# Labor Competition and Open Innovation

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**Abstract:** Innovation, a key driver of competitive advantage, increasingly occurs through informal partnerships between firms collaborating on public goods. However, competitive forces may influence contribution patterns. Existing studies primarily consider the role competition plays in closed and private innovation. Therefore, we utilize data on millions of firm contributions to open source software, a crowdsourced public good, to measure the relationship between the level of competition a firm faces and its participation in informal innovation partnerships. We further create a novel measure of the labor competition a firm faces using Lightcast data on job postings. While the relationship between labor and product market competition is nuanced and warrants further investigation, labor competition is particularly important in innovative and technology-focused contexts. We find that labor market competition and open source contributions exhibit an inverted U-relationship. The current findings hint at open innovation being a potentially strategic choice in hiring decisions during times of low labor market power of firms.

**JEL-Classification:** L20, J20, M20

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# 1 Introduction

*General Motors announced the creation of its own open-source software protocol ... The move comes as the auto industry scrambles to hire more software developers and programmers.* (The Verge 2023)

Labor is arguably the most critical input to the innovation process. Maintaining a competitive edge through innovation hinges on a firm's ability to attract and retain highly skilled workers (Horbach and Rammer, 2020). Competitive pressures can be exacerbated by labor mobility: skills in innovation-oriented roles tend to be highly transferable between firms and industries (Arrow, 1962; Pakes and Nitzan, 1983). As the quote above suggests, the way in which firms compete for talent might influence the nature of the innovation output itself. Here, General Motor's labor competition strategy is to offer the potential to work on open source software (OSS) as a fringe benefit to entice highly skilled workers to join or stay in the firm by increasing their commitment to generate open innovation. In this paper we seek to empirically study the relationship between labor market competition and open innovation from the perspective of the firm.

A particularly important case of open innovation is the development of OSS, a digital public good developed through incremental contribution efforts of individuals who release their code under relatively permissive licensing. It's important to acknowledge that a nontrivial share of these individuals contribute as part of their job or at the behest of their employers (Nagle et al., 2020). The use and creation of OSS confers benefits not only to society as large but importantly to both firms and their contributing employees (Hoffmann, Nagle, and Zhou, 2024). On one hand, employees contributing to open source may benefit from learning new skills from the wider community, creating a public resume to signal to potential employers, or simply gain intrinsic benefits by contributing to OSS (Lakhani and Wolf, 2003; Lerner and Tirole, 2002). On the other hand, firms can leverage open source code to lower production costs, crowd source development, or widely distribute software complementary to their priced goods (West and Gallagher, 2006; Shah and Nagle, 2020).[1] Importantly, if potential employees value working on OSS projects, firms highly active in

[1] For example, the availability of OSS components can reduced fixed costs of development by mitigating the need

the OSS space might be better positioned to attract critical talent in highly contested labor markets. Hence it may be the case that firm-driven contribution to open source software is in some part a byproduct of firms using non-wage benefits to compete for skilled workers critical to their competitive advantage.

Our primary objective in this study is to empirically assess the relationship between labor competition and OSS development by firms. To do so, we assemble an empirical sample based on firm-attributed activity on the OSS forge GitHub (Section 3). Our procedure links OSS project development activity with individual firms using the contributor's email address.[2] The result is a firm-month panel with millions of observations of OSS activity for $19,303$ firms spanning from January 2016 through June 2023. Our primary measure of firms participating in OSS development is the number of commits firm employees make to public repositories in a given month.

A first order issue in studying the relationship between competition and innovation is simply revisiting what competition means. Previous research has considered the number of product market rivals, profit margins or markups, and product market shares (Aghion et al., 2005). However, these measures are subject to a variety of shortcomings, such as a narrow focus on output markets, dependence on indicators observed only for small samples of firms[3], and limited variation (Haans, Pieters, and He, 2016). Our approach in this paper instead considers the role of competition between firms on the demand side of labor markets. In Section 4 we develop a measure of competition based on the extent to which an individual firm faces competition for workers. Derived from online postings for job vacancies (Lightcast), this firm-level labor competition measure has a number of key advantages. For example, the measure can be observed for a wide range of individual firms and exploits granular variation in labor demand across time, space, and job types.[4]

to "reinvent the wheel". Firms can also reduce variable costs by using OSS instead of paying recurring licensing fees or service subscriptions.

[2]In OSS, it is a strongly followed norm to use your work email address if your employer is sponsoring your open source activity and your personal email address otherwise.

[3]Compared with labor markets, even defining which output market a firm operates in can often be more challenging to define precisely. Further, private or pre-profit firms are typically not required to disclose financial statements used by researchers to estimate profit margins or markups.

[4]The Lightcast U.S. job postings dataset contains the near universe of online job vacancies posted since October 2010 (Azar et al., 2020).

Moreover labor market competition is particularly relevant to firms participating in innovation and technology heavy sectors since workers and their skill sets are highly mobile across firms.

In Section 5 we present descriptive evidence for the relationship between labor market competition and open innovation by firms. Consistent with the competition-innovation literature, the relationship between labor market competition and OSS contribution follows an “inverted-U” shape pattern: contributions are maximized near the center of the labor competition distribution while firms at the extremes tend to contribute the least. This pattern is borne out graphically, under regression analysis (both in the cross section and time series), and is robust to the inclusion of both firm and year-month fixed effects as well as control variables. We further explore the robustness of this result in Section 6. To address the potential endogeneity of the labor market competition measure, we exploit the granularity of the measure to develop several Bartik (i.e. ”shift-share”) instruments. Section 6 shows that the inverted-U relationship between labor competition and OSS output remains robust under instrumental variable estimation. We make arguments to assuage concerns over instrument validity raised in the recent literature (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2022).

This study makes contributions to the strains of literature on competition and innovation, labor, and firm engagement and strategy in OSS. We document a robust non-linear relationship between a firm’s engagement in open innovation and the competitive environment it operates in. While much of the existing literature focuses on competition occurring in the product market, we instead demonstrate that competition in critical input markets such as labor exhibits an “inverted-U” relationship with a firm’s participation in OSS.[5] To this end, we develop a novel measure of firm-level labor market competition using data on online postings for job vacancies following similar approaches gaining traction in the recent literature on monopsony power in labor markets (Dube et al., 2020; Azar, Marinescu, and Steinbaum, 2022; Hazell et al., 2022). We additionally demonstrate that this measure exhibits a similar relationship with firm-level patenting activity, i.e. there

[5] A systematic relationship between power in a firm’s input and output markets is nuanced and part of a nascent literature at the moment (Kroft et al., 2020; Yeh, Macaluso, and Hershbein, 2022). Indeed in our empirical setting, we find mixed evidence for correlations between measures of product market competition and our labor competition measure (see Table A1).

is also an inverted-U relationship between labor market competition and closed innovation for the secondary market of patents. By doing so, we provide evidence that firm propensities to engage in both open and proprietary innovation are maximized nearer the middle of the labor market competition distribution. Overall these findings underscore the fact that competitive pressure in labor markets play a critical, yet nuanced, role in shaping firm-level innovation.

The remainder of this paper proceeds as follows. In Section 2 we discuss the theoretical groundwork for a non-linear relationship between competition and innovation from the perspective of the firm. In Section 3 we characterize our empirical setting and discuss the construction of our sample. We develop an intuition for and construct a measure of labor market competition in Section 4. The first phase of our analysis summarizes correlational results (Section 5). In an effort to further establish robustness of our results, the second phase develops an identification strategy to give a more causal interpretation to the estimated relationship (Section 6). Section 7 concludes.

# 2 Theory

We first discuss how the present study fits within the existing literature. We highlight linkages to open innovation in general, the relationship between labor competition and innovation, and how such a relationship might follow an "inverted-U" pattern common in the competition-innovation literature (Aghion et al., 2005).

The open innovation paradigm and its benefits have garnered considerable interest by researchers (West and Gallagher, 2006; Chesbrough, 2006b; Cropf, 2008). Compared with closed or "siloed" innovation, the free flow of information and other resources beyond the firm boundaries of the firm have the potential to generate strong productivity externalities. A special case of open innovation is "coopetition" between rival firms. Conditions under which firms may be incentivized to share information or informally collaborate with each other has been studied at length in the literature (Von Hippel, 1987; Schrader, 1991; Fauchart and Von Hippel, 2008; Almirall and Casadesus-Masanell, 2010). In the case of OSS collaboration, firms can capitalize on value generated by external user communities by investing fewer resources into infrastructure and management than if they did not build upon these open innovations (Belenzon and Schankerman, 2015; Shah and Nagle, 2020).

The core interest of this paper is how labor competition between firms can influence their willingness to engage in open innovation. We consider some ways in which this relationship might manifest. One key feature of our empirical setting is that OSS is produced by workers with skills easily transferable across firms (Freedman, 2008). For example, a software developer can easily take what they have learned from a previous employer to their new job, creating scope for knowledge spillovers to accelerate the pace of innovation in general. Indeed, empirical evidence exists to suggest that increased worker mobility results in net increases to overall patenting activity (Cooper, 2001; Kaiser, Kongsted, and Rønde, 2015). However, labor mobility in equilibrium can be influenced by strategic responses of firms. For example, non-poaching arrangements between firms reduce worker bargaining power, which can actually foster innovation by limiting worker turnover (Ferrés, Kankanhalli, and Muthukrishnan, 2022) at the cost of wage markdowns (Lafontaine, Slade et al., 2023).[6] It may also be the case that increased OSS output by firms is the result of strategic behavior and competitive labor markets. When relatively many firms are competing for a relatively small segment of the labor pool, an individual firm's monopsony power (and therefore ability to influence wage offers) is limited (Azar et al., 2020). Firms may therefore offer the opportunity to work on OSS projects as a non-wage benefit to attract skilled workers.

If some relationship between competition and innovation is indeed present, the exact nature of this pattern is certainly of interest. Are there certain competitive conditions under which innovation is maximized? In their seminal paper, Aghion et al. (2005) use an industry-year panel to estimate the relationship between industrial competition, measured by the industry's Lerner index, and proprietary innovation, measured using citation-weighted patents. Their finding of a parabolic relationship between competition and innovation, in which innovation intensity is maximized for

[6]As an alternative to collusive labor practices, firms can also turn to legal channels by actively enforcing patents they hold. Using data from the U.S. semiconductor industry, Agarwal, Ganco, and Ziedonis (2010) find that while increased patent enforcement reduces labor mobility overall, employee-inventors that do leave firms actually increase their innovation productivity.

firms near the center of the competition distribution, has sparked considerable interest.[7] The authors seek to explain their finding with a theoretical model under which the incentives to innovate are stronger for rivals who are more technologically "neck-and-neck" compared to those who lag well behind leaders. Under specific initial conditions in the competitive landscape, this tension can generate an inverted-U dispersion in strategic R&D along the product market competition index.

Why might we expect to find a similar "inverted-U" shaped relationship between labor market competition and open innovation? A number of different mechanisms have been suggested by the literature. First, relative labor market competition can influence the wage setting power of firms and therefore, ultimately, labor costs. Chen et al. (2023) suggest that while firms confronted with increasing wage costs face stronger incentives to innovate but suffer from reduced capacity do so, since firm resources may be allocated away from R&D expenditures. Second, highly concentrated labor markets can often be associated with increased worker mobility, as workers enjoy an improved set of outside options. Worker mobility can also be associated with increased turnover or churn to the detriment of firm-level innovation intensity (Eriksson, Qin, and Wang, 2014). In fact, Müller and Peters (2010) find an inverted-U relationship between labor turnover and R&D intensity.

# 3 Data

To empirically study the relationship between firm-driven open innovation and labor market competition, we assemble a panel of firm-month observations that combines firm OSS activity on the GitHub platform with the level of labor market competition they face. We leverage three main data sources: i) a set of firms drawn from the CompuStat and Pitchbook databases, ii) firm open source activity gathered from the GitHub platform, and iii) firm participation in labor markets

[7] Additional empirical evidence considering the relationship identified in Aghion et al. (2005) is somewhat mixed. For example, Tingvall and Poldahl (2006), Polder and Veldhuizen (2012), and Peneder and Wörter (2014) find similar inverted-U competition-innovation patterns in different settings while Mulkay (2019) and Correa (2012) do not. Hashmi (2013) reexamination of Aghion et al. (2005) suggests that either linear or non-linear patterns can be found, depending on the empirical setting and model assumptions.

derived from Lightcast data on job vacancies. We restrict our study window to January 2016 through June 2023, a period over which GitHub became the dominant OSS platform for both firms and individual contributors.[8]

**Firm data.** We first form a sample of firms drawing from the union of the CompuStat and Pitchbook company databases. While there is some overlap between these firm databases, they target different types of firms. CompuStat contains information on publicly traded firms documented through their quarterly financial statements.[9] The Pitchbook venture capital data contains information on private firms, in particular startups who have received some initial funding. The Pitchbook data contains information on competitors, employment, and industry classifications, and other firm characteristics. It is of particular importance for the construction of our empirical sample that both databases contain information on the firm's main website, which we use to attribute open source contribution activity by firm-affiliated individuals to their respective employer. We begin with the union of unique firms across the CompuStat and Pitchbook databases.

**Open Innovation data.** GitHub is the world's most popular software forge and has become the *de facto* hub for collaborative OSS development. The platform hosts the source code repositories of OSS projects and provides infrastructure for contributors to distribute and collaboratively develop software. We use contribution activity to public GitHub repositories to proxy for firm engagement in open innovation.[10] The atomistic unit of software contribution is a *commit*.[11] A requirement of the git version control system (VCS) is that each commit must be timestamped and signed by the author's email.[12] With assistance from GitHub, we use the author email information for each commit to match individual activity on GitHub to firms in our CompuStat/Pitchbook sample.[13] We received proprietary information from GitHub that linked our firm list with GitHub

[8]While GitHub was founded in April 2008, most of the contribution activity attributed to firms gains momentum around 2015 through 2016. Hence, our choice of time frame captures most of the open-source software variation over time.

[9]We use the union of firms found in the North American and Global CompuStat databases.

[10]A public repository on GitHub is accessible to anyone and typically is distributed under an OSS license.

[11]A commit is a collections of changes to a codebase and forms the basis of version control systems which seek to facilitate the management of complex software projects.

[12]Note that git is the software tool that forms the backbone of the GitHub platform, which is more accurately described as a decentralized VCS collaboration platform.

[13]The procedure works as follows: we send GitHub our list of firms identified by the top-level domains of their

commit activities. This allows us to study firm involvement in OSS by observing firm employees committing to public software repositories on GitHub.

**Labor market data.** The data from Lightcast (previously known as BurningGlass) contain the near universe ($\approx 70\%$) of U.S. job vacancies posted on the internet (Hazell et al., 2022). We consider data job postings to be a reasonable proxy for firm labor demand over time.[14] Job postings not only capture the what (job types), when (timing), and where (region) of firm hiring activity but also the extent to which firms compete directly in the same labor markets. Rich variation in the job postings data allows us to construct an intuitive measure of labor market competition and develop a credible identification strategy. We focus on Lightcast's United States job postings sample, which collects $270+$ million distinct posts from October 2010 through June 2023.[15] Within these vacancy postings, we observe $2.56+$ million distinct employers hiring for $73,165$ job types across $387$ metropolitan statistical areas (MSAs). The data from Lightcast also contain information on skill and education requirements for each posted job role, as well as salary ranges when available.

— Table 1 about here —

Table 1 depicts the merging process when merging the firm data, to the open innovation GitHub data, and finally when merging the Lightcast labor market data onto it. We extracted a list of 55,549 firms from CompuStat and 489,819 firms from Pitchbook. We then took the union of the two datasets, leaving us with a list of 500,222 firms with distinct URLs.[16] Once we obtained our list of firms from the firm dataset, we send them to GitHub to identify company-related open-source software work. Finally, we merge the firm-matched open innovation data with labor market data from Lightcast. The final sample based on strict matching of URLs includes $19,303$ U.S. based

primary website. GitHub then matches individual commits to firms in this list by the domain name in the committer's email address. For example, a commit signed by an author with an email ending in "@microsoft.com" would be associated with Microsoft. The result is a set of timestamped commits for which we observe the commit hash, the committer's firm affiliation, and the repository the commit belongs to.

[14] The use of online job postings data has gained traction in recent years and is used to study a wide range of labor-related topics (Azar et al., 2020; Hansen et al., 2023; Lafontaine, Slade et al., 2023).

[15] The Lightcast U.S. job postings dataset spans October 2010 through the present. Other job postings datasets exists but have more limited temporal coverage.

[16] Some firms occur in both datasets, e.g. Microsoft. Others did not have a traceable URL, and were therefore dropped.

firms active on GitHub.[17]

# 4 Measuring Labor Market Competition

Most measures of product market competition have considerable limitations, are very difficult to obtain due to data availability, or have mainly variation from the cross-section. As an alternative, we propose a firm-level measure of labor market competition that leverages both cross- and time-series variation. Intuitively, we seek to characterize a firm's exposure to competition by the extent to which they compete with other firms for workers. Our resulting measure is a weighted sum of concentration indices across each labor market they participate in. A labor market's concentration is measured by calculating the (inverse) Herfindahl-Hirschmann index for its demand side. By the granularity of the raw postings data, we can disaggregate labor markets by region and job title. Finally, we weight each concentration index by the firm's relative hiring intensity in that particular labor market. The remainder of this section gives a detailed overview of the intuition and construction of the labor competition measure from the Lightcast job vacancies data, and it highlights several of its key properties.

To arrive at our preferred labor market competition measure, we must first introduce some notation. Let $p_{ijgt}$ denote the number of job postings of firm $i \in 1, \ldots, I$ for job role $j \in 1, \ldots, J$ in region $g \in 1, \ldots, G$ during period $t \in 1, \ldots, T$.[18] Next, we can aggregate this granular count of job postings to develop intermediate quantities necessary to arrive at our final measure:

$$p_{it} \equiv \sum_j \sum_g p_{ijgt}$$

$$p_{jgt} \equiv \sum_i p_{ijgt}$$

where $p_{it}$ is the number of job vacancies that firm $i$ posts at time $t$, which we call the overall labor

[17]The restriction to U.S. based firms arises from our use of the Lightcast dataset which contains solely postings for jobs located withtin the U.S. As mentioned previously, this product has the best temporal coverage compared with the other regional offerings from Lightcast.

[18]We collect $p_{ijgt}$ by aggregating postings that appear in the raw Lightcast data.

demand intensity for firm $i$. Similarly, $p_{jgt}$ counts the total number of postings for role $j$ in region $g$ across all firms in period $t$, therefore measuring total demand intensity for a particular segment of the labor market (i.e. title-region). Total labor demand is relevant for the level of competition that firms face which hire for job role $j$ in region $g$. Next, we use these intermediates to create more intuitive building blocks for our labor competition measure:

$$
\begin{aligned}
s_{ijgt} &\equiv \frac{p_{ijgt}}{p_{it}} \\
m_{ijgt} &\equiv \frac{p_{ijgt}}{p_{jgt}}
\end{aligned}
$$

where $s_{ijgt}$ is the firm specific demand intensity for job role $j$ in region $g$ at time $t$ and $m_{ijgt}$ is the firm specific market share. Following a conventional approach from the industrial organization literature, we can aggregate the market shares for each firm to form an (inverse) Herfindahl-Hirschman Index (HHI):

$$
h_{jgt} \equiv \left( \sum_i m_{ijgt}^2 \right)^{-1} .
$$

The measure $h_{jgt}$ aggregates the squared market shares over all $I$ firms for a particular job role $j$ in region $g$ at time $t$. This measure converges to 0 when one firm has all of the labor market power for one particular job role at a given point in time. This implies that one firm is related to all job postings for this one job role. Conversely, the measure converges to infinity when there is perfect competition in the labor market and an infinite number of firms competing for $j$ job roles at time $t$. Finally, we pull all of these components together to define our measure of labor market competition ($l_{it}$) at the firm level:

$$
l_{it} = \sum_j \sum_g s_{ijgt} h_{jgt}
$$

where $h_{jgt}$ defines the inverted HHI of the labor market competition a firm $i$ faces for role $j$ at time period $t$ in region $g$, while $s_{ijgt}$ are weights on the inverted HHI that capture the demand dependency of a firm $i$ for role $j$ in region $g$ in a particular point in time $t$.

We can see that $l_{it}$ is non-negative and positively correlated with the level of labor market competition faced by firm $i$.[19] Moreover, our measure captures variation in a firm's competitive exposure across several dimensions: (1) across time, (2) across space, and (3) across labor types. Finally, it is important to note that the measure reflects competition arising from any rival firm and job market contained in the Lightcast data, not just from firms or job titles active on GitHub, i.e., it includes the hiring behavior of firms that do not end up in our final sample, but are competing for labor against the firms in our final sample.

The advantages of our labor market measure of competition compared with measures defined by output markets are palpable. Labor markets are far easier to define compared with product markets and observing direct competitors in labor markets operates simply through revealed preferences.[20] The broad coverage of the job postings source data builds confidence that we are accurately characterizing both labor market concentration and firm hiring intensities.[21] Finally, the granularity of the measure allows for potential variation across several different facets of what leads to competition.

# 5 Main Results

## 5.1 A Correlational Depiction

We organize key measures and covariates for the final sample of $19,303$ firms into a balanced panel of $1,811,841$ firm-month observations. With our empirical sample in hand, we first investigate the pure empirical relationship of labor market competition and open innovation.

— Figure 1 about here —

[19] Due to the nature of the job postings data, there may be periods in our study window during which a firm does not post any vacancies. However, we argue that the firm nonetheless is still subject to labor market competition as job vacancies posted by rivals present outside options for the firm's incumbent employees. We therefore interpolate missing values in for each firm's labor market competition time series.

[20] This is in contrast to competitor identification in often nebulously defined product markets, or relies on truth disclosures by the firm itself (e.g. SEC 10-K filing) or accurate classification by a market analyst.

[21] The data cover firms of all sizes, spanning many diverse industries, and under different ownership structures.

Figure 1 shows the cross-sectional relationship of employee open innovation as measured by average open source commits for each firm over labor market competition of a firm. We find a non-linear relationship of open innovation and labor market competition. Under low and high levels of labor market competition firms contribute fewer OSS innovations, while firms that have a medium level of competition contribute at high levels to OSS innovations. Interestingly, in an additional exercise we show that this relationship with our labor market competition measure also holds for patenting in the secondary market (see Figure A1).[22]

Importantly, we are particularly interested in how labor market competition causally affects open innovation. However, open source contributions may be used to attract labor and as such it may lead to a relatively more competitive environment for firms that are starting out at low levels of labor market competition. Similarly, increasing open source contributions may shift the demand of the firm towards particular types of job roles and this may reduce labor market competition for firms that are in highly competitive environments. So, the inverted U shape may be driven by reversed causality. Hence, we need to move towards causality. We will do so, by including time-invariant characteristics and by leveraging purely exogenous variation in labor market competition through an instrumental variable approach.

## 5.2 Regression Analysis

In this step, we move beyond the simple correlations and closer towards causality to better understand the robustness of the results. We run the following specification:

$$y_{it} = \rho_1 l_{it} + \rho_2 l_{it}^2 + \boldsymbol{\rho}_3{}' \boldsymbol{X}_{it} + \rho_t + \rho_i + \epsilon_{it}$$

where $Y_{it}$ is the measure of open innovation, such as $log(commits)$ as the dependent variable while we introduce our measure of labor market competition in linear and quadratic form with $l_{it}$

[22]The "secondary market" involves case in which a firm other than the original applicant acquires the patent and presents an alternative strategic channel to establish competitive advantage. See Chesbrough (2006a) and Burstein (2015) for detailed discussions of secondary markets for patents.

and $l_{it}^2$, respectively.[23] In a full specification, we include a vector of controls, $\boldsymbol{X}_{it}$, containing total employment and the cumulative number of commits in the prior month. Finally, the most extensive model specification contains firm and month-year fixed effects, $\rho_i$, $\rho_t$, respectively.

— Table 2 about here —

Table 2 shows the relationship between labor market competition and $log(commits)$. Panel A displays results from ordinary least square regressions leveraging variation from the cross-sectional comparison of firms where some firms have higher labor market competition than other ones. It shows a positive relationship between labor market competition and open innovation (column 1). Adding a quadratic (column 2) shows the inverted-U relationship that is portrayed in the cross-section (see Section 5.1). This relationship is attenuated but still remains robust and significant when we add controls (column 3). Panel B employs fixed effects regressions controlling for time-invariant company characteristics. The fixed effects approach leverages variation in labor market competition within firms over time. The linear relationship now becomes even minutely negative (column 1) while the inverted-U relationship is robust when introducing the quadratic (column 2). When adding controls the coefficients remain stable (column 3).

Using coefficient estimates from our preferred specification (panel B, column 3), we can see that wirm monthly commits are maximized at $l_{it}^* = 2.21$, or the 58th percentile for our sample's labor competition distribution. For a firm in the 25th percentile of the labor competition distribution $(1.11)$, a one standard deviation increase in the labor competition $(1.11)$ is associated with a $29.3\%$ *increase* in monthly (log) commits relative to the sample mean $(0.515)$.[24] Naturally, this relationship reverses once firm reach higher levels of labor market competition. For a firm in the 75th percentile of the labor competition distribution $(2.84)$, a one standard deviation increase in competition is associated with a $24.1\%$ *decrease* in monthly commits relative to the sample mean.

To further understand the inverted-U relationship, we consider alternative measures of OSS

[23] In our application, we use $log(commits + 1)$ to account for months in which a firm makes no commits.

[24] To arrive at this back-of-the-envelope interpretation, we use the linear approximation $\rho_1 + 2\rho_2 l_{it}$ and standardize coefficients. Note that contribution on GitHub is skewed across firms and time. In levels, the average firm makes $0.674$ commits in a month but the median firm does not commit at all.

innovation activity. We find the same pattern when using the firm's number of distinct committers, new repositories, and quality-adjusted commits in logs as outcome variable (see Table A2, Table A3, Table A4).

# 6 Effect of Competition on Open Innovation

In order to further establish robustness and progress towards causal identification of the relationship between labor market competition and open innovation, we next introduce a 2SLS approach leveraging two instruments.

## 6.1 Instruments

By construction, our labor competition measure bears a resemblance to so-called "shift-share" variables. We can think of the inverse HHIs $h_{jgt}$ shifts and the firm's demand intensity weights $s_{ijgt}$ as shares. While intuitive, the measure almost certainly is subject to endogeneity and likely biases our fixed effect estimates for the competition-innovation relationship. Owing in part to the granularity of the competition measure, we can address this concern by constructing instruments for our endogenous labor competition measure in the spirit of Bartik (1991). Our approach relies on the simple idea that moving to a higher level of aggregation results in firms having less control over the labor market competition measure (Breuer, 2022). As such, we we propose instruments based on different levels of aggregation: i) regions and ii) job titles.

We define the regional instrument as follows:

$$z_{it} = \sum_{g} s_{ig} h_{gt}$$

Empirically, we redefine the inverse Herfindahl index at a higher level of aggregation, $h_{gt}$, considering only fluctuations in labor market concentration across regions and time. Similarly, we use time-invariant firm hiring shares $s_{ig}$ which capture the firm's long run[25] hiring intensity across 387 metropolitan areas. This implies that we are leveraging differences in competition across jobs within regions. Our particular choice of aggregation is designed to address two concerns raised by recent literature on the validity of the exclusion restriction for Bartik instruments. First, we argue that the firms long run demand intensity share $s_{ig}$ is less subject to endogenous choices of the firm compared with it's time-varying counterpart (Goldsmith-Pinkham, Sorkin, and Swift, 2020). Second, we argue that regional inverse HHI $h_{gt}$ generates variation that is plausibly exogenous from the perspective of any single firm (Borusyak, Hull, and Jaravel, 2022).

Following the same approach, we can also define a second instrument based instead on labor markets delineated by job titles as follows:

$$z_{it} = \sum_{j} s_{ij} h_{jt}$$

Empirically, we aggregate the inverse Herfindahl index $h_{jgt}$ as well as the firm demand $s_{ijgt}$ jobs $j$ from the most granular measure within 73,165 job titles. This implies that we are leveraging differences in competition within jobs across regions. We empirically validate the latter measure by plotting both labor market competition components (firm demand weights and the inverse Herfindahl index) across the United States and find not only substantial variation across the country within each measure but also that each of them adds separate variation (see Figure 2 and Figure 3.

## 6.2 Empirical Model

To estimate the impact of labor market competition on open innovation, we need at least to instruments to account for the potential quadratic impact. Hence, we first run the following two

[25] We define $s_{ig}$ as the share of job postings by firm $i$ in region $g$.

first stages:

$$l_{it} = \alpha_1 z_{1,it} + \alpha_2 z_{1,it}^2 + \boldsymbol{\alpha}_3' \boldsymbol{X}_{it} + \alpha_t + \alpha_i + \nu_{it}$$
$$l_{it}^2 = \gamma_1 z_{2,it} + \gamma_2 z_{2,it}^2 + \boldsymbol{\gamma}_3' \boldsymbol{X}_{it} + \gamma_t + \gamma_i + \eta_{it}$$

Here $z_{1,it}$ is our first instrument that we used to instrument the linear component of the labor market competition measure $l_{it}$, while $z_{2,it}$ is the second instrument for the quadratic term of the labor market competition measure, $l_{it}^2$. We will leverage different combinations of the regions and jobs instruments while controlling in the final specification for firm characteristics $\boldsymbol{X}_{it}$ as well as firm and month-year fixed effects $\gamma_t$, $\gamma_i$

To obtain the intent-to-treat (reduced form) effects, we can run the following regressions.

$$y_{it} = \beta_1 z_{1,it} + \beta_2 z_{1,it}^2 + \boldsymbol{\beta}_3' \boldsymbol{X}_{it} + \beta_t + \beta_i + \epsilon_{it}$$
$$y_{it} = \delta_1 z_{2,it} + \delta_2 z_{2,it}^2 + \boldsymbol{\delta}_3' \boldsymbol{X}_{it} + \delta_t + \delta_i + \xi_{it}$$

In this model, $y_{it}$ is our firm outcome of open innovation, such as $log(commits)$.

In a very simple model, we would scale up the reduced form by the first stage compliers to obtain the instrumental variable estimate. However, in this case, we cannot easily scale, due to the non-linear nature and the two stages. Hence, we obtain the predicted values $\hat{l}_{it}$, $\hat{l}_{it}^2$ from the two first stages and we then estimate a two-stage least squares (2SLS) model in the following manner:

$$y_{it} = \theta_1 \hat{l}_{it} + \theta_2 \hat{l}_{it}^2 + \boldsymbol{\theta}_3' \boldsymbol{X}_{it} + \theta_t + \theta_i + \zeta_{it}$$

In the 2SLS estimation, we are interested to understand whether $\theta_1$ is significantly positive and $\theta_2$ significantly negative.

## 6.3 Results

In the following results, we move empirically from fixed effects to our instruments allowing us to estimate the non-linear impacts of labor market competition.

— Table 3 about here —

Table 3 portrays first and second stages using both the job titles and regions instrument. We use both instruments on the higher level of aggregation for job titles and regions and instrument once the linear and another time the on-linear component of our labor market competition measure. Our instruments are highly relevant with F-statistics beyond 400,000 which is above the commonly used critical threshold of an F-value of 10. After instrumenting both components of our labor market measure, we find in the second stage a strong inverted U relationship with the linear coefficient being positive and the non-linear coefficient being negative. This relationship is even stronger than the fixed effects panel regressions in Section 5. Additional 2SLS regressions where we use only the regional or the job titles instrument separately, shows similar results. (Table A5 and Table A6). Overall, this further re-assures us about the robustness of the relationship between open innovation and labor market competition and it provides unique insights into the pathway where labor market competition non-linearly impacts open innovation. Among others, the current results are consistent with firms being more likely to offer OSS as fringe benefits for programmers in the middle of the distribution and less likely to innovate when they are under financial distress under high competition.

# 7 Conclusion

Labor market competition is an important area of study due to the transferable nature of skills in the software domain. We find that labor market competition is non-linearly related to open innovation, which is consistent with findings on product market competition and closed innovation in the literature. While competition and innovation is a broadly studied subject, the relationship of competition and open innovation was unclear until now. Open innovation is an area with unique characteristics differing from closed innovation (e.g. patenting) due to almost instantaneous spillover benefits and, as such, it was not ex-ante predicable which relationship we should expect. Further, labor market competition is a markedly different metric from product market competition, and as such we are adding to a better understanding of market power of firms in the input market instead of the output market.

While mechanisms still ought to be explored, recruitment strategies where open source is a fringe benefit as well as high labor market turnover at the highest level of competition are consistent with our findings and add substantial value for managers and policy-makers. Finally, our findings further speaks to the idea that there may be an optimal level of competition to support a public good such as open source software.

# References


Agarwal, Rajshree, Martin Ganco, and Rosemarie H Ziedonis. 2010. “Job-Hopping in the Shadow of Patent Enforcement.” Tech. rep., Working Paper, Lundquist College of Business, University of Oregon.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. “Competition and innovation: An inverted-U relationship.” *The quarterly journal of economics* 120 (2):701–728.

Almirall, Esteve and Ramon Casadesus-Masanell. 2010. “Open versus closed innovation: A model of discovery and divergence.” *Academy of management review* 35 (1):27–47.

Arrow, Kenneth J. 1962. “The economic implications of learning by doing.” *The review of economic studies* 29 (3):155–173.

Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2022. “Labor market concentration.” *Journal of Human Resources* 57 (S):S167–S199.

Azar, José, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska. 2020. “Concentration in US labor markets: Evidence from online vacancy data.” *Labour Economics* 66:101886.

Bartik, Timothy J. 1991. “Who benefits from state and local economic development policies?” .

Belenzon, Sharon and Mark Schankerman. 2015. “Motivation and sorting of human capital in open innovation.” *Strategic Management Journal* 36 (6):795–820.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. “Quasi-experimental shift-share research designs.” *The Review of Economic Studies* 89 (1):181–213.

Breuer, Matthias. 2022. “Bartik instruments: An applied introduction.” *Journal of Financial Reporting* 7 (1):49–67.

Burstein, Michael J. 2015. “Patent markets: a framework for evaluation.” *Ariz. St. LJ* 47:507.

Chen, Feng-Wen, Jingwei Xu, Jiang Wang, Zhilong Li, and Yongqiu Wu. 2023. “Do rising labour costs promote technology upgrading? A novel theoretical hypothesis of an inverted U-shaped relationship.” *Structural Change and Economic Dynamics* .

Chesbrough, Henry. 2006a. “Emerging secondary markets for intellectual property: US and Japan comparisons.” *National Center for Industrial Property Information and Training (INPIT), Tokyo* .

———. 2006b. “Open innovation: a new paradigm for understanding industrial innovation.” *Open innovation: Researching a new paradigm* 400:0–19.

Cooper, David P. 2001. “Innovation and reciprocal externalities: information transmission via job mobility.” *Journal of Economic Behavior & Organization* 45 (4):403–425.

Correa, Juan A. 2012. “Innovation and competition: An unstable relationship.” *Journal of Applied Econometrics* 27 (1):160–166.

Cropf, Robert A. 2008. “Benkler, Y.(2006). The Wealth of Networks: How Social Production Transforms Markets and Freedom. New Haven and London: Yale University Press. 528 pp. $40.00 (papercloth)."$ *Social Science Computer Review* $26\ (2) : 259--261.$

Dube, Arindrajit, Jeff Jacobs, Suresh Naidu, and Siddharth Suri. 2020. “Monopsony in online labor markets.” *American Economic Review: Insights* 2 (1):33–46.

Eriksson, Tor, Zhihua Qin, and Wenjing Wang. 2014. “Firm-level innovation activity, employee turnover and HRM practices—Evidence from Chinese firms.” *China Economic Review* 30:583–597.

Fauchart, Emmanuelle and Eric Von Hippel. 2008. “Norms-based intellectual property systems: The case of French chefs.” *Organization Science* 19 (2):187–201.

Ferrés, Daniel, Gaurav Kankanhalli, and Pradeep Muthukrishnan. 2022. “Anti-Poaching Agreements, Corporate Hiring, and Innovation: Evidence from the Technology Industry.” Tech. rep.

Freedman, Matthew L. 2008. “Job hopping, earnings dynamics, and industrial agglomeration in the software publishing industry.” *Journal of Urban Economics* 64 (3):590–600.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. “Bartik instruments: What, when, why, and how.” *American Economic Review* 110 (8):2586–2624.

Haans, Richard FJ, Constant Pieters, and Zi-Lin He. 2016. “Thinking about U: Theorizing and testing U-and inverted U-shaped relationships in strategy research.” *Strategic management journal* 37 (7):1177–1195.

Hansen, Stephen, Peter John Lambert, Nicholas Bloom, Steven J Davis, Raffaella Sadun, and Bledi Taska. 2023. “Remote work across jobs, companies, and space.” Tech. rep., National Bureau of Economic Research.

Hashmi, Aamir Rafique. 2013. “Competition and innovation: The inverted-U relationship revisited.” *Review of Economics and Statistics* 95 (5):1653–1668.

Hazell, Jonathon, Christina Patterson, Heather Sarsons, and Bledi Taska. 2022. “National wage setting.” Tech. rep., National Bureau of Economic Research.

Hoffmann, Manuel, Frank Nagle, and Yanuo Zhou. 2024. “Value of Open Source Software.” Tech. rep., Working Paper.

Horbach, Jens and Christian Rammer. 2020. “Labor shortage and innovation.” *ZEW-Centre for European Economic Research Discussion Paper* (20-009).

Kaiser, Ulrich, Hans Christian Kongsted, and Thomas Rønde. 2015. “Does the mobility of R&D labor increase innovation?” *Journal of Economic Behavior & Organization* 110:91–105.

Kroft, Kory, Yao Luo, Magne Mogstad, and Bradley Setzler. 2020. "Imperfect competition and rents in labor and product markets: The case of the construction industry." Tech. rep., National Bureau of Economic Research.

Lafontaine, Francine, Margaret Slade et al. 2023. "No-Poaching Clauses in Franchise Contracts, Anticompetitive or Efficiency Enhancing?" *Anticompetitive or Efficiency Enhancing* .

Lakhani, Karim R and Robert G Wolf. 2003. "Why hackers do what they do: Understanding motivation and effort in free/open source software projects." *Open Source Software Projects (September 2003)* .

Lerner, Josh and Jean Tirole. 2002. "Some simple economics of open source." *The journal of industrial economics* 50 (2):197–234.

Mulkay, Benoît. 2019. "How does competition affect innovation behaviour in french firms?" *Structural Change and Economic Dynamics* 51:237–251.

Müller, Kathrin and Bettina Peters. 2010. "Churning of R&D personnel and innovation." *ZEW-Centre for European Economic Research Discussion Paper* 1 (10-032).

Nagle, Frank, David Wheeler, Hila Lifshitz-Assaf, Haylee Ham, and Jennifer L. Hoffman. 2020. "Report on the 2020 FOSS Contributor Survey." Tech. rep., Linux Foundation Core Infrastructure Initiative, Linux Foundation and Laboratory for Innovation Science at Harvard.

Pakes, Ariel and Shmuel Nitzan. 1983. "Optimum contracts for research personnel, research employment, and the establishment of" rival" enterprises." *Journal of labor economics* 1 (4):345–365.

Peneder, Michael and Martin Wörter. 2014. "Competition, R&D and innovation: testing the inverted-U in a simultaneous system." *Journal of Evolutionary Economics* 24:653–687.

Polder, Michael and Erik Veldhuizen. 2012. "Innovation and competition in the Netherlands: Testing the inverted-U for industries and firms." *Journal of Industry, Competition and Trade* 12:67–91.

Schrader, Stephan. 1991. "Informal technology transfer between firms: Cooperation through information trading." *Research policy* 20 (2):153–170.

Shah, Sonali and Frank Nagle. 2020. "Why do user communities matter for strategy?" *Strategic Management Review* 1 (2):305–353.

Tingvall, Patrik Gustavsson and Andreas Poldahl. 2006. "Is there really an inverted U-shaped relation between competition and R&D?" *Economics of Innovation and New Technology* 15 (2):101–118.

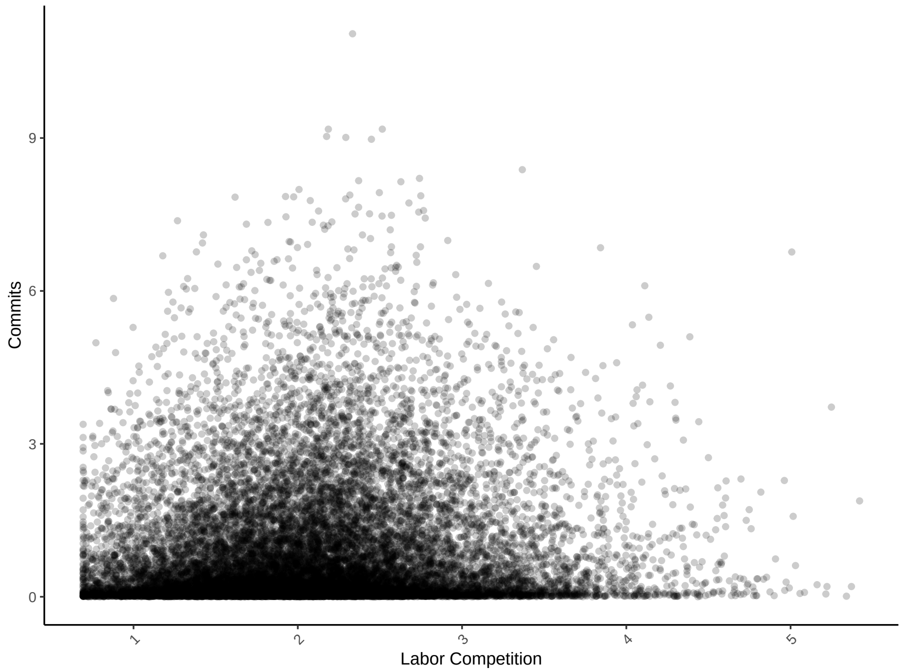
Von Hippel, Eric. 1987. "Cooperation between rivals: Informal know-how trading." *Research policy* 16 (6):291–302.

West, Joel and Scott Gallagher. 2006. "Challenges of open innovation: the paradox of firm investment in open-source software." *R&d Management* 36 (3):319–331.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein. 2022. "Monopsony in the US labor market." *American Economic Review* 112 (7):2099–2138.

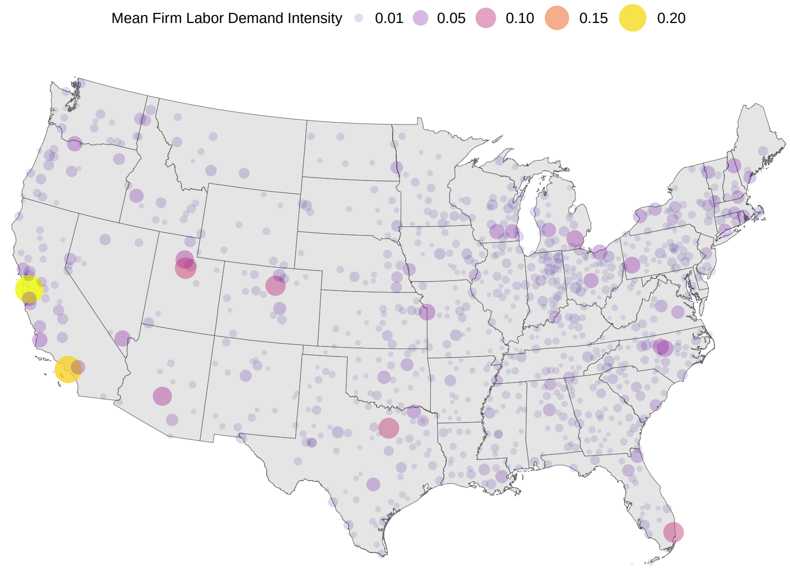
# Figures and Tables

Figure 1: LABOR MARKET COMPETITION AND OSS CONTRIBUTION



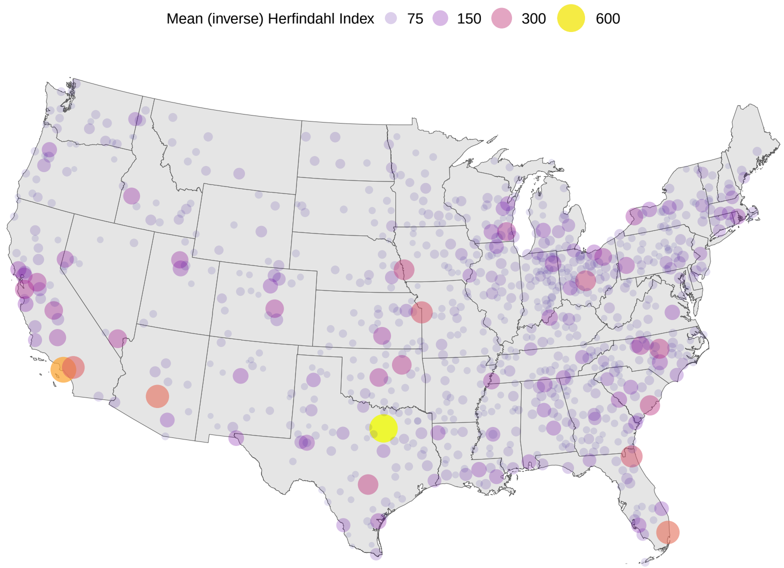

*Note:* The figure shows cross-sectional open source contributions of employees committing to GitHub projects (repositories) across labor market competition. Commits are measured as commits + 1 and then logged. Each dot represents the mean contributions for a firm within the time frame of January 1, 2016 to June 1, 2023.

Figure 2: VARIATION IN FIRM LABOR DEMAND INTENSITY ACROSS THE UNITED STATES




*Note:* The figure depicts the variation in the the shares $s_{igt}$ for the regional instrument. Each dot represents the average demand intensity across all jobs for firms within a metropolitean statistical area within the time frame of January 1, 2016 to June 1, 2023.

Figure 3: INVERSE HERFINDAHL VARIATION ACROSS THE UNITED STATES




*Note:* The figure depicts the variation in inverse HHIs $h_{gt}$ for the regional instrument. Each dot represents the average demand intensity across all jobs for firms within a metropolitan statistical area within the time frame of January 1, 2016 to June 1, 2023.

Table 1: DATA MERGING PROCESS

| Stage | Intersection of | Data | Characteristics |
|---|---|---|---|
| 1 | - | Firm data | CompuStat: 55,549 firms<br>Pitchbook: 489,819 firms |
| 2 | - | GitHub firm-matched commits | 79.9+ million commits<br>407,352 distinct contributors<br>63,666 firms |
| 3 | - | Lightcast job postings | 270+ million unique postings<br>73,165 distinct jobs<br>387 MSAs<br>2.56+ firms |
| 4 | 1,2,3 | Final Empirical Sample | 30.7+ million commits<br>173,882 distinct contributors<br>34.7+ million job posts<br>69,509 distinct jobs<br>387 MSAs<br>19,303 firms |

Table 2: LABOR MARKET COMPETITION AND COMMITS (LOG)

| **Panel A: OLS** | Linear | Quadratic | Quadratic & Controls |
|---|---|---|---|
| $l_{it}$ | 0.044*** | 0.277*** | 0.030*** |
| | (0.001) | (0.003) | (0.003) |
| $l_{it}^2$ | | -0.047*** | -0.004*** |
| | | (0.001) | (0.001) |
| N | 1,749,436 | 1,749,436 | 1,654,056 |
| **Panel B: FE** | Linear | Quadratic | Quadratic & Controls |
| $l_{it}$ | -0.006* | 0.058*** | 0.031*** |
| | (0.003) | (0.009) | (0.008) |
| $l_{it}^2$ | | -0.013*** | -0.007*** |
| | | (0.002) | (0.002) |
| N | 1,749,436 | 1,749,436 | 1,654,056 |

Table 3: 2SLS LABOR MARKET COMPETITION ON OPEN INNOVATION

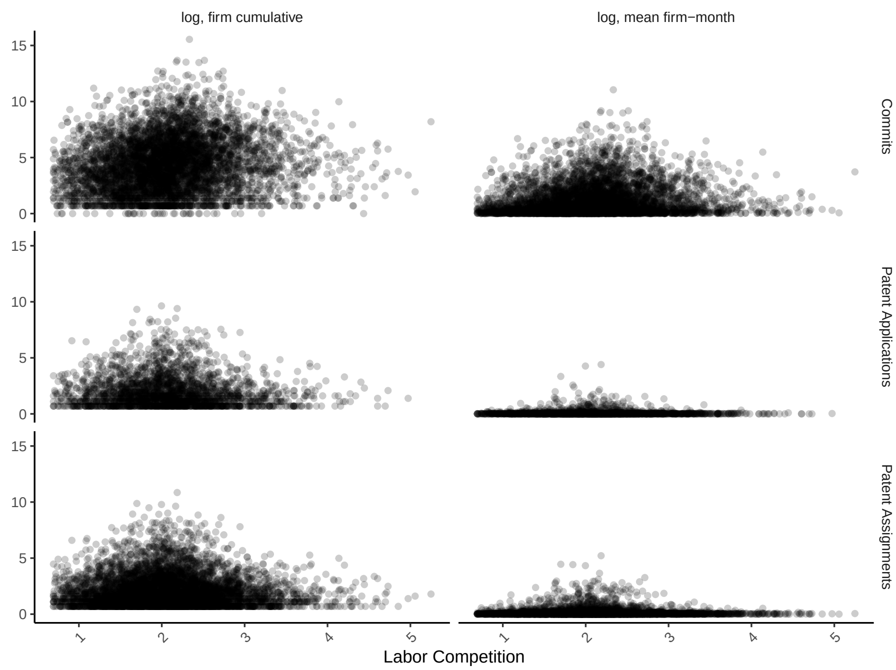
| | First Stage $l$ | First Stage $l^2$ | Second Stage $Y_{it}$ |
|---|---|---|---|
| $z_{1,it}$ : $titles$ | 0.532*** | 2.536*** | |
| | (0.003) | (0.018) | |
| $z_{2,it}$ : $regions$ | 0.025*** | -0.004 | |
| | (0.003) | (0.016) | |
| $\hat{l}_{it}$ | | | 0.383*** |
| | | | (0.090) |
| $\hat{l}_{it}^2$ | | | -0.078*** |
| | | | (0.019) |
| F | 523,332 | 407,618 | |
| N | 1,654,056 | 1,654,056 | 1,654,056 |

Note: The table shows the first stages and second stages of labor market competition and open innovation. The first (second) column displays the first stage using the titles and geographic instrument to instrument the linear (non-linear) term of the most granular labor market competition measure. The third column displays the second stage of the predicted linear and non-linear components of the labor market competition measure with log commits.

# Appendices

## Appendix A More Tables and Figures

Figure A1: LABOR MARKET COMPETITION, OPEN AND CLOSED INNOVATION




*Note:* The figure shows cross-sectional open and closed innovation activities of Firms across labor market competition where we measure open innovation via commits and closed innovation via patenting. In the first row, each dot represents the mean commit activity for a firm within the time frame of January 1, 2016 to June 1, 2023. The second row shows the number of patent applications filed by the same sample. The third row shows the number of patents acquired in the secondary market. Finally, the first column shows log cumulative activities whereas the second column shows log activities.

Table A1: CORRELATION OF PRODUCT COMPETITION WITH LABOR COMPETITION

| | |
|---|---|
| Lerner Index (annual) | $-0.043$ |
| Number of Competitors (log) | $0.013*$ |
| Number of Startups in Vertical (log) | $-0.006$ |
| TNIC 2-Digit (annual log sum) | $-0.174***$ |

Note: The table shows the correlation of product market competition measures with the measure of labor market competition used in this paper.

Table A2: LABOR MARKET COMPETITION AND COMMITTERS (LOG)

| **Panel A: OLS** | Linear | Quadratic | Quadratic & Controls |
|---|---|---|---|
| $l_{it}$ | 0.025*** | 0.176*** | 0.021*** |
| | (0.000) | (0.002) | (0.002) |
| $l_{it}^2$ | | -0.031*** | -0.003*** |
| | | (0.000) | (0.000) |
| N | 1,603,291 | 1,603,291 | 1,520,691 |
| **Panel B: FE** | Linear | Quadratic | Quadratic & Controls |
| $l_{it}$ | -0.003* | 0.032*** | 0.019*** |
| | (0.001) | (0.005) | (0.004) |
| $l_{it}^2$ | | -0.007*** | -0.004*** |
| | | (0.001) | (0.001) |
| N | 1,603,291 | 1,603,291 | 1,520,691 |

Note: The table shows the relationship of committers and labor market competition. The outcome variable committers is logged.

Table A3: LABOR MARKET COMPETITION AND NEW REPOSITORIES (LOG)

| **Panel A: OLS** | Linear | Quadratic | Quadratic & Controls |
|---|---|---|---|
| $l_{it}$ | 0.011*** | 0.093*** | 0.015*** |
| | (0.000) | (0.001) | (0.001) |
| $l_{it}^2$ | | -0.017*** | -0.003*** |
| | | (0.000) | (0.000) |
| N | 1,603,291 | 1,603,291 | 1,520,691 |
| **Panel B: FE** | Linear | Quadratic | Quadratic & Controls |
| $l_{it}$ | -0.001 | 0.019*** | 0.013*** |
| | 0.000 | (0.003) | (0.003) |
| $l_{it}^2$ | | -0.004*** | -0.003*** |
| | | (0.001) | (0.000) |
| N | 1,603,291 | 1,603,291 | 1,520,691 |

Note: The table shows the relationship of new repositories and labor market competition. Prior to logging The outcome variable new repositories, we add one.

Table A4: LABOR MARKET COMPETITION AND QUALITY-ADJUSTED CONTRIBUTIONS

| **Panel A: OLS** | Linear | Quadratic | Quadratic & Controls |
|---|---|---|---|
| $l_{it}$ | 0.020*** | 0.115*** | 0.013*** |
| | (0.000) | (0.002) | (0.001) |
| $l_{it}^2$ | | -0.019*** | -0.002*** |
| | | (0.000) | (0.000) |
| N | 1,603,291 | 1,603,291 | 1,520,691 |
| **Panel B: FE** | Linear | Quadratic | Quadratic & Controls |
| $l_{it}$ | -0.002 | 0.016*** | 0.007* |
| | (0.001) | (0.004) | (0.003) |
| $l_{it}^2$ | | -0.004*** | -0.001)* |
| | | (0.001) | (0.001) |
| N | 1,603,291 | 1,603,291 | 1,520,691 |

Note: The table shows the relationship of quality-adjusted contributions by stars and labor market competition.

Table A5: 2SLS REGIONS INSTRUMENT

| | First Stage $l$ | First Stage $l^2$ | Second Stage $Y_{it}$ |
|---|---|---|---|
| $z_{it} : regions$ | 0.131*** | 0.197** | |
| | (0.013) | (0.063) | |
| $z_{it}^2 : regions^2$ | 0.006*** | 0.067*** | |
| | (0.002) | (0.008) | |
| $l_{it}$ | | | 0.556*** |
| | | | (0.107) |
| $l_{it}^2$ | | | -0.119*** |
| | | | (0.026) |
| F | 26,421 | 17,230 | |
| N | 1,520,691 | 1,520,691 | 1,520,691 |

Note: The table shows the first stages and second stages of labor market competition and open innovation. The first (second) column displays the first stage using the regions instrument to instrument the linear (non-linear) term of the most granular labor market competition measure. The third column displays the second stage of the predicted linear and non-linear components of the labor market competition measure with log commits.

Table A6: 2SLS TITLES INSTRUMENT

| | First Stage $l$ | First Stage $l^2$ | Second Stage $Y_{it}$ |
|---|---|---|---|
| $z_{it} : titles$ | 0.654*** | 2.229*** | |
| | (0.008) | (0.046) | |
| $z_{it}^2 : titles^2$ | -0.028*** | 0.070*** | |
| | (0.002) | (0.012) | |
| $l_{it}$ | | | 0.100*** |
| | | | (0.027) |
| $l_{it}^2$ | | | -0.017*** |
| | | | (0.006) |
| F | 474,837 | 369,604 | |
| N | 1,520,691 | 1,520,691 | 1,520,691 |

Note: The table shows the first stages and second stages of labor market competition and open innovation. The first (second) column displays the first stage using the titles instrument to instrument the linear (non-linear) term of the most granular labor market competition measure. The third column displays the second stage of the predicted linear and non-linear components of the labor market competition measure with log commits.