Knowledge Without Borders?

Brexit and the Geography of Technical Q&A*

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Abstract

In this paper, we examine the impact of the Brexit referendum on online technical knowledge-seeking and innovative activity in the UK. Using a novel dataset of geo-located Stack Overflow questions and answers, along with GitHub repositories matched to developers who posted questions between 2015 and 2019, we assess changes in user engagement following the referendum. Our results indicate a significant increase in Stack Overflow activity – particularly novel, high-quality, and code-related questions – in high-tech regions such as London, Oxford, and Cambridge. These regions also experience increases in the inflow of answers from outside the UK, suggesting intensified international engagement. More peripheral UK regions show little change. Though GitHub repository creation, used as a proxy for innovation, remains stable, on average, in the UK post-Brexit, there is a strong decline in high-tech regions and, in particular, among less reputable developers suggesting that only the already advantaged and known developers could compensate for lost local knowledge through virtual communities. More peripheral UK regions show little change, underscoring regional disparities in producing innovation and in responding to changes in knowledge flows. Conceptually, we frame Brexit as a policy-driven shock that disrupted knowledge flows, notably by restricting the inflow of European talent. Consequently, UK tech communities adapted by increasing their reliance on digital knowledge communities, but only in advanced, globally connected regions. As such, our study advances our understanding of how local knowledge flows influence geographically concentrated online technical knowledge production and innovation.

Keywords: *Specialized Knowledge*, *Stack Overflow*, *Firm Performance*, *Labor Mobility*, *Brexit*

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1 Introduction

Technical knowledge production and innovation are critical drivers of economic growth shaping productivity and competitiveness across the globe (Robertson et al., 2023). The production of knowledge and innovation typically thrives on face-to-face interactions, close collaboration, and knowledge spillovers enabled through co-location with other knowledge producers (Jacobs, 1969; Gaspar & Glaeser, 1998; Rosenthal & Strange, 2001; Moretti, 2004). While decades of research provide pervasive evidence that physical co-location benefits innovation through, e.g., rapid idea-sharing and co-creation (Reagans et al., 2005; Cowgill et al., 2009; Kerr & Kominers, 2015; Catalini, 2018; Atkin et al., 2022), firms and individuals are increasingly supplementing physical interactions with online ones through virtual communities such as Stack Overflow and GitHub, especially when expertise is unavailable locally (Brown & Roche, 2023; Conti et al., 2025b).

Local policy disruptions have been found to significantly affect patterns of in-person collaboration and innovation, altering the conditions under which technical knowledge is produced and shared (Bloom, 2009). One such important policy-driven economic and political shock is the 2016 Brexit Referendum[1], which ultimately led to the departure of the UK from the European Union (EU) (Acosta & Marinoni, 2025).[2] One consequence of the exit was a curtailing of inner-European labor mobility cutting off critical access to technically skilled labor for UK firms (Grassi, 2023).

In this paper we ask: How did Brexit impact online knowledge-seeking and innovation activities in the UK? We focus specifically on software development as a domain characterized by modular tasks and asynchronous workflows. This is a critical feature, since the nature of work makes it arguably, the least sensitive to local access to labor and interactions (Sorenson, 2023). Any results we find would represent an upper bound.

Based on prior work, we may expect an increase in the reliance on online knowledge platforms post-Brexit given a lack of locally available skilled labor. However, it is also possible that we observe a decrease as the UK turned more inward in search for knowledge or that Brexit had no meaningful effect on the reliance on online knowledge platforms in the UK. Critically, we further expect to find considerable regional heterogeneity in the response, with high-tech regions showing more pronounced changes (Forman et al., 2009, 2016). High-tech regions are the most likely to rely on dense local networks, specialized labor markets, and frequent in-person interactions to sustain rapid knowledge exchange and innovation (Kerr & Robert-Nicoud, 2020). As such, Brexit

[1] In this paper, when we refer to "Brexit", we mean the June 2016 Referendum, not the ultimate departure date.
[2] In this paper we refer to EU as the 27 member countries of the European Union without the UK.

likely disproportionately impacted these regions by undermining crucial mechanisms underlying their competitive advantage in knowledge production: face-to-face collaboration, talent mobility, and informal knowledge spillovers. Regions with less developed or less concentrated high-tech sectors may have experienced fewer immediate disruptions, as they depend less intensely on tightly integrated local ecosystems (or lack activity in the first place). As a consequence, the magnitude of the regional response will likely hinge on the sensitivity of innovation activities to changes in the local conditions essential for technical knowledge production and innovation.

The referendum and its outcome were both highly unexpected. Taking place on June 23, 2016, the UK voted to leave the EU by a majority of 52%. The nature and outcome of the referendum lend itself for use in our estimation strategy for a quasi-experimental set-up. It provides useful variation in uncertainty around immigration policies on knowledge flows. In particular, it enables us to compare knowledge-seeking and innovation outcomes of UK developers and regions to those in other EU member states pre- and post-Brexit. EU nationals in the UK were arguably exposed to an increase in immigration uncertainty, which initiated returns home and dampened attempts to immigrate to the UK (see Acosta and Marinoni (2025) for a detailed description of Brexit).

Focusing on innovation and talent, the UK presents a useful setting for our study. Beyond the natural variation introduced by the Brexit referendum, several factors lend the UK for examining the dynamics of innovation ecosystems. First, the UK has long been a magnet for highly skilled European talent, with EU nationals comprising around 41% of its immigrant population between 2013 and 2015, which lies well above the EU average of 31% (Acosta & Marinoni, 2025). Second, Great Britain stands out as Europe's leading entrepreneurial and innovation hub consistently ranking at the top. It has been extremely attractive to European and foreign entrepreneurs: before the Brexit announcement, 25% of firms had at least one foreign founder, and half of these had at least one European (EU, non-UK) founder. The UK also excels on multiple innovation metrics, including its high share of foreign doctoral students, strong exports of knowledge-intensive services, and the relative ease of starting a business (Reid et al., 2025). The software industry, in particular, has been central to leveraging the UK's existing innovation strengths (Forman et al., 2003; Department for Science, Innovation and Technology & Department for Business, Energy & Industrial Strategy, 2021).

To empirically examine our research question, we construct a novel data set comprising information on knowledge-workers' behavior on Stack Overflow and GitHub pre- and post-Brexit (2015–2019). Stack Overflow (SO) and GitHub (GH) provide suitable empirical settings to ob-

serve knowledge-seeking (i.e., SO) and innovation activities (i.e., GH) (Feldman, 2017; Xu et al., 2020; Patel, 2022; Conti et al., 2025a). Anecdotal evidence indicates that many developers rely significantly on these platforms to discover new technologies and understand their implementation. Indeed, copying and pasting code snippets from Q&A sites like SO is often considered "a top method of troubleshooting among developers"(Feldman, 2017). Given the importance of geography in our analyses, we precisely geo-locate SO interactions and GH repositories using developer locations from historical snapshots and applying rigorous geocoding procedures to map user-reported locations to NUTS3 regions. Besides the UK, we collect the same information for non-treated countries such as Ireland, and the Netherlands to create a comparable control group. We further enrich our dataset by classifying questions into technology clusters using K-means clustering and large language models. Additionally, we match SO users to GH profiles enabling integration of repository-level data into our analysis. Finally, we aggregate question-level data by NUTS3 region, calendar quarter, and technology class, tracking user activity through log-in histories to accurately capture regional variations in technology-related collaboration and engagement before and after Brexit.

Applying difference-in-differences and event study analyses, we find suggestive evidence of increased SO question posting per user post-Brexit, especially in high-tech regions. Controlling for this rise in question volume, we detect a shift in question characteristics: posts increasingly originate from new or more reputable users, demonstrate higher quality, and explore newer technological fields relative to those already explored in the region. Critically, questions post-Brexit tend to attract more answers and exhibit a notable change in geographic origin. In the post-period, they increasingly originate from users located outside the UK. Despite these shifts, there is no corresponding increase in innovation, which we proxy using GH repository creation, after Brexit. In fact, we find a reduction in repository creation post-Brexit, which is driven by users who have lower reputation on SO. This suggests that only the most prolific developers with high visibility can compensate for lost local collaborators in terms of their innovation output using online communities in the short and medium term.

Taken together, our study contributes to at least three streams of research by furthering our understanding of how external political shocks, such as Brexit, influence geographically concentrated online innovation communities. Importantly, we provide nuanced insights into regional disparities in adaptation of knowledge-sourcing strategies and innovation in response to changes in the access of skilled labor.

First, our work provides important nuance to the literature on the geography of innovation. Decades of research underscore that physical co-location enhances knowledge sharing and idea exchange (e.g., Sorenson and Audia (2000) and Feldman and Kogler (2010)). These interactions dissipate sharply with physical distance (Festinger et al., 1950; Allen, 1977; Stuart & Sorenson, 2003; Moretti, 2004; Storper & Venables, 2004; Alcácer & Chung, 2007; Arzaghi & Henderson, 2008; Lin, 2011; Catalini, 2018) as does subsequent adoption of technologies (Roche et al., 2024). Our study extends this work by providing empirical evidence for one way developers may substitute physical proximity – by seeking knowledge through online communities. Importantly, we find that only the most reputable developers can compensate in terms of their innovation output for lost access to local skilled labor by seeking help on SO and this is despite the nature of work being the most suitable to do so.

Second, we contribute to research on how political shocks and policy-driven uncertainty reshape innovation and knowledge flows. Prior work shows that political disruptions can stall investment, reallocate resources, and disrupt international collaborations, which ultimately affects innovation activity (e.g., Bloom (2009) and Baker et al. (2016)). We focus on one key channel through which these shocks operate: the flow of skilled labor (Gaulé, 2014; Acosta & Marinoni, 2025). By analyzing online knowledge-seeking behavior and digital innovation activity before and after Brexit, we provide empirical evidence on how such disruptions may reshape local innovation dynamics. We find that local innovation systems are unevenly impacted, with technologically advanced and globally connected regions adapting by intensifying their digital engagements, whereas peripheral regions seem the most negatively impacted. These insights highlight the nuanced role of regional characteristics in moderating responses to political and economic shocks and unveil critical uneven impacts where already disadvantaged regions appear to feel the negative impacts relatively more.

Third, we provide critical insight into work on online communities as spaces of innovation and knowledge-sharing (e.g., Faraj et al. (2011), Dahlander and Frederiksen (2012), and Conti et al. (2025b)). This literature underscores how online communities can enable wide-ranging collaboration, democratize access to expertise, and promote innovation across organizational and geographical boundaries (Conti et al., 2025a). Our contribution lies in empirically exploring whether online communities can effectively substitute for physical, geographically localized innovation systems. The results of our analyses suggest that substitution is limited to regions and developers that already possess a knowledge-based advantage and visibility potentially exacerbating inequalities. We speculate that geography rather than the virtual space may act as an equalizer by offering shared ac-

cess to local talent, infrastructure, and knowledge networks, enabling innovators and entrepreneurs from diverse backgrounds to compete on more level ground.

2 Conceptual Background

For decades, innovation has consistently been shown to geographically concentrate in few regions across the globe (Marshall, 1890; Arrow, 1962; Romer, 1986; Audretsch & Feldman, 1996). Mechanisms underlying this clustering range from localized knowledge spillovers, specialized labor pools, to the availability of complementary assets (Jacobs, 1969; Porter, 1996; Feldman & Kogler, 2010). High-tech clusters typically exhibit dense networks of interactions that amplify the intensity and effectiveness of local knowledge flows (Saxenian, 1994; Kerr & Robert-Nicoud, 2020).

At the core of all these mechanisms are people (Duranton & Puga, 2004). People are the critical input enabling innovation to take root and thrive (Campbell et al., 2012). It is individuals who exchange ideas, form networks, launch new products, and apply technologies. The spatial co-location of skilled and creative workers not only facilitates unplanned encounters and rapid feedback cycles, but also sustains a shared culture that encourages experimentation and risk-taking (Audretsch & Feldman, 1996; Glaeser, 2011). In a way, the geography of innovation is fundamentally a geography of human interaction.

These people may be "grown" locally or "imported" from elsewhere. Endogenous growth theory makes a strong argument for investing in local human capital and R&D, especially through education and training programs (Romer, 1986), as a pathway to long-term economic growth. Yet, investments alone may not always be sufficient. Skilled immigration plays a vital role in fostering innovation and economic dynamism by introducing diversity in backgrounds, expertise, and perspectives. Highly skilled immigrants not only directly contribute to innovation but often facilitate knowledge spillovers by bringing specialized expertise and international networks into regional innovation clusters. As a consequence, they significantly enhance local productivity, creativity, and entrepreneurship (e.g., Kerr & Lincoln, 2010; Foley & Kerr, 2013; Kerr & Kerr, 2020a).

Immigration-driven diversity has also been found to enrich team composition, stimulating problem-solving, creativity, and adaptability within firms (e.g., Choudhury & Kim, 2019; Hernandez & Kulchina, 2020; Azoulay et al., 2022). Prior work has provided suggestive evidence that regions and firms with greater diversity in skilled labor exhibit higher innovation outcomes, increased patenting activities, and robust entrepreneurial ecosystems (Alesina et al., 2016). Immigrants are

thus not merely carriers of knowledge, but also catalysts for the conditions that drive and sustain regional innovation ecosystems.

Immigration policies directly influence the flows of skilled labor, shaping regional specialization and economic competitiveness. Flexible policies that attract skilled migrants, such as those targeting STEM workers, have been associated with higher productivity and innovative performance in host regions (Kerr et al., 2015, 2017). Skilled immigrant entrepreneurs also disproportionately contribute to firm creation, particularly in technology-intensive sectors, further enhancing regional growth and competitive advantage (Fairlie, 2008; Kerr & Kerr, 2020b). As a consequence, immigration can contribute to filling critical skill gaps fueling broader innovation dynamics (Branstetter et al., 2021).

Limiting immigration curtails the movement of skilled workers and with it precisely those individuals who carry and apply specialized knowledge (Kogut & Zander, 1992). When such knowledge is no longer accessible through local labor markets, the question emerges: How can firms and knowledge workers compensate for reduced physical proximity to talent and expertise?

One increasingly important way is through online communities. Online communities (e.g., SO, GH) have become critical infrastructures for knowledge creation, sharing, and innovation, particularly in technology-intensive sectors (Dahlander & Frederiksen, 2012). Hosted on platforms, these communities provide virtual spaces where geographically dispersed users collaborate, innovate, and resolve technical uncertainties (Conti et al., 2025a). Online communities have the ability to overcome geographic barriers by facilitating distributed innovation, allowing users worldwide to co-create and access specialized expertise (Jeppesen & Lakhani, 2010). Research consistently indicates that networked interactions on community platforms like GH significantly enhance learning by increasing user exposure to diverse knowledge sources and facilitating interactions. Such interactions have also been found to help innovators launch their first products and attract funding (Conti et al., 2025b). At their core, platforms such as Stack Overflow are designed around problem-solving: they aim to fill specific gaps in users' technical understanding that traditional resources may not adequately address. Thus, they are not meant to replace formal education, textbooks, or even basic documentation, which typically provide foundational knowledge about a technology's general use. These platforms, in turn, offer a different pathway to accessing the type of tacit knowledge that developers would usually gain by working in close physical proximity with others. Such practical know-how is inherently situational, making it challenging to articulate or document in advance, and is often best transferred through direct interactions and proximity (Gray et al., 2015; Lee, 2019).

Digital platforms, through their capacity for targeted responses and real-time demonstration of solutions, may therefore be particularly effective in facilitating this type of knowledge sharing.

In this paper, we make use of the Brexit referendum, which set in motion the UK's withdrawal from the European Union, as an unexpected event that limited access to European (skilled) labor to examine how firms and individuals compensate for reduced physical proximity to talent and expertise.

The call for the referendum and result was highly unexpected (Acosta & Marinoni, 2025). Initially, the referendum led to an extended period of uncertainty because it was unclear whether the UK wanted to leave the EU's single market and abandon freedom of movement. PM Theresa May confirmed this decision in January 2017, despite a lack of understanding how. Subsequently, the government issued official notice that it was leaving the EU. This initiated Article 50 of the Treaty of Lisbon (this treaty is considered the reformed EU constitution), which lays out the procedure for a Member State to withdraw – by choice – from the European Union. January 2020 marked the date of withdrawal.

The Brexit referendum triggered a profound shock to the UK's institutional environment, creating sustained uncertainty around immigration policy, especially with respect to EU nationals. While formal rules governing free movement remained in place during the transition period, the prospect of future restrictions introduced ambiguity for employers and workers alike. Many firms began adjusting expectations and hiring practices in anticipation of a more restrictive regime, and the inflow of workers from EU countries slowed considerably with some existing EU migrants chose to leave the UK amid growing uncertainty and perceived hostility (Cuibus, 2023). These immigration shifts occurred well before the eventual policy changes in January 2020.[3]

Supporters of Brexit had argued that leaving the European Union would give the UK more sovereignty, emphasizing immigration control and reductions in pressures on the healthcare and education systems. Some also proposed that absent membership in the EU, UK businesses would be less constrained. Polls consistently indicated immigration as one of the top reasons voters cited for supporting Brexit. The belief was that leaving the EU would allow Britain greater control over immigration policies and reduce the inflow of EU migrants who were thought to compete for jobs, housing, and drain public services.

Provided the importance of co-located talent and expertise for knowledge flows, we expect that

[3]A points-based immigration system, similar to those in Canada and Australia, was introduced in 2020, after our period of analysis.

following Brexit-induced immigration decline, actors may increasingly turn to online knowledge platforms to compensate for reduced direct access to external talent and international collaboration. These platforms may become alternative channels for accessing knowledge, intensifying digital interactions.

Regions vary in their capacity to absorb knowledge, shaped by their initial endowments of human capital, international connectedness, and industry specialization (Sorenson & Audia, 2000). High-tech clusters (Forman et al., 2016; Kerr & Robert-Nicoud, 2020) may respond distinctly due to their dense global networks and heavy reliance on international collaboration, compared to more peripheral regions that may not have been impacted as much by the loss of EU labor.

We expect *that Brexit led to differentiated responses across UK regions. High-tech regions, being deeply integrated into international networks, may exhibit increases in online knowledge-seeking, whereas peripheral regions with fewer international ties may exhibit minimal adaptation in digital knowledge-seeking behavior.*

Ultimately, we expect knowledge-seeking behavior to be linked to innovation outcomes. Those individuals, firms and regions that can compensate through knowledge-seeking from online communities may be able to maintain or even increase innovative output (at least in the short and medium term), whereas those that cannot, will experience a reduction in innovative output.

3 Data

We use the Stack Overflow public dataset hosted on Google BigQuery, which provides a comprehensive and regularly updated record of activity on the platform. Stack Overflow is one of the largest online communities for software developers and technical professionals, where users post and respond to programming-related questions. The dataset includes detailed information on posts (questions and answers), tags, votes, badges, and user profiles.

Our initial sample includes all questions posted between the first quarter of 2015 and the fourth quarter of 2019. This period provides a pre-Brexit trend window and excludes the post-2020 COVID-19 period, during which online behavior shifted markedly.

To restrict the analysis to users of our countries of interest –the UK, Ireland, and the Netherlands[4]– we require information on users' location over time. Because the version of the Stack Overflow dataset hosted on BigQuery reflects user locations as of 2022, it cannot be used to infer

[4]As mentioned later, in some robustness analyses we will also include France and Germany in the control group, in addition to Ireland and the the Netherland.

historical location. We therefore rely on two static snapshots of the Stack Exchange dataset—one from late 2015 (the closest snapshot before the referendum we could retrieve) and one from 2019 (our terminal year)—which contain user-level attributes including self-reported location. We retain only questions of users who report being located in one of the target countries in either snapshot. This approach enables us to identify a consistent sample of ≈49,000 users with reliably observed locations and to track changes in their posting behavior before and after Brexit, resulting in a total of ≈300,000 questions asked.

The user location field in the Stack Overflow dataset is a free-text entry, which is often noisy and sometimes incomplete. In some cases, users report only their country or a broad region, whereas our analysis requires more granular geographic information to match users to NUTS3 regions. The NUTS3 classification captures small geographic units, often aligned with local labor markets, enabling us to examine regional patterns in developer activity and economic participation across both the UK and the control countries. Thus, we implement a series of data cleaning and geocoding procedures to standardize location entries, map them to cities, and assign the corresponding NUTS3 codes wherever possible. Despite these efforts, approximately 30% of users who reported a location in either 2015 or 2019 remain unmatched, typically because they provided insufficient geographic detail (e.g., only the country). As shown in Figure 2, there is a strong positive correlation between the density of questions asked and the level of technological development in a NUTS-3 region.

For each user, we retrieve all questions they posted on Stack Overflow. For each question, we extract detailed metadata, including the user ID, creation date and time, textual content, associated tags, number of answers and comments, provenance of the answers, number of upvotes and downvotes, whether an accepted answer exists, the question score, number of views, and the number of times the question was starred by other users.

Each question is associated with specific technologies, which are indicated by user-assigned tags. Our objective is to classify questions into broader technology areas. To do so, we represent each question as a dense vector by averaging the GloVe embeddings of its assigned tags. This approach captures the semantic content of a question based on its tags, enabling us to group together questions that pertain to similar technologies, even when they do not share identical tag labels. This method is preferable to using raw tags directly, as the tag vocabulary is large, highly granular, and inconsistently applied across questions. We then cluster these question-level embeddings using the K-Means algorithm. The optimal number of clusters is selected by maximizing the silhouette score, which balances within-cluster compactness and between-cluster separation.

The resulting solution yields 17 clusters, which we interpret as high-level technology areas to which each question is assigned. To enhance interpretability, we use a large language model (LLM) to assign descriptive names to each cluster, based on the most frequently occurring tags within that group. The resulting technology areas are: *C++ Development & GUI Frameworks*, *Data Science*, *Backend Development & DevOps*, *PHP & Web Development*, *Frontend Web Development*, *R Programming & Data Visualization*, *General Programming & Scripting*, *Cross-Language Software Development*, *Angular & TypeScript Development*, *Cross-Platform Mobile Development*, *Databases & SQL*, *Java Development & Spring Framework*, *Machine Learning*, *Microsoft Azure & Cloud Computing*, *Android UI & Architecture*, *JavaScript & Web Frameworks*, and *.NET & ASP.NET Development*. These technology areas are depicted in Figure 1, which visualizes semantic relationships between topic clusters of Stack Overflow questions.

To evaluate the innovation output of Stack Overflow users, we employ a matching procedure that links Stack Overflow accounts to GitHub accounts. This approach is grounded in prior research demonstrating that the repositories created on GitHub constitute a credible proxy for measuring users' innovative contributions (Conti et al., 2025b, 2025a). Given that our primary matching criterion is the account username, we augment this process with additional metadata, specifically the associated username location, to enhance the accuracy of the match. Leveraging this enriched information, we successfully identify a corresponding GitHub account for approximately 18% (or 8,900) of Stack Overflow users who generated approximately 67,000 repositories. These repositories are described by readme files, which we leverage to classify each repo into the same technology domains used to classify the Stack Overflow questions.

Our analyses will be conducted using a panel dataset structured at the NUTS-3 region, technology area, and calendar quarter level. Accordingly, we aggregate user activities from both Stack Overflow and GitHub to this level of observation.

4 Empirical Strategy

To evaluate whether and how Brexit influenced Stack Overflow activity among UK users, we employ a difference-in-differences regression design. Specifically, we examine how activity on Stack Overflow in UK regions and specific technology domains changed after Brexit, relative to activity in corresponding European regions and the same technology domains. As outlined earlier, our underlying assumption is that Brexit led to a persistent emigration of skilled European (non-UK)

professionals from the UK, as well as a reduction in the rate at which new skilled professionals from Europe migrated to the UK (Cuibus, 2023). Consequently, UK residents may have had to compensate for the resulting loss of human capital—particularly in certain geographic and technological areas—by increasingly relying on knowledge inputs from online platforms such as Stack Overflow in order to continue innovating.

In a panel dataset at the NUTS 3–technology area–quarter level, we follow Acosta and Marinoni (2025) and treat the second quarter of 2016—when the Brexit referendum took place—as the starting point of the UK's separation from the European Union. This choice is motivated by the fact that the referendum outcome was largely unexpected (Acosta & Marinoni, 2025), making it plausible that Stack Overflow users did not adjust their behavior in anticipation of Brexit's consequences. As both anecdotal accounts and large-scale evidence (Bloom et al., 2019; Cuibus, 2023; Amuedo-Dorantes & Romiti, 2024) suggest, many European citizens began leaving the UK shortly after the referendum, even before the UK government implemented new regulations on migration in 2020. This early departure was driven by the policy uncertainty Brexit introduced regarding labor market conditions and long-term career prospects.

In our difference-in-differences design, we focus on the 17 technology areas identified using the machine learning algorithm described in Section 3. Accordingly, we compare Stack Overflow activity in these areas by users in NUTS 3 regions of the UK to that of users in NUTS 3 regions of Ireland and the Netherlands. We select Ireland and the Netherlands as the comparison group due to the similarities between their economies and that of the UK, as well as the widespread use of English in both countries.[5] Supporting our choice, we observe that during the post-Brexit period, the ratio of Stack Overflow users migrating from the UK to either Ireland or the Netherlands, relative to those moving in the opposite direction, is approximately 2 to 1. As we detail below, this panel specification allows us to control for technology trends that might be concurrent with Brexit.

One potential concern with our approach is that some European residents of the UK may have migrated—particularly to Ireland—given the high degree of integration between the Irish and UK economies. This movement could violate the Stable Unit Treatment Value Assumption (SUTVA), which requires that the treatment of one unit does not affect the outcome of another. However, such a violation would likely introduce a downward bias in our estimates, implying that our results represent a lower bound of the true effect. To address this issue, we conduct robustness checks in which we exclude Ireland from the control group and include larger countries such as France and

[5]The three economies are open, service-oriented, and possess a significant skilled labor force.

Germany, where spillover effects are expected to be less pronounced.

We measure Stack Overflow activity using several outcome variables, including the number of questions posted and the number of answers provided by users. Additionally, we differentiate these metrics based on various dimensions: the type of asker (whether they were active prior to Brexit and their reputation level), the type of question (whether it includes code and whether it is novel relative to the existing expertise in a given NUTS 3 region), and the type of answerer (specifically, whether the user is located in the UK or not). Additionally, to assess whether and how Brexit may have simultaneously affected innovation activity within NUTS 3–technology areas, we incorporate GitHub data and analyze the number of original repositories[6] created by Stack Overflow users. As all these outcomes are count variables, we estimate the following difference-in-differences Poisson Quasi-Maximum Likelihood (PQML) specification at the level of NUTS 3 region i, technology area k, observed in quarter t:

$$E(Y_{ikt}|X_{ikt}) = \gamma_{ik} \exp(\beta \cdot UK_i \cdot I[t > Q2\ 2016] + \delta \cdot NUsers_{it} + \tau_{tk}). \tag{1}$$

UK_i is a (0/1) indicator equal to 1 for UK NUTS 3–technology area. The coefficient of interest in this model is β. It represents the post-Brexit change in activity on Stack Overflow/GitHub in UK regions and specific technology domains changed after Brexit, relative to activity in corresponding European regions and the same technology domains. In alternative specifications, we distinguish between high-technology UK regions and other regions, with the former defined as the NUTS 3 areas that include Cambridge, London, and Oxford.

We observe four quarters prior to the Brexit referendum quarter and 14 quarters thereafter. This observation window is motivated by the relative sparsity of Stack Overflow activity—and particularly GitHub activity—before 2015.[7] Furthermore, the effects of Brexit may not have manifested immediately following the referendum.

$NUsers_{it}$ is the natural logarithm of the count of active Stack Overflow users in a given NUTS 3 region. This variable accounts for macroeconomic trends at the NUTS 3–quarter level—including changes in the size of the Stack Overflow user base at risk of asking questions. We define a user as active at any point in time t if t falls between the quarter in which the user created their account and the last recorded time they visited the website. The $\gamma_i k$ are NUTS 3–technology area fixed

[6] These repositories are created from scratch, without forking existing ones. Consistent with Conti et al. (2025a), we use them as a proxy for original innovative output.

[7] Before 2015, GitHub users were limited in the number of repositories they could create without paying.

effects that absorb fixed differences across region–technology–areas, while τ_{tk} are year-quarter by technology area fixed effects, which absorb the effects of possible technology shocks.

Summary statistics for the variables of interest are reported in Table Table 1. Moreover, the descriptive statistics reported in Figure 3 offer a glance into the phenomenon we plan to investigate. We display the 3-quarter moving average of the ratio of the number of questions per user in the UK to the number in the control countries (black dashed line), the ratio in UK high-tech regions (blue line), and the ratio in UK low-tech regions (green line), all relative to the control group baseline. As shown, the overall UK ratio increases following the Brexit referendum, with this increase primarily driven by questions asked in UK high-tech regions.

⟨ Insert Figure 3 about here ⟩

5 Results

5.1 Questions Asked

We begin by examining the results for the number of questions asked by Stack Overflow users. Table 2 presents the estimates from Eq. (1), with standard errors clustered at the NUTS 3 regional level. Column (1) shows that the number of questions asked by UK-based Stack Overflow users increased by 4% (i.e., $exp(\beta)-1$ with $\beta = 0.039$) after Brexit (p-value: 0.215). When we distinguish between high-tech regions and other UK regions, the results become more nuanced. In high-tech regions, the number of questions increases by 6%, and this effect is statistically significant at the 5% level. In contrast, the estimated effect for other regions is close to zero and statistically insignificant. These findings suggest that the impact of Brexit was particularly pronounced in high-tech regions—those more vulnerable to the outflow of highly skilled human capital—where remaining workers may have increasingly relied on online communities to substitute for lost expertise. These effects become larger in both magnitude and statistical significance in columns (3) and (4), where the outcome variable is restricted to the number of questions that contain software code. In column (3), we find that, following Brexit, the number of code-related questions asked by UK-based Stack Overflow users increased by 6%. Moreover, the effect is particularly pronounced in high-tech regions of the UK, where the number of such questions rose by 18%. In columns (5) and (6), we narrow our focus to high-quality questions, which we define as those that received a score (i.e. upvotes minus downvotes) above the median. The results indicate that, post-Brexit, the number of high-quality questions asked by users in UK high-tech regions increased by 13%. This suggests

that users in these regions became more likely to pose questions of greater impact and technical relevance, potentially reflecting a shift toward more deliberate and value-added engagement with online knowledge communities.

⟨ Insert Table 2 about here ⟩

To inspect the presence of pre-trends, Figure 4 reports the results from a dynamic version of Eq. (1) that replaces the $I[t > Q2\ 2016]$ term with time indicators for each year-quarter to/from the Brexit referendum. The reported coefficients represent the additional proportion of new questions that UK Stack Overflow users ask each quarter relative to other European users. Panel A reports the effects (and the corresponding 90% confidence intervals) of Brexit on the number of questions asked on Stack Overflow. Panel B reports the effects on the number of questions with code, while Panel C displays the effects for the number of high-quality questions. We distinguish between the effects for UK high-tech regions (blue dots) and the effects for other UK regions (red diamonds). We highlight three main patterns. First, we observe no pre-trends regardless of the outcome and the type of UK region examined, suggesting that, in the absence of Brexit, these outcomes would have evolved similarly across regions. Second, the increase in the number of questions, code-related questions, and high-quality questions by users in UK high-tech regions becomes more pronounced starting in the fifth quarter after Brexit. This delayed response indicates that the behavioral adjustment by Stack Overflow users was not immediate, consistent with the notion that the outflow of highly skilled European talent from the UK occurred gradually. Third, the impact of Brexit appears to be both persistent and statistically significant thereafter, highlighting a sustained shift in user engagement patterns.

⟨ Insert Figure 7 about here ⟩

We further investigate our baseline findings by examining heterogeneity in the effects of Brexit across different types of users asking questions. The results are reported in Table 3, where we control for the number of questions asked by users in a given NUTS 3–technology area. We first examine the effects of Brexit on the number of questions asked by users who were active before the referendum (columns (1) and (2)) and by new users who joined Stack Overflow afterward (columns (3) and (4)). The coefficient reported in column (1) suggests a 6% post-Brexit increase in the number of questions asked by existing users, while the coefficient in column (3) indicates a 19% increase among new users, all else equal. However, neither of these effects is statistically significant at conventional levels. When we distinguish between users in high-tech UK regions and those in

other regions (columns (2) and (4)), a more nuanced picture emerges. We observe a statistically significant and sizable increase in the number of questions asked by both existing and new users located in UK high-tech regions. Specifically, the effect for existing users corresponds to an 18% increase, and for new users, a 29% increase in question activity post-Brexit. Overall, these findings suggest that Brexit particularly spurred new users—likely less experienced—to ask more questions on Stack Overflow, possibly in response to the outflow of skilled talent from the UK. Nonetheless, the increase in activity among existing users in high-tech regions also indicates a broader behavioral shift within the UK developer community.

We next distinguish between questions asked by more reputable users (columns (5) and (6)) and less reputable users (columns (7) and (8)), again controlling for the total number of questions asked. As mentioned above, Stack Overflow identifies user reputation based on the upvotes and downvotes received for questions and answers.[8] To adjust for variation in the duration of account activity, we normalize each user's reputation by the length of time since account creation. We classify a user as *highly reputable* if their normalized reputation exceeds the sample mean[9], and as *less reputable* otherwise. Using this classification, we aggregate the number of questions asked by each user type at the NUTS 3–technology area level. The results indicate a statistically significant and economically meaningful increase in the number of questions asked by both highly and less reputable users located in UK high-tech regions. However, the magnitude of the effect is greater for highly reputable users, who exhibit a 24% increase in question activity post-Brexit, compared to a 15% increase for less reputable users. The event study estimates presented in Figure 5 continue to show no evidence of significant pre-trends (Panels A, C, and D). Moreover, starting around the fifth quarter following the Brexit referendum, there is a notable increase in the number of questions asked—particularly by new and highly reputable users located in UK high-tech regions (Panels A and C).

⟨ Insert Table 3 and Figure 5 about here ⟩

Another dimension of our analysis considers whether the questions asked by Stack Overflow users pertain to technological areas that are new relative to the existing specialization of their respective NUTS 3 regions. This distinction is relevant because the loss of human capital following Brexit may have been particularly costly for users engaging with novel technologies, as opposed to those operating within a region's established areas of expertise. For this purpose, we define

[8] https://stackoverflow.com/help/whats-reputation

[9] The distribution of this variable is skewed, and the median is equal to zero. For this reason, we use the mean cutoff.

a novel question as one characterized by a combination of tags that is new to a given NUTS-3 region and technology area, relative to the set of tags associated with questions asked in the preceding four quarters. Using this definition, we aggregate the number of novel questions at the NUTS-3–technology area level.

The results are presented in Table 4 and Figure Figure 6. Column (1) of Table 4 shows a 7% increase in the number of novel questions asked by UK users following the Brexit referendum. Column (2) indicates that this increase is primarily driven by users located in UK high-tech regions, where the post-Brexit rise reaches 18%. The event study in Figure 6 supports these findings, revealing a steady and persistent increase in novel questions from users in high-tech regions of the UK, particularly from the fifth quarter onward.

⟨ Insert Table 4 and Figure 6 about here ⟩

5.2 Answers Received

In this section, we examine the responses provided by users on Stack Overflow to questions posed on the platform. Specifically, we first assess whether, conditional on the number of questions asked, treated and control groups differ in the post-Brexit period with respect to the number of questions answered. We interpret this as a proxy for the relevance or appeal of the questions being asked.

Next, we analyze the provenance of the answers, distinguishing between those provided by users based in the UK and those from users elsewhere. The results are presented in Table 5. Columns (1) and (2) report estimates from a Poisson quasi-maximum likelihood model for the total number of answers to questions within each NUTS3 technology area, controlling for both the number of questions asked and the number of active users.

As shown in column (1), the number of answers to questions posted by UK users increases by 8% in the post-Brexit period. This effect is more pronounced in high-tech regions of the UK, where the number of answers rises by 19% (column (2)). In columns (3) to (6), we partition answers by the geographic origin of the answerers and control for the total number of answers received. We observe an increase in responses from both UK-based users and those outside the UK, with the latter group driving most of the overall effect. The increase is especially pronounced for questions originating from high-tech regions in the UK.

⟨ Insert Table 5 about here ⟩

Figure 7 presents the event study estimates. Panel A shows that the number of accepted answers to questions posted by users in UK high-tech regions increases relative to other European countries

beginning in quarter 5 of the post-Brexit period. In contrast, no significant change is observed for questions originating from other UK regions. Importantly, we find no significant pre-trends for any UK region, supporting our identification strategy.

Panels B and C further disaggregate the responses by the provenance of the answerers. The observed increase in accepted answers is particularly pronounced for those provided by users located outside the UK, especially in the later quarters of the post-Brexit period. Taken together, these findings suggest that online platforms such as Stack Overflow may have played a role in mitigating the effects of human capital outflows from the UK following Brexit, by facilitating access to alternative sources of technical knowledge.[10]

⟨ Insert Figure 7 about here ⟩

5.3 Innovation Output

What are the implications of the shift in UK user behavior on Stack Overflow for innovation output? We follow Conti et al. (2025a) and proxy innovation with the number of original repositories—those fully created by users without forking existing repositories—produced by individuals in a given NUTS-3 region and technology area. We estimate a variant of Equation (1), using this innovation measure as the outcome variable. The results are reported in Table 6.

Columns (1) and (2) indicate a post-Brexit decline in the number of repositories created by UK users, particularly those users located in UK high-tech regions. Columns (3) through (6), however, reveal a more nuanced pattern once we differentiate between users by their Stack Overflow reputation. Specifically, we find that repository creation by less reputable UK users declines after Brexit, particularly in high-tech regions, while the number of repositories generated by more reputable users in these regions remains largely unchanged.

These findings are further supported by the event study estimates in Figure 8, which show a post-Brexit decline in repository creation by less reputable users, alongside a flat trend in output by more reputable users in UK high-tech regions. Taken together, these results suggest that the knowledge input from the Stack Overflow platform may have enabled more active and experienced users to at least partially offset the negative impact of Brexit-induced losses in skilled human capital—particularly in regions most exposed to such losses.

⟨ Insert Table 6 and Figure 8 about here ⟩

[10] All results presented thus far are robust to alternative control groups: they hold when Ireland is excluded from the control group (Tables A-1-A-4) and when France and Germany are included in the control group (Tables A-5-A-8).

6 Conclusion

This paper examines how policy-driven economic and political shocks, specifically, the Brexit referendum, may alter the conditions under which knowledge is produced and shared. We ask whether, and to what extent, online communities can substitute for geographically proximate collaboration when access to skilled labor is disrupted. Focusing on software developers in the UK, we analyze activity on Stack Overflow and GitHub between 2015 and 2019 to trace changes in knowledge-seeking and innovation behavior before and after Brexit.

We provide suggestive evidence that developers in high-tech UK regions increase their reliance on Stack Overflow following the referendum, asking more questions. These emanate particularly from newer or higher-reputation users. Critically, our results indicate that the questions asked attract more responses from international contributors. Taken together, our findings seem to indicate that although online communities may help sustain access to knowledge exchange in the face of disruption, they can only help developers with high reputation compensate for lost local collaborators in terms of their innovation output in the short and medium term.

The patterns we unveil provide three central insights. First, while online communities play an increasingly important role in global innovation systems, they are not frictionless substitutes for in-person collaboration. Their effectiveness depends on users' prior reputation and embeddedness in technical communities. Second, innovation responses to immigration shocks are not uniform: regions with strong high-tech sectors show both greater disruption and stronger compensatory behavior, while peripheral regions appear less responsive. This may raise concerns about widening regional inequalities. Third, policies that disrupt access to skilled labor may erode local innovation capabilities even in domains, like software development, that are likely most suitable for digital, distributed collaboration.

We contribute to at least three strands of literature. First, we speak directly to the literature on the geography of innovation, where decades of research provides compelling evidence that physical (co-)location of skilled labor fosters knowledge exchange (e.g., Sorenson and Audia (2000), Moretti (2004), and Feldman and Kogler (2010)). The distance at which these benefits activate are (Arzaghi & Henderson, 2008; Catalini, 2018) short and have important ramifications for subsequent adoption of technologies (Roche et al., 2024).

Second, we add to the body of literature on how political shocks and policy-driven uncertainty reshape innovation and knowledge flows. Political disruptions have been found to hamper invest-

ment, redistribute resources, and hamper international collaborations, which influence innovation activity (e.g., Bloom (2009), Baker et al. (2016), and Choudhury et al. (2024)). Focusing on the flow of skilled labor(Gaulé, 2014; Acosta & Marinoni, 2025), we uncover crucial uneven impacts of such disruptions.

Third, we bring the literature on online communities as spaces of innovation and knowledge-sharing (e.g., Forman et al. (2009), Faraj et al. (2011), Dahlander and Frederiksen (2012), Brown and Roche (2023), and Conti et al. (2025b)) together with the conversation on the role of physical space for innovation. While this literature stresses the importance of online communities in democratizing access to expertise and promoting innovation across boundaries (Conti et al., 2025a), we find evidence suggesting that substitution of physically present knowledge endowments with virtual ones is limited to regions and developers that already possess a knowledge-based advantage and visibility. These patterns may, in fact, potentially exacerbate inequalities.

Beyond the literature, our work also offers valuable insights for policy-makers and firms alike. As suggested by prior work, the geographical distribution of economic activity depends critically on local spillovers and long-term externalities (e.g., Kline and Moretti (2014), Fajgelbaum and Gaubert (2025), and Gaubert et al. (2025)). Placed-based policies (driven by governments but also consortia of firms) may need to recognize for one, how restrictions to skilled immigration may hurt efforts, but also the limits to substituting in-person interactions with virtual ones. Human capital is a fundamental resource for localities to recover and reinvent themselves (Glaeser, 2005) and distortions in human capital can significantly influence urban growth and decline (Franck & Galor, 2021). As highlighted by Heblich et al. (2025), diversity is critical, and a short term perspective may have dire consequences in the long-run.

Our findings also hold significant implications for policy concerning emerging digital tools, particularly artificial intelligence (AI). While some scholarship highlights AI's potential to democratize innovation (Dell'Acqua et al., 2023; Meincke et al., 2024), our results suggest a different interpretation. Consistent with arguments presented by Acemoglu and Restrepo (2019) and Acemoglu et al. (2022), we observe uneven distribution of the benefits derived from online platforms, such as Q&A communities, indicating that rather than leveling the playing field, these tools may exacerbate existing inequalities in innovation and knowledge dissemination.

Naturally, our study is not without limitations. For one, Brexit represents a highly specific political and economic event, which may potentially limit the extent to which we can generalize our findings to other settings of knowledge disruptions. For another, our analyses are restricted to a

shorter time window to be able to avoid potential confounds and to provide the most robust evidence we can. This choice, however, limits the extent to which we can make long-term claims. Finally, while our data are comprehensive and cover many different major online communities critical to software development (at the time of our study, GH was the worldwide largest platform for open source software (Conti et al., 2025b, 2025a), and SO the largest Q&A platform (Patel, 2022)[11]), we do not have access to the universe of activities, nor the geographic locations of all developers and longer term outcomes. Our results could be biased if the provision of location information is also associated with a specific type of Q&A or innovative behavior. As a consequence, we are careful in the interpretation of our results and provide a series of robustness checks to rule out alternative explanations.

In sum, our study provides suggestive evidence that physical place continues to matter even in digital-first sectors. Although online communities may help bridge some gaps in knowledge access, their ability to sustain innovation is heterogeneous. It appears that existing advantages in reputation, visibility, and innovation capacity may exacerbate inequalities in the face of policy-driven economic and political shocks, such as Brexit. As such, our findings offer a word of caution. Although virtual spaces may be valuable complements, they are unlikely to fully substitute for the institutional, interpersonal, and spatial foundations of vibrant physical innovation ecosystems.

[11] As of 2022, Stack Overflow has over 18 million users from around the world, and more than 23 million questions have been posted to the site.

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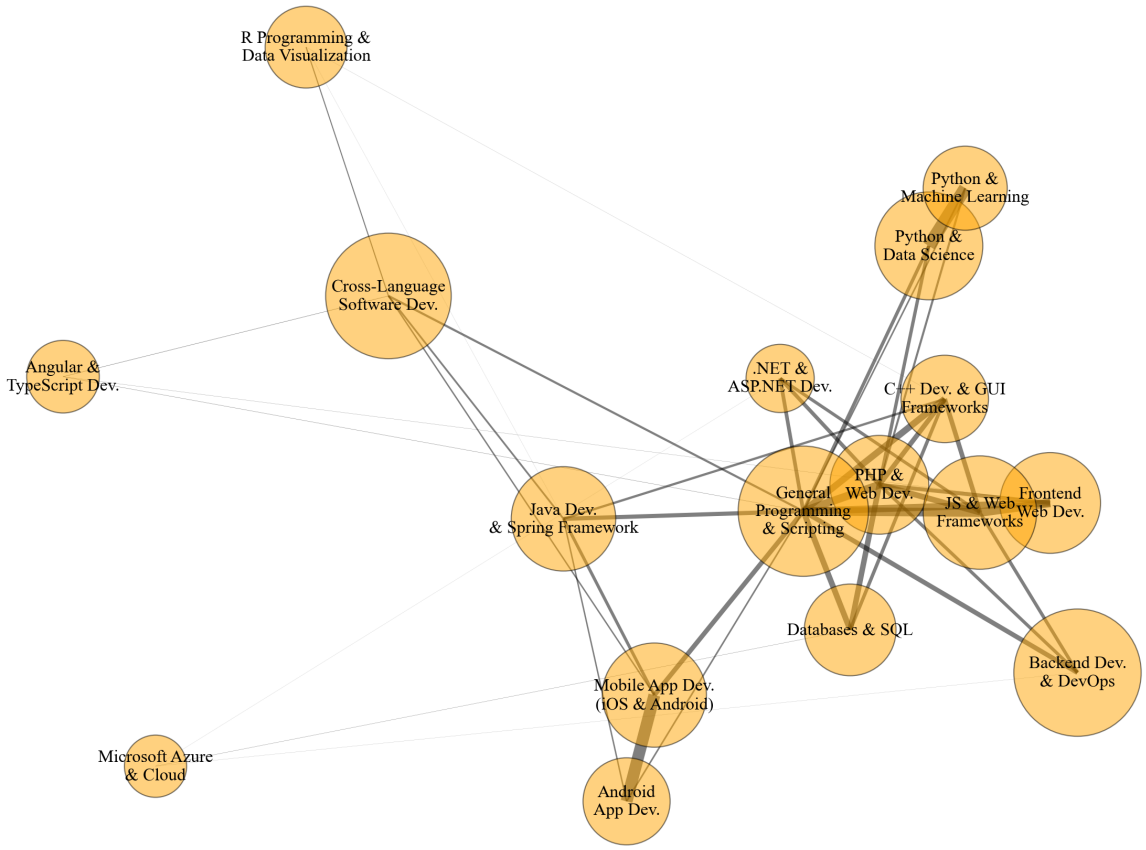
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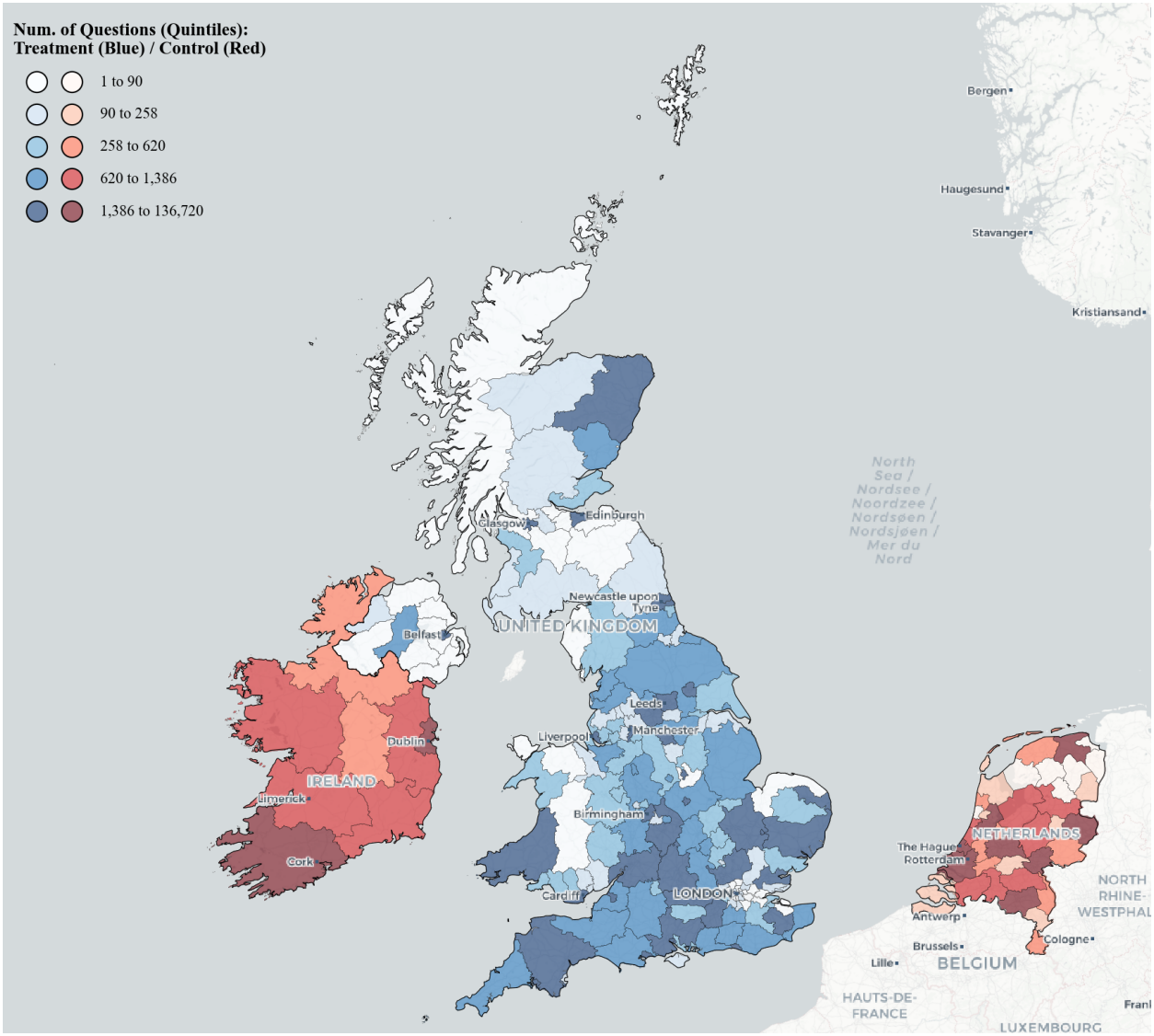
Figures and Tables

Figure 1: Technology Cluster Similarity Cloud



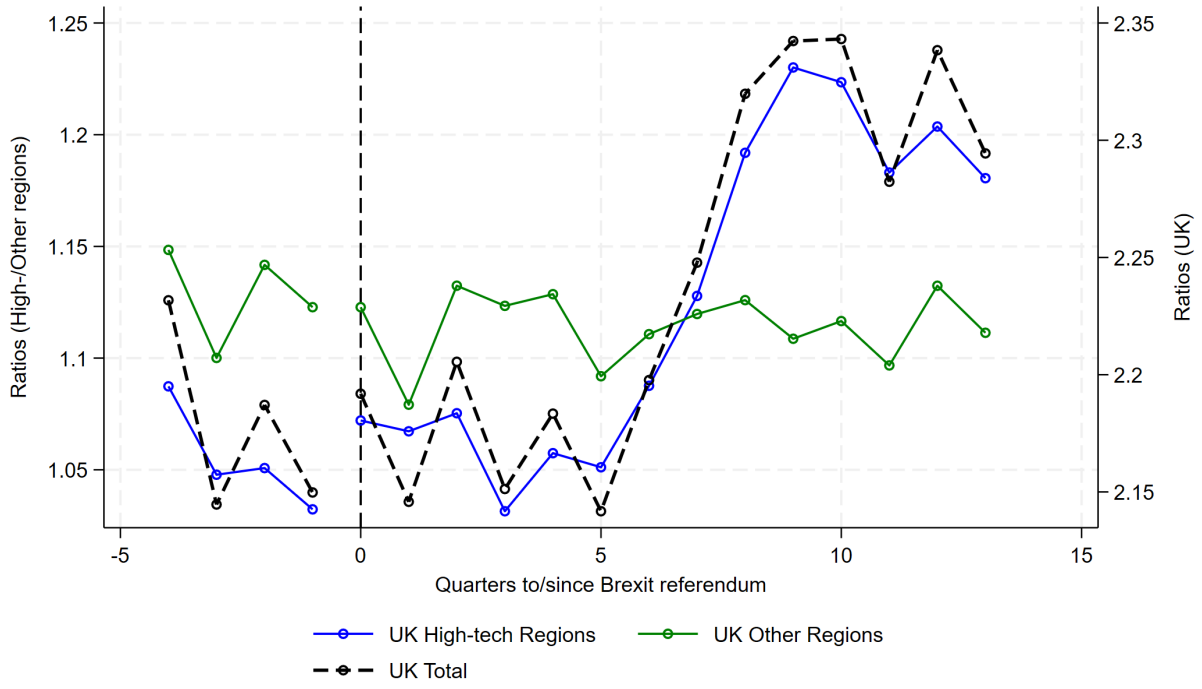
Notes: This network graph visualizes semantic relationships between topic clusters of Stack Overflow questions, derived from k-means clustering on GloVe-based tag embeddings. Each node represents a cluster, and its size reflects the number of questions it contains. The spatial layout is computed using multidimensional scaling applied to the pairwise cosine dissimilarity between cluster centroids. Thus, the physical distance between nodes approximately reflects how different the clusters are: closer nodes represent more similar topics, while distant nodes are more distinct. Edges connect each cluster to its top 3 most similar neighbors, and their thickness encodes the strength of similarity: thicker lines indicate stronger semantic overlap.

Figure 2: Number of Questions by NUTS-3 and Treatment Group



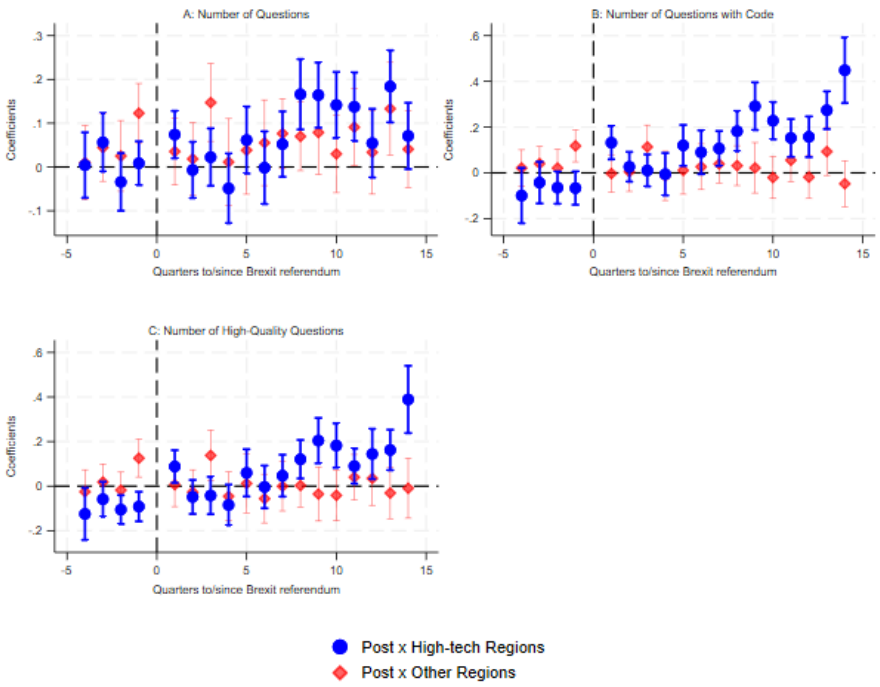
This map displays the number of Stack Overflow questions asked over the full study period, aggregated at the NUTS-3 regional level. Treated areas (NUTS-3 regions in the UK) are shown in blue, while control areas (NUTS-3 regions in Ireland and the Netherlands) are shown in red. Shading is based on shared quantile thresholds across all regions; only the color schemes differ between treated and control groups.

Figure 3: Stack Overflow Question Activity in UK Regions vs. Control Countries



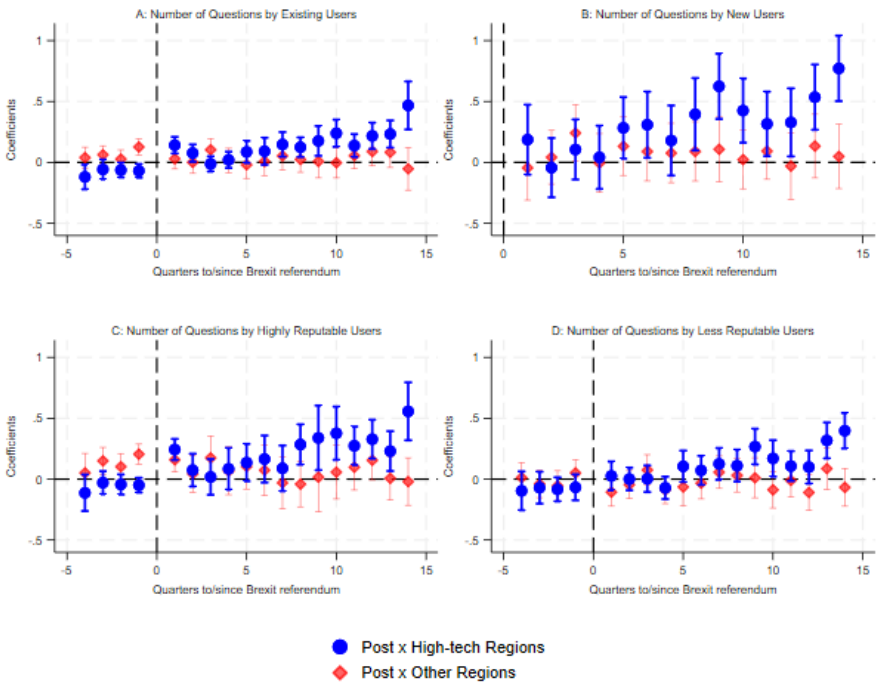
This figure reports the 3-quarter moving average of the ratio of the number of questions per user in the UK to the number in the control countries (black dashed line), the ratio in UK high-tech regions (blue line), and the ratio in UK low-tech regions (green line), all relative to the control group baseline.

Figure 4: Event Studies for the Number of Questions Asked: Distinguishing by UK region



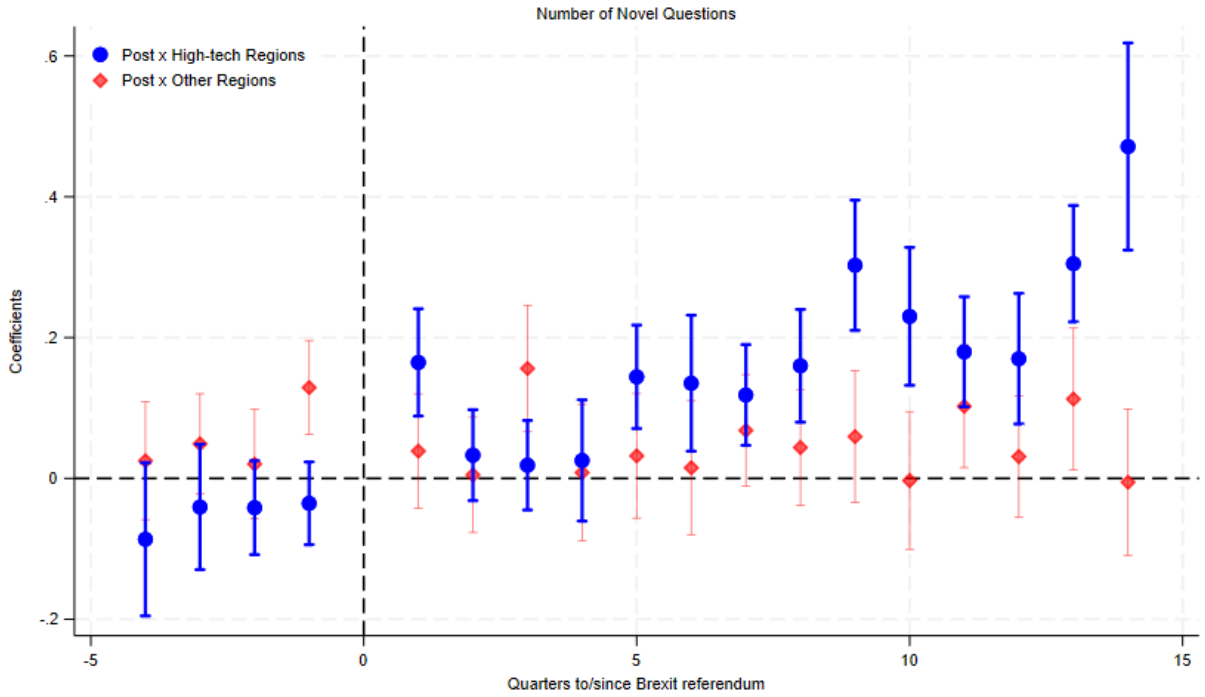
This figure presents estimates from a dynamic version of Eq. (1), where the variable *Post Brexit* is replaced with a series of time indicators for each year-quarter to/from the Brexit referendum. The reported coefficients correspond to the interactions between these time indicators and the *UK High-Tech Reg.* (blue dots) and *UK Other Reg.* (red dots) indicators. The outcome in Panel A is the quarterly number of questions asked by Stack Overflow users from a given NUTS 3 region in a specific technology area. The outcome in Panel B is the quarterly number of questions that include code. The outcome in Panel C is the quarterly number of high-quality questions. Vertical bars represent 90% confidence intervals.

Figure 5: Event Studies for the Number of Questions Asked: By Asker Type and Distinguishing by UK region



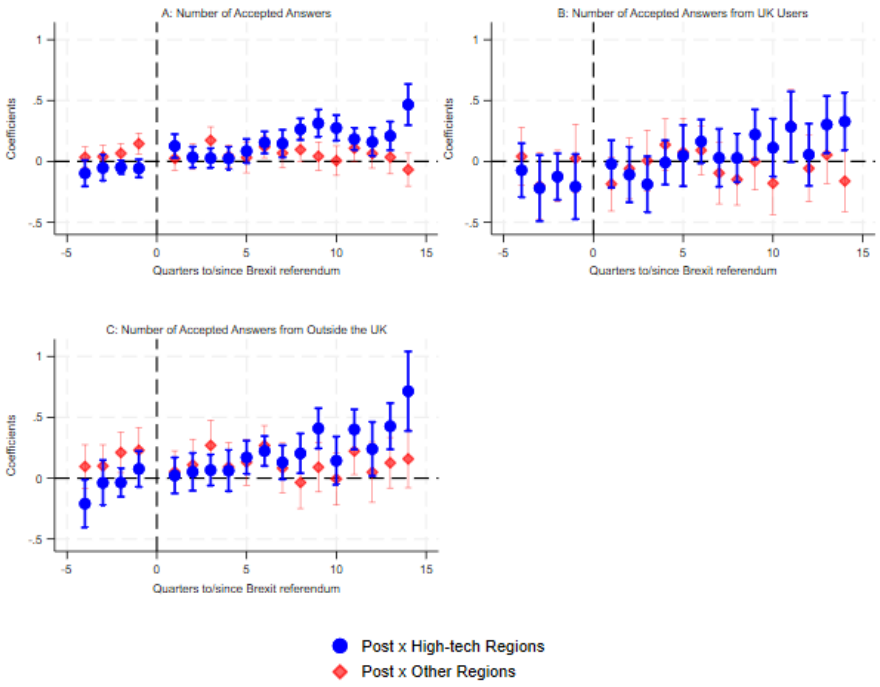
This figure presents estimates from a dynamic version of Eq. (1), where the variable *Post Brexit* is replaced with a series of time indicators for each year-quarter to/from the Brexit referendum. The reported coefficients correspond to the interactions between these time indicators and the *UK High-Tech Reg.* (blue dots) and *UK Other Reg.* (red dots) indicators. The outcome in Panel A is the quarterly number of questions asked by Stack Overflow users who were active pre-Brexit. The outcome in Panel B is the quarterly number of questions asked by new users. The outcome in Panel C is the quarterly number of questions asked by highly reputable users, while the outcome in Panel D is the quarterly number of questions asked by less reputable users. Vertical bars represent 90% confidence intervals.

Figure 6: Event Studies for the Number of Novel Questions Asked: Distinguishing by UK region



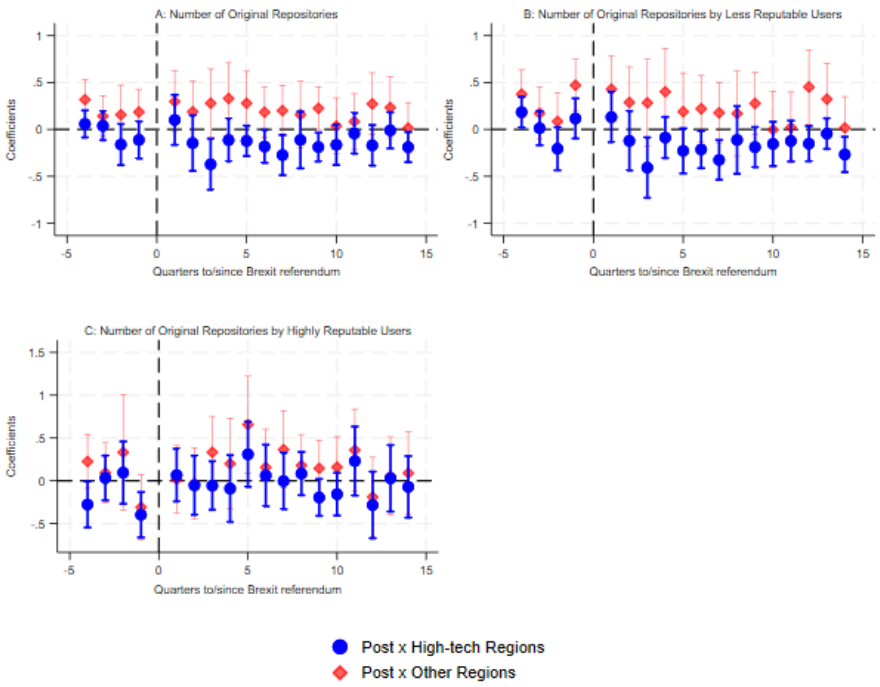
This figure presents estimates from a dynamic version of Eq. (1), where the variable *Post Brexit* is replaced with a series of time indicators for each year-quarter to/from the Brexit referendum. The reported coefficients correspond to the interactions between these time indicators and the *UK High-Tech Reg.* (blue dots) and *UK Other Reg.* (red dots) indicators. The outcome is the quarterly number of novel questions asked by Stack Overflow users. Vertical bars represent 90% confidence intervals.

Figure 7: Event Studies for the Number of Accepted Answers to Questions Asked: Distinguishing by UK region



This figure presents estimates from a dynamic version of Eq. (1), where the variable *Post Brexit* is replaced with a series of time indicators for each year-quarter to/from the Brexit referendum. The reported coefficients correspond to the interactions between these time indicators and the *UK High-Tech Reg.* (blue dots) and *UK Other Reg.* (red dots) indicators. The outcome in Panel A is the quarterly number of answers to questions asked by Stack Overflow users from a given NUTS 3 region in a specific technology area. The outcome in Panel B is the quarterly number of answers from UK users. The outcome in Panel C is the quarterly number of answers from outside the UK. Vertical bars represent 90% confidence intervals.

Figure 8: Event Studies for the Number of Original Repositories Created on GitHub: Distinguishing by UK region



This figure presents estimates from a dynamic version of Eq. (1), where the variable *Post Brexit* is replaced with a series of time indicators for each year-quarter to/from the Brexit referendum. The reported coefficients correspond to the interactions between these time indicators and the *UK High-Tech Reg.* (blue dots) and *UK Other Reg.* (red dots) indicators. The outcome in Panel A is the quarterly number of original repositories created by Stack Overflow users from a given NUTS 3 region in a specific technology area. The outcome in Panel B is the quarterly number of original repositories created by less reputable Stack Overflow users, while the outcome in Panel C is the quarterly number of original repositories created by highly reputable Stack Overflow users. Vertical bars represent 90% confidence intervals.

Table 1: Summary Statistics for the NUTS-3-Region-Technology Panel

Variable	Mean	Std. Dev.	Min.	Max.	N
N. Questions Asked on Stack Overflow	3.05	20.61	0	640	73321
N. Questions w. Code	2.64	17.88	0	599	73321
N High-Quality Questions	1.41	10.38	0	453	73321
N. Questions by Existing Users	2.22	16.3	0	640	73321
N. Questions by New Users	0.84	6.54	0	306	73321
N. Questions by Highly Reputable Users	1.33	10.5	0	435	73321
N. Novel Questions	2.58	16.52	0	640	73321
N. Accepted Answers	1.63	11.29	0	442	73321
N. Accepted Answers from UK Users	0.3	2.55	0	133	73321
N. Accepted Answers from Outside the UK	0.24	1.51	0	62	73321
N. Original Repos (GitHub)	0.33	4.15	0	200	73321
N. Original Repos by Highly Reputable Users	0.11	2.05	0	141	73321
N. Original Repos by Less Reputable Users	0.24	3.56	0	200	73321

Table 2: Effect of the Brexit Referendum on Questions Asked on Stack Overflow

	N. Questions		N. Questions w. Code		N High-Qual. Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Brexit × UK	0.039		0.062*		0.043	
	(0.031)		(0.032)		(0.040)	
Post Brexit × UK High-Tech Reg.		0.061**		0.164***		0.119**
		(0.031)		(0.059)		(0.054)
Post Brexit × UK Other Reg.		0.019		-0.015		-0.018
		(0.034)		(0.034)		(0.041)
N. Questions			0.003*	0.003**	0.003**	0.003**
			(0.002)	(0.002)	(0.001)	(0.002)
N. Users (log)	0.952***	0.992***	0.694***	0.819***	0.523***	0.636***
	(0.133)	(0.132)	(0.145)	(0.136)	(0.147)	(0.145)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y
N	61294	61294	59869	59869	46037	54492

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of questions (columns 1 and 2), questions with code (columns 3 and 4), and higher-quality questions (columns 5 and 6) asked by Stack Overflow users from a given NUTS 3 region in a given technology area. Questions of higher quality are defined as those that received a score (i.e. upvotes minus downvotes) above the median. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. *N. Users* is the natural logarithm of the count of active Stack Overflow users in a given NUTS 3 region. We define a user as active at any point in time t if t falls between the quarter in which the user created their account and the last recorded time they visited the website. In the models reported in columns 4 to 6, we control for the number of questions asked on Stack Overflow by users from a given NUTS 3 region, within a specific technology area and quarter. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 3: Effect of the Brexit Referendum on Questions Asked on Stack Overflow: By Asker Type

	N. Questions by:							
	Existing Users		New Users		Highly Rep. Users		Less Rep. Users	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Brexit × UK	0.057		0.173		0.081		0.047	
	(0.040)		(0.127)		(0.072)		(0.039)	
Post Brexit × UK High-Tech Reg.		0.163***		0.258*		0.216**		0.138***
		(0.058)		(0.143)		(0.087)		(0.053)
Post Brexit × UK Other Reg.		-0.020		0.084		-0.033		-0.015
		(0.043)		(0.132)		(0.071)		(0.045)
N. Questions	0.003**	0.004**	0.003	0.003	0.003**	0.004**	0.002	0.003*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
N. Users (log)	-0.191	-0.049	1.416***	1.428***	-0.176	0.028	1.080***	1.170***
	(0.150)	(0.146)	(0.289)	(0.285)	(0.311)	(0.296)	(0.134)	(0.128)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y	Y	Y
N	55537	55537	39360	39360	43434	43434	58356	58356

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of questions asked by Stack Overflow users active pre-Brexit (column 1), new users (column 2), highly reputable users (column 3) and less reputable users (column 4) from a given NUTS 3 region in a given technology area. Stack Overflow identifies user reputation based on the upvotes and downvotes received for questions and answers. To adjust for variation in the duration of account activity, we normalize each user's reputation by the length of time since account creation. We classify a user as *highly reputable* if their normalized reputation exceeds the sample mean, and as *less reputable* otherwise. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 4: Effect of the Brexit Referendum on Questions Asked on Stack Overflow: Novel Questions Asked

	Novel Questions	
	(1)	(2)
Post Brexit × UK		0.071**
	(0.029)	
Post Brexit × UK High-Tech Reg.		0.162***
		(0.053)
Post Brexit × UK Other Reg.		0.007
		(0.030)
N. Users (log)	0.729***	0.822***
	(0.126)	(0.121)
N. Questions	0.003*	0.003*
	(0.002)	(0.002)
Tech x Year-Quarter FE	Y	Y
NUTS 3 Region x Tech FE	Y	Y
N	61275	61275

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of novel questions asked by Stack Overflow users from a given NUTS 3 region in a given technology area. We define a novel question as one characterized by a combination of tags that is new to a given NUTS-3 region and technology area, relative to the set of tags associated with questions asked in the preceding four quarters. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 5: Effect of the Brexit Referendum on Answers Received from Stack Overflow Users

	N. Ans.		N. Ans. from the UK		N. Ans. from Out. the UK	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Brexit × UK	0.079**		0.080		0.056	
	(0.033)		(0.056)		(0.037)	
Post Brexit × UK High-Tech Reg.		0.176***		0.142**		0.156*
		(0.057)		(0.068)		(0.088)
Post Brexit × UK Other Reg.		0.006		0.043		-0.010
		(0.035)		(0.057)		(0.045)
N. Questions	0.003*	0.004**	0.003**	0.003**	0.003	0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
N. Accepted Answers			0.000	0.001	0.001**	0.002**
			(0.000)	(0.001)	(0.000)	(0.001)
N. Users (log)	0.690***	0.817***	0.200	0.260	0.686***	0.750***
	(0.173)	(0.168)	(0.265)	(0.274)	(0.224)	(0.221)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y
N	55708	55708	37069	37069	34701	34701

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of answers to questions asked (columns 1 and 2), answers from the UK (columns 3 and 4), and answers from outside the UK (columns 5 and 6). Questions are asked by Stack Overflow users from a given NUTS 3 region in a given quarter and technology area. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. emphN. Users is the natural logarithm of the count of active Stack Overflow users in a given NUTS 3 region. We control for the number of questions asked, and in the models reported in columns 4 to 6, we also control for the number of answers received. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 6: Effect of the Brexit Referendum on Original Repositories Created on GitHub

	N. Original Repos		N. Original Repos (by Less Rep. Users)		N. Original Repos (by Highly Rep. Users)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Brexit × UK	-0.049		-0.112		0.117	
	(0.080)		(0.083)		(0.111)	
Post Brexit × UK High-Tech Reg.		-0.109*		-0.187***		0.111
		(0.064)		(0.067)		(0.101)
Post Brexit × UK Other Reg.		0.045		0.016		0.129
		(0.119)		(0.136)		(0.184)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y
N	16394	16394	14488	14488	8200	8200

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of original repositories (columns 1 and 2), repositories generated by highly reputable Stack Overflow Users (columns 3 and 4), and repositories generated by less reputable Stack Overflow Users (columns 5 and 6) from a given NUTS 3 region in a given technology area. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Knowledge Without Borders?
Brexit and the Geography of Technical Q&A

Appendix
(for online publication)

Figure A1: Technology Cluster Similarity Cloud



Notes: This panel displays word clouds for each topic clusters identified from Stack Overflow question tags using k-means clustering. Each subplot corresponds to a cluster, labeled with its technology class name. The word size in each cloud reflects the relative frequency of each tag within that cluster with larger words indicating more commonly used tags.

Table A-1: Effect of the Brexit Referendum on Questions Asked on Stack Overflow - Excluding Ireland from the Control Group

	N. Questions		N. Questions w. Code		N High-Qual. Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Brexit × UK	0.007		0.036		-0.004	
	(0.025)		(0.025)		(0.028)	
Post Brexit × UK High-Tech Reg.		0.028		0.134**		0.067
		(0.024)		(0.053)		(0.043)
Post Brexit × UK Other Reg.		-0.012		-0.037		-0.061**
		(0.029)		(0.029)		(0.031)
N. Questions			0.003**	0.003**	0.003**	0.003**
			(0.001)	(0.002)	(0.001)	(0.001)
N. Users (log)	0.920***	0.961***	0.668***	0.796***	0.495***	0.609***
	(0.138)	(0.138)	(0.152)	(0.142)	(0.153)	(0.152)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y
N	58786	58786	58786	58786	58786	58786

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of questions (columns 1 and 2), questions with code (columns 3 and 4), and higher-quality questions (columns 5 and 6) asked by Stack Overflow users from a given NUTS 3 region in a given technology area. Questions of higher quality are defined as those that received a score (i.e. upvotes minus downvotes) above the median. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. *N. Users* is the natural logarithm of the count of active Stack Overflow users in a given NUTS 3 region. In the models reported in columns 4 to 6, we control for the number of questions asked on Stack Overflow by users from a given NUTS 3 region, within a specific technology area and quarter. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A-2: Effect of the Brexit Referendum on Questions Asked on Stack Overflow: By Asker Type - Excluding Ireland from the Control Group

	N. Questions by:							
	Existing Users		New Users		Highly Rep. Users		Less Rep. Users	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Brexit × UK	0.026		0.097		0.018		0.027	
	(0.029)		(0.145)		(0.062)		(0.046)	
Post Brexit × UK High-Tech Reg.		0.127**		0.180		0.145*		0.116**
		(0.050)		(0.160)		(0.075)		(0.057)
Post Brexit × UK Other Reg.		-0.048		0.011		-0.089		-0.033
		(0.035)		(0.148)		(0.060)		(0.051)
N. Questions	0.003**	0.003**	0.003	0.003	0.003**	0.004**	0.002*	0.002*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
N. Users (log)	-0.231	-0.084	1.422***	1.435***	-0.275	-0.065	1.095***	1.189***
	(0.157)	(0.152)	(0.296)	(0.292)	(0.333)	(0.318)	(0.138)	(0.132)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y	Y	Y
N	53105	53105	37605	37605	41306	41306	55894	55894

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of questions asked by Stack Overflow users active pre-Brexit (column 1), new users (column 2), highly reputable users (column 3) and less reputable users (column 4) from a given NUTS 3 region in a given technology area. Stack Overflow identifies user reputation based on the upvotes and downvotes received for questions and answers. To adjust for variation in the duration of account activity, we normalize each user's reputation by the length of time since account creation. We classify a user as *highly reputable* if their normalized reputation exceeds the sample mean, and as *less reputable* otherwise. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A-3: Effect of the Brexit Referendum on Questions Asked on Stack Overflow: Novel Questions Asked - Excluding Ireland from the Control Group

	Novel Questions	
	(1)	(2)
Post Brexit × UK	0.043*	
	(0.025)	
Post Brexit × UK High-Tech Reg.		0.134***
		(0.051)
Post Brexit × UK Other Reg.		-0.017
		(0.027)
N. Users (log)	0.711***	0.806***
	(0.133)	(0.127)
N. Questions	0.003*	0.003*
	(0.001)	(0.002)
Tech x Year-Quarter FE	Y	Y
NUTS 3 Region x Tech FE	Y	Y
N	58767	58767

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of novel questions asked by Stack Overflow users from a given NUTS 3 region in a given technology area. We define a novel question as one characterized by a combination of tags that is new to a given NUTS-3 region and technology area, relative to the set of tags associated with questions asked in the preceding four quarters. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A-4: Effect of the Brexit Referendum on Answers Received from Stack Overflow Users - Excluding Ireland from the Control Group

	N. Ans.		N. Ans. from the UK		N. Ans. from Out. the UK	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Brexit × UK	0.045*		0.040		0.048	
	(0.026)		(0.057)		(0.040)	
Post Brexit × UK High-Tech Reg.		0.139***		0.099		0.136*
		(0.051)		(0.070)		(0.081)
Post Brexit × UK Other Reg.		-0.024		0.004		-0.010
		(0.028)		(0.057)		(0.045)
N. Questions	0.003**	0.004**	0.003**	0.003**	0.003	0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
N. Accepted Answers			0.000	0.001*	0.001*	0.002**
			(0.000)	(0.001)	(0.000)	(0.001)
N. Users (log)	0.688***	0.820***	0.184	0.243	0.703***	0.768***
	(0.181)	(0.175)	(0.271)	(0.281)	(0.227)	(0.225)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y
N	55708	55708	37069	37069	34701	34701

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of answers to questions asked (columns 1 and 2), answers from the UK (columns 3 and 4), and answers from outside the UK (columns 5 and 6). Questions are asked by Stack Overflow users from a given NUTS 3 region in a given quarter and technology area. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. *N. Users* is the number of XXX. We control for the number of questions asked, and in the models reported in columns 4 to 6, we also control for the number of answers received. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A-5: Effect of the Brexit Referendum on Questions Asked on Stack Overflow - Including France and Germany in the Control Group

	N. Questions		N. Questions w. Code		N High-Qual. Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Brexit × UK	0.005		0.057**		0.039	
	(0.020)		(0.025)		(0.024)	
Post Brexit × UK High-Tech Reg.		0.030		0.188***		0.140***
		(0.019)		(0.070)		(0.054)
Post Brexit × UK Other Reg.		-0.018		-0.058**		-0.057**
		(0.025)		(0.025)		(0.025)
N. Questions			0.004**	0.005**	0.005**	0.005**
			(0.002)	(0.002)	(0.002)	(0.002)
N. Users (log)	1.084***	1.097***	0.840***	0.880***	0.710***	0.748***
	(0.083)	(0.080)	(0.085)	(0.080)	(0.081)	(0.078)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y
N	151468	151468	146338	146338	127224	127224

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of questions (columns 1 and 2), questions with code (columns 3 and 4), and higher-quality questions (columns 5 and 6) asked by Stack Overflow users from a given NUTS 3 region in a given technology area. Questions of higher quality are defined as those that received a score (i.e. upvotes minus downvotes) above the median. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. *N. Users* is the natural logarithm of the count of active Stack Overflow users in a given NUTS 3 region. In the models reported in columns 4 to 6, we control for the number of questions asked on Stack Overflow by users from a given NUTS 3 region, within a specific technology area and quarter. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A-6: Effect of the Brexit Referendum on Questions Asked on Stack Overflow: By Asker Type - Including France and Germany in the Control Group

	N. Questions by:							
	Existing Users		New Users		Highly Rep. Users		Less Rep. Users	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Brexit × UK	0.008		0.416***		0.021		0.050*	
	(0.038)		(0.092)		(0.048)		(0.028)	
Post Brexit × UK High-Tech Reg.		0.132**		0.526***		0.186**		0.167***
		(0.060)		(0.118)		(0.079)		(0.059)
Post Brexit × UK Other Reg.		-0.098***		0.298***		-0.146***		-0.039
		(0.037)		(0.104)		(0.047)		(0.030)
N. Questions	0.004**	0.005**	0.005*	0.005*	0.005**	0.006**	0.003*	0.004**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
N. Users (log)	-0.018	0.028	1.238***	1.241***	0.261*	0.324**	1.109***	1.136***
	(0.099)	(0.098)	(0.248)	(0.247)	(0.137)	(0.131)	(0.097)	(0.093)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y	Y	Y
N	128326	128326	92100	92100	93157	93157	141046	141046

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of questions asked by Stack Overflow users active pre-Brexit (column 1), new users (column 2), highly reputable users (column 3) and less reputable users (column 4) from a given NUTS 3 region in a given technology area. Stack Overflow identifies user reputation based on the upvotes and downvotes received for questions and answers. To adjust for variation in the duration of account activity, we normalize each user's reputation by the length of time since account creation. We classify a user as *highly reputable* if their normalized reputation exceeds the sample mean, and as *less reputable* otherwise. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A-7: Effect of the Brexit Referendum on Questions Asked on Stack Overflow: Novel Questions Asked - Including France and Germany in the Control Group

	Novel Questions	
	(1)	(2)
Post Brexit × UK	0.051*	
	(0.027)	
Post Brexit × UK High-Tech Reg.		0.180***
		(0.061)
Post Brexit × UK Other Reg.		-0.047**
		(0.023)
N. Users (log)	0.896***	0.925***
	(0.074)	(0.070)
N. Questions	0.004**	0.005**
	(0.002)	(0.002)
Tech x Year-Quarter FE	Y	Y
NUTS 3 Region x Tech FE	Y	Y
N	151411	151411

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of novel questions asked by Stack Overflow users from a given NUTS 3 region in a given technology area. We define a novel question as one characterized by a combination of tags that is new to a given NUTS-3 region and technology area, relative to the set of tags associated with questions asked in the preceding four quarters. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A-8: Effect of the Brexit Referendum on Answers Received from Stack Overflow Users - Including France and Germany in the Control Group

	N. Ans.		N. Ans. from the UK		N. Ans. from Out. the UK	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Brexit × UK	0.056*		0.057		0.076*	
	(0.029)		(0.045)		(0.045)	
Post Brexit × UK High-Tech Reg.		0.182***		0.141**		0.275**
		(0.067)		(0.069)		(0.113)
Post Brexit × UK Other Reg.		-0.053*		0.001		-0.090*
		(0.028)		(0.045)		(0.047)
N. Questions	0.005**	0.005**	0.004**	0.003**	0.003***	0.003***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
N. Accepted Answers			0.000	0.001	0.004*	0.006*
			(0.000)	(0.001)	(0.002)	(0.003)
N. Users (log)	0.810***	0.852***	0.361**	0.394**	0.827***	0.826***
	(0.098)	(0.093)	(0.170)	(0.170)	(0.110)	(0.111)
Tech x Year-Quarter FE	Y	Y	Y	Y	Y	Y
NUTS 3 Region x Tech FE	Y	Y	Y	Y	Y	Y
N	130530	130530	61579	61579	87058	87058

Notes: We estimate variants of the Poisson quasi-maximum likelihood model described in Eq. (1) for the quarterly number of answers to questions asked (columns 1 and 2), answers from the UK (columns 3 and 4), and answers from outside the UK (columns 5 and 6). Questions are asked by Stack Overflow users from a given NUTS 3 region in a given quarter and technology area. *Post Brexit* is a (0/1) indicator taking value 1 starting from 2016Q3. *UK High-Tech Reg.* is a (0/1) indicator identifying the NUT 3 regions comprising London, Oxford, and Cambridge. *UK Other Reg.* is a (0/1) indicator identifying the remaining NUTS 3 UK regions. *N. Users* is the number of XXX. We control for the number of questions asked, and in the models reported in columns 4 to 6, we also control for the number of answers received. Standard errors (in parentheses) are clustered by NUTS 3 region. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.