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EXPERIMENTATION, LEARNING AND STRESS.

THE ROLE OF DIGITAL TECHNOLOGIES IN STRATEGY CHANGE

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Experimentation, Learning and Stress. The Role of Digital Technologies in Strategy Change

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Abstract

With the increasing availability of digital technologies, many firms are planning to develop digitally-enabled business models. Digital technologies can give an impulse to realign strategies through two channels: Initial use of digital technologies may help firms spot their potential and encourage firms to develop digitally-supported business models, or emerging digital technologies may present a threat to firms, who then initiate a process of strategic renewal to relieve the pressure. We study how the adoption of new digital technologies is associated with changes to the strategy of the firm, and how both are shaped by a firm's perception of the competitive stress created by new technological developments. Using two detailed survey-based datasets on firms' expectations, adoption and strategy renewal for a wide range of AI and digital technologies, we find a strong positive association between the degree of strategy change and the adoption of advanced digital technologies. This relationship does not seem mediated by the level of competitive stress from digital technology, which is itself strongly associated with strategy change. Our results suggest a tight coupling between (technological) structure and strategy.

Keywords:

Digital transformation, Strategic Organization Design, Technology adoption, Strategic renewal, Digital strategy, Big data, Artificial Intelligence.

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1. Introduction

Rapid progress in digital technologies pushes firms to change their strategy to respond quickly to the new threats and opportunities it raises. The emergence of digital technologies has coincided with a wave of strategic change initiatives by firms and an increase in the perceived stress from sweeping technological changes. While these trends may simply coexist, it seems unlikely that they are not interdependent. Indeed, digital technologies enable certain forms of strategy change through the adoption of new technologies, and competitive stress (or pressure) is a well-established trigger of firm actions (Zucchini et al. 2018).

Yet little is known to date about the interdependence and timing of technology adoption and strategy change and how the perceived level of competitive stress may drive both processes (Kretschmer et al. 2013). 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 seek empirical evidence on the interdependence of strategy change at the corporate level and digital technology adoption and diffusion within the firm. Our empirical analysis uses data from two distinct surveys led by the consulting firm McKinsey & Company in 2017. The first looks at digitization as a whole (focusing on the adoption of new generations of technology) and how firms have adapted to the threats and opportunities created by these technologies. The second focuses on artificial intelligence, its awareness, adoption and expected impact among firms.

Both samples cover a wide range of firms (in terms of size, ownership structures and geographies) and industries to give a broad view on the phenomenon.

Based on a simple conceptual framework inspired by the Strategic Organization Design (SOD) literature and the Strategic Alignment literature in IS, we estimate the association of digital technology adoption and perceived stress from digitalization with strategy renewal (a radical form of strategy change, following Agarwal and Helfat 2009) and look for a possible mediation effect of the latter (perceived stress from digitalization) on the former (association of digital technology adoption with strategy renewal). Our results show that (a) higher perceived levels of stress from digitalization and technology adoption are both positively associated with strategy renewal, and (b) that their associations are independent, suggesting that actual technology adoption significantly correlates with strategy renewal beyond the effect of firm fears or anticipations, and vice versa. These results are robust to a battery of robustness tests, are consistent across our two samples, and are robust to the use of instrumental variables.

Overall, our results support the view that digital technology is indeed a strategic resource (Agarwal and Helfat 2009). They have important implications for our understanding and the management of digitalization and emphasize the tight interdependence between strategic renewal processes and technology adoption.

2. Theoretical background and conceptual model

2.1. A SOD perspective on strategic and organizational change

Work on SOD looks at the interplay between a firm's strategy and the way an organization is designed and structured. This stream of research has its origins in the work by Chandler (1962) on the relationship between firm strategy[1] and structure[2] (see e.g. Galan and Sanchez-Bueno 2009). Early scholars suggested that "Structure follows Strategy", i.e. that firms will design an organization that lets them reach their (previously set) strategic goals in an optimal manner. Hall and Saias (1980) challenged this notion and suggested that the strategic choices are limited by the firm's pre-existing organizational structure. These two views were reconciled by Mintzberg (1990), who stated that "*structure follows strategy as the left foot follows the right in walking*". Empirical tests find a reciprocal relationship between strategy and structure (Amburgey and Dacin 1994), but strategy seems to affect structure more than the reverse.

The SOD literature advances this discussion and posits that strategy and structure (or design) are determined simultaneously by the firm's decisionmakers (Englmaier et al. 2018; Nadler and Tushman 1988; Galbraith 1974). Hence, a strategy will be chosen with the structural limits in mind, while the strategic goals of the firm are considered when designing an organization.

Organization design captures both formal and informal elements of an organization and governs the interactions within the organization necessary to coordinate towards a common output (Puranam, Raveendran, Knudsen 2012). Importantly, organization design therefore also covers the technology in place to support these coordination and communication mechanisms, including any digital technology shaping interaction within and outside the firm.[3]

The SOD perspective has important implications on the dynamics of organizational and strategy change. Specifically, if there is a(n exogenous) change in one dimension, the theory of SOD calls for an adjustment in the other dimension. For example, changes in regulatory restrictions on the governance structure (e.g. foreign ownership, legal limits to suppliers' liability etc.) may lead a firm to reconsider their strategic options. Conversely, a change in the strategy space (e.g. through dergulation, new consumer demands etc.) may trigger changes in the organization design to optimally take advantage of this new situation. This relates to the literature on organizational adaptation, which posits that managers cope with changes in their firm's external environment through the choice of an appropriate strategy and the design of a matching structure (Andrews 1971, Ansoff 1979, Schendel and Hofer 1979).

As far as strategy[4] is concerned, the degree (or intensity) of change matters, from gradual or incremental to punctuated or radical. It encompasses any type of modification, whether incremental (such as marginal extensions, additions or deletions) or radical (such as a full replacement) (see Leavy 1997 for a review). 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*." We focus on one such attribute, the strategy itself. In the remainder of the paper, we will therefore use the term "strategy renewal" to denote a refreshment or replacement of the firm's strategy.[5]

2.2. Digital technology and strategy change

In the context of digitalization, with new generations of technology emerging rapidly, the SOD perspective suggests that firms will continuously adjust their strategy to keep up with the corresponding technological changes. Specifically, if a new technology appears, firms have to decide whether to adapt to the new circumstances (and if so, to what extent) or not.[6] Moreover, fears of technological displacement and the threat of disruptive innovation (Bower and Christensen, 1995) push firms towards a form of strategic change. Our main interest lies in linking strategy changes and digital technology advancements.

As has been extensively shown, progress in information technology has an important impact on firm productivity (Cardona et al. 2013, Melville et al. 2004), often through corresponding changes in the organization of firms (Caroli and Van Reenen 2001, Bresnahan et al. 2002, Bloom et al. 2012, Bloom et al. 2014). However, the channels through which the availability of new technologies affects the organization and strategy of a firm have been studied in less detail.

Although strategic renewal has received wide attention in the scholarly literature (Crossan and Berdrow 2003, Floyd and Lane 2000, Agarwal and Helfat 2009), how the concept applies to digitally-enabled renewal is still understudied. This question speaks to the literature on the strategic alignment of information systems (IS). Work in this space discussed the structure-strategy duality in an IT context (Tallon and Pinsonneault 2001, Wu et al. 2015, Liang et al. 2017). Henderson and Venkatraman (1999) proposed different processes and trajectories to align business and IT (strategic alignment) while ensuring integration between strategies and organizations (functional fit). Strategic alignment is positively correlated with firm performance (Chan et al. 1997) and is considered strategically important (Kearns and Sabherwal 2006; Liang et al. 2017).

A cornerstone of the "alignment view" is that business strategy directs firms' IT/IS strategy. However, as digital technologies become increasingly available and development cycles shorter, digital technologies enable new functionalities that can fundamentally reshape traditional business strategy (Sambamurthy et al.

2003, Bharadwaj et al. 2013). Recognizing the pervasive role of (emerging) digital resources in creating business value, competitive advantage and strategic differentiation, research on "digital business strategy", i.e. organizational strategy formulated and executed by leveraging digital resources to create differential value, has gathered momentum (Bharadwaj et al. 2013, Mithas et al. 2013). However, knowledge on the dynamic interdependencies between (new) digital technologies and alignment processes in firm strategy remains scarce.

Our framing suggests that technology adoption and strategy renewal need to emerge in parallel and inform one another. We hypothesize indeed that a firm cannot devise a new strategy without assessing the real potential of new technologies and its ability to acquire the necessary skills and resources, and conversely that it cannot adopt every new piece of digital technology without a strategic plan to leverage it. This implies that, as firms progress in their adoption of digital technology (from experimentation, to local adoption, to diffusion at scale), they should become more likely to renew their strategy substantially.

2.3. A simple framework

We illustrate our conceptual framework in Figure 1. The emergence of digital technologies represents an exogenous shock to firms, which can have an impact in multiple ways: First, and most obviously, the availability of new technologies allows firms to adopt them and integrate them into their existing operations. However, using a new technology can take different forms and intensities: a firm may experiment with the new technology on a limited scale or make it available locally in the organization (Chakravarty 1982). But the full impact of a new technology will only be realized if it is actually used at scale throughout the firm.

*** FIGURE 1 HERE ***

Second, the emergence of a new technology may also increase the stress a firm perceives as it may change the business logic of the industry. If an innovation is competence-destroying (Tushman and Anderson 1996), the firm cannot continue being successful without changing. As competitors realize new technological opportunities, the focal firm's profits declines and the pressure to act increases.

2.4. Expected correlations

2.4.1 Technology structure and strategy change (marked (1) in Figure 1)

In keeping with the SOD logic, strategies are devised with the organization's design in mind. Therefore, if a firm adopts emerging digital technologies, which reflects the firm's willingness to seize new technological opportunities, the firm's strategy space may change. Since the underlying assumption is one of interdependence between structure and strategy, investment into a digital technology is expected to correlate with a strategy change towards a digital business strategy.

The extent to which a strategy relies on digital technology may depend on the extent of adoption throughout the organization. This is theoretically interesting as for example the mere establishment of a business case using a digital technology may be sufficiently demonstrated by limited experimentation, while more extensive adoption and use would be necessary if a strategy is based on extensive prior experience and learning by the entire workforce. We thus expect the extent of technology adoption to correlate with the extent of strategy change.

2.4.2 Perceived stress and strategy change (2)

Often, the difference between a firm adjusting their strategy at the margins and undergoing a sweeping renewal is driven by the tension between *inertia* and *stress* (Huff et al. 1992). Firms try to minimize disruptions and avoid highly uncertain initiatives, but high perceived or real stress pushes the firm towards strategic renewal as "*stressful forces erode the fit between the organization and its environment*" (Huff et al. 1992). There is a wide body of work studying the propensity of organizations to stick to their strategic direction even as their environment changes (Huff et al. 1992, Leavy 1997), which ultimately leads to gradual rather than extensive strategic change processes. This also relates to the notion of inertia, which builds over time as organizational routines further crystalize, and may lead firms to first ignore signals of a mismatch between their strategy and environment until they get large enough for the firm to respond to it, then in a more discontinuous way (Leavy 1997).

Indeed, as changes occur in the firm's environment, including technological change, the fit between the firm's strategy and its environment may deteriorate, resulting in stress. And perceived stress – whatever its source – can be a driver for a change in strategy (Zucchini et al. 2018). The extensive literature on competitive dynamics and competitive pressure (or stress) has shown that rival actions tend to trigger responses by an incumbent firm. Similarly, Bloom et al. (2016) have shown that pressure from Chinese imports leads to increased technological adoption and productivity growth in UK firms. Consequently, we expect perceived stress to be positively associated with strategy renewal. Moreover, one should expect the intensity of the signal of a threat to the firm's ability to create and capture value (i.e. the degree of perceived stress) to correlate with the degree of strategy change.

2.4.3 Moderation of perceived stress and technology adoption (3)

The association between technology adoption and strategy change may depend on the extent to which digital technologies can potentially disrupt the firm's operations. Specifically, higher perceived stress may trigger a firm to fully utilize the digital technologies they are already using to some extent. Hence, the higher the perceived stress, the more positive the association between technology adoption and strategy change. However, if the key role of adopting digital technologies is to outline opportunities for digital business strategies (i.e. showing the upside), the degree of perceived stress (reflecting the downside) may not affect the association between technology adoption and strategy change. Ultimately, we consider this an empirical question.

2.4.4 Mediation of technology adoption by perceived stress (4)

Another scenario is that the main source of association between technology adoption and strategy change is by the stress it exerts on the firm. Hence, the adoption of digital technologies makes the firm aware of the potential disruptive changes the technology will have on the entire industry because the technology's potential will eventually become known not just to the focal firm, but also competitors and new entrants. Hence, there will be no independent correlation between technology adoption and strategy change, and perceived stress acts as a mediator between the two. This is theoretically interesting as it suggests that experience with a technology does not trigger strategy change and that change is based on the perception of the technology's impact, not the actual use case.

3. Data and Empirical Approach

3.1. Estimation Model

We estimate the likelihood for a firm to implement a strategy change S_i as a function of its own perception of the stress created by digital technologies (E_i, reflecting the downside of technology) and its actual adoption of these technologies (A_i, reflecting an attempt at identifying or seizing the upside), after controlling for firm characteristics (X_i) and industry effects (I_i), in equation (1):

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

This reduced-form model, however, can only capture an aggregate effect of adoption and expectations 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 therefore, we run the model at different margins of strategy change (from ad-hoc tactical changes to major strategy renewal) and/or for different margins of stress and adoption. Assuming firms first experiment with a technology before adopting it in one specific (often localized) use case until they are able to 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 also provide support to the view that these technologies are strategic in the sense that they play an important role in the implementation and success of strategies.

We use a logit model to estimate equation (1) and subsequently subject our baseline model to a series of robustness tests using a different sample, different specifications of the dependent and independent variables and a different estimation technique. We also use instrumental variables regressions to assess potential bias due to unobserved heterogeneity. We use adoption of two technologies that are more basic than the others (Web and cloud computing) as instruments. Our results are robust to all those changes, which we introduce and discuss in our results section.

3.2. Data

We run our empirical model on two distinct datasets. Both are cross-sections of firms across a wide range of characteristics, industries and geographies. Both surveys were separately run by TNS Soffres on behalf of McKinsey in the first half of 2017 toward a panel of CxOs. The first survey (Survey I) looks at digitization at large and contains roughly 1600 responses, the second (Survey II) has about 3000 firm respondents and focuses on Artificial Intelligence (AI) technologies. Summary statistics for both surveys are in Table I. Due to some missing values, our final samples are of size 955 (in Survey I) and 2453 (in Survey II) respectively. Correlations among the main variables are in Table II.

*** TABLE I HERE ***

*** TABLE II HERE ***

Measuring strategy renewal. Our measure of strategy change is built from a unique question included in both surveys: "*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.*

We code our dependent variable (strategy renewal) as a dummy equal to 1 if the focal firm has at least changed its long-term corporate strategy (i.e. levels 4 and 5 on the survey response scale) to address the changes, but we will test the sensitivity of our results to different margins of change, i.e. response (3), having at least developed a coordinated plan, and response 2, ad-hoc initiatives and actions. In Survey I, 46% of the respondents have at least changed their corporate strategy and 66% have at least developed a coordinated plan. In Survey II, the corresponding rates are 31% and 51% respectively. 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 both surveys. Survey I asks these questions for a set of 10 broad families of digital technologies.[7] Survey II asks these questions for a set of 10 AI technologies.[8] For both surveys, 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 III reports adoption rates by technology across the two samples for each of the three different margins of adoption.

*** TABLE III HERE ***

In Survey I, traditional web applications and cloud-based services stand out as almost universally 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, theses 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 dependent variables. We do, however, report the results of our main estimations with these technologies included in the dependent variables, and our results hold.

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. We take advantage of this feature to use their adoption by the focal firm as an instrument for the focal firm's adoption of other technologies.

Measuring perceived stress. We capture firm perceived stress from digital technologies through specific questions. In Survey I, the question we use asks "*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*?" In Survey II, 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*?" Answers to both questions are recoded as dummy variables indicating whether the focal firm has negative expectations about the impact of digital technologies, which we use as proxy for perceived stress.[9] In both surveys, we build an alternative – more restrictive – version of this variable: in Survey I, it is based on the third quartile (50% of revenues at risk or more) instead of the median answer, while in Survey II it is based on the two higher levels of negative expectations only (i.e. either "major negative" or "very significantly negative" impact). In Survey I, 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). In Survey II, only 14% of the firms in our sample have negative expectations about AI (high stress, baseline) and 9% have major negative expectations (very high stress). We attribute these lower levels of stress in Survey II to the narrower focus of the question (limited to AI technologies v. all digital technologies in Survey I).

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). However, we control for two key sources of heterogeneity at the firm level, industry and size, proxied by revenues in Survey I and the number of employees in Survey II. We use ranges for both controls included as dummy variables in our model. In Survey I, we also observe the primary type of activity of the focal firm (B2C v. B2B, Product v. Service, Mono-product v. Portfolio) and whether the firm is publicly listed (we do not observe these variables in Survey II).

4. Results

4.1. Baseline

We perform our main analysis on the first sample (Survey I). Results with the alternative sample (Survey II), reported in Table VI, are qualitatively consistent (see below).

We start by estimating equation (1) on Survey I, 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 IV. Columns 1 and 2 introduce the main independent variables separately. Column 3 serves as the baseline with both linear effects, technology adoption and perceived stress. Column 4 includes the interaction between adoption and stress to assess whether the two interact. In columns 5 and 6 we split the sample by the stress level and report results for low and high perceived stress as another way of gauging the association between technology adoption and strategy renewal.

We first find that both technology adoption and perceived stress are positively associated with strategy change. The estimated coefficients of the standalone terms (in columns 1 and 2 respectively) correspond to a 21 percentage points higher incidence of strategy renewal among firms that have adopted at least one technology and 13 percentage points in the presence of high perceived stress (marginal effects computed at sample means). Given a baseline incidence of strategy renewal of 46% (see Table I), these marginal effects represent 44% and 28% increases from technology adoption and perceived stress respectively.

Interestingly, and speaking to the question of whether perceived stress acts as a mediator for technology adoption, magnitude and significance of the adoption coefficient remain similar once both terms are jointly introduced (in column 3). This implies that the link between technology adoption and strategy renewal is not mediated by perceived stress.

Turning to possible moderation effects, we see in column 4 that the interaction term is not significant in column 4. Further, while the technology adoption coefficient is larger in the subsample of high-stress firms (column 6) than in the low-stress subsample (column 5), this difference is not significant at conventional significance levels.[10]

These results are broadly supportive of an independent positive association of high perceived stress with strategy change. This apparent independence suggests that actual technology adoption significantly correlates with strategy renewal beyond the effect of firm anticipations or stress.

*** TABLE IV HERE ***

4.2. Robustness

In Table V, we use the more fine-grained nature of our survey responses regarding our key independent variables as well as our dependent variable. We run regressions using the different extents of technology adoption first one by one (columns 1-3) and then jointly (column 4). As expected, the point estimate increases with a higher degree of adoption and eventually mirrors column 3 in Table V (column 3). Column 4 then shows that only the highest extent of adoption (diffusion at scale) is significantly associated with strategy renewal.

Columns 4 to 6 test our full specification against 3 different versions of the (dummy) dependent variable. Column 4 is our baseline (strategy renewal). Column 5 corresponds to the lowest level of response (ad-hoc initiatives only). Column 6 uses the intermediate level of reaction (having a coordinated plan but no effective change to the long-term strategy yet). Comparing these three columns, we find that the lowest level of adoption (experimentation) only correlates positively and significantly with the lowest level of response (ad-hoc initiatives, column 5), whereas (in column 4) only the highest level of adoption (diffusion at scale) is positively and significantly associated with the highest degree of reaction (strategy renewal, our default) and in fact negatively correlates with the lowest level of reaction (ad-hoc initiatives). In column 6 where the dependent variable is exclusively having a plan, none of the adoption variables are significantly different from zero.[11] This pattern resurfaces on column 7 which uses a continuous reaction level. This indicates 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.

Finally, we consider different nuances of (negative) expectations about the impact of new technologies. Since expectations are expressed as the share of turnover potentially at risk, we built a dummy for each quartile in terms of revenues at risk and use them as reflecting different levels of perceived stress (the first quartile, representing the lowest level of stress, serves as a reference). Again, we find (in column 8) that the point estimate goes up with the extent of perceived stress.

*** TABLE V HERE ***

In Table VI, we replicate the main results from Tables IV and V using Survey II, which is more focused on the use of AI technologies. Columns 1 to 6 mirror Table IV, while columns 7 to 9 account again for different degrees of technology adoption and strategy change and column 10 considers different levels of expectations (column 11). An identical picture to Survey I emerges. This suggests that the effects at play are indeed capturing a general phenomenon rather than a specific snapshot of questions or technologies.

*** TABLE VI HERE ***

In Table VII, we explore the sensitivity of our results to different margins of perceived stress and of adoption. In columns 1 and 2, we use a more restrictive measure of perceived stress that corresponds to the fourth quartile of perceptions in our sample (instead of the median as we do by default). Columns 3 and 4 use two alternative measures of adoption. In column 3, 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). In column 4, we use a dummy that is 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 5 and 6 consider two alternative versions of our core adoption measure, including the two technologies that we had excluded given their widespread adoption (traditional Web and cloud-based services). Both are included in the diffusion variable in column 5 and only Web (the most widespread, with the highest rate of diffusion) is excluded in column 6. Note that we have also replicated all our estimates (in Tables IV and V) with these versions of the key explanatory variable and all our results hold.[12]

In addition, Table A1 in the appendix reports estimates of our main specifications using an OLS model. All robustness checks are qualitatively consistent with our baseline logit estimates.

*** TABLE VII HERE ***

4.3. Identification issues and instrumental variables regressions

In a cross-sectional setting like ours, results can hardly be interpreted in any causal way. Two features of our empirical setting need however to be emphasized. On the one hand, the relationship we are documenting here is one of a mutually reinforcing learning-by-doing process, in which technology exploration and strategy renewal processes are mutually dependent. Our theoretical foundations suggest indeed that the relationship is reciprocal. The strong positive association we find between the two is therefore consistent with our conceptual model. So our key point is that technology adoption and strategy change inform each other and are jointly formed, but the question of which causes which matters less.

On the other hand, our empirical strategy is not immune to potential omitted variable bias. 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 very 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 overnight or every other month since it is changing the long-term strategy of 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 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 unlikely to drive a correlation between technology adoption at scale and strategy renewal.

Nonetheless, we run instrumental variables regressions in which we endogenize our core measure of adoption. To this end, we make use of the widespread and more basic nature of two of the technologies considered in our survey (Web applications and cloud-based services), which we 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. Given their widespread adoption and more established character, they are less likely to be correlated with strategy renewal but might well serve as instruments for our core adoption measure.

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 in Table VIII (column 1) for the first stage and in Table IX (column 1) for the second stage. Column 2 of these tables replicate our model with the interaction term.

*** TABLES VIII AND IX 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. Note that the level of perceived stress appears to have a small positive effect on adoption as well. The second stage results are fully consistent with our non-IV estimates: technology adoption is still strongly and positively associated with strategy change but doesn't seem to interact with the level of stress.[13]

These results will not allow us to fully exclude any potential omitted variable bias, but we take them as supportive evidence of a direct, mutual, influence between technology adoption and strategy change, not moderated or mediated by stress.

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 digitalize 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?

Using data from two different surveys of executives, our empirical analysis suggests that firms by and large do both and that the two processes occur in parallel and in close connection with each other. 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 one potentially important source of motivation for a strategic renewal as predicted by the literature (Leavy 1997). Both results are robust if both key constructs (technology diffusion and perceived stress) are included. This is interesting because it suggests that both are independent channels of emerging technologies and strategy change. Further tests show that the independent associations between technology diffusion and strategy change do not interact – the association is no stronger (or weaker) for specific ranges of the other variable.

At first glance, these results highlight the strategic nature of new digital technologies. Such a tight and robust association with strategy change implies that these technologies do affect *the long-term prospects of the company and [have] a critical influence on its success or failure*" (Agarwal and Helfat 2009).

Our results however offer another, more intriguing, conclusion: Firms react differently to the emergence of new digital technologies. Some learn about them by using them at different intensities, others feel pressured by their emergence, and some do both (and some do not react at all). Importantly, both margins – experimentation and stress – go along with strategy change, so that times of technological change are likely to coincide with episodes of widespread changes in firm behaviour, although this may happen for different reasons, depending on the firm. In future research, it would be interesting to study if the performance of firms undergoing strategy renewal differs by the extent of prior experimentation and/or the degree of stress perceived by the firm.

Another interesting finding relates to the gradually strengthening association between degrees of technology experience and degree of strategy change as well as the extent of perceived stress and the degree of strategy change. We find a gradual effect: firms in which at least one new digital technology has fully diffused are most likely to also engage in wide-ranging strategy renewal, while firms that perceive significant stress from new technologies are the most likely to also engage in large-scale strategy renewal. One possible interpretation of this is that experience with new technologies reveals new strategic opportunities gradually, and more extensive experience coincides with more pronounced strategy change. If merely establishing a use case (e.g. through a pilot within the firm) or knowledge about the technology would be enough, the association between any type of technology diffusion and strategy change would be the same. Again, future research is needed to uncover the (causal) impact of different degrees of technology adoption on the propensity to change a firm's strategy.

These results have important implications for research and practice. In terms of research, our findings first bring empirical support to the view of new digital technologies such as AI, robotics and the Internet of Things (IoT) as strategic resources, i.e. resources that have the potential to affect the long-term prospects of the firm. Second, our research backs up the view that digital technology adoption 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. First, 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 technology they have not yet experimented with. One may hypothesize that experimentation is needed as much to clarify the actual possibilities of a technology as to start building the right skills and capabilities that would be needed to leverage the technology. 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. Although we replicate our study across two distinct surveys (with different sets of questions and a different technological focus), which gives us confidence in our findings, both datasets are cross-sectional and therefore subject to potential unobserved heterogeneity biases, despite our use of instrumental variables regressions. This limitation primarily prevents us from inferring causal relationships or – more importantly – from uncovering the actual timing and event dynamics within the relationships we identify. More research, ideally using longitudinal data, would help uncover these dynamic processes with more details and confidence. We hope that this paper will help inspire some efforts in this direction.

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Tables and Figures

Figure 1. Conceptual Framework

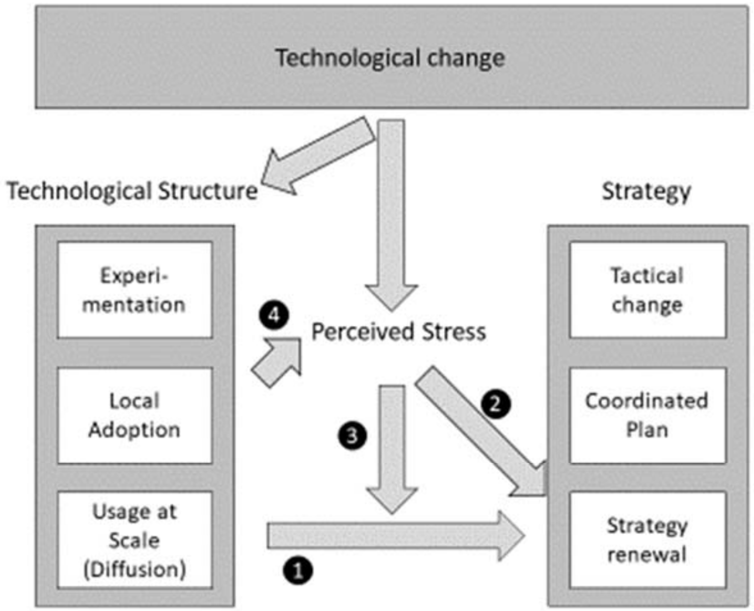

Table I. Summary statistics

	Survey I					Survey II				
Variable	**Obs**	**Mean**	**StDev**	**Min**	**Max**	**Obs**	**Mean**	**StDev**	**Min**	**Max**
Level of strategic reaction	955	3.22	1.16	1	5	2453	2.68	1.35	1	5
Strategic renewal (baseline)	955	0.46	0.50	0	1	2453	0.31	0.46	0	1
Strategic renewal (wider definition)	955	0.66	0.47	0	1	2453	0.51	0.50	0	1
At least one technology experimented with	955	1.00	0.06	0	1	3073	0.62	0.49	0	1
At least one technology experimented with (excl. Web)	955	0.98	0.12	0	1					
At least one technology experimented with (excl. Web & Cloud)	955	0.94	0.25	0	1					
At least one technology adopted locally	955	0.94	0.24	0	1	3073	0.45	0.50	0	1
At least one technology adopted locally (excl. Web)	955	0.87	0.34	0	1					
At least one technology adopted locally (excl. Web & Cloud)	955	0.72	0.45	0	1					
At least one technology diffused at scale	955	0.75	0.43	0	1	3073	0.22	0.41	0	1
At least one technology diffused at scale (excl. Web)	955	0.56	0.50	0	1					
At least one technology diffused at scale (excl. Web & Cloud)	955	0.37	0.48	0	1					
Cloud computing technologies have been diffused at scale	945	0.43	0.50	0	1					
Traditional Web technologies have been diffused at scale	948	0.66	0.48	0	1					
Expectations are negative	955	0.51	0.50	0	1	3073	0.11	0.32	0	1
Expectations are strongly negative	955	0.29	0.45	0	1	3073	0.08	0.26	0	1
Firm's business is primarily around products	955	0.65	0.48	0	1					
Firm's business is mono-product	955	0.18	0.38	0	1					
Firm's primary focus is on B2C	955	0.30	0.46	0	1					
Firm is publicly-listed	955	0.41	0.49	0	1					
Firm's revenues are larger than $1B	955	0.37	0.48	0	1					
Number of employees:										
Less than 10						3073	0.27	0.30	0	1
Between 10 and 50						3073	0.14	0.35	0	1
Between 50 and 250						3073	0.11	0.32	0	1
Between 250 and 500						3073	0.10	0.30	0	1
Between 500 and 1,000						3073	0.10	0.31	0	1
Between 1,000 and 5,000						3073	0.15	0.35	0	1
Between 5,000 and 10,000						3073	0.06	0.23	0	1
More than 10,000						3073	0.07	0.26	0	1

Table II. Correlations (Survey I)

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Level of strategic reaction	1.000														
2	Strategic renewal (baseline)	0.875*	1.000													
3	Strategic renewal (wider definition)	0.844*	0.658*	1.000												
4	At least one technology experimented with (excl. Web & Cloud)	0.130*	0.082	0.110*	1.000											
5	At least one technology adopted locally (excl. Web & Cloud)	0.167*	0.145*	0.175*	0.422*	1.000										
6	At least one technology diffused at scale (excl. Web & Cloud)	0.215*	0.202*	0.208*	0.202*	0.478*	1.000									
7	Cloud computing technologies have been diffused at scale	0.218*	0.197*	0.193*	0.164*	0.306*	0.305*	1.000								
8	Traditional Web technologies have been diffused at scale	0.232*	0.198*	0.225*	0.150*	0.314*	0.241*	0.448*	1.000							
9	Expectations are negative	0.128*	0.131*	0.121*	0.050	0.110*	0.117*	0.164*	0.049	1.000						
10	Expectations are strongly negative	0.065	0.089*	0.058	0.054	0.103*	0.095*	0.126*	0.045	0.618*	1.000					
11	Firm's business is primarily around products	0.062	0.031	0.098*	0.072	0.109*	0.043	0.007	0.047	-0.062	-0.035	1.000				
12	Firm's business is mono-product	-0.146*	-0.113*	-0.158*	-0.109*	-0.126*	-0.122*	-0.063	-0.078	-0.034	0.022	-0.161*	1.000			
13	Firm's primary focus is on B2C	0.070	0.047	0.102*	0.024	0.049	0.033	-0.053	0.007	0.013	-0.002	0.102*	-0.022	1.000		
14	Firm is publicly-listed	0.070	0.049	0.111*	0.167*	0.121*	0.052	0.014	0.124*	-0.026	-0.047	0.208*	-0.140*	0.152*	1.000	
15	Firm's revenues are larger than $1B	0.089*	0.068	0.143*	0.156*	0.092*	-0.009	0.062	0.138*	-0.105*	-0.102*	0.206*	-0.175*	0.176*	0.657*	1.000

** : correlation coefficient is significant at the 1% probability level*

Table III. Adoption rates

Technology	Not at all	Experimentation	Adoption	Diffusion
Survey I				
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%
IoT	48%	26%	16%	11%
AI (computer vision, virtual agents…)	55%	30%	11%	4%
Other AI (NLP, NLG…)	56%	27%	12%	5%
Robotics & RPA	61%	20%	14%	6%
Deep learning	64%	24%	9%	3%
AR/VR	68%	22%	7%	3%
Additive manufacturing	77%	14%	7%	2%
Survey II				
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%
Robotic Process Automation (RPA)	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 IV. Estimates of equation 1 using Survey I

	Diffusion dummy only	Expectations only	Baseline	Baseline + Interaction	Baseline - Low perceived stress	Baseline - High perceived stress
At least one technology diffused at scale (excl. Web & Cloud)	0.8282***		0.7931***	0.7544***	0.7546***	0.8451***
	(0.1429)		(0.1441)	(0.2124)	(0.2182)	(0.1994)
High perceived stress		0.5229***	0.4631***	0.4367**		
		(0.1421)	(0.1452)	(0.1813)		
Diffusion X High perceived stress (excl. Web & Cloud)				0.0712		
				(0.2872)		
Firm is product-based	-0.0978	-0.0621	-0.0844	-0.0842	-0.1589	-0.0299
	(0.1590)	(0.1567)	(0.1593)	(0.1594)	(0.2473)	(0.2237)
Firm is mono-product/service	-0.4689**	-0.5540***	-0.4599**	-0.4595**	-0.4429	-0.5109*
	(0.1892)	(0.1875)	(0.1909)	(0.1910)	(0.2834)	(0.2743)
Firm is mainly B2C	-0.0163	0.0054	-0.0399	-0.0383	-0.2064	0.0628
	(0.1679)	(0.1695)	(0.1700)	(0.1699)	(0.2561)	(0.2293)
Firm is public	-0.1294	-0.0961	-0.1618	-0.1626	-0.0387	-0.2037
	(0.1890)	(0.1885)	(0.1908)	(0.1907)	(0.2657)	(0.2866)
Firm is large (Rev>1b$)	0.2706	0.2636	0.3360*	0.3352*	0.4534	0.1304
	(0.1959)	(0.1939)	(0.1986)	(0.1985)	(0.2769)	(0.2978)
Constant	0.5139	0.6351	0.5067	0.5124	-1.0005	-0.9740
	(0.8138)	(0.8189)	(0.8132)	(0.8135)	(0.7325)	(1.2624)
Pseudo-R^2	0.07	0.05	0.08	0.08	0.08	0.07
Log likelihood	-615.03	-625.25	-609.86	-609.83	-287.68	-314.00
N	955	955	955	955	465	490
Industry dummies	Y	Y	Y	Y	Y	Y

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Table V. Exploring intensive margins using Survey I

	Experimentation dummy	Adoption dummy	Diffusion dummy	Baseline + All adoption dummies	Reaction = Tactical	Reaction = Coordinated plan	Reaction level (continuous) (OLS)	Degrees of expectations
At least one technology experimented with (excl. Web & Cloud)	0.5044*			0.1018	0.6349*	0.1328	0.2496	
	(0.2985)			(0.3274)	(0.3353)	(0.3967)	(0.1926)	
At least one technology adopted locally (excl. Web & Cloud)		0.5250***		0.1364	-0.0197	0.0990	0.0678	
		(0.1590)		(0.1945)	(0.1973)	(0.2323)	(0.1039)	
At least one technology diffused at scale (excl. Web & Cloud)			0.7931***	0.7258***	-0.7810***	-0.1257	0.3914***	0.7611***
			(0.1441)	(0.1622)	(0.1877)	(0.1940)	(0.0829)	(0.1451)
High perceived stress	0.5084***	0.4795***	0.4631***	0.4539***	-0.3029*	-0.1158	0.2294***	
	(0.1428)	(0.1436)	(0.1452)	(0.1456)	(0.1632)	(0.1770)	(0.0762)	
Perceived stress in second quartile								0.2992
								(0.2054)
Perceived stress in third quartile								0.5145***
								(0.1960)
Perceived stress in fourth quartile								0.9797***
								(0.2406)
Firm is product-based	-0.0662	-0.1014	-0.0844	-0.0940	-0.1853	0.4735**	0.0228	-0.0652
	(0.1573)	(0.1586)	(0.1593)	(0.1602)	(0.1730)	(0.2053)	(0.0815)	(0.1597)
Firm is mono-product/service	-0.5324***	-0.5106***	-0.4599**	-0.4515**	0.3971**	-0.1118	-0.2901***	-0.4510**
	(0.1887)	(0.1897)	(0.1909)	(0.1918)	(0.1896)	(0.2340)	(0.1010)	(0.1927)
Firm is mainly B2C	0.0166	-0.0129	-0.0399	-0.0386	-0.2578	0.3770*	0.0484	-0.0430
	(0.1693)	(0.1697)	(0.1700)	(0.1704)	(0.1947)	(0.1974)	(0.0890)	(0.1710)
Firm is public	-0.1222	-0.1283	-0.1618	-0.1699	0.0620	0.2066	-0.0453	-0.1605
	(0.1879)	(0.1887)	(0.1908)	(0.1906)	(0.2131)	(0.2145)	(0.0966)	(0.1925)
Firm is large (Rev>1b$)	0.2495	0.2605	0.3360*	0.3265*	-0.6913***	0.2858	0.1745*	0.3478*
	(0.1936)	(0.1936)	(0.1986)	(0.1981)	(0.2320)	(0.2180)	(0.1006)	(0.2004)
Constant	0.1420	0.4860	0.5067	0.3803	-0.5641	-2.4845***	3.2808***	0.4442
	(0.8721)	(0.7876)	(0.8132)	(0.8618)	(0.9383)	(0.6765)	(0.5639)	(0.8212)
Pseudo-R^2	0.05	0.06	0.08	0.08	0.08	0.04	0.09	0.08
Log likelihood	-623.78	-619.66	-609.86	-609.42	-522.01	-458.51	-1,435.45	-606.16
N	955	955	955	955	955	950	955	955
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Table VI. Main estimates using alternative sample (Survey II)

	Diffusion dummy only	Expectations only	Baseline	Baseline + Interaction	Baseline - Low perceived stress	Baseline - High perceived stress	Baseline + All adoption dummies	Reaction = Tactical	Reaction = Coord. plan	Degrees of expectations
At least one technology experimented with							0.2724	0.7234***	1.1629***	
							(0.1817)	(0.1492)	(0.1775)	
At least one technology adopted locally							0.5572***	-0.3452**	0.0953	
							(0.1572)	(0.1357)	(0.1383)	
At least one technology diffused at scale	1.5421***		1.5437***	1.5345***	1.5980***	1.1318***	1.1674***	-0.7158***	-0.7884***	1.4859***
	(0.1084)		(0.1085)	(0.1166)	(0.1210)	(0.2700)	(0.1276)	(0.1487)	(0.1422)	(0.1099)
High perceived stress		0.3001**	0.3171**	0.2983*			0.3378**	-0.3736**	0.3121**	
		(0.1374)	(0.1459)	(0.1756)			(0.1472)	(0.1572)	(0.1415)	
Diffusion X High perceived stress				0.0659						
				(0.3124)						
Perceived stress: small negative impact										-0.4233
										(0.2959)
Perceived stress: major negative impact										0.3777*
										(0.2229)
Perceived stress: very significant negative impact										1.0284***
										(0.2755)
Constant	-2.2742***	-1.9693***	-2.3054***	-2.3032***	-2.3444***	-1.8015***	-2.7189***	-1.8991***	-2.8411***	-2.2756***
	(0.2369)	(0.2234)	(0.2372)	(0.2375)	(0.2606)	(0.6055)	(0.2454)	(0.2109)	(0.2471)	(0.2382)
Pseudo-R^2	0.21	0.14	0.21	0.21	0.23	0.16	0.22	0.04	0.09	0.22
Log likelihood	-1,199.67	-1,303.28	-1,197.05	-1,197.03	-982.37	-194.01	-1,181.35	-1,260.56	-1,133.67	-1,188.44
N	2,453	2,453	2,453	2,453	2,112	341	2,453	2,453	2,453	2,453
Industry & Size dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Table VII. Robustness on the baseline using Survey I

	Baseline - More restrictive measure of negative expectations	All dummies - More restrictive measure of negative expectations	Baseline - Diffusion count	Baseline - Relative diffusion rate	Baseline - Including all technologies	Baseline - Excluding Web, including Cloud
At least one technology experimented with (excl. Web & Cloud)		0.1089				
		(0.3247)				
At least one technology adopted locally (excl. Web & Cloud)		0.1475				
		(0.1944)				
At least one technology diffused at scale (excl. Web & Cloud)	0.8089***	0.7363***				
	(0.1432)	(0.1618)				
At least one technology diffused at scale					1.2413***	
					(0.1794)	
At least one technology diffused at scale (excl. Web)						1.0169***
						(0.1439)
Number of technologies diffused at scale (excl. Web & Cloud)			0.2449***			
			(0.0758)			
Firm is in top 50% of adopters at scale (excl. Web & Cloud)				0.6198***		
				(0.2027)		
High perceived stress			0.4787***	0.4866***	0.5087***	0.4554***
			(0.1436)	(0.1435)	(0.1463)	(0.1470)
Perceived stress is very high (higher than the 75th percentile)	0.3044*	0.2922*				
	(0.1558)	(0.1561)				
Firm is product-based	-0.0941	-0.1052	-0.1015	-0.0860	-0.0963	-0.1025
	(0.1592)	(0.1602)	(0.1579)	(0.1581)	(0.1634)	(0.1607)
Firm is mono-product/service	-0.4827**	-0.4729**	-0.5098***	-0.5313***	-0.5803***	-0.5524***
	(0.1892)	(0.1901)	(0.1890)	(0.1875)	(0.1944)	(0.1916)
Firm is mainly B2C	-0.0267	-0.0256	-0.0186	-0.0173	0.0193	0.0202
	(0.1687)	(0.1693)	(0.1695)	(0.1700)	(0.1729)	(0.1714)
Firm is public	-0.1339	-0.1429	-0.1451	-0.1296	-0.1482	-0.0837
	(0.1890)	(0.1888)	(0.1882)	(0.1878)	(0.1939)	(0.1911)
Firm is large (Rev>1b$)	0.3004	0.2903	0.3007	0.2791	0.1916	0.2494
	(0.1965)	(0.1961)	(0.1957)	(0.1942)	(0.1997)	(0.1977)
Constant	0.5142	0.3794	0.6277	0.6682	0.5402	0.4924
	(0.8117)	(0.8588)	(0.8094)	(0.8170)	(0.8077)	(0.8094)
Pseudo-R^2	0.07	0.07	0.06	0.06	0.09	0.09
Log likelihood	-613.13	-612.62	-618.07	-620.28	-598.40	-599.29
Industry dummies	Y	Y	Y	Y	Y	Y
N	955	955	955	955	955	955

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Table VIII. Instrumental Variables Estimates (2SLS) - First stage

	Baseline	With interaction
Cloud computing technologies have been diffused at scale	0.2639***	0.1967***
	(0.0350)	(0.0433)
Traditional Web technologies have been diffused at scale	0.1380***	0.1067**
	(0.0341)	(0.0417)
Cloud technologies diffused X High perceived stress		0.0883***
		(0.0336)
Web technologies diffused X High perceived stress		0.0345
		(0.0346)
High perceived stress	0.0553*	-0.3452***
	(0.0312)	(0.1039)
Firm is product-based	0.0222	0.0223
	(0.0347)	(0.0346)
Firm is mono-product/service	-0.1435***	-0.1425***
	(0.0375)	(0.0375)
Firm is mainly B2C	0.0712**	0.0743**
	(0.0358)	(0.0356)
Firm is public	0.0801*	0.0797*
	(0.0418)	(0.0418)
Firm is large (Rev>1b$)	-0.1326***	-0.1286***
	(0.0431)	(0.0432)
Constant	0.1886	0.1917
	(0.1637)	(0.1698)
Adjusted R^2	0.13	0.14
N	955	955
Industry dummies	Y	Y

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Table IX. Instrumental Variables Estimates (2SLS) - Second stage

	Baseline	With interaction
At least one technology diffused at scale (excl. Web & Cloud)	0.5995***	0.5696***
	(0.1017)	(0.2056)
High perceived stress	0.0633*	0.0501
	(0.0364)	(0.0824)
Diffusion X High perceived stress (excl. Web & Cloud)		0.0384
		(0.2317)
Firm is product-based	-0.0307	-0.0303
	(0.0386)	(0.0386)
Firm is mono-product/service	-0.0375	-0.0389
	(0.0455)	(0.0458)
Firm is mainly B2C	-0.0294	-0.0282
	(0.0407)	(0.0411)
Firm is public	-0.0715	-0.0715
	(0.0474)	(0.0469)
Firm is large (Rev>1b$)	0.1188**	0.1180**
	(0.0496)	(0.0496)
Constant	0.5268***	0.5328***
	(0.1929)	(0.1958)
Adjusted R^2	-0.07	-0.07
Log likelihood	-698.75	-695.85
N	955	955
Industry dummies	Y	Y
Underidentification test: LM statistic (P-value)	110.45 (0.00)	34.71 (0.00)
Weak identification test: F statistic (Stock-Yogo 10% max relative bias)	65.11 (n.a.)	9.15 (7.56)
Overidentification test: Hansen J statistic (P-value)	1.41 (0.24)	4.22 (0.12)

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Table A1. OLS estimates of the main models using Survey I

	Baseline	Baseline + All tech dummies	Reaction = Tactical	Reaction = Coordinated plan	Degrees of expectations
At least one technology experimented with (excl. Web & Cloud)		0.0217	0.1274*	0.0197	
		(0.0680)	(0.0664)	(0.0549)	
At least one technology adopted locally (excl. Web & Cloud)		0.0295	-0.0098	0.0157	
		(0.0438)	(0.0417)	(0.0365)	
At least one technology diffused at scale (excl. Web & Cloud)	0.1837***	0.1691***	-0.1379***	-0.0199	0.1754***
	(0.0334)	(0.0377)	(0.0332)	(0.0310)	(0.0336)
High perceived stress	0.1043***	0.1021***	-0.0544*	-0.0173	
	(0.0332)	(0.0333)	(0.0302)	(0.0281)	
Perceived stress in second quartile					0.0635
					(0.0452)
Perceived stress in third quartile					0.1125***
					(0.0433)
Perceived stress in fourth quartile					0.2189***
					(0.0535)
Firm is product-based	-0.0192	-0.0211	-0.0356	0.0697**	-0.0151
	(0.0362)	(0.0364)	(0.0334)	(0.0294)	(0.0361)
Firm is mono-product/service	-0.0988**	-0.0967**	0.0817**	-0.0173	-0.0954**
	(0.0411)	(0.0412)	(0.0408)	(0.0323)	(0.0410)
Firm is mainly B2C	-0.0088	-0.0085	-0.0437	0.0584*	-0.0094
	(0.0392)	(0.0393)	(0.0345)	(0.0317)	(0.0392)
Firm is public	-0.0358	-0.0378	0.0121	0.0312	-0.0350
	(0.0438)	(0.0438)	(0.0389)	(0.0342)	(0.0439)
Firm is large (Rev>1b$)	0.0760*	0.0739	-0.1216***	0.0458	0.0781*
	(0.0454)	(0.0454)	(0.0404)	(0.0356)	(0.0457)
Constant	0.6127***	0.5847***	0.3587*	-0.1312*	0.5960***
	(0.1887)	(0.1960)	(0.2123)	(0.0710)	(0.1883)
Adjusted R^2	0.07	0.07	0.06	0.01	0.08
N	955	955	955	955	955
Industry dummies	Y	Y	Y	Y	Y

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Table A2. Multinomial logit estimates (Survey I)

	Coordinated plan	Strategic change
At least one technology experimented with (excl. Web & Cloud)	0.1602	0.1355
	(0.4159)	(0.3496)
At least one technology adopted locally (excl. Web & Cloud)	0.1649	0.1798
	(0.2539)	(0.2138)
At least one technology diffused at scale (excl. Web & Cloud)	0.4923**	0.9438***
	(0.2330)	(0.1937)
High perceived stress	0.2100	0.5478***
	(0.2039)	(0.1685)
Firm is product-based	0.5474**	0.1217
	(0.2277)	(0.1805)
Firm is mono-product/service	-0.3804	-0.5821***
	(0.2506)	(0.2076)
Firm is mainly B2C	0.4891**	0.1769
	(0.2312)	(0.2008)
Firm is public	0.1597	-0.0982
	(0.2482)	(0.2206)
Firm is large (Rev>1b$)	0.6731***	0.6196***
	(0.2601)	(0.2358)
Constant	-14.7899***	-0.0804
	(0.8974)	(0.8972)
Pseudo-R^2	0.09	
Log likelihood	-912.08	
N	955	
Industry dummies	Y	

*Robust standard errors in parentheses. Levels of significance: * 10%, ** 5%, *** 1%.*

Notes

[1] Chandler (1962)'s defines strategy as "*the determination of the basic long-term goals of an enterprise, and the adoption of courses of action and the allocation of resources necessary for carrying out these goals.*"

[2] Chandler (1962) defines structure as "*the design of the organization through which strategy is administered.*"

[3] 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).

[4] I.e. activities affecting "*the long-term prospects of the company and [that have] a critical influence on its success or failure*" (Agarwal and Helfat 2009).

[5] This is in contrast to "strategic renewal" as defined by Agarwal and Helfat (2009), which involves a broader set of changes to both the structure and the strategy.

[6] The three "adaptive states" of high, medium and low levels of adaptation in Chakravarty's (1982) terminology.

[7] 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), Other artificial-intelligence tools (e.g., smart workflows, natural-language processing, cognitive agents), 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 technologies, Internet of Things (i.e., devices that can communicate with each other as part of a network).

[8] The categories are: Natural language processing (NLP), Natural language generation (NLG), Speech recognition, Image recognition and video processing, Machine learning and deep learning, Virtual agents or Artificial Conversational Entities, Robotics (incl. swarm intelligence), Robotics process automation, Decision management.

[9] In Survey I, we have created a dummy 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. In survey II, responses are coded on a 7-level scale ranging from "very significant negative impact" to "very significant positive impact". Our baseline dummy variable is equal to 1 if the response is "small negative impact, not significant", "major negative impact, but not changing the fundamental ways in which the industry operates" or "very significant negative impact, fundamentally changing the ways in which the industry operates" and 0 otherwise.

[10] The p-value of the test of equality of the coefficients is 0.71.

[11] A similar, slightly more contrasted pattern emerges in our baseline estimates using Survey II (columns 7 to 9 of Table 6): experimentation is positively associated with the lowest levels of reaction (ad-hoc initiatives or having a plan only) while full adoption (diffusion at scale) is negatively associated with the lowest level of change and positively with the highest level.

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

[13] Standard diagnostic tests of our IV estimates are reported at the bottom of Table 9. They are supportive of our set of instruments since we can reject the hypotheses of under-, weak or over identification under standard assumptions. Our instruments appear however a bit weaker in the second specification (with the interaction term).

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