dig17_q17_1	dig17_q17_2	dig17_q17_4	dig17_q17_5	dig17_q17_6	dig17_q17_9	dig17_q17_10	dig17_q17_312AI	All
Big data diffused	0.6674***								0.6399***
	(0.1365)								(0.1507)
Deep learning diffused		0.4671							0.1334
		(0.2933)							(0.3823)
Robotics & RPA diffused			0.1904						0.2194
			(0.1941)						(0.2106)
Additive manuf. diffused				-0.0194					-0.0897
				(0.2923)					(0.3497)
Mobile Internet diffused					0.2986***				0.2569**
					(0.1052)				(0.1198)
AR/VR diffused						0.2333			-0.0413
						(0.2528)			(0.3237)
IoT diffused							0.3555**		0.2571
							(0.1441)		(0.1720)
AI diffused								0.0974	-0.1957
								(0.1842)	(0.2216)
High perceived stress	0.2243**	0.2224**	0.2464***	0.2737***	0.2468***	0.2523***	0.2450***	0.2729***	0.1870**
	(0.0891)	(0.0893)	(0.0885)	(0.0888)	(0.0887)	(0.0900)	(0.0891)	(0.0875)	(0.0949)
Firm is product-based	-0.0399	-0.0192	-0.0677	-0.0201	-0.0152	-0.0582	-0.0492	-0.0277	-0.0953
	(0.1000)	(0.1003)	(0.0997)	(0.1001)	(0.0991)	(0.1014)	(0.1001)	(0.0980)	(0.1065)
Firm is mono-product/service	-0.3913***	-0.3920***	-0.3972***	-0.3561***	-0.3682***	-0.3890***	-0.3273***	-0.3733***	-0.3003**
	(0.1192)	(0.1177)	(0.1176)	(0.1169)	(0.1175)	(0.1185)	(0.1178)	(0.1160)	(0.1243)
Firm is mainly B2C	0.0506	0.0337	0.0662	0.0349	0.0392	0.0748	0.0256	0.0365	0.0663
	(0.1064)	(0.1079)	(0.1070)	(0.1080)	(0.1063)	(0.1089)	(0.1084)	(0.1048)	(0.1144)
Firm is public	-0.0948	-0.0669	-0.0561	-0.0813	-0.0757	-0.0806	-0.1050	-0.0409	-0.1165
	(0.1199)	(0.1212)	(0.1190)	(0.1206)	(0.1196)	(0.1240)	(0.1210)	(0.1174)	(0.1296)
Firm is large (Rev>1b$)	0.1841	0.1266	0.1307	0.1724	0.1569	0.1462	0.1649	0.1475	0.1117
	(0.1227)	(0.1255)	(0.1224)	(0.1245)	(0.1238)	(0.1274)	(0.1243)	(0.1209)	(0.1338)
Firm is an incumbent	-0.2460*	-0.3262**	-0.3719***	-0.3690***	-0.3187**	-0.3521***	-0.3653***	-0.3526***	-0.2050
	(0.1389)	(0.1374)	(0.1353)	(0.1355)	(0.1364)	(0.1361)	(0.1350)	(0.1331)	(0.1465)
Constant	0.7667	0.8624	0.9685*	0.9512*	0.8974*	0.9568*	0.9538*	0.9339*	0.6615
	(0.5323)	(0.5281)	(0.5206)	(0.5298)	(0.5326)	(0.5255)	(0.5318)	(0.5305)	(0.5392)
Pseudo-R^2	0.08	0.07	0.06	0.06	0.07	0.07	0.07	0.06	0.10
Log likelihood	-593.65	-592.08	-600.71	-596.44	-600.15	-577.92	-594.49	-620.89	-521.44
N	935	918	930	922	933	899	923	956	838
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y

Dependent variable is our baseline (binary) measure of strategy renewal. Standard Errors in parentheses. Coefficients significant at the * 10%, ** 5% or ***1% probability levels.

Table 9. Exploring industry differences

	Manufacturing	Finance	For profit services	High tech, media & telecom	Public services, healthcare & energy
At least one technology diffused at scale (excl. Web & Cloud)	0.3631**	0.6297***	0.5005***	0.4029**	0.6579**
	(0.1757)	(0.2225)	(0.1925)	(0.1806)	(0.3271)
High perceived stress	0.2800	0.5263**	0.0670	0.3224*	-0.1019
	(0.1823)	(0.2075)	(0.1858)	(0.1861)	(0.3189)
Firm is product-based	-0.0224	0.1166	0.1335	-0.0814	-0.4932
	(0.2200)	(0.2103)	(0.2013)	(0.1899)	(0.3400)
Firm is mono-product/service	-0.4441*	-0.4050	-0.4202*	-0.1556	-0.9083**
	(0.2310)	(0.2758)	(0.2378)	(0.2811)	(0.4388)
Firm is mainly B2C	-0.0408	0.2381	0.5945***	-0.1348	-0.2832
	(0.1906)	(0.2241)	(0.2308)	(0.2175)	(0.3592)
Firm is public	-0.0466	-0.1191	-0.1363	-0.0401	-0.0958
	(0.2064)	(0.2709)	(0.2934)	(0.2668)	(0.4652)
Firm is large (Rev>1b$)	0.4189**	0.3113	-0.2866	0.1720	-0.3128
	(0.2075)	(0.2644)	(0.3266)	(0.2684)	(0.4928)
Firm is an incumbent	-0.2066	0.3154	-0.4771	-0.4146*	-0.5515
	(0.3219)	(0.4165)	(0.2908)	(0.2329)	(0.4053)
Constant	-0.4167	-1.2583**	-0.2953	1.1700***	1.7633**
	(0.4156)	(0.5075)	(0.4785)	(0.4083)	(0.7604)
Pseudo-R^2	0.06	0.11	0.09	0.08	0.13
Log likelihood	-156.88	-111.09	-132.33	-144.04	-52.07
N	247	181	215	228	89
Industry dummies	N	N	N	N	N
Region Dummies	Y	Y	Y	Y	Y

Dependent variable is our baseline (binary) measure of strategy renewal. Standard Errors in parentheses. Coefficients significant at the * 10%, ** 5% or ***1% probability levels.

Appendix

Appendix. Estimates of equation 1 using alternative dataset (AI Survey)

	Baseline	Experimentation	Local adoption	All adoption levels	Reaction = Ad-hoc (tactical)	Reaction = Only having a plan	Reaction level (continuous) (OLS)
At least one technology diffused at scale	0.9379***			0.7296***	-0.4170***	-0.4481***	0.6301***
	(0.0657)			(0.0773)	(0.0845)	(0.0817)	(0.0625)
At least one technology experimented with		0.6693***		0.1357	0.4556***	0.6533***	0.4348***
		(0.0766)		(0.1004)	(0.0875)	(0.0969)	(0.0659)
At least one technology adopted locally			0.7584***	0.3135***	-0.2094**	0.0600	0.2449***
			(0.0617)	(0.0911)	(0.0820)	(0.0832)	(0.0648)
High perceived stress	0.2044**	0.1961**	0.2170***	0.2129**	-0.2158**	0.1792**	0.2126***
	(0.0862)	(0.0829)	(0.0835)	(0.0869)	(0.0888)	(0.0828)	(0.0649)
Constant	-1.6593***	-1.5783***	-1.5470***	-1.8695***	-0.9093***	-1.5908***	1.3926***
	(0.1577)	(0.1288)	(0.1290)	(0.1624)	(0.1459)	(0.1593)	(0.1015)
Pseudo/Adjusted R^2	0.23	0.17	0.19	0.24	0.05	0.09	0.41
Log likelihood	-1,169.98	-1,263.79	-1,225.08	-1,156.33	-1,249.61	-1,130.24	-3,548.66
N	2,453	2,453	2,453	2,453	2,453	2,453	2,453
Size dummies	Y	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y	Y
Region Dummies	Y	Y	Y	Y	Y	Y	Y

In columns 1 through 4, the dependent variable is our baseline (binary) measure of strategy renewal. Columns 5 and 6 use a different margin of strategy change (tactical in column 5, plan only in column 6). Column 7 uses a discrete measure from 1 (no change) to 4 (renewal) and 5 (disruption). Standard Errors in parentheses. Coefficients significant at the * 10%, ** 5% or ***1% probability levels.