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A Firm-level Analysis

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Abstract

The study provides evidence with respect to some topics of inter- and intra-firm diffusion of digital technology so far neglected in research. The analysis is based on a slightly extended version of the encompassing model of Battisti et al. (2009). We use a unique dataset that provides for the entire business sector information on the diffusion of 24 digital technologies ranging from old ones up to others developed only in recent years. We use the model, firstly, to analyse the determinants of the inter- and intra-firm diffusion of the entire set of digital technologies. Secondly, we do the same for six subfields of digital technology we identified by use of a factor analysis. Thirdly, we examine the effect of in-house learning on the intra-firm diffusion of digital technology. We distinguish between "cross-learning" (learning from previous experience with such technologies in subfields other than that considered) and "cumulative learning" (effect of previous application of relatively "old" digital technologies on the intensity of usage of advanced technology in the same or a closely related subfield). Finally, we analyse the determinants of a firm's decision to digitalise a particular combination of two or more functional fields of its activity (fabrication, storage, marketing, etc.). The findings of this paper strongly support the underlying model in the case of the first and the second topic, whereas the evidence is somewhat weaker with regard to the third and the fourth element of the study. Finally, we find that complementing the "Battisti model" with variables representing firm-specific anticipated benefits is highly sensible, as these are powerful drivers of adoption and diffusion, which points to a strong forward-looking behaviour of firms in the diffusion process.

JEL O30, O31, O32, O33

Keywords Adoption and diffusion of digital technologies; Extent of digitalisation of business; Inter- and intra-firm diffusion; Rank, stock/order and epidemic effects; Effects of learning on the diffusion of IT; Digitalisation of functional fields of firm activity

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1 Introduction

Digitalisation of business activities is very high on the agenda in most companies. The same is true for governments, which, in the perspective of securing the international competitiveness of the economy, aim at improving the digital infrastructure as well as the capabilities of firms and employees necessary to manage the transition to this rapidly evolving “technological paradigm”. Nevertheless, digitalisation is not a new phenomenon, as this process is underway since the early 1960s, when firms increasingly introduced CNC machinery and, later on, flexible manufacturing systems. In recent years, however, the process of digitalisation accelerated, particularly as a consequence of the diffusion of the Internet, which triggered off many new digital applications in a short period of time. Moreover, digitalisation meanwhile has reached a high level in many companies.

In this study, we present for the entire business sector a broadly based investigation of the *determinants of the adoption of digital technologies of firms (inter-firm diffusion)* and the *extent of usage within firms (intra-firm diffusion)*. The analysis includes the diffusion of “old” digital technologies like CNC machines up to several technologies developed only in recent years (3D printing, Internet of Things, autonomously driving vehicles, etc.).

The research on the determinants of the diffusion of ICT (and new technology in general) has been dominated until the turn of the century by studies that dealt with *inter-firm diffusion*, i.e. the (first) adoption of a new technology by firms (for a review, see, e.g., Karshenas and Stoneman 1995; Sarkar 1998; Geroski 2000; Canepa and Stoneman 2004). In the last two decades, a number of papers became available, which analyse empirically the extent of usage of digital technology within companies (*intra-firm diffusion*), either in parallel to inter-firm diffusion, or focusing exclusively on intra-firm diffusion.[1] Nevertheless, as Stoneman and Battisti (2010) emphasise in their literature survey, the evidence with respect to intra-firm diffusion is still limited, primarily due to a lack of suitable longitudinal data, an assessment that is still valid.

Moreover, previous research mostly included a small number of technologies and covered only the manufacturing sector, with the exception of some studies dealing with E-commerce or (elements of) the basic ICT infrastructure. We thus assert that, to the best of our knowledge, there are no comprehensive firm-level studies analysing for the *entire business sector* the factors determining *both types of diffusion* for a *large number of digital technologies*, which include older ones (i.e. ICT introduced in the early 1960s) as well as technologies developed only in recent years.[2]

Against this background, we seek, *firstly*, to identify the factors determining the *inter*- and *intra-firm diffusion of digital technology as a whole*, i.e. the aggregate of the 24 individual technologies included in our database. These largely cover the whole field of current applications of ICT (see Table 1).[3] *Secondly*, we analyse the determinants of the *inter- and intra-firm diffusion for six subfields* of digital technologies, each field comprising technologies that, according to a factor analysis, are similar technologically and/or in terms of their scope of application (for the results

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1 To mention are: Battisti (2000); Arvanitis and Hollenstein (2001); Fuentelsaz et al. (2003); Battisti and Stoneman (2003, 2005); Astebro (2004); Hollenstein (2004); Fabiani et al. 2005; Battisti et al. (2007); Bayo-Moriones and Léra-Lopes (2007); Bocquet and Brossard (2007); Hollenstein and Woerter (2008); Battisti et al. (2009); Ben Youssef et al. (2011); Haller and Siedschlag (2011); Lucia-Palacios et al. (2014); Giotopoulos et al. (2017).

2 Previous studies investigating the diffusion of digital technologies *developed in recent years* focus exclusively on *inter-firm diffusion*; see, e.g., Loukis et al (2017) for cloud computing, or Yeh and Chen (2018) for 3D printing.

3 The analysis does not include technologies belonging to the basic ICT infrastructure of a company such as PC/notebook, servers, Internet, standard office software, databases. etc.

of the factor analysis, see Table A.2 in the appendix). In so doing, we are able to identify similarities and differences between the six subfields with respect to the determinants of diffusion and can compare the results for the individual subfields with those for the total of digital technologies. To the best of our knowledge, this paper is the first one dealing with this topic. *Thirdly*, we examine whether, and to what extent, *in-house learning* enhances the extent of usage of digital technologies. To this end, we distinguish between *"cross-learning"* (learning from the prior usage of digital technologies in subfields other than that considered) and *"cumulative learning"* (learning from the usage of older technology vintages belonging to the same or a closely related subfield). Earlier studies dealing with the impact of learning on the diffusion of ICT covered only the manufacturing sector drawing on data for the 1980s or 1990s (see, e.g., Colombo and Mosconi 1995; Arvanitis and Hollenstein 2001). *Finally*, based on information on the *use of digital technology in different functional fields of firm activity* (R&D, procurement, fabrication, marketing, storage, and administration), we analyse the determinants of a firm's decision to digitalise a *particular combination* of two or more functional fields. To our knowledge, this topic so far did not get any attention in diffusion research.[4] Overall, our detailed and comprehensive analysis of the inter- and intra-firm diffusion of digital technologies may fill several gaps and deficiencies of previous research in this field.

Theoretical framework of the empirical analysis is the "encompassing model" of Battisti et al. (2009), which extends the work of Karshenas and Stoneman (1993, 1995), Battisti (2000), and Battisti and Stoneman (2003, 2005). The model integrates the most important theoretical approaches of previous research. That is (a) the disequilibrium model of diffusion emphasising *"epidemic effects"* (Mansfield 1968), which dominated the empirical research until the 1980s, and (b) three types of equilibrium models, which stress *"rank effects"* (see, e.g., Davies 1979), *"stock effects"* (see, e.g., Reinganum 1981) and *"order effects"* (see, e.g., Fudenberg and Tirole 1985). Furthermore, we slightly extend the model of Battisti et al. (2009), presuming that the four categories of effects cannot fully capture the firm- and technology-specific costs and benefits of applying digital technologies. Therefore, we additionally draw on detailed information regarding firm-specific *barriers to adoption* (adoption costs) and *objectives pursued by using digital technologies* (interpreted as anticipated benefits of diffusion). In so doing, we take account of the diversity of costs and the forward-looking character of the investments necessary to adopting digital technologies or to intensify their usage. A few empirical studies successfully applied this extended model in the case of E-commerce (Hollenstein and Woerter 2008) or energy-saving technologies (Arvanitis and Ley 2013; Stucki and Woerter 2016).

The present paper uses a *unique firm-level dataset* containing information from 1390 companies of the entire Swiss business sector. The firms responded to a comprehensive survey conducted in the autumn 2016 by the KOF Swiss Economic Institute (ETH Zurich) in co-operation with the Chair of Work and Organizational Psychology (ETH Zurich) and the School of Applied Psychology (University of Applied Sciences, Northwestern Switzerland). The survey is based on a random sample of firms, stratified by industry and firm size classes, which is drawn from the official enterprise census. The response rate of 35% is satisfactory in view of the highly demanding questionnaire. The available data allow a rich specification of the dependent variables and the explanatory part of the empirical model, which captures the main elements of the theoretical framework (epidemic, rank, stock, order effects as well as barriers to and objectives

[4] Arvanitis and Hollenstein (2001) analysed the use of "advanced manufacturing technologies" for some functional fields of firm activity separately (fabrication, planning, etc.), whereas we aim at explaining the choice of a *particular combination* of function fields where digital technology is applied (two to six *mutually exclusive* combinations).

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of adoption). The survey allows to constructing a cross-section dataset for 2016, with some variables lagged by three years. The cross-section nature of the data is a problem we have to consider in formulating the theoretical and empirical model as well as with regard to the interpretation of the results. However, we share this shortcoming with most studies in this field (see the survey of Stoneman and Battisti 2010).

The *empirical results* with respect to the inter- and intra-firm diffusion of *digital technologies as a whole* as well as those with regard to most *subfields of ICT-based technologies* are largely in line with the theoretical and empirical model, including our extension of Battisti et al. (2009). Rank and epidemic effects are somewhat stronger in the case of intra-firm diffusion in comparison to inter-firm diffusion, which might reflect the higher complexity of the first type of diffusion. The differences between the six subfields of digital technology, as expected, are larger for inter- than for intra-firm diffusion, probably as an increase of the intensity of usage (intra-firm diffusion) is challenging quite irrespective of the subfield considered. The effect of *in-house learning* on diffusion in a particular subfield due to the prior usage of digital technologies in other subfields ("cross-learning") and/or experience with older technology vintages in the same or a closely related subfield ("cumulative learning") is *statistically* highly significant. However, the impact on diffusion is rather small, which primarily is due to the relatively weak influence of "cross-learning". "Epidemic effects", which largely reflect *learning from other firms of the same industry* (including information spillovers), may be even more relevant than "in-house learning". Finally, based on information on the use of digital technologies in several *functional fields of firm activity* (R&D, procurement, fabrication, etc.), we identify *six combinations of fields* for which estimates are feasible. The model explains quite well the use of digital technology in the case of the most far-reaching combination of functional fields (digitalisation in all six fields). In contrast, the explanatory power of the model is weak for the least complex combination (three fields), and it is somewhere in between for companies having digitalised an intermediate number of fields (two different combinations of four and one with five fields). However, as the model also performs quite well for this category of combinations, we conclude that the evidence, at least partly, is in line with the empirical model.

The paper is organised as follows: The next section provides information on the dataset and the diffusion of the 24 digital technologies included in this study in the years 2013 and 2016. In Section 3, we present the theoretical framework of the analysis, the specification of the empirical model, and the hypotheses to be tested. In Section 4, we show the estimation results with respect to (a) the factors determining the inter- and intra-firm diffusion of digital technologies as a whole and for six subfields of such technologies, (b) the influence on diffusion exerted by the two types of in-house learning, and (c) the determinants of the decision to apply digital technologies in a particular combination of functional fields of firm activity. In Section 5, we summarise and point to some limitations of the analysis.

2 Data

2.1 Sample

The data we use in this study stem from a special survey conducted in the Swiss business sector in the autumn 2016 by the KOF Swiss Economic Institute (ETH Zurich) in co-operation with the Chair of Work and Organizational Psychology (ETH Zurich) and the School of Applied Psychology (University of Applied Sciences, Northwestern Switzerland). The survey dealt with the use of digital technologies and its effects on sales, value added, employment, etc. The survey is based on a random sample of firms (20 or more employees) drawn from the official enterprise census. The sample is stratified by twenty-nine industries and three industry-specific firm size classes (with full coverage of large companies). The survey provides data for 1400 firms implying a response rate of 35%, which is satisfactory given the highly demanding questionnaire. The final sample used for model estimation contains 1390 of the 1400 respondents.

The survey yields firm-level information on the diffusion of 24 digital technologies ("adopted in the first half of 2013 or before", "adopted in the period of mid-2013 to mid-2016", and "not (yet) adopted in mid-2016").[5] In addition, the dataset contains information on the use of digital technologies in six functional fields of firm activity (R&D, procurement, fabrication, marketing, storage, and administration) as well as on barriers to and objectives of the adoption of such technologies. Furthermore, we have data on the share of employees with different degrees of education and digital qualifications. Besides, the survey provides information on some structural characteristics of a company (size, age, export orientation, industry affiliation, etc.), several dimensions of a firm's innovative activities (R&D expenditures, sales share of innovative products, innovation-based cost reductions), sales and value added, investment expenditures, and, finally, on some characteristics of a firm's product market (market structure, intensity of price and non-price competition).

A unit non-response analysis did not show any signs of a serious selectivity bias with respect to the basic sample. Moreover, we corrected for item non-response by imputing missing values ("multiple imputation"; see Rubin 1987) to avoid a loss of observations that could have introduced a bias to the estimates. Table A.1 in the appendix shows the composition of the final dataset by 5 sectors and 29 industries, which is largely representative for the basic sample of firms that received the questionnaire.

Based on the survey results two reports have been published. First, Arvanitis et al., (2017) provides descriptive statistical information about the use of digital technologies, the relationship between digitalisation and employment, and obstacles for digitalization. Second, Bienefeld et al. (2018) presents the results concerning the achievement of goals in the use of digital technologies, required professional competences and work organisation factors relevant for digitalisation. In the present paper, we use the data specifically to estimate differentiated models of inter- and intra-firm diffusion of digital technologies. Because of the cross-section nature of the data (although some variables can be lagged), we have to simplify the theoretical and the empirical model (see Section 3). Consequently, we have to be aware of the fact that a cross-section analysis does not allow to establish causal links.

2.2 Pattern of the diffusion of digital technologies

Table 1 shows the number and percentage share of users of 24 digital technologies in the Swiss economy in 2013 and 2016. For example, 38.5% of the 1390 companies included in the final sample used CAD (computer-aided design) in 2013, that is, they adopted this technology in that year or earlier. The proportion of users of CAD increased to 48.5% until 2016. The share of adopters is lower for the majority of the other digital technologies. This holds true particularly for some highly advanced technologies that still are in an early stage of development (e.g. Internet of Things, autonomously driving vehicles, etc.).

The same table also shows the diffusion pattern for *six subfields* of digital technologies (*FABRIC*, *PROCESS*, *CONTROL*, *EXTERNAL*, *IOT*, and *ADVANCED*). The definition of these subfields is based on a *principal component factor analysis* of the diffusion of the 24 individual technologies. This method allows to synthesising the information contained in the measures of diffusion of the individual technologies into a small number of variables (FACTORS). The factors are uncorrelated

5 In the following, we refer to the reference periods by using simply the labels 2013 and 2016.

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standardised variables that capture the common information of the 24 original variables. The choice of the number of factors is, on the one hand side, a matter of statistical significance (eigenvalues of the individual variables of at least one; high share of the original variance accounted for by the sum of the chosen number of factors; high values of the variables in the rotated factor pattern matrix). On the other hand, the number of factors should also be "reasonable" in terms of the problem at hand (see Brachinger and Ost 1996). In this sense, the six subfields should contain technologies, which, from an economic and/or technological point of view, may be interpreted as elements of a "common field of application".

In the present case, the factor analysis yields a solution with six factors, whose statistical properties are satisfactory (see Table A.2 in the appendix). According to the "rotated factor pattern matrix" shown in that table, the factor F1 (FABRIC: *fabrication-oriented technologies*) emphasises CAD (computer-aided design), CAM (computer-aided manufacturing), CNC/DNC (computerised numerical control machines) and robots, which, in the first place, are technologies reflecting basic elements of the "shop-floor" of production. Factor F2 (PROCESS: *process-oriented technologies*) refers primarily to digital technologies that capture different aspects of the firm-internal organisation of the production process (ERP, CRM, SCM, business analytics, social media for internal use, telework). Factor F3 (CONTROL: *control and support-oriented technologies*) reflects several digital control technologies, i.e. PLC (programmable logic controllers), computerised automated control systems and CSS (internal and external co-operation support systems). Factor F4 (EXTERNAL: *outward-oriented technologies*) captures digital technologies related to a firm's external exchanges and relationships (E-selling, E-purchasing, social media for external use, cloud computing services). Factor F5 (IOT: Internet of Things) covers two elements of this only recently developed field of technology, which differ with regard to their complexity. Finally, factor F6 (ADVANCED) contains four types of advanced digital technologies, which are in an early stage of development and started to be adopted only in recent years (3D printing, autonomously driving vehicles, RFID (radio frequency identification), and rapid prototyping/simulation). Although these elements are quite different in character, ADVANCED has, on the whole, a special focus on the fabrication sphere. Altogether, the factors F1 to F6 reflect quite convincingly specific subfields of digital technologies, which are satisfactory not only statistically but are also sensible in economic and/or technological terms.

In the following, we characterise, based on Table 1, the *pattern of inter-firm diffusion* of digital technologies (percentage share of adopters). In so doing, we focus on the adoption at the level of the six subfields of digital technologies, i.e. from FABRIC up to ADVANCED. In addition, we provide information for an aggregated category, i.e. MODERN, which is the sum of the categories IOT and ADVANCED. The aggregated field MODERN will be used in some of the econometric analyses because of a too low number of observations in the case of IOT.

Firstly, we comment on the *level of diffusion* reached in 2016. We find that PROCESS and EXTERNAL are the two fields of digital technologies that show by far the highest degree of adoption. With a share of about 80%,[6] the inter-firm diffusion in these two fields of application is probably near to the saturation level that always is lower than 100% (Karshenas and Stoneman 1992). Another two fields show an intermediate level of adoption (FABRIC, CONTROL). Finally, the inter-firm diffusion of IOT and ADVANCED was still very low in 2016, which is not surprising given the early stage of development of the corresponding technologies in that year. Aggregating the two fields into MODERN does not much change this assessment. Moreover, we observe that in

[6] One should keep in mind that this figure means that 80% of the firms have adopted *at least one element* of PROCESS (out of six elements) and EXTERNAL (out of four elements) respectively. The criterion for being an adopter (*inter-firm diffusion*) at the level of the subfields of digital technology is thus not very strong.

the case of two subfields, one single technology stands out by far in terms of adoption, i.e. CAD in the subfield FABRIC, and ERP in the case of PROCESS. To a lesser extent, the same is true for E-purchasing in the category EXTERNAL. In contrast, we do not find any individual technology that dominates within the remaining three subfields of digital technologies.

Secondly, we deal with the *change of the inter-firm diffusion* between 2013 and 2016. We concentrate on the *percentage change of the share of adopters* rather than on the difference of the share of adopters in percentage points between the two years. Not surprisingly, we notice that the *categories of digital technologies* with a very low share of adopters in the "starting year" 2013 (IOT, ADVANCED, MODERN) show the highest percentage increase over the three years (more than a doubling). The gain was also strong in the case of EXTERNAL (almost 80%), although the inter-firm diffusion rate in 2013 already was quite substantial. In contrast, we notice only a small percentage change of the share of adopters in the case of PROCESS (24%), which, however, is not surprising given the very high share in the year 2013 (66%). We find a similar percentage change for FABRIC (27%), although the starting level was much lower than for PROCESS. Finally, the inter-firm diffusion of CONTROL increased moderately (45%), departing from a relatively low level in the year 2013.

With respect to the change of inter-firm diffusion of the *individual digital technologies*, we again observe that technologies used by a low proportion of firms in the starting year (2013) show an increase of adopters that is clearly higher than that of the whole technology subfield to which they belong. Examples are robots, business analytics, social media, support systems for co-operation, cloud computing services, and 3D printing.

Table 1 *(about here)*

3 Model and hypotheses

3.1 Theoretical background

The conceptual framework adopted in this paper is largely taken from Battisti et al. (2009), which is an extension of the early work of Karshenas and Stoneman (1993, 1995), Battisti (2000), and Battisti and Stoneman (2003, 2005). The model proposed in these papers integrates the inter- and intra-firm diffusion into an encompassing framework that takes account of different theoretical approaches of demand side modelling of technology adoption. Three of them are equilibrium models (rank, stock and order models), and the fourth one is a disequilibrium approach (the epidemic model) that dominated diffusion research until the 1980s.

The model of Battisti et al. (2009) states that a firm i in industry j will adopt a technology for the first time or increase its use within the firm when the marginal profit gain in time t is larger than the adoption costs C_i. The model hypothesises that the profits depend on four groups of variables that reflect the different approaches of explaining technology diffusion mentioned in the previous paragraph. As our dataset refers to a single cross-section, we drop in the following the time subscript t.

The adoption and the extent of intra-firm diffusion x_i of firm i is determined by four categories of variables that capture rank effects, stock effects, order effects and epidemic effects.

1. A set of characteristics of firm i and its industry-specific environment j, which reflect heterogeneities across firms and industries leading to different potentials of gains due to technology adoption (*firm- and industry-specific rank effects* R_i and R_j; see, e.g., Davies 1979). These effects are either positive or negative.

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2. Two variables representing the strategic behaviour of competitors with respect to technology adoption. In this perspective, the extent of technology usage at industry level captures between-firm *stock* and *order* effects SO*j*, i.e. pecuniary *market-intermediated externalities*. Stock effects rest on the hypothesis that the profits from adoption of firm *i* decreases as the number of rival firms also adopting the technology increases (see, e.g., Reinganum 1981). Order effects reflect the assumption of first mover advantages in the use of a new technology, for example, because, in an early phase of the diffusion process, the first adopter may benefit from an easier access to knowledge and qualified personnel necessary for applying the new technology. Therefore, early adopters earn higher profits from using a new technology than latecomers. The latter become adopters only when the price of the technology decreases (see, e.g., Fudenberg and Tirole 1985). In general, stock and order effects SO*j* should negatively affect adoption. However, we cannot exclude an insignificant (or even a positive) sign, as non-market intermediated externalities (see the next paragraph) may (more than) compensate for the stock and order effects SO*j*.

3. We further take account of the fact that firms learn from other firms that use the new technologies, primarily from companies belonging to the same industry. These "*epidemic effects*" (E*j*), which reflect the spread of information, learning and risk-reduction (*non-market intermediated externalities*), were postulated as the main drivers of technology adoption in the early years of diffusion research (see, e.g., Mansfield (1963, 1968). In addition to E*j*, in-house learning (E_i), based on previous experience with digital technologies, may also positively affect the diffusion of such technologies.

4. Finally, the *costs of the technology* (C*i*) should negatively affect diffusion. C*i* consists of the price of the technology in the narrow sense, which is largely the same for all firms, and, more importantly, firm- and technology-specific installation, adjustment and switching costs. In a firm-level analysis, only the second component of technology costs is relevant. Obviously, this cost component is a *multidimensional factor*, with the significance of the single dimensions varying among firms.[7]

In addition, we presume that a model based on rank, stock/order and epidemic effects is too general to capture the (future) benefits accruing from the application of digital technologies. Therefore, we slightly extend the model of Battisti et al. (2009) by taking account of several variables reflecting *firm-specific anticipated benefits from adoption* (B*i*).[8] The use of B*i* as an additional set of variables was successfully applied in earlier research (see, e.g., Arvanitis and Hollenstein 2001; Hollenstein 2004; Hollenstein and Woerter 2008).[9]

We summarise the theoretical model as follows:

$$\mathrm{x}i = \mathrm{f}\,(\mathrm{R}i,\ \mathrm{R}j,\ \mathrm{SO}j,\ \mathrm{E}i,\ \mathrm{E}j,\ \mathrm{C}i,\ \mathrm{B}i) \qquad (1)$$

As already mentioned, our dataset is a single cross section. Under these circumstances, it is not feasible to identify the effect of a firm's own experience with digital technology (E_i) on its diffusion. Therefore, we *drop Ei in the basic model*. However, we include E_i again in the *special subsection*

7 See, e.g., Cainarca et al. (1990) for a review of some dimensions of adoption costs.

8 See, e.g., Milgrom and Roberts (1990) or Brynjolfsson and Hitt (2000) for a discussion of a set of potential benefits of adopting ICT.

9 Stornelli et al. (2021) provide a very detailed study of the role of barriers and enablers (benefits) of the adoption of advanced manufacturing technology *at various stages of adoption*. However, the number of barriers and enablers considered is much too large and so differentiated that it is impossible to include them in a formal model.

4.2, which is devoted to *the effect of in-house learning on diffusion* due to the prior *usage* of digital technologies.[10]

Furthermore, in a cross-section setting it is not feasible to separate the stock/order effects from the epidemic type of learning. Therefore, we include the usage of digital technology at *industry level* as a proxy variable reflecting the *combined effect of* E*j and* SO*j*. To capture this "combined variable", we follow Battisti et al. (2007, 2009), which, to this end, use two variables reflecting (a) the *breadth* and (b) the *depth* of usage of digital technologies *at the industry level*. The first element is represented by *the proportion of firms* in industry *j* having *adopted at least one* technology of the corresponding category of digital technologies (variable Inter*j*), the second one by the *mean number of digital technologies* used by the firms of industry *j* in the corresponding field of technology (variable Intra*j*).

We thus arrive at the following equation which is *the basic model* used for the empirical analyses.

$$x_i = f(R_i, R_j, Inter_j, Intra_j, C_i, B_i) \qquad (2)$$

In the following, we specify several empirical models we apply to analyse the inter- and intra-firm diffusion of digital technologies. The models differ only with respect to the dependent variables (digital technologies as a whole; different subfields of digital technology; combinations of functional fields of activity where digital technology is used), In contrast, the explanatory variables throughout remain the same. Only in this way, we are able to assess whether the factors determining the two types of diffusion are the same, or whether they differ. Moreover, this approach allows to identifying similarities and divergences of the explanatory pattern between different subfields of digital technologies.

3.2 Specification of the empirical model

3.2.1 Dependent variables

We estimate several models for inter- and intra-firm diffusion. The second type of diffusion is at the core of this study as most companies already used at least one digital technology in 2016. More precisely, 94% of the firms applied in that year at least one of the 24 digital technologies included in this analysis (see Table 1, subsection 2.2).

Inter-firm diffusion

As shown in the *upper part of Table 2* (heading A), the *inter-firm diffusion as a whole* is represented by a *binary variable* with value 1 in the case a firm adopted in 2016 at least one of the 24 digital technologies and value 0 otherwise (variable TOTAL_1). Similarly, we use six binary variables to capture *inter-firm diffusion in the subfields of digital technology* (FABRIC_1, PROCESS_1, CONTROL_1, EXTERNAL_1, IOT_1, and ADVANCED_1). We also present results for the dependent variable MODERN_1, which reflects the use of at least one technology in the subfields IOT *or* ADVANCED (see the upper part of Table 2, heading B).

Intra-firm diffusion

Intra-firm diffusion refers to the *extent of usage* of digital technologies within a firm. In a first step, we include five alternative measures of *intra-firm diffusion as a whole*, as shown in the lower part of Table 2, heading A. By using alternative measures, we seek to check the robustness of the model estimates. One of the variables is a quantitative measure (FACTOR_sum), the other ones are

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[10] We measure the "prior usage" of digital technologies by inserting appropriate variables *lagged by three years*. Unfortunatly, our database does not allow a specification based on time-series data.

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measured on an ordinal scale with four (TECH_intensity, FACTOR_quartiles) or six measurement levels (TECH_fields, FIRM_functions).

Besides, we estimate models for the *intra-firm diffusion of digital technologies in the six subfields* defined in the lower part of Table 2 (heading B). For each field, we specify an *ordinal variable* based on the number of digital technologies included in that particular field. For example, in the case of FABRIC, we distinguish three measurement levels (number of technologies: 3 to 4; 1 to 2; with 0 as reference level). In the same way, we measure the intra-firm diffusion for the other five subfields. For the majority of them, a three-level scale is most appropriate; exceptions are PROCESS and IOT with 4 and 2 levels respectively.[11]

Finally, we capture intra-firm diffusion by using *mutually exclusive nominal variables*, which represent *different combinations of functional fields of activity where a firm applies digital technologies* (COMBINATION OF FUNCTIONAL FIELDS), as shown in the lowest part of Table 2 (heading C). The survey provided information on the digitalisation in up to six *functional* fields of firm activity: R&D, procurement, fabrication, marketing, storage, and administration. For the firms using digital technologies in at least two fields, we identified 25 different combinations. To ensure reliable model estimates, we only used *combinations* chosen by *at least 25 companies*. As a result, we got *six nominal variables*, each capturing a specific combination of digitalised functional fields of firm activity. Four combinations differ by the number of fields (two, three, five, and six fields respectively) and another two combine different combinations of four fields. In model estimation, the combination of two fields (marketing and administration) serves as reference category.[12]

Table 2 (*about here)*

3.2.2 Independent variables

Table 3 shows the specification of the explanatory variables included in the basic model. According to equation (2) we derived in subsection 3.1, the independent variables represent firm-specific and industry-specific *rank effects* R*i* and R*j*, the combination of industry-specific *epidemic and stock/order effects* (Inter*j,* Intra*j*), firm-specific *costs of adoption* C*i*, and *anticipated benefits of using digital technologies* B*i*. We formulate sign expectations based primarily on our assessment of the results of the available empirical research.

Firm-specific rank effects* R*i

Firm size: We insert this variable (SIZE; log of the number of employees) to capture several factors we are not able to include *explicitly* as explanatory variables due to missing data. To mention are, for example, divergences with regard to the availability of resources for further education of employees, the capacity to absorb risks, the potential for economies of scale and scope, management capabilities, etc. In the case of inter-firm diffusion, the available studies mostly obtain a positive effect of firm size (see the surveys of Karshenas and Stoneman 1995; Geroski 2000; Stoneman and Battisti 2010). The results are more controversial in the case of intra-firm diffusion. Some researchers find that small firms are more intensive users of ICT than large ones (see, e.g., Hollenstein 2004; Bajo-Moriones and Lera-Lopez 2017). Others identify a positive size effect (see, e.g., Fuentelsaz et al. 2003; Ben Youssef et al. 2011; Arvanitis and Ley 2013), while several papers get mixed or insignificant results for this variable (see, e.g., Battisti and Stoneman 2005,

11 We defined the ordinal scales in a way that makes sure that the number of observations is similar for all measurement levels.

12 There are other combinations of only two fields of firm activity. We choose the one with the largest number of observations, i.e. “marketing and administration”.

Hollenstein and Woerter 2008; Haller and Siedschlag 2011). We thus expect a positive sign in the case of inter-firm diffusion, whereas, with respect to intra-firm diffusion, we do not have a priori a specific sign expectation.

Firm age: The impact of firm age (AGE; log of the number of years elapsed since the establishment of the firm) is not clear from the outset. One could argue that older firms are more experienced in taking up new technologies (Nooteboom 1993; Giunta and Trivieri 2007). In contrast, younger companies may be more flexible and/or use digital technologies from the very beginning of their business activity. Besides, the costs of switching to new technologies might be higher in older firms because of sunk costs and the stickiness of established work practices (Ichniowski et al. 1995). It is thus not surprising that previous research yields mixed results, in particular with respect to intra-firm diffusion. Ben Youssef et al. (2011) find a positive effect, whereas other researchers identify a negative sign or get insignificant results (see, e.g., Dunne 1994; Arvanitis and Hollenstein 2001; Battisti and Stoneman 2005; Haller and Siedschlag 2011). In view of these mixed findings we do not postulate a specific sign expectation.

Foreign ownership: Foreign-owned firms (dummy variable FOREIGN), in general, are more innovative than domestic companies, as they have to compensate for the fact that they are less familiar with the local conditions of doing business (institutional framework, long-standing market presence of domestic firms, etc.). Moreover, the domestic affiliates may profit from knowledge inflows from their foreign parent company. We thus expect a positive effect of foreign ownership on the usage of digital technology, although some (of the few) studies using this variable do not get significant results or even find a negative effect on diffusion (see, e.g., Haller and Siedschlag 2011).

Member of a company group: More or less in line with the comments made on foreign ownership, we argue that a firm belonging to a company group (dummy variable GROUP) may profit from knowledge inputs of other affiliates of the group or the parent firm that often is particularly active in developing new technologies. We thus expect a positive sign, what is quite in accordance with some previous evidence (see, e.g., Cainarca et al. 1990; Battisti and Stoneman 2005; Bajo-Moriones and Lera-Lopez 2017).

R&D input: For this variable (dummy variable RD), which is often included in diffusion models, we expect a positive effect on diffusion, particularly as R&D activities strengthen a firm's absorptive capacity for new technologies (Cohen and Levinthal 1989).

Innovative activity: Similarly, we argue that other innovation-related activities favour diffusion. Such a positive effect is in accordance with previous evidence (see, e.g., Hollenstein 2004; Battisti et al. 2007; Hollenstein and Woerter 2008). We insert in our empirical model a product-oriented innovation variable (INNO_SALES; log of the sales share of innovative products) as well as a measure related to process innovations (dummy variable INNO_COSTRED; cost reduction due to process innovations).

Human capital: As in the case of R&D and innovativeness, we expect that firms with a large share of highly qualified personnel have a higher propensity to adopt and increase the extent of usage of digital technology. We use an ICT-related human capital variable (ICT_UNIV; proportion of university-level ICT-employees) rather than a general measure of human capital intensity. In view of the complexity of some of the digital technologies included, an ICT-specific measure of human capital may be more adequate.[13]

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[13] Nevertheless, estimations based on a general human capital variable provide similar results, but the effect on diffusion is somewhat weaker.

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Export orientation: We expect that export-oriented companies (dummy variable EXPORT) tend to use digital technologies more often and to a higher extent than the average firm, as they need to be near to the technological frontier, in order to succeed on the highly competitive international markets. This holds true in general, but also with respect to digitalisation. Previous research, however, yielded mixed results. Whereas some studies find the expected positive sign (see, e.g., Hollenstein 2004; Haller and Siedschlag 2011), other ones do not get a significant effect of this variable (see, e.g., Battisti and Stoneman 2005; Stucki and Woerter 2016). Nevertheless, we stick to expecting a positive impact of exports on adoption and the extent of diffusion.

Industry-specific rank effects Rj

Market structure: Market structure (concentration) is often used as a variable capturing the competitive pressure to which a firm is exposed. As Reinganum (1981) shows, most game theoretic models do not arrive at unambiguous results. Hence, whether a "high market concentration", as postulated in the tradition of Schumpeter, exerts a positive effect on technology diffusion that is stronger than the "free competition effect" is an empirical question. It is thus not surprising that the review of Stoneman and Battisti (2010) does not report conclusive results of the empirical work in this matter. We thus do not predict a specific sign of our measure of concentration (dummy variable CONC_10 with value 1 for firms being active on markets with *less* than ten principal competitors).

Competitive pressure: Market concentration usually refers to domestic markets, which is no longer sensible in a global economy, particularly in the case of a small economy like Switzerland. Therefore, we insert two variables to capture *directly* the competitive pressure on *a firm's relevant markets worldwide* as assessed by the companies themselves. The two measures reflect the intensity of price competition (IPC) and non-price competition (INPC). In view of the theoretical and empirical results with respect to market concentration mentioned above, we do not expect a particular sign of the two variables. The few empirical studies having used this special type of variables obtain some evidence for a positive effect on diffusion but the results were not very robust (see, e.g., Arvanitis and Hollenstein 2001; Arvanitis and Ley 2013).

Sector affiliation: Finally, we include five sector dummies (knowledge-intensive services, other services, construction sector, low-tech industry, and, as a reference group, high-tech industry) to control for structural differences with regard to the potential to benefit from the usage of digital technologies. In addition, these dummies serve to reduce an omitted variable bias.[14]

Overall, previous research with respect to the role of *industry-specific rank effects* in the diffusion process yielded mixed results. Therefore, it would not be a surprise if we could not find a robust pattern of explanation of the impact of this category of variables on the inter- and the intra-firm diffusion of digital technologies.

***Epidemic and stock/order effects* (E*j*, SO*j*)**

As shown in subsection 3.1, we are not able to separate epidemic and stock/order effects, because of the cross-section nature of the analysis. Therefore, following Battisti et al. (2009), we include the two *industry-level variables* INTER*j* (*proportion* of adopters of digital technologies in a firm's industry) and INTRA*j* (*average number* of digital technologies used by the *adopters* in a firm's industry). The two measures capture the *breadth and the depth of the usage of digital technologies* at industry level and stand for the combined effect of E_j (positive sign) and S_j (negative sign). The *net epidemic effect* is positive, if the epidemic effects dominate the stock/order effects, and negative if the latter are larger than the former. If the net effect is insignificant, the two (countervailing) effects are equal or have no impact on diffusion at all.

[14] The use of sector dummies is superior to including two-digit industry dummies.

In the case of the estimates for the *six subfields* of digital technology, the variables INTER*j* and INTRA*j* reflect the share and the *extent of usage at the industry level in each subfield* (variables INTER_FABRIC up to INTER_MODERN as well as INTRA_FABRIC up to INTRA_MODERN). In presenting the model estimates, for sake of simplicity, we use throughout the labels INTER and INTRA (i.e., we leave out the postfixes), although, as mentioned above, the *precise labels* of the variables measuring the net epidemic effects differ between the various subfields of digital technology (see Table 3). This simplification should not lead to misunderstandings.

The variables INTER_j and INTRA_j are lagged by three years (they are thus measured for 2013), as we assume that learning from other firms and integrating the new knowledge into a firm's knowledge base takes some time.[15]

***Costs of adoption* (C*i*)**

Our survey provides firm-level information on the relevance of eleven *barriers to the adoption* of digital technologies as assessed by the firms themselves. The relevance throughout is measured on a five-point scale. A factor analysis of these variables yields *four factors*, which stand for firm-specific categories of adoption costs (see Table A.3 in the appendix). The variable COMPLEXITY indicates organisational and technological complexities of digital technologies, which may impede adoption. The factor RESOURCES reflects a firm's deficiencies with respect to financial, technological and knowledge resources. UNCERTAINTY points to the fact that the potential for using digital technologies is not sufficiently clear and signals doubts on whether new and existing technologies are compatible. Finally, there may be concerns with respect to the security of digital technologies, to some extent also reflecting a (too) high degree of decentralization of decision-making processes (SECURITY). We basically expect that these cost variables have a negative effect on the inter- and intra-firm diffusion of digital technologies. However, as such barriers may be more binding at high than at low levels of diffusion, we should not be surprised if we get a positive sign for (some of) the four variables (see, e.g., Baldwin and Lin 2002).

Anticipated benefits of adoption (B*i*)

The survey yields firm-level information on the relevance of twelve *objectives* a firm may pursue by adopting digital technologies. We assume that these objectives, as assessed by the firms themselves, guide decision-making with respect to the investments necessary to adopt digital technology or to increase the level of its usage. We thus interpret these variables as measures of *anticipated benefits of the inter- and intra-firm diffusion* of digital technologies. In order to condense the information on the relevance of the twelve types of objectives, throughout measured on a five-point scale, we perform a factor analysis. This procedure yields *three factors*, which stand for firm-specific categories of anticipated benefits of adoption (see Table A.4 in the appendix). The variable EFFICIENCY indicates that a firm, by using digital technologies, expects to be able to increase internal flexibility and efficiency, to improve the integration of firm-internal processes and to reduce labour costs. MARKET captures several dimensions of expected improvements of a firm's market position, particularly, enhanced knowledge of markets and clients, increased market flexibility, a better integration into value chains and a market-oriented adaptation of the business model. Finally, LABOUR stands for the firm's view that adopting digital technology is a useful instrument to attract top quality employees and to create motivating jobs. Obviously, we expect a positive sign for the three variables.

Table 3 *(about here)*

[15] 2013 is the only year for which the survey provides information on the previous use of digital technologies.

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3.3 Hypotheses

3.3.1 Digital technologies as a whole

Firstly, we ask whether our empirical model is able to explain the *inter-firm as well as the intra-firm diffusion of digital technologies as a whole*, i.e., the aggregate of the 24 individual technologies included in this paper (see subsection 2.2, Table 1).

We postulate:

H1a: The empirical model, which primarily builds on the theoretical framework presented in its most recent form by Battisti et al. (2009), is well suited to explain *the inter-firm as well as the intra-firm diffusion of digital technologies as a whole*.

H1b: Even if hypothesis H1a is confirmed, we expect that the relevance of the different *categories of explanatory variables* (firm-specific and industry-specific rank effects; epidemic effects (net of stock/order effects); barriers to and anticipated benefits from adoption) *differs to some extent for the two types of diffusion*. We posit that the estimates are more strictly in line with the basic model in the case of intra-firm diffusion, as this type diffusion is more demanding than the adoption of only one single element of digital technology (inter-firm diffusion).

To ensure a reliable test of the two hypotheses we use for both types of diffusion the same set of explanatory variables.

3.3.2 Fields of digital technology

There are hardly any studies focusing on the determinants of the diffusion of specific *categories of digital technologies*. There are only some studies dealing with *individual technologies* such as E-selling and E-purchasing (Hollenstein and Woerter 2008), or a number of elements of the basic ICT infrastructure of a firm such as the availability of internet, intranet, extranet, etc. (Bayo-Moriones and Lera-Lopez 2007). Against this background, our investigation enters quite unexplored terrain.[16]

In the following, we focus on the *six fields of digital technologies* we identified by use of a factor analysis of the 24 individual technologies. Each field contains two up to six technologies (see Table A.2 in the appendix).[17] As the different fields are quite diverse in terms of scope, application and complexity, we expect that the drivers of diffusion are not the same for all fields, although the differences probably are not fundamental, as all fields rest largely on a common knowledge base. To guarantee reliable comparisons, we use for the six fields of technology and the two types of diffusion the same set of explanatory variables.

We postulate:

H2: The determinants of diffusion are not the same for *all fields of digital technology*. This holds true for inter-firm as well as for intra-firm diffusion. However, in view of the similar knowledge base, we expect that the estimates for most fields and both types of diffusion are largely in accordance with the basic empirical model.

3.3.3 "Cross-learning"

There are several studies dealing with the impact of *complementarities between digital technologies* on diffusion. Examples are Colombo and Mosconi (1995) for some elements of "Flexible

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[16] A similar study as ours is Arvanitis and Ley (2013), whose topic, however, is different, as it deals with the diffusion of energy-saving technologies.

[17] Model estimation at the level of the 24 individual technologies is not feasible because of high correlations between certain technologies and a too small number of observations in several cases.

Manufacturing Systems”,[18] Stoneman and Kwon (1994), Stoneman and Toivanen (1997) as well as Battisti and Stoneman (2005) for relatively old digital technologies in manufacturing. To mention is also Arvanitis and Hollenstein (2001), which dealt with complementarity effects for several categories of “Advanced Manufacturing Technologies. These studies focus almost exclusively on the effect of complementarities on *inter-firm* diffusion (adoption), based on relatively old data (1980s and 1990s). According to most of this research, complementarities positively affect the adoption of ICT.[19]

In the majority of these papers, the complementarity between technologies is traced back to *technological conditions*, based on the view that adopting a new technology requires more or less necessarily the adoption of another one, which belongs to the same or a similar field of technology. As we do not focus on individual technologies but on *the relationship between whole fields of digital technology*, we assume that complementarities are not primarily due to specific technological conditions. We rather assert that the extent of usage of digital technology in a particular field (intra-firm diffusion) increases due to the *prior usage of similar technologies in other fields of application* (positive learning effect). We denote this type of complementarity as *“cross-learning”*.

As we have at our disposal data on the use of digital technologies only for two cross-sections (2013, 2016), we assume that learning largely takes place within a period of three years (which may not be too restrictive in view of the rapid progress of digital technology). We thus use three-year lags for the explanatory learning variables. We focus on the *intra-firm* diffusion effect of “cross-learning” in five fields of digital technology: FABRIC, PROCESS, CONTROL, EXTERNAL, and MODERN (i.e. the aggregate of IOT and ADVANCED).

To provide an example of our procedure, we investigate, whether the *extent of usage of digital technology in the field FABRIC in 2016* (dependent variable) is positively affected by the *usage* of digital technology in the other four fields of application in the year 2013, that is PROCESS, CONTROL, EXTERNAL, and MODERN (independent variables). We apply the same procedure successively for the intra-firm diffusion *in each of the other four subfields*. Of course, we control for the impact of the explanatory variables included in the basic empirical model.

We thus postulate:

H3: The *extent of usage* of digital technologies (*intra-firm diffusion*) in a *particular field* is positively affected by the intensity of *prior usage* (three-year lag) of such technologies in *other fields* of application (“*cross-learning*”).

To conclude this subsection, we like to remind the relationship between in-house learning and the theoretical model presented in subsection 3.1. Remember that we had to exclude from the final equation of the model the term E_i, which stands for firm-internal experience (see equation 1 and 2 in subsection 3.1), because of the cross-section nature of the analysis. However, in this special section, we are able to do without this simplification, as the data allow to use the “learning variables” with a three-year lag.

[18] For the economics of “Flexible Manufacturing Systems”, see the reference study of Milgrom and Roberts (1990).

[19] Due to missing data, we do not take account of (potential) complementarities between *organisational innovations and the adoption of digital technologies* due to missing data. Moreover, we remind that this topic has been widely investigated in previous work. To mention is, particularly, the research dealing with complementarities between “New Work Organisation”, ICT and human capital (see, e.g., Brynjolfsson and Hitt 2000; Breshnahan et al. 2002; for a review of the work in this field, see, e.g., Arvanitis and Loukis 2009).

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3.3.4 “Cumulative learning”

In this subsection, we deal with the effect of *learning from the prior use of “old vintages”* of digital technology on the intra-firm diffusion of more *“advanced vintages”* of the same or a closely related technological field (*“cumulative learning”*). Colombo and Mosconi (1995) identified positive cumulative learning effects for flexible manufacturing technologies. Similarly, Arvanitis and Hollenstein (2001) found that the prior use of an “old IT-based fabrication technology” fostered the later usage of a more advanced vintage of production technology. These studies used data referring to the 1970s up to the mid-1990s. Hollenstein (2004) and Hollenstein and Woerter (2008) performed a similar analysis for E-commerce.

However, these studies throughout dealt with *inter-firm diffusion*. Therefore, we analyse the topic again, *focusing on intra-firm diffusion*, which, to the best of our knowledge, has not be done before. Moreover, we can draw on a more recent database (2013 and 2016), which, in addition, is much broader in terms of the set of technologies considered and also includes the non-manufacturing sector. Again, we assume that learning largely takes place within a period of three years. Correspondingly, the explanatory learning variables are lagged by three years.

We postulate:

H4: The *extent of usage* of *advanced digital technologies* in a particular field (intra-firm diffusion) is higher in firms that previously (three-year lag) used *older vintages of such technologies in the same or a closely related field of technology* (*“cumulative learning”*).

3.3.5 Usage of digital technologies in combinations of functional fields of firm activity

Our dataset distinguishes six *functional fields of firm activity*: R&D, procurement, fabrication, marketing, storage, and administration. In subsection 4.1.1 below (Table 5), we present empirical results for the *intra-firm diffusion of digital technologies as a* whole, using five alternative dependent variables. One of them is the *number of functional fields* of firm activity where the firm applies digital technology (variable “FIRM_functions”; Table 5 column 5). The corresponding estimates, together with the results based on the other four measures of *intra-firm diffusion as a whole* shown in the same table, provide a test of hypothesis H1a.

In contrast, the analysis of hypothesis H5, although it focuses on the digitalisation of the *same functional fields*, should not be confounded with the above-mentioned empirical investigation that refers to hypothesis H1a. In the present case, we explain a *mutually exclusive nominal variable* that reflects the *digitalisation of specific combinations of functional fields of firm activity*. In so doing, we exclude combinations chosen by less than 25 firms as, otherwise, the model estimates would not be reliable. Based on this threshold, we find six different combinations of functional fields of activity where firms use digital technology.

To test hypothesis H5, we seek to identify, using our basic empirical model, the factors determining a firm’s *choice of one particular out of the six combinations of functional fields of activity*. To the best of our knowledge, there are no studies dealing with this aspect of intra-firm diffusion.

We postulate:

H5: The basic empirical model is appropriate to explain *a firm’s choice of a particular combination of functional fields* of activity, *where it uses digital technologies*. We expect that the explanatory power of the model is higher for combinations of a large number of digitalised fields of firm activity than for combinations of only few fields, since digitalisation is more complex and demanding in the first case.

3.4 Estimation problems

The available data provide information on the diffusion of digital technologies (dependent variables) for two cross-sections (2013, 2016), whereas the explanatory variables predominantly refer to the second cross-section (2016). Under these circumstances, we had to simplify the theoretical framework (see subsection 3.1) and, accordingly, the empirical model (see subsection 3.2). In the final model, only the variables capturing epidemic effects (net of stock/order effects), which primarily reflect learning from other firms that use digital technologies, are an exception (three-year lag). Similarly, we use lagged variables in the special section devoted to the effect of in-house learning on intra-firm diffusion (subsections 3.3.3 und 3.3.4).

However, lagging these explanatory variables does *not fundamentally* change the cross-section nature of the analysis, as it is not a substitute for time-series data. This implies that, in a strict sense, most explanatory variables possibly are endogenous, with the effect that the model estimates would be biased. Moreover, based on cross-section data, we cannot really analyse the genuinely dynamic process of technology diffusion.

In practice, however, the problem of endogeneity is mitigated. Firstly, several explanatory variables, primarily those referring to firm- and industry-specific rank effects, reflect “structural characteristics”, which do not much and rapidly change (e.g. firm size, R&D activity yes/no, exporting yes/no, market concentration high/low, sector affiliation, etc.). Secondly, as already mentioned, a few variables (in-house learning; learning from outside sources, i.e. epidemic effects) are lagged by three years.

Nevertheless, we cannot really overcome the weaknesses of the cross-section nature of the analysis, although, considering the previous paragraph, the problem of endeogeneity may not be as serious as assessed from a strict econometric point of view. In view of these weaknesses, we interpret the parameter estimates as *conditional correlations* and *do not make any causal claims*. However, this interpretation of the estimates does not preclude an evaluation of the various hypotheses, particularly as the specification of the empirical model is theoretically well founded. In the following, for sake of simplicity, we remain using (“causality-related”) expressions like “effect” or “impact” on diffusion, always being aware of the fact that we cannot identify causalities. To conclude, we may indicate that most econometric studies of diffusion, particularly those related to intra-firm diffusion, also rest on cross-section data (see the review of Stoneman and Battisti 2010).

Finally, we may indicate that we estimate the inter- and intra-firm equation *separately*. Hence, we do not condition the decision on the extent of usage of digital technology (intra-firm diffusion) upon the decision to adopt this type of technology for the first time (inter-firm diffusion). Since almost 94% of the firms used at least one digital technology in 2016 (see the last row of Table 1), it is unlikely that this simplification will noticeably bias the estimates.[20] Moreover, it is worth mentioning that previous studies that compare the results from estimating the two diffusion equations independently (as we do) with those obtained by taking account of potential dependencies (bivariate probit estimation, Heckman model, etc.) do not find substantial differences (see, e.g., Battisti et al. 2007; Hollenstein and Woerter 2008; Arvanitis and Ley 2013; Stucki and Woerter 2016). We thus conclude that estimating the two types of diffusion equations *separately* provides reliable results.

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[20] The problem of biased coefficients may be larger in the case of inter-firm diffusion in subfields of digital technology with a relatively low the rate of adoption (e.g. ADVANCED).

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4 Empirical results

4.1 Inter-firm vs. intra-firm diffusion

4.1.1 Digital technologies as a whole

Results with respect to H1a

Inter-firm diffusion: In Table 4, column 1, we present the model estimates for the *inter-firm diffusion as a whole* (TOTAL_1: dummy variable with value 1, if one or more of the 24 digital technologies are adopted, and value 0 otherwise). All *categories* of explanatory variables, with the exception of "barriers to adoption", are statistically significant and the model fit is high according to the relevant test statistics. The estimates for the core variables of the *firm-specific rank effects* are statistically significant and show the predicted sign with one important exception, namely the three innovation-related variables (R&D, product and process innovation). The latter finding, which may be surprising at first sight, is probably due to the fact, that not much innovative activity is required to adopt *only one* out of the total of 24 technologies, the more as all firms presumably are familiar with a certain minimum number of elementary ICT applications (whose diffusion we do not consider: e.g., Internet, Homepage, WLAN, or other elements of the basic ICT infrastructure). Moreover, we get the expected positive effects of firm size and firm age as well as group membership of a firm. Among the *industry-specific rank effects*, only the variable "market concentration" (positive sign) and the sector dummies are statistically significant. Besides, with respect to the *epidemic effects (net of stock/order effects),* we find a positive impact of the (lagged) industry share of technology users (INTER), whereas the (lagged) extent of usage of digital technology at industry level (INTRA) does not exert a significant influence. This pattern of epidemic effects is in line with practically all research dealing with inter-firm diffusion (see, e.g., Battisti et al. 2007; Arvanitis and Ley 2013).[21] Our findings imply that the positive epidemic effects are stronger than the (potential) negative stock/order effects. Furthermore, *anticipated benefits* of adoption heavily affect inter-firm diffusion, which points to a distinctive forward-looking behaviour of Swiss firms in this matter. Finally, as already mentioned, *barriers to adoption*, contrary to our expectations, are statistically insignificant. This may be due to the fact that the adoption of only one out of 24 digital technologies is not a real problem for the large majority of firms, given that they already have a certain minimum of IT-infrastructure (Internet, WLAN, etc.).

Table 4 *(about here)*

Intra-firm diffusion: Table 5 shows the model estimates for the *intra-firm diffusion as a whole*, based on *five alternative measures* of the dependent variable. By using five specifications, we seek to get some insight into the robustness of the results. We remind that *TECH_intensity* is a 4-level ordinal variable reflecting the number of digital technologies adopted by a firm, ranging from a "very high" degree of application (use of 10-24 technologies) to a "very low" degree (use of zero or one technology only). *FACTOR_sum* is a "quasi-quantitative variable", standing for the "sum of the six factor scores" resulting from a principal component factor analysis of the 24 digital technologies (see Table A.2 in the appendix). The variable *FACTOR_quartiles* is a 4-level ordinal variable reflecting the quartiles of FACTOR_sum. *TECH_fields* is a 6-level ordinal variable that captures the number of fields of digital technology identified by the above-mentioned factor

[21] An exception is Battisti et al. (2009). They find for the case of *E-commerce* that inter-firm diffusion, additionally, benefits from the industry's extent of the use of E-commerce (INTRA). As our research considers a much broader spectrum of digital technologies, it cannot be excluded that the diverging result with respect to INTRA is due to the different dependent variable. This example shows that one should be cautious in translating results from one study to another one if it diverges with regard to the variable to be explained.

analysis (sum of FABRIC_1, PROCESS_1, CONTROL_1, EXTERNAL_1, IOT_1 and ADVANCED_1). Finally, *FIRM_functions* also is a 6-level ordinal variable that represents the number of *functional* fields where a firm applies digital technology (sum of the dummy variables reflecting digital technology use in the following functional fields: R&D, purchasing, fabrication, marketing, storage, and administration. For the precise definition of the five measures of intra-firm diffusion as a whole, we refer to the *lower* part of Table 2 under heading (A); see subsection 3.2.1.

The estimates for the *five measures of intra-firm diffusion as a whole* in Table 5 show that, in the case of three measures (TECH_intensity, FACTOR_sum, FACTOR_quartiles; columns 1 to 3 of the table), all *categories* of explanatory variables have a significant effect on this type of diffusion. Moreover, the number of statistically significant coefficients of the individual variables is large in these cases. Accordingly, the model fit is quite high. The statistics are less satisfactory in the case of TECH_fields (although the number of significant variables is high as well) and particularly for FIRM_functions. In the former case, there is no evidence for epidemic effects, whereas in the latter firm-specific rank effects are rather weak. From a comparison of the five equations, we conclude that *TECH_intensity* is the most suitable dependent variable in an equation explaining the intra-firm diffusion of digital technologies as a whole.

The results for *inter*-firm diffusion as a whole reported above (TOTAL_1; see Table 4, column 1) and those for the preferred measure of *intra*-firm diffusion as a whole (TECH_intensity; see Table 5, column 1) show that in both cases all *categories* of variables are statistically significant, with the exception of the barriers to adoption in the inter-firm equation. In other words, the empirical model is able to explain both types of diffusion, which confirms *hypothesis H1a*. A comparison of the results for the two types of diffusion we present in the next paragraph indicates that the model, as expected, is more strictly in line with the data in the case of intra-firm diffusion.

Table 5 *(about here)*

Results with respect to H1b

To evaluate *hypothesis H1b*, we *compare*, as already mentioned, the results for the *inter-firm diffusion as a whole* (*TOTAL_1*; Table 4, column 1) with those for the preferred specification of the *intra-firm diffusion as a whole (TECH_intensity;* Table 5, column 1). The results for the two models essentially show *three divergences*. Firstly, firm-specific rank effects are clearly more important as determinants of intra-firm than inter-firm diffusion. This result can be traced back to the strong influence on intra-firm diffusion exerted by the three innovation variables included in the model (R&D, INNO_sales, INNO_costred). This difference is not surprising, as forging ahead towards using several and more complex elements of digital technologies requires a higher intensity of innovative activity than the uptake of only one element of ICT. Secondly, whereas the model for inter-firm diffusion yields, in line with previous research, positive epidemic effects (net of stock/order effects) *only* for the industry share of technology adopters (INTER), we find for the case of intra-firm diffusion that companies benefit from both types of epidemic effects (INTER, INTRA). To the best of our knowledge, this is a new result. Thirdly, the findings show that the variable UNCERTAINTY is an important barrier to extending a firm’s use of digital technologies in the case of intra-firm diffusion, which is not the case for inter-firm diffusion. This difference again is not surprising, as firms in the course of intensifying digitalisation enter a “complex terrain” they did not explore so far. UNCERTAINTY primarily captures problems related to deficiencies regarding the assessment of the potential of such technologies, problems of compatibility with existing (or other new) technologies, or insufficient technology-related knowledge of the management. Quite obviously, such difficulties are much less relevant in the case of the adoption of a first element of digital technology.

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Altogether, we find (a) that the pattern of explanations in the case of the two types of diffusion shows some significant (and plausible) differences, and (b) that the explanatory power of the empirical model is higher in the case of intra-firm diffusion, which is not surprising, as increasing the intensity of the usage of digital technologies is more demanding than the adoption of a first element of digital technology. Overall, the estimates support the *hypothesis H1b*.

4.1.2 Fields of digital technology

Results with respect to H2

In the following, we comment on the results from estimating the models with respect to *inter-firm* and *intra-firm diffusion* differentiated by *six fields of digital technology*. We remind that the definition of these fields emerges from a principal component factor analysis of the data for the diffusion of the 24 digital technologies included in this paper (see Table A.2 in the appendix). As mentioned in that table, we label these (dependent) variables as follows: FABRIC (four fabrication-oriented technologies), PROCESS (six technologies used to optimise intra-firm processes), CONTROL (four technologies applied to controlling and supporting firm-internal tasks), EXTERNAL (four technologies at the interface of the firm and its environment), IOT (two elements of the Internet of Things), and, finally, ADVANCED (four highly advanced digital technologies primarily focusing on fabrication). For some analyses, we shall merge IOT and ADVANCED into an aggregated category (MODERN), as the number of users of IOT is quite low.

Hypothesis 2 postulates that the *determinants* of diffusion *diverge between the six fields* of digital technology for inter- and intra-firm diffusion. However, it also asserts that the estimates for all fields and both types of diffusion remain largely in accordance with the basic empirical model formulated in subsection 3.2.

We present the corresponding empirical results for the *inter-firm* diffusion in *Table 4*, columns 2 to 8 (see above) and for intra-firm diffusion in *Table 6*, column 1 to 7 (see below). In order to assess the hypothesis 2, we use primarily two criteria: (a) the relevance of the *five categories of explanatory variables*, i.e. firm-specific and industry-specific rank effects, epidemic effects (net of stock/order effects), barriers to and anticipated benefits of adoption; (b) the *number of statistically significant individual variables* – obviously a quite simple criterion. We neglect potential interdependencies between the different fields of digital technology.[22]

Inter-firm diffusion: The differences among the six fields of technology with respect to the explanatory variables are quite large. The pattern of explanation is nearest to the basic empirical model in the case of CONTROL_1, PROCESS_1, ADVANCED_1 and MODERN_1 (i.e. the aggregate of IOT_1 and ADVANCED_1). The correspondence is lower with regard to the other two fields that include technologies known since many years (FABRIC_1) or being less complex (EXTERNAL_1). The deviations from the basic model are particularly large with respect to firm-specific rank effects. On the other hand, the pattern of explanation is very similar with regard to the anticipated benefits from adoption (very high effect) and the epidemic effects (net of stock/order effects). The latter variable, throughout, shows a positive sign only for INTER (i.e. a firm is more likely to adopt a digital technology if the *industry share of adopters* is high), whereas INTRA (*industry intensity of usage of*) is not significant in any of the fields of digital technology.[23]

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[22] Arvanitis and Ley (2013) tested whether the decision of firms to adopt a particular *category* of energy-saving technologies is independent from the adoption of other categories. They found that there are some interdependencies. However, independent estimates of the adoption equations yielded practically the same results as those taking account of interdependencies.

[23] As already mentioned, Battisti et al. (2009) is the only study that finds a positive impact of both types of epidemic effects (INTER, INTRA) on *inter*-firm diffusion (adoption) of E-commerce. A one-to-one comparison with our study is not feasible, as E-commerce is only one of the four digital technologies covered by EXTERNAL_1.

Intra-firm diffusion: In this case, the divergences of the results among the fields of technology are less accentuated. Differences are discernible in the case of the epidemic effects (net of stock/order effects) and, to some extent, the barriers to diffusion. In the latter case, we find for two fields (CONTROL, IOT) that uncertainty and security problems are significant obstacles to intensifying diffusion. With respect to epidemic effects, we obtain for two fields (FABRIC, EXTERNAL) that both the industry share of adopters (INTER) and the industry intensity of use (INTRA) favour intra-firm diffusion. For three fields (CONTROL, IOT, ADVANCED), there is evidence only for INTER, and in the case of PROCESS only for INTRA. In spite of these differences, *epidemic effects as a whole* obviously play an important role for explaining the intra-firm diffusion in all fields of technology. Moreover, anticipated benefits of adoption exert a strong (positive) effect on the extent of diffusion in all fields. The same holds largely for firm-specific rank effects, as the core elements of this category of variables (i.e. firm size, three innovation-related variables, ICT-related human capital) have a large impact on the intra-firm diffusion. In contrast, industry-specific rank effects throughout are practically irrelevant.

Altogether, we find, as expected, that the pattern of explanation quite clearly differs between the six fields of digital technology in the case of inter-firm diffusion, whereas the divergences are relatively small with regard to intra-firm diffusion. The latter result may reflect the fact that *intensifying the use* of digital technologies is quite *demanding in any field* of digital technology. Moreover, in the case of intra-firm diffusion, the results for the six subfields are largely in line with the basic empirical model, whereas the evidence in this respect is weaker for the inter-firm diffusion. Nevertheless, even in the latter case, the estimates are *sufficiently* in line with the basic model for the majority of the six fields of technology. Overall, we may conclude that the empirical results largely confirm *hypothesis H2*.

A final remark: The diverging results we get for some of the fields of digital technology in the case of *inter-firm diffusion* imply that one has to be cautious in translating the insights from studies dealing with (only) *one specific field* (e.g. E-commerce, which is the most prominent topic of empirical diffusion research in the last two decades) to other fields or to the total of digital technologies (and vice versa). Such a carry-over is less problematic in the case of *intra-firm diffusion*.

Table 6 (about here)

4.2 Learning effects

4.2.1 "Cross-learning"

Results with respect to H3

Hypothesis H3 asserts that the extent of usage of digital technology (*intra-firm diffusion*) in a particular field is fostered by the intensity of a firm's prior use of such technologies in other fields of application ("cross-learning").

To capture this effect we estimate *five equations*, each using as dependent variable the *intra-firm diffusion* in a particular field of digital technology. The set of explanatory variables comprises, *in addition to those of the basic empirical model*, the *intra-firm diffusion* in the four fields of digital technology not used as dependent variable. For example, in estimates with FABRIC as dependent variable, the additional explanatory variables are the intra-firm diffusion in the other four fields of

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technology, i.e. PROCESS, CONTROL, EXTERNAL and MODERN. We lag these explanatory variables by three years presuming that learning takes some time.[24]

The first part of Table 7 (row 1 to 5) shows the *effect of "cross-learning"* in the case of *intra*-firm diffusion in the five fields of digital technology (column 1 to 5). We find for four of these fields (i.e. FABRIC, PROCESS, CONTROL, MODERN) two statistically significant effects of "cross-learning", but the sources of learning differ quite substantially. CONTROL and EXTERNAL are important sources of experience fostering the extent of usage of PROCESS. Moreover, prior use of digital technologies in the fields of PROCESS and MODERN contributes to an increase of the intensity of use of CONTROL. In addition, there also are two sources of learning in the fields of FABRIC and MODERN. Solely EXTERNAL benefits only from one source of learning (i.e. from PROCESS).

In total, we identify nine variables representing "cross-learning" (out of a potential maximum of twenty) that exert a statistically significant influence on the intra-firm diffusion of digital technologies in the five fields of application. Moreover, the results for the explanatory variables of the basic empirical model (firm- and industry-specific rank effects, epidemic effects (net of stock/order effects), barriers to and anticipated benefits of adoption) remain largely the same as those for the model that does not consider "cross-learning". The findings of this analysis of "cross-learning" are thus quite in line with the hypothesis H3, although not all potential sources of intra-firm learning are statistically significant. The results are consistent with those of earlier studies dealing with this topic, although these refer to the *inter-firm diffusion* in *manufacturing* (see subsection 3.3.3).

A closer look at the results shows, however, that the *overall impact of "cross-learning" on intra-firm diffusion is small,* although the coefficients of quite many of the learning variables are statistically significant. This assessment follows from a comparison of the test statistics with regard to "cross-learning" (pseudo-R^2, measure of concordance, number of statistically significant coefficients) in Table 7 with those of the estimates of the basic model, i.e. excluding learning effects (Table 6).

All in all, the positive effect of "cross-learning" between different fields of digital technology on the intra-firm diffusion in the five fields of technology we consider is confirmed. However, the *additional* contribution of "cross-learning" seems to be rather small. We thus conclude that the evidence for hypothesis H3 is not overwhelming.

Table 7 *(about here)*

4.2.2 "Cumulative learning"

Results with respect to H4

Hypothesis 4 asserts that the prior usage of "old" digital technology belonging to a particular field of application enhances the extent of usage (intra-firm diffusion) of more advanced vintages of technologies of the same or a closely related field ("cumulative learning").

Unfortunately, the data allow to analyse this proposition only for ADVANCED,[25] which primarily includes digital *fabrication technologies that became available only in recent years* (for the definition of this field of application, see Table A.2 in the appendix). Specifically, the model

[24] Using *lagged* variables also reduces the problem of endogeneity that is inherent in cross-section analyses.

[25] In the case of PROCESS, CONTROL, EXTERNAL, and IOT, we are not able to separate old and new vintages of digital technologies.

explains the *intra-firm diffusion* of ADVANCED by the intensity of the *prior* usage of CNC/DNC (three-year lag), which is a relatively old fabrication technology. Alternatively, we approximate the usage of the "old technology vintage" by the intra-firm diffusion of FABRIC, again using a three-year lag. This field of digital technology includes, in addition to CNC/DNC, another three fabrication-oriented technologies (see Table A.2 in the appendix), which also are available since quite many years. For estimating the effect of "cumulative learning", we add the explanatory variable that represents the "old technology vintage" (CNC/DNC and FABRIC respectively) to the explanatory part of the basic model of diffusion.

We present the estimates of this extended model in the first two columns of Table 8. Both CNC/DNC and FABRIC show the expected positive sign and have a statistically significant effect on the intra-firm diffusion of ADVANCED. Hence, "cumulative learning" as additional explanatory variable improves the model fit in both specifications. The pseudo R^2 increases from 0.18 in the basic empirical model (see Table 6, column 6) to 0.23 in both equations including "cumulative learning" (Table 8, column 1 and 2). We conclude that, in line with hypothesis H4, "*cumulative learning*" favours intra-firm diffusion of digital *fabrication* technologies.

Table 8 *(about here)*

To identify the *total effect of in-house learning* on the extent of usage of ADVANCED ("intra-firm diffusion"), we complement the explanatory part of the "cumulative learning" model by the four variables representing "cross-learning" (see the previous subsection). The results presented in Table 8 (columns 3 and 4) show that the two alternative variables measuring cumulative learning in ICT-based fabrication (CNC/DNC and FABRIC respectively) remain statistically significant, and two of the four variables standing for "cross-learning" are statistically significant as well (CONTROL, IOT). The *combined effect* of "cumulative learning" and "cross-learning" leads to a substantial improvement of the model fit. The pseudo R^2 increases from 0.18 in the basic model (see Table 6, column 6) to 0.27 in the two equations including both types of learning (Table 8, columns 3 and 4). However, this increase of the pseudo R^2 overestimates the *total effect of in-house learning* on the intra-firm diffusion, as it is partly due to the larger number of explanatory variables in the extended version of the model.

Overall, we find a statistically significant positive effect for learning from older vintages of ICT-based fabrication technologies, i.e. *"cumulative learning"*, on the intra-firm diffusion of "advanced digital fabrication technologies" (hypothesis 4). Based on the results for the two types of learning (Table 7 and 8), the *evidence for "cumulative learning" might be more convincing than that for "cross-learning"* (hypothesis 3; see the previous subsection).

We are able to compare the results for the two types of learning with Arvanitis and Hollenstein (2001), which also refers to the Swiss economy. They analyse the significance of "cumulative learning" and "cross-learning" in a similar setting as we do, though only for *manufacturing* and based on *relatively old data* (1980s and 1990s). To enable a comparison, we re-estimated our models of learning for *manufacturing firms*. We find that, in our case, "cross-learning" contributes less to the explanation of the diffusion of digital technologies than it was the case in Arvanitis and Hollenstein (2001), whereas "cumulative learning" has a larger effect in our study. Overall, the process of intra-firm learning seems to have changed over the last thirty years. However, it may not be excluded that the difference between the findings of the two studies may partly be due to the fact that the (dominant) digital technologies of today differ from those of the 1990's.

Finally, it is worth mentioning that, in addition to *in-house learning* ("cross-learning", "cumulative learning"), we get highly significant estimates for *"learning from other companies"* that apply

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digital technology ("epidemic effects"). We thus conclude that learning enhances the extent of usage of digital technologies through three channels: "learning from outside sources", "in-house cross-learning", and "in-house cumulative learning".

4.3 Use of digital technologies in different functional fields of firm activity

In this subsection, we seek to explain, using our basic model, a firm's decision to choose a *particular combination of functional fields of activity where it applies digital technologies*.

As mentioned in subsection 3.3.5, we distinguish *six functional fields of firm activity*: R&D (R), procurement (P), fabrication (F), marketing (M), storage (S), and administration (A). We calculate the number of companies that apply digital technologies in *combinations of two or more of these fields*. To ensure a reliable analysis, we only consider combinations that are chosen by at least 25 firms. In so doing, we end up with a sample of 619 firms as against 1390 in the total sample.

Based on this reduced sample, we find *six combinations of digitalised functional fields of firm activity*, which we label by using the abbreviations used in the previous paragraph. Four combinations differ by the *number and type* of digitalised fields of firm activity: RPFMSA, PFMSA, FMA, and MA. In addition, we find two combinations of four fields referring to *different types* of digitalised functional fields (PFMA, FMSA).

Results with respect to H5

As mentioned above, we expect that the explanatory pattern differs among the six combinations identified. The explanation, in terms of our basic model, should be most convincing in the case of firms using digital technologies in combinations made up by a large number of functional fields of activity. The reverse should be the case for combinations of a small number of fields.

We assess this hypothesis by estimating a *multinomial logit model*, which is an adequate procedure as the six combinations are mutually exclusive (unordered) categories (*nominal variables*). The model estimates provide for five combinations *separate coefficients for every explanatory variable*, with the sixth combination (MA) used as reference group. The results yield some evidence with respect to the explanatory power of the empirical model as a whole. Moreover, they provide insights into the *similarities and differences of the explanatory patterns between the individual combinations*.

Overall, the results shown in Table 9 indicate a satisfactory fit of the model to the data (pseudo $R^2 = 0.28$). This could not be taken for granted in advance, given the large number of coefficients to be estimated. Moreover, the table reveals, as hypothesised, that the explanatory power strongly diverges between the different combinations of digitalised functional fields of firm activity.[26] It is particularly high in the case of RPFMSA, and, at the other end, very low for the least complex combination FMA, which does not much deviate from the reference group MA. The explanatory performance is somewhere in between for the three "intermediate" combinations (PFMSA, PFMA, FMSA).

More specifically, the pattern of explanation *in the case of RPFMSA* is similar to that we found for the intra-firm diffusion of the total of digital technologies (see subsection 4.1.1, Table 5). To highlight are the broadly based firm-specific rank effects, the strong epidemic effects and a substantial impact of the anticipated benefits of adoption. On the *other extreme (FMA)*, we observe, in comparison to the reference group MA, very few significant effects of the explanatory variables. We only find some firm-specific rank effects which, at least, are related to two core elements of

[26] As criterion for comparing the model fit for the individual combinations, we use the *number of statistically significant variables* of the five equations. This simple procedure is obviously a rough approximation.

this category of variables (innovation and human capital intensity). Furthermore, the number of significant coefficients is the same for the three "intermediate types of firms" (digitalisation of PFMSA, PFMA or FMSA). On the one hand, the accordance with the basic model is clearly lower than in the case of the most far-reaching combination (RPFMSA), on the other, it is much higher compared to the least complex combination (FMA).

The pattern of results for the three *"intermediate types of companies"* shows *similarities* with respect to several (categories of) explanatory variables but also substantial *differences*. Firm size is highly relevant as an explanatory variable in the case of PFMSA and FMSA, whereas all other firm-specific rank effects are insignificant for these two types of companies. Highly important for companies of the three categories of firms are the anticipated benefits from the usage of digital technologies. Barriers to adoption are relevant for all intermediate types, but only in the case of FMSA more than one type of obstacle are significant (high complexity of digital technologies; uncertainty with respect to the potential of ICT). Finally, epidemic effects have an impact only for one of the three intermediate combinations (PFMSA); in this respect, PFMSA is similar to the category of firms using digital technologies in all fields (RPFMSA).

Altogether, we find that the model explains quite well the overall pattern of a firm's choice of a particular combination of functional fields of activity where it applies digital technology. The empirical model is highly convincing in explaining a firm's decision to use such technologies in *all functional fields* of activity (combination of six fields). Lower is the explanatory power of the model in the case of firms combining the use of ICT in an intermediate number of fields (i.e. four or five fields), whereas the performance of the model is poor if only three or two functional fields are digitalised.

All in all, we conclude that the empirical results, *at least partly*, are *in line with hypothesis 5*. The results underline the importance of distinguishing between firms that digitalise different combinations of functional fields of activity, particularly in terms of the number, broadness and complexity of application.

Table 9 *(about here)*

4.5 Synopsis of the empirical results and assessment

All model estimates are based on a slightly enhanced version of the encompassing model of technology diffusion of Battisti et al. (2009), which covers the dominant categories of explanatory variables of earlier research (rank, stock, order and epidemic model) complemented by variables representing barriers to and anticipated benefits of adoption.

The estimates are consistent with *hypothesis H1a*, which asserts that the basic empirical model is well suited to explain both the inter-firm and the intra-firm diffusion of the *total of digital technologies*. Practically all categories of explanatory variables are statistically significant. As expected, the estimates are more strictly in line with the empirical model in the case of intra-firm diffusion. Particularly, firm-specific rank effects are more important with regard to intra-firm diffusion, and the same is true for the epidemic effects. In the case of intra-firm diffusion, both elements of epidemic effects (industry share of adopters; industry intensity of technology usage) are relevant, whereas for inter-firm diffusion only the first one is important. Overall, the results are in line with *hypothesis H1b*.

Furthermore, the model estimates show that the pattern of explanation of inter-firm diffusion, as expected, differs quite significantly among the *six fields of digital technologies*, which we derived by a factor analysis of the 24 individual technologies considered in this study. With regard to intra-firm diffusion, the divergences are clearly less accentuated, which probably reflects the fact that

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intensifying the usage of digital technology beyond a certain level is demanding *in any field* of this technology. In the case of intra-firm diffusion, the correspondence with the basic empirical model is quite large for all fields of technology. Moreover, even with respect to the inter-firm diffusion, the estimates are *sufficiently in line* with the basic empirical model for most of the six fields of technology. Overall, we may conclude that the empirical results largely confirm *hypothesis H2.*

The hypotheses 3 and 4 refer to the role of *in-house learning* as a variable to explain intra-firm diffusion. *Hypothesis H3* asserts that the intra-firm diffusion of digital technology in a particular field of usage is higher in companies with experience from using such technologies in other fields of application (*"cross-learning"*). *Hypothesis H4* postulates that an intensive usage of older vintages of digital technologies in a particular field augments the extent of usage of more advanced technologies in the same or a closely related field of application (*"cumulative learning"*). We find that both types of in-house learning have a statistically significant positive effect on intra-firm diffusion. However, the influence of "cross-learning", beyond that exerted by the explanatory variables of the basic model, is relatively small. Therefore, the evidence for *hypothesis H3* is not overwhelming. In contrast, the positive effect of "cumulative learning" in the case of fabrication-related technologies (an analysis for the other fields of digital technology is not feasible) is more accentuated and thus supports *hypothesis H4*. Considering the findings with respect to H3 and H4, we conclude that the *total effect of in-house learning* is relevant, but not to the extent we expected. We remind that "learning from other firms" ("epidemic effects") are also an effective channel to foster inter- and intra-firm diffusion. This *"external learning effect"* could be even more important than in-house learning.

The companies use digital technologies in one up to six *functional fields of firm activity* (R&D, procurement, fabrication, marketing, storage, and administration). *Hypothesis H5* postulates that our model is able to explain a firm's choice of a *particular combination of functional fields where it applies digital technology*. Moreover, we expect that the explanatory pattern differs among the various combinations. As predicted, we find that the model primarily is able to explain a firm's decision to use digital technology in the most far-reaching combination of functional fields (all six fields). At the other extreme (three fields only), the performance of the model is poor. The explanatory power is somewhere in between for combinations of an intermediate number of digitalised functional fields of activity (two different combinations of four fields and one of five fields). Hence, the model does not succeed to explain the choice of *each* combination of the digitalisation of a firm's functional fields of activity. However, as it performs quite well even in combinations of only an intermediate number of functional fields, we conclude that the evidence, is quite satisfactory and supports, *at least partly*, the *hypothesis H5*.

Finally, we get interesting results with respect to the effect on inter- and intra-firm diffusion that can be traced back to firm- and technology-specific costs (*barriers to adoption*) and anticipated benefits of applying digital technologies (*objectives of adoption*), which the encompassing model of Battisti et al. (2009) does not sufficiently consider. It turns out that the *anticipated benefits* of digital technologies are a very important factor driving digitalisation, whereas – with the exception of "technological uncertainty" – there are hardly any specific *barriers* slowing down technology diffusion. This finding indicates that Swiss companies are strongly forward-looking in their decisions on adopting digital technologies or increasing their usage.

5 Summary and conclusions

The aim of the study is to provide new empirical evidence with respect to the factors determining inter- and intra-firm diffusion of digital technologies. We especially emphasise intra-firm diffusion, as our knowledge is still limited in this respect. The database we draw on is much broader than in previous work. It provides information for the entire business sector (and not only manufacturing) and a large number of digital technologies, as we may include information for 24 technologies. These range from old ones (e.g. CNC/DNC machines) up to advanced technologies developed and adopted only in recent years (e.g. Internet of Things). The data allow to analyse several problems so far neglected in diffusion research.

The empirical analysis of inter- and intra-firm diffusion basically rests on the *theoretical approach* formulated by Battisti et al. (2009), which integrates the core elements of previous diffusion models, i.e. rank, stock, order and epidemic model. We slightly *extend this encompassing approach*, as we also consider firm-specific costs and anticipated benefits of adoption, which, in our view, may not be fully covered by the general elements of the "Battisti model".

Using this theoretical framework and its empirical specification, we investigate *four topics*: *Firstly*, we analyse whether the empirical model is able to explain the inter- and intra-firm diffusion of the *total of digital technologies*, i.e. the aggregate of the 24 individual technologies included in our database. This step also serves to check the appropriateness of the model underlying the study. *Secondly*, and this is a novel element of diffusion research, we use the model to identify the determinants of the *two types of diffusion* for *six subfields of digital technology*, with the aim to identifying similarities and differences among them, as well as deviations from the results for the total of digital technologies. *Thirdly*, we deal with the impact of *two types of in-house learning* on the extent of usage of digital technologies. On the one hand, we identify for each subfield the impact of learning on the intra-firm diffusion due to previous experience with digital technologies in other subfields (*"cross-learning"*). On the other hand, we determine the influence exerted by the prior use of "old vintages" of digital fabrication technology on the current extent of usage of advanced fabrication-related technologies (*"cumulative learning"*). The few studies dealing with the effects of in-house learning refer only to manufacturing firms and use rather old data (1980s or 1990s). *Finally*, we explore whether our model is able to explain a firm's choice of a *specific combination of two or more functional fields of activity* where it applies digital technology. The functional fields considered are R&D, procurement, fabrication, marketing, storage, and administration. To our knowledge, this topic, so far, did not get any attention in diffusion research.

We shortly *summarise the results* of the empirical investigation (see also subsection 4.5). *Firstly*, we find that the underlying empirical model succeeds quite well to explain the inter- and intra-firm diffusion of digital technology as a whole. Practically all categories of variables, though not to the same extent, are statistically significant for both types of diffusion. The evidence for our model, as expected, is stronger in the case of intra-firm diffusion, as deepening digitalisation is more demanding than adopting only one individual element of these technologies. *Secondly*, we find that in the case of inter-firm diffusion, the explanatory pattern quite substantially differs between the six subfields of digital technology we identified by a factor analysis. This result implies that one should be cautious in translating findings for a specific category of digital technology to other ones. In the case of intra-firm diffusion, the divergences among the six subfields are rather small. This result is plausible as, in every field, an increase of the extent of usage of digital technology becomes more difficult beyond a certain minimum level. All in all, even in the case of inter-firm diffusion, the estimates are "sufficiently" in line with the basic empirical model. *Thirdly*, the effect of in-house learning based on the prior use of digital technology, though positive and statistically significant, is not as strong as expected. This is particularly true in the case of "cross-learning" (learning from the previous use of digital technology in fields of application other than that considered). The effect on diffusion is larger

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for "cumulative learning" (learning from the experience with older vintages of digital technology as a means to augmenting the usage of advanced technologies in the same or a closely related field). In view of the large epidemic effects in most model estimates, we conclude that "in-house learning" may be even less important in the diffusion process than "learning from other firms" (a conclusion that deserves a more detailed analysis). *Fourthly*, we find that the empirical model, at least partly, is able to explain the use of digital technologies in specific combinations of functional fields of firm activity. The explanatory power of the model is very high in the case of the most far-reaching combination (digitalisation of all six functional fields). In contrast, the explanatory power of the model, not surprisingly, is low at the other end of complexity (combination of two or three fields), whereas the findings for the three "intermediate" combinations (two different types with four and one with five digitalised functions), though not overwhelming, are acceptable. *Finally*, it is worth mentioning that the extension of the encompassing model of Battisti et al. (2009) by adding as explanatory variables some firm-specific barriers and, particularly, some measures of anticipated benefits of adoption is highly valuable. We find that the anticipated benefits are strong drivers of digitalisation, whereas barriers to adoption – with the exception of technological uncertainty – do not effectively slow down the diffusion process.

In sum, we conclude that our broadly based analysis, which allows to investigate some new or neglected aspects of the inter- and intra-firm diffusion of digital technologies, may substantially contribute to a better understanding of the factors driving the adoption and diffusion in this field of technology.

Notwithstanding, we have to point to some *limitations* of the study. The most important one is due to the cross-section nature of the data. Therefore, we interpret the findings as conditional correlations rather than causal relationships. However, the problem is mitigated as we could use lagged variables with regard to epidemic effects and in-house learning. Moreover, a few explanatory variables are structural firm characteristics that change only slowly (e.g., firm size, firm age, export-oriented firm yes/no, etc.), meaning that they are "quasi-fixed" factors in the short run.[27] In spite of the deficiencies of a cross-section analysis, it is still possible to assess whether the empirical results are consistent with the underlying hypotheses, particularly as the empirical model we apply is theoretically well founded. Nevertheless, econometric studies of the issues investigated in this paper based on longitudinal data would be highly welcome. Such studies exist in the case of inter-firm diffusion but are very rare with regard to intra-firm diffusion of technology.[28]

A second shortcoming refers to the separate estimation of the equations for the inter- and the intra-firm diffusion of digital technologies, as we do not condition the estimation of the latter equation on the estimates of the former. One could eliminate this deficiency, for example, by using a Heckman correction. However, the available studies that allow to compare the results of independent estimates of the two equations with those controlling for a potential selectivity bias *consistently* show that an independent estimation does not yield (significantly) biased coefficients (see, e.g., Astebro 2004; Battisti and Stoneman 2005; Battisti et al. 2007; Hollenstein and Woerter 2008; Battisti et al. 2009; Stucki and Woerter 2016). Against this background, we do not expect a serious bias of the estimated coefficients. Therefore, we content ourselves with the simpler procedure of independent model estimation.

Thirdly, digitalisation gained momentum a lot during the last few years, whereas our data refer to 2016. We just may mention artificial intelligence, big data analysis, visual reality, intelligent

[27] For this argument, see Bresnahan et al. (2002).

[28] To mention are Fuentelsaz et al. (2003) and Battisti and Stoneman (2003).

robots, or IT-based surveillance and security technologies. The process of broadening and deepening digitalisation will go on in the years to come, probably at an even higher speed than today. Therefore, studies with more recent data than ours could yield new insights.

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Table 1: Diffusion of digital technologies in the Swiss economy [a, b]
(Number and percentage share of users by technology and field of technologies)

Digital technologies	2013 No. of users	2013 Share (%)	2016 No. of users	2016 Share (%)
FABRIC	*617*	*44.4*	*777*	*55.9*
CAD (computer aided design)	536	38.5	675	48.5
CAM (computer aided manufacturing)	206	14.8	268	19.3
CNC/DNC (computerised numerical control machines)	300	21.6	383	27.5
Robots and other robotic technologies	213	15.3	316	22.7
PROCESS	*914*	*65.7*	*1133*	*81.5*
ERP (enterprise resource planning)	774	55.6	995	68.7
CRM (customer relationship management)	433	31.1	654	47.0
SCM (supply chain management)	192	13.8	268	19.3
Business analytics	366	26.3	542	39.0
Social media for internal use	236	17.0	530	38.1
Telework	453	32.6	674	48.5
CONTROL	*449*	*32.3*	*653*	*46.9*
Computerised automated control systems	190	13.7	302	21.7
PLC (programmable logical controllers)	168	12.1	230	16.5
CSS-internal (co-operation support systems for *internal* use)	239	17.2	415	29.8
CSS-external (co-operation support systems for *external* use)	183	13.2	311	22.4
EXTERNAL	*606*	*43.6*	*1072*	*77.1*
Social media for external use	199	14.3	603	43.5
E-selling	233	16.8	419	30.1
E-purchasing	460	33.1	798	57.4
Cloud computing services	84	6.0	413	29.7
IOT	*66*	*4.7*	*175*	*12.6*
Collecting/processing data through things	50	3.6	147	10.6
Autonomous organisation and sharing information between things	47	3.4	127	9.1

To be continued

ADVANCED	*146*	*10.5*	*310*	*22.3*
Rapid prototyping; simulation	57	4.1	112	8.1
Fully/partly autonomously driving vehicles	35	2.5	68	4.9
3D printing	38	2.7	141	10.1
RFID (radio frequency identification)	68	4.9	153	11.0
Additional information				
MODERN (sum of the six technologies belonging to IOT or ADVANCED)	212	13.4	400	28.8
TOTAL (use of at least one of the 24 digital technologies)	1063	76.4	1305	93.8

[a] In each field of digital technologies (FABRIC, PROCESS, CONTROL, EXTERN, IOT, ADVANCED), a firm is an *adopter* as soon as it is using *at least one* of the technologies belonging to the particular category. The same holds for the supplementary category MODERN. In the same way, the TOTAL shows the number of firms that adopted *at least one* of the 24 digital technologies for which data is available.

[b] The composition of the six *categories* of digital technologies is based on the results of the principal component factor analysis shown in the appendix (Table A.2).

Table 2: Definition of the *dependent* variables

Inter-firm diffusion *(Adoption)*	
(A) *TOTAL_1*	1: at least 1 of the 24 technologies listed in Table 1; 0: otherwise
(B) *FIELDS OF TECHNOLOGY*	
- FABRIC_1	1: at least 1 out of the 4 technologies belonging to this group; 0: otherwise
- PROCESS_1	1: at least 1 out of the 6 technologies belonging to this group; 0: otherwise
- CONTROL_1	1: at least 1 out of the 4 technologies belonging to this group; 0: otherwise
- EXTERNAL_1	1: at least 1 out of the 4 technologies belonging to this group; 0: otherwise
- IOT_1	1: at least 1 out of the 2 technologies belonging to this group; 0: otherwise
- ADVANCED_1	1: at least 1 out of the 4 technologies belonging to this group; 0: otherwise
- MODERN_1	1: at least 1 out of the 6 technologies belonging to this group; 0: otherwise
	The assignment of the 24 technologies to the six fields, i.e. FABRIC up to ADVANCED, rests on the factor analysis presented in Table A.2 in the appendix.
Intra-firm diffusion	
(A) TOTAL	*To check the robustness of the estimates we use several alternative measures for the extent of use of digital technology as a whole*
- TECH_intensity	4-level ordinal variable (number of digital *technologies*): 10 to 24; 6 to 9; 2 to 5; with 1 as reference level
- FACTOR_sum	Quantitative variable: *sum of the scores* of the 6 factors according to a factor analysis of 24 digital technologies (see Table A.2 in the appendix)
- FACTOR_quartiles	4-level ordinal variable: *quartiles of the variable FACTOR_sum* (with the lowest quartile as reference level)
- TECH_fields	6-level ordinal variable (*number of fields of digital technologies*) ranging from FABRIC up to ADVANCED (see Table A.2 in the appendix), with firms that digitalised only one field as reference level
- FIRM_functions	6-level ordinal variable (*number of functional fields of firm activity that are digitalised*): The maximum level of 6 is reached if a firm digitalised all functional fields (i.e., R&D, procurement, production, marketing, storage, and administration); firms with only one of the six functional fields of firm activity serve as reference level

To be continued

(B) FIELDS OF TECHNOLOGY	
- FABRIC	3-level ordinal variable (no. of technologies): (3, 4); (1, 2); with 0 as reference level
- PROCESS	4-level ordinal variable (no. of technologies): (5, 6); (3, 4); (1, 2); with 0 as reference level
- CONTROL	3-level ordinal variable (no. of technologies): (2, 3, 4); (1); with 0 as reference level
- EXTERNAL	3-level ordinal variable (no. of technologies): (2, 3, 4); (1); with 0 as reference level
- IOT [a]	2-level ordinal variable (no. of technologies): (1, 2); with 0 as reference level
- ADVANCED	3-level ordinal variable (no. of technologies): (2, 3, 4); (1); with 0 as reference level)
- MODERN	Sum of IOT and ADVANCED: 3-level ordinal variable (no. of technologies): (2, 3, 4, 5, 6); (1); with 0 as reference level
	The assignment of the 24 technologies to the six fields, i.e. FABRIC up to ADVANCED, *rests on the factor analysis presented in Table A.2 in the appendix*
(C) COMBINATION OF FUNCTIONAL FIELDS (that are digitalised)	Based on the *six functional fields of firm activity* where firms may use digital technologies (R&D, procurement, fabrication, marketing, storage, and administration), we find *six combinations* (having excluded combinations chosen by less than 25 firms).[b] We got one combination with 6, 5, 3 and 2 fields respectively, as well as two different combinations with 4 fields. The combination with two fields ("marketing and administration") is used as reference category. The six combinations are *nominal variables*. For the precise definition, see Table 9 (note [a])

[a] The estimates for the inter- and intra-firm diffusion do not differ in the case of IOT as we are not able to define more than two levels of intra-firm diffusion.

[b] We use this threshold as model estimates are only reliable if the number of observations for each combination is higher than a certain minimum level.

Table 3: Definition of the *explanatory* variables

Variables	Definition
Firm-specific rank effects	
SIZE	No. of employees (log); full-time equivalents; end of 2015
AGE	Age of the firm in years (log)
FOREIGN	Firm is owned by a foreign parent company (yes/no)
GROUP	Firm is part of a group (yes/no)
RD	R&D activities (yes/no) in the period 2013-2015
INNO_SALES	Sales share of innovative products (log) in the period 2013-2015
INNO_COSTRED	Cost reduction due to innovations (yes/no) in the period 2013-2015
ICT_UNIV	Share of university-level ICT employees (%); end of 2015
EXPORT	Firm is exporting goods/services (yes/no)
Industry-specific rank effects	
CONC_10	The firm has less than ten principal competitors worldwide (yes/no)
IPC	Intensity of price competition (1: value 4 or 5 of the original five-point intensity scale; 0: otherwise)
INPC	Intensity of non-price competition (1: value 4 or 5 on a five point ordinal intensity scale; 0: otherwise)
SECTOR	Five dummy variables: "high-tech industry", "low-tech industry", "construction sector", "knowledge-intensive services", "other services" ("high-tech industry" is used as reference group)
Epidemic effects [a]	
INTER (2013)	
INTER_FABRIC INTER_PROCESS INTER_CONTROL INTER_EXTERNAL INTER_IOT INTER_ADVANCED INTER_MODERN	*Share of firms (%) by 2-digit NACE industries* using *at least one digital technology* in the corresponding field in 2013 (i.e. from FABRIC to MODERN as well as the TOTAL of firms); For the definition of the fields of technology, see Table 1 and Table A.1 in the appendix
INTRA (2013)	
INTRA_FABRIC INTRA_PROCESS INTRA_CONTROL INTRA_EXTERNAL INTRA_IOT INTRA_ADVANCED INTRA_MODERN	*Adopting firms only;* *Mean of the number of adopted digital technologies* in the corresponding field of technology in 2013 by *2-digit NACE industries.* For the definition of the fields of technology, see Table 1 and Table A.1 in the appendix
Costs of adoption Represented by the scores of a principal component *factor analysis* of eleven "*barriers to the adoption"* of digital technologies. We identified *four factors* we may interpret as *categories of firm-specific costs of adoption* (see Table A.3 in the appendix).	
COMPLEXITY	Digital technologies are not (yet) sufficiently developed; connecting digital technologies is too complex in technical and organisational terms
RESOURCES	Lack of financial resources; lack of knowledge and qualified employees; lack of information on promising applications of such technologies
UNCERTAINTY	Potential of digital technologies not sufficiently clear; insufficient compatibility with the (existing) manufacturing processes; lack of managerial support and deficiencies of the corporate structure
SECURITY	Security problems; highly decentralised decision-making processes

To be continued

Anticipated benefits of adoption Represented by the scores of a principal component *factor analysis* of *twelve* "*objectives of the adoption*" of digital technologies. We identified *three factors* we may interpret as *categories of firm-specific anticipated benefits* of adoption (see Table A.4 in the appendix).	
EFFICIENCY	Increase of internal efficiency; integration of firm-internal processes; higher internal flexibility; higher transparency of firm processes; reduction of labour costs
MARKET	Increase of knowledge on markets and clients; more flexibility on the market; integration into external value chains; creating a new business model
LABOUR	Securing the best junior staff members; designing motivating labour tasks; reducing the time to market

[a] *Net* of stock/order effects

Table 4: Determinants of the *inter-firm diffusion* of digital technologies *as a whole* and differentiated *by field of technology* in 2016 [a, b]

Explanatory variables	TOTAL_1 (Probit)	FABRIC_1 (Probit)	PROCESS_1 (Probit)	CONTROL_1 (Probit)	EXTERNAL_1 (Probit)	IOT_1 (Probit)	ADVANCED_1 (Probit)	MODERN_1 [c] (Probit)
Firm-specific rank effects								
SIZE	.208***	.196***	.439***	.192***	.090**	.092**	.277***	.222***
	(.06)	(.04)	(.06)	(.03)	(.04)	(.04)	(.04)	(.03)
AGE	.265***	.018	.163**	.057	.060	-.073	-.096*	-.066
	(.08)	(.06)	(.07)	(.05)	(.06)	(.06)	(.06)	(.05)
FOREIGN	.156	-.062	.289	-.017	-.175	.073	-.043	-.001
	(.26)	(.13)	(.22)	(.11)	(.12)	(.13)	(.11)	(.11)
GROUP	.416**	.119	.395***	.156*	-.148	.062	-.043	.013
	(.17)	(.10)	(.14)	(.09)	(.10)	(.11)	(.10)	(.09)
RD	-.081	.096	.626***	.246**	.089	.057	.241**	.211**
	(.22)	(.12)	(.20)	(.10)	(.12)	(.12)	(.11)	(.10)
INNO_SALES	.019	.040**	.007	.034**	.012	.075***	.035*	.055***
	(.03)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
INNO_COSTRED	-.099	.060	.016	.163*	-.043	.150	.197**	.174*
	(.19)	(.10)	(.15)	(.09)	(.10)	(.11)	(.09)	(.09)
ICT_UNIV	.016**	.004**	.019***	.005***	.001	.003	.006***	.005***
	(.01)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
EXPORT	.649***	.251**	.410***	-.042	.109	-.176	.115	-.007
	(.16)	(.10)	(.13)	(.09)	(.10)	(.11)	(.10)	(.10)
Industry-specific rank effects								
CONC_10	.219*	.038	.101	.010	-.097	.143	-.020	.051
	(.13)	(.09)	(.11)	(.08)	(.09)	(.10)	(.09)	(.08)
IPC	-.174	-.163	-.150	-.064	.059	.051	-.038	.006
	(.15)	(.11)	(.13)	(.09)	(.10)	(.12)	(.11)	(.10)
INPC	-.040	-.075	.158	.062	-.045	-.046	.027	-.053
	(.14)	(.09)	(.12)	(.08)	(.09)	(.10)	(.09)	(.08)
SECTOR (5 dummies)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic effects [d]								
INTER (2013)	.015*	.037***	.023***	.012**	.012***	.055***	.042***	.029***
	(.01)	(.00)	(.01)	(.01)	(.00)	(.02)	(.01)	(.01)
INTRA (2013)	-.087	-.047	-.259	-.251	.113	-.115	.161	.159
	(.14)	(.12)	(.28)	(.26)	(.18)	(.10)	(.16)	(.13)

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Barriers to adoption								
COMPLEXITY	-.010	.018	-.125**	-.029	-.033	.049	.047	.050
	(.06)	(.04)	(.05)	(.04)	(.04)	(.05)	(.04)	(.04)
RESOURCES	.075	-.046	.068	.077**	.028	.014	.056	.037
	(.06)	(.04)	(.05)	(.04)	(.04)	(.05)	(.04)	(.04)
UNCERTAINTY	-.085	.008	-.053	-.119***	.002	-.164***	-.061	-.112***
	(.06)	(.04)	(.05)	(.04)	(.04)	(.05)	(.04)	(.04)
SECURITY	-.022	-.048	-.009	.049	-.011	.105**	.005	.042
	(.06)	(.04)	(.06)	(.04)	(.04)	(.05)	(.04)	(.04)
Objectives of adoption								
EFFICIENCY	.589***	.191***	.433***	.219***	.367***	.131**	.162***	.186***
	(.06)	(.05)	(.05)	(.04)	(.04)	(.06)	(.05)	(.05)
MARKET	.284***	.047	.171***	.106***	.343***	.188***	.127***	.153***
	(.08)	(.05)	(.06)	(.04)	(.05)	(.05)	(.04)	(.04)
LABOUR	.125	.106***	.086	.157***	.119***	.092**	.061	.092**
	(.08)	(.03)	(.06)	(.04)	(.05)	(.04)	(.04)	(.04)
Statistics								
Number of observations	1390	1390	1390	1390	1390	1390	1390	1390
LR chi^2	418***	721***	596***	368***	245***	143***	302***	295***
Pseudo-R^2	0.43	0.38	0.45	0.19	0.16	0.14	0.20	0.18
Concordant (%)	93	88	92	78	76	76	80	78

[a] The estimates of the intercept are throughout omitted. The significance of the parameters is indicated with ***, ** and * resp. representing the 1%, 5% and 10%-level with robust standard errors in brackets.

[b] The definition of *the fields of digital technologies* is based on the results of the factor analysis with the 24 *single* technologies listed in Table 1. The factor analysis yielded six factors that we clearly may interpret as different technology fields (see Table A.2 in the appendix).

[c] MODERN is the combination of the technology fields IOT and ADVANCED. We combined the two fields as the category IOT contains relatively few adopting firms.

[d] The epidemic variables INTER_2013 and INTRA_2013 are calculated specifically for each technological field.

Table 5: Determinants of the *intra-firm diffusion of digital technologies as a whole* in 2016 [a, b]

Explanatory variables	TECH_intensity (Ordered probit)	FACTOR_sum (OLS)	FACTOR_quartiles (Ordered probit)	TECH_fields (Ordered probit)	FIRM_functions (Ordered probit)
Firm-specific rank effects					
SIZE	.348***	.492***	.288***	.247***	.150***
	(.03)	(.04)	(.03)	(.03)	(.03)
AGE	.071*	-.012	.039	.006	.041
	(.04)	(.07)	(.04)	(.04)	(.04)
FOREIGN	.020	.089	-.004	-.064	.070
	(.09)	(.14)	(.08)	(.08)	(.09)
GROUP	.252***	.107	.180**	.123*	-.086
	(.07)	(.11)	(.07)	(.07)	(.07)
RD	.290***	.624***	.241***	.314***	.847***
	(.09)	(.13)	(.08)	(.08)	(.08)
INNO_SALES	.045***	.083***	.047***	.030**	.013
	(.01)	(.02)	(.01)	(.01)	(.01)
INNO_COSTRED	.162**	.477***	.131*	.182***	.096
	(.08)	(.12)	(.07)	(.07)	(.07)
ICT_UNIV	.007***	.011***	.006***	.006***	.001
	(.00)	(.00)	(.00)	(.00)	(.00)
EXPORT	.324***	.152	.195***	.121*	.266***
	(.07)	(.12)	(.07)	(.07)	(.07)
Industry-specific rank effects					
CONC_10	.172***	.291***	.139**	.075	.005
	(.07)	(.10)	(.06)	(.06)	(.06)
IPC	-.106	-.192	-.096	-.068	.091
	(.08)	(.12)	(.08)	(.08)	(.08)
INPC	-.004	.062	-.036	-.037	-.012
	(.07)	(.10)	(.07)	(.06)	(.06)
SECTOR (5 dummies)	Yes	Yes	Yes	Yes	Yes
Epidemic effects					
INTER_total (2013)	.007*	.003	.006	.004	.008*
	(.00)	(.01)	(.00)	(.00)	(.00)
INTRA_total (2013)	.130*	.215**	.131**	.072	.084
	(.07)	(.10)	(.07)	(.06)	(.06)

To be continued

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Barriers to adoption					
COMPLEXITY	.010	.010	.038	-.002	.023
	(.03)	(.05)	(.03)	(.03)	(.03)
RESOURCES	.017	.022	.032	.052*	-.032
	(.03)	(.05)	(.03)	(.03)	(.03)
UNCERTAINTY	-.091***	-.199***	-.107***	-.124***	-.052*
	(.03)	(.05)	(.00)	(.03)	(.03)
SECURITY	.028	.085*	.019	.030	.016
	(.03)	(.05)	(.03)	(.03)	(.03)
Objectives of adoption					
EFFICIENCY	.355***	.333***	.301***	.208***	.271***
	(.01)	(.05)	(.03)	(.04)	(.04)
MARKET	.342***	.057***	.311***	.160***	.234***
	(.01)	(.05)	(.03)	(.03)	(.03)
LABOUR	.180***	.276***	.171***	.119***	.114***
	(.01)	(.05)	(.03)	(.03)	(.03)
Statistics					
Number of observations	1390	1390	1390	1304	1229
Number of response levels	4	numeric	4	6	6
Adjusted R^2	-	0.47	-	-	-
F value	-	50.5***	-	-	-
LR chi^2	1063***	-	848***	594***	610***
Pseudo-R^2	0.29	-	0.22	0.13	0.14
Concordant (%)	85	-	81	76	77

[a] The estimates of the intercept are throughout omitted. The significance of the parameters is indicated with ***, ** and * resp. representing the 1%, 5% and 10%-level with robust standard errors in brackets.

[b] To check the robustness of the estimates, we use five specifications of the dependent variable to represent the total of the 24 digital technologies listed in Table 1.

Table 6: Determinants of the *intra-firm diffusion* of digital technologies differentiated by *field of technology* in 2016 [a, b]

Explanatory variables	FABRIC (Ordered probit)	PROCESS Ordered probit)	CONTROL (Ordered probit)	EXTERNAL (Ordered probit)	IOT (Ordered probit)	ADVANCED (Ordered probit)	MODERN [c] (Ordered probit)
Firm-specific rank effects							
SIZE	.193***	.417***	.185***	.105***	.092**	.264***	.196***
	(.03)	(.03)	(.03)	(.03)	(.04)	(.03)	(.03)
AGE	.029	.029	.033	.077*	-.073	-.069	-.060
	(.05)	(.04)	(.05)	(.04)	(.06)	(.05)	(.05)
FOREIGN	.018	.367***	.030	-.153	.073	-.024	-.002
	(.10)	(.09)	(.09)	(.09)	(.13)	(.11)	(.10)
GROUP	.008	.350***	.132*	-.078	.062	-.089	-.005
	(.08)	(.07)	(.08)	(.08)	(.11)	(.09)	(.09)
RD	.231**	.283***	.188**	.088	.057	.299***	.256***
	(.09)	(.09)	(.09)	(.09)	(.12)	(.10)	(.10)
INNO_SALES	.028*	.007	.029*	.033**	.075***	.046**	.059***
	(.02)	(.01)	(.02)	(.02)	(.02)	(.02)	(.02)
INNO_COSTRED	.183**	.095	.169**	-.088	.150	.193**	.172**
	(.08)	(.07)	(.08)	(.08)	(.11)	(.09)	(.08)
ICT_UNIV	.002	.007***	.004***	.003**	.003	.005***	.004***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
EXPORT	.296***	.263***	-.017	-.005	-.176	.137	.025
	(.08)	(.07)	(.08)	(.08)	(.11)	(.10)	(.09)
Industry-specific rank effects							
CONC_10	.098	.079	.100	-.006	.143	.019	.070
	(.07)	(.06)	(.07)	(.07)	(.10)	(.08)	(.08)
IPC	-.209**	.019	-.096	-.022	.051	-.046	-.025
	(.09)	(.08)	(.09)	(.08)	(.12)	(.10)	(.09)
INPC	-.005	.066	.104	.003	-.046	.042	-.043
	(.07)	(.07)	(.07)	(.07)	(.10)	(.08)	(.08)
SECTOR (5 dummies)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Epidemic effects [d]							
INTER (2013)	.030***	.004	.010*	.014***	.055***	.042***	.027***
	(.00)	(.00)	(.01)	(.00)	(.02)	(.01)	(.01)
INTRA (2013)	.320***	.696***	-.085	.371**	-.115	.167	.192
	(.09)	(.16)	(.24)	(.15)	(.10)	(.16)	(.13)

To be continued

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Barriers to adoption							
COMPLEXITY	.018	-.003	-.038	-.024	.049	.021	.043
	(.03)	(.03)	(.03)	(.03)	(.05)	(.04)	(.04)
RESOURCES	-.038	-.015	-.050	.022	.014	.042	.013
	(.03)	(.03)	(.03)	(.03)	(.05)	(.04)	(.04)
UNCERTAINTY	-.027	-.034	-.123***	-.022	-.164***	-.067	-.127***
	(.04)	(.03)	(.04)	(.03)	(.05)	(.04)	(.04)
SECURITY	-.037	-.001	.068*	.012	.105**	.002	.038
	(.04)	(.03)	(.04)	(.03)	(.05)	(.04)	(.04)
Objectives of adoption							
EFFICIENCY	.213***	.305***	.220***	.274***	.131**	.157***	.170***
	(.04)	(.03)	(.04)	(.04)	(.06)	(.05)	(.05)
MARKET	.053	.289***	.134***	.353***	.188***	.155***	.182***
	(.04)	(.03)	(.04)	(.04)	(.05)	(.04)	(.04)
LABOUR	.136***	.124***	.147***	.084**	.092**	.063*	.086**
	(.03)	(.03)	(.03)	(.03)	(.04)	(.04)	(.04)
Statistics							
Number of observations	1390	1390	1390	1390	1390	1390	1390
No. of response levels	3	4	3	3	2	3	3
LR chi^2	951***	1067***	396***	358***	143***	340***	315***
Pseudo-R^2	0.33	0.28	0.14	0.12	0.14	0.18	0.14
Concordant (%)	87	85	75	73	76	79	76

[a] The estimates of the intercept are throughout omitted. The significance of the parameters is indicated with ***, ** and * resp. representing the 1%, 5% and 10%-level with robust standard errors in brackets.

[b] The definition of *the fields of digital technologies* is based on the results of the factor analysis with the 24 *single* technologies listed in Table 1. The factor analysis yielded six factors that we clearly may interpret as different technology fields (see Table A.1 in the appendix). Depending on the number of technologies belonging to each field and the number of users of the single technologies within each field, we define the number of response levels. For most fields, we end up we three response levels.

[c] MODERN is the combination of the technology fields IOT and ADVANCED.

[d] The epidemic variables INTER_2013 and INTRA_2013 are specific for each technological field. They thus differ, for example, in the equation explaining the diffusion of FABRIC technologies from those referring to PROCESS technologies.

Table 7: *Cross-learning*: Impact of the *intra*-firm diffusion in several fields of digital technologies in 2013 on the *extent* of usage in other fields of digital technology in 2016 [a, b]

	Intra-firm diffusion in 2016				
Explanatory variables	FABRIC (Ordered probit	PROCESS Ordered probit	CONTROL (Ordered probit	EXTERNAL (Ordered	MODERN [c] Ordered probit
Intra-firm diffusion in 2013					
FABRIC (2013)	///	027	.014	.038	.164***
		(.05)	(.06)	(.06)	(.06)
PROCESS (2013)	.003	///	.203***	.213***	.058
	(.05)		(.06)	(.05)	(.05)
CONTROL (2013)	.086*	.299***	///	.045	.244***
	(.05)	(.05)		(.05)	(.05)
EXTERNAL (2013)	.010	.224***	.032	///	.010
	(.05)	(.04)	(.05)		(.05)
MODERN (2013)	.271***	.017	.421***	.037	///
	(.07)	(.07)	(.07)	(.08)	
Firm-specific rank effects					
SIZE	.169***	.396***	.122***	.052*	.173***
	(.03)	(.03)	(.03)	(.03)	(.03)
AGE	.035	.023	.029	.067	-.056
	(.05)	(.04)	(.05)	(.04)	(.05)
FOREIGN	.000	.363***	-.033	-.206**	-.025
	(.10)	(.09)	(.10)	(.10)	(.10)
GROUP	.018	.374***	.116	-.108	.024
	(.08)	(.07)	(.08)	(.08)	(.09)
RD	.234**	.269***	.173*	.052	.224**
	(.09)	(.09)	(.09)	(.09)	(.10)
INNO_SALES	.022	.003	.022	.035**	.059***
	(.02)	(.01)	(.02)	(.02)	(.02)
INNO_COSTRED	.166**	.090	.154*	-.104	.138*
	(.08)	(.08)	(.08)	(.08)	(.09)
ICT_UNIV	.002	.006***	.004***	.002	.004**
	(.00)	(.00)	(.00)	(.00)	(.00)
EXPORT	.295***	.245***	-.042	-.045	.011
	(.08)	(.08)	(.08)	(.08)	(.09)

To be continued

Industry-specific rank effects					
CONC_10	.084	.082	.083	.014	.060
	(.07)	(.07)	(.07)	(.07)	(.08)
IPC	-.204**	.034	-.109	-.019	-.004
	(.09)	(.08)	(.09)	(.08)	(.10)
INPC	-.010	.053	.114	.004	-.059
	(.07)	(.07)	(.07)	(.07)	(.08)
SECTOR (5 dummies)	Yes	Yes	Yes	Yes	Yes
Epidemic effects [d]					
INTER (2013)	.030***	.003	.009*	.011***	.028***
	(.00)	(.00)	(.01)	(.00)	(.01)
INTRA (2013)	.329***	.663***	-.084	.395***	.169
	(.10)	(.16)	(.24)	(.15)	(.13)
Barriers to adoption					
COMPLEXITY	.016	-.001	-.034	-.021	.043
	(.03)	(.03)	(.03)	(.03)	(.04)
RESOURCES	-.041	-.020	.049	.026	.007
	(.04)	(.03)	(.03)	(.03)	(.04)
UNCERTAINTY	-.019	-.021	-.117***	-.022	-.116***
	(.04)	(.03)	(.04)	(.03)	(.04)
SECURITY	-.041	-.006	.064*	.015	.032
	(.04)	(.03)	(.04)	(.03)	(.04)
Objectives of adoption					
EFFICIENCY	.201***	.269***	.198***	.246***	.140***
	(.04)	(.04)	(.04)	(.04)	(.05)
MARKET	.037	.257***	.096***	.328***	.187***
	(.04)	(.03)	(.04)	(.04)	(.04)
LABOUR	.126***	.103***	.145***	.081**	.065*
	(.04)	(.03)	(.03)	(.03)	(.04)
Statistics					
Number of observations	1390	1390	1390	1390	1390
No. of response levels	3	4	3	3	3
LR chi^2	972***	1155***	458***	391***	349***
Pseudo-R^2	0.33	0.31	0.16	0.14	0.16
Concordant (%)	87	86	77	74	77

To be continued

[b] The definition of *the fields of digital technologies* is based on the results of the factor analysis with the 24 *single* technologies listed in Table 1. The factor analysis yielded six factors that we clearly may interpret as different technology fields (see Table A.1 in the appendix). Depending on the number of technologies belonging to each field (see Table 1) and the number of users of the single technologies within each field, we define the number of response levels. For most fields, three response levels were optimal (see Table 2).

[c] MODERN is the combination of the technology fields IOT and ADVANCED. We combined the two fields as the category IOT contains relatively few adopting firms.

[d] The epidemic variables INTER_2013 and INTRA_2013 are specific for each technological field. They thus differ, for example, in the equation explaining the diffusion of FABRIC technologies from those referring to PROCESS technologies.

Table 8: *"Cumulative learning"*: Learning from prior use of older vintages of digital fabrication technologies in 2016 [a]

	ADVANCED [b]		ADVANCED	
	(Ordered probit)	(Ordered probit)	(Ordered probit	(Ordered probit)
Explanatory variables	*Without controlling for* learning from *non-fabrication fields* of digital technologies		*Controlling for* learning from *non-fabrication fields* of digital technologies	
***"Old vintages" of digital technologies* [c]**				
CNC (2013)	.320***	///	.298***	///
	(.10)		(.10)	
FABRIC (2013)	///	.352***	///	.254***
		(.09)		(.10)
Other fields of digital technologies				
PROCESS (2013)	///	///	.102	.063
			(.12)	(.12)
CONTROL (2013)	///	///	.266***	.255***
			(.09)	(.09)
EXTERNAL (2013)	///	///	.026	.039
			(.09)	(.09)
IOT (2013)	///	///	.628***	.595***
			(.11)	(.11)
Firm-specific rank effects				
SIZE	.255***	.244***	.234***	.231***
	(.03)	(.03)	(.04)	(.04)
AGE	-.075	-.064	-.064	-.055
	(.05)	(.05)	(.06)	(.06)
FOREIGN	-.029	-.024	-.061	-.053
	(.11)	(.11)	(.11)	(.11)
GROUP	-.086	-.092	-.095	-.098
	(.09)	(.09)	(.09)	(.09)
RD	.276***	.266***	.265***	.265***
	(.10)	(.10)	(.10)	(.10)
INNO_SALES	.045**	.047**	.034*	.036*
	(.02)	(.02)	(.02)	(.02)
INNO_COSTRED	.180**	.195**	.148*	.161*
	(.09)	(.09)	(.09)	(.09)
ICT_UNIV	.005***	.005***	.004***	.004***
	(.00)	(.00)	(.01)	(.00)
EXPORT	.102	.110	.134	.148
	(.10)	(.10)	(.10)	(.10)

Industry-specific rank effects				
CONC_10	.006	.012	-.016	-.008
	(.08)	(.08)	(.08)	(.08)
IPC	-.046	-.037	-.053	-.044
	(.10)	(.10)	(.10)	(.10)
INPC	042	.051	.143	.051
	(.08)	(.08)	(.09)	(.09)
SECTOR (5 dummies)	Yes	Yes	Yes	Yes
Epidemic effects [d]				
INTER (2013)	.043***	.039***	.042***	.039***
	(.01)	(.01)	(.01)	(.01)
INTRA (2013)	.122	.172	.138	.183
	(.16)	(.16)	(.16)	(.16)
Barriers to adoption				
COMPLEXITY	.024	.018	.015	.010
	(.04)	(.04)	(.04)	(.04)
RESOURCES	.045	.045	.033	.032
	(.04)	(.04)	(.04)	(.04)
UNCERTAINTY	-.067	-.067	-.041	-.042
	(.04)	(.04)	(.04)	(.04)
SECURITY	.006	.006	-.016	-.016
	(.04)	(.04)	(.04)	(.04)
Objectives of adoption				
EFFICIENCY	.151***	.141***	.121**	.120**
	(.05)	(.05)	(.05)	(.05)
MARKET	.167***	.158***	.135***	.130***
	(.04)	(.04)	(.04)	(.04)
LABOUR	.057	.063*	.040	.046
	(.04)	(.04)	(.04)	(.04)
Statistics				
Number of observations	1390	1390	1390	1390
No. of response levels	3	3	3	3
LR chi^2	351***	356***	398***	397***
Pseudo-R^2	0.23	0.23	0.27	0.27
Concordant (%)	79	80	81	81

To be continued

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[a] The estimates of the intercept are throughout omitted. The significance of the parameters is indicated with ***, ** and * resp. representing the 1%, 5% and 10%-level with robust standard errors in brackets.

[b] ADVANCED (*the dependent variable*) contains *"recent types of digital fabrication technologies"* (i.e. rapid prototyping/simulation, fully/partly autonomously driving vehicles, 3D printing, RFID).

[c] We consider two different measures of *"old vintages of digital fabrication technologies"*: firstly, CNC/DNC, which is the oldest digital fabrication technology used in Swiss manufacturing, secondly, FABRIC, which, in addition to CNC/DNC, also contains CAD, CAM and robots).

Table 9: Determinants of specific *combinations of digitalised functional fields of firm activity* [a, b]

Explanatory variables	*Multinomial logit* estimates, with MA ("marketing and administration") as reference group				
	RPFMSA (2a)	PFMSA (2b)	PFMA (2c)	FMSA (2d)	FMA (2e)
Firm-specific rank effects					
SIZE	.675***	.448***	.202	.391*	.199
	(.18)	(.16)	(.18)	(.22)	(.24)
AGE	.003	.008	.017	-.349	.339
	(.29)	(.26)	(.11)	(.35)	(.44)
FOREIGN	-.557	-.712	-1.06*	-1.20	-.957
	(.60)	(.55)	(.66)	(.87)	(.99)
GROUP	.048	.446	.842*	.123	-1.01
	(.49)	(.44)	(.50)	(.63)	(.73)
RD	2.97***	-.205	.057	.678	-.873
	(.63)	(.64)	(.74)	(.78)	(.97)
INNO_SALES	.045	.042	.000	.067	.284**
	(.09)	(.08)	(.09)	(.12)	(.12)
INNO_COSTRED	1.06**	.677	.205	1.03	.216
	(.53)	(.50)	(.60)	(.68)	(.70)
ICT_UNIV	.017***	.009	.000	.006	.019*
	(.01)	(.01)	(.01)	(.01)	(.01)
EXPORT	.745*	.608	.538	-.091	-.128
	(.45)	(.38)	(.45)	(.59)	(.57)
Industry-specific rank effects					
CONC_10	.191	.226	.615	-1.12*	-.015
	(.32)	(.38)	(.45)	(.60)	(.56)
IPC	-.420	-.017	.093	-.434	1.19
	(.51)	(.44)	(.55)	(.65)	(.91)
INPC	-.328	-.153	-.065	-.208	-.476
	(.44)	(.39)	(.45)	(.58)	(.57)
SECTOR (5 dummies)	Yes	Yes	Yes	Yes	Yes
Epidemic effects					
INTER (2013)	-.076	-.020	-.014	-.005	-.053
	(.05)	(.04)	(.05)	(.08)	(.07)
INTRA (2013)	.454*	.373*	.147	.072	.034
	(.24)	(.22)	(.27)	(.34)	(.36)

To be continued

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Barriers to adoption					
COMPLEXITY	.224	.111	.303	.540*	-.071
	(.21)	(.18)	(.22)	(.28)	(.29)
RESOURCES	-.255	-.181	-.327	.037	.237
	(.21)	(.18)	(.21)	(.28)	(.28)
UNCERTAINTY	-.280	-.324*	-.141	-.525*	-.157
	(.22)	(.19)	(.22)	(.29)	(.28)
SECURITY	.272	.141	463.**	.350	.126
	(.21)	(.19)	(.22)	(.28)	(.28)
Objectives of adoption					
EFFICIENCY	.874***	1.25***	.896***	.623**	.300
	(.25)	(.22)	(.26)	(.32)	(.33)
MARKET	.593***	.580***	.939***	.413	-.157
	(.22)	(.20)	(.23)	(.29)	(.30)
LABOUR	.187	.269	.177	-.291	.047
	(.20)	(.17)	(.22)	(.29)	(.27)
Statistics					
Number of observations			619		
Distribution of N by combinations	36.8	34.6	9.1	4.0	4.5
of functional fields of activity (%)	(the reference group MA includes 11.0 % of the firms)				
No. of response levels			6		
LR chi^2			1159***		
Pseudo-R^2			0.28		

[b] The estimates of the intercepts are throughout omitted. The significance of the parameters is indicated with ***, ** and * resp., representing the 1%, 5% and 10% level with robust standard errors in brackets.

[a] The combinations refer to the firms' *use of digital technologies in six functional fields of activity*, with R = research & development, P = procurement, F = fabrication, M = marketing, S = storage, and A = administration. Based on these fields of activity, we find *six combinations* that contain at least 25 observations. As the combinations are nominal dependent variables (unordered categories), the *multinomial logit model* is an appropriate estimation procedure. We present the estimates in the columns 1a (RPFMSA) to 2e (FMA), with the least complex combination MA as reference category.

APPENDIX

Table A.1: Composition of the final sample by industry

Sector / Industry	N	% of firms
Low-tech manufacturing	*410*	*29.3*
Food, beverages, tobacco	56	4.0
Textiles, clothing	19	1.4
Wood products	26	1.9
Paper	17	1.2
Printing	22	1.6
Non-metallic minerals	26	1.9
Metals	17	1.2
Metal products	116	8.3
Watchmaking	31	2.2
Other manufacturing	23	1.6
Energy	40	2.8
Water	17	1.2
High-tech manufacturing	*291*	*20.8*
Chemicals	37	2.6
Pharmaceuticals	14	1.0
Rubber, plastics	34	2.5
Non-electrical machinery, vehicles	114	8.1
Electrical machinery	36	2.6
Electronics, instruments	56	4.0
Construction	*135*	*9.6*
Knowledge-intensive services	*160*	*11.4*
Telecommunication, media	20	1.4
IT-services	22	1.6
Banking, insurance	70	5.0
R&D, technical services	48	3.4
Other services	*404*	*28.9*
Wholesale trade	116	8.3
Retail trade	93	6.7
Hotels, restaurants	45	3.2
Transport, storage, logistics	70	5.0
Real estate, renting	30	2.1
Personal and other services	50	3.6
Total	1400	100

Table A.2: Factor analysis of digital technologies

Digital technologies	Rotated factor pattern (varimax) [a]					
	F1	F2	F3	F4	F5	F6
ERP (enterprise resource planning)	0.30	**0.70**	0.04	0.01	-0.05	-0.02
CRM (customer relationship management)	0.01	**0.71**	-0.03	0.15	-0.02	0.16
SCM (supply chain management)	0.17	**0.48**	0.21	-0.02	0.09	0.27
Business analytics	0.00	**0.67**	0.22	0.10	0.11	0.06
CSS (co-operation support systems) for						
- internal use	-0.01	0.30	**0.69**	0.12	0.09	0.09
- external use	-0.05	0.04	**0.74**	0.14	-0.01	0.17
Social Media for						
- internal use	0.05	**0.53**	0.21	0.27	0.08	0.12
- external use	-0.05	0.27	0.02	**0.60**	-0.02	0.20
Cloud computing services	0.02	0.16	0.15	**0.60**	0.12	0.00
E-selling	-0.18	0.13	-0.01	**0.60**	-0.00	0.19
E-purchasing	0.20	-0.03	0.19	**0.66**	0.11	-0.20
Telework	0.12	**0.54**	0.27	0.23	0.09	-0.05
Computerised automated control systems	0.20	0.23	**0.57**	0.12	0.18	0.10
PLC (programmable logic controllers)	0.39	0.17	**0.49**	-0.02	0.11	0.05
CAD (computer aided design)	**0.74**	0.18	0.00	-0.05	0.13	-0.03
CAM (computer aided manufacturing)	**0.74**	0.09	0.09	0.03	0.01	0.16
Rapid prototyping; simulation	0.37	0.08	0.06	0.09	0.12	**0.60**
CNC/DNC (computerised numerical control machines)	**0.79**	0.00	0.00	-0.03	-0.08	0.08
Robots and other robotic technologies	**0.57**	0.13	0.1	-0.00	0.04	0.29
Fully/partly autonomously driving vehicles	-0.03	0.07	0.26	-0.13	0.04	**0.56**
3D printing	**0.41**	0.06	-0.06	0.16	0.08	**0.57**
RFID (radio frequency identification)	0.07	0.14	0.11	0.19	0.15	**0.51**
IOT (Internet of Things)						
- Collecting/processing data through things	0.04	0.10	0.13	0.07	**0.88**	0.17
- Autonomous organisation and sharing information between things	0.04	0.10	0.13	0.07	**0.88**	0.17

To be continued

Statistics						
Number of observations						1391
Kaiser's overall measure of sampling adequacy (MSA)						0.85
Eigenvalues of the individual factors	5.26	2.38	1.61	1.25	1.10	1.08
Final communality estimate (total)						12.7
Variance accounted for by the individual factors (%)	21.9	9.91	6.73	5.23	4.59	4.50
Variance accounted for by the sum of the six factors (%)						53.9
Root mean square off-diagonal residuals (RMSE)						0.06
Characterisation of the six factors						
Factor 1: Fabrication-oriented technologies (FABRIC)						
Factor 2: Process-oriented technologies used internally (PROCESS)						
Factor 3: Control and support-oriented technologies (CONTROL)						
Factor 4: Outward-oriented technologies (EXTERNAL)						
Factor 5: Internet of Things (IOT)						
Factor 6: Highly advanced (fabrication-oriented) technologies (ADVANCED)						

[a] Factor values greater than 0.40 are in bold.

Table A.3: Factor analysis of the barriers to the adoption of digital technologies

Barriers to adoption	Rotated factor pattern (varimax) [a]			
	F1	F2	F3	F4
Compatibility with the existing manufacturing processes is insufficient	0.20	-0.04	**0.72**	-0.11
Lack of management support and deficiencies of the corporate culture	0.01	0.32	**0.68**	0.25
Potential of digital technologies is not sufficiently clear and difficult to measure	0.24	0.10	**0.68**	0.19
Decision-making processes are too much decentralised	0.06	0.11	0.19	**0.80**
Concerns with respect to security problems	0.29	0.10	-0.06	**0.77**
Digital technologies are not sufficiently developed	**0.72**	0.12	0.05	0.29
Connection of digital technologies is too complex in technological terms	**0.63**	0.17	0.20	0.05
Connection of digital technologies is too complex in organisational terms	**0.70**	0.24	0.31	0.12
Lack of financial resources	0.03	**0.80**	0.02	0.09
Lack of knowledge and qualified employees	0.25	**0.81**	0.13	0.07
Lack of information on promising applications of digital technologies	0.39	**0.61**	0.18	0.13
Statistics				
Number of observations				1391
Kaiser's overall measure of sampling adequacy (MSA)				0.83
Eigenvalues of the individual factors	3.90	1.18	1.09	0.97
Final communality estimate (total)				7.14
Variance accounted for by the individual factors (%)	35.5	10.7	9.9	8.8
Variance accounted for by the sum of the four factors (%)				64.9
Root mean square off-diagonal residuals (RMSE)				0.09
Characterisation of the four factors				
Factor 1: Technological/organisational complexity (COMPLEXITY)				
Factor 2: Lack of financial / technological / human resources (RESOURCES)				
Factor 3: Uncertain benefits; compatibility problems (UNCERTAINTY)				
Factor 4: Concerns with respect to security problems (SECURITY)				

[a] Factor values greater than 0.40 are in bold.

Table A.4: Factor analysis of the objectives of the adoption of digital technologies

Objectives of adoption	Rotated factor pattern (varimax) [a]		
	F1	F2	F3
Creating a new business model	0.09	**0.74**	0.18
Integration into external value chains	0.25	**0.59**	0.05
Integrating firm-internal processes	**0.77**	0.18	0.05
Reducing labour costs	**0.49**	-0.03	0.32
Increasing internal efficiency	**0.80**	0.15	0.10
Increasing internal flexibility	**0.64**	0.26	0.23
Increasing flexibility at the market	0.33	**0.58**	0.15
Increasing the transparency of firm processes	**0.61**	0.23	0.07
Increasing the knowledge on markets and clients	0.16	**0.63**	0.21
Reducing the time to market	0.06	0.28	**0.58**
Recruiting the best junior employees	0.09	0.15	**0.82**
Establishing motivating jobs	0.28	0.13	**0.68**
Statistics			
Number of observations			1390
Kaiser's overall measure of sampling adequacy (MSA)			0.85
Eigenvalues of the individual factors	3.97	1.24	0.97
Final communality estimate (total)			6.18
Variance accounted for by the individual factors (%)	33.1	10.4	8.1
Variance accounted for by the sum of the three factors (%)			51.6
Root mean square off-diagonal residuals (RMSE)			0.09
Characterisation of the three factors			
Factor 1: Increasing firm-internal efficiency and flexibility (EFFICIENCY)			
Factor 2: Market-related knowledge/flexibility and integration into external value chains (MARKET)			
Factor 3: Recruiting and motivation of employees (LABOUR)			

[a] Factor values greater than 0.40 are in bold.