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Adoption and Diffusion of Blockchain Technology

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Abstract

A widespread approach to measuring the innovative capacity of companies, sectors, and regions is the analysis of patents and trademarks or the use of surveys. In emerging digital technologies this approach may, however, not be sufficient for mapping technology diffusion. This applies to blockchain technology which is in essence, a decentralized and distributed database (management system) that is increasingly used well beyond its originally intended purpose as the underlying infrastructure for a peer-to-peer payment system. In this article, we use an alternative method based on web-analysis and deep learning techniques that allow us to identify companies that use blockchain technology to determine its diffusion. Our analysis shows that blockchain is still a niche technology with only 0.88% of the analyzed firms using it. At the same time, certain sectors, namely ICT, banking & finance, and (management) consulting, show higher adoption rates ranging from 3.50% to 4.50%. Most blockchain companies are located at or close to one of the financial centers. Young firms whose business model is (partly) based on blockchain technology also locate themselves close to these centers. Thus, despite blockchain technology often being explicitly characterized as decentralized and distributed in nature, these adoption and strategic location decisions lead to "blockchain clusters".

Keywords: technology adoption, blockchain technology, geographical distribution of firms, natural language programming
JEL-Classification: C45, O33, R30

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1 INTRODUCTION

New technologies play a key role in driving economic growth. In particular, new technology adoption is of paramount importance in enhancing the competitiveness and operational capabilities of companies (e.g. Czarnitzki et al., 2023; Griffith et al., 2006). Policy makers and industry practitioners are therefore interested in gaining insights into the emergence and diffusion of new technologies. However, information on adoption and diffusion are often limited. Researchers therefore rely on data derived from public information on intellectual property, such as patent applications, or in surveys to capture and identify inventive activity and innovation (e.g. Moser, 2013). Accounting and balance sheet information including spending on investments and R&D is typically only available for publicly listed companies which restricts the analysis of the role of small and emerging companies in new technology diffusion.

Identifying relevant patents or trademarks for interdisciplinary technologies such as blockchain is particularly challenging. Blockchain is an emerging new technology with transformation potential but also high regulatory uncertainty. The potential adopters are also highly heterogeneous with developers and users and important stakeholders, such as organisations that provide training and information about the technology. Given its nascent nature trying to capture the diffusion requires capturing all relevant actors and organisations which is challenging when relying on traditional sources of information.

This study addresses these issues by using a methodology to map the adoption and diffusion of blockchain technology relying on website information. In doing so, we combine web mining and deep learning following the work of Kinne and Lenz (2021). The value of using website texts as a source of information for innovation research has already illustrated in previous studies (see Axenbeck and Breithaupt, 2021; Dörr et al., 2022; Kinne and Axenbeck, 2020; Kinne and Lenz, 2021; Mirtsch et al., 2020; Rammer et al., 2020; Schmidt et al., 2022; Schwierzy et al., 2022). We extend this research to the context of blockchain as another complex and emerging multi-purpose technology that is hard to track using traditional methods.

Specifically, we analyse textual content from company websites which we identify based on keyword search in universe of available websites by companies and organisations obtained from the ORBIS database for Germany, Austria and Switzerland, i.e. approximately 1.4 million companies. We screen passages for predefined blockchain-related keywords and train a machine learning model that understands the context in which a keyword is mentioned on a subset of companies. Finally, we use this model to assess blockchain use in the full population of companies. The model further generates predictions for the intensity of engagement in blockchain technology. These results allows us to map the adoption and diffusion of blockchain technology within and across the three countries, and to examine the intensity and variation of adoption across sectors and regions. We find that - although it is a niche technology - applied by only 0.88% of the companies analysed, there are multiple core centres of adoption. The intensity of regional adoption is higher in locations with more established companies. This may be the result of their higher use-potential due to their technological relatedness in blockchain applications.

This article contributes to earlier research in multiple ways. First, we provide a test of web-mining as means of identifying users and diffusers of digital technology. This is particularly valuable for innovation research as new digital technologies are challenging to capture using traditional ways based on sector affiliations and patents. Second, we provide a novel way to analyze crypto startups, which was previously only possible by observing an Initial Coin Offering (ICO) and thus unlikely to capture all relevant activity. Newly founded firms are seen to play a crucial role for technology adoption, development and diffusion, but are more difficult to capture in traditional sources of data. Third, we identify agglomeration patterns which inform policy makers, entrepreneurs and managers about the state of blockchain diffusion.

2 Blockchain Technology

This section provides some theoretical background on the blockchain technology which helps understanding the rate of adoption as well as the geographical dispersion of the blockchain technology which we investigate in the following. In addition, we related our analysis to the literature on the adoption and diffusion of break-through technological advances. In particular, we address how the latter can be measured for a technology that heavily relies on open source code and is usually not protected by patents or trademarks.

The blockchain technology is a rather young data storage technology whose theoretical foundation was first presented to the public on October 31, 2008, when a link to the seminal white paper authored by Satoshi Nakamoto – a pseudonym used by a still unknown person or group of people – was posted to a cryptography mailing list (Nakamoto, 2008). The first working implementation of the blockchain technology is the Bitcoin software (known as *Bitcoin Core*) which was described in the same white paper and which was first implemented on January 3, 2009. Since then there has been an increasing number of studies that deal with the roots, applications and implications of the blockchain technology (among many others, Christidis and Devetsikiotis, 2016, Tapscott and Tapscott, 2016, Yermack, 2017, Zheng et al., 2017, or Golosova and Romanovs, 2018). In addition, some recent articles (H. S. Ali et al., 2023, Fromberger, 2022, Vujicic et al., 2018, and Böhme et al., 2015) provide an economic perspective on the blockchain technology in general and on Bitcoin in specific.[1]

Generally speaking, the main purpose of the Bitcoin blockchain, and thus, the first use case of the blockchain technology, was to provide a peer-to-peer electronic cash system that allows online payments without the need for a trustworthy, centralized institution such as a bank/central bank or any other third-party payment service provider (compare Nakamoto, 2008). Besides the use as a decentralized payment system mainly intended for transferring the respective blockchain inherent cryp-

1. See also Joseph Abadi and Brunnermeier (2022), Gschnaidtner (2022), Halaburda et al. (2022), or Huberman et al. (2019) for additional economic, legal, and technical aspects of the blockchain technology.

tocurrency, various other applications of the technology have been proposed. These include, among many others, potential applications in (i) supply chain management (e.g. tracking of goods and preventing/identifying counterfeits, see Cozzio et al., 2023), (ii) healthcare (e.g. digital patient records, W. Chen et al., 2018), (iii) public administration (e.g. land registries, digital identities), (iv) the media industry (e.g. copyright records, automated royalties, digital collectibles such as NFTs[2], W. Chen et al., 2018), or in (v) academia/education sector (e.g. recording and verification of academic credentials).

However and thus, returning to the originally intended purpose of a decentralized payment system (i.e. "cryptocurrencies"), the vast majority of proposed and in several cases already implemented applications of the blockchain technology are in the area of finance. First of all, the use of cryptocurrencies for (cross-border) payments such as remittances and its increasing acceptance as an alternative asset class (see e.g. Adhami and Guegan, 2020) has led to a widespread offer of corresponding services such as crypto custody or trading platforms. Furthermore, the blockchain technology allows for the tokenization of various forms of assets (e.g. debt, real estate, securities) with the aim of making these divisible and easily transferable.[3] However, the adoption of the blockchain technology is not only limited to these two major use-cases but affects the entire finance industry and its well-established processes in general – a development that is usually summarized under the term *Decentralized Finance* (DeFi) and described by, e.g. Schär (2021) and Meyer et al. (2021). These various use cases illustrate that up until now the main area of application of the blockchain technology lies within the financial sector. This also holds for the academic literature on the blockchain technology which is, beyond the field of computer science, mainly dominated by finance related articles (Kher et al., 2021). Here, the main focus lies on

2. Non-fungible tokens (NFTs) allow for uniquely verifying/identifying digital assets such as (digital) work of art (cf. M. Ali and Bagui, 2021, Bao and Roubaud, 2022 , or Chandra, 2022).

3. Tokenization can be thought of as a (digital) form of the in the finance sector long existing process of securitization additionally allowing for programmability by deploying in particular *smart contracts*, i.e. self-executing computer code that is programmed on the blockchain (Buterin, 2014, Shermin, 2017, or Kher et al., 2021).

monetary and payment issues related to Bitcoin and other cryptocurrencies (Böhme et al., 2015, Huberman et al., 2019, or Halaburda et al., 2022). In addition, a large body of research related to the application of the blockchain technology has emerged in the area of entrepreneurial finance as *Initial Coin Offerings* (ICOs) have – despite some fraudulent activity associated to them, as e.g. reported by Hornuf et al. (2022) – become increasingly popular among new ventures as an alternative form of raising capital (cf. Momtaz, 2019, Bellavitis et al., 2021, Block et al., 2021, Hornuf et al., 2022, Bellavitis et al., 2022, Bertoni et al., 2022, Fisch et al., 2022, or Mansouri and Momtaz, 2022). Particular start-ups that are themselves engaged in the distributed ledger and blockchain technology space use ICOs as a method to finance their operations (see Adhami et al., 2018, Fisch, 2019, or Schückes and Gutmann, 2021).

Yet, the blockchain technology serves not only as a mean to finance newly founded ventures but also enables new business ideas that – particularly in the area of financial technology (fintech) – yield substantial value to the respective innovators (see M. A. Chen et al., 2019). While there are several examples for blockchain-based business models of start-ups in the field of finance (see Goldstein et al., 2019, Y. Chen and Bellavitis, 2020) or in the music industry (cf. Chalmers et al., 2021), Tönnissen et al. (2020) develop a taxonomy of blockchain-based business models of start-ups taking various dimensions into consideration. However, they focus only on the level of engagement of the start-up with the blockchain technology rather than on the area or industry in which the blockchain technology is applied. Within our analysis we overcome this research gap and shed light on the use and adoption of the blockchain technology within different industries. Besides the adoption within various industries, the geographical dispersion of the blockchain technology is of great interest, particularly when deriving policy implications regarding e.g. the path of adoption of new technologies. Saiedi et al. (2021), for example, estimates the global spread of the blockchain technology by analyzing, among others, active bitcoin nodes and merchants who self-report to accept Bitcoin as a means of payment. Within our analysis, we provide a more industry and firm-level oriented picture of the dispersion and adoption of blockchain technology. In this manner, our analysis is similar to Huang et al. (2020) who analyze the geographical distribution of ICOs and thus, start-ups who use ICOs as a way to finance their operations (in contrast to our more general analysis of all firms within the D/A/CH region). Interestingly, both Huang et al. (2020) and Saiedi et al. (2021) find that blockchain adoption is greatest in the area of already developed financial systems and thus, the blockchain technology rather acts as a complement than a substitute for the traditional financial sector. This is in sharp contrast to the original intention of establishing an alternative payment or even an entire financial system, it does however confirm the notion put forward by Hornuf et al. (2021) that traditional banks collaborate – either by investing or entering partnerships – with start-ups that offer financial services based on newly developed technologies. Geographical proximity, as we will show in our article, might be a fierce promoter of such collaborations – even for decentralized technologies such as blockchain (e.g. Glückler, 2007, Harrison et al., 2010, or Brown and Mason, 2017).[4] In addition, our analysis supports, adds to, and, broadly speaking, extrapolates the findings of Gazel and Schwienbacher (2021) for fintech data from France to the D/A/CH region: New fintech ventures seem to geographically cluster, specifically in or close to major financial hubs. Indeed, this geographical proximity is advantageous for both, established players in the financial markets such as banks or regulatory authorities and fintech startups who can partner with the corporates as well as contribute to the regulatory change process (Alaassar et al., 2022).[5]

4. While mentioning nothing about the effect of geographical proximity on the likelihood of cooperation in general, Hornuf et al. (2021) find that traditional banks that are located in the same country as the financial technology (fintech) start-up are more likely to enter a partnership with compared to investing into the fintech start-up. This seems, at least to some extent at a regional level, in contrast to Cumming and Schwienbacher (2018) who find that venture capital funded fintech start-ups are usually not located within countries with a major financial center. It also opposes the finding of Alaassar et al. (2022) that digitization (in combination with local intermediaries) improves entrepreneurs' accessibility to non-local ecosystems.

5. The latter is of particular importance for new technologies such as blockchain where startups are indeed "teaching them [regulators, ed.] what bitcoin and crypto are and what's happening in its underlying world" Alaassar et al. (2022, p. 2168).

3 Measuring Blockchain Adoption

Both from a technological as well as an economic and societal perspective it is important to understand the process behind the adoption and dispersion of new breakthrough technologies. Blockchain technology, in particular, is a potentially transformative technology that has the potential to disrupt multiple industries by enabling secure, decentralized, and transparent transactions of different kinds. To understand this potential, it is essential to measure the adoption and dispersion of this technology.

It is, however, not trivial to identify companies that adopt new technologies, particularly in an area where it is usually challenging to obtain global protection through patents, trademarks, or copyrights. This holds for software development (i.e., open source) and for blockchain technology, given its decentralized nature, in particular.[6] Hence, new approaches are necessary to track the adoption and diffusion, and ultimately with that the innovative strength of a region or country regarding such technologies – in our case, regarding the blockchain technology. In this article, we present and apply such a recently developed method which is described in the following sections.

In summary, we follow a four stage approach (S1 - S4) to (1) identify and categorize companies that either provide information about the blockchain technology or even offer a product or service (beyond simple information provision) that can be linked to this new decentralized data storage and management technology, as well as to (2) quantify the firm specific rate of adoption of the blockchain technology:

S1: First, we determined – in a partly structured manner but also partly based on experience in and knowledge of the domain – a list of relevant keywords that allowed us to identify companies that can be linked to the blockchain technology. (Section 3.1)

6. For example in Europe, computer software is, according to Article 52(2)c of the European Patent Convention (EPC), not patentable (see https://www.epo.org/en/legal/epc/2020/a52.html).

S2: Based on these keywords, the (official) company websites of approximately 1.4 million firms were searched for the keywords determined in the prior step. The websites' paragraphs/excerpts in which one or more keywords were located were then extracted and downloaded – a process usually referred to as web scraping.[7] (Section 3.2)

S3: A randomly chosen selection of 3,500 website excerpts that contain one or more of the keywords and that were obtained in the previous step were then manually labeled by the authors and with the additional help of a priori trained research assistants. The objective of the labeling task was to classify the website excerpts – and, on an aggregate level, the respective firms – whether they are either providing (general) information on the blockchain technology and related topics or whether they are even adopting this new technology, i.e. either by offering and/or using a product, respectively service that is associated with the blockchain technology. (Section 3.3)

S4: The 3,500 website excerpts then served as training and validation data for a Natural Language Processing (NLP) model, i.e. a deep learning algorithm that is specifically developed for processing language input.[8] In our case, the trained NLP model was used to classify all of the 1.4 millions company websites on which one or more of the previously mentioned keywords were identified as either providing information (label *(Information*) or using a product or service (label *(Know-how*) that is connected to the blockchain technology. (Section 3.4)

Each step S1 to S4 of the four stage approach is also described in more (technical) detail below. A conceptually similar, yet in several aspects different approach was also used by Schwierzy et al. (2022). Significant deviations from their procedure are also emphasized below.

7. In this step, we relied on the web analysis tool *webAI* developed by ISTARI.AI which is described in more detail in Kinne and Axenbeck (2020).

8. Again, in this step, we fall back on the before-mentioned web analysis tool.

3.1 Extraction of Blockchain Keywords (S1)

Before commencing with the identification of blockchain associated companies in the D/A/CH region, it was first necessary to define a set of keywords that allows to detect firms that are related to the blockchain technology as well as to unambiguously distinguish these from firms that are not involved in this new form of data storage and management. While, at first, this seems to be a trivial and straightforward task, several aspects have to be carefully considered when setting up a keyword list:
First of all, it is important that the keywords are uniquely related to the blockchain realm and are not (commonly) used in other industry sectors or in contexts other than blockchain. For example, the word *mining* is very common in the context of blockchain.[9] However, it is also used in various other industry sectors (metal, oil, ...) and is even a sector itself. While this is a rather obvious example, also more intricate cases have to be accounted for. One of such examples is the keyword *Ether*; it is either a means of payment on the *Ethereum* blockchain, the second most important blockchain after the Bitcoin blockchain (see, e.g. Gschnaidtner, 2022) but, at the same time, also a class of organic compounds, i.e. a major term in the chemical sector. Hence, keywords need to be rather specific (and unique) to the blockchain technology to prevent (too many) companies being identified as associated to the new technology (i.e. false positives).
Second, while keywords should neither be ambiguous nor too general (see previous point), only highly specific keywords lead at the same time to too few companies being recognized as blockchain related. Particularly, technological or programming terminology are an example of keywords that are, if exclusively used, too specific. While providing evidence of an understanding of the technology that goes beyond purely information provision, technological terminology is rarely used on company public websites as these are commonly targeted to customers or the wider public.

9. In the context of blockchain, mining refers to the process of adding new data (e.g. transactions) to the blockchain, usually by solving complex mathematical/cryptographic problems using specialized computer hardware. Mining is an integral part of the proof-of-work consensus mechanism that lies at the heart of the Bitcoin and various other blockchains (cf. Böhme et al., 2015, Tapscott and Tapscott, 2016, or Fromberger, 2022).

Examples include, among others, *aave*, *byzantine fault*, or *erc*, *ipfs*. Despite being rather technological, these terms are nonetheless included in the final keyword list as they allow us to capture deep/high technology startups.

Last but not least important, the keyword list should suffice high scientific standards. In particular, it should be as unbiased as possible from the authors' knowledge, understanding, perception, or assessment of the blockchain industry and its associated firms.

To ensure that the final list of keywords meets the criteria outlined above, with a particular focus on the last one, we proceeded as follows in obtaining candidates for the keywords:

1. First, to acknowledge the various aspects of the blockchain technology we decided on utilizing online glossaries (n=9) to extract blockchain associated expressions as well as related concepts that are defined there.[10] To preclude on missing out on companies whose websites are either rather general in nature and targeted to a broader audience as well as companies that are either envisioned for blockchain experts and developers or designed for business-to-business (B2B) purposes, we ensured that both, technological and non-technological terminology was included in the final list of keywords. The terms extracted from the websites were complemented with a list of the most important blockchains and crypto tokens as well as other concepts that were deemed important by the authors but not mentioned/defined in the above glossaries.[11] This resulted in a first list of $1,132$ keywords.

2. In a second step, we aimed at identifying and quantifying the most important among these to render the list of keywords more precisely. To this end

10. A full list of the online glossaries consulted and the respective websites can be found in Table A1 in the Appendix.

11. The following terms were manually added to the list of potential keywords obtained from the online glossaries: *Ethereum*, *ConsenSys Quorum*, *Stellar*, *EOSIO*, *Tezos*, *R3 Corda*, *Hyperledger Sawtooth*, *Hyperledger Fabric*, *IBM Blockchain*, *Maker*, *Uniswap*, *Chainlink*, *Axie Infinity*, *Aave*, *Compound*, *SushiSwap*, *Status*, *Kyber Network*, *Basic Attention Token*, *Decentraland*, *Litecoin*, *Chia*, *Ripple*, *EOS*, *TRON*, *Monero*, *Solana*, *Stellar*, *NEO*, *Dogecoin*

and thereby ensuring objectivity, we downloaded all scientific publications ($n=972$)[12] listed on SSRN's Cryptocurrency Research Hub[13] and, since SSRN covers mainly academic contributions from the social sciences, also all scientific publications ($n=2,967$)[14] from arXiv[15] that matched the query *blockchain* to account for more technical papers as well. Searching all downloaded papers, we then counted the number of appearances of all keywords that were obtained in step 1. Notice that to prevent general keywords that do not uniquely relate to the blockchain realm entering the final list, stop words[16] and other commonly used, non-blockchain related words were removed from the papers first. Considering only keywords with at least one appearance we were able to reduce the number of entries deemed appropriate to 870 keywords.

3. This list was then passed on to a subgroup of two authors and one research assistant that were up to this point not yet involved in the keyword selection process. Following the above criteria, they were asked to mark among the 870 keywords the ones they associate the most with the blockchain industry. In this way, we were able to further pin down the number of potential candidates for the final keyword list to 237.

The preliminary list of blockchain terminology resulting from this rigorous process was then used to scrape a sub-sample of (official) company websites ($n=3.500$). All keywords resulting in only few or even no hits at all were eliminated. In addition, relying partly on domain knowledge as well as on the literature, the preliminary list was manually aggregated and condensed further by generalizing[17] as well as

12. As of July 29th, 2022.

13. SSRN is an open-access online scientific pre-print distribution service specializing in social sciences, but currently branching out into other disciplines. SSRN and specifically, SSRN's Cryptocurrency Research Hub can be accessed via https://www.ssrn.com/index.cfm/en/cryptocurrency/.

14. As of July 31st, 2022.

15. arXiv is a free distribution service and an open-access archive for scholarly articles in the fields of physics, mathematics, computer science, quantitative biology, quantitative finance, statistics, electrical engineering/systems science, and economics. It is provided by Cornell University and can be accessed via https://arxiv.org/.

16. For a general introduction to stop words see, amongst many others, Gerlach et al. (2019) or Sarica and Luo (2021).

17. For example, the terms *bitcoin address*, *bitcoin core*, or *bitcoin script* that were part of the preliminary list were merged under the umbrella term *bitcoin*.

specifying[18] selected keywords. Once more, this has been done to ensure that the above criteria (specifically, 1 and 2) are met. This lead to a final number of 90 terms which are presented in the keywords list in Table A2.

3.2 Scraping of company websites (S2)

In the next step we use the list of keywords in Table A2 to analyze (official) websites of companies in the D/A/CH region and, in this way, to identify firms that are utilizing the blockchain technology. The websites of the companies were obtained from the ORBIS database which contains various information on the majority of economically active companies in the D/A/CH region, i.e. in Germany, Austria, and Switzerland. [19] After eliminating duplicates of websites, or more specifically of their respective URLs, we end up with 1.4 million unique companies whose websites are searched for the keywords listed in Table A2 using webAI technology by ISTARI.AI. Here, it is important to notice that, due to the high number of companies, for each website only the main domain and 25 sub-domains – prioritized according to the length (i.e. shortness) of the URL representing its hierarchical order on the website – are scraped. Overall, the keywords from Table A2 were found a total of 199,120 times on the specified websites. The majority of hits (approx. 80%) are linked to the four keywords *Bitcoin*, *Blockchain*, *Crypto*, and *Ethereum* (for a comprehensive overview of the distribution of the identified keywords see also Table A3). Since, as pointed out above, the NLP-model classifies the websites based on excerpts/paragraphs in which keywords were identified rather than on the keywords themselves, not the amount of hits but the number of unique excerpts is relevant – both for the classification task as well as for the prior model training and validation. The number of unique website excerpts/paragraphs in which at least one keyword was identified amounts to a total of approx. $60,000$ across all almost 1.4 million company websites.

18. E.g., *consensus* was specified and split up in *consensus algorithm* and *consensus mechanism* to be added to the final list of keywords.

19. For more details on the ORBIS database which is provided by Moody's Bureau van Dijk see https://www.bvdinfo.com/. Besides the here relevant D/A/CH region, the ORBIS database also covers private and non-private companies in all (major) global economies.

3.3 Labeling of training data (S3)

Before we are finally able to train and validate the NLP-model which classifies the websites and hence, the companies into ones that inform about the blockchain technology (label *Information*) and those that use or offer services or products related to the blockchain technology and thus, are assumed to have some form of know-how in the blockchain and corresponding technologies (label *Know-how*), it is necessary to prepare a set of training and validation data. To this end, a random sample of $3,500$ paragraphs is drawn from the total of $60,000$ unique paragraphs. These paragraphs are then in a next step labeled by a team of twelve researchers[20] and research assistants. Prior to this labeling task, they were however first introduced to the blockchain technology, informed about its various applications as well as extensively trained in manually labelling the randomly sampled paragraphs. The labelling task itself consisted of assigning either of the following labels to each website excerpt:

- *Know-how*, for paragraphs in which it becomes clear that the owner of the website either uses or offers products/services regarding the blockchain technology or is employing/searching to actively hire workforce that requires blockchain domain knowledge/skills
- *Information*, for paragraphs that are merely of informing character (e.g., online newspaper articles or blog posts) and from which it cannot be derived that the owner of the website is offering blockchain related products or services
- *Non-Blockchain related*, for paragraphs/entire websites which were, despite containing at least one of the keywords in Table A2, clearly not related to the blockchain technology (e.g. websites/firms that offer internet domain names for sale that include one of the keywords in Table A2).

The labelling of the paragraphs was conducted online using *Amazon's* cloud machine-learning platform *SageMaker*.[21] Here, for each instance to be labeled not only

20. 3 out of the 4 authors of this article were also among those researchers.
21. More information on *Amazon SageMaker* can be found at https://aws.amazon.com/de/sagemaker/.

the original plain text of the respective paragraph was provided to the members of the labeling team but also its translation[22], its live preview in HTML format as well as various other metadata – including the title, the description, the keywords of and the URL to the source website of the paragraph (compare also Figure in the appendix). Despite the additional information, the members of the labelling team were encouraged to base their labelling decision mainly or even, if possible, solely on the information that could be derived from the respective paragraph as the NLP-model was trained exclusively on these paragraphs. To improve the robustness and to ensure a consistent labelling, each of the $3,500$ paragraphs was shown to three different members of the labelling team. For the model training described below, only those paragraphs were used for which the labelling was unanimous. The paragraphs, for which only two out of three labels were identical, are in turn used for validating the model.

The results of the labeling process are presented in Figure 1 which shows the distribution of the assigned labels on an overall basis as well as the number of labels for which there is complete agreement among those three members of the labelling team that labeled the respective paragraphs. In addition, Figure 2 depicts the percentage share of labels for which any two different members of the labelling team agree as well as the total number of labeled paragraphs by each individual member (top number in the diagonal boxes in the heat map matrix in Figure 2).

3.4 NLP model training and validation (S4)

Having identified paragraphs on the company websites containing one of the keywords and having manually labeled a random sample of $3,500$ of these, a Natural Language Processing (NLP) model was trained by ISTARI.AI that is able to automatically classify the remaining paragraphs that have not been manually classified during the labeling process described above. As starting-point of our NLP

22. All paragraphs were automatically translated to English.

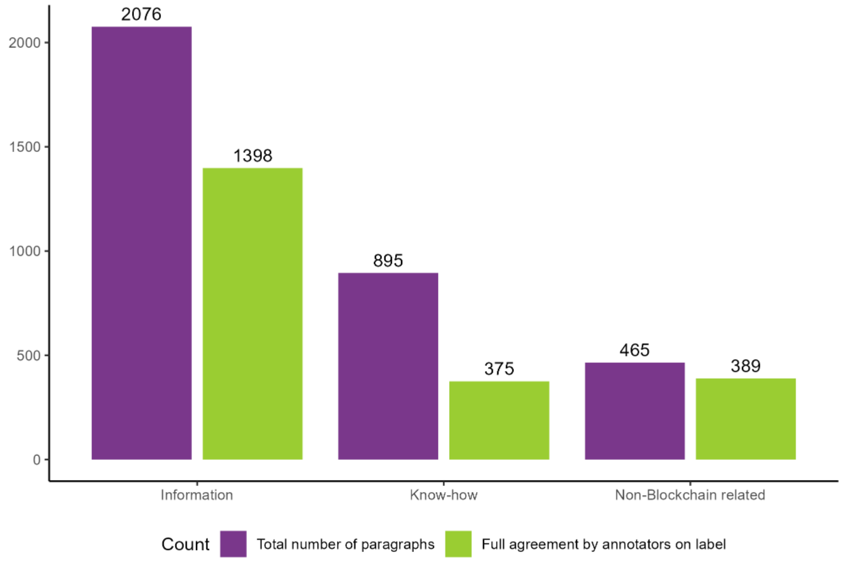


Fig. 1: Distribution of the labels manually assigned by the labelling team to the randomly sampled paragraphs. Note: The total number of labelled paragraphs does not sum up to $3,500$ as for 64 observations the three annotators fully disagreed on the correct label.

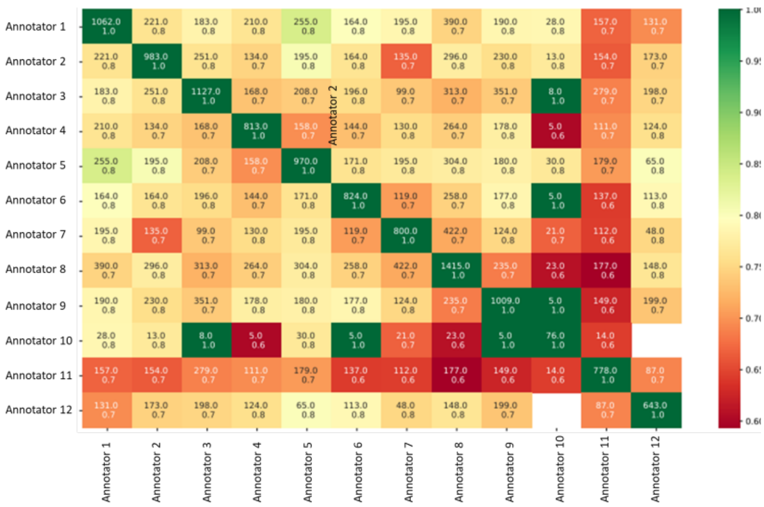


Fig. 2: Heat map depicting the number of paragraphs (top number) that were labeled by any two members of the labelling team as well as the percentage share of paragraphs for which the two labels of the team members agree (bottom number). The diagonal boxes show for each annotator the number of paragraphs that were labeled in total.

model, we use a BERT-based model[23] as proposed by Devlin et al. (2019).[24]

Due to the small size of the training data set – the potential training data set

23. BERT stands for Bidirectional Encoder Representations from Transformers.

24. For more information on the Sentence-BERT model refer to the original article by Reimers and Gurevych (2019) or to the corresponding website https://huggingface.co/sentence-transformers/paraphrase-multilingual-mpnet-base-v2.

consists of $2,162$ observations as the model is only trained on those of the $3,500$ paragraphs for which there is an unanimous decision on the correct label among the respective three annotators[25] – we adopt for the training of the model a domain adaptation training strategy using our manually annotated data set. This approach allows us to develop a robust NLP model that, despite the small size of the training data, adapts well to new/general types of websites not seen during the training process and thus, shows comparably high out-of-sample performance. In particular, the pre-trained and fine-tuned NLP model has an accuracy of more than 95% in the classification of those paragraphs for which the annotators completely agree on the correct label but which were not used for the model training ($n = 250$, i.e. an accuracy of approximately 95% for unseen test data (compare also Figure 3). For paragraphs, where only two out of three annotators agree upon the same label (majority voting; $n = 1,150$), the accuracy however drops to 72%. Yet, this is to be expected since even the annotators do not arrive at a clear agreement on the label.

Having trained and validated the model, we use the final NLP model to classify both, the manually labeled as well as the remaining unlabeled website excerpts which contain at least one of the specified keywords. Based on this classification of the paragraphs we are now also able to assign a corresponding label to the respective website and hence, also to the owner (i.e. the company) of the respective website. Assuming that companies that are strongly engaged in the development or use of the blockchain technology and its applications are more likely to report on a larger scale – in terms of the percentage share of text on their websites – about blockchain related topics, our approach also allows for the construction of a measure that indicates, based on the scraped website excerpts, a companies degree of engagement in the blockchain technology. We refer to this measure as blockchain intensity score which is

25. In fact, of these $2,162$ observations, we finally use only $1,912$ observations for training purposes and the other 250 observations for testing – out of the 250 observations, 239 observations are either labeled *Know-how* or *Information* while the remaining 11 observations are *"Non-Blockchain related"*. This approach enables us to conduct model testing on data for which, given the unanimous decision of the annotators, we are sure about the correct label.

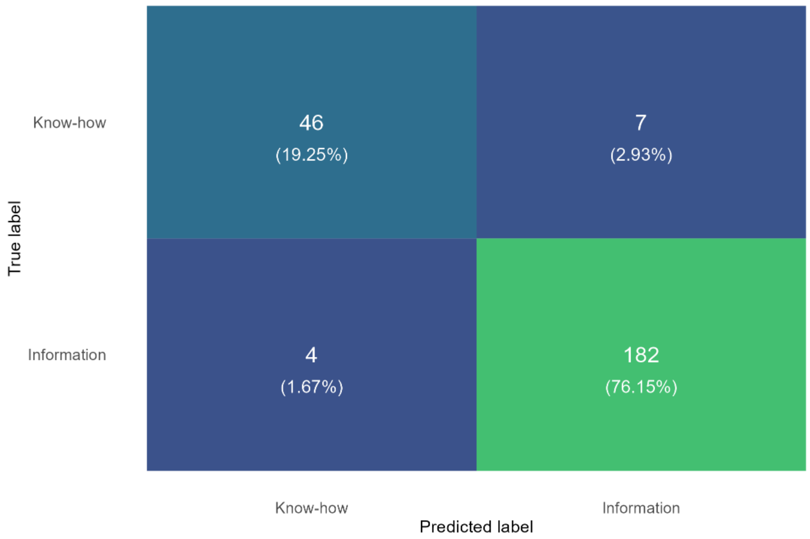


Fig. 3: Confusion matrix depicting the results of testing the fined-tuned NLP model on pre-labeled data ($n = 250$) for which the true label was unanimously determined by the annotators.

calculated by relating the number of respective paragraphs to the overall text length of the website. Thus, a company website with keywords that are in paragraphs that are labeled either as *Know-how* or as *Information*, the respective intensity is positive; for all others it has a value of 0.0.

The results obtained from the classification as well as the obtained *Know-how*- and *Information*-intensity scores are described in detail in the following sections.

4 Data and Methodology

Following the methodology of identifying blockchain companies presented in the previous sector, we are able to collect blockchain indicators – both, in the category *Information* and in the category *Know-how* – for almost 1.4 million companies covered by Bureau van Dijk's ORBIS entity database in the D/A/CH region.[26]

26. As pointed out before, we are limited to companies covered by the ORBIS database, as the proposed methodology for analyzing the blockchain activity of companies in the D/A/CH region relies on the availability of official company websites. Besides other company specific information, ORBIS also provides these for a high percentage of the companies covered.

4.1 Additional data

The retrieved data set is enriched with further firm specific information – also included in the ORBIS database – which enables us to gain a better insight into the companies that are adopting the blockchain technology as well as in those that are not (compare also Table 1 for an overview of the available variables). Besides information on the respective number of employees, the companies' founding date, or the industry the companies are mainly operating in, we utilize in particular the companies' postal addresses[27] as basis for geolocating them, i.e. for identifying the longitudinal and latitudinal coordinates of their exact company location.

TABLE 1: Overview of the variables at the firm and regional level

Variable	# observations	Data source
Firm level		
Blockchain use	1,347,907	ISTARI.AI
Information	1,347,907	ISTARI.AI
Know-how	1,347,907	ISTARI.AI
Employees	1,218,839	ORBIS
Legal Form	10,845	ORBIS
Year founded	1,334,358	ORBIS
Sector	1,257,858	ORBIS
Geolocation	1,347,907	ISTARI.AI, OSM, Google
Major city (10km)	1,347,907	Statista[28]
Country	1,347,907	ORBIS
Finance center (10km)	1,347,907	GFCI
Regional level		
NUTS region	462	Eurostat
Country	462	Eurostat
Urban type	462	Eurostat
Finance center	462	GFCI
Major city	462	Statista[28]
Patent applications	462	EPO[29]
%-share financial sector	462	ORBIS

For the geolocation of the companies, we use data from ISTARI.AI and the open geographic database OpenStreetMap (OSM).[30] Provided the voluntary and not-for-profit nature of the OSM project, geolocation via OpenStreetMap is in most cases but not always sufficiently accurate. In addition, OSM does not cover all

27. In case of companies with several locations, usually the postal address of the headquarter is used.
28. Major cities are based on the number of inhabitants and are defined depending on the size of the country: for Germany, major cities are cites with more than 500.000 inhabitants, for Switzerland and Austria, cities with more than 100.000 inhabitants. An overview of the major cities can be found in Table A4 in the appendix.
29. European Patent Office
30. For more information on the OpenStreetMap, see https://www.openstreetmap.org/.

countries/regions equally well leading to missing geolocation data (i.e. longitudinal and latitudinal data) in several cases.[31]. As a result, for $41,256$ out of the 1.4 million firms (i.e. approx. 3%) we do have clearly inaccurate or even no geolocation data at all. We solve this issue by using the geolocation services offered by Google Maps.[32] However, in contrast to OSM, using Google Maps for a large data set (e.g., our data set) that requires more geolocation requests than the limited quota of requests that is accessible for free, this becomes quite costly which makes it almost impossible for research applications. Hence, we adopt a rather pragmatic approach: we generally rely on OSM for the geolocation of the companies' addresses. If a geolocation via OSM is not possible or clearly leads to inaccurate results ($n = 41.256$) – e.g. a German company close to the German-Dutch border is falsely located in the Netherlands, i.e. firms for which the postal address is according to Orbis either in Germany, Austria, or Switzerland but which is geolocated by OSM such that it is assigned to a different country – we then fall back on the services provided by Google Maps.

As mentioned above, the blockchain technology was originally intended to be used as a peer-to-peer payment system that might eventually (partially) replace the then prevailing financial system (see, e.g. Nakamoto, 2008, Gschnaidtner, 2022). Hence, it might not come as a surprise that, as of today, many applications of the blockchain technology are related to the financial sector. In order to account for this fact and to verify that indeed the financial industry is a major driver of the blockchain technology, we also consider the distance of companies in the data set to financial centers within the D/A/CH region. Similar to Cumming and Schwienbacher (2018), we consider a city to be a (major) financial center if it is listed on The Global Financial Centres Index (GFCI), an index that is published by the London based commercial

31. An elaborated discussion on the shortcomings of OSM and its implications for our research project can be found in section 6.2 below.

32. Commercial and thus, not free of charge geolocation services such as Google Maps allow for a more accurate geolocation and also provide a more comprehensive register of streets/roads enabling an almost seamless identification of the companies' correct geolocation. In addition and comparable to OSM, geolocation using Google Maps can also be automated using its geolocation API making it possible for simultaneously geolocating large numbers of companies. For more details, see https://mapsplatform.google.com/intl/de/.

think-tank Z/Yen on a semi-annual basis.[33] Table 2 provides – according to the most recent GFCI 32 – a list of all financial centers within the D/A/CH region. An overview of all variables available for the companies in the data set as well as descriptive statistics at the firm level are presented below in section 5.1.

TABLE 2: Global Financial Centres Index

City	GFCI 32	GFCI 33	Country	NUTS 3 ID
Frankfurt	18	17	Germany	DE712
Geneva	20	23	Switzerland	CH013
Zurich	22	20	Switzerland	CH040
Munich	24	18	Germany	DE212
Berlin	26	26	Germany	DE300
Hamburg	38	43	Germany	DE600
Stuttgart	39	47	Germany	DE111
Vienna	50	51	Austria	AT130
Lugano	58	56	Switzerland	CH070

Note: Financial centers within the D/A/CH region according to The Global Financial Centres Index (GFCI) 32 and 33; cities are sorted according to the assigned rank in the GFCI 32.

Besides analysing blockchain activity at the firm level we are also interested in the geographical distribution of blockchain companies in the D/A/CH region. To this end, we also aggregate the firm data on a regional level as defined by the nomenclature of territorial units for statistics (NUTS[34]). Specifically, we use the NUTS 2021 classification provided by Eurostat. Geographical analyses are conducted mainly at the NUTS 3 level (i.e., small regions that are specifically appropriate for specific diagnoses) as well as on the coarser NUTS 2 (basic regions) and NUTS 0 (countries) levels. In addition to analyses of the regional distribution, the aggregation of firm data at the regional level enables us to compute and utilize additional measures such as the sectoral economic structure or the level of urbanization. A complete description of the geographical variables as well as their derivation can be found in Table 1 and in Section 5.3 below. Finally, to examine various drivers for blockchain adoption at the firm specific as well as at the regional/country specific level, we extend our dataset

33. For the purpose of our study, we use the most recent index, i.e., GFCI 32, published in September 2022; see also Mainelli and Wardle (2022).

34. NUTS originally stands for *Nomenclature des unités territoriales statistiques*.

with several additional variables from Bureau van Dijks' ORBIS database, Statista, Eurostat, and the European Patent Office (EPO). An overview of the variables as well as the respective number of observations and the corresponding data source is provided in Table 1.

4.2 Methodology

The aim of the empirical analysis is twofold: First, using standard as well as advanced descriptive methods, we want to shed light on the adoption and (geographical) diffusion of the blockchain technology at the firm as well as at the regional level. Second, using standard regression analyses, we are interested in (i) the determinants that lead firms to engage in the new technology, (ii) the decision of start-ups to locate close to a major financial center, and (iii) the characteristics determining a region's %-share of blockchain firms. For (i) and (ii), we use the common logistic regression models at the firm level (i):

$$\begin{aligned}\text{LogOdds}(\textit{Blockchain use}_i) = &\beta_0 + \beta_1 \cdot \textit{Finance center (10km)}_i + \beta_2 \cdot \textit{Employees (in thous.)}_i + \\ &+ \textit{City controls}_i + \textit{Region controls}_i + \textit{Country Controls}_i + \\ &+ \textit{Sector controls}_i + \textit{Year controls}_i + \epsilon\end{aligned} \tag{i}$$

$$\begin{aligned}\text{LogOdds}(\textit{Financial center as location}_i) = &\beta_0 + \beta_1 \cdot \textit{Blockchain use}_i + \beta_2 \cdot \textit{Employees (in thous.)}_i + \\ &+ \textit{City controls}_i + \textit{Country Controls}_i + \\ &+ \textit{Sector controls}_i + \textit{Year controls}_i + \epsilon\end{aligned} \tag{ii}$$

Both, for (i) and (ii), we also conduct the regression analysis using *blockchain know-how* and *blockchain information* instead of *blockchain use*, to allow for deeper insights.

To determine the %-share of blockchain firms within the NUTS 3 regions (iii), standard linear or logistic regression models are, due to the proportional nature of the dependent variable, not applicable. Instead, we rely on a fractional logit regression model at the regional level (j). Fractional logit regression model are, e.g. proposed in K. Chen et al. (2017) and Warton and Hui (2011) and date back to Papke and Wooldridge (1996).[35]

$$\text{LogOdds}(\textit{Blockchain use (\%-share of firms)}_j) = \beta_0 + \beta_1 \cdot \textit{Finance center}_j + \beta_2 \cdot \textit{\% of firms in financial serv.}_j + \\ + \textit{Region controls}_j + \textit{Country Controls}_j + \epsilon \qquad \text{(iii)}$$

Again, the regression is conducted not only for *blockchain use (%-share of firms)* but also for *blockchain information (%-share of firms)*, and *blockchain know-how (%-share of firms)* to obtain a deeper understanding of the dynamics present.

5 Results

The result section is split up in two parts. First, we provide descriptive analysis regarding the characteristics of the identified blockchain companies including the size, legal form, founding year, and industry. Second, we show the technology diffusion on a spatial dimension and examine the role of financial centers for its adoption.

5.1 Company Characteristics

The adoption rates of *Know-how*, *Information*, and blockchain in general, split across the different size classes of companies, were consistent with the size class distribution of the overall sample data (see Table 3 and Table A5). Using the definition of SME size classes, we found that 63% of all enterprises adopting blockchain are micro enterprises with 1-9 employees (see Table 3). Small firms with 10-49 employees accounted for 18% of the results, followed by large companies with more than 500

35. Alternatively, we could also use beta regression to model proportional data (cf. Kieschnick and McCullough, 2003 or Ferrari and Cribari-Neto, 2004). Beta regression does, however, not allow for the dependent variable to take up values at the boundary of 0 and 1. Since we expect that there are NUTS 3 regions without firms that engage in the blockchain technology, we refrain from using beta regression. Here, we intentionally disregard the availability of adaptations of the original beta regression model by, e.g. Smithson and Verkuilen (2006) circumventing the issues at the boundary values via transformations of the dependent variable. By doing so, we follow K. Chen et al. (2017) who emphasize the superiority of fractional logit regression models.

employees accounting for 11% of our dataset. 8% of the companies found were medium-sized (50-499 employees). When examining the averages, we find that companies with *Know-how* employ an average of 12.4 individuals, while *Information* companies have 12.1 employees. On the other hand, the average for all identified blockchain companies stands at 10.9 employees (refer to Table A5). Despite the predominantly micro or small size of most blockchain companies, an increase in the number of employees, ceteris paribus, enhances the likelihood of adoption (as demonstrated in Table A5).

TABLE 3: Companies' size

	Micro	Small	Medium	Large	**Total**
All companies	63%	18%	8%	11%	1,390,184
Blockchain use	63%	18%	8%	11%	11,972
Know-How	64%	18%	8%	10%	5,444
Information	62%	19%	8%	11%	6,528

This table depicts the adoption of blockchain based on companies' size. The size of a company is measured by the number of employees and follows the definition of SME size classes from Welter et al., 2016.

The legal form of the companies that had blockchain *Know-how* or only provided *Information* about it (see Table 4) also matched the results in terms of company size. 20% of the companies found were stock corporations, which also matched our observation that many of the companies adopting blockchain have more than 500 employees, as large companies tend to use this legal form. 71% of the companies in our results were limited liability companies, 6% were nonprofit organizations, and 3% of the companies had some other legal form.

TABLE 4: Companies' legal form

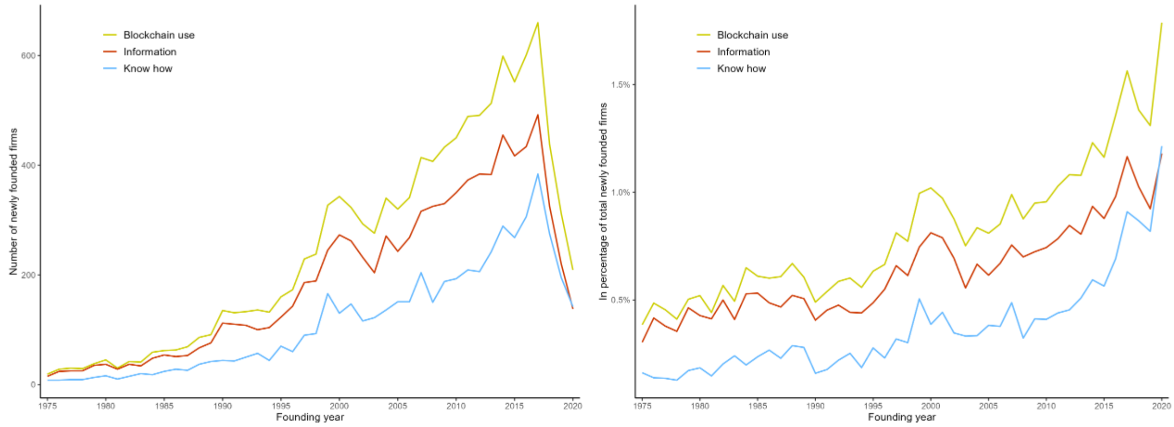
	Stock Corporations	Limited Liability	Non-Profit	Other	**Total**
Blockchain use	20%	71%	6%	3%	10,845
Know-How	23%	70%	4%	3%	5,075
Information	17%	72%	7%	3%	5,770

The fact that blockchain is a relatively young technology could also be seen in the founding years of companies adopting blockchain (see Figure 4a and Figure 6). We found relatively steady growth rates since 1970, which showed that companies of different ages were already adopting or informing about blockchain in their business. However, there were also certain periods with major ups and downs. For example, many companies adopting blockchain were founded during the first Internet hype, and there were also fewer companies in the period just after the dotcom bubble. However, there has been a sharp increase in start-ups after that time, leading to an all-time high in 2017. The latest data showed that far fewer companies adopting blockchain were founded in 2018 or later. The utilization of an older version of Orbis in this study contributes to the observed decrease in the number of blockchain startups over recent years. Analyzing the marginal effect of our regression (i), we observe a consistent rise in predicted values depending on the founding year, with a significant upturn occurring after 2015 (refer to Figure 6) indicating the rising relevance of blockchain technologies for startups.

Comparing the founding years of companies with blockchain *Know-how* with those with *Information*, we found that especially after 2015 newly found companies had a higher share of know-how than information whereas in almost all years before the rate of newly founded companies informing was higher than the rate of companies having *Know-how* (see Figure 4a and 4b). Table A5 underlines the finding that companies with *Know-how* are in average younger than companies with information.

5.2 Industry Structure

Next, we shed light on the dispersion of blockchain applications across different industries to obtain an overview in which sectors the new technology is (mainly) used as well as on the level of its diffusion within each sector. Given that many of the use cases lie within finance, it is no surprise that indeed – as Figure 5 shows – the financial sector is among the industries with the highest rate of adoption of the blockchain technology: Almost 3.8% of firms (i.e. $1,098$) that are assigned to *Financial services* either have *Know-How* in or present *Information* about the blockchain technology on their website.



(a) Absolute number

(b) Relative number

Fig. 4: Newly founded firms that adopt the blockchain technology, either by acquiring and/or offering know-how or by providing information about the technology, in absolute (top) and in relative numbers (bottom).

This is, in relative terms, only surpassed by companies that are located within the *ICT services* sector with a rate of diffusion of 4.6% (equivalent to $2,918$ firms). Closely following the financial sector is the *Consulting* industry with $1,886$ companies (3.5%) that engage with the blockchain technology (cf. Figure 5). Despite being certainly an interesting finding, this does not come as a surprise: First, the blockchain and its underlying components are a technology that originate from the Information and Communication Technology (short: ICT) area. Hence, blockchains and complimentary products are likely developed and implemented by ICT companies, even if it is on behalf of firms from the finance or other sectors. Second, consulting usually operate at the technological forefront, thus tending to engage rather early with new technology. In addition, the financial sector is a worthwhile target of consulting companies even further strengthening their interest in the blockchain technology. Besides these rather expected observations, two further insights emerge. In absolute numbers, there are comparably many firms ($1,091$) within the *retail* sector that are either directly using or at least informing about the blockchain technology. It can be assumed that these are mainly retailers that accept Bitcoin or other cryptocurrencies as a form of payment. Yet, when considering relative numbers, i.e. the share of firms within the sector, it becomes obvious that the blockchain technology is far from widespread among retailers (0.6%. The opposite is true for the *media* sector, where the absolute number of blockchain engaged firms (272) does not stand out, but the relative share of firms is, with 2.0%, astonishingly high. This effect is, however, mainly driven by the fact that media companies extensively inform about blockchain related topics but usually do not posses *Know-how* in the technology, as defined above (compare Figures A1 and A2 in the appendix). The very same holds for companies that are considered as *Interest groups*. Companies from the *ICT*, *Consulting*, and *Financial services* industries, on the other hand, exceed in both categories, *Information* and *Know-how*. While the just mentioned sectors do stand out, in the majority of industries the adoption rate is well below 1%. At the overall picture, it is also interesting to notice that, independent of the sector, more firms are classified as providing *Information* about compared to having *Know-how* in the blockchain technology. This confirms the notion that blockchain is still a niche technology.

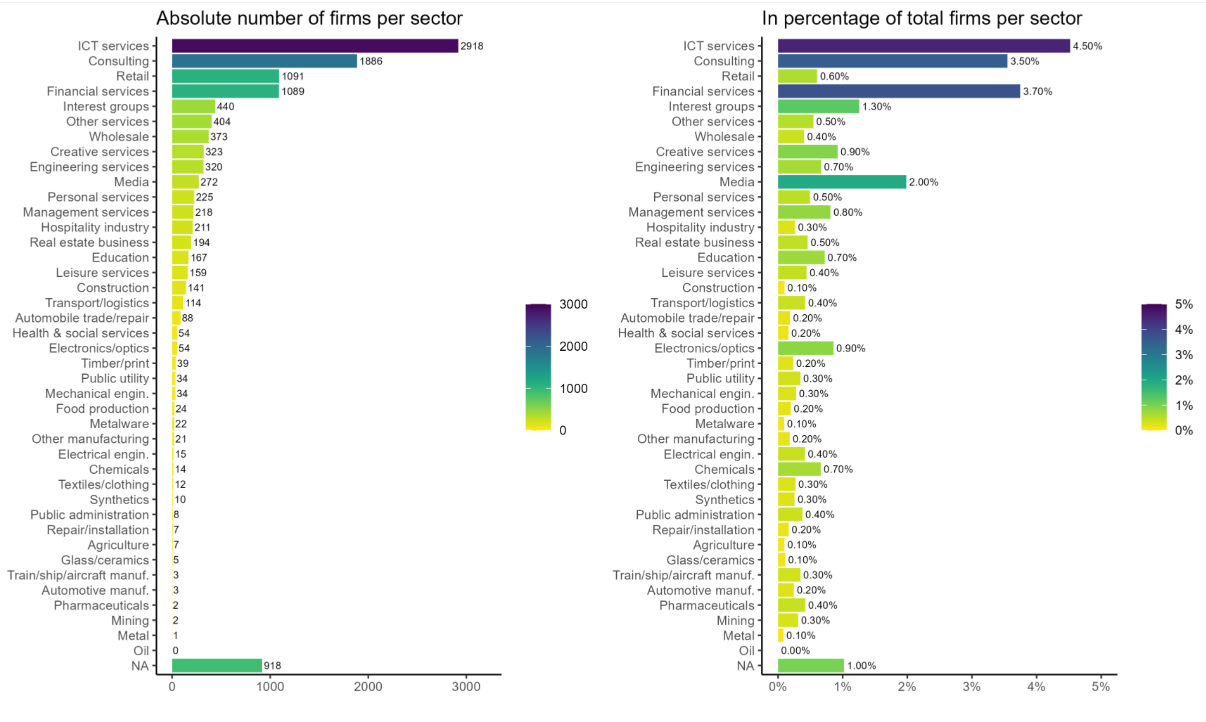


Fig. 5: Adoption of blockchain technology across industry sectors

5.3 Geographical distribution

Despite blockchain and DLT often being denoted a decentralized or distributed technology, the geographical dispersion of firms that can be related to the blockchain technology is far from being "distributed". Instead, companies that can be related to the blockchain technology tend to locate themselves (in case of newly founded companies) or are already located (in case of established companies that have adopted the new technology) close to financial centers. This holds, independent of the companies providing *Information* about this new technology or of offering services/products related to blockchain. This can clearly be seen in Figures A3a and A3b which show the absolute numbers of blockchain related companies at the NUTS 3 regional level. While this is to be expected since financial centers are usually (large) cities with a high number of firms and hence, also with a high number of blockchain firms, a similar picture results when looking at the relative number of firms that we can relate to the blockchain technology (see Figures 7 to A3b). A similar picture emerges from table A6: in regions with a financial center 2.3% of companies can be related to the blockchain technology (1.8% providing *Information* and almost 1.2% with blockchain *Know-How*), while in regions without financial centers the share of blockchain companies is with only 0.5% (*Information:* 0.39%, *Know-how:* 0.2%) much lower. Considering the results of the industry-sector-specific analysis above, this can mainly (but not exclusively) be contributed to a higher %-share of firms operating within the financial service sector. To reinforce this point, Figure 7 provides close-ups of various financial centers and large cities: While the status of a financial center (as determined by the GFCI 32; see Mainelli and Wardle, 2022) positively correlates with the percentage share of blockchain firms – as can be visually deduced from maps A3a and A3b for *Know-How* and *Information* companies where finance centers are in red font – other factors such as crypto-friendly institutions and a well-established blockchain ecosystem, both being true for Zug[36], imply also a higher share of blockchain related commercial activity in

36. Even though Zug is not classified as a financial center by the GFCI 32, it is nonetheless a major financial, trading/commercial, and business location in Switzerland and beyond.

the region.

This is also confirmed by the logistical regression analysis in Table A9. Independent of examining either the use of the blockchain technology in general or of blockchain *Know-How* and blockchain *Information* provision in specific, a firm within a 20 kilometer radius of any of the financial centers listed in Table 2 is significantly more likely to generally use (odds-ratios ranging from 1.49 to 3.17) and thus, either to provide information about (odds-ratios between 1.43 and 3.25), or to have *Know-how* ($1,57$ - 3.37) in the blockchain technology. Aggregating firm data at the regional level (NUTS3), a similar pattern arises: NUTS3 regions in which a financial center is located has a higher share of blockchain related firms (odds-ratio of 1.72). Moreover, even when controlling for financial centers and urban type, an increase in the share of firms in a NUTS3 region that are operating in the financial services sector by 1%-point increases the odds for an increase in the percentage share of blockchain firms by a factor of 1.72 (compare Table A10).

Hence, from the geographical analysis it becomes clear that the blockchain technology is embraced by companies that are operating in the financial services sector and that are located close to or are part of a financial center.

However, neither maps nor the regression analyses allow us to infer causal relationships on the adoption of the blockchain technology by incumbent (financial) firms as well as the (endogenous) location decision by newly founded companies/start-ups (e.g., fintechs) that are utilizing this new technology. To answer this research question, one would usually rely on panel data regarding the firm specific use of blockchain technology. Unfortunately, our data set only indicates if a company uses the blockchain technology and not the point in time when it started to use it. Hence, to still be able to gain some insights on the choice of established firms to adopt this new technology as well as on the location decision of (about to be) newly founded companies, we are forced to make several assumptions:

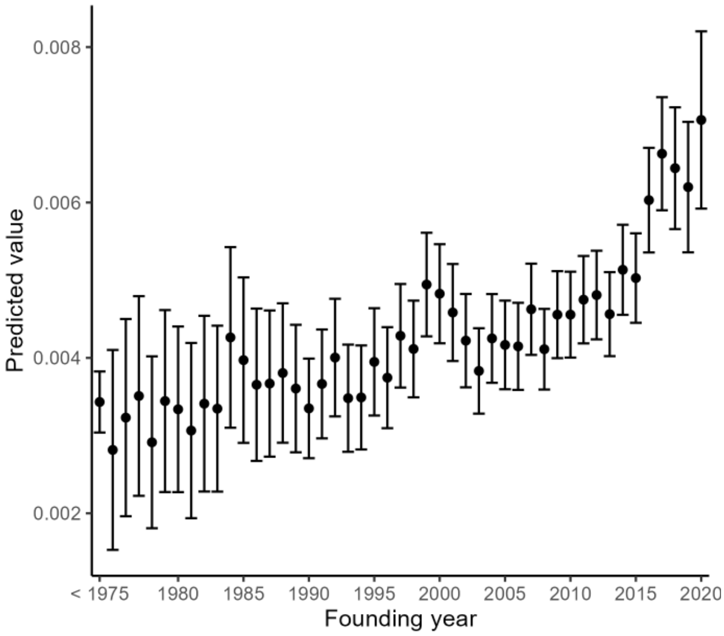


Fig. 6: Marginal predictive values (depending on the founding year) for firms that are referring to the blockchain technology on their website.

1) Companies that were founded in or before the year 2015[37] and use the blockchain technology are assumed to be established firms that adopt the blockchain technology to expand their line of business.
2) Companies that are identified as using the blockchain technology and that were founded after the year 2015 are considered to be newly founded blockchain companies (i.e., start-ups) whose business idea is mainly built around the blockchain technology and who (strategically) decide on where to locate the company office/headquarter.[38]

Table A11 shows the results of the corresponding regression analysis yielding that firms that were founded after 2015 and that are using the blockchain technology are significantly more likely to locate in a financial center than firms that do not use the blockchain technology (odds-ratio of 1.92). The same holds when using the provision of information on the blockchain technology (odds-ratio of 1.94) or the

37. We choose 2015 as this constitutes the year in which the ethereum blockchain was fully developed and in which the network, that is frequently used for various blockchain applications, went live (see e.g., Buterin, 2014).

38. It is important to mention here, that ORBIS defines the founding date of a company as the point in time at which it adopted its current legal form. Hence, the terminology start-up does not apply to all, yet the majority of firms in the sample.

existence of *Know-how* (odds-ratio of 2.11) as the main variable of interest in the regression analysis.

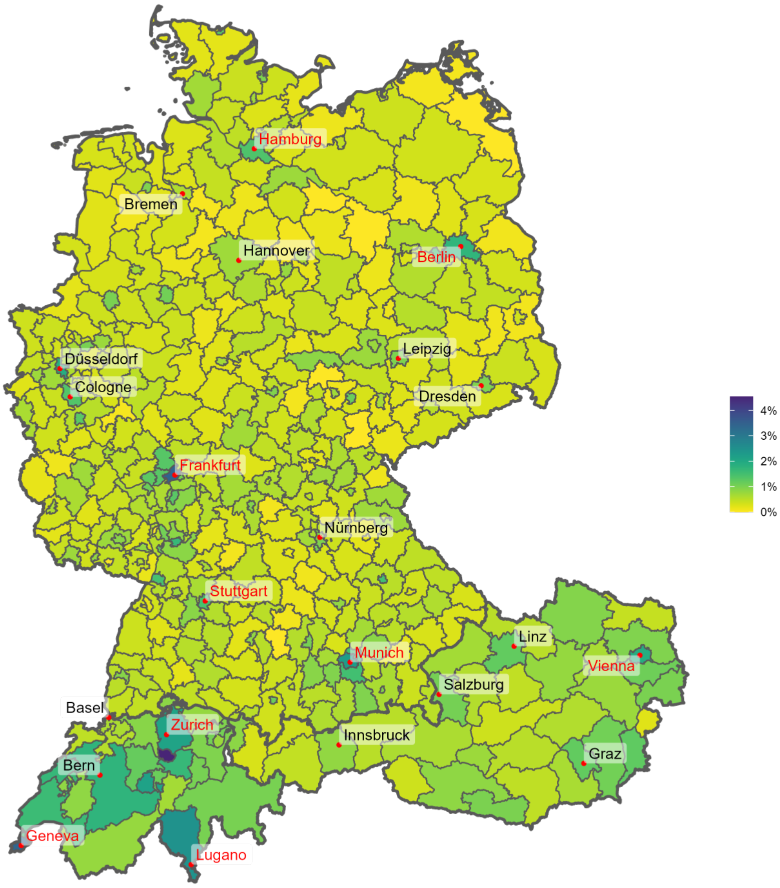


Fig. 7: Percentage share of firms at NUTS 3 regional level that are, given their online appearance, related to the blockchain technology (financial centers in red).

6 Discussion and Conclusions

6.1 Main findings and policy implications

The previous analysis leads to several key findings. First, we show that the web-analysis plausibly identifies companies that adopt a technology whose applications are not necessarily protected by patents. Analyzing their websites, 11.922 of the 1.35 million companies in the D/A/CH region that are covered in our database are identified to use the blockchain technology (this is equal to 0.88% of all covered firms in the region). Hereby, 9.223 or 0.68% of companies provide *Information* and 5.420 (0.40%) companies are categorized in having actual *Know-how*, i.e. using or offering a blockchain related product or service. Second, we show that younger companies are more likely to use the blockchain technology indicating that the technology diffuses through the creation of new companies. However, companies that were founded around the year 2000 (mostly, in the ICT sector) also have a higher tendency of adopting this new technology. This indicates that having experience in use-fields is also a driver of blockchain adoption. Thirdly, firms that adopt and/or the blockchain technology are located or locate themselves (in case of newly founded firms) close to financial centers. This is not surprising given that the most prominent applications of the blockchain technology are within the financial sector. Our findings have implications for innovation and technology policy as well as for understanding regional patterns of technology diffusion in various contexts. While the finance sector already adopts the blockchain technology well, other sectors in which blockchain technology could be utilized are still lacking behind. Encouraging cooperation and knowledge sharing across sectors could facilitate blockchain use beyond applications in the financial sectors. Currently, despite increasing attention in news coverage of the crypto sector, the application developed within this area still only occupy a niche in the cross-country region investigate here. One implication is that geographical clustering is strong even in a digital technology such as blockchain. Yet, we see that there is some technology spread also to more remote locations. This pattern can be used to build 'competence cores' that bundle technology specific knowledge making it easier for companies in other locations that seek networking activities.

6.2 Limitations

This study has several limitations that should be considered when interpreting as well as extrapolating the results. First, the data used in this study covers the D/A/CH region (i.e. Germany, Austria, and Switzerland), which is not representative of the global blockchain industry. Second, the geolocation of companies was determined using Open-Street-Maps (OSM), which is not as accurate as Google maps (e.g., companies close to borders – both, on the country as well as on the regional level – are sometimes assigned to the wrong country/region as their (latitudinal and longitudinal) location is not accurately determined). This could lead to some degree of inaccuracy in the regional data analyzed. Third, various other location aspects such as universities, research centers, and accelerators were not considered, which may have provided a more comprehensive picture of the blockchain ecosystem in the region and allows for a better understanding of the factors influencing the location decision by blockchain companies. Fourth, no *on-chain*[39] analysis of blockchain firms was performed in this study, which may have provided a more in-depth understanding of the companies and their activities. At the same time, conducting the on-chain activity of companies on public companies might also only render an excerpt of the entire picture since most blockchain activity of traditional companies is usually conducted on private/permissioned blockchains. Fifth, our results do not allow us to draw conclusions about causal relationships, as we currently have data collected on a specific point in time. However, repeating this approach will allow collected time series information for studying the diffusion of blockchain over time. Finally, due to computational constraints, the keyword search for each company was only limited to the main website and 25 sub-websites. Hence, our data may not represent the entire population of blockchain firms in the D/A/CH region and thus, the number of blockchain firms identified within this study are a rather conservative estimate and are to be interpreted with caution. Furthermore, we can only draw conclusions on firms that have a website. There may be activities that are not recorded if they are using different channels of communication or are not communicating publicly about the use of (blockchain) technology.

39. *On-chain* refers to all activities that are conducted on the blockchain and thus, recorded by it. Hence, an on-chain analysis implies investigating and evaluation (all) traces of a firm on the blockchain.

7 OUTLOOK AND FUTURE RESEARCH

With the web-analysis approach, we provide novel insights on the scope and scale of companies adopting or informing about blockchain. While our results show that blockchain remains a niche technology, we can also conclude that the proposed approach allows identifying technology-users and diffusers in such a case.

Analysing characteristics of companies shows that younger firms and firms founded around 2000 are more likely to use blockchain technology, stressing the role of new companies in adopting and spreading new technology. Adoption rates vary widely across industries, with higher adoption rates in sectors such as ICT, banking and finance, and (management) consulting. In terms of regional distribution, our analyses reveal that blockchain companies are located in close proximity to financial centers, suggesting that, contrary to its decentralised nature, blockchain-using companies still cluster.

Further research should expand our data coverage to other countries and keep tracking diffusion patterns in the future. Our classification could also be extended by differentiating between distinct applications and use cases beyond the binary distinction of *Know-How* and *Information*. This would help deepen our analyses of the adoption of blockchain technology by companies.

In conclusion, while this article provided new and valuable insights into the blockchain ecosystem in the D/A/CH region, some limitations should be carefully taken into account when interpreting the results. Further research is needed to address these limitations and provide a more comprehensive understanding of the blockchain industry in the region and beyond.

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APPENDIX

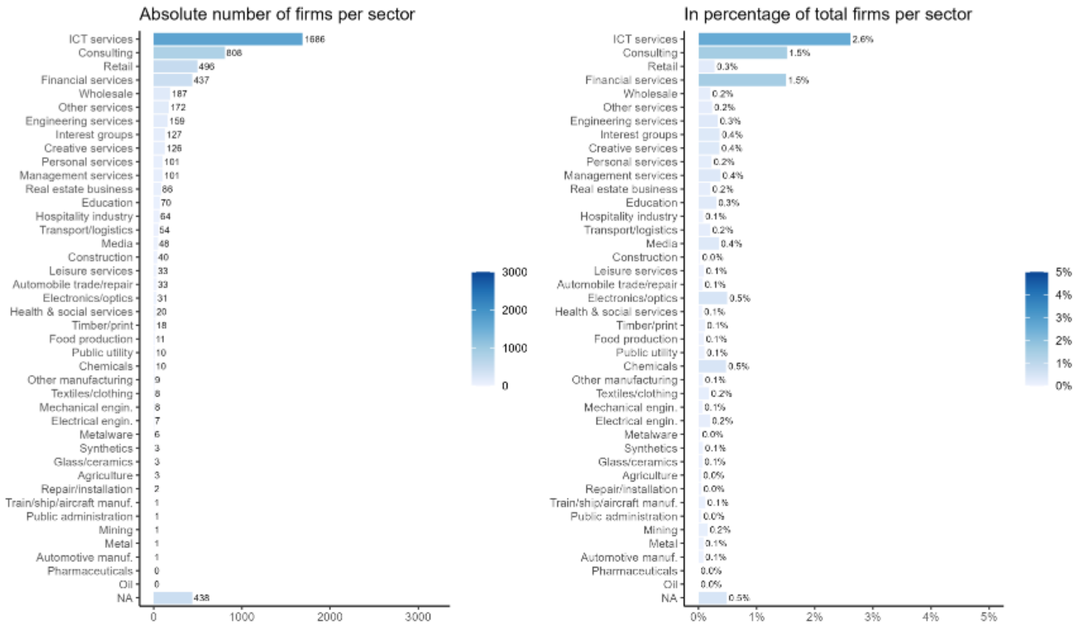


Fig. A1: Blockchain know how adoption rates across industry sectors

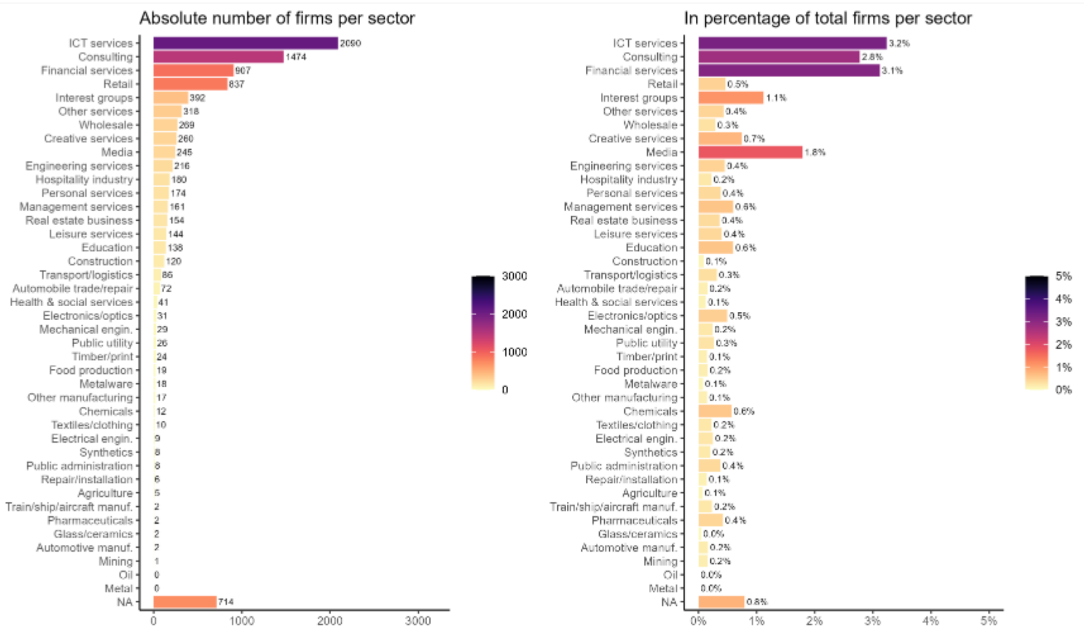
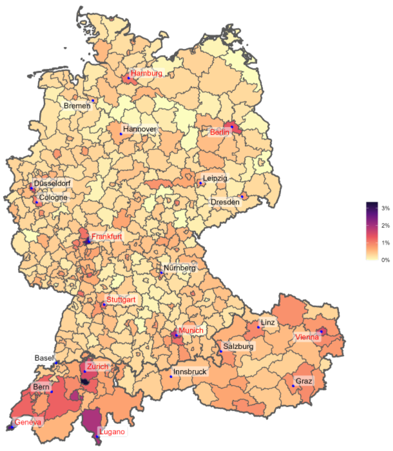
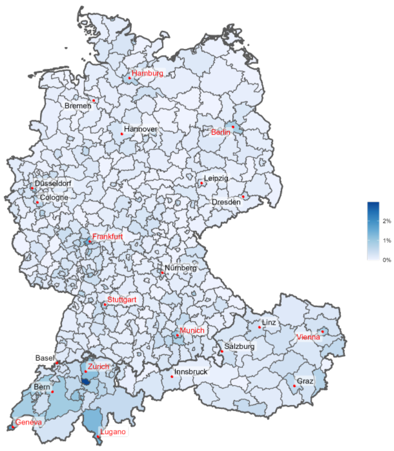


Fig. A2: Blockchain information adoption rates across industry sectors

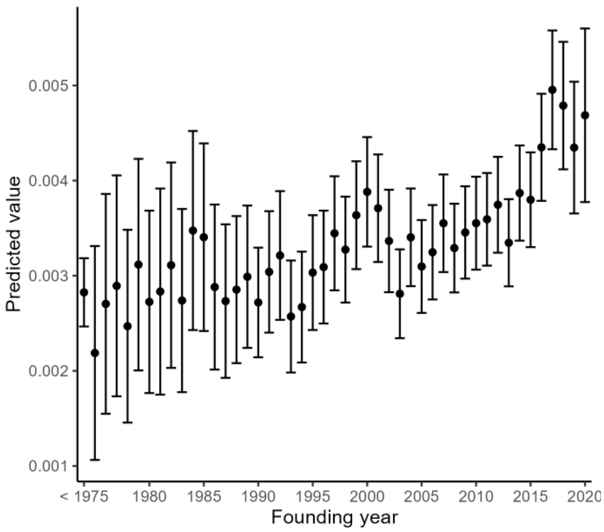


(a) Information

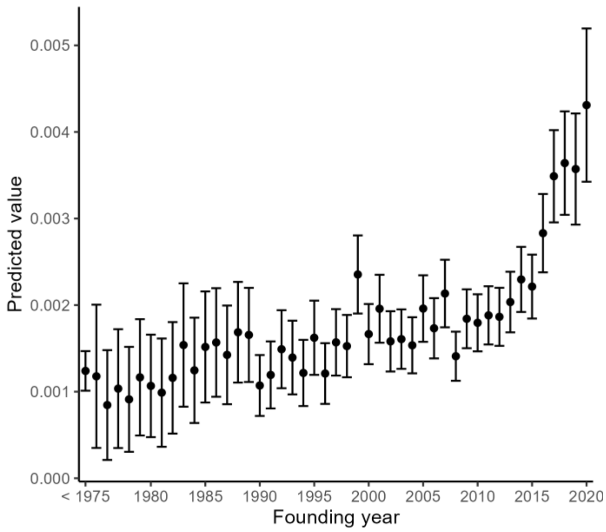


(b) Know-how

Fig. A3: Percentage share of firms at NUTS 3 regional level that, given their online appearance, provide information about (left) or are considered to have know-how in the blockchain technology (right). Financial centers are marked red).

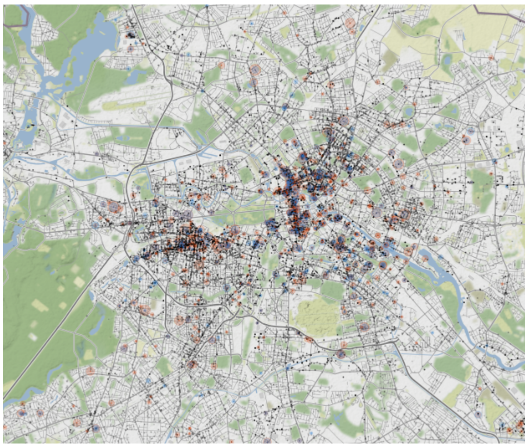


(a) Dependent variable: Information

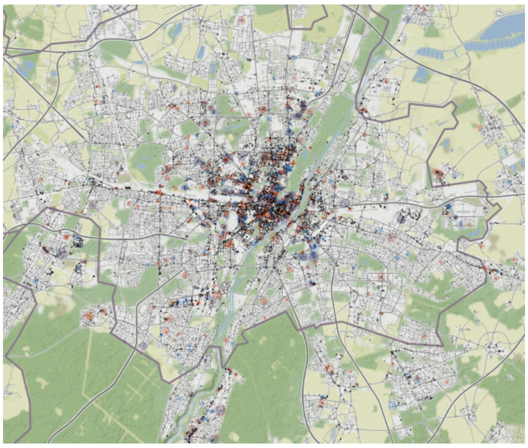


(b) Dependent variable: Know-how

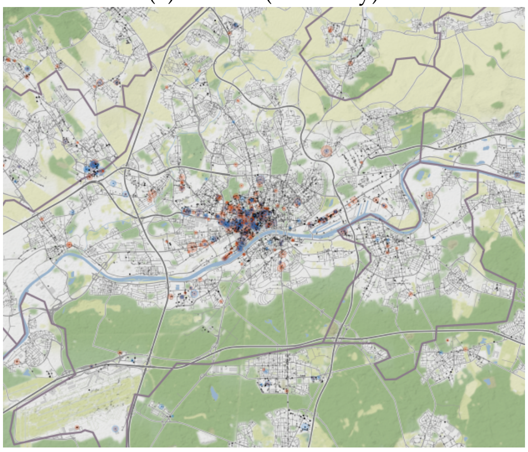
Fig. A4: Marginal predictive values (depending on the founding year) for firms that provide information about (left) or are classified as having know-how in the blockchain technology on their website (right).



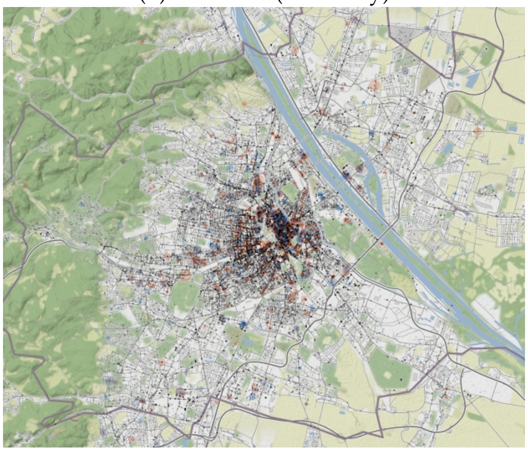
(a) Berlin* (Germany)



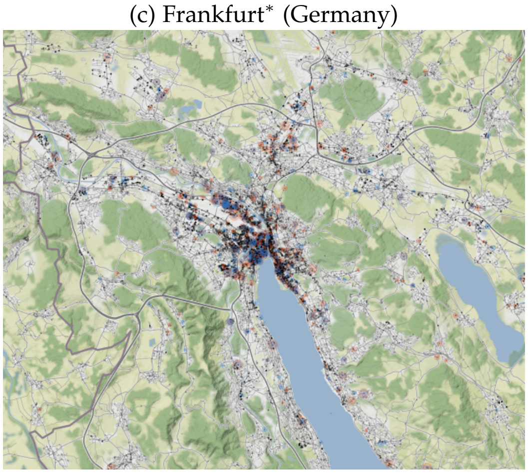
(b) Munich* (Germany)



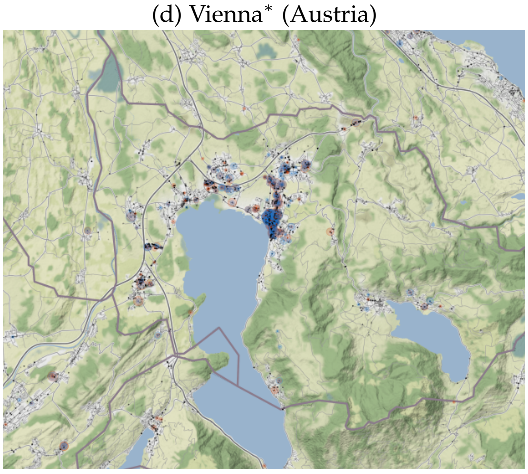
(c) Frankfurt* (Germany)



(d) Vienna* (Austria)



(e) Zurich* (Switzerland)



(f) Zug (Switzerland)

Fig. A5: Location of companies in different cities (financial centers are marked by an asterisk *). Non-blockchain firms are depicted as black points. Firms that provide information on the blockchain technology are included as red points and firms with know-how in the technology are represented by blue points. For blockchain firms (both, information and know-how), the size of the encompassing circle is related to the information and know-how intensity, respectively.

TABLE A1: Overview of online glossaries used to obtain potential (non-scientific) keywords.

Nr.	Website	Short description of (main) website
1	101blockchains.com/blockchain-definitions/	101 Blockchains is a website that offers blockchain and web3 training and certification programs.
2	academy.binance.com/en/glossary	Binance is by volume the world largest cryptocurrency exchange.
3	academy.bit2me.com/en/crypto-dictionary/	Bit2Me is a Spanish cryptocurrency trading broker.
4	blockchaintrainingalliance.com/pages/glossary-of-blockchain-terms	Blockchain Training Alliance is a US-based blockchain education company that offers online course material, instructions, and certifications on the blockchain technology.
5	www.codingem.com/nft-glossary/	Codingem.com is a tech blog that includes coding tutorials and provides software reviews.
6	consensys.net/knowledge-base/a-blockchain-glossary-for-beginners/	ConsenSys is a software company that offers a product suite that helps developers and enterprises to build applications on the Ethereum blockchain.
7	www.forbes.com/advisor/investing/cryptocurrency/crypto-glossary/	Forbes is a global media company, focusing on business, investing, technology, entrepreneurship, leadership, and lifestyle.
8	academy.moralis.io/blog/defi-encyclopedia-the-ultimate-list-of-decentralized-finance-terms	Moralis offers APIs to access as well as real-time blockchain data. In addition Moralis Academy provides programming courses.
9	objectcomputing.com/expertise/blockchain/glossary	Object Computing is a consulting company that provides consulting services by applying current technology.

TABLE A2: Final list of keywords associated to the blockchain technology which were used to identify companies that provide information on or use/offer products and services using the blockchain technology.

aave	decentralized applications	pegged currency
altcoin	decentralized autonomous applications	permissioned ledger
altcoins	decentralized autonomous organization	proof of stake
atokens	decentralized exchange	proof-of-authority
binance	decentralized exchanges	proof-of-stake
bitcoin	decentralized finance	proof-of-work
blockchain	devcon	siacoin
byzantine fault	dexes	sidechain
cbdc	distributed ledger technology	smart contract
central bank digital currency	dogecoin	smart contracts
chainlink	dyor	smart legal contract*
coinbase	eclipse attack	smart-contract
consensus algorithm	eosio	smart-contracts
consensus mechanism	erc-20	stablecoin
crypto	erc-721	stablecoins
cryptoassets	erc20	tezos
cryptocurrencies	ethereum	tokenomics
cryptocurrency	etherscan	total-value-locked
cryptoeconomics	genesis block	transaction block
cryptojacking	governance tokens	uniswap
ctokens	gwei	unspent transaction output
dappradar	hyperledger	usd coin
dapps	initial coin offering	usdc
de-fi	ipfs	usdt
decentralised applications	litecoin	utility tokens
decentralised autonomous applications	makerdao	utreexo
decentralised autonomous organization	mimblewimble	utxo
decentralised exchange	mining pool	ytokens
decentralised exchanges	multichain*	zero-knowledge-proof#
decentralised finance	non-fungible tokens	zk-snarks#

Note: Keywords marked with the pound/hash sign (#) were ex-post manually added to the list but were already part of the first list of keywords that resulted from the web-scraping of online blockchain glossaries. Keywords marked with an asterisk (*) were ex-post manually added to the list and do not result from the above described process.

TABLE A3: Blockchain keywords which were used to identify blockchain related companies and their respective frequency of occurrence on the firm websites within the analyzed data set.

Keyword	Frequency	Keyword	Frequency
bitcoin	61,029	mining pool	108
blockchain	54,914	smart-contract	104
crypto	31,087	multichain	89
ethereum	11,501	cryptojacking	88
cryptocurrency	8,011	central bank digital currency	86
cryptocurrencies	4,033	etherscan	80
binance	3,173	decentralized exchanges	76
coinbase	2,671	dexes	75
smart contracts	2,580	decentralised finance	60
litecoin	2,151	smart-contracts	53
dogecoin	1,705	decentralised applications	46
smart contract	1,340	utility tokens	46
altcoins	1,060	consensus mechanism	45
devcon	994	makerdao	44
usdt	921	gwei	35
cbdc	725	decentralized autonomous organization	32
stablecoins	697	utxo	31
distributed ledger technology	628	de-fi	30
decentralized finance	606	consensus algorithm	22
dapps	585	byzantine fault	18
chainlink	534	genesis block	17
stablecoin	524	cryptoeconomics	16
uniswap	505	eosio	16
non-fungible tokens	488	decentralised exchange	10
altcoin	394	governance tokens	10
hyperledger	389	zk-snarks	10
tezos	389	proof-of-authority	8
usdc	386	unspent transaction output	6
proof-of-stake	348	zero-knowledge-proof	6
ipfs	335	mimblewimble	5
proof-of-work	302	smart legal contract	5
initial coin offering	280	dappradar	4
proof of stake	280	decentralised exchanges	2
erc20	278	permissioned ledger	2
aave	249	transaction block	2
siacoin	206	ctokens	1
erc-20	203	pegged currency	1
dyor	199	atokens	0
tokenomics	189	decentralised autonomous applications	0
decentralized applications	185	decentralised autonomous organization	0
cryptoassets	184	decentralized autonomous applications	0
erc-721	157	eclipse attack	0
sidechain	148	total-value-locked	0
usd coin	145	utreexo	0
decentralized exchange	123	ytokens	0

Note: Keywords are sorted in descending order according to the frequency of occurrence.

TABLE A4: List of major cities in Germany, Austria, and Switzerland.

Germany	**Austria**	**Switzerland**
Berlin*	Vienna*	Zurich*
Hamburg*	Graz	Geneva*
Munich*	Linz	Basel
Cologne	Salzburg	Lausanne
Frankfurt*	Innsbruck	Bern
Stuttgart*	Klagenfurt	Winterthur
Düsseldorf		
Leipzig		
Dortmund		
Essen		
Bremen		
Dresden		
Hannover		
Nürnberg		

Note: The list is based on the number of inhabitants with the minimum of required inhabitants varying according to the country. In Germany, major cities are cites with more than 500.000 inhabitants, in Switzerland and Austria, cities with more than 100.000 inhabitants. (Cities are sorted according to the number of inhabitants; major financial centers, as determined by the GFCI, are marked with an asterisk*.)

TABLE A5: Descriptive statistics at the firm level.

	All firms					
	N	Mean	Median	St. Dev.	Min	Max
Founding year	1334358	1999	2004	22.09	1000	2020
Employees (in thous.)	1218839	0.03334	0.004	1.036	0.001	298.655
Finance center (within 20 km)	1347907	0.2457	0	0.4305	0	1
Information intensity	1347907	0.003025	0	0.0619	0	5.8133
Know-how intensity	1347907	0.001646	0	0.04112	0	4.1005
	Blockchain					
	N	Mean	Median	St. Dev.	Min	Max
Founding year	11831	2004	2008	16.77	1723	2020
Employees (in thous.)	10828	0.1089	0.004	2.67	0.001	210.533
Finance center (within 20 km)	11922	0.4781	0	0.4995	0	1
Information intensity	11922	0.342	0.1527	0.5632	0	5.8133
Know-how intensity	11922	0.186	0	0.3961	0	4.1005

	Information					
	N	Mean	Median	St. Dev.	Min	Max
Founding year	9147	2004	2008	17.07	1723	2020
Employees (in thous.)	8352	0.1207	0.004	3.016	0.001	210.533
Finance center (within 20 km)	9223	0.4798	0	0.4996	0	1
Information intensity	9223	0.4421	0.1866	0.6048	0.0662	5.8133
Know-how intensity	9223	0.1749	0	0.4298	0	4.1005

	Know-how					
	N	Mean	Median	St. Dev.	Min	Max
Founding year	5378	2006	2010	16.46	1723	2020
Employees (in thous.)	4984	0.1242	0.004	3.129	0.001	210.533
Finance center (within 20 km)	5420	0.5113	1	0.4999	0	1
Information intensity	5420	0.3827	0.0757	0.7069	0	5.8133
Know-how intensity	5420	0.4092	0.1785	0.5038	0.0677	4.1005

Note: The table includes all firms in the data set, subdivided by firms that are engaged with the blockchain technology, either by providing *Information* about it or by having *Know-how* in the technology.)

TABLE A6: Descriptive statistics at the NUTS 3 regional level.

	All firms					
	N	Mean	Median	St. Dev.	Min	Max
# firms	462	2918	1896	4372	272	52122
Rel. # firms (blockchain)	462	0.005569	0.0044	0.004619	0	0.0454
Rel. # firms (info)	462	0.004355	0.0035	0.003614	0	0.0335
Rel. # firms (know-how)	462	0.002289	0.0017	0.002583	0	0.0296
Ø info. intensity	462	0.4106	0.3693	0.3017	0	2.9127
Ø know-how intensity	462	0.3224	0.285	0.2866	0	2.1747
Sectoral variety (Entropy)	462	4.427	4.4578	0.1371	3.6017	4.6396
% of firms in financial services sector	462	0.02023	0.019	0.007109	0.0058	0.0642

	Regions with financial center					
	N	Mean	Median	St. Dev.	Min	Max
# firms	12	20500	15038.5	14670	5866	52122
Rel. # firms (blockchain)	12	0.02341	0.0202	0.009804	0.0137	0.0454
Rel. # firms (info)	12	0.01828	0.0152	0.007567	0.0104	0.0335
Rel. # firms (know-how)	12	0.01182	0.0097	0.006513	0.0061	0.0296
Ø info. intensity	12	0.4627	0.4345	0.08466	0.3842	0.712
Ø know-how intensity	12	0.4281	0.4064	0.08772	0.3574	0.693
Sectoral variety (Entropy)	12	4.33	4.4048	0.1951	3.9408	4.5103
% of firms in financial services sector	12	0.03083	0.0306	0.009141	0.0143	0.0478

	Regions without financial center					
	N	Mean	Median	St. Dev.	Min	Max
# firms	450	2449	1818.5	2424	272	34800
Rel. # firms (blockchain)	450	0.005093	0.0043	0.003289	0	0.0214
Rel. # firms (info)	450	0.003983	0.0034	0.002585	0	0.019
Rel. # firms (know-how)	450	0.002035	0.0016	0.001823	0	0.0107
Ø info. intensity	450	0.4092	0.3585	0.3053	0	2.9127
Ø know-how intensity	450	0.3196	0.2789	0.2895	0	2.1747
Sectoral variety (Entropy)	450	4.43	4.458	0.1346	3.6017	4.6396
% of firms in financial services sector	450	0.01994	0.0189	0.006837	0.0058	0.0642

Note: The table includes all NUTS 3 regions in the data set subdivided by regions with and without a financial center.)

TABLE A7: Descriptive statistics for NUTS 0, NUTS 1, and NUTS 2 regions.

NUTS		# firms				Rel. # firms			Ø info. intensity		Ø know-how intensity	
Name	ID	(all)	(blockch.)	(info.)	(know-how)	(blockch.)	(info.)	(know-how)	(all firms)	(info.)	(all firms)	(know-how)
Austria	**AT**	**117,481**	**1,295**	**1,033**	**520**	**0.0110**	**0.0088**	**0.0044**	**0.0037**	**0.4160**	**0.0017**	**0.3857**
Ostösterreich	*AT1*	*49,991*	*739*	*589*	*315*	*0.0148*	*0.0118*	*0.0063*	*0.0050*	*0.4265*	*0.0023*	*0.3709*
Burgenland	AT11	3,202	31	23	16	0.0097	0.0072	0.0050	0.0030	0.4164	0.0030	0.6085
Niederösterreich	AT12	18,472	164	132	56	0.0089	0.0071	0.0030	0.0028	0.3855	0.0008	0.2742
Wien	AT13	28,317	544	434	243	0.0192	0.0153	0.0086	0.0067	0.4395	0.0032	0.3775
Südösterreich	*AT2*	*21,304*	*194*	*150*	*81*	*0.0091*	*0.0070*	*0.0038*	*0.0031*	*0.4357*	*0.0016*	*0.4170*
Kärnten	AT21	6,796	59	51	25	0.0087	0.0075	0.0037	0.0043	0.5667	0.0016	0.4456
Steiermark	AT22	14,508	135	99	56	0.0093	0.0068	0.0039	0.0025	0.3682	0.0016	0.4043
Westösterreich	*AT3*	*46,186*	*362*	*294*	*124*	*0.0078*	*0.0064*	*0.0027*	*0.0025*	*0.3852*	*0.0011*	*0.4027*
Oberösterreich	AT31	18,460	159	128	58	0.0086	0.0069	0.0031	0.0028	0.4031	0.0013	0.4028
Salzburg	AT32	9,408	85	71	26	0.0090	0.0075	0.0028	0.0028	0.3694	0.0007	0.2704
Tirol	AT33	12,919	79	63	27	0.0061	0.0049	0.0021	0.0020	0.4058	0.0011	0.5424
Vorarlberg	AT34	5,399	39	32	13	0.0072	0.0059	0.0024	0.0018	0.3079	0.0009	0.3771
Switzerland	**CH**	**187,547**	**3,175**	**2,353**	**1,700**	**0.0169**	**0.0125**	**0.0091**	**0.0062**	**0.4972**	**0.0042**	**0.4588**
Région lémanique	CH01	24,713	514	406	256	0.0208	0.0164	0.0104	0.0084	0.5127	0.0050	0.4789
Espace Mittelland	CH02	47,400	719	524	383	0.0152	0.0111	0.0081	0.0054	0.4867	0.0036	0.4418
Nordwestschweiz	CH03	23,343	221	159	114	0.0095	0.0068	0.0049	0.0026	0.3757	0.0018	0.3614
Zürich	CH04	37,090	785	561	433	0.0212	0.0151	0.0117	0.0074	0.4876	0.0048	0.4111
Ostschweiz	CH05	25,735	239	176	117	0.0093	0.0068	0.0045	0.0031	0.4582	0.0018	0.3953
Zentralschweiz	CH06	23,400	551	412	321	0.0235	0.0176	0.0137	0.0105	0.5946	0.0083	0.6034
Ticino	CH07	5,866	146	115	76	0.0249	0.0196	0.0130	0.0082	0.4165	0.0049	0.3820
Germany	**DE**	**1,042,879**	**7,452**	**5,837**	**3,200**	**0.0071**	**0.0056**	**0.0031**	**0.0024**	**0.4245**	**0.0012**	**0.3867**
Baden-Württemberg	*DE1*	*148,146*	*918*	*719*	*397*	*0.0062*	*0.0049*	*0.0027*	*0.0020*	*0.4077*	*0.0010*	*0.3599*
Stuttgart	DE11	52,711	355	287	160	0.0067	0.0054	0.0030	0.0021	0.3825	0.0012	0.3862
Karlsruhe	DE12	38,121	300	232	125	0.0079	0.0061	0.0033	0.0024	0.4019	0.0012	0.3557
Freiburg	DE13	31,733	148	108	63	0.0047	0.0034	0.0020	0.0015	0.4421	0.0006	0.2858
Tübingen	DE14	25,581	115	92	49	0.0045	0.0036	0.0019	0.0017	0.4608	0.0007	0.3799
Bayern	*DE2*	*186,199*	*1,555*	*1,204*	*672*	*0.0084*	*0.0065*	*0.0036*	*0.0026*	*0.4040*	*0.0015*	*0.4044*
Oberbayern	DE21	76,827	982	751	463	0.0128	0.0098	0.0060	0.0040	0.4079	0.0025	0.4209
Niederbayern	DE22	15,560	60	49	20	0.0039	0.0031	0.0013	0.0011	0.3620	0.0005	0.3743
Oberpfalz	DE23	13,711	87	65	39	0.0063	0.0047	0.0028	0.0020	0.4167	0.0011	0.3847
Oberfranken	DE24	13,809	63	58	12	0.0046	0.0042	0.0009	0.0020	0.4822	0.0002	0.2507
Mittelfranken	DE25	22,914	134	102	53	0.0058	0.0045	0.0023	0.0017	0.3729	0.0009	0.3698
Unterfranken	DE26	17,478	97	78	32	0.0055	0.0045	0.0018	0.0019	0.4204	0.0006	0.3041
Schwaben	DE27	25,900	132	101	53	0.0051	0.0039	0.0020	0.0014	0.3614	0.0009	0.4155
Berlin	*DE3*	*52,122*	*912*	*721*	*433*	*0.0175*	*0.0138*	*0.0083*	*0.0067*	*0.4813*	*0.0033*	*0.4017*
Brandenburg	*DE4*	*27,593*	*118*	*92*	*54*	*0.0043*	*0.0033*	*0.0020*	*0.0019*	*0.5660*	*0.0008*	*0.3858*
Bremen	*DE5*	*8,223*	*45*	*38*	*17*	*0.0055*	*0.0046*	*0.0021*	*0.0020*	*0.4244*	*0.0009*	*0.4342*
Hamburg	*DE6*	*32,557*	*456*	*353*	*215*	*0.0140*	*0.0108*	*0.0066*	*0.0053*	*0.4864*	*0.0026*	*0.3970*
Hessen	*DE7*	*65,855*	*687*	*544*	*297*	*0.0104*	*0.0083*	*0.0045*	*0.0033*	*0.4011*	*0.0018*	*0.3940*
Darmstadt	DE71	46,630	614	481	273	0.0132	0.0103	0.0059	0.0041	0.3995	0.0023	0.3952

Gießen	DE72	9,298	31	28	7	0.0033	0.0030	0.0008	0.0012	0.4077	0.0003	0.4646
Kassel	DE73	9,927	42	35	17	0.0042	0.0035	0.0017	0.0015	0.4179	0.0006	0.3452
Mecklenburg-Vorpommern	*DE8*	*16,909*	*46*	*41*	*17*	*0.0027*	*0.0024*	*0.0010*	*0.0015*	*0.6007*	*0.0004*	*0.3636*
Niedersachsen	*DE9*	*92,202*	*394*	*311*	*150*	*0.0043*	*0.0034*	*0.0016*	*0.0012*	*0.3532*	*0.0005*	*0.3339*
Braunschweig	DE91	15,042	69	53	26	0.0046	0.0035	0.0017	0.0013	0.3775	0.0006	0.3459
Hannover	DE92	26,109	147	115	60	0.0056	0.0044	0.0023	0.0016	0.3546	0.0007	0.3129
Lüneburg	DE93	19,802	66	50	28	0.0033	0.0025	0.0014	0.0009	0.3728	0.0004	0.2590
Weser-Ems	DE94	31,249	112	93	36	0.0036	0.0030	0.0012	0.0010	0.3271	0.0005	0.4185
Nordrhein-Westfalen	*DEA*	*228,411*	*1,459*	*1,133*	*612*	*0.0064*	*0.0050*	*0.0027*	*0.0021*	*0.4149*	*0.0010*	*0.3814*
Düsseldorf	DEA1	69,027	530	414	228	0.0077	0.0060	0.0033	0.0024	0.4058	0.0012	0.3667
Köln	DEA2	60,267	469	353	207	0.0078	0.0059	0.0034	0.0023	0.4007	0.0013	0.3739
Münster	DEA3	30,392	123	106	32	0.0040	0.0035	0.0011	0.0014	0.3877	0.0004	0.3617
Detmold	DEA4	26,624	126	95	57	0.0047	0.0036	0.0021	0.0017	0.4699	0.0009	0.4013
Arnsberg	DEA5	42,101	211	165	88	0.0050	0.0039	0.0021	0.0018	0.4541	0.0009	0.4316
Rheinland-Pfalz	*DEB*	*47,035*	*217*	*174*	*83*	*0.0046*	*0.0037*	*0.0018*	*0.0015*	*0.3922*	*0.0007*	*0.4220*
Koblenz	DEB1	19,012	69	58	23	0.0036	0.0031	0.0012	0.0015	0.4791	0.0007	0.5719
Trier	DEB2	6,355	26	17	13	0.0041	0.0027	0.0020	0.0006	0.2305	0.0003	0.1689
Rheinhessen-Pfalz	DEB3	21,668	122	99	47	0.0056	0.0046	0.0022	0.0017	0.3690	0.0009	0.4187
Saarland	*DEC*	*10,511*	*52*	*42*	*23*	*0.0049*	*0.0040*	*0.0022*	*0.0022*	*0.5408*	*0.0008*	*0.3452*
Sachsen	*DED*	*49,475*	*258*	*202*	*95*	*0.0052*	*0.0041*	*0.0019*	*0.0016*	*0.4020*	*0.0007*	*0.3806*
Dresden	DED2	20,887	117	91	44	0.0056	0.0044	0.0021	0.0018	0.4122	0.0008	0.3618
Chemnitz	DED4	16,211	50	40	17	0.0031	0.0025	0.0010	0.0010	0.3990	0.0005	0.5029
Leipzig	DED5	12,377	91	71	34	0.0074	0.0057	0.0027	0.0022	0.3905	0.0009	0.3439
Sachsen-Anhalt	*DEE*	*18,047*	*75*	*65*	*21*	*0.0042*	*0.0036*	*0.0012*	*0.0019*	*0.5243*	*0.0003*	*0.2755*
Schleswig-Holstein	*DEF*	*37,683*	*170*	*130*	*79*	*0.0045*	*0.0034*	*0.0021*	*0.0015*	*0.4208*	*0.0008*	*0.3850*
Thüringen	*DEG*	*21,911*	*90*	*68*	*35*	*0.0041*	*0.0031*	*0.0016*	*0.0013*	*0.4032*	*0.0006*	*0.3811*

Note: The table includes an overview of firms' blockchain statistics both, for *Information* and for *Know-how*). The data is aggregated on NUTS 0 (countries, in **bold font**), NUTS 1 (major socio-economic regions, in *italic font*), and NUTS 2 level (basic regions). Average values of the information (info) and know-how intensity are indicated by Ø and are calculated relative to all firms as well as only to firms that are identified providing information on or possessing know-how in the blockchain technology, respectively.

TABLE A8: Descriptive statistics at the sector level.

Sector	# firms				Rel. # firms			Ø info. intensity		Ø know-how intensity	
	(all)	(blockch.)	(info.)	(know-how)	(blockch.)	(info.)	(know-how)	(all firms)	(info.)	(all firms)	(know-how)
Agriculture	7, 142	7	5	3	0.0010	0.0007	0.0004	0.0002	0.3307	0.0001	0.2337
Automobile trade/repair	47, 475	88	72	33	0.0019	0.0015	0.0007	0.0007	0.4306	0.0002	0.3405
Automotive manuf.	1, 228	3	2	1	0.0024	0.0016	0.0008	0.0002	0.1169	0.0003	0.3981
Chemicals	2, 119	14	12	10	0.0066	0.0057	0.0047	0.0015	0.2636	0.0008	0.1669
Construction	140, 335	141	120	40	0.0010	0.0009	0.0003	0.0005	0.5991	0.0001	0.3164
Consulting	53, 140	1, 886	1, 474	808	0.0355	0.0277	0.0152	0.0099	0.3585	0.0056	0.3661
Creative services	35, 027	323	260	126	0.0092	0.0074	0.0036	0.0027	0.3622	0.0012	0.3258
Education	23, 126	167	138	70	0.0072	0.0060	0.0030	0.0023	0.3804	0.0012	0.3870
Electrical engin.	3, 614	15	9	7	0.0042	0.0025	0.0019	0.0005	0.2153	0.0005	0.2535
Electronics/optics	6, 295	54	31	31	0.0086	0.0049	0.0049	0.0016	0.3310	0.0022	0.4373
Engineering services	48, 040	320	216	159	0.0067	0.0045	0.0033	0.0014	0.3116	0.0010	0.3015
Financial services	29, 071	1, 089	907	437	0.0375	0.0312	0.0150	0.0146	0.4676	0.0068	0.4515
Food production	12, 142	24	19	11	0.0020	0.0016	0.0009	0.0011	0.7065	0.0004	0.3884
Glass/ceramics	4, 608	5	2	3	0.0011	0.0004	0.0007	0.0004	0.8070	0.0001	0.1147
Health & social services	33, 501	54	41	20	0.0016	0.0012	0.0006	0.0005	0.3883	0.0001	0.2315
Hospitality industry	80, 924	211	180	64	0.0026	0.0022	0.0008	0.0012	0.5378	0.0002	0.2804
ICT services	64, 564	2, 918	2, 090	1, 686	0.0452	0.0324	0.0261	0.0161	0.4969	0.0127	0.4855
Interest groups	35, 051	440	392	127	0.0126	0.0112	0.0036	0.0048	0.4305	0.0011	0.3059
Leisure services	35, 963	159	144	33	0.0044	0.0040	0.0009	0.0020	0.5059	0.0003	0.2725
Management services	26, 916	218	161	101	0.0081	0.0060	0.0038	0.0020	0.3395	0.0014	0.3845
Mechanical engin.	12, 195	34	29	8	0.0028	0.0024	0.0007	0.0006	0.2472	0.0002	0.3386
Media	13, 711	272	245	48	0.0198	0.0179	0.0035	0.0061	0.3402	0.0011	0.3134
Metal	1, 195	1	0	1	0.0008	0.0000	0.0008	0.0000	0.0000	0.0001	0.1592
Metalware	23, 218	22	18	6	0.0009	0.0008	0.0003	0.0002	0.3214	0.00002	0.0950
Mining	645	2	1	1	0.0031	0.0016	0.0016	0.0007	0.4293	0.0003	0.1630
Oil	44	0	0	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Other manufacturing	11, 668	21	17	9	0.0018	0.0015	0.0008	0.0007	0.4925	0.0003	0.3886
Other services	73, 823	404	318	172	0.0055	0.0043	0.0023	0.0019	0.4363	0.0008	0.3487
Personal services	45, 546	225	174	101	0.0049	0.0038	0.0022	0.0016	0.4289	0.0008	0.3654
Pharmaceuticals	475	2	2	0	0.0042	0.0042	0.0000	0.0007	0.1569	0.0000	0.0000
Public administration	2, 119	8	8	1	0.0038	0.0038	0.0005	0.0013	0.3480	0.0002	0.3186
Public utility	9, 846	34	26	10	0.0035	0.0026	0.0010	0.0006	0.2169	0.0002	0.2312
Real estate business	42, 387	194	154	86	0.0046	0.0036	0.0020	0.0013	0.3669	0.0007	0.3296
Repair/installation	4, 233	7	6	2	0.0017	0.0014	0.0005	0.0003	0.1998	0.0001	0.2719
Retail	180, 510	1, 091	837	496	0.0060	0.0046	0.0027	0.0025	0.5499	0.0011	0.4051
Synthetics	3, 914	10	8	3	0.0026	0.0020	0.0008	0.0011	0.5197	0.0003	0.3819
Textiles/clothing	4, 443	12	10	8	0.0027	0.0023	0.0018	0.0017	0.7335	0.0008	0.4482
Timber/print	16, 604	39	24	18	0.0023	0.0014	0.0011	0.0005	0.3739	0.0002	0.1913
Train/ship/aircraft manuf.	866	3	2	1	0.0035	0.0023	0.0012	0.0002	0.0933	0.0001	0.0826
Transport/logistics	27, 168	114	86	54	0.0042	0.0032	0.0020	0.0013	0.3993	0.0005	0.2554
Wholesale	92, 853	373	269	187	0.0040	0.0029	0.0020	0.0011	0.3747	0.0007	0.3307
NA	90, 049	918	714	438	0.0102	0.0079	0.0049	0.0036	0.4585	0.0022	0.4545

TABLE A9: Logistic regression analyses for firms that adopt the blockchain technology.

	Dependent variable:					
	Blockchain use		Information		Know-how	
	Coefficient	Odds-ratio	Coefficient	Odds-ratio	Coefficient	Odds-ratio
Finance center (10km)	0.327*** (0.036)	1.387	0.357*** (0.041)	1.429	0.372*** (0.052)	1.451
Zug (10km)	0.361*** (0.077)	1.435	0.349*** (0.088)	1.418	0.618*** (0.103)	1.855
Major city (10km)	0.266*** (0.033)	1.305	0.244*** (0.038)	1.276	0.323*** (0.048)	1.381
Urban type 2 (intermediate regions)	−0.060** (0.027)	0.942	−0.067** (0.031)	0.935	−0.024 (0.041)	0.977
Urban type 3 (mainly rural regions)	−0.233*** (0.045)	0.792	−0.205*** (0.051)	0.815	−0.385*** (0.075)	0.681
Austria	0.446*** (0.040)	1.562	0.468*** (0.045)	1.597	0.359*** (0.062)	1.432
Switzerland	0.666*** (0.026)	1.946	0.622*** (0.029)	1.863	0.796*** (0.037)	2.218
Avg. number of patent applications	0.00003* (0.00002)	1.000	0.00003 (0.00002)	1.000	0.00004* (0.00003)	1.000
% of firms in financial services sector	0.225*** (0.017)	1.253	0.227*** (0.019)	1.255	0.224*** (0.025)	1.252
Employees (in thous.)	0.013*** (0.003)	1.013	0.013*** (0.003)	1.013	0.013*** (0.004)	1.013
Constant	−5.610*** (0.072)	0.004	−5.787*** (0.080)	0.003	−6.594*** (0.112)	0.001
Sector controls	Yes		Yes		Yes	
Year controls	Yes		Yes		Yes	
Wald test for sector ($\mathcal{X}^2$)	9193.247***		6900.274***		4818.043***	
Pseudo-R^2 (McFadden)	0.13		0.119		0.147	
Observations	1,208,909		1,208,909		1,208,909	
Log Likelihood	−53,583.690		−43,695.950		−27,464.800	
Akaike Inf. Crit.	107,365.400		87,589.910		55,127.610	

Note: The dependent variable is binary and indicates whether a firm is respectively classified ($Y = 1$) as *Blockchain use* (1), *Information* (2), or *Know-how* (3) or not ($Y = 0$). The main independent variables are whether the firm's headquarter is located within a 10 km-radius of a major financial center (as determined by GFCI 32) and the number of employees (in thousand).The table reports for each resulting coefficient the statistical significance (*p<0.1; **p<0.05; ***p<0.01), the standard error (in brackets), as well as the odds-ratio. Dummy control variables for the sectors the companies are operating in and for the years they were founded in are included.

TABLE A10: Fractional logistic regression of the percentage share of firms adopting the blockchain technology at the NUTS 3 regional level.

	Dependent variable:					
	Blockchain use (in % of all firms)		Information (in % of all firms)		Know-how (in % of all firms)	
	Coefficient	Odds-ratio	Coefficient	Odds-ratio	Coefficient	Odds-ratio
Finance center	0.227*** (0.039)	1.255	0.347*** (0.032)	1.415	0.326*** (0.041)	1.385
Austria	0.390*** (0.050)	1.477	0.686*** (0.039)	1.986	0.677*** (0.053)	1.968
Switzerland	0.602*** (0.034)	1.826	0.738*** (0.029)	2.092	1.043*** (0.035)	2.839
Urban type 2 (intermediate regions)	−0.113*** (0.037)	0.893	−0.219*** (0.029)	0.804	−0.218*** (0.038)	0.804
Urban type 3 (mainly rural regions)	−0.307*** (0.069)	0.736	−0.432*** (0.047)	0.649	−0.622*** (0.069)	0.537
% of firms in financial services sector	0.224*** (0.019)	1.251	0.378*** (0.015)	1.460	0.427*** (0.019)	1.533
Avg. number of patent applications	0.0001** (0.00002)	1.000	0.0001*** (0.00002)	1.000	0.0001*** (0.00002)	1.000
Most freq. sector (hospitality industry)	−0.111 (0.190)	0.895	0.151 (0.107)	1.163	−0.200 (0.189)	0.818
Most freq. sector (retail)	0.242*** (0.053)	1.274	0.293*** (0.038)	1.340	0.362*** (0.053)	1.436
Most freq. sector (wholesale)	0.522*** (0.087)	1.686	0.481*** (0.065)	1.618	0.374*** (0.084)	1.453
Constant	−4.200*** (0.069)	0.015	−6.314*** (0.051)	0.002	−7.094*** (0.069)	0.001
Observations	462		462		462	
Log Likelihood	−1,059.281		−1,470.423		−1,219.978	
Akaike Inf. Crit.	2,140.563		2,962.846		2,461.955	

Note: The dependent variables is proportional and indicates the %-share of firms within the NUTS 3 region that are classified as *Blockchain use* (1), *Information* (2), or *Know-how* (3). The main independent variables are whether the NUTS 3 region contains a major finance center (as determined by GFCI 32) and the %-share of firms that operate in the financial services sector. The table reports for each resulting coefficient the statistical significance (*p<0.1; **p<0.05; ***p<0.01), the standard error (in brackets), as well as the odds-ratio.

TABLE A11: Logistic regression analyses for the choice of start-ups (firms founded in 2016 and later) to locate close to a major financial center dependent on the adoption of the blockchain technology.

	Dependent variable:					
	Financial center as firm location					
	(1)		(2)		(3)	
	Coefficient	Odds-ratio	Coefficient	Odds-ratio	Coefficient	Odds-ratio
Blokchain use	0.634*** (0.084)	1.885				
Blokchain information			0.654*** (0.098)	1.923		
Blokchain know-how					0.652*** (0.112)	1.919
Employees (in thous.)	−0.017 (0.021)	0.983	−0.018 (0.021)	0.983	−0.017 (0.021)	0.983
Urban type 2 (intermediate regions)	−5.917*** (0.148)	0.003	−5.916*** (0.148)	0.003	−5.916*** (0.148)	0.003
Urban type 3 (mainly rural regions)	−14.143 (176.850)	0.000	−14.147 (176.857)	0.000	−14.151 (176.879)	0.000
Major city (10km)	20.923 (79.022)	1,221,259,114	20.924 (79.024)	1,222,261,749	20.923 (79.036)	1,221,129,864
Austria	1.824*** (0.066)	6.199	1.825*** (0.066)	6.205	1.824*** (0.066)	6.198
Switzerland	1.075*** (0.035)	2.930	1.077*** (0.035)	2.937	1.076*** (0.035)	2.932
Constant	−20.559 (79.022)	0.000	−20.558 (79.024)	0.000	−20.550 (79.036)	0.000
Sector controls	Yes		Yes		Yes	
Year controls	Yes		Yes		Yes	
Wald test for sector ($\mathcal{X}^2$)	295.312***		305.96***		307.081***	
Pseudo-R^2 (McFadden)	0.648		0.648		0.648	
Observations	137,397		137,397		137,397	
Log Likelihood	−21,376.120		−21,382.540		−21,388.240	
Akaike Inf. Crit.	42,860.250		42,873.080		42,884.490	

Note: The dependent variable is binary and indicates whether a start-up locates its headquarter within a 10 km-radius of a major financial center ($Y = 1$) or not ($Y = 0$). The main independent variables are whether the start-up generally adopts (1), provides information about (2), or even has knowledge in the blockchain technology (3). The table reports for each resulting coefficient the statistical significance (*p<0.1; **p<0.05; ***p<0.01), the standard error (in brackets), as well as the odds-ratio. Dummy control variables for the sectors the companies are operating in and for the years they were founded in are included.

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