Make or Buy your Artificial Intelligence?

Complementarities in Technology Sourcing

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Abstract

We investigate firm decisions to adopt artificial intelligence (AI) technology and how adoption is sourced: by purchasing commercial readymade software, by developing or customizing solutions in-house, or both. Using a cross-sectional data set of 3143 firms from across Europe, we examine the extent to which sourcing strategies exhibit complementarity or substitution. We find that adoption of AI using readymade software as a sourcing strategy is now increasingly commonplace but differs across industrial sectors. Further, complementarities between sourcing strategies are common across sectors, though with some differences in strength and some exceptions. Our results show that sourcing strategies play an important role in shaping AI adoption decisions among firms.

Keywords: Artificial Intelligence, Technology Adoption, Complementarities

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Data Statement

The data that support the findings of this study are available from the Directorate-General for Communications Networks, Content and Technology from the European Commission. Restrictions apply to the availability of these data, which were used under license for this study.

1. Introduction

While the adoption and use of artificial intelligence (AI) are now significant, overall adoption rates remain low (Kazakova et al 2020; McElheran et al 2023; Zolas et al 2020). One recent line of work has argued that AI represents a type of general-purpose technology (GPT) (Bresnahan and Trajtenberg 1995; Trajtenberg 2019; Furman and Seamans 2019), and so requires significant downstream innovation to adapt general solutions to unique user needs (Brynjolfsson, Rock, and Syverson 2019, 2021; Goldfarb, Taska, and Teodoridis 2023). At the firm level, this will require a combination of business process innovation but also the development of software that will fit the unique needs of firms. This need for complementary adaptation and innovation has historically proven to be difficult (Bresnahan and Greenstein 1996).

Historically, enterprise software like AI has been deployed in a range of ways: developing new software in-house, custom development by third parties, or through readymade commercial software (hereafter referred to as readymade software). Readymade software often appears over time as downstream needs become more stabilized, and as vendors accumulate best practices learned through multiple engagements.[1] In some historical types of software applications like ERP, readymade software applications such as those produced by firms like EDS, Oracle, and SAP became a dominant way in which firms deployed new technologies (Bresnahan 2019). Despite the historical importance of these types of readymade software applications to the diffusion of enterprise computing technology, there has been little empirical evidence of their importance to the diffusion of AI and how they are deployed within the broader set of AI software applications. In this paper, we take the first step of offering a framework and preliminary empirical evidence, in the hopes that our research will encourage future work in this area.

Readymade and developed software could be complements or substitutes to one another; which of these holds has important implications for the diffusion of AI software in business. Deploying readymade software may have lower costs than developing internally. Further, successful developers of readymade software can benefit from economies of scale in software development costs and may pass these benefits on to users. By accumulating best practices from multiple engagements, readymade software may also help to facilitate the business process innovation that commonly accompanies enterprise software adoption and use (Cortada 1998).[2]

However, readymade software may still require complementary investments by firms. In this case, custom development and readymade software are likely to be complements particularly if, as has been recently argued, firm investments in AI require investments in skills that represent vintage-specific human capital (Chari and Hopenhayn 1991; Chen et al 2021; Choudhury, Starr, and Agarwal 2020). Adoption will be constrained by a scarcity of talent or require costly training by the adopting firm.

[1] ERP software, and enterprise software company SAP in particular, is one well-known example of this (e.g., Mirchandani 2014).

[2] Though the ease with which these “spill outs” occur may vary significantly across industries and contexts (Bresnahan 2023), and vendors may take efforts to prevent them (Bresnahan 2019). We address these issues in further detail, below.

In this paper, we establish a framework for investigating whether complementarities or substitution shape the adoption of readymade and internally developed software. This framework and empirical approach are motivated by prior research on the sourcing of other types of innovations; in particular, whether internal and external sources of innovation are complements or substitutes (e.g., Arora and Gambardella 1990, 1994; Cassiman and Veugelers 2006; Ceccagnoli, Higgins, and Palermo 2014; Veugelers and Cassiman 2006). Findings from this literature have frequently highlighted the presence of complementarity between sourcing strategies and can play a significant role in helping firms to integrate and evaluate external innovations (Cohen and Levinthal 1989, 1990; Arora and Gambardella 1994). [3]

We apply this approach to a unique multi-industry survey of firms across Europe. These firms are asked questions about their adoption of AI software. Further, they are asked how they obtained this software, selecting from a list of options spanning from buying ready-made software to complete in-house development.

We estimate a cross-sectional model that relies on the correlation approach for testing complementarities (Brynjolfsson and Milgrom 2013). Because our measures of application sourcing are binary, we follow work that has sought to estimate complementarities through models of user choice of multiple decisions, including a separate parameter to identify complementarities between decisions (Gentzkow 2007). Because of the substantial differences in the costs and benefits of applying AI to business problems (e.g., Agrawal, Gans, and Goldfarb 2022, 2023; Bresnahan Forthcoming), we allow for heterogeneity in complementarity based upon the focal firm's sector.

Readymade software adoption is common. In the unconditional statistics, among adopters of AI, 58.3% reported adopting readymade applications. In our choice model estimates, we find that several sectors that have tended to be historical lead users of IT (Forman, Goldfarb, and Greenstein 2003; Jorgenson, Ho, and Stiroh 2005) – including scientific research, finance and real estate and, to a lesser extent, IT – tend to favor in-house development. In contrast, others such as human health, construction, and agriculture, forestry, and fishing have preferences for readymade solutions.

Further, we observe evidence of complementarities between the two sourcing strategies, especially in the scientific research, retail trade, financial, and manufacturing sectors. Perhaps surprisingly, only the IT sector shows evidence of substitution between sourcing strategies.

Our survey data are unusual in that they explicitly measure the sourcing strategies used by firms, and so allow us an unusual opportunity to provide insights into an important phenomenon. However, because we only observe a cross-section of responses, they also present unique challenges in identifying complementarities. These issues have been highlighted in conjunction with applied and methodological papers related to measuring complementarity among innovation sourcing strategies (e.g., Arora 1996; Arora and Gambardella 1990; Veugelers and Cassiman 1999) and in those related to the testing for complementarities more generally (e.g., Athey and Stern 1998; Brynjolfsson and Milgrom 2013). Our research provides documentation on the importance of

[3] In one exception, Forman, Goldfarb, and Greenstein (2008) provide evidence of localization of substitution between internal and external firm resources within the content of firm adoption of the commercial internet. We provide further details on differences between that study and this one below.

readymade software to the diffusion of AI in businesses. We provide a framework, drawing from prior literature, on why complementarity between sourcing strategies may be important to AI-enabled digital transformation, and the implications complementarity may have for the human capital needs of adopters. We provide preliminary evidence on the extent of complementarity within and across sectors, but also document limitations of our empirical approach and discuss how our framework can be applied in future work.

We make several contributions to prior literature. Recent work has highlighted that AI, like prior generations of information and communication technology, requires business process innovation to be deployed successfully within firms (e.g., Bresnahan 2019, Forthcoming; Brynjolfsson, Jin, and McElheran 2021; Brynjolfsson, Rock, and Syverson 2019, 2021; Agrawal, Gans, and Goldfarb 2022, 2023). Our research is informed by this perspective, however our focus on the sourcing of AI is unique. As noted above, readymade software can help to lower the barriers to adopting AI that have been highlighted in prior work by codifying processes and best practices into software. Indeed, readymade software can be argued to be a means of facilitating the knowledge-sharing that is a feature of technological convergence (Rosenberg 1963). However, in many business environments, such spillovers across users of business applications may be ineffective (Bresnahan 2019, Forthcoming). Our focus on complementarities provides an implication for imperfect knowledge-sharing across users and uses of AI applications.

Our results also contribute to the literature on the sourcing of innovations (e.g., Arora, Cohen, and Walsh 2016; Arora and Gamardella 1990, 1994; Cassiman and Veugelers 2006; Veugelers and Cassiman 1999). Our results are consistent with earlier findings that provide evidence of complementarity between internal and external innovation sources. However, we advance this literature by applying these frameworks to the study of the sourcing of AI software.

2. Theoretical Framework

2.1 Enterprise software and business process innovation

By now a long literature has documented how the adoption of enterprise software involves both adaptations to software to meet the idiosyncratic needs of firms as well as changes to the organization in which the software is embedded. These often involve adaptations to processes, decision rights, organizational structure, and human capital (e.g., Bresnahan, Brynjolfsson, and Hitt 2002; Bloom, Sadun, and Van Reenen 2012; Brynjolfsson, Jin, and McElheran 2021). This process has been labeled co-invention (Bresnahan and Greenstein 1996). The importance of co-invention and business process innovation to the deployment of machine learning and artificial intelligence software has been argued for in an increasingly broad range of papers (Agrawal Gans, and

Goldfarb 2022, Forthcoming; Brynjolfsson, Rock, and Syverson 2019, 2021; Bughin and van Zeebroeck 2018). [4]

We will focus on the sources of software development for AI and how they are influenced by the need for complementary business process innovation. We motivate our approach using prior work that has examined the sources of R&D product and process innovation (e.g., Arora, Cohen, and Walsh 2016; Arora and Gambardella 1990, 1994; Cassiman and Veugelers 2006; Ceccagnoli et al 2014; Veugelers and Cassiman 1999). This approach is useful because there are commonalities in the mechanisms shaping the sourcing of enterprise software decisions to that for other types of innovation sourcing. A focus of this earlier line of work is whether innovations are sourced internally or externally and the interdependencies between them: whether they are complements or substitutes.

2.2 Types of software: when to make or buy

Software can be developed through a variety of means. One approach is to develop custom software or to modify solutions developed elsewhere. The advantage of this type of software is that it can be written to be closely aligned with the firm's needs. However, building software is expensive, and once developed is hard to change (Davenport 2000; Goodhue et al 2009).

Third party readymade software is standardized and can be deployed in a variety of different environments. Because software development involves significant fixed costs, such readymade software will benefit from economies of scale arising from the ability to spread software development costs across sales. Readymade software also has another advantage. Enterprise software developers who engage in many projects can incorporate lessons learned from earlier engagements into future ones, incorporating best practices into their software (Cortada 1998). Thus, enterprise software will benefit from sources of learning that cannot be replicated by in-house development. Indeed, by embedding lessons learned within their software, readymade software vendors can play a role in the cross-industry learning that has been associated with prior generations of business computing (Bresnahan 2019; Forthcoming). Thus, by some metrics, readymade software has significant cost advantages for firms over internally developed software.

One disadvantage to readymade software is that they are generally generic solutions that may be difficult to customize to specific firm circumstances (O'Leary 2000). The generality of these solutions will vary based on the solution's nature and application. These will influence the speed with which they can be adopted across a range of settings. For example, finance and accounting were historically the first modules to be adopted within ERP systems like SAP (Davenport 1998), while other modules were adopted later or not at all depending on firm needs and costs of deployment.

Because readymade solutions are standardized, custom-made systems are often used in contexts where systems represent a core source of value creation for the firm (Bharadwaj 2000): for example, Walmart's proprietary logistics systems are commonly attributed as a significant advantage that has helped it to maintain lower prices than competitors (e.g., Bessen 2020). Related, the decision to develop internally or acquire readymade software will be related to the existence within the firm of knowledge that

[4] Related, it has been argued that AI is an example of a general purpose technology (GPT) (Brynjolfsson, Rock, and Syverson 2019, 2021; Cockburn, Henderson, and Stern 2019; Goldfarb, Taska, and Teodoridis 2023, Trajtenberg 2019, Furman and Seamans 2019). For our purposes, like prior generations of ICTs, AI shares features that are commonly associated with GPTs.

will facilitate and enable the development of software (Grant 1996, Prahalad and Hamel 1990, Wernerfelt 1984). In the case of enterprise software, this involves not only technical expertise to develop software but also the knowledge of how to incorporate that expertise into business processes (Sambamurthy et al 2003).

In prior work related to technology innovation enabled by R&D investments, transaction costs and hold up have traditionally shaped the decision to make versus buy (e.g., Williamson 1985; Grossman and Hart 1986; Pisano 1990). These issues can loom large in settings in which product or process innovation is outsourced to a third party that uses the buyer's dependence on the third party to hold up the buyer. These risks will be particularly large when the buying firm must make significant firm- and relationship-specific investments. However, while the acquisition of readymade software will involve firm- and relationship-specific investments such as software configuration, many aspects of the service that are provided by the vendor – such as licensing costs, support, and core software functionality – may be relatively standardized. As a result, problems arising directly from vendor hold-up may be less acute than in other settings.

2.3 Sources of complementarity and substitution

Firms often use readymade and developed software together (Bresnahan and Greenstein 1996). In fact, complementarities – where the benefit of adopting readymade software is increasing in the presence of internally written software (and vice versa) —may also be present.

Complementarities between building and buying software may arise for several reasons. First, as highlighted in research on R&D and innovation, firms may need to develop internal expertise to modify and extend innovations developed elsewhere (Cohen and Levinthal 1989, 1990). In particular, the ability to utilize external innovations may depend on a firm's absorptive capacity, defined as a firm's ability to assimilate, transform, and apply external knowledge (Cohen and Levinthal 1989, 1990).

External sourcing can benefit from internal knowledge assets for several reasons. First, in-house knowledge assets may help firms to better utilize innovations that have been acquired elsewhere (Arora and Gambardella 1994). While this process has been most thoroughly documented within the context of R&D-enabled product and process innovation (e.g., Arora and Gambardella 1990, 1994), similar mechanisms hold in software. For example, due in part to the complexity of process innovation needed when implementing enterprise software, there exists significant knowledge transfer between readymade software developers, third party consultants, and business users during its implementation (Ko, Kirsch, and King 2005). Knowledge transfer is needed to ensure that software is aligned with business processes (Davenport 2000). This process of aligning software with the needs of the firm can also mean that the firm needs to deploy additional functionality that is not included in external offerings. Historically, readymade enterprise software systems like enterprise resource planning (ERP) have deployed "user exits" into their products so that it is easier to deploy internally developed and additional third-party systems into the core ERP system (Goodhue et al 2009). Related, readymade software developed by third parties can be used to augment in-house systems.

Further, in-house knowledge assets can also help firms to evaluate new external innovations (Arora and Gambardella 1994). Prior experience will be helpful both in evaluating where new software projects can be used in the organization as well as in evaluating the software offerings of competing vendors. Related, prior experience may help using firms in their plans to extend the functionality of existing software projects. For example, ERP projects are often described as multi-year journeys in which new features are implemented over time (e.g., Davenport, Harris, and Cantrell 2005).

Absorptive capacity is often defined as a function of prior relevant knowledge. Thus, internal investments in innovation have the secondary benefit of developing absorptive capacity (Cohen and Levinthal 1989). Within the context of IT-enabled business process innovation, absorptive capacity is frequently viewed as a function of a firm's prior IT investments (Chang and Gurbaxani 2012; Huang et al 2022).

However, recent work highlights that the knowledge to deploy AI systems may have both industry and technology specificity as in vintage-specific human capital (Chari and Hopenhayn 1991; Choudhury, Starr, and Agarwal 2020). As a result, the deployment of AI systems likely relies at least in part upon new training and skills that had not been acquired from prior IT investments (Allen and Choudhury 2022; Choudhury et al 2020). In our setting, investments in AI systems developed in-house may help firms develop the absorptive capacity to better identify opportunities available in and better exploit externally developed AI systems.

While the bulk of prior literature has highlighted the potential for complementarity between internal and external resources for innovation, substitution is also a possibility. This is particularly the case at the level of a particular piece of software functionality. Historically, while a firm might extend functionality from readymade software (e.g., a module for processing and reporting firm financials) using developed software, the original piece of readymade software functionality replaces that which could have been developed internally. This example highlights how the extent of complementarity or substitution will depend in part upon the level at which the software innovation is defined. As the unit of innovative output is defined more narrowly, we are more likely to observe substitution and less complementarity. Indeed, prior literature has argued the incidence of "make and buy" in organizations may sometimes reflect different inputs (Krzeminska et al 2013). Within our setting, particular software functionality or point solutions are more likely to be deployed internally or externally, but not both. However, software is often deployed as part of a system of business and process changes and software changes, each of which may be sourced differently.[5]

Due in part to data limitations, we will follow prior work that has examined complementarity and substitution between internal and external innovation and define our unit of analysis broadly, as a firm-decision to deploy AI. As a result, we are more likely to observe complementarity than if we studied the sourcing of particular software applications.

2.4 Key assumptions of approach

Firm decisions on how to source software are complex. As noted above, we will focus on two aspects of the sourcing decision: whether firms develop software internally or use ready-made software. This framing of the decision problem carries with it several key

[5] A related but slightly different perspective demonstrates that local inputs to IT-enabled business process innovation are substitutes (Forman et al 2008).

assumptions regarding other aspects of the sourcing decision. We clarify these and discuss the implications for our analysis.

First, we do not study whether software is developed on-premises or using cloud computing. One reason is that enterprise software today is commonly offered as software as a service (SaaS) (Roche, Schneider, and Shah 2020). Further, many of the issues highlighted in research on decisions to adopt SaaS (e.g., Xin and Levina 2008) are like those regarding other types of readymade software above.

However, because this decision remains unmodeled, two issues have the potential to influence our estimates of complementarities. Adoption of cloud computing may lower the costs of experimenting with new business applications in software (Jin and McElheran 2019; Kerr et al 2014). These types of experiments have been argued to be essential to the successful adoption of and obtaining value from AI (Bresnahan Forthcoming). Further, cloud computing may have fewer customization options to adapt software to idiosyncratic firm processes (Jin and McElheran 2019; Schneier 2015). Both issues – lower costs of experimentation and fewer customization options – will weaken the factors that contribute to the complementarities that are the focus of our research. From the standpoint of our model, adopters of readymade cloud software may have lower values of estimated complementarities than would otherwise be the case. This will weaken our estimated complementarities parameter.

Second, both package software investment and in-house development are sometimes accompanied by complementary software development work from third-party software contractors such as outsourcing firms. However, as we describe below, it is difficult to directly observe the context in which outsourcing firms are being used. Programming by such firms is bundled with other services that do not explicitly relate to programming, such as hosting and maintenance services. As we discuss in further detail below, due to data limitations we will not explicitly consider the employment of such contractors in our analysis.

3. Model

Two tests are widely used in estimating complementarities among organizational practices (Brynjolfsson and Milgrom 2013). The performance approach estimates the output or productivity implications of combinations of practices; In contrast, using the assumption that managers behave rationally, the correlation approach uses the co-occurrence of decisions to infer complementarity between them (Brynjolfsson and Milgrom 2013).

Because they rely on different sets of assumptions to identify complementarities, there are advantages to using both approaches together (Brynjolfsson and Milgrom 2013). However, several features of our setting make it difficult to employ the performance test. First, while the performance benefits of adopting a new technology like AI are likely to arrive with some delay (Brynjolfsson, Rock, and Syverson 2019, 2022; Dranove et al 2014), our data are very recent, making it difficult to observe the longer run performance implications of adoption. Our survey data on AI adoption is from 2020, and the most recent performance data that we can obtain is from the same year. Second, the inputs required to run performance regressions are widely missing for some countries in Europe (Gal 2013), further complicating any efforts to estimate a productivity model: We discuss this problem of missing data in further detail in the Data section. The issue of missing data is magnified when multiple years of data are required, as would be the case for estimating a performance model. As a result, we focus our efforts on the correlation test.

One method of testing for complementarities using the correlation approach would be to estimate a probit model of the decision to develop or use readymade software with an endogenous dummy variable. However, given that both of our decisions are binary, this would have an incoherence problem (Heckman 1978). Instead, we follow prior work by Gentzkow (2007) and Miravete and Pernías (2008) and estimate complementarities via discrete choice.

Our model assumes that agents, in this case firms, make their decisions according to the utility they derive from each of the options. Each firm has four possible options:

- not adopting any AI-based solution (we represent this option by the letter O),
- adopting a solution by implementing a readymade package (represented by the letter P),
- developing their own solution either "from scratch" or by modifying an open-source or commercial software package (this option is represented by the letter D),
- or both adopting a readymade package and engaging in development (represented by the letter B).

In our model, the utilities of the agents depend on some exogenous factors. The first factor that influences their utility is the sector, or industry, the firm operates in. This parameter denoted α_{k_i} in the equations below (k_i being the sector to which agent i belongs), represents the utility of a company of that sector obtains for choice k. As described in further detail below, we allow the utility that the agent derives from a particular sourcing choice to depend upon firm- and location- specific factors such as firm size and age, among others. This is represented by E_i, which is multiplied by a coefficient β that is estimated based on the data.

Identification of complementarities in our model relies upon the presence of an exclusion restriction (Gentzkow 2007): in our setting, this is a variable that influences one type of sourcing strategy (P or D) but not the other. The exclusion restriction is based on the distance to leading European non-profit institutions working on AI research, and is motivated by recent approaches using US data that have used firm connections to educational institutions active in AI research as an instrument for AI adoption (Babina et al Forthcoming). Distance to a leading AI institution will influence adoption of AI software that requires in-house development through labor market effects as well as through possible knowledge spillovers from leading AI researchers in such institutions (Bessen, Cockburn, and Hunt 2021). However, proximity to leading AI institutions should not directly influence the likelihood of readymade software that is likely produced at a distance from the firm.[6] We provide further details on the motivation for our exclusion restriction and its construction in the Data section below. We denote the resulting "Distance to Leading AI Research Institution" W_i.

Each agent is allowed to have an idiosyncratic preference, or taste, for the implementation of ready-made solutions or new software development. This term,

[6] For an earlier, related, exclusion restriction for readymade ERP software using distance to the headquarters location of SAP, see Bloom et al (2014).

denoted ε, is distributed according to a multivariate normal of mean μ (which might equivalently be considered as an intercept leaving the taste coefficient zero-centered) and a covariance matrix Σ.

Finally, we add a term enabling the identification of complementarity or substitution among the alternative. This term, Γ, is to be interpreted, as shown in Gentzkow (2007), as a sign of the presence of complementarity if it is positive and of substitution if it is negative. We allow the complementarity term to vary based on agent i's sector k and denote this as Γ_{k_i}

The utilities of agents are computed as follows:

$U_i(O) = 0$

$U_i(P) = \alpha_{Pk_i} + \beta_P E_i + \varepsilon_{Pi}$

$U_i(D) = \alpha_{Dk_i} + \beta_D E_i + \delta_D W_i + \varepsilon_{Di}$

$$U_i(B) = U_i(P) + U_i(D) + \Gamma_{k_i}$$

Once the utilities are computed, the probability of an agent choosing any of the options is proportional to the utility she derives from it through the intermediary of a logit link function. As such, for option $x \in C := [O, P, D, B]$, the probability of option x being chosen is given by

$$P_i(x) = \frac{e^{U_i(x)}}{\sum_{y \in C} e^{U_i(y)}} \qquad (1)$$

This model corresponds to a variant of the logit utility model as detailed in McFadden (1973). However, this last equation relies on an axiom of Independence of Irrelevant Alternatives (IIA), which states that the odds ratio of an alternative being chosen over another remains constant no matter the full choice set.

Because this condition is quite restrictive and not verified in many experimental settings, we favor the mixed logit model. In this model, we allow the coefficients α, β and δ to vary at the level of the individual according to a certain distribution. This possible alternative, evoked in Gentzkow (2007), is also recommended as a possible way to overcome the limitation imposed by the IIA assumption.

The estimation of the model is done under the form of a Bayesian hierarchical model.[7] As mentioned in Train (2009), this method alleviates numerical difficulties associated with the Simulated Maximum Likelihood one would run into using a multivariate probit. Considering the large number of respondents (several thousands, as detailed in the next section), this is a significant advantage of the Bayesian technique. Moreover, recent advances in the fields of computational statistics, with the advent of more efficient Markov Chain Monte Carlo algorithms and high-level libraries,[8] makes the limitations evoked by Train (2009) less relevant.

In order to be able to discriminate between differences in pattern across sectors, the complementarity term varies according to the sector in which a firm operates (i.e. to

[7] Gelman et al. (2013)

[8] We use Phan, Pradhan and Jankowiak (2019) for the estimations and Kumar et al (2019) for the computations of the convergence statistics.

estimate the coefficient as Γ_{k_i}). This model allows for a rich interpretation of the data as, considering the broad scope of the survey (see next section), there is little reason to think the magnitude of complementarities or substitution, if they exist, are of the same nature in a high-tech company as in a company active in the agricultural sector. In fact, it is highly likely that both technological and managerial resources and practices are sufficiently different in different sectors. These differences warrant separate estimates of this term across sectors.

As in many of the papers in this prior literature, our data rely on a cross-sectional survey, creating challenges for the identification of complementarities both because of unobserved organizational features that may create co-occurrence of decisions (for surveys and further detail, see Arora 1996; Athey and Stern 1998; Brynjolfsson and Milgrom 2013) and also because of heterogeneity in the types of innovation in AI within firms that may bias us towards observing both internal and external development for different types of AI innovation (Veugelers and Cassiman 1999). As we discuss in further detail below, we frame a set of issues that are both relevant for the adoption of AI and have not been widely explored. We acknowledge the limitations of our approach and in the Discussion section discuss ways to extend it to new settings to further evaluate the salience of our findings.

4. Data

The data used in the present article originates from a survey commissioned by the Directorate General of Communications Networks, Content & Technology from the European Commission and performed by the well-known survey firm IPSOS. It was originally commissioned to gather quantitative data on AI adoption across the 27 countries of the European Union.

The sampling strategy was defined by the Directorate General (DG) together with IPSOS, with the aim of representing the universe of European enterprises and to fit the data collection objective to align with the requirements of the DG. The sample unit was enterprises (as defined by Eurostat), which may theoretically comprise one or more establishments. However, for this survey, only respondents from the headquarters of the firms were interviewed. The target respondent was described as “an employee who is familiar with how technology is used within the firm”. (Going forward we will use the terms “enterprise” and “firm” interchangeably.)

This survey was conducted between January 16, 2020, and March 9, 2020, via computer assisted telephone interviews (CATI)[9]. The response rate varied according to the countries but ranged between 5 and 19% (with an average of 7% over the sample). There was no incentive provided to respondents. The complete survey is available in the Appendix to Kazakova et al (2020).

The dataset analyzed lacks information about the location of some firms and, similarly, not all countries from the dataset belong to the EU and have NUTS2-level statistics reported by Eurostat. Concretely, this means that we exclude all the observations for Norway, Iceland, as well as Malta and Cyprus (due to the relatively low number of observations). Except where noted, in the descriptive statistics below we report results

[9] A copy of the survey questionnaire is available in Kazakova et al (2020) and is reproduced in the appendix of the present paper.

using this sample of 8730 observations. Appendix Table A.1 provides the distribution of firms across countries, showing broad coverage across countries within the EU with an oversampling of smaller countries.

Besides the geographical reach, the dataset is also cross-industry. While not completely consistent with NACE codes, the question eliciting the industrial sector is fairly similar to the standard. The sizes and sector representation of the sampled firms are relatively consistent with Eurostat's Structural Business Statistics, which provides this information at the level of the Member State. According to Kazakova et al. (2020), the weighting efficiency across countries ranged from 79% to 100%.[10]

Table 1 shows the distribution of observations across sectors in our data. We also compare the share of firms by sector in our data to the comparable share in the Eurostat Structural Business Statistics. The data sets are not directly comparable: The Eurostat data do not include sectors such as finance, insurance, and real estate; human health; and the public sector. As a result, our sectoral shares from the Eurostat data exclude these sectors from the total, which has implications for the share computations for all sectors in the data. Further, some sectors in our data are reported together in the Eurostat statistics.

Despite these limitations, the table shows that our data have broad representation across sectors, with an oversampling of the manufacturing sector relative to the population of firms covered in the Eurostat data.

Table 1: Survey sample size, per industry

Industry	**Observations**	**Share (EU share)**
Accommodation and Recreation	345	3.95% (7.94%**)
Agriculture, Forestry and/or Fishing	326	3.73% (0.07%)
Construction	1033	11.83% (15.25%)
Finance, Insurances and Real Estate	445	5.10% (*)
Food	387	4.43% (7.94%**)
Human health	368	4.22% (*)
IT	360	4.12% (4.97%)
Manufacturing	1671	19.14% (8.89%)
Other technical and/or scientific sectors	830	9.51% (19.37%)
Public Sector	462	5.29% (*)
Trade, retail	1610	18.44% (24.51%)
Transport	587	6.72% (5.52%)
Utilities	306	3.51% (1.05%***)

*Table Note: This tally was obtained after reconciliation with Eurostat data (see above) * - Sector not reported in the Eurostat Structural Business Statistics; ** - Sectors reported together in Eurostat Structural*

[10] The weighting efficiency is a diagnostic statistic used in survey design. It measures the fit of the weighted responses to the target population. It is computed as the ratio between the squared sum of weights divided by the number of cases in the different categories and the sum of squared weights. The target for this statistic is usually to be between 80% and 100%, which is the case for most of the countries in the sample, with values between 70% and 80% being still considered as exploitable.

*Business Statistics under NACE code I; *** - Sum of NACE codes D (Electricity, gas, steam and air conditioning supply) and E (Water Supply; Sewerage, Waste Management and Remediation Activities)*

Appendix Table A.1 also provides the distribution by firm size. The sample does not include firms with fewer than 5 employees and significantly oversamples firms with over 50 employees relative to the distribution of firms in the EU. This choice was made so that comparisons could be made across all size classes of firms, given the large fraction of micro firms in the population.

Adoption of AI is increasing in firm size both in our sample (Kazakova et al 2020) and in other surveys of AI use such as the US Census Bureau's Annual Business Survey (Zolas et al 2020). Increases in adoption with firm size is common in studies of information technology (IT) adoption; indeed, as a result prior studies have sometimes conditioned samples on firms and sub-firm units of sufficient size (e.g., Forman, Goldfarb, and Greenstein 2005, 2008, 2012) to capture behavior among entities who are at risk of adoption. In short, the size distribution of firms in our sample will enable us to capture the behavior of the most active firms in our data in terms of AI adoption.

The survey is unique in the sense that it singles out several AI applications and includes questions on how firms implement AI, as well as the major hurdles they had to overcome when implementing applications in their organization. The survey also gathered the state of technology adoption and, if any AI application was adopted, the way it was adopted (e.g. through internal development, external consultants, readymade software, etc.). Although we only present a few aspects of the data here, more general descriptive statistics are available in the final report of the survey (Kazakova et al., 2020).

The survey distinguishes several applications based on artificial intelligence. We provide the list of application categories and how they were measured here.

1. Speech recognition, machine translation or chatbots, also known as natural language processing. Excluding grammar or spell checkers.
2. Visual diagnostics, face or image recognition, also known as computer vision
3. Fraud detection or risk analysis, also known as anomaly detection
4. Analysis of emotions or behaviours, also known as sentiment analysis
5. Forecasting, price optimisation and decision-making using machine learning algorithms. Excluding the use of classical statistical techniques.
6. Process or equipment optimisation using artificial intelligence. Excluding optimisation via Programmable Logic Controllers.
7. Recommendation & personalisation engines using artificial intelligence to produce customised recommendations, via matching algorithms or information retrieval. Excluding classical CRM systems or automated email campaigns.
8. Process automation using artificial intelligence, including warehouse automation or robotics process automation (RPA).
9. Autonomous machines, such as smart and autonomous robots or vehicles[11]
10. Creative and experimentation activities, such as virtual prototyping, data generation, artificial music or painting

[11] While this option might encompass self-driving car, the fact that they are not yet allowed on the roads in most geographies indicate that firms replying they have adopted those are likely indicating their use of industrial autonomous vehicle such as automated forklifts or drones for agricultural monitoring.

The possible answers to the adoption questions were the following: “I am not aware of it”, “We do not use it or have plans to use it”, “We currently use it”, “We have plans to start using it in the next 2 years” and “Don’t know”. Table 2, shown below, displays the adoption rate of the different applications in the sectors presented above in an aggregated fashion. There is significant variation in use and intention to use across applications. For example, the percentage of firms reporting that they are currently using a specific AI application ranges from a high of 13.4% for anomaly detection to a low of 2.6% for sentiment analysis.

Table 2: Adoption and usage of AI applications

Application	Don’t know	I am not aware of it	We do not use it or have plans to use it	We have plans to start using it in the next 2 years	We currently use it
Anomaly Detection	0.95%	13.10%	65.05%	7.50%	13.39%
Autonomous Machines	0.31%	3.57%	79.98%	6.84%	9.30%
Computer Vision	0.47%	4.75%	79.07%	6.76%	8.95%
Creative Applications	0.38%	10.17%	78.22%	4.02%	7.21%
Forecasting	0.72%	10.32%	68.95%	9.73%	10.29%
Natural language Processing	0.21%	5.15%	76.68%	8.00%	9.97%
Process Automation	0.38%	6.84%	69.43%	11.07%	12.29%
Process Optimisation	0.78%	10.74%	64.83%	10.93%	12.71%
Recommender Systems	0.72%	12.55%	70.71%	6.87%	9.14%
Sentiment Analysis	0.40%	10.85%	83.56%	2.61%	2.58%

This list of technologies was created after extensive review of the literature by the survey design team. It hinges on an application-based taxonomy to avoid having to resort to specialists to answer the survey (which would have likely been the case if the question was about specific algorithms). The purpose of this list of application categories was not to be exhaustive. Indeed, there is currently no agreement on a single taxonomy of AI applications within the AI literature. Moreover, a lot of techniques previously considered AI in the past are now considered part of the run-of-the-mill computer science. For instance, genetic algorithms were considered to be a subfield of AI for a long time but are now largely considered to be part of the subfield of discrete optimisation today. This is also the case, for instance, for logit regression, once the domain of AI specialists but which is largely considered as a model belonging to the standard statistical or econometric toolbox. An extreme case is optical character recognition (OCR), which mostly relies on neural networks (hence formally part of AI) but is now considered a mere feature of standard applications.

This difficulty of identifying and properly classifying AI technologies through respondent answers was tackled using a set of examples and counterexamples that were systematically presented to the respondents as they heard the options. This was done to set them in the correct frame of mind and ensure that they had an understanding of what was meant in the question. The drawback of the method is that doing so leaves some applications that one might have considered AI out of the scope of the survey.

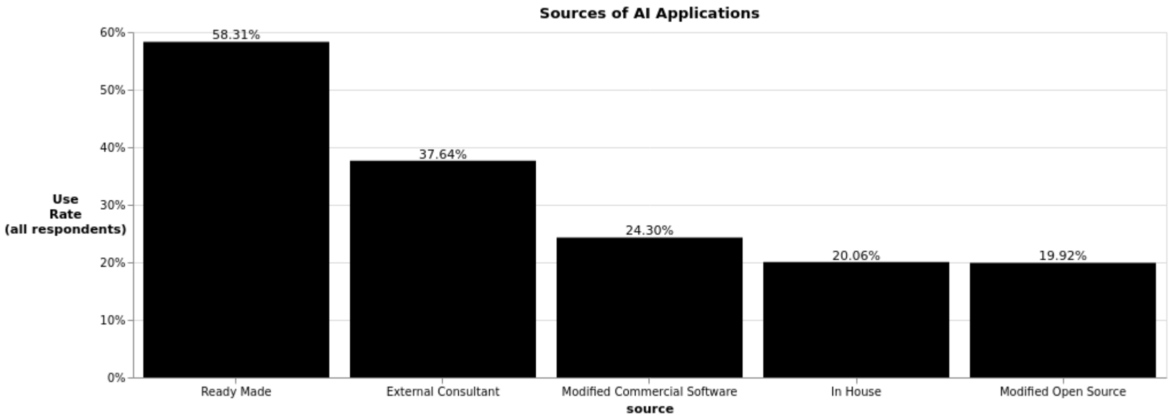
These examples also aim at mitigating the risk of having respondents count "cosmetic" AI applications (such as having small components of otherwise traditional systems) as full AI applications. Indeed, the examples provided involve for the most part relatively sophisticated training of machine learning models (i.e., requiring a large amount of data to obtain significant benefits for the business) or conception phases (meaning that it must be implemented by people specialized in artificial intelligence rather than by other IT specialists). Thus, while we capture the extensive margin of adoption our measure requires significant investment on the part of the businesses we study. While this approach is not a substitute for a real intensity of AI use, such a measure would probably be hard to insert in a large-scale survey anyway (because intensity of use depends crucially on the exact application one considers. For instance, it is difficult to imagine an intensity measure that would hold both for Natural Language Processing applications and Industrial Autonomous Vehicles alike).

Adoption rates are heterogeneous across sectors (see Figure A1 in the appendix). Some applications, such as anomaly detection, are widely spread across companies in IT or finance while others, such as process automation or optimization are predominant among companies in the manufacturing or utilities sectors. This should sound as a warning. Indeed, when talking about AI, we are in fact talking about a set of techniques that are used by different sectors in several ways. While, at the technical level, AI comprises a relatively narrow set of techniques (although the narrowness of the set depends on the definition one ascribes to the term), those techniques may be used to fulfill a broad array of purposes and, therefore, may be produced in different contexts, using a different mix of methods.

Another important point is that applications are not necessarily used "in a vacuum". Indeed, rather than being completely independent and mutually exclusive applications, AI implementations are often paired. This is, of course, linked to the business model, with some firms being more eager to favor algorithms and automated processes against labor inputs, but the bundles of applications can shed light on the ways companies use AI in their operations. To explore the extent to which firms adopt bundles of applications, in Figure A.2 we provide correlations between variables that indicate the binary adoption decisions of different applications (the last column in Table 2). While those remain descriptive statistics, they illustrate an underlying structure to the adoption decisions for these applications. Most notably, the highest Pearson correlation in our data is that between process optimization and process automation (0.39), while the lowest include those between sentiment analysis and each of process automation (0.09) and autonomous machines (0.10), and that between natural language processing and autonomous machines (0.11).

Finally, the data for the way the firm implements AI-based solutions comes from the second question of the questionnaire, which relates to the manner of implementation. The question reads as: "Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply." The possible options were: "We purchased software or systems ready to use", "We hired external providers to develop it", "We developed it fully in-house", "We modified commercial software or systems", or "We modified open-source software or systems”. The distribution of the different replies, among those respondents who have adopted at least one AI application, is shown in Figure 1.

Figure 1. Source of the AI-based solution implementation. The proportions represented here were computed on the set of respondents having adopted at least 1 AI-based application.



In the model, we distinguish between two possibilities: the one where firms have implemented ready-made solutions (the first reply option), and the one where firms either modified a commercial or open-source software or developed a solution in-house (the last three options). For simplicity, we will frequently refer to this latter option as developed software. As noted above, the choice “external consultant” was left out of the analysis below as it might be ambiguous; A firm can hire an external consultant to implement a readymade software package as well as to develop custom software. In the models below, it is therefore an unmodelled choice.Since the options could be selected simultaneously, we can compute a correlation matrix. This is done in Figure 2 below, which shows the correlation between implementation methods among the set of firms who adopt at least one AI application.

Figure 2. Pearson Correlation of implementation method of AI-based solutions, based on firms who have adopted at least one AI application.

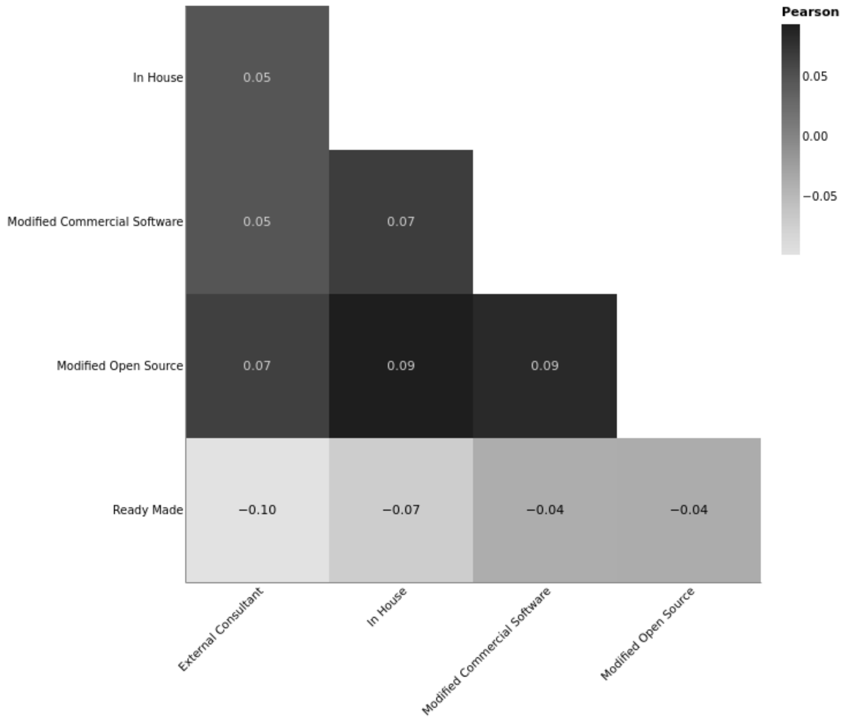
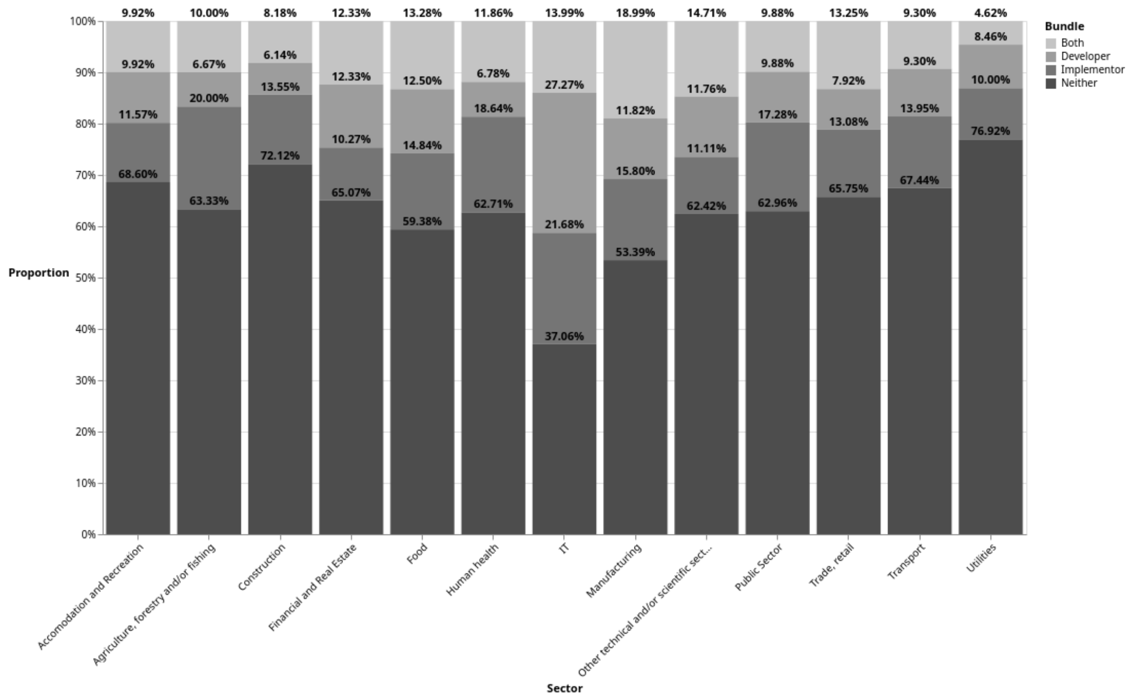


Figure 2 seems to indicate some substitution between the implementation of readymade solutions and the other methods, conditional on adopting AI. In contrast, other sourcing strategies tend to be clustered together. It is important to note that these results reflect neither complementarity nor substitution; they do not control for firm features that may influence adoption and since they are conditioned on adopting some type of AI they capture a different margin of firm activity than in the econometric model that is used below.

Figure 3 shows adoption rates and manner of adoption by sector. As will be described in further detail below, in constructing our final estimation sample we lose observations due to missing data. To assist in interpreting our final model estimates, Figure 3 shows these statistics using the final estimation sample of 3143 firms.

The figure shows substantial variation in whether and how firms adopt AI across sectors. The IT sector – both a potential provider of inputs for AI and also widely considered a "lead user" IT industry (Forman, Goldfarb, and Greenstein 2003; Jorgenson, Ho, Stiroh 2005) has the highest probability of being involved in development, either individually (27.27%) or in conjunction with readymade (27.27% + 13.99% = 41.26%). In contrast, utilities both has one of the lowest overall adoption rates and also the lowest probability of being a developer, when considering the total share of firms developing (8.46% + 4.62% = 13.08%). These differences motivate our modeling choice to allow the extent of complementarity/substitution to vary across sectors.

Figure 3: Distribution of type of AI adoption by sector



Number of observations=3143.

4.1 Control Variables

Recent work has shown that AI and ML adoption will be shaped by firm characteristics such as firm size, age, and industry (Alekseeva et al 2021; Babina et al 2020; McElheran et al 2023; Zolas et al 2020; Ameye et al Forthcoming). In addition to industrial sector (which was collected in the survey that is the source of our AI data (Kazakova et al., 2020)), we control for firm-level factors in our choice models using additional data from Orbis.

The Orbis database is a large-scale company information database that covers all countries and has been used as a data source in many articles (Kalemli-Ozcan et al., 2015). Using data from Orbis, we control for the age of the firm and its square (based upon the year of last incorporation) to control for potential differences in the IT infrastructure of the firm and skills of its employees that may be correlated with age. For example, young firms may be "digital natives" that have a higher propensity to adopt newer technologies (Jin and McElheran 2019). An extensive prior literature has investigated the relationship between the scale of a firm and its implications for IT adoption and resulting productivity; the balance of this literature has found a positive relationship between establishment and firm scale and adoption (e.g., Bresnahan and Greenstein 1996; Forman, Goldfarb, and Greenstein 2005; Brynjolfsson and McElheran 2016). To allow for differences in the propensity to adopt based on these differences, we control for the (log of) last known revenue and (log of) total employment. Since businesses with high capital intensity may be more intensive users of new technologies (Dinlersoz and Wolf 2018; McElheran et al 2023), we also control for (log of) total firm capital and whether the firm's capital is in the top 1% of its industry across the Orbis European database.

Location-specific factors such as population size and density have been shown to influence adoption; large locations may have complementary inputs that increase the net benefits to adopting IT (Forman, Goldfarb, and Greenstein 2005, 2008; Dranove et al 2014). To control for differences in the likelihood of adoption based on location size, we also enriched the data with information about the (log of) total population in the NUTS2 area where the respondent was located. The data was retrieved from the Eurostat website for the year of the survey (2020). The summary statistics of the controls and the exclusion restriction mentioned below are available in table A.4 in the appendix.

4.2 Motivation and construction of exclusion restriction

As noted above, the identification of complementarities relies upon the presence of an exclusion restriction (Gentzkow 2007): in our setting, this is a variable that influences one type of sourcing strategy but not the other.

The exclusion restriction for this model is based on the distance to leading European non-profit institutions working on AI research. We argue that distance to such leading institutions will shift the probability of developing software but not shift the probability of readymade. The starting point for this exclusion restriction is that for a firm to develop its own software, it will need access to some human capital related to the production of AI algorithms. One method of obtaining access to this human capital is through knowledge transfer from universities or through direct hiring of workers that have obtained educational training at universities or other related institutions of learning. Using similar logic, Babina et al (Forthcoming) instrument for AI investments using the focal firm's exposure to AI talent from leading universities. Their measure of AI investments is based upon the extent to which the firm has hired workers with AI skills, which are related to the production of AI algorithms.

To our knowledge, data on firm hiring networks do not exist for the European firms in our sample. As a result, we use variance in geography to capture access to human capital generated and associated with universities. Recent work using US data has found that investment in workers with AI skills will be greater for firms located near AI research hotspots (Bessen, Cockburn, and Hunt 2021),[12] arguing that distance will facilitate innovation related to AI either through worker movements or through localization of knowledge flows (e.g., Agrawal, Cockburn, and McHale 2006; Jaffe, Trajtenberg, and Henderson 1993).

Proximity to the human capital related to leading producers of AI-related research will be particularly valuable for developing software that requires deep knowledge related to frontier AI algorithms. Such proximity has been found to be particularly valuable for innovation in new technologies in the early years of their diffusion (Bloom et al. 2021). That is, theoretically, proximity to research-producing institutions will be particularly valuable for the technical innovation that is required for developing software but less valuable for readymade software, for which business process innovation is likely to be more important relative to the technical innovation that is needed produce software that relies upon AI algorithms.

A potential empirical threat to the validity of our exclusion restriction is if proximity to leading AI producers is correlated with other location-specific characteristics that

[12] For research that has shown that distance to centers of innovation can influence adoption of an earlier enterprise IT technology, see Bloom et al (2014).

facilitate the use of readymade software. Firm location in large regions has been shown to increase the likelihood of adopting new IT technologies (Forman, Goldfarb, and Greenstein 2005, 2008) and has also been shown to influence the productivity of these investments (Tambe 2014). As a result, we allow the probability of developing or using readymade software to increase in the (log of) the local NUTS2 population.

In short, our identification assumption is that conditional on location size (which will benefit both developing software and using readymade software), decreases in the distance to a leading AI-producing institution will increase the probability of developing AI software but will not change the probability of readymade adoption. We probe identification concerns related to the risk that firms may self-select into AI-innovative regions by exploring the robustness of our results to a subset of firms in our sample that were incorporated prior to 2012, a period in which firms were not widely seeking to incorporate AI into products and processes. That said, a different threat to our approach arises if, conditional on our location size controls, there exist unobserved location-specific factors that are correlated with distance to leading AI-producing universities and which increase the likelihood of adopting readymade software.

To create our exclusion restriction, we gather data on AI publications from 2005-2010 through the OpenAlex database.[13] This database catalogues scientific publications and makes the information available to researchers through an API. The retrieval first involves filtering by time, topic, location, and type of institution. In the case of the topic, we chose to limit ourselves to works that OpenAlex identified as being part of the Artificial Intelligence "concept." This concept is attributed, according to the website of the database, based on "the title, abstract, and the title of its host venue". It is to be noted that, while the retrieval already yields a significant number of publications, we did not include concepts that might be subordinate to the concept of "Artificial Intelligence" and that we also left out the related but different concept of "Data Science." We included only non-profit institutions in our query; most such institutions will be educational (e.g., universities) but the measure also includes research institutes.

We chose to associate a publication with an institution if at least one co-author on the publication is from that institution. The institution is then geolocated using the latitude and longitude provided by OpenAlex. In the end, the exclusion restriction captures two related concepts: the number of AI researchers in an institution as well as their aggregated scientific output over the covered period (2005-2010). We focus on this earlier period because it precedes the widespread use of AI within firms. Based on this aggregate scientific output, we identify the institutions in Europe that are in the top 5% of AI publications among this group.

We then computed the great circle distance between the focal firm's location and each of the institutions in the set of top AI research producers, and took the smallest distance between the focal firm and any of these institutions (in kilometers) as the variable.

The above control variables and exclusion restriction are critical to our strategy of estimating complementarities. However, not all respondents could be cross-referenced across the datasets used to construct these variables. As a result, we lost some observations in the process of matching our survey data to Eurostat, Orbis, and OpenAlex. The variable that generates the largest number of missing values is the

[13] Available under the URL http://openalex.org/

distance to the closest research institution as it depends on geolocating the respondent, which is frequently missing in the matched Orbis database. It is single-handedly responsible for the removal of 1,769 observations. The rest of the missing values are due to the other controls (the other important loss is due to the company revenues which is responsible for 1,555 missing values). Table 3 shows the dataset size after the consecutive treatments to obtain the data that was used as the basis for the regressions.

Table 3: Estimation Sample Construction

Step	Observations Remaining
Original survey	9640
After matching with Eurostat	8730
After ORBIS Cross-reference	7132
After geolocating and filtering observations with missing values	3143

5. Results

5.1 Main Model

Table 4 shows the estimation of the coefficients of the model described in equation (1). This table shows some aspects of the posterior (i.e., after estimation) distributions of the coefficients corresponding to the means of the agent-level coefficients.
The first part of the table presents the parameter estimates of primary interest, those for the complementarity parameters Γ_{k_i} that vary by sector. The second part of the table shows the sectoral parameters α_{k_i}, while the last part of the table shows the parameters related to the controls β. For the choice of developing or adapting software, we also include the parameter estimate δ_D for the distance to closest top AI institution.

Table 4. Coefficients for the main model.

Aspect	Mean	SD	HDI 3%	HDI 97%
Both Developing and Ready-Made (Complementarity)				
Sectors				
Agriculture, forestry and/or fishing	0.038	0.821	-1.454	1.625
Accommodation and Recreation	0.527	0.554	-0.526	1.579
Construction	0.509	0.466	-0.381	1.373
Financial and Real Estate	0.737	0.564	-0.329	1.803
Food	0.185	0.575	-0.904	1.267
Human health	0.127	0.671	-1.153	1.401
IT	-1.757	0.757	-3.158	-0.348
Manufacturing	0.645	0.353	-0.024	1.291
Other technical and/or scientific sectors	1.057	0.551	0.023	2.089
Public Sector	-0.113	0.644	-1.292	1.125
Trade, retail	1.008	0.429	0.196	1.807
Transport	0.427	0.564	-0.616	1.525
Utilities	0.112	0.718	-1.247	1.478
Developing or Adapting				
Intercept	-2.269	0.476	-3.129	-1.333
Sectors				
Agriculture, forestry and/or fishing	-0.527	0.799	-2.034	0.941
Accommodation and Recreation	-0.283	0.603	-1.443	0.829
Construction	-1.179	0.603	-2.357	-0.073
Financial and Real Estate	0.062	0.564	-1.021	1.094
Food	0.224	0.613	-0.935	1.319
Human health	-0.529	0.632	-1.705	0.673
IT	1.843	0.553	0.763	2.852
Manufacturing	0.187	0.535	-0.837	1.190
Other technical and/or scientific sectors	0.093	0.556	-0.954	1.111
Public Sector	-0.297	0.660	-1.495	0.968
Trade, retail	-0.776	0.615	-1.898	0.367
Transport	-0.395	0.579	-1.474	0.692
Utilities	-0.995	0.670	-2.300	0.205
Implementing Ready-Made Solutions				
Intercept	-1.176	0.477	-2.033	-0.256
Sectors				
Agriculture, forestry and/or fishing	0.229	0.709	-1.107	1.541
Accommodation and Recreation	-0.570	0.600	-1.751	0.532
Construction	-0.382	0.534	-1.403	0.632
Financial and Real Estate	-0.718	0.605	-1.856	0.399
Food	-0.089	0.600	-1.211	1.041
Human health	0.481	0.707	-0.807	1.778
IT	1.378	0.752	0.052	2.874
Manufacturing	0.268	0.491	-0.665	1.184
Other technical and/or scientific sectors	-0.761	0.607	-1.889	0.369
Public Sector	0.104	0.625	-1.090	1.264
Trade, retail	-0.378	0.541	-1.362	0.623
Transport	-0.527	0.602	-1.687	0.597
Utilities	-1.134	0.731	-2.517	0.205
Controls and Exclusion Restriction				
Distance to Research Institution	-0.151	0.107	-0.354	0.054
Developing or Adapting				
Number Employees	-0.098	0.082	-0.249	0.057
Age	0.058	0.076	-0.085	0.201
Age^2	-0.045	0.084	-0.214	0.101
Capital	0.013	0.082	-0.133	0.167
Capital Dummy	0.027	0.073	-0.105	0.165
Revenue	-0.128	0.133	-0.369	0.126
Population in NUTS2	-0.035	0.139	-0.296	0.227
Implementing Ready-Made Solutions				
Number Employees	0.021	0.082	-0.131	0.178
Age	-0.071	0.121	-0.287	0.152
Age^2	0.184	0.084	0.022	0.338
Capital	-0.009	0.080	-0.165	0.141
Capital Dummy	-0.095	0.062	-0.211	0.025
Revenue	-0.045	0.100	-0.235	0.138
Population in NUTS2	0.075	0.101	-0.119	0.258

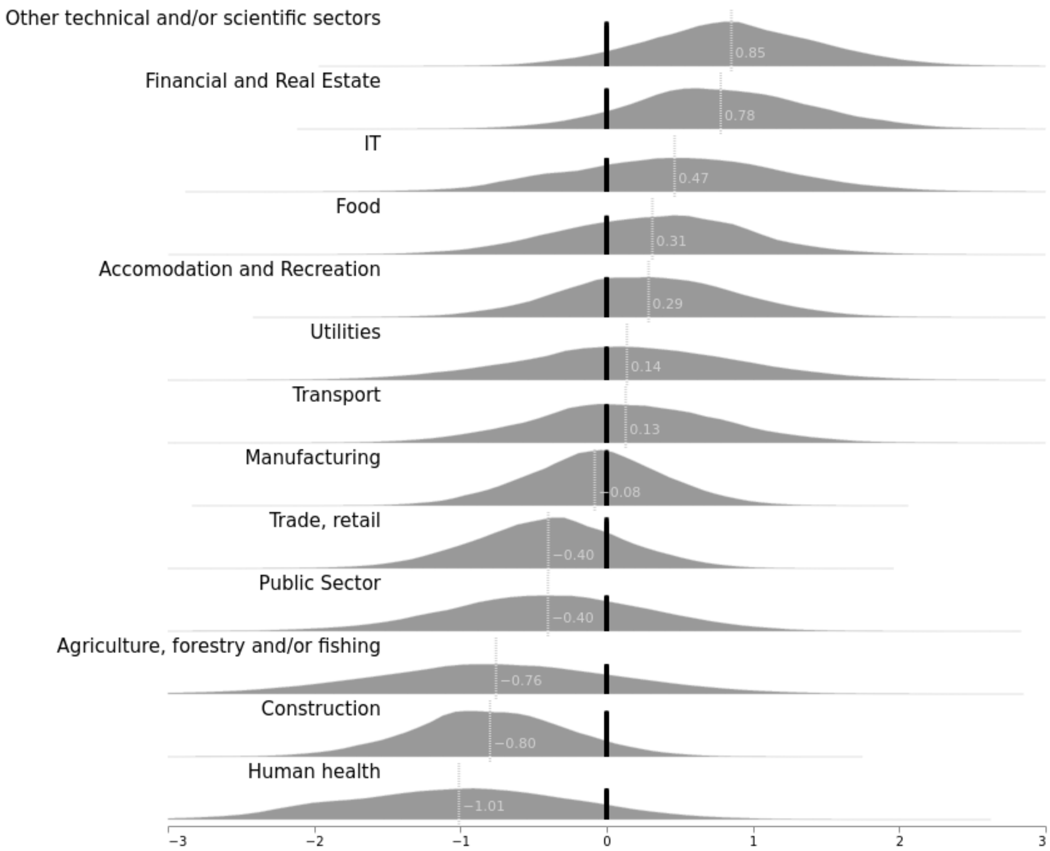
Table Note: *SD stands for Standard Deviation and HDI means Highest Density Interval, the interval concentrating most of the density of the posterior.*
N. Observations: 3143

Reflecting the low adoption rates in our sample, the estimation shows that the relative net utility of adopting AI solutions is still, on average, negative. This is evidenced by the negative intercepts. The sectoral coefficients for the "Implementing Ready-Made Solution" and "Developing or Adapting" options are mostly centered around zero. The mean of the parameter estimate for our exclusion restriction, distance to a top-tier research institution, is -0.151 and the Highest Density Interval ranges from –0.354 to 0.054. Thus, most of the distribution sits below zero which is consistent with our earlier argument that firms that are closer to such institutions will benefit from access to human capital that will facilitate the development of software.

Of more interest is the analysis of the difference in the sector coefficients between the "developing or adapting" option and the "implementing ready-made solutions" option. These are shown in Figure 4. In the chart, the average firm in sectors for which the distribution of the statistic is to the right of the y-axis prefers developing or adapting their AI solutions while the typical company in sectors on the left of the axis favors implementing ready-made solutions.

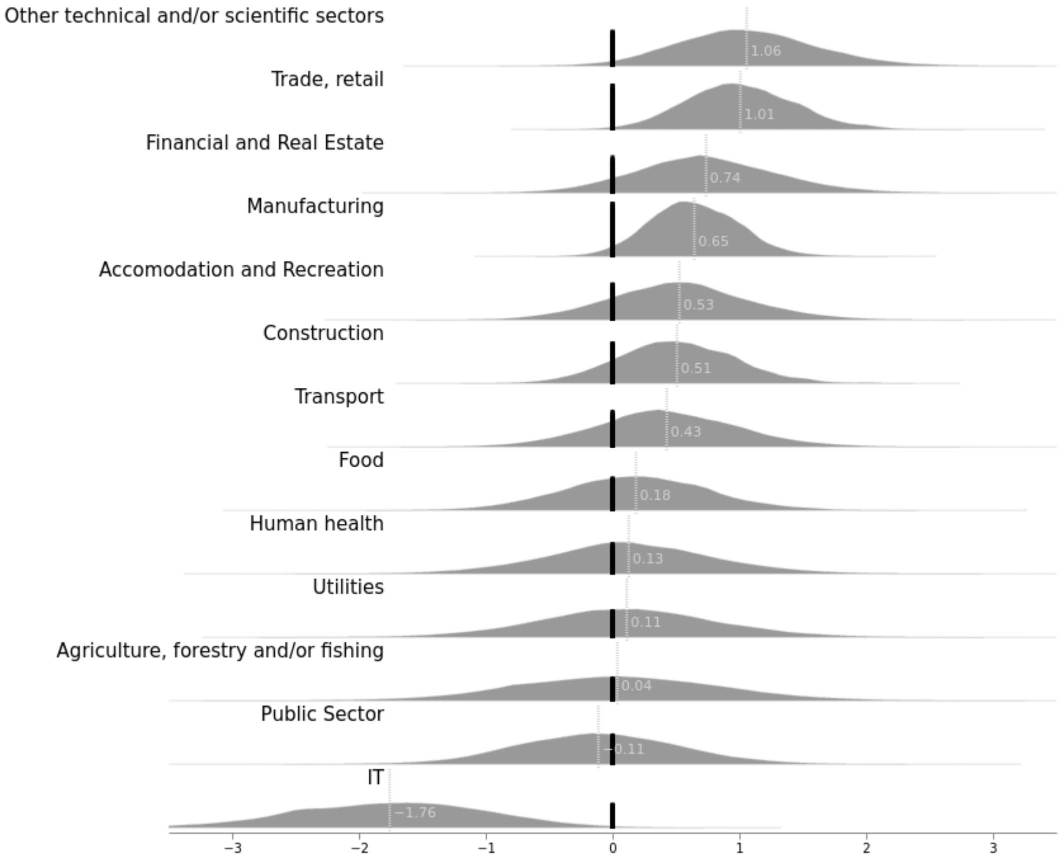
The financial and scientific sectors and, to a lesser extent, IT, seem to prefer developing and customizing. On the other hand, agriculture, construction, and human health prefer readymade. There may be several reasons for these cross-sector differences. One, as noted above, is that historically there have been persistent cross-sector differences in the availability of internal human capital to facilitate the development and adaptation of software (e.g., Bresnahan and Greenstein 1996). Second, there are systematic differences in the nature of applications used across sectors. Some AI applications may be more mature or may be like existing applications related to predictive analytics that are based on technologies that may have preceded AI and that may already have been developed by existing large vendors. Third, the data used in certain types of AI applications may be associated with significant security or privacy concerns. If developed software is less secure, this might give rise to a sectoral preference for readymade software. This latter concern could be one reason for the large negative coefficient on human health.

Figure 4. Representation of the differences of sectoral intercepts for developing and implementing ready-made solution. A higher score here indicates a sectoral preference for developing or adapting.



A second aspect of the development process is whether adopting a ready-made AI-based solution is a complement or substitute to developing one's own solution (or customizing a commercial or open-source solution). Because the internal human capital and external application needs likely vary across sectors, we allow our Γ_{k_i} parameter, the estimate of complementarity or substitution between sourcing strategies, to vary across sectors. These sector-specific parameters are displayed in Table 4 under the option "Both Developing and Ready-Made" and represented graphically in Figure 5.

Figure 5. Representation of the sectoral complementarity coefficients. A higher score here indicates a preference for using both ready-made solutions and producing new software.



There is a clear preference in the scientific, retail, finance and real estate, and manufacturing sectors for complementing ready-made packages with custom development. The mean values of the accommodation and recreation, construction, and transport parameters are also positive, though there is substantial within-sector variation.

Perhaps surprisingly, the only sector that shows strong evidence of substitution is IT. Given the data that are available to us, it is difficult to discern directly the reasons for this result, however we offer some potential reasons. Our theoretical framework highlights the value of learning in one sourcing strategy on the value of using another; in particular, how in-house development can help firms to better adopt, use, and extend readymade software. However, IT firms may have alternative channels through which to acquire these skills that are not available to firms in other sectors, including in-house research and product development, and access to research and skills in the IT field. IT firms may also be able to apply lessons learned from other types of technology investment to the deployment of AI, without direct investment in developing AI technology. Further research of these conjectures would rely on additional data related to firm R&D activities and related IT investments and are unfortunately outside of the scope of this study: we highlight it as an area for potential future research.

Figure 6 illustrates the effects of the complementarity term per sector. It computes the odds ratio difference between the propensity of using both readymade software along with some custom development that we observe in the data of the survey against the counterfactual propensity that would be observed if the complementarity coefficients were exactly 0. This chart represents the distribution of the medians of this difference of odds at the level of the respondent.

Concretely, a median of the distribution on the chart located at 100% means that, amongst firms in that sector, the median firm is twice as likely to use both readymade software and their own development together than if there were no complementarity.[14]

The lower whisker is systematically much longer than the upper one for sectors with complementarity and the contrary is observed when there is substitution (i.e., for the IT sector). This might be an artifact of the estimation method. Indeed, the priors of all coefficients were centered (for symmetric distributions) or originated with a sizeable density (for distributions that are one-sided) on zero. This might have brought part of the estimate closer to zero than what would have been observed if the priors were completely flat.

As one can see, the presence of complementarities in the model has important consequences, increasing the share of firms that choose the bundle with both ready-made and own development by a significant margin. This is especially true in the scientific and retail trade sectors where the utility derived from complementarities more than doubles the odds of choosing the bundle with both ready-made and custom software, even though the wide distribution of the complementarity coefficient might have brought one to suspect that the effect would be more diffused.

Figure 6. Ratio of median adoption between observed values and counterfactual model with complementarity term held to 0.

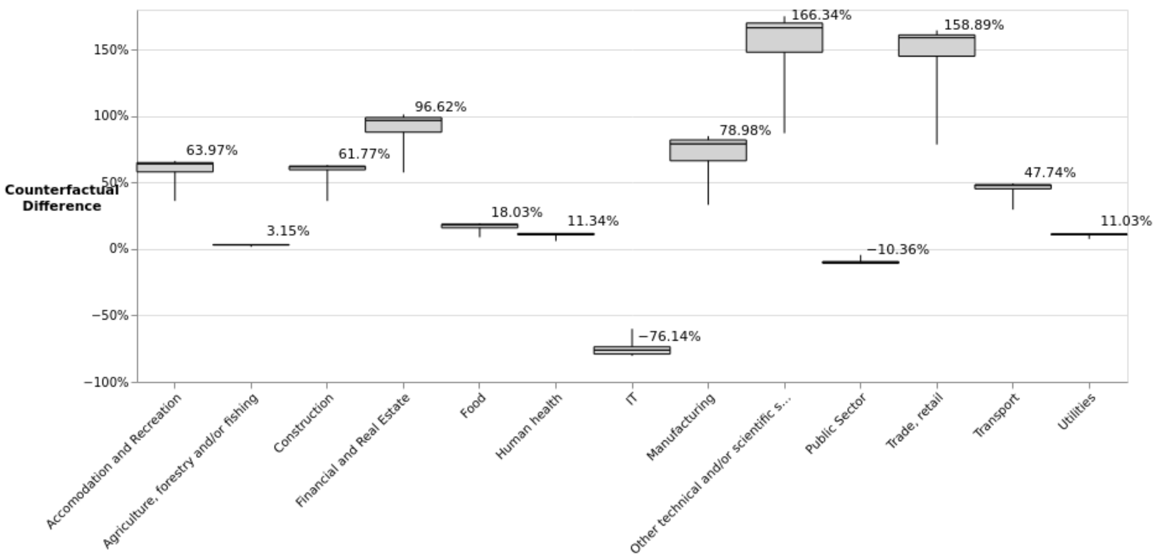


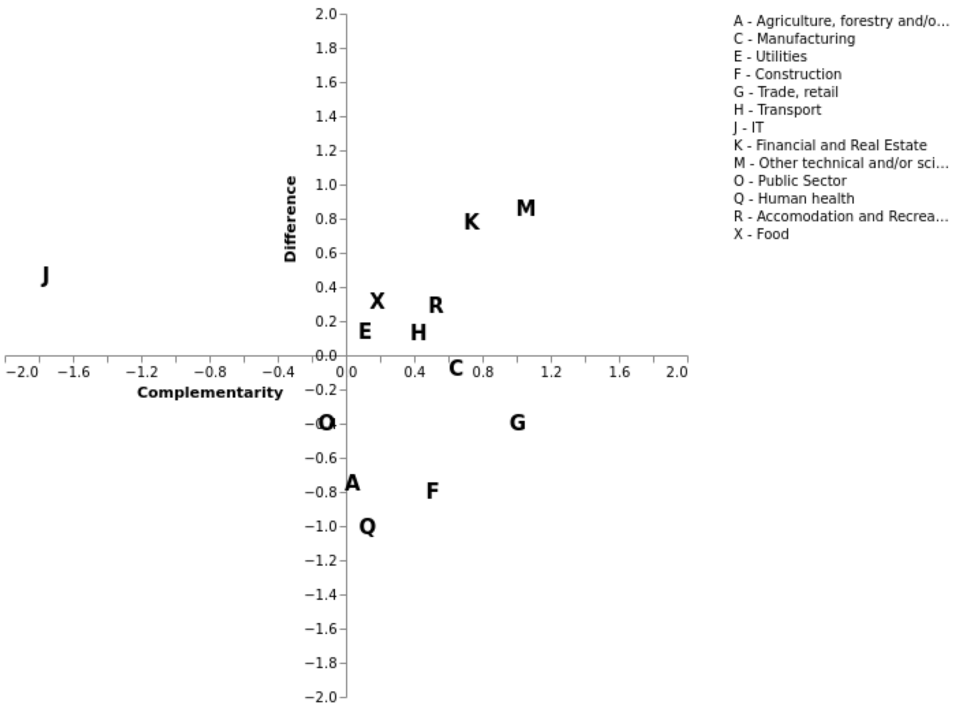
Figure 7, below, shows the different sectors on the difference/complementarity axes. It summarizes the results in Figures 4 and 5. Mirroring our discussion above, the figure highlights the varying preferences for complementarity and readymade (versus developing and adapting) across sectors. We turn to some of the highlights below.

[14] For the reader familiar with the concept of *do-calculus (Pearl, 2012),* this operation corresponds to the application of the do-operator to the complementarity. We fix the variable to 0 while keeping all other random variables fixed to analyze the effect on another random variable, the probabilities in the choice model in this case.

Firms in the IT sector have a large preference for developing or adapting solutions and display surprising evidence of substitution between readymade solutions and custom development. In contrast to the IT sector, firms in the scientific, retail trade, and finance and real estate sectors exhibit strong evidence of complementarities. However, they differ in their preference for readymade software versus developing and adapting. Both the scientific and finance and real estate sectors show strong preferences for developing software along with complementarity, while the mean of the retail trade sector displays a preference for readymade but with significant within-sector variance. The case of the scientific sector is particularly interesting as it is one in which the prediction benefits of modern AI tools can be applied directly to existing problems, while retail trade also has straightforward prediction applications related to forecasting stockouts and payment risks (Bresnahan Forthcoming). All three industries – scientific, retail trade, and finance and real estate – are widely thought of as traditionally lead user industries of IT (Forman, Goldfarb, and Greenstein 2003; Jorgenson, Ho, and Stiroh 2005).

Firms in the human health and agriculture sectors favor ready-made packages but on average show evidence neither of complementarity nor substitution. Finally, companies in the construction sector seem to prefer ready-made solutions but seem to find some value in the complementarity between such solutions and their own development or customizations.

Figure 7. Means of sectors on the difference-complementarity axes.



Notes: The vertical access denotes the difference in the mean of the distribution of sectoral parameters for developing versus implementing readymade solutions, displayed earlier in Figure 4 and denoting sectoral preferences for developing over implementing. The horizontal axis shows the mean of the sectoral complementarity parameters in Figure 5.

5.2 Robustness Tests

In this section, we detail two robustness checks to our main analysis. First, we examine the robustness of our results to a set of older firms in our data who have a lower risk of pre-sorting into locations in anticipation of their use of AI. Second, we re-estimate our model using a different model that relies upon a different set of distributional and identification assumptions.

5.2.1 Pre-Existing Firms

Our exclusion restriction uses the distance between the firm and the closest top-tier AI research-producing institution over the period 2005-2010. Motivated by work from Babina et al (Forthcoming), we use this period that predates the widespread commercialization of AI in part to mitigate risks that firms self-selected into regions in anticipation of their AI investments. However, if there is persistence in the strength of AI universities then firms might later presort into similar regions after AI becomes more widely commercialized.

To investigate the potential risks that this might create to our estimates, we re-estimate the model omitting firms that were incorporated before 2012. Indeed, this year is the one during which convolutional neural networks started winning competitions in the field of computer vision, which in turn sparked a sort of revival related to AI-enabled innovation.

Figures 8 and 9 replicate Figures 4 and 5 using the new sample (Table A.2 provides the complete set of results in the Appendix). Using this older set of firms, the estimation sample fell in size from 3143 to 2771.

The results show that the model evaluated on this sub-sample exhibits broadly the same characteristics as the one evaluated on the full sample. The sectors that prefer developing or adapting over readymade are finance, the scientific sector, and food, which were three of the top four sectors in terms of preference for developing or adapting in our baseline regression. The sector that changed the most was IT—for which the preference to develop is now weaker – perhaps because this is an industry that exhibits significant dynamism in terms of entry and exit and so who might be most influenced by this sample change. Similarly, the sectors that prefer readymade software remain broadly similar.

The interpretation of the complementarity parameters is also broadly similar: the scientific sector, retail trade, finance and real estate, and manufacturing remain industries with significant complementarities, and once again IT remains the only sector that displays significant substitution. To summarize, these results suggest that our earlier estimates are not substantially “contaminated” by self-sorting of firms into regions that have proximity to top AI institutions.

Figure 8. Representation of the differences of sectoral intercepts for developing and implementing ready-made solution. A higher score here indicates a sectoral preference for developing or adapting.

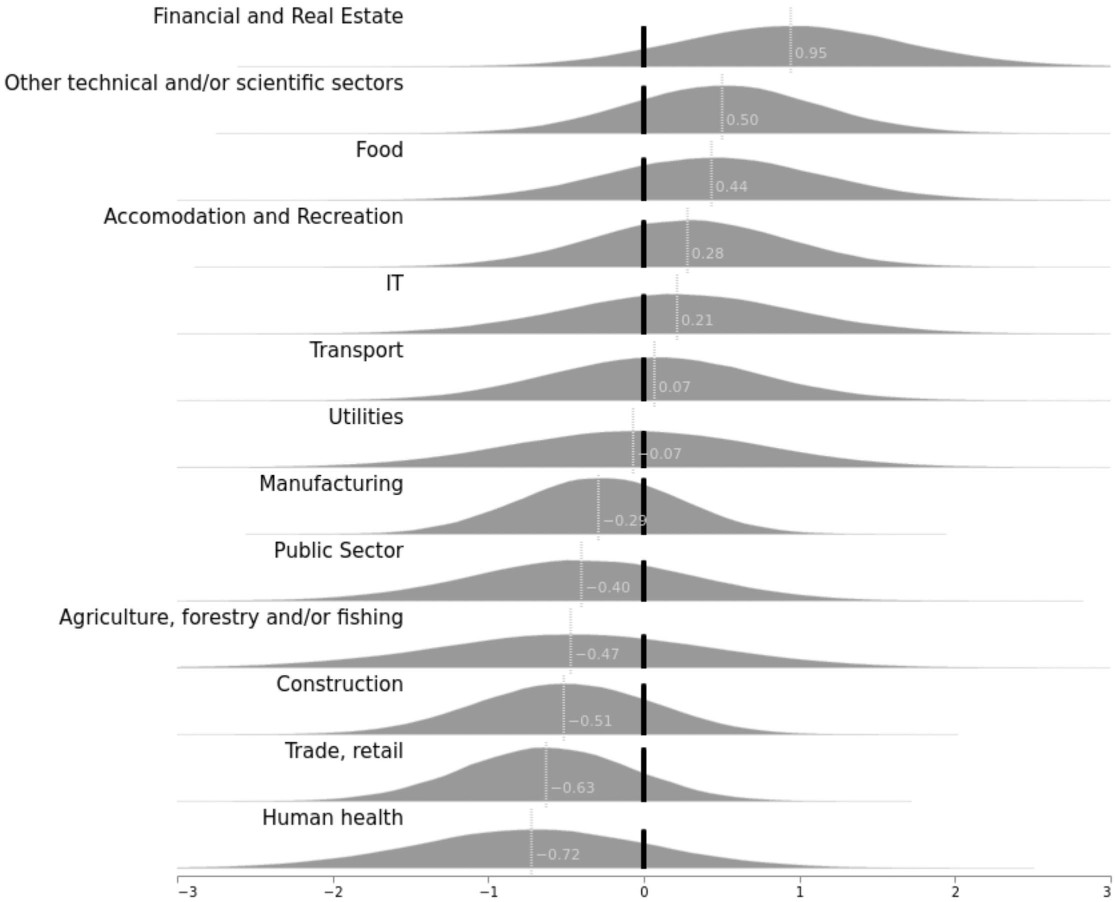
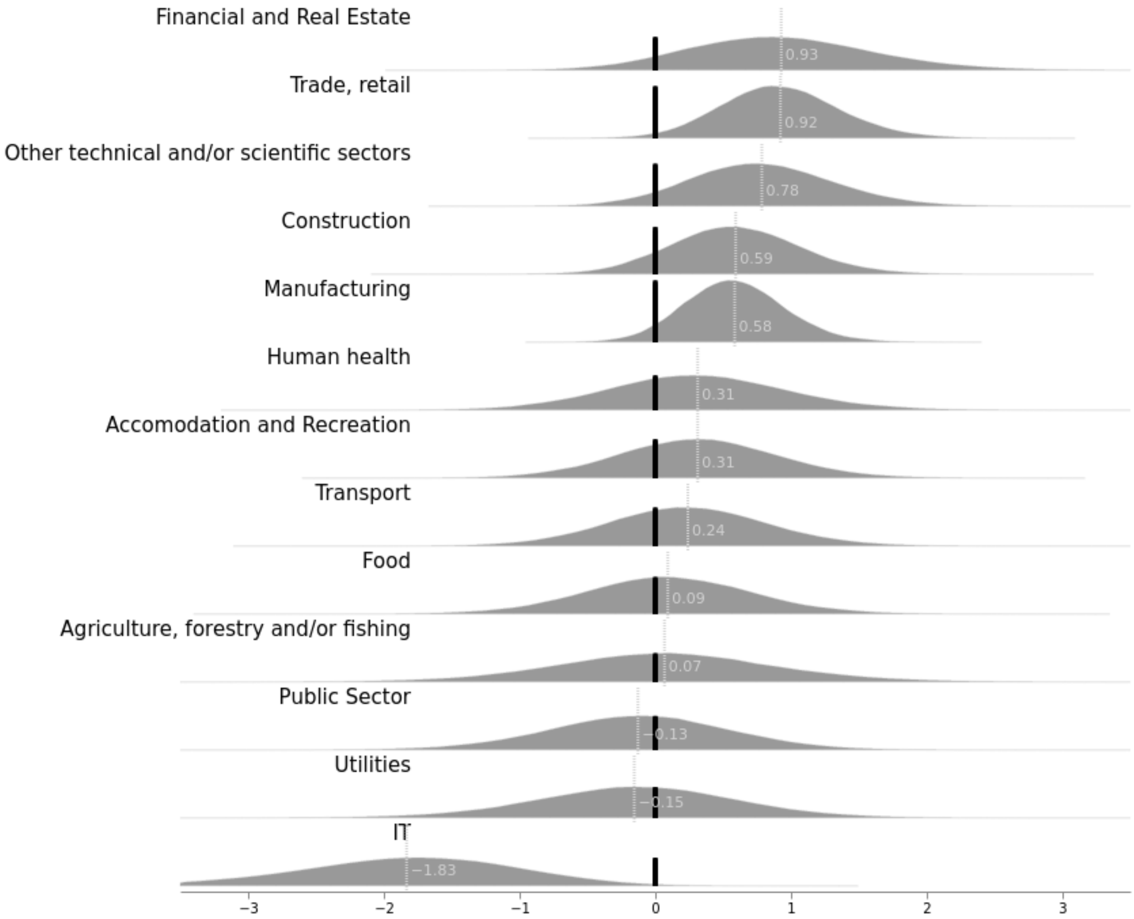


Figure 9. Representation of the sectoral complementarity coefficients. A higher score here indicates a preference for using both ready-made solutions and producing new software.



5.2.3 OLS models

As noted above, we estimate a choice model because our sourcing strategies are binary variables and so cross-sectional OLS estimation of one sourcing strategy on another may generate inconsistent estimates. For comparison, however, we also estimate linear models in which the dependent variable is one sourcing strategy (e.g., readymade) and in which the right-hand side variables include the other sourcing strategy (e.g., developing or adapting) and that sourcing strategy interacted with all our sectoral dummies to allow for heterogeneity in complementarity estimates. We also include all the other control variables from our choice regression on the right-hand side. We do not instrument for the right-hand side sourcing strategy, both because this approach will deliver inconsistent estimates (Arora 1996) and because the interaction of sourcing strategy and sectoral dummies generates many endogenous variables for which we would need to instrument.[15]

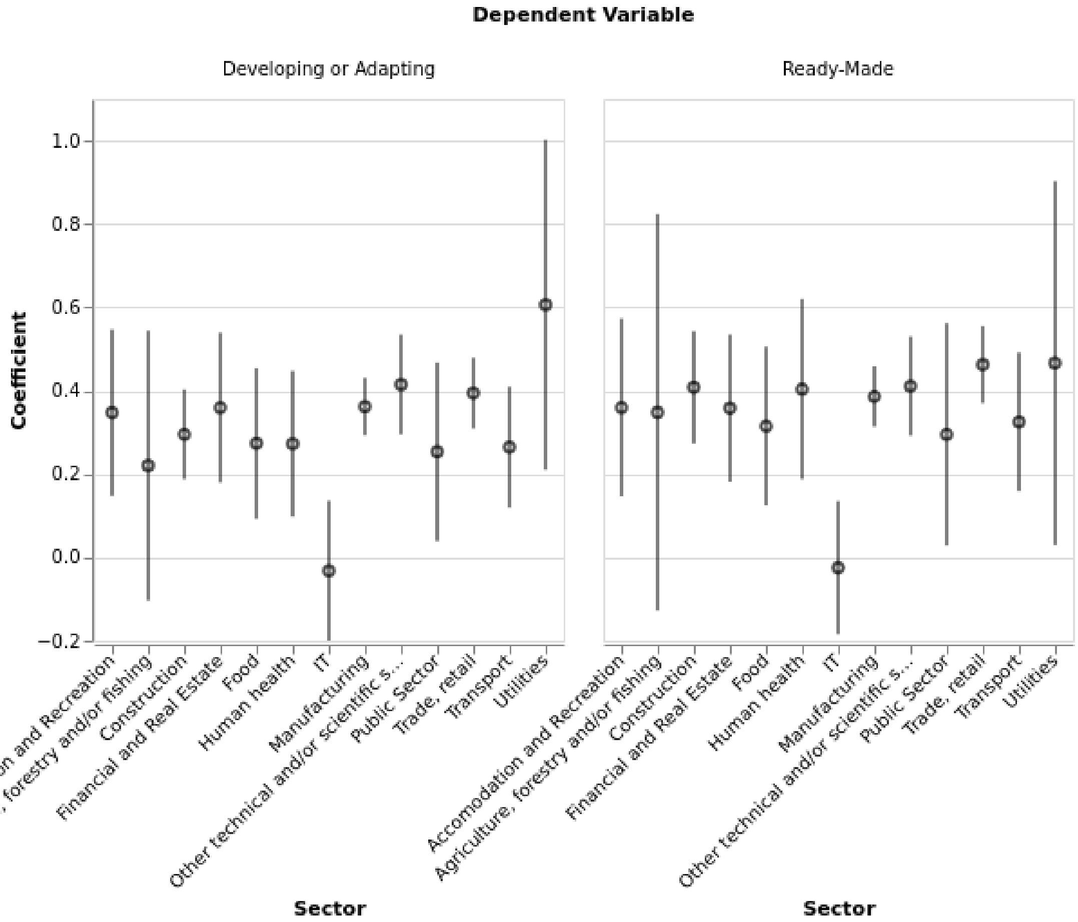
We present the regression results in Appendix Table A.3. In Figure 10 we present the marginal effect of the use of one sourcing strategy on the probability of using another

[15] In the model in which we regress readymade software on developing and adapting in-house, we experimented with instrumenting for the developing and adapting strategy and its interaction with each of our sectoral dummies using our exclusion restriction (distance to top AI institution) interacted with each of these sectoral dummies as instruments. Likely due to the large number of endogenous variables and instruments, the parameter estimates from this regression were quite noisy.

sourcing strategy, by sector. That is, the left side of the figure shows the marginal effect of ready-made software on the probability of developing or adapting (by sector), while the right side shows the converse: the marginal effect of developing or adapting on the probability of ready-made software.

While the estimates of the two models – our baseline and the linear model – are not directly comparable, some commonalities in the estimates are worth noting. In both sets of models, positive estimates on sectoral-specific complementarities are widespread, however, distributions of the implied complementarity estimates overlap significantly across sectors. Further, in both sets of models, the IT sector remains a significant outlier in showing evidence of substitution between sourcing strategies.

Figure 10. Marginal effect (in percentage points) of one sourcing strategy on the likelihood of using another sourcing strategy



6. Discussion and concluding remarks

If digital technology has the potential to yield an advantage to the firms who adopt it, then who adopts may prove a very critical question for firm growth and survival. Recent literature has examined the diffusion of AI, highlighting how its usage in firms is influenced by factors such as firm size and the availability of complementary human capital (Acemoglu et al 2021; Alekseeva et al 2021; Babina et al 2020; Chen et al 2021; McElheran et al 2023; Zolas et al 2020). We add to this recent work by providing evidence on how firms adopt AI solutions, examining the use of readymade and in-house developed software and the extent to which they are substitutes or complements. The extent to which readymade software is used, and can substitute for in-house development, has implications for whether the means of adoption can mitigate the need for AI-related skills identified in earlier work (Choudhury, Starr, and Agarwal 2020; Goldfarb, Taska, and Teodoridis 2023).

Using a cross-section of European firms, we estimate a discrete choice model to measure the extent of observed complementarities between two main sourcing strategies: purchasing a readymade software package and developing or adapting software. Our main estimates, based on the co-occurrence of sourcing strategies, allow the complementarity term to vary at the sector level. While the use of readymade software is common, it is often used in conjunction with in-house development. There is evidence of complementarity between sourcing decisions, especially in the science, retail trade, finance and real estate, and manufacturing sectors. The IT-producing sector is the only one in which we observe strong evidence of substitution. The presence of widespread sectoral complementarities suggests that investments in developing or adapting software may help firms to develop skills that they use to customize and extend investments in readymade software as well as evaluate new potential opportunities arising from package software development.

The findings of this paper could be extended further in future work, exploring the nature and source of the complementarity that we have observed in our data. For example, when complementarity is identified, is it because the firm has building blocks developed elsewhere (for instance, using an off-the-shelf automatic differentiation library such as TensorFlow) and/or has developed business-specific applications to suit the specific needs of the business? Or are such firms complementing end-to-end AI-based applications developed fully by external parties with other end-to-end AI-based applications developed in-house? These are important questions that will require new instruments besides the survey we have explored here.

More broadly, additional research is needed to explore how combining both sourcing strategies creates superior utility. Is it through functional enhancements? Through integration with other systems or functions within the firm? Or is it simply a necessity, an option without which adoption would simply be impossible?

We find little evidence that traditionally less technology-intensive industries are using readymade software to substitute for the human capital necessary to adopt new AI technologies, at least over our sample period. However, we remain at an early stage in the diffusion of AI technologies. Readymade software usually appears over time, once user requirements become more standardized and best practices are better understood. As a result, interdependencies between sourcing strategies may change in the future. Our purpose is to highlight a set of issues that have so far received limited attention and offer one framework for evaluating their importance. We leave it to future work to assess their future salience.

For management practice, complementarities between sourcing strategies matter on several counts. The presence of complementarities suggests that AI adoption may continue to be slow and entail significant costs for adopters. Since it requires both the implementation of readymade software and developing in-house solutions, the hybrid sourcing strategy that seems to appeal to many firms is probably the longest and most expensive path. Given the scarcity of AI experts, the necessity to rely – at least partly – on developing suggests that in the short run, readymade software may not allow firms without the requisite in-house skills to obtain significant value from their AI investments.

Our findings also have implications for how researchers measure AI adoption. Recent cross-industry studies have examined the causes and implications of investments in AI skills (e.g., Acemoglu et al 2021; Alekseeva et al 2020; Babina et al Forthcoming; Bessen, Cockburn, and Hunt 2021; Goldfarb et al 2023). This approach has enabled researchers to overcome the lack of systematic data on AI adoption and use that has limited research in the area (McElheran 2018; Seamans and Raj 2018). During the diffusion of prior generations of IT, diffusion began with in-house software and then packaged software was developed and diffused as user preferences stabilized and best practices became increasingly known. Our finding of widespread complementarity suggests that firm-level adoption measures based primarily on AI skills will capture much of the extensive margin of AI investment, however may miss some of the intensive margin. Further, adoption using skills-based measures may miss some adoption among firms who view these sourcing strategies as substitutes. Recent attempts to combine AI skill-based measures with those that capture skills related to external packages, such as those used in Babina et al (Forthcoming), will be a particularly useful tool to assess the importance these issues as AI-related software packages diffuse more widely.

We highlight limitations that point toward the potential for future work in this area. First, our estimation strategy relies on a cross-sectional analysis of the co-occurrence of sourcing decisions which, despite our controls for firm and location characteristics, may tend to bias us toward finding complementarities due to the potential presence of unobserved factors that may influence both readymade and developed software (Athey and Stern 1998; Brynjolfsson and Milgrom 2013). New data and estimation strategies that include time-varying data and analysis of firm performance will help to validate and further inform our understanding of sourcing strategies.

Another caveat is that among firms adopting several AI technologies, we observe sourcing strategies only in the aggregate rather than application by application. AI technologies may exhibit differences in the necessity or opportunity to combine readymade and in-house developed solutions. This is particularly striking because we consider here technologies that all belong to what people generally refer to as AI, which is itself one dimension of digital technologies. This points to the importance of taking technology specificities into account in measuring adoption and complementarities.

Related, because we focus only on AI adoption in the aggregate, the presence of different sourcing strategies could be capturing in part different sourcing strategies for different AI applications. This issue has been highlighted in earlier work on sourcing of innovations (Veugelers and Cassiman 1999). Future attempts to examine the adoption and implications of sourcing strategies could estimate models application-by-application in contexts where firms adopt a bundle of technologies. Further, the issues above are intensified due to our use of firm-level data, which aggregates the sourcing and adoption decisions across multiple units within the firm. Studies that use sub-firm unit data, such as that available through the US Census Bureau (Zolas et al 2020; McElheran et al 2023), could help to mitigate these issues.

In short, our research has taken first steps toward highlighting the importance of sourcing strategies to understanding the diffusion of AI. After developing a framework for understanding whether these approaches might be complements or substitutes, we offer some preliminary evidence. However, there are many ways in which our results could be investigated further and extended. We hope that our readers will do so.

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Online Appendix

Table A.1: Survey sample size, per country and company size

Country	Large (>250 employees)	Medium (50-249 employees)	Small (10-49 employees)	Micro (5-9 employees)	Total obs. per country	Share (EU27 Share)
Austria	23	80	100	130	333	3.84% (1.41%)
Belgium	22	100	130	140	392	4.53% (2.93%)
Bulgaria	15	85	145	135	380	4.39% (1.46%)
Croatia	17	35	70	76	198	2.29% (0.77%)
Cyprus	*1*	*10*	*15*	*15*	*41*	*0.47% (0.25%)*
Czechia	32	85	100	100	317	3.66% (4.57%)
Denmark	30	80	130	140	380	4.39% (0.98%)
Estonia	3	20	110	114	247	2.85% (0.37%)
Finland	15	50	160	144	369	4.26% (1.01%)
France	60	110	200	180	550	6.35% (13.19%)
Germany	54	160	160	180	554	6.40% (10.63%)
Greece	12	50	125	126	313	3.61% (3.04%)
Hungary	20	60	80	100	260	3.00% (2.86%)
Ireland	20	60	85	90	255	2.94% (1.16%)
Italy	15	100	230	250	595	6.87% (15.57%)
Latvia	10	60	80	100	250	2.89% (0.48%)
Lithuania	5	40	75	75	195	2.25% (0.98%)
Luxembourg	5	15	45	45	110	1.27% (0.15%)
Malta	*1*	*5*	*10*	*5*	*21*	*0.24% (0.13%)*
the Netherlands	100	130	130	140	500	5.77% (5.83%)
Poland	50	120	125	120	415	4.79% (8.84%)
Portugal	30	80	125	126	361	4.17% (3.92%)
Romania	32	100	135	121	388	4.48% (3.92%)
Slovenia	10	50	85	94	239	2.76% (0.64%)
Slovakia	5	15	90	100	210	2.42% (2.22%)
Spain	55	110	130	114	409	4.72% (11.48%)
Sweden	23	80	150	126	379	4.38% (2.82%)
Norway	*30*	*100*	*140*	*150*	*420*	
Iceland	*3*	*10*	*27*	*32*	*72*	
UK	125	125	125	112	487	
Total	**823**	**2125**	**3312**	**3380**	**9640**	
Share (EU Share)*	**7.68% (0.19%)**	**21.82% (0.89%)**	**34.87% (1.96%)**	**35.63% (96.96%)**		

Source: Kazakova et al (2020)

Table Note: Cyprus, Malta, Iceland and Norway and the UK were excluded from the final dataset. The first three on account of the few observations and Norway and the UK because of challenges in the merge with Eurostat data.

**- The share only takes into account EU27 members. Eurostat Structural Business Statistics reports the counts of all businesses, not the ones largest than 5 employees as was used in the survey.*

Table A.2. Coefficients for the model using firms that were incorporated prior to 2012.

Aspect	Mean	SD	HDI 3%	HDI 97%
Both Developing and Ready-Made (Complementarity)				
Sectors				
Agriculture, forestry and/or fishing	0.068	0.838	-1.539	1.650
Accommodation and Recreation	0.312	0.592	-0.806	1.426
Construction	0.592	0.482	-0.302	1.514
Financial and Real Estate	0.928	0.691	-0.341	2.251
Food	0.092	0.627	-1.074	1.311
Human health	0.313	0.664	-0.931	1.580
IT	-1.833	0.808	-3.379	-0.355
Manufacturing	0.584	0.372	-0.091	1.309
Other technical and/or scientific sectors	0.784	0.536	-0.208	1.808
Public Sector	-0.128	0.678	-1.396	1.167
Trade, retail	0.921	0.440	0.103	1.761
Transport	0.240	0.595	-0.867	1.379
Utilities	-0.155	0.757	-1.598	1.272
Developing or Adapting				
Intercept	-2.343	0.467	-3.217	-1.460
Sectors				
Agriculture, forestry and/or fishing	-0.277	0.806	-1.780	1.257
Accommodation and Recreation	-0.286	0.612	-1.461	0.837
Construction	-1.026	0.624	-2.229	0.118
Financial and Real Estate	0.013	0.593	-1.112	1.128
Food	0.370	0.588	-0.730	1.469
Human health	-0.539	0.637	-1.782	0.620
IT	1.646	0.577	0.569	2.736
Manufacturing	0.049	0.551	-1.001	1.054
Other technical and/or scientific sectors	0.058	0.574	-1.019	1.143
Public Sector	-0.343	0.660	-1.595	0.885
Trade, retail	-0.798	0.611	-1.952	0.356
Transport	-0.303	0.593	-1.469	0.773
Utilities	-1.138	0.699	-2.485	0.144
Implementing Ready-Made Solutions				
Intercept	-1.114	0.464	-1.986	-0.244
Sectors				
Agriculture, forestry and/or fishing	0.192	0.728	-1.156	1.584
Accommodation and Recreation	-0.568	0.577	-1.664	0.500
Construction	-0.512	0.546	-1.533	0.511
Financial and Real Estate	-0.933	0.687	-2.229	0.344
Food	-0.065	0.634	-1.279	1.090
Human health	0.184	0.652	-1.037	1.419
IT	1.431	0.743	0.021	2.812
Manufacturing	0.339	0.489	-0.571	1.260
Other technical and/or scientific sectors	-0.445	0.595	-1.592	0.641
Public Sector	0.058	0.632	-1.141	1.237
Trade, retail	-0.169	0.529	-1.168	0.813
Transport	-0.371	0.622	-1.550	0.793
Utilities	-1.070	0.754	-2.506	0.328
Controls and Exclusion Restriction				
Distance from Research University	-0.163	0.113	-0.373	0.052

Developing or Adapting				
Number Employees	-0.188	0.115	-0.401	0.026
Age	0.098	0.084	-0.062	0.254
Age^2	0.009	0.089	-0.160	0.175
Capital	0.091	0.081	-0.061	0.243
Capital Dummy	0.078	0.078	-0.070	0.223
Revenue	0.083	0.147	-0.187	0.361
Population in NUTS2	-0.043	0.140	-0.306	0.222
Implementing Ready-Made Solutions				
Number Employees	0.006	0.095	-0.173	0.187
Age	-0.257	0.123	-0.491	-0.022
Age^2	0.059	0.094	-0.117	0.236
Capital	-0.155	0.123	-0.384	0.077
Capital Dummy	-0.014	0.092	-0.188	0.156
Revenues	0.012	0.112	-0.202	0.220
Population in NUTS2	0.013	0.109	-0.193	0.220

Table Note: SD stands for Standard Deviation and HDI means Highest Density Interval, the interval concentrating most of the density of the posterior.

N. Observations: 2771

Table A.3 Marginal Effect of One Sourcing Strategy on the Probability of Observing Another

Endogenous variable	**Readymade**	**Developed In-House**	**Readymade**	**Developed In-House**
Exogenous variables				
Developped In-House	0.3641*** (0.020)		0.2433** (0.121)	
Readymade		0.3227*** (0.019)		0.2191** (0.110)
Interaction terms				
Agriculture			0.1048 (0.271)	0.0014 (0.198)
Accomodation			0.1166 (0.163)	0.1283 (0.150)
Construction			0.1646 (0.139)	0.0763 (0.123)
Financial			0.1146 (0.151)	0.1404 (0.143)
Food			0.0718 (0.155)	0.0547 (0.144)
Human health			0.1607 (0.164)	0.0537 (0.142)
IT			-0.2679* (0.146)	-0.2510* (0.139)
Manufacturing			0.1430 (0.127)	0.1429 (0.115)
Other technical			0.1677 (0.135)	0.1957 (0.126)
Public Sector			0.0521 (0.182)	0.0347 (0.155)
Trade, retail			0.2192* (0.130)	0.1751 (0.118)
Transport			0.0821 (0.148)	0.0456 (0.133)
Utilities			0.2231 (0.185)	0.387** (0.171)
Controls				
Distance to University		-0.0414*** (0.01)		-3.86e-02*** (1e-02)
Number employees	1.504e-05 (1.6e-05)	-8.907e-06 (7.66e-06)	1.278e-05 (1.41e-05)	5.461e-06 (6.54e-06)
Age	0.0004 (0.001)	-8.057e-05 (5.74e-05)	2e-04 (1e-03)	-9.451e-05* (5.72e-05)
Age^2	2.291e-06 (7.21e-06)	-2.1e-03* (1e-03)	3.441e-06 (7.04e-06)	-2.2e-03*** (1e-03)
Capital	-0.0039 (0.004)	0.0226*** (0.005)	-2.6e-03 (3e-03)	2.31e-02*** (5e-03)
Capital Dummy	-0.0032 (0.003)	-0.0026 (0.003)	6.43e-02 (3.2e-02)	-2.9e-03 (3e-03)
Revenues	0.0635** (0.032)	1.464e-05** (6.39e-06)	-3.8e-03 (4e-03)	1.416e-05** (6.34e-06)
Population	0.0072 (0.011)	0.0125 (0.030)	6e-03 (1.1e-02)	1.23e-02 (3.0e-02)

P-values: *** : < 0.01, ** : < 0.05, * : < 0.1

Table A.4 Descriptive Statistics for the regressions

	Mean	Std	Min	Median	Max
Distance to top university	117.51	113.87	0.24	96.56	1408.28
Employees	120.57	766.33	1	18	35,211
Capital	2,310,572	15,644,440	-47	47,613	520,054,400
Revenues	35,344,350	294,092,600	-11,935	2,974,229	8,938,515,000
Age	23.86	17.24663	0	21	220
Population	2,835,102	2,398,337	289,606	2,059,729	12,291,560

Figure A1 : Applications adoption rate in different industries

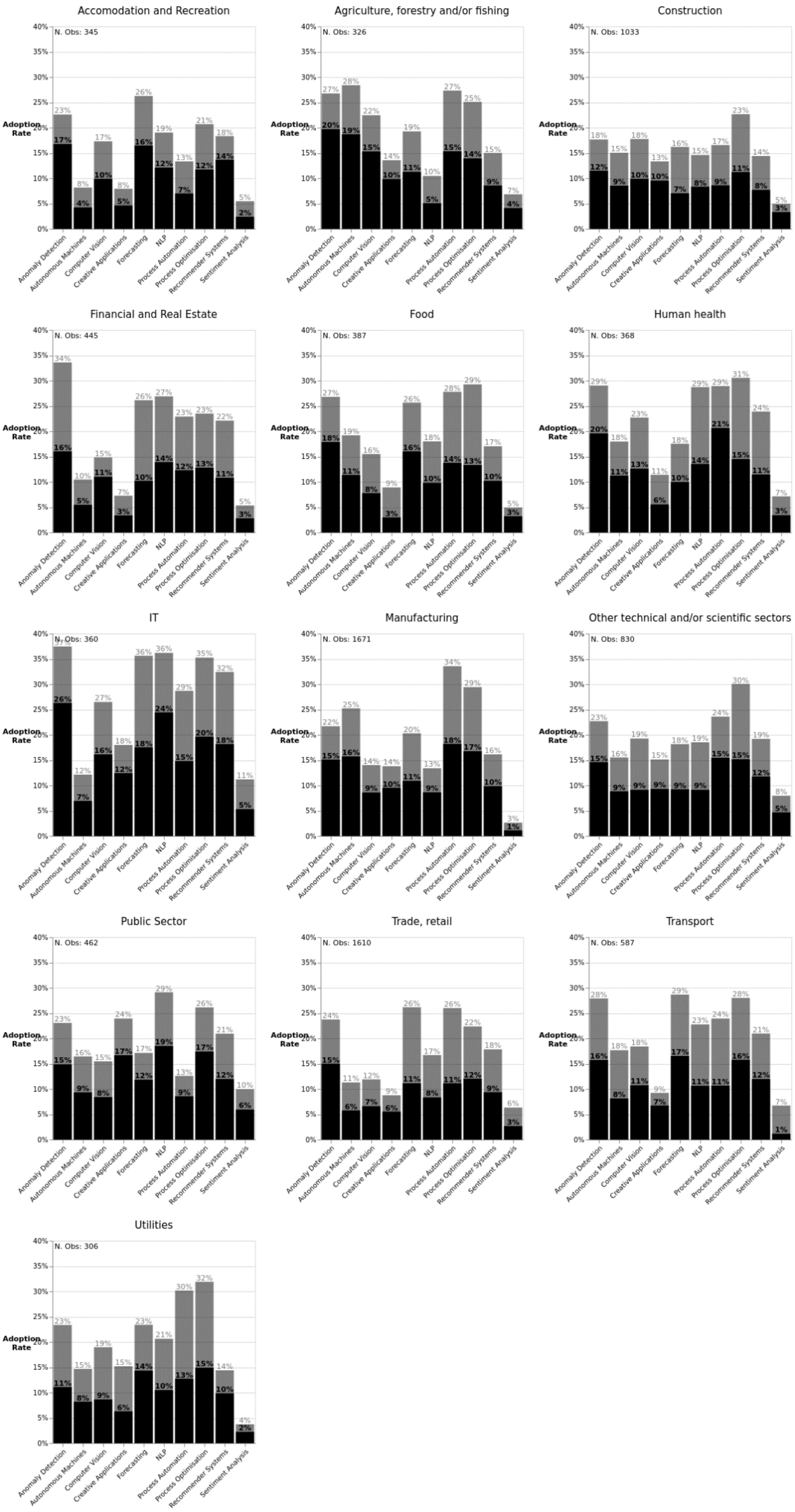
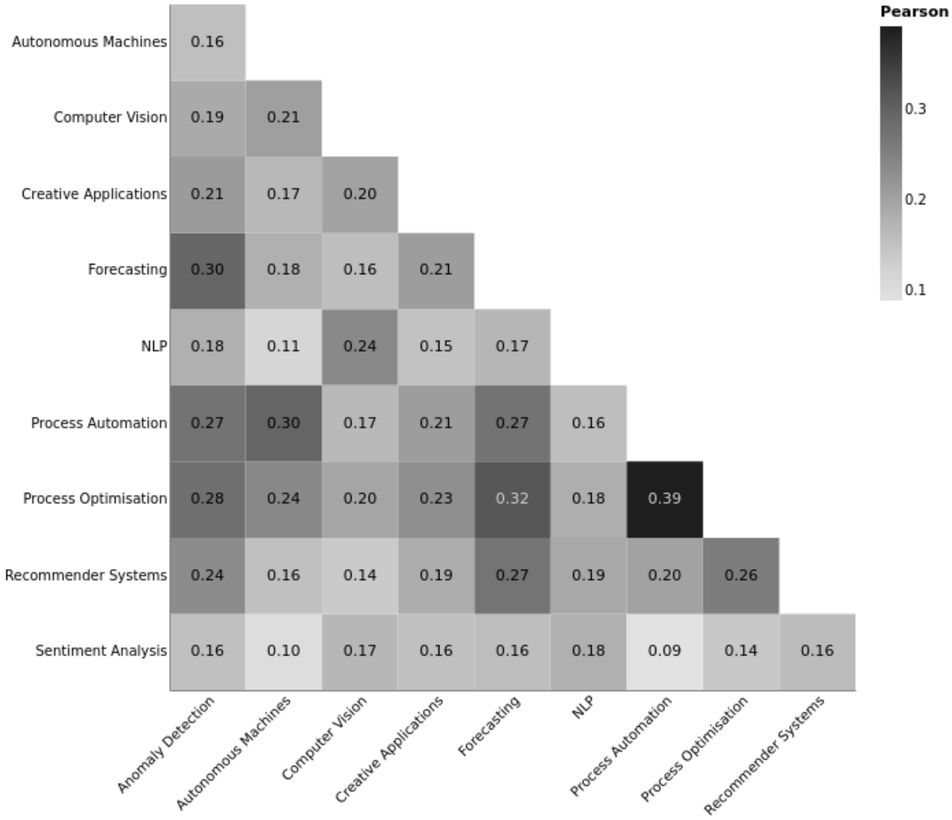


Figure A.2: Pearson Correlations of the adoption of pairs of AI applications



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