Export Markets, Local Disruptions, and the Composition of Hiring

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Abstract

How does foreign demand shape local hiring when domestic economic interactions are disrupted? Using a database of 122 million online job postings in China, we examine how the relationship between local mobility disruptions and hiring varies with industry export growth. We find that stronger export growth is associated with smaller declines in postings, advertised vacancies, and recruiting firms when local mobility disruptions are more severe. Export growth also moderates the shift toward non-routine cognitive occupations and accompanies greater non-routine manual physical intensity in the occupational mix. An alternative measure based on trading partners' import demand yields a similar pattern for recruiting quantities. In the broader labor market, local disruptions coincide with higher education and experience requirements and a greater cognitive orientation of vacancies, particularly in services. The findings connect foreign demand to both the scale and occupational composition of hiring, highlighting an external-market buffer during domestic disruptions.

Keywords: Foreign demand; international trade; vacancy creation; occupational composition; local mobility

JEL codes: F14, F16, J23, J24, R12.

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1 Introduction

Local labor markets connect firms to workers and nearby customers, while international trade connects them to demand beyond the local economy. These connections need not move together. Disruptions to movement within a city can restrict workplace access, reduce customer foot traffic, and interrupt face-to-face coordination even as overseas demand for its products expands. How do external market conditions shape local hiring under these circumstances? The answer matters for understanding the labor-market consequences of trade: an external source of demand can influence both how much firms recruit and the kinds of positions they advertise.

China's experience during the COVID-19 pandemic provides a setting in which domestic interaction and export-market conditions followed distinct paths. Local outbreaks, containment policies, and voluntary responses generated repeated reductions in mobility across cities during 2020–2022. Over the same period, Chinese exports expanded as global spending shifted toward goods and production conditions varied across countries. This combination allows us to examine recruiting when access to nearby workers and customers was disrupted but demand from foreign markets remained an important source of activity.

We bring together online vacancy postings, within-city mobility, and industry trade flows. Our vacancy database contains 122 million matched postings from three major Chinese recruitment platforms over 2015–2022. We use the 2020–2022 observations to construct a monthly panel covering 281 prefectures and 97 two-digit industries. The postings record advertised positions, firm identity, education and experience requirements, posted wages, and job descriptions. A concordance to O*NET provides measures of the occupational task composition of recruiting, while job-description text supplies complementary information on the activities emphasized in advertisements.

We measure local interaction disruptions using reductions in within-prefecture movement from Baidu Maps. Mobility connects several economically relevant activities: commuting, consumption, and face-to-face work. Recent research shows that work and non-work travel are interdependent, with changes in commuting affecting demand for nearby services (Miyauchi et al., 2025). The value of in-person work also depends on the presence of other workers (Monte et al., 2026). In our setting, the mobility measure summarizes the local environment in which firms recruit. Its positive relationships with recorded infections and policy stringency, together with its relationship to local output, connect observed movement to the intensity of pandemic disruptions.

The central empirical analysis asks whether the relationship between local disruptions and recruiting varies with external market conditions. We measure these conditions using year-over-year export growth in the same industry across all Chinese provinces other than the province containing the prefecture. This construction removes the focal province's exports from the measure and links each recruiting cell to export conditions elsewhere in its industry. We interact this measure with local mobility disruptions, controlling for prefecture, industry, year-month, and province-by-year fixed

effects. A complementary specification uses trading partners' annual import growth weighted by provinces' 2019 export-destination shares. Together, these measures connect recruiting to industry export performance and to demand in foreign destination markets.

Three results organize the paper. First, stronger export growth is associated with a smaller contraction in recruiting during larger local mobility disruptions. The interaction is positive for job postings, advertised vacancies, and the number of recruiting firms. The consistency across these outcomes shows that the pattern extends to both the scale of recruiting and the set of firms posting vacancies. The alternative importer-demand measure yields the same direction of adjustment for all three quantities. These results identify a recurring empirical pattern: external market strength accompanies greater continuity in local recruiting during domestic disruptions.

Second, export conditions also shape the occupational composition of hiring. In the trade-linked sample, larger mobility disruptions tilt postings toward occupations intensive in non-routine cognitive analytical and interactive tasks. Stronger export growth moderates that tilt and is associated with a greater non-routine manual physical component. The joint results connect stronger external markets to more sustained recruiting and a smaller shift toward cognitive-intensive occupations during a local contraction. Among established platform recruiters, stronger export growth during larger disruptions is also associated with higher posted wages.

Third, the broader labor-market evidence places this trade result in context. Across the full prefecture-industry panel, larger mobility disruptions coincide with fewer postings, advertised positions, and recruiting firms, alongside higher education and experience requirements. The occupational mix shifts toward non-routine cognitive tasks, particularly in services. Text-based evidence shows greater emphasis on analytical activities and a changing mix of interactive activities. This sectoral pattern is consistent with the exposure of local services to customer movement and face-to-face interaction, while the export analysis highlights a source of demand extending beyond the local economy.

Our main contribution is to the literature on trade and adjustment to economic disruptions. Almunia et al. (2021) show that firms expand exports when domestic demand falls, documenting the capacity of foreign markets to absorb activity during a domestic slump. Bonadio et al. (2021) show that international input linkages can transmit foreign disruptions and cushion domestic ones. Kramarz et al. (2020) emphasize how concentrated customer relationships shape the risks associated with exporting. We examine the recruiting margin of this broader relationship between trade and local adjustment. Our contribution is to connect external market conditions to the joint response of vacancy quantities and occupational composition when domestic economic interactions are disrupted.

Our paper also contributes to research on the labor-market incidence of foreign demand. Garin and Silvério (2024) study wage responses to firm-specific export demand, Dhyne et al. (2025) emphasize the role of fixed labor costs and domestic production linkages, and Boehm et al. (2026) examine

the local employment and wage consequences of exporting. Online vacancy data reveal an additional margin: the characteristics of new labor demand. He et al. (2021) study Chinese firms' hiring responses to the trade war, and Javorcik et al. (2025) examine how tariffs affect US job opportunities across skill groups. We focus on the interaction between external markets and domestic disruptions, using monthly recruiting records to trace how both the volume and task mix of vacancies vary with that interaction.

This composition perspective is useful for interpreting the connection between trade and skills. Export opportunities can encourage quality and workforce upgrading (Verhoogen, 2008). At the same time, contractions can raise the average skill content of posted vacancies through changes in which occupations are being recruited. Research on recessions and hiring standards documents related changes in posted requirements (Hershbein and Kahn, 2018; Modestino et al., 2020), while Deming and Kahn (2018) show the value of vacancy text for measuring skill demand.[1] Our evidence brings these margins together: stronger export growth coincides with more sustained recruiting and a more limited reorientation toward cognitive-intensive occupations during local disruptions. The interaction concerns the composition of recruiting in a downturn, a distinct margin from the average skill premium associated with exporting.

Finally, our paper relates to the literature on spatial economic interaction. Monte et al. (2018) show that goods-market and commuting linkages jointly shape local employment responses. Miyauchi et al. (2025) study how linked work and consumption trips generate local demand externalities, and Monte et al. (2026) analyze coordination in the choice between remote and in-person work. We connect this local-interaction perspective to firms' external product markets. The resulting evidence clarifies a setting in which trade can support local recruiting: domestic interactions weaken while foreign customers continue to provide demand.

The remainder of the paper is organized as follows. Section 2 describes the data and recruiting measures. Section 3 introduces the setting, mobility measure, and empirical framework. Section 4 presents the export-market results. Section 5 examines the broader local recruiting adjustment and its occupational and sectoral composition. Section 6 concludes.

2 Data and Measurement

2.1 Vacancy Postings and Firm Records

We construct a database of online vacancy postings from three major Chinese recruitment platforms: 51job.com, Zhaopin.com, and Liepin.com. The raw collection contains 165.36 million entries from January 2015 to December 2022. Each entry records the posting date, job title, available occupation code,

[1] Related vacancy-based evidence documents the contraction in hiring during the pandemic (Forsythe et al., 2020; Zeng et al., 2025) and changes in within-occupation skill requirements following stay-at-home orders (Gu and Zhong, 2023). We connect recruiting quantities and occupational composition to external market conditions.

number of advertised positions, wage, education and experience requirements, firm name, location, and job description. The 2015–2022 database provides the pre-pandemic recruitment history and the observations used to study hiring during 2020–2022.

The platforms cover a broad range of industries and locations and offer recruitment, resume-search, and other human-resource services. According to the 2021 iResearch industry report, together they accounted for approximately two-thirds of China's online recruitment market and more than 24 million monthly mobile-device visits in 2020. Established in 1998, 51job.com accounted for 34.2% of the market and approximately 11 million monthly mobile-device visits in 2020. Appendix A.1 provides further information on the platforms.

We consolidate records across platforms and remove duplicate postings. An entry is treated as a cross-platform duplicate when the firm name, job title, occupation code, work location, and number of positions coincide. We apply this comparison within weekly windows, consistent with the platforms' minimum interval of one week for updating postings. Distinguishing advertisements from advertised positions allows us to measure both the frequency and the scale of firms' recruitment activity.

We link postings to the Firm Registration Database maintained by China's State Administration for Market Regulation. These records provide registration dates, location, industry, registered capital, ownership, owner characteristics, shareholding structures, and registration cancellation or revocation dates. We standardize firm names and use manual corrections and historical name-change records to improve matching. The resulting database contains 122 million matched postings from 4.2 million enterprises over 2015–2022. Firm identifiers allow us to count recruiting firms and distinguish prior platform users from firms first observed posting during the pandemic. Registration dates provide an alternative measure of firm age.

2.2 Occupations, Tasks, and Posted Job Requirements

Occupation classification. We map platform occupation categories and job titles to six-digit Standard Occupational Classification (SOC) codes. The reference classification contains 763 occupations and connects postings to O*NET measures of work activities, work context, abilities, and skills.[2] Approximately 1,360 platform-specific occupation categories can be mapped manually to SOC codes. Postings with these labels account for 70.74% of the database.

For the remaining 29.26%, we train a supervised Long Short-Term Memory classifier on labeled entries. The classifier uses job title, firm name, prefecture, year, and month to predict occupation codes, allowing contextual information to distinguish titles used in different activities. Its in-sample classification accuracy is 71.9%.[3] The final matched sample contains 383 distinct six-digit SOC codes.

[2]Details on the O*NET-SOC taxonomy are available at https://www.onetcenter.org/taxonomy.html.

[3]The availability of occupation labels varies with platform design over time; unlabeled entries are more common after 2020.

Occupation-based task content. Following Acemoglu and Autor (2011), we characterize occupations along five dimensions: non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP). Each index sums the relevant O*NET components and is standardized across reference occupations to have mean zero and standard deviation one. For example, NRCA combines analyzing information, thinking creatively, and interpreting information for others. Appendix Table A1 lists the components and their scales. Because these indices are assigned at the occupation level, changes in their averages describe changes in the occupational task composition of posted vacancies.

The components in Appendix Table A1 give the indices their economic content. Cognitive-interactive tasks include maintaining relationships, supervising and motivating colleagues, and coaching. The routine-manual index captures repetitive and machine-paced work, whereas the non-routine manual physical index includes operating vehicles or equipment, manual dexterity, and spatial orientation. The five dimensions therefore describe different attributes of work, rather than successive rungs on a single skill ladder. An occupation can combine cognitive and physical activities. This distinction matters for the export analysis: a change in the average physical-task index describes a different mix of advertised occupations, not a direct change in workers' educational attainment or job quality.

Text-based task content. We also measure activities described directly in advertisements. A random sample drawn at approximately 2% from postings between January 2019 and December 2022 contains 770,102 entries. Following Spitz-Oener (2006) and Atalay et al. (2020), we extract verbs, using verb–noun combinations to resolve ambiguity, and map the 500 most frequent verbs to the five task categories. Examples include analyzing and designing, advising and coordinating, repairing and serving, calculating and measuring, and operating equipment. The regression measures multiply word counts by 1,000 and divide by $\log(1+\text{text length})$. These measures provide a complementary view of the activities emphasized in job descriptions alongside the occupation-based indices. Panel B of Appendix Table A2 describes this sample.

The two approaches answer related questions at different levels of description. Occupation-based indices summarize which kinds of jobs are advertised using a common reference for their task content. Text measures record the activities employers choose to mention in the advertisements themselves. Their combination lets us connect a shift toward analytically intensive occupations to the vocabulary of analytical work, while also examining differences among activities within a broad task category. This provides a richer description of recruiting adjustment than either education requirements or an occupation label alone.

2.3 Trade Data and External Demand

We use Chinese Customs export records at the province–product–month level and map products to the two-digit industries used in the vacancy data. The main export measure tracks year-over-year industry export growth in provinces other than the prefecture's own province. We also examine own-province industry export growth and an importer-demand measure that combines annual product-level import data from China's trading partners with provinces' export-destination composition in 2019. These measures connect external market conditions to the prefecture–industry–month recruitment panel. Section 4 explains their construction and use in the empirical analysis.

2.4 Coverage and Aggregate Patterns

We compare the geographic and sectoral coverage of the postings with prefecture statistical yearbooks for 2015, 2017, and 2019 and the 1% sample of the 2015 Mini Population Census. The census comparison uses approximately one million individuals aged 15–70 with non-missing industry and occupation information. Online recruitment is especially prevalent in professional and higher-skill occupations; the comparisons characterize the labor-market segments represented in the data.

Geographic coverage. Figure 1 evaluates the data along two dimensions. Panel (a) relates the log number of postings to log employment in each prefecture. In all three comparison years, larger labor markets have substantially more online recruiting. Appendix Table A3 quantifies this relationship: the year-specific slopes range from 1.81 to 1.98, with R^2 values close to 0.80. The slopes above one indicate that online postings are especially concentrated in larger labor markets. This is useful for interpreting the data's geographic coverage: the platform records capture a broad employment gradient, while their unit of observation is a flow of recruiting opportunities rather than the stock of existing jobs.

Panel (b) of Figure 1 makes the corresponding comparison for wages. Prefectures with higher yearbook wages tend to have higher posted wages, although the observations are more dispersed than in the count comparison. The three year-specific wage slopes in Appendix Table A3 are 0.878, 0.509, and 0.549. The wage comparison establishes a second link to local labor-market conditions, beyond city size. Together, the panels support using the data to study the geography of recruiting and advertised compensation, with the regression design subsequently absorbing persistent prefecture differences.

Industry and occupational coverage. Figure 2 compares log posting counts with log census employment across two-digit industries and broad occupations. The industry panel shows a positive association across agriculture, manufacturing, and services, alongside differences in online recruiting intensity within these broad sectors. The occupational panel shows substantial recruiting activity

in management, business and finance, computing, administration, and sales relative to their employment counts. Several manual and personal-service occupations occupy a different part of the distribution. These patterns clarify the market captured by the platforms and make occupational composition a substantive outcome: a change in total recruiting can be accompanied by a change in the types of jobs represented in the posting flow.

Coverage across types of prefectures. The three figures in Appendix A.3 examine whether this geographic coverage spans different local economic structures. Figure A1 identifies provincial capitals in the 2019 comparisons. They are concentrated toward the high-employment, high-posting end of the distribution, while the positive posting-employment relationship extends across other prefectures. Their wage observations overlap with those of other locations at similar yearbook wage levels. The figure locates administrative centers within the national recruiting distribution and gives context to the later analysis of prefecture groups.

Figure A2 separates prefectures by whether the share of university students in their population is above or below the median. Both groups display a positive relationship between employment and posting counts, with high-student-share prefectures more prominent toward the upper end. Posted wage observations overlap extensively. This comparison places the higher-skill orientation of the vacancy data in the geographic context of educational institutions; the grouping measures the presence of university students, rather than the educational attainment of the entire resident workforce.

Figure A3 instead groups prefectures by manufacturing's share of local GDP. Both high- and low-manufacturing locations follow the positive relationship between employment and online recruiting, and their wage distributions occupy overlapping ranges. These observations show that the data span local economies with different production structures. This coverage is pertinent to our central comparison between recruiting exposed to local service activity and recruiting linked to external product markets. The figure groups locations by their manufacturing intensity; the sector-specific regressions below separately classify postings by the employer's industry.

Aggregate recruiting and composition. Figure 3 brings the quantity and composition measures together over 2019–2022. Panels (a)–(c) show declining posting counts, advertised positions, and recruiter participation in late 2019 and early 2020, followed by an uneven recovery. The three series follow related but distinct paths, illustrating why we track both the number of advertisements and the number of positions sought, as well as the employers involved. Panel (d) shows that average posted wages settle at a lower level by early 2020 and subsequently fluctuate. The aggregate wage change begins before the pandemic and describes the evolving pool of advertisements.

Panels (e)–(f) show higher education and experience requirements around the beginning of 2020. Education requirements remain elevated for much of 2020–2021 before falling substantially during

2022; experience requirements generally remain above their 2019 range. The task panels add further variation. Analytical and interactive cognitive intensity rise relative to late 2019, with interactive intensity easing after its early-2021 peak. Routine cognitive intensity varies within a comparatively narrow range, while both manual indices increase during much of the later period. The resulting picture is one of changing recruitment composition along several dimensions, rather than a uniform movement in every skill measure.

These national trends provide the setting for the local analysis. They summarize the advertisements present in each month, combining changes across locations, industries, and occupations. Our regressions absorb common year-month movements and ask how recruiting differs with local mobility disruptions and external market conditions. Consequently, the aggregate paths and the conditional regressions provide complementary information: Figure 3 describes when the national mix changed, while the estimates relate local adjustments to the two economic conditions at the center of the paper.

2.5 The Prefecture–Industry–Month Panel

The main estimation sample comprises 281 prefectures, 97 two-digit industries, and 33 months during January 2020–December 2022, yielding 899,481 cells. June–August 2020 are excluded because mobility data are unavailable. The balanced panel includes cells with zero postings. As shown in Panel A of Appendix Table A2, the average cell contains 38 postings, 227 advertised positions, and eight recruiting firms.

Appendix Table A2 also shows substantial dispersion: the standard deviations of posting and vacancy counts are approximately 509 and 4,883, respectively. Recruitment is concentrated in a subset of local industry cells, alongside cells with no observed recruiting. Including the latter in the quantity panel allows us to capture the appearance and disappearance of recruiting activity as well as changes where recruiting continues. This distribution motivates the count transformation discussed in Section 3.3 and the positive-posting comparison reported in the results.

We calculate cell-level averages of education requirements, minimum experience, and posted wages for cells with available postings. Task averages are constructed from postings linked to O*NET. The task sample contains 330,612 cells; samples for posted job characteristics contain up to 337,294 cells, depending on outcome availability. Some cells contain only one or two postings without an O*NET match. The panel therefore captures recruitment volume, the characteristics of advertised jobs, and the occupational task composition of recruitment at the same geographic and industry level.

The two panels of Appendix Table A2 distinguish these cell-level measures from the individual advertisements used in the text analysis. Panel A reports average requirements of about 11 years of education and 1.9 years of experience. Its task means are expressed relative to the standardized occupation reference: a negative manual index indicates below-reference intensity, not an absence

of manual work. Panel B describes the text sample, in which an advertisement seeks 6.63 workers on average. Its means reflect individual postings over 2019–2022, whereas Panel A averages local industry cells during the estimation period. Keeping these observation units explicit is important when interpreting the text evidence alongside the main quantity and composition results.

3 Local Disruptions, Export Markets, and the Empirical Framework

3.1 Domestic Interaction and International Trade

China experienced repeated local disruptions during 2020–2022. The timing and severity of outbreaks and containment policies varied across prefectures (Fang et al., 2020). Stay-at-home orders, neighborhood lockdowns, public transport suspensions, workplace access restrictions, and digital health-code requirements affected movement within cities. Together with voluntary responses to infection risks, these measures changed the conditions under which workers reached workplaces, consumers visited businesses, and firms coordinated production (Hsiang et al., 2020; Fajgelbaum et al., 2021).

The local consequences of reduced movement extend across work and consumption. Miyauchi et al. (2025) show that travel itineraries link commuting to demand for nontraded services. Monte et al. (2026) analyze complementarities in in-person work that can sustain changes in city structure after a temporary disruption. These studies motivate treating within-city movement as a measure of local economic interaction encompassing workplace access, consumer activity, and face-to-face coordination.

Export markets followed a different trajectory. World merchandise trade contracted sharply in 2020 and recovered in 2021, with the recovery particularly strong in Asia.[4] Figure 6 shows the expansion in China's exports over the pandemic period. Changes in spending toward goods and differences in production conditions across countries shaped this expansion. Pandemic-related supply and demand disturbances also propagated through international production and trade, as analyzed by Bonadio et al. (2021) and Berthou and Stumpner (2024).

Figure 6 distinguishes the level of export sales from their growth rate. The solid line, measured on the left axis, rises from the early-2020 trough and reaches levels in 2021–2022 above those observed in 2019. The dashed line, measured on the right axis, records the associated year-over-year growth: the strong expansion through much of 2021 gives way to slower growth and then negative growth late in 2022. Thus, the period includes both strengthening and weakening export conditions. For our question, the important feature is the coexistence of substantial overseas sales opportunities with recurring local disruptions, rather than a uniformly favorable export environment. The national series establishes this context; the regressions use the more disaggregated industry export variation defined in Section 4.

[4] See the World Trade Organization's *World Trade Statistical Review 2022*, available at https://www.wto.org/english/res_e/booksp_e/wtsr_2022_e.pdf.

This setting brings two margins of local adjustment into the same empirical framework. Domestic interaction disruptions affect the local environment for production and recruiting, while external product markets provide demand beyond the city. When foreign sales opportunities remain strong, recruiting in trade-linked industries may be more sustained even during periods of weak local activity. The empirical analysis examines both the quantity of advertised positions and their occupational composition.

3.2 Measuring Local Mobility Disruptions

We use anonymized and aggregated mobility data from Baidu Maps. The data report daily population inflows, outflows, and movement within prefectures. Our focus is within-prefecture movement, which corresponds closely to the geographic scope of workplace-access restrictions, neighborhood controls, and interruptions to local public transport.

The within-prefecture index measures local movement using the share of people who leave home for at least 500 meters for more than 30 minutes. We aggregate it to the month and define the disruption measure for prefecture i in month t as

$$D_{it} = -\left(\text{MobilityIndex}_{it} - \text{MobilityIndex}_{i0}\right), \tag{1}$$

where the reference month 0 is January 2019. Higher values of D_{it} represent lower mobility relative to that reference. With prefecture fixed effects, the comparison is based on changes in local movement over time within a prefecture. The measure summarizes the joint local consequences of containment policies, infection risks, and behavioral responses.

Figure 4 plots the observed monthly path of changes in within-prefecture mobility, with a sharp trough in February 2020, a subsequent recovery, and further fluctuations during 2021–2022. Its sign is the reverse of D_{it}: a downward movement in the plotted series corresponds to greater disruption. The recovery therefore describes a changing local environment rather than a permanent treatment beginning in January 2020. The figure includes observations into 2023 to show the subsequent mobility path; the recruiting regressions use the 2020–2022 window with matched vacancy data. Missing portions of the plotted series represent unavailable observations, which are excluded from the corresponding estimation window.

Figure 5 adds the geographic dimension through maps for January and February 2020 and July 2021 and 2022. The broad red pattern in February 2020 contrasts with the predominantly blue maps in the two later Julys, while differences within each map show that prefectures did not share a single mobility path. Red denotes negative mobility changes and blue positive changes; gray marks unavailable data. Read together, Figures 4 and 5 motivate separating common monthly conditions from local movements. The monthly panel allows the analysis to follow repeated changes in local interaction, while year-month fixed effects account for the national component shared across prefectures.

Appendix Table A4 relates mobility to public-health conditions, policy, and local output. Panel A regresses the disruption measure on confirmed infections and the provincial stringency index from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021), including prefecture and year-month fixed effects. Both relationships are positive when considered separately and when included together: in Column (3), the coefficients are 0.091 for log confirmed cases and 0.014 for policy stringency. Their joint association helps characterize the measure as the realized local environment surrounding both health risks and restrictions. It is this environment, experienced by workers and customers, that enters the recruiting analysis.

Appendix Table A5 describes the containment and closure policy components used to characterize stringency. The listed components cover schools and workplaces, public events and gatherings, transport, stay-at-home requirements, and restrictions on domestic and international movement. Their coding distinguishes recommendations from requirements and records differences in the breadth of restrictions. Workplace access and local travel are directly relevant to firms' ability to operate and recruit; other components affect the surrounding pattern of daily activity. The table makes the policy comparison transparent and explains why observed movement and announced restrictions are related but distinct measures of the conditions faced by a local labor market.

Panel B of Appendix Table A4 turns to economic activity, relating annual mobility changes to changes in prefecture GDP, both measured relative to 2019. The GDP coefficient remains positive as prefecture and year fixed effects are added, and equals 0.825 in Column (6). Prefectures with a larger increase in output also tend to show a larger recovery in movement. This comparison gives the mobility measure an economic interpretation alongside its public-health and policy correlates. Together, the two panels connect the high-frequency movement data to restrictions on interaction and to broader local activity, providing the motivation for using mobility to organize the vacancy evidence.

3.3 Empirical Framework

We organize the analysis around a prefecture-industry-month panel. Let Y_{ikt} denote a recruiting outcome in prefecture i, two-digit industry k, and year-month t. The baseline specification is

$$Y_{ikt} = \alpha + \beta D_{it} + \delta_t + \lambda_i + \theta_k + \phi_{p(i),y(t)} + \varepsilon_{ikt}, \tag{2}$$

where δ_t, λ_i, θ_k, and $\phi_{p(i),y(t)}$ are year-month, prefecture, industry, and province-by-year fixed effects. The sample covers January 2020–December 2022, excluding June–August 2020 because mobility data are unavailable. Standard errors are clustered at the prefecture level. These estimates describe how recruiting varies with local disruptions after accounting for common monthly movements, persistent prefecture and industry differences, and province-specific annual conditions.

The different dimensions of this specification connect the descriptive figures to the empirical comparison. Year-month effects absorb national developments visible in the aggregate recruiting and mo-

bility series. Prefecture and industry effects account for persistent differences in the level of recruiting, while province-by-year effects allow broad regional conditions to evolve annually. The coefficient on D_{it} therefore summarizes the remaining relationship between local movement and recruiting within this structure. The export interaction then asks whether that relationship differs with the external market conditions faced by an industry. Keeping these two comparisons in the same framework makes it possible to relate the domestic adjustment to a specific source of demand outside the local economy.

We study three sets of outcomes. The first comprises the number of job postings, the number of positions advertised in those postings, and the number of distinct recruiting firms. We retain zero-posting cells in the balanced panel and apply the inverse hyperbolic sine transformation, $\operatorname{asinh}(y) = \log(y + \sqrt{y^2 + 1})$. Coefficients on these outcomes are reported in transformed units. For large positive counts, the transformation approaches a logarithm.

The second set comprises average required years of education, minimum work experience, and log posted wages. The third comprises the five cell-average occupation-level O*NET task indices. These averages are calculated for cells with posted vacancies and available outcome information. Thus, the quantity outcomes measure the scale of recruiting, while requirements and task indices describe the composition of the positions being advertised.

Our central trade specification augments equation (2) with industry export growth and its interaction with D_{it}. Section 4 defines these terms and presents the results. Section 5 then uses the broader panel to place the export findings within the overall adjustment of recruiting.

4 Export Markets and the Quantity and Composition of Hiring

4.1 External Market Conditions

We examine how export-market conditions shape recruiting during local interaction disruptions. Almunia et al. (2021) show that firms can expand exports when domestic demand weakens. Our focus is the recruiting response: whether local contractions in vacancy creation, and the accompanying changes in occupational composition, are smaller when external market conditions are stronger.

We measure year-over-year industry export growth as the change in log export value using Chinese customs records. For a prefecture in province p, we aggregate exports in the same two-digit industry across all other provinces. Denote the resulting measure by $E_{pkt}^{(-p)}$. Excluding province p removes its own export performance from the measure; the remaining variation records the export conditions facing that industry elsewhere in China. We match this measure to the prefecture-industry-month recruiting panel using the customs-to-industry concordance.

The export specification is

$$Y_{ikt} = \alpha + \beta D_{it} + \gamma E^{(-p(i))}_{p(i)kt} + \eta \left(D_{it} \times E^{(-p(i))}_{p(i)kt} \right) + \delta_t + \lambda_i + \theta_k + \phi_{p(i),y(t)} + \varepsilon_{ikt}. \quad (3)$$

The fixed effects and prefecture-level clustering follow equation (2). The analysis uses cells with matched trade data. The coefficient η measures how the relationship between local disruptions and recruiting varies with external export conditions. For quantity outcomes, a positive η corresponds to a smaller contraction at higher export growth. The coefficients on occupational task indices describe the corresponding change in the mix of advertised positions.

More precisely, the fitted relationship with disruption has slope $\beta+\eta E$, conditional on the included fixed effects. The coefficient β therefore describes the slope at zero export growth, while η records how that slope changes with export conditions. Conversely, the slope with respect to export growth is $\gamma + \eta D$. This distinction separates the level of recruiting associated with export growth from the interaction between external markets and local conditions. The interaction is central to our question: whether recruiting varies less sharply with local disruption when the industry's export market is stronger.

4.2 Recruiting Quantities

Columns (1)–(3) of Table 1 show a consistent pattern across three measures of recruiting. The coefficients on local disruption are negative, while the coefficients on export growth and on its interaction with disruption are positive. The interaction coefficients are 0.004 for job postings, 0.004 for advertised vacancies, and 0.003 for recruiting firms. Stronger industry export growth thus accompanies a less pronounced contraction in all three quantities during periods of reduced local movement.

The three outcomes capture distinct recruiting margins. Posting counts measure advertising activity, vacancy counts incorporate the number of workers sought in each advertisement, and firm counts record participation in recruiting. Their common sign pattern links export conditions to both the availability of advertised opportunities and the range of employers offering them. It is economically informative that the association extends beyond the number of advertisements to advertised positions and recruiting firms: external market strength accompanies a broader recruiting presence as well as more advertised opportunities. The coefficients are expressed in inverse-hyperbolic-sine units. This joint pattern provides a hiring-based counterpart to the role of foreign sales during domestic slumps documented by Almunia et al. (2021).

Appendix Table B5 focuses on cells with positive postings. Panel A reports negative disruption coefficients for all three quantities, and Panel B records positive export interactions of 0.007, 0.009, and 0.005. The latter specification retains the main fixed effects and prefecture clustering. This compar-

ison locates the export-related quantity pattern among actively recruiting cells, alongside the main estimates that include zero-posting cells. It connects external market conditions to variation in the amount of recruiting within this observed active segment.

We examine two complementary trade measures in Appendix Table B9. Panel A uses the focal province's own industry export growth. Panel B uses annual industry import growth in China's trading partners, weighted by each province's 2019 export-destination composition. The latter links the recruiting panel directly to changes in destination-market imports using pre-pandemic weights. Both panels show positive interaction coefficients for job postings, advertised vacancies, and recruiting firms. The importer-demand interaction coefficients are 0.008, 0.006, and 0.006, respectively.

Each alternative changes the perspective on external conditions. Own-province exports place the measure closer to the locations supplying the products; its quantity interactions are 0.010, 0.012, and 0.008. Importer demand instead organizes variation around destination markets, with fixed 2019 weights preserving the province's pre-pandemic destination mix. The appendix specifications include prefecture, year-month, and industry fixed effects, and report heteroskedasticity-robust standard errors. The main specification additionally includes province-by-year fixed effects and clusters by prefecture. The shared quantity pattern therefore provides complementary evidence across these reported measures and specifications. In the requirement columns, importer demand has a negative experience interaction of -0.004. These columns describe an additional screening margin; the appendix's principal contribution is the recurrence of the quantity pattern across measures of trade conditions.

4.3 Occupational Composition and Posted Requirements

Columns (7)–(11) of Table 1 show how export growth moderates the task composition of recruiting. The interaction coefficients are negative for non-routine cognitive analytical and interactive task intensity, at -0.002 and -0.003, and positive for non-routine manual physical task intensity, at 0.002. Thus, at higher export growth, the cognitive tilt associated with local disruptions is smaller and the non-routine manual physical component is larger.

This composition result adds to the quantity evidence. Because O*NET task scores are assigned at the occupation level, changes in these indices trace shifts in the occupational mix of advertised jobs. The joint pattern connects stronger external markets to more sustained recruiting and a smaller shift toward cognitive-intensive occupations during a local contraction. It relates export-market conditions to the types of positions firms advertise, in addition to their total recruiting activity.

The lower block of Table 1 also clarifies which task dimensions carry this relationship. The routine cognitive and routine manual interaction estimates are approximately zero at the reported precision, whereas the analytical, interactive, and physical dimensions display the signed pattern described above. The task indices are separate occupational attributes, so their coefficients describe several as-

pects of the vacancy mix. Together, the two blocks connect a quantity contraction to a change in the kinds of work advertised. The smaller cognitive tilt at higher export growth is a compositional feature of recruiting during a contraction, rather than a ranking of the quality of the jobs on offer.

The distinction between different types of labor offers one perspective on this result. Dhyne et al. (2025) show that fixed and variable labor requirements shape firms' responses to foreign demand. When activity contracts, recruiting needs can adjust at different rates across occupations, changing the average task content of new vacancies. Stronger export conditions can support recruiting on margins that otherwise contract more sharply. The vacancy evidence complements this perspective by describing the occupational composition of new labor demand.

For example, if recruiting for production-related positions falls more sharply than recruiting for analytical or coordination roles, the average cognitive intensity of the remaining postings can rise even as employers advertise fewer jobs overall. External sales opportunities could sustain some of the positions that contract more sharply, producing both a smaller quantity decline and a smaller change in average cognitive intensity. This example illustrates the compositional logic linking the two blocks of Table 1. The empirical contribution is to document their joint pattern: the external-market relationship concerns which kinds of work remain represented in recruiting, as well as the overall number of advertised opportunities.

Formal requirements provide an additional view of adjustment. In Columns (4)–(5), the coefficients on local disruption are positive for education and experience. The export-interaction point estimates are -0.005 for education and -0.002 for experience, with standard errors of 0.014 and 0.004; Column (6) reports a wage interaction of 0.002 with a standard error of 0.002. These columns characterize qualifications and compensation within the advertised vacancy pool; the task columns characterize its occupational mix. The most clearly estimated export-related compositional pattern is in the latter measures. Economically, variation across occupations can change the task mix even when average formal requirements move comparatively little. This finding concerns how trade conditions interact with a local contraction, a distinct margin from the average relationship between exporting, product quality, and workforce upgrading studied by Verhoogen (2008).

4.4 Recruiter History and Posted Wages

Table 2 separates firms first observed recruiting on the platforms during the pandemic from those already recruiting before 2020. The export-growth interaction is positive for postings, advertised vacancies, and recruiting firms in both groups. The quantity pattern therefore extends across firms with different histories of platform participation.

Panel A's quantity interactions are 0.004, 0.003, and 0.003; Panel B's are 0.003, 0.004, and 0.002. Each panel establishes the direction of the relationship within its own recruiting-history sample. Their joint contribution is to place both groups within the export-market account of local hiring: firms

newly observed online and established platform users each display the quantity pattern. Platform history identifies an observed recruiting history, with first appearance marking entry into the recorded platform sample.

Among established platform recruiters, the export-growth interaction for log posted wages is 0.003, with a standard error of 0.001. For new platform recruiters, the point estimate is 0.005 with a standard error of 0.003. The established-recruiter result gives a more precisely estimated view of posted compensation alongside the common quantity pattern. Education-interaction point estimates are negative in both panels, while experience interactions have different signs. These columns describe the terms attached to the changing pool of advertised jobs; the two panels provide group-specific evidence rather than a decomposition of a common sample.

Posted wages describe the compensation offered in new advertisements, so their economic role here is to characterize new labor demand alongside its volume. An employer may revise the number of openings, the occupations sought, and the compensation attached to those openings on different margins. Table 2 makes these margins visible across recruiting histories and links the export-market question to the terms offered to applicants. This perspective complements wage studies that follow the earnings of continuing employees.

These findings connect to research on foreign-demand transmission to labor markets. Garin and Silvério (2024) examine wage responses to firm-specific export demand, while Dhyne et al. (2025) connect demand changes to labor costs and production networks. Our contribution is to show how external market conditions relate to the joint adjustment of recruiting quantities, advertised occupations, and posted compensation during domestic interaction disruptions.

5 Local Recruiting and Occupational Adjustment

The export results describe a source of demand that varies across industries and locations. We now place those results within the broader adjustment of recruiting, using the full prefecture-industry panel and equation (2). The analysis proceeds from aggregate recruitment to the content of advertised jobs, then considers how the adjustment varies across sectors, places, and recruiter histories. These comparisons establish the domestic quantity and composition patterns against which the export-market buffer operates.

5.1 Recruiting Quantities and Posted Requirements

Table 3 applies the baseline specification to three related dimensions of recruiting. Posting counts measure the frequency of advertisements, vacancy counts measure the number of positions advertised, and firm counts measure the breadth of employer participation. Columns (1)–(3) include prefecture-industry-month cells with zero postings, capturing adjustment across the full recruiting panel. Larger mobility disruptions coincide with reductions in all three outcomes: a one-unit increase in disruption

corresponds to declines of 0.063, 0.064, and 0.044 inverse-hyperbolic-sine units, respectively. A unit is close to the disruption measure's full-panel standard deviation of 0.95. The agreement across outcomes shows that the contraction extends to both the number of positions advertised and the number of employers seeking workers.

Columns (4)–(6) turn to the characteristics of jobs advertised in cells with available postings. Education requirements rise by 0.087 years and minimum experience by 0.018 years per unit of disruption, against sample means of 11.0 and 1.9 years. The quantity margin carries the clearest aggregate adjustment, while the coefficient on average log posted wages is approximately zero. Fewer advertised opportunities therefore coexist with a more selective mix of posted requirements. These are characteristics of the recruitment flow: they describe the jobs available to applicants as employers revise their hiring plans.

This joint pattern connects to research on how hiring standards vary over the business cycle. Hershbein and Kahn (2018) document changes in skill requirements during the Great Recession, and Modestino et al. (2020) relate posted education and experience requirements to labor-market conditions. In our setting, Table 3 supplies the domestic benchmark for the trade analysis: the relevant adjustment combines a contraction in opportunities with changes in the composition of those that remain.

5.2 The Task Composition of Recruiting

Occupation-based measures. Columns (7)–(11) of Table 3 describe the occupational task mix using the five O*NET indices. A one-unit increase in disruption corresponds to increases of 0.009 and 0.007 task-index units in non-routine cognitive analytical and interactive intensity. The routine cognitive, routine manual, and non-routine manual physical coefficients are -0.001, 0.001, and -0.003. The cognitive dimensions thus account for the clearest reorientation of vacancies.

The task coefficients are expressed in standardized index units. Their economic content lies in the direction and composition of the recruiting shift: a higher average cognitive index can coexist with fewer advertised positions, including in cognitive-intensive occupations. These measures track the occupation-specific task content represented in the recruiting flow. An average cognitive index rises when occupations with higher cognitive intensity account for a greater share of postings. Read together with the quantity results, the estimates describe a smaller recruiting flow with a greater cognitive orientation. This interpretation connects directly to Section 4: stronger export growth accompanies both a smaller quantity contraction and a more limited reorientation of this occupational mix.

Activities in job descriptions. Table 4 examines the activities named in advertisements, using the randomly sampled posting texts described in Section 2. Each outcome is a verb's frequency multiplied

by 1,000 and normalized by $\log(1+\text{text length})$. The regressions include year-month, province-by-year, and prefecture-by-industry fixed effects. They therefore describe changes in advertised activities after accounting for persistent differences between local industry cells and the specified time effects.

Panel A shows greater emphasis on analytical activities, including *analyze*, *design*, *develop*, *predict*, and *research*. For *analyze*, the coefficient of 0.687 is approximately 1.3% of the outcome's mean of 53.3. The corresponding coefficients for *design* and *develop* are 1.148 and 1.177. These words give concrete content to the increased analytical orientation measured by the occupation-based indices.

Panel B shows how activities within the interactive category can move differently. The coefficients on *sell* and *communicate* are negative, while those on *recruit* and *operate* are positive, at 1.067 and 0.614. This pattern distinguishes customer-facing activities from activities associated with staffing and operations. Panel C records a decline in *calculate* of 0.349 normalized-frequency units. Panels D and E show declines in *equipment operation* and *maintain* of 0.365 and 0.416 units. Together, the panels describe changes within the broad vocabulary of cognitive and manual work, adding detail to the average task indices. The table's contribution is a complementary account of advertised activities in the changing posting mix.

5.3 Sectoral and Geographic Patterns

Manufacturing and services. Tables 5 and 6 apply the baseline specification separately to manufacturing and service postings, preserving the prefecture-industry-month unit of analysis. The posting and vacancy coefficients are -0.058 and -0.052 in manufacturing, compared with -0.074 and -0.079 in services. Firm-count coefficients are also negative in both sectors, at -0.043 and -0.051. The point estimates place the larger recruiting contraction in services while showing that adjustment extends across both parts of the economy.

Formal requirements rise in both sectoral samples. Education and experience coefficients are 0.094 and 0.020 in manufacturing and 0.079 and 0.017 in services. The task results add a distinct dimension: the NRCA and NRCI coefficients are 0.005 and 0.005 in manufacturing, compared with 0.009 and 0.007 in services. The service results thus provide a particularly clear example of a quantity contraction accompanied by cognitive reorientation.

Many service activities depend on customer movement, local consumption, and in-person interaction. The linked work and consumption trips studied by Miyauchi et al. (2025), and the local-service consequences of remote work documented by Althoff et al. (2022), provide an economic context for this pattern. The two tables locate the broader adjustment across sectors; the trade-linked analysis separately relates recruitment to the strength of external product markets. This distinction helps connect local interaction conditions to recruiting without treating sector membership itself as a measure of foreign demand.

Prefecture groups. Table 7 interacts disruption with indicators for three prefecture groups within a common specification.[5] The posting coefficient is -0.125 in both Tier-1 and Tier-2 prefectures, compared with -0.035 in the remaining group. The vacancy and firm-count estimates likewise place the larger quantity contractions in the first two groups.

The geographic pattern for composition differs. NRCA and NRCI coefficients are 0.008 and 0.005 in Tier-2 prefectures and 0.011 and 0.009 elsewhere; the corresponding Tier-1 estimates are -0.001 and 0.002. Education requirements also rise in Tier-2 and other prefectures, with coefficients of 0.108 and 0.088. These estimates show why recruitment volume and occupational composition are useful separate outcomes: the locations with the largest contraction need not display the largest cognitive shift. The table gives a spatial dimension to the adjustment described by Monte et al. (2018) and places the export findings within heterogeneous local labor markets.

Recruiter history. Tables 8 and 9 construct separate recruiting panels for firms first observed posting during the pandemic and firms observed before 2020. This classification describes the history of platform participation. In the former group, the posting, vacancy, and firm-count coefficients are -0.078, -0.082, and -0.055. Among established platform recruiters, they are -0.045, -0.040, and -0.026. The reported point estimates associate recent platform participation with a larger contraction in recruiting quantities.

Both groups contribute to cognitive reorientation: their NRCA and NRCI coefficients are 0.007 and 0.006. Education coefficients are positive in both groups, at 0.095 and 0.081, while the experience coefficient is 0.009 for new platform recruiters and 0.024 for established recruiters. Thus, different recruitment histories coexist with a shared shift in occupational task composition. Read together with Table 2, these tables show why recruiter history is useful: the positive export-growth interaction extends across groups with different overall quantity adjustments.

Work-from-home feasibility. Appendix Table B6 examines a further dimension of industry composition. We aggregate the occupational feasibility scores of Dingel and Neiman (2020) using posting shares and standardize the industry index. It measures the potential to perform tasks remotely. Because the index is standardized, its interaction coefficient gives the change in the disruption slope associated with a one-standard-deviation increase in industry teleworkability.

The interactions are -0.023, -0.035, and -0.017 for postings, vacancies, and recruiting firms. Higher teleworkability is therefore associated with a more negative quantity slope in this sample. The NRCI interaction is -0.007, indicating a smaller interactive-cognitive reorientation in industries

[5] Tier-1 comprises Beijing, Shanghai, Guangzhou, and Shenzhen. The Tier-2 group comprises Tianjin, Shijiazhuang, Taiyuan, Hohhot, Shenyang, Dalian, Changchun, Harbin, Nanjing, Ningbo, Hefei, Fuzhou, Xiamen, Nanchang, Jinan, Qingdao, Zhengzhou, Wuhan, Changsha, Nanning, Haikou, Chongqing, Chengdu, Guiyang, Kunming, Xi'an, Lanzhou, Xining, Yinchuan, and Urumqi.

with greater remote-work feasibility; routine cognitive and routine manual interactions are also negative. The table establishes that the pattern of recruitment varies with task feasibility as well as with sector and location. Its role is to characterize this industry dimension of adjustment alongside the separate export-market relationship.

5.4 Additional Comparisons

The appendix examines how the recruiting patterns change with time controls, outcome definitions, statistical inference, and sample composition. Each comparison addresses a different feature of the empirical framework.

Appendix Table B1 replaces prefecture and province-by-year fixed effects with prefecture-by-year effects. This comparison absorbs annual conditions specific to each city and emphasizes variation across months within a prefecture-year. The quantity coefficients are -0.066, -0.065, and -0.045, close to the baseline estimates. NRCA and NRCI coefficients are 0.013 and 0.010, and the education coefficient is 0.109. The log posted-wage coefficient is -0.011, also linking within-year disruptions to the compensation advertised in this specification. The table thus gives a view of recruiting and posted compensation after absorbing each city's annual conditions. The joint quantity and cognitive-composition pattern remains visible with these more localized controls.

Appendix Table B2 instead allows each industry to have its own annual component. This absorbs differences in industries' year-to-year paths while retaining prefecture, year-month, and province-by-year effects. The posting and vacancy coefficients are -0.063 and -0.064, and the two cognitive coefficients are 0.009 and 0.007. The comparison shows that the central pattern is also present after accounting for industry-specific annual developments.

Appendix Table B3 expresses each outcome relative to its January–March 2019 average. This gives the estimates a common pre-pandemic reference at the prefecture-industry level. The quantity coefficients are -0.057, -0.059, and -0.038; education and experience coefficients are 0.078 and 0.017. Both cognitive indices have coefficients of 0.008. For posted requirements and tasks, this comparison uses cells observed in both periods. The result connects the pandemic-period pattern to changes from local industries' earlier recruiting profiles.

Appendix Table B4 reports inference allowing disturbances to be correlated within prefectures and within industries. This matters because recruiting cells may share both local conditions and industry developments. The standard errors for the three quantity coefficients are 0.006, 0.007, and 0.005; those for NRCA and NRCI are each 0.003. The table continues to show a well-defined negative quantity relationship and positive cognitive-composition relationship under this clustering treatment.

Appendix Table B5 restricts attention to cells with positive postings. Panel A's quantity coefficients are -0.066, -0.067, and -0.050. The comparison retains the IHS transformation and locates the domestic contraction within the set of cells actively recruiting. It therefore complements the balanced-panel

results, which also include zero-posting cells. Together with the Panel B export interactions discussed in Section 4, this result connects the domestic quantity adjustment and the external-market relationship within that active segment.

Appendix Tables B7 and B8 use administrative registration dates to classify firms, offering a perspective on firm age alongside platform history. The post-2020 registration group's posting and vacancy coefficients are -0.071 and -0.077, compared with -0.054 and -0.050 for firms registered before 2020. The cognitive coefficients are positive in both tables: 0.010 and 0.007 for the former group and 0.008 and 0.007 for the latter. Using the samples and specifications reported in those tables, the registry-based comparisons reproduce the combination of a larger quantity contraction among younger firms and cognitive reorientation in both groups.

Finally, Appendix Table B10 relates outcomes from 2016–2018 to subsequent disruption measures observed in 2020–2022. Its purpose is to place the pandemic-period relationships against an earlier recruiting benchmark. The pre-period quantity coefficients are -0.001, -0.002, and -0.002, and the analytical and interactive task coefficients are approximately zero and 0.001. These magnitudes contrast with the larger quantity and cognitive-composition coefficients in the pandemic-period baseline. Experience has a positive pre-period coefficient of 0.010, compared with 0.018 in the baseline; the historical comparison therefore provides an outcome-specific benchmark for that requirement.

Across these comparisons, the central economic pattern remains a contraction in recruiting accompanied by higher posted requirements and a greater cognitive orientation of the occupational mix. Export-market conditions add a further margin to this adjustment: stronger export growth accompanies smaller quantity contractions and a more limited cognitive reorientation during local disruptions.

6 Conclusion

Foreign markets are a potential source of demand when local economic interactions are disrupted. This paper studies that margin using China's experience during the COVID-19 pandemic. We combine online recruiting data with within-prefecture mobility and industry trade flows to examine how external market conditions shape the quantity and composition of hiring during domestic disruptions.

Three findings organize the evidence. First, stronger export growth accompanies smaller contractions in job postings, advertised vacancies, and the number of recruiting firms when local mobility falls. The same quantity pattern appears using trading partners' import growth weighted by pre-pandemic export destinations. Second, export growth moderates the shift toward cognitive-intensive occupations and is associated with greater non-routine manual physical intensity in the occupational mix. Third, the broader recruiting adjustment combines fewer vacancies with higher education and experience requirements, with the cognitive reorientation particularly visible in services.

These findings add a hiring-composition perspective to the labor-market consequences of inter-

national trade. External demand matters for the mix of occupations represented in new vacancies as well as for the scale of recruiting. This perspective complements research on export responses to domestic slumps, foreign-demand transmission to employment and wages, and the spatial linkages between commuting and local consumption.

The setting also clarifies when a demand buffer can operate: local economic interactions weaken while foreign markets continue to provide sales opportunities. The evidence points to this conditional role of international demand in sustaining recruiting during domestic disruptions and shows how high-frequency vacancy data can reveal adjustments that extend beyond aggregate labor demand.

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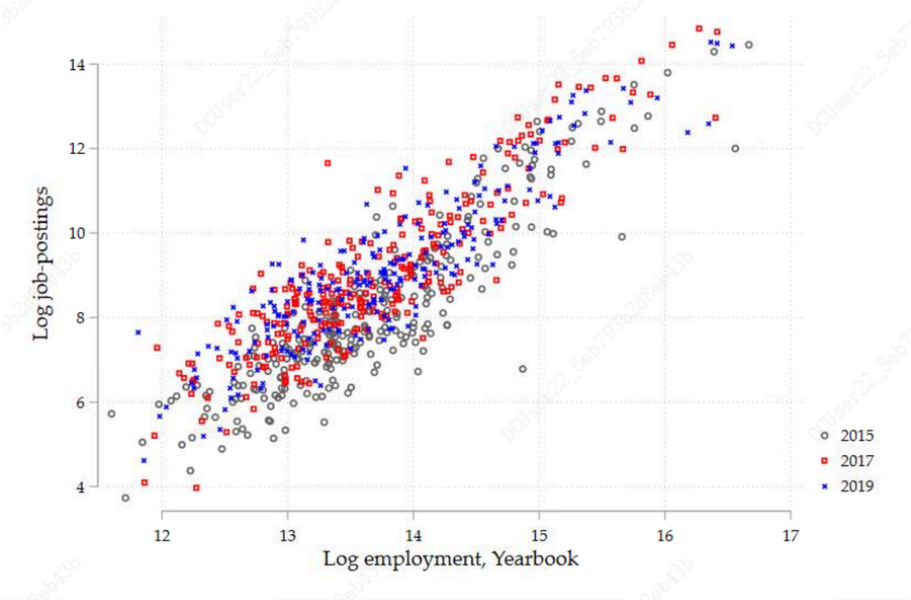
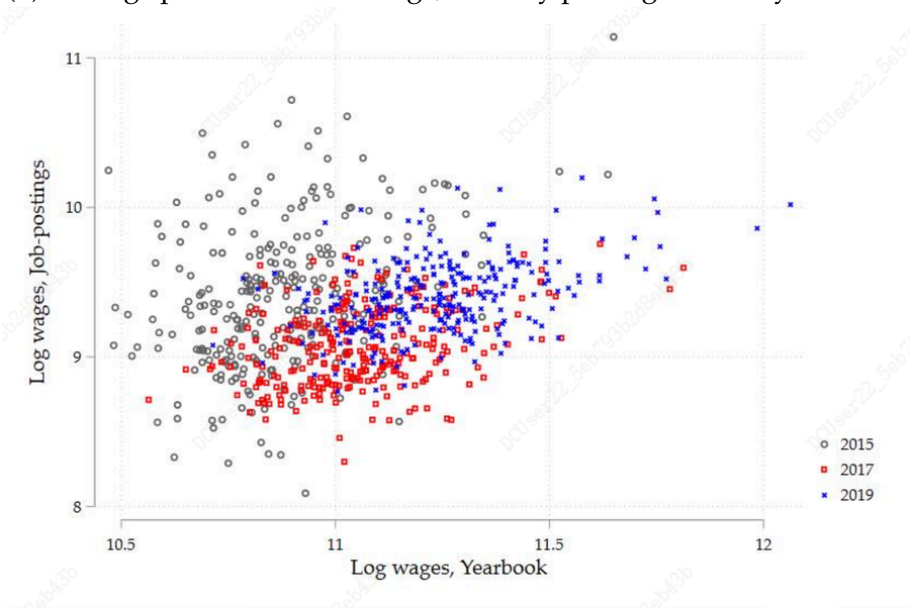
Figures and Tables

Figure 1: Geographic Coverage of Online Recruiting: Comparison with Prefecture Yearbooks

(a) Prefecture-level job postings and yearbook employment



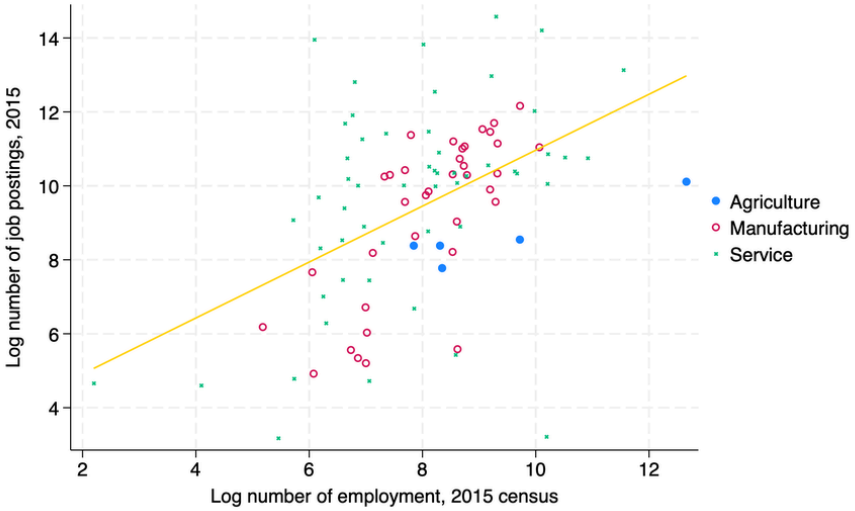
(b) Average prefecture-level wage, vacancy posting data vs. yearbooks



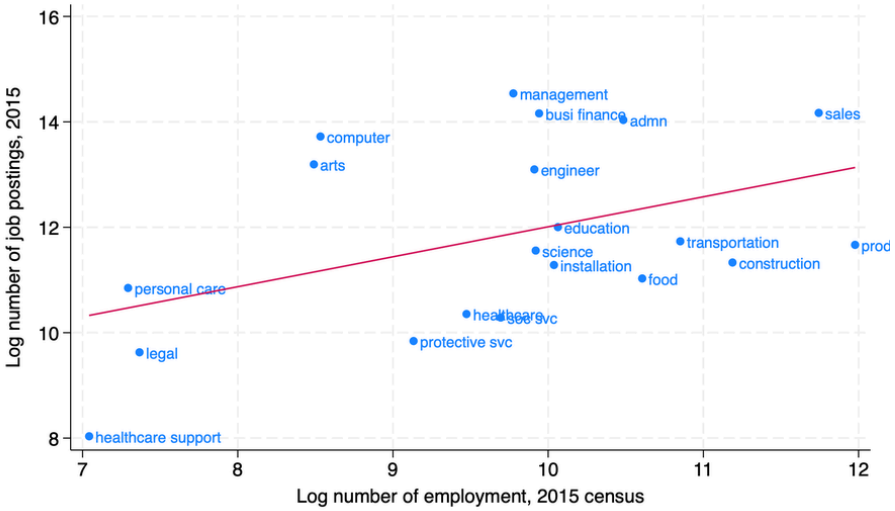
Note: This figure compares online recruiting with yearbook measures at the prefecture level in 2015, 2017 and 2019. Panel (a) plots log job-posting counts (vertical axis) against log employment from Prefecture Statistical Yearbooks (horizontal axis). Panel (b) plots log average posted wages (vertical axis) against log average yearbook wages (horizontal axis). The corresponding pooled regressions include year fixed effects; their estimates and the separate year-by-year comparisons are reported in Appendix Table A3.

Figure 2: Industry and Occupational Coverage: Comparison with Census Employment

(a) Industry-level postings and census employment

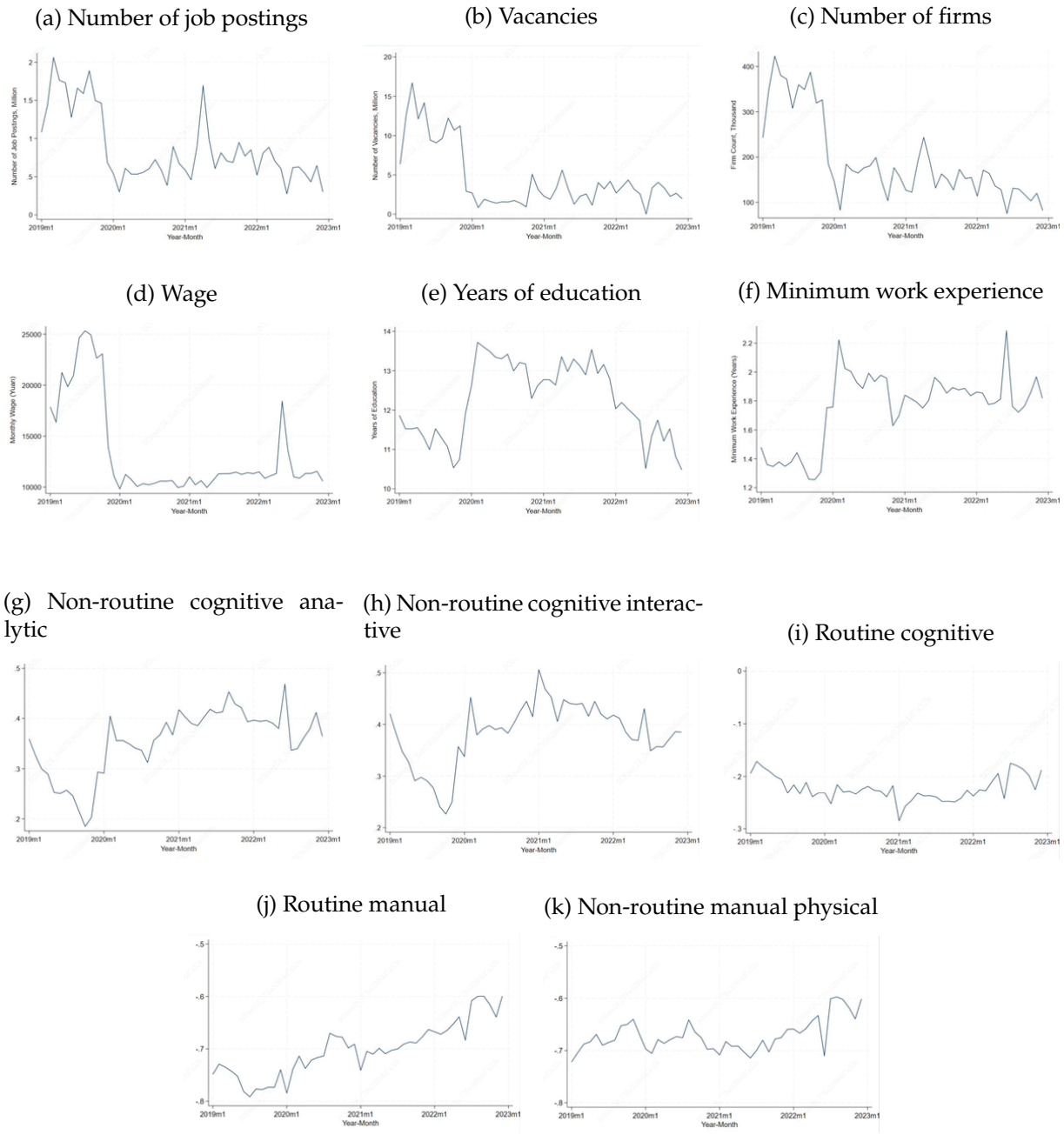


(b) Occupational postings and census employment



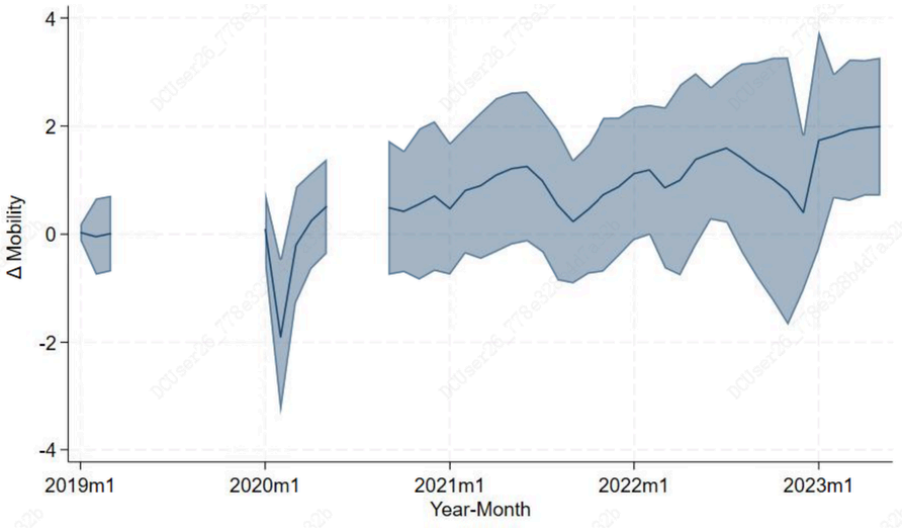
Note: This figure compares log online job-posting counts (vertical axes) with log employment from the 2015 census (horizontal axes). Panel (a) aggregates observations to the two-digit industry level; Panel (b) aggregates them to broad occupational groups. The fitted lines describe the cross-industry and cross-occupation relationships.

Figure 3: Trends in Vacancy Creation, Posted Job Requirements and Task Content, 2019–2022



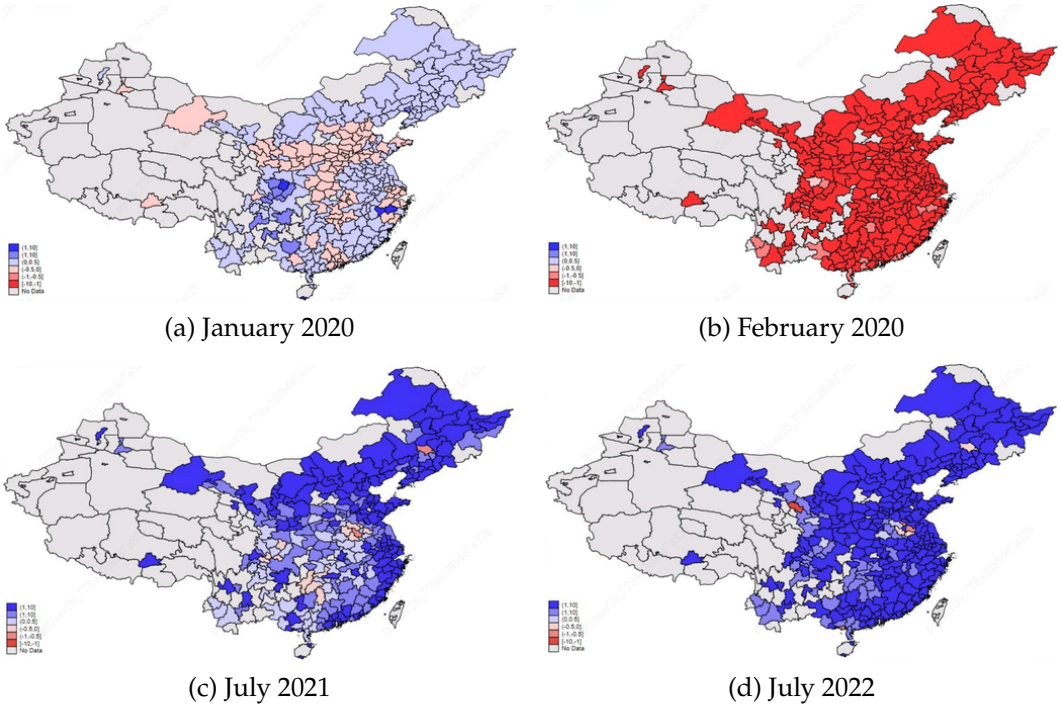
Note: This figure presents the trends in labor market outcomes and skill requirements from 2019 to 2022, constructed from the job vacancy posting data described in Section 2. Subfigures (a)-(d) depict recruiting quantities and posted wages: (a) job postings, (b) advertised vacancies, (c) recruiting firms, and (d) posted wage. Subfigures (e)-(k) depict skill requirements: (e) Years of education, (f) Minimum work experience, (g) Non-routine cognitive analytic, (h) Non-routine cognitive interactive, (i) Routine cognitive, (j) Routine manual, and (k) Non-routine manual physical. Subfigures (a)-(c) are aggregated to the year-month level. Subfigures (d)-(k) report the year-month average.

Figure 4: Changes in Within-Prefecture Mobility in China, 2019–2023



Note: This figure shows monthly observations of within-prefecture mobility changes relative to the baseline, from January 2019 to May 2023, derived from the Baidu Migration Index. Negative changes correspond to greater local disruption; the disruption measure in equation (1) reverses the sign of the mobility change. The shaded area represents the 95% confidence interval. Gaps indicate unavailable observations.

Figure 5: Geographic Variation in Within-Prefecture Mobility Changes



(a) January 2020

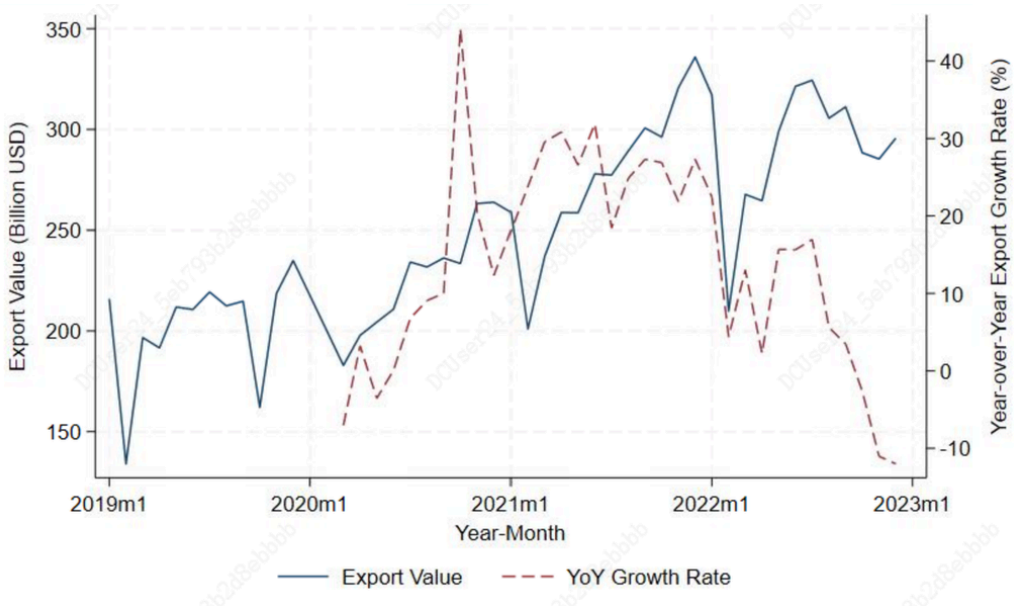
(b) February 2020

(c) July 2021

(d) July 2022

Note: This figure shows mobility changes across Chinese prefectures for January 2020, February 2020, July 2021 and July 2022, based on the Baidu Migration Index. Blue areas indicate positive mobility changes, red areas indicate negative changes, and gray areas indicate unavailable data. Negative mobility changes correspond to greater disruption in the recruiting regressions.

Figure 6: China Monthly Export Value and Year-over-Year Growth Rate, 2019-2022



Note: This figure shows the monthly export value (in billion USD, left axis) and the year-over-year growth rate (in percentage, right axis) of China from January 2019 to December 2022. Data are sourced from China Customs data, which reports export value at the province-product-month level; we aggregate these data by summing across provinces and products to obtain the national monthly export value series shown here.

Table 1: Export Growth, Local Disruptions, and Recruiting Outcomes

Variables	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Experience	(6) Log Wage
Local disruption	-0.060***	-0.057***	-0.043***	0.088***	0.020**	0.006
	(0.006)	(0.006)	(0.004)	(0.026)	(0.009)	(0.004)
Δ Log Export Value	0.008***	0.011***	0.006***	-0.007	-0.008	0.002
	(0.001)	(0.002)	(0.001)	(0.017)	(0.006)	(0.003)
Local disruption	0.004***	0.004***	0.003***	-0.005	-0.002	0.002
× Δ Log Export Value	(0.001)	(0.002)	(0.001)	(0.014)	(0.004)	(0.002)
Mean (s.d.) of Y	1.3 (1.8)	1.3 (2.0)	0.8 (1.2)	11.8 (4.1)	2.1 (1.3)	8.9 (0.5)
Observations	261,330	261,330	261,330	111,253	111,253	111,253
R-squared	0.608	0.531	0.656	0.090	0.064	0.173
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Local disruption	0.007***	0.011***	-0.008***	-0.004**	-0.002	
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	
Δ Log Export Value	0.004**	0.002	0.000	0.000	-0.003	
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	
Local disruption	-0.002**	-0.003***	-0.000	0.000	0.002***	
× Δ Log Export Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Mean (s.d.) of Y	-0.03 (0.6)	0.1 (0.6)	-0.1 (0.4)	-0.2 (0.6)	-0.2 (0.6)	
Observations	151,790	151,790	151,791	151,792	151,793	
R-squared	0.077	0.096	0.132	0.122	0.041	

Note: This table examines the buffering effect of exports on labor market outcomes. The key explanatory variable Δ Log Export Value is constructed as year-over-year export growth at the two-digit industry level, aggregating all provinces other than the focal province. The sample is restricted to prefecture-industry-month observations where export data are available. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Export Growth and Recruiting by Platform History

Variables	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Experience	(6) Log Wage
Panel A: New platform recruiters						
Local disruption	-0.061***	-0.058***	-0.041***	0.120**	0.006	-0.001
	(0.008)	(0.007)	(0.005)	(0.042)	(0.011)	(0.006)
Δ Log Export Value	0.005***	0.006***	0.003***	-0.051	-0.006	0.004
	(0.001)	(0.001)	(0.001)	(0.034)	(0.011)	(0.005)
Local disruption	0.004***	0.003***	0.003***	-0.016	-0.001	0.005
× Δ Log Export Value	(0.001)	(0.001)	(0.001)	(0.025)	(0.007)	(0.003)
Mean (s.d.) of Y	0.6 (1.2)	0.6 (1.4)	0.4 (0.8)	10.4 (5.2)	2.0 (1.4)	8.8 (0.6)
Observations	261,330	261,330	261,330	67,137	67,137	67,137
R-squared	0.423	0.326	0.471	0.072	0.058	0.200
Panel B: Established platform recruiters						
Local disruption	-0.049***	-0.039***	-0.031***	0.069***	0.019**	0.007**
	(0.005)	(0.006)	(0.004)	(0.023)	(0.008)	(0.004)
Δ Log Export Value	0.005***	0.010***	0.004***	-0.000	0.001	0.003
	(0.001)	(0.002)	(0.001)	(0.012)	(0.004)	(0.002)
Local disruption	0.003***	0.004***	0.002***	-0.009	0.004	0.003**
× Δ Log Export Value	(0.001)	(0.001)	(0.001)	(0.012)	(0.004)	(0.001)
Mean (s.d.) of Y	1.1 (1.7)	1.1 (1.9)	0.7 (1.1)	12.3 (3.8)	2.1 (1.3)	8.9 (0.5)
Observations	286,617	286,617	286,617	106,021	106,021	106,021
R-squared	0.596	0.530	0.647	0.083	0.076	0.151

Note: This table relates local disruptions and export growth to recruiting by platform history. Panel A uses firms first observed posting during the pandemic; Panel B uses firms observed posting before 2020. The key explanatory variable Δ Log Export Value is constructed as year-over-year export growth at the two-digit industry level, aggregating all provinces other than the focal province. The sample is restricted to prefecture-industry-month observations where export data are available. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (4-6) are restricted to prefecture–industry–month cells with at least one job posting. All regressions include prefecture, year-month, two-digit industry, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Local Disruptions, Recruiting Quantities, and Vacancy Composition

Dep. Var.	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.063***	-0.064***	-0.044***	0.087***	0.018***	0.000
	(0.004)	(0.005)	(0.003)	(0.018)	(0.005)	(0.005)
Mean (s.d.) of Y	1.2 (1.6)	1.2 (1.9)	0.8 (1.1)	11.0 (4.6)	1.9 (1.3)	8.8 (0.6)
Observations	899,481	899,481	899,481	337,294	337,294	337,294
R-squared	0.623	0.557	0.658	0.171	0.125	0.250
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.009***	0.007***	-0.001	0.001	-0.003	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Mean (s.d.) of Y	-0.01 (0.6)	0.1 (0.6)	−0.1 (0.5)	-0.3 (0.6)	-0.2 (0.6)	
Observations	330,612	330,612	330,612	330,612	330,612	
R-squared	0.077	0.065	0.051	0.143	0.110	

Note: This table presents regression results examining the relationship between local mobility disruptions and recruiting outcomes. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Local Disruptions and Activities in Job Descriptions

	(1)	(2)	(3)	(4)	(5)
Panel A: non-routine cognitive analytical					
	Analyze	Design	Develop	Predict	Research
Local disruption	0.687***	1.148***	1.177***	0.085**	0.380***
	(0.262)	(0.330)	(0.323)	(0.035)	(0.128)
Mean (s.d.) of Y	53.3(126.6)	49.4(177.2)	48.3(141.5)	1.7(19.3)	9.0(59.4)
Panel B: non-routine cognitive interactive					
	Sell	Communicate	Recruit	Operate	Test Drive
Local disruption	-1.336**	-0.948**	1.067***	0.614**	0.034***
	(0.531)	(0.582)	(0.338)	(0.315)	(0.012)
Mean (s.d.) of Y	102.6(249.9)	85.1(123.6)	34.2(150.4)	35.1(141.8)	0.1(5.9)
Panel C: routine cognitive					
	Process	Collect	Calculate	Inspect	Account
Local disruption	-0.396	-0.265**	-0.349***	0.149	-0.116
	(0.284)	(0.134)	(0.106)	(0.149)	(0.120)
Mean (s.d.) of Y	33.7(93.0)	19.1(62.6)	10.1(50.3)	10.5(55.3)	7.0(52.1)
Panel D: routine manual					
	Execute	Produce	Operate Equipment	Print	Monitor
Local disruption	-0.079	0.034	-0.365***	-0.093***	0.082
	(0.212)	(0.291)	(0.142)	(0.031)	(0.073)
Mean (s.d.) of Y	32.7(90.7)	31.0(150.8)	22.4(73.5)	1.4(18.1)	7.1(42.6)
Panel E: non-routine manual physical					
	Construct	Maintain	Test	Build	Film
Local disruption	0.112	-0.416***	-0.081*	-0.186***	-0.111
	(0.175)	(0.145)	(0.180)	(0.056)	(0.086)
Mean (s.d.) of Y	13.8(101.1)	9.0(66.4)	6.7(64.1)	4.8(33.0)	4.2(51.1)

Note: This table examines the effect of local mobility disruptions on skill-specific requirements extracted from online job advertisement texts. The dependent variables are normalized word frequencies, calculated as (word counts per posting × 1000) divided by $\log(1 + \text{text length})$. All columns control for year-month fixed effects, province-by-year fixed effects, and prefecture-by-industry fixed effects. The dependent variables are the frequencies of high-frequency verbs identified in job postings, categorized into five task-based groups. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Local Disruptions and Recruiting: Manufacturing

Dep. Var.	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.058***	-0.052***	-0.043***	0.094***	0.020***	0.007*
	(0.006)	(0.006)	(0.004)	(0.025)	(0.008)	(0.004)
Mean (s.d.) of Y	1.3 (1.6)	1.3 (1.8)	0.8 (1.0)	11.9 (4.0)	2.1 (1.3)	8.9 (0.5)
Observations	287,463	287,463	287,463	123,455	123,455	123,455
R-squared	0.611	0.535	0.659	0.088	0.063	0.171
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.005	0.005	0.003	0.003	-0.002	
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	
Mean (s.d.) of Y	-0.03 (0.6)	0.1 (0.6)	-0.1 (0.4)	-0.2 (0.6)	-0.2 (0.6)	
Observations	121,631	121,631	121,631	121,631	121,631	
R-squared	0.081	0.068	0.041	0.127	0.101	

Note: This table examines the relationship between local mobility disruptions and recruiting outcomes in manufacturing. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Local Disruptions and Recruiting: Services

Dep. Var.	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.074***	-0.079***	-0.051***	0.079***	0.017***	-0.002
	(0.005)	(0.006)	(0.004)	(0.023)	(0.006)	(0.006)
Mean (s.d.) of Y	1.3 (1.7)	1.4 (2.1)	0.9 (1.2)	10.5 (4.8)	1.8 (1.3)	8.8 (0.7)
Observations	550,742	550,742	550,742	197,691	197,691	197,691
R-squared	0.688	0.615	0.716	0.198	0.161	0.308
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.009***	0.007***	-0.001	0.002	-0.002	
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	
Mean (s.d.) of Y	0.01 (0.6)	0.2 (0.6)	-0.1 (0.5)	-0.3 (0.5)	-0.3 (0.6)	
Observations	193,342	193,342	193,342	193,342	193,342	
R-squared	0.086	0.065	0.066	0.148	0.125	

Note: This table examines the relationship between local mobility disruptions and recruiting outcomes in services. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Local Disruptions and Recruiting by Prefecture Group

Variables	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Experience	(6) Log Wage
Local disruption	-0.125***	-0.085***	-0.101***	-0.018	0.016*	0.008
× Tier-1 prefecture	(0.017)	(0.023)	(0.006)	(0.023)	(0.009)	(0.018)
Local disruption	-0.125***	-0.117***	-0.091***	0.108***	0.027***	-0.001
× Tier-2 prefecture	(0.009)	(0.008)	(0.007)	(0.021)	(0.006)	(0.006)
Local disruption	-0.035***	-0.043***	-0.022***	0.088***	0.011**	0.000
× other prefecture	(0.005)	(0.006)	(0.003)	(0.022)	(0.006)	(0.005)
Mean (s.d.) of Y	1.1 (1.8)	1.2 (2.2)	0.8 (1.3)	11.0 (4.6)	1.9 (1.3)	8.8 (0.6)
Observations	889,481	889,481	889,481	337,294	337,294	337,294
R-squared	0.623	0.557	0.658	0.171	0.125	0.250
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	-0.001	0.002	-0.000	0.009	0.009	
× Tier-1 prefecture	(0.004)	(0.003)	(0.003)	(0.007)	(0.006)	
Local disruption	0.008***	0.005***	0.001	0.005*	-0.002	
× Tier-2 prefecture	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	
Local disruption	0.011***	0.009***	0.001	-0.003	-0.006**	
× other prefecture	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	
Mean (s.d.) of Y	-0.01 (0.6)	0.1 (0.6)	−0.1 (0.5)	-0.3 (0.6)	-0.2 (0.6)	
Observations	330,612	330,612	330,612	330,612	330,612	
R-squared	0.077	0.065	0.051	0.143	0.110	

Note: This table examines the relationship between local mobility disruption and recruiting outcomes, by prefecture tier. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Local Disruptions and Recruiting: New Platform Recruiters

Dep. Var.	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.078***	-0.082***	-0.055***	0.095***	0.009	-0.001
	(0.007)	(0.007)	(0.005)	(0.025)	(0.006)	(0.006)
Mean (s.d.) of Y	0.7 (1.4)	0.7 (1.8)	0.5 (1.0)	9.6 (5.3)	1.8 (1.4)	8.8 (0.7)
Observations	880,935	880,935	880,935	235,670	235,670	235,670
R-squared	0.534	0.451	0.570	0.142	0.120	0.279
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.007**	0.006**	0.001	0.003	-0.001	
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	
Mean (s.d.) of Y	-0.05 (0.6)	0.1 (0.7)	-0.1 (0.5)	-0.3 (0.6)	-0.2 (0.6)	
Observations	229,733	229,733	229,733	229,733	229,733	
R-squared	0.082	0.071	0.056	0.132	0.107	

Note: This table examines the heterogeneous effects of local mobility disruptions on labor demand and skill requirements, using firms first observed recruiting on the platforms during the pandemic. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Local Disruptions and Recruiting: Established Platform Recruiters

Dep. Var.	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.045***	-0.040***	-0.026***	0.081***	0.024***	0.002
	(0.003)	(0.005)	(0.003)	(0.016)	(0.005)	(0.004)
Mean (s.d.) of Y	0.9 (1.7)	1.0 (2.0)	0.6 (1.2)	12.0 (4.)	2.0 (1.3)	8.9 (0.6)
Observations	899,481	899,481	899,481	299,715	299,715	299,715
R-squared	0.587	0.536	0.618	0.101	0.116	0.197
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.007**	0.006**	-0.002	0.001	-0.001	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Mean (s.d.) of Y	0.03 (0.6)	0.2 (0.6)	-0.1 (0.5)	-0.3 (0.6)	-0.3 (0.6)	
Observations	293,753	293,753	293,753	293,753	293,753	
R-squared	0.082	0.071	0.044	0.149	0.112	

Note: This table examines the relationship between local mobility disruptions and recruiting outcomes, using firms observed recruiting on the platforms before 2020. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Online Appendices

(Not for publication)

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A Data Appendix

A.1 Additional Description of Vacancy Posting Platforms

According to the "2021 China Online Recruitment Industry Market Development Research Report" published by iResearch, a leading market consulting firm founded in 2002, the total revenue of China's listed recruitment market in 2020 reached 157 million USD. Among the major platforms, 51job.com held the largest market share (34.2%), followed by Liepin.com (17.3%) and Zhaopin.com (15.1%). In terms of mobile traffic, Zhaopin.com and 51job.com each averaged over 11 million monthly mobile device visits in 2020, significantly surpassing BOSS Zhipin (5 million) and Liepin.com (2 million).

The three platforms are briefly described as follows:

- 51job.com: Founded in 1998, 51job.com is a leading human resources service provider catering to diverse industries and job levels. It became the first Chinese HR service firm listed on Nasdaq in 2004 and reported 2021 revenues of 4.42 billion yuan, a 20% increase. In 2022, it completed a privatization deal and delisted from Nasdaq.

- Zhaopin.com: Established in 1994, Zhaopin.com was once the largest online recruitment platform in China, covering nearly all urban occupations except civil service roles. It has over 374 million professional users, partnerships with 14.36 million enterprises, and a team of 5,000 employees operating across 35 branches in more than 400 cities.

- Liepin.com: Founded in 2011, Liepin.com initially specialized in headhunting for mid-to-high-end recruitment. It now serves over 86 million professionals, 210,000 verified headhunters, and 1.1 million certified enterprises, while recently expanding into general job-seeking services.

A.2 O*NET Dataset on Task Contents

Table A1: Work activities, work context, and ability importance scales used to construct composite task intensity measures

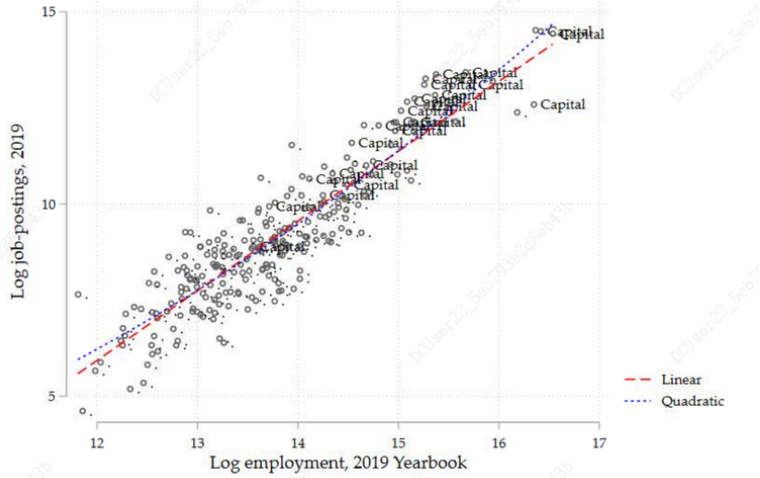
Item	Category	Variable in O*NET
Non-routine cognitive: analytical (NRCA)		
Analyzing data/information	activities	analyzing
Thinking creatively	activities	thinking
Interpreting information for others	activities	interpreting
Non-routine cognitive: interactive (NRCI)		
Establishing and maintaining personal relationships	activities	establishing
Guiding, directing and motivating subordinates	activities	guiding
Coaching/developing others	activities	coaching
Routine cognitive (RC)		
Importance of repeating the same tasks	context	repeating
Importance of being exact or accurate	context	accurate
Structured v. Unstructured work (reverse)	context	structured
Routine manual (RM)		
Routine manual		
Pace determined by speed of equipment	context	pace
Controlling machines and processes	activities	controlling
Spend time making repetitive motions	context	motions
Non-routine manual physical (NRMP)		
Operating vehicles, mechanized devices, or equipment	activities	operating
Spend time using hands to handle, control or feel objects, tools or controls	context	hands
Manual dexterity	abilities	manual dexterity
Spatial orientation	abilities	spatial orientation

Note: This table lists Work activities, work context and ability importance variables from ONET data that are relevant for construction of the composite task intensity measures. We aggregate the above work characteristic indexes to occupational level for each five job types: (1) non-routine cognitive analytical (NRCA), (2) non-routine cognitive interactive (NRCI), (3) routine cognitive (RC), (4) routine manual (RM), (5) non-routine manual physical (NRMP). For each occupation, we compute composite task measures by summing the respective constituent scales, which are weighted by their importance ratings on a scale from 1 to 5. These composite measures are then standardized to have a mean of zero and a standard deviation of one. We aggregate 879 SOC 8-level characteristics to 763 SOC 6-level occupations by taking a simple average.

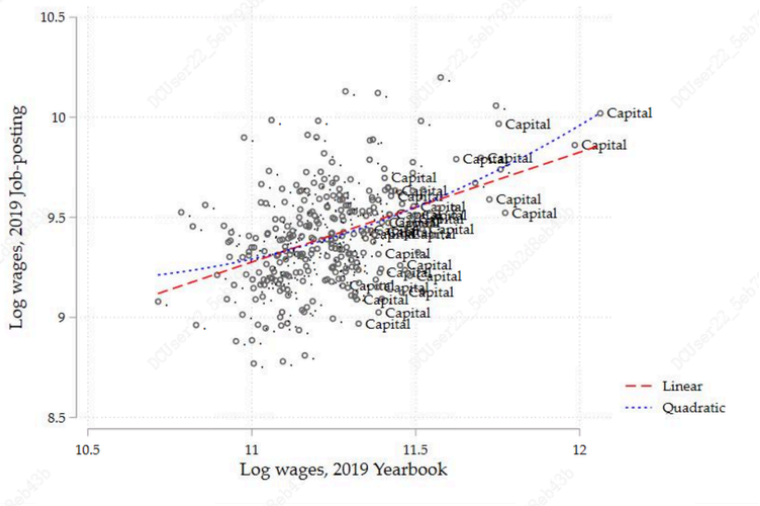
A.3 Additional Evidence on Data Coverage

Figure A1: Representativeness of job-posting data, compared to Prefecture Yearbooks, by provincial capital cities

(a) Log employment



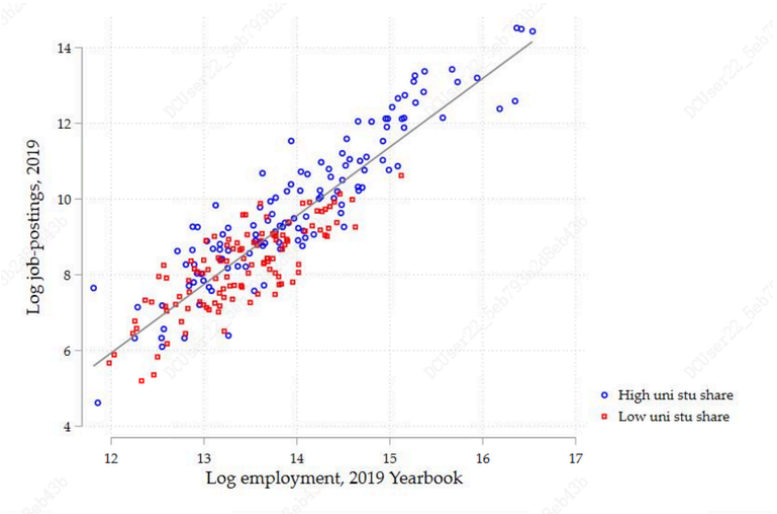
(b) Log wages



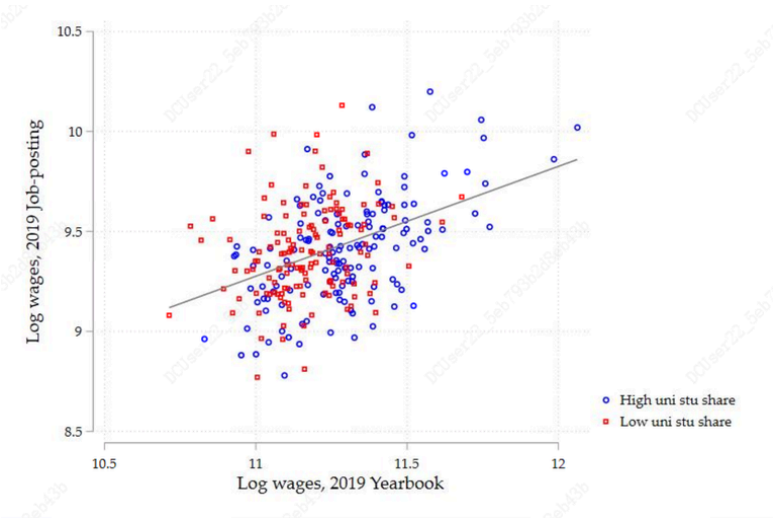
Note: This figure compares the coverage of online recruiting across prefectures, with provincial capitals identified in the scatter. Panel (a) plots the log of total job postings against the log of employment from the 2019 Prefecture Yearbook. Panel (b) plots the log of average posted wages against the log of average wages from the 2019 Prefecture Yearbooks. Each point represents a prefecture. Linear and quadratic fits are shown for the displayed observations.

Figure A2: Representativeness of job-posting data, compared to Prefecture Yearbooks, by share of university students

(a) Log employment



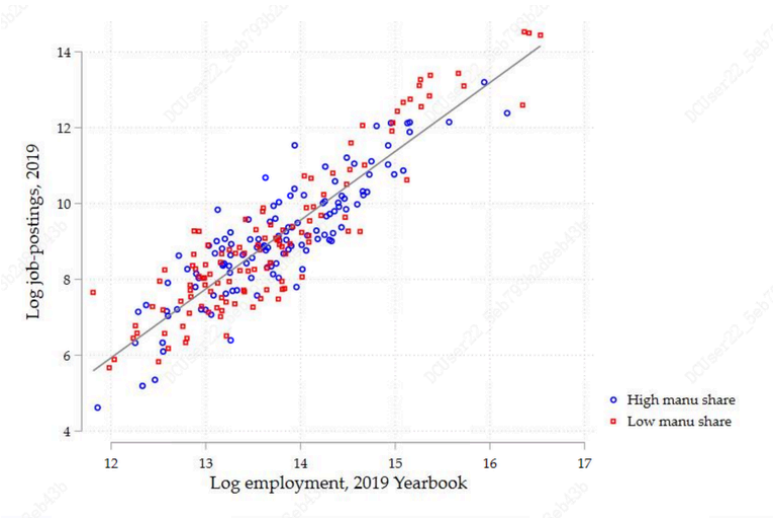
(b) Log wages



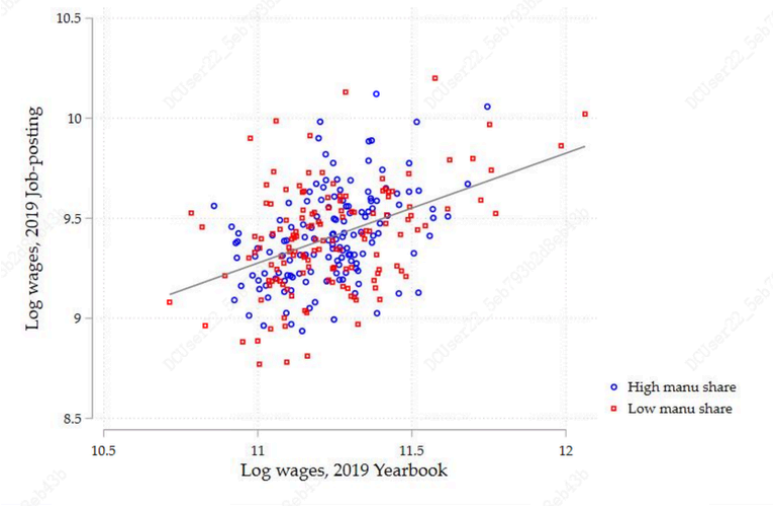
Note: This figure compares the coverage of online recruiting at the prefecture level by the share of university students in the population. Prefectures are split into above- and below-median groups using data from the Prefecture Yearbooks. Each point represents a prefecture, with blue points for the high-share group and red points for the low-share group.

Figure A3: Representativeness of job-posting data, compared to Prefecture Yearbooks, by share of manufacturing

(a) Log employment



(b) Log wages



Note: This figure compares the coverage of online recruiting across sectors. Prefectures are grouped by whether their share of GDP from the manufacturing sector is above or below the national median, based on the 2019 City Yearbooks. Points represent prefectures, with blue points shown for high-share groups, and red points for low-share groups.

Table A2: Summary Statistics

Variables	Obs	Mean	Std.Dev	Min	Max
Panel A. Variables at the city-industry-monthly level (full sample)					
Job Posting	899,481	38.18	508.96	0	78,166
Vacancies	899,481	227.34	4882.50	0	1,216,599
Firm count	899,481	8.00	88.04	0	9,987
Years of education	337,294	11.04	4.58	0	21
Minimum work experience	337,294	1.93	1.33	0	10
Wage	337,294	8134.41	10356.21	105	945,909.1
Shock to mobility	899,481	-0.79	0.95	-3.86	4.09
Task contents (based on O*NET)					
Non-routine cognitive analytic	330,612	-0.01	0.58	-2.46	2.16
Non-routine cognitive interactive	330,612	0.15	0.61	-2.85	2.81
Routine cognitive	330,612	-0.14	0.46	-2.67	3.12
Routine manual	330,612	-0.29	0.57	-1.86	2.26
Non-routine manual physical	330,612	-0.24	0.56	-1.78	2.22
Panel B. Variables at the job-posting level (subsample of text analysis)					
Vacancies	770,102	6.63	41.67	0	999
Years of education	770,090	11.43	6.38	0	21
Minimum work experience	758,671	1.80	1.99	0	10
Wage	757,877	10326.35	8370.85	2,400	60,000
Shock to mobility	770,102	-1.25	1.04	-3.86	4.09
Task contents (based on O*NET)					
Non-routine cognitive analytic	689,189	-0.02	0.95	-2.46	2.15
Non-routine cognitive interactive	689,189	0.12	1.01	-2.85	2.81
Routine cognitive	689,189	-0.15	0.80	-2.67	3.12
Routine manual	689,189	-0.31	0.91	-1.86	2.26
Non-routine manual physical	689,189	-0.25	0.92	-1.78	2.22

Note: This table summarizes the key features of the data. Panel A shows the summary statistics of variables at the city-industry-monthly level. The sample includes 281 prefectural cities and 97 two-digit industries from January 2020 to December 2022. Panel B shows the summary statistics of variables at the job-posting level from the subsample used in the text analysis. The sample includes 770,102 job posts randomly drawn from the full sample.

Table A3: Representativeness of vacancy posting data at the prefecture level, employment and wages, compared to data from prefecture yearbooks, regression results

Panel A: Log Job-postings				
Variables	(1) All three years	(2) 2015	(3) 2017	(4) 2019
Log employment, Yearbook	1.922***	1.983***	1.964***	1.814***
	(0.035)	(0.061)	(0.061)	(0.057)
Constant	-18.219***	-18.960***	-17.870***	-15.828***
	(0.0474)	(0.835)	(0.830)	(0.783)
Observations	1,124	281	281	281
R-squared	0.811	0.799	0.798	0.810
Panel B: Log wages, job-posting				
Variables	(1) All three years	(2) 2015	(3) 2017	(4) 2019
Log wages, Yearbook	0.644***	0.878***	0.509***	0.549***
	(0.060)	(0.146)	(0.082)	(0.069)
Constant	2.404***	-0.141	3.439***	3.235***
	(0.655)	(1.590)	(0.911)	(0.780)
Observations	1,124	281	281	281
R-squared	0.268	0.115	0.120	0.183
Year FE	Y	NA	NA	NA

Note: This table reports the regression comparisons corresponding to Figure 1. Panel A regresses log job-posting counts on log employment from Prefecture Statistical Yearbooks. Panel B regresses log average posted wages on log average yearbook wages. The pooled regressions include year fixed effects. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Correlation of Mobility Shocks with COVID and GDP

Panel A: Monthly correlation of mobility shock with COVID			
Dep. Var.	Mobility Shock		
	(1)	(2)	(3)
Log Confirmed Cases	0.109***		0.091***
	(0.009)		(0.009)
Stringency Index		0.015***	0.014***
		(0.001)	(0.001)
Observations	11,088	11,088	11,088
R-squared	0.702	0.714	0.716
Prefecture FE	Y	Y	Y
Year-Month FE	Y	Y	Y
Panel B: Annual correlation of difference in mobility with GDP			
Dep. Var.	Diff in Mobility		
	(4)	(5)	(6)
Diff in GDP	3.675***	5.216***	0.825***
	(0.184)	(0.140)	(0.253)
Observations	843	843	843
R-squared	0.322	0.842	0.906
Prefecture FE	N	Y	Y
Year FE	N	N	Y

Note: This table examines the correlation of mobility shocks on government policies, confirmed cases and annual GDP. In Panel A, local disruption is the negative change in within-prefecture mobility defined in equation (1). Stringency Index is sourced from the Oxford COVID-19 Government Response Tracker. In Panel B, Difference in mobility and GDP are calculated as the difference between its annual average in 2020, 2021, and 2022, compared to its 2019 annual average at the city level. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: COVID-19 Stringency Index

ID	Description	Coding
C1	Closings of schools and universities	0 - no measures 1 - recommend closing or all schools open with alterations 2 - require closing (only some levels or categories, eg just high school) 3 - require closing all levels
C2	Closings of workplaces	0 - no measures 1 - recommend closing or all businesses open with alterations 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) for all-but-essential workplaces
C3	Cancelling of public events	0 - no measures 1 - recommend canceling 2 - require cancelling
C4	Cut-off size for limits on gatherings	0 - no restrictions 1 - restrictions on very large gatherings (the limit is above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less
C5	Closing of public transport	0 - no measures 1 - recommend closing (or significantly reduce volume/route/means of transport) 2 - require closing (or prohibit most citizens from using it)
C6	Orders to "shelter-in-place" and otherwise confine to the home	0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for 'essential' trips 3 - require not leaving house with minimal exceptions
C7	Restrictions on internal movement between cities/regions	0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place
C8	Restrictions on international travel	0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure

Note: This table lists containment and closure policy components C1–C8 from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021).

B Additional Empirical Results

B.1 Additional Specifications for Recruiting Outcomes

Table B1: Recruiting Outcomes with Prefecture-by-Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	IHS Job Postings	IHS Vacancies	IHS Firm Count	Years of Education	Min Work Experience	Log Wage
Local disruption	-0.066***	-0.065***	-0.045***	0.109***	0.019***	-0.011**
	(0.004)	(0.005)	(0.003)	(0.018)	(0.005)	(0.005)
Observations	899,481	899,481	899,481	337,294	337,294	337,294
R-squared	0.624	0.558	0.658	0.174	0.128	0.260
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Local disruption	0.013***	0.010***	-0.000	-0.004*	-0.008***	
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	
Observations	330,612	330,612	330,612	330,612	330,612	
R-squared	0.081	0.068	0.054	0.147	0.114	

Note: This table presents regression results examining the effects of COVID-19 mobility disruptions with labor market outcomes and task contents, replacing the prefecture fixed effects and province-by-year fixed effects in Table 3 with prefecture-by-year fixed effects. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for industry fixed effects, prefecture-by-year fixed effects, and time fixed effects. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2: Recruiting Outcomes with Industry-by-Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	IHS Job Postings	IHS Vacancies	IHS Firm Count	Years of Education	Min Work Experience	Log Wage
Local disruption	-0.063***	-0.064***	-0.044***	0.087***	0.018***	-0.000
	(0.004)	(0.005)	(0.003)	(0.018)	(0.005)	(0.005)
Observations	899,481	899,481	899,481	337,294	326,710	336,724
R-squared	0.625	0.559	0.660	0.174	0.128	0.261

	(7)	(8)	(9)	(10)	(11)
Dep. Var.	NRCA	NRCI	RC	RM	NRMP
Local disruption	0.009***	0.007***	0.001	0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	330,612	330,612	330,612	330,612	330,612
R-squared	0.081	0.068	0.054	0.147	0.114

Note: This table presents regression results examining the effects of COVID-19 mobility disruptions on labor market outcomes and task contents, replacing the industry fixed effects in Table 3 with industry-by-year fixed effects. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns also control for prefecture fixed effects, year-month fixed effects, and province-by-year fixed effects. Robust standard errors in parentheses are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B3: Recruiting Outcomes Measured Relative to Early 2019

Dep. Var.	(1) Δ IHS Job Postings	(2) Δ IHS Vacancies	(3) Δ IHS Firm Count	(4) Δ Years of Education	(5) Δ Min Work Experience	(6) Δ Log Wage
Local disruption	-0.057***	-0.059***	-0.038***	0.078***	0.017***	-0.001
	(0.004)	(0.004)	(0.003)	(0.018)	(0.005)	(0.004)
Observations	899,481	899,481	899,481	304,322	304,322	304,322
R-squared	0.108	0.157	0.157	0.066	0.039	0.098
Dep. Var.	(7) Δ NRCA	(8) Δ NRCI	(9) Δ RC	(10) Δ RM	(11) Δ NRMP	
Local disruption	0.008***	0.008***	-0.001	0.000	-0.004*	
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	
Observations	297,874	297,874	297,874	297,874	297,874	
R-squared	0.055	0.036	0.025	0.067	0.070	

Note: This table presents regression results examining the effects of local mobility disruptions with labor market outcomes and task contents, using difference of outcome variables. $Y_{i,k,t}$ represents a labor market outcome of interest in prefecture i, two-digit industry k, and time (year-month) t, spanning from January 2020 to December 2022. The difference (Δ) is calculated relative to the baseline period, defined as the average of January, February, and March 2019. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B4: Recruiting Outcomes with Two-Way-Clustered Standard Errors

Variables	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.063***	-0.064***	-0.044***	0.087***	0.018***	0.000
	(0.006)	(0.007)	(0.005)	(0.020)	(0.005)	(0.005)
Observations	899,481	899,481	899,481	337,294	326,710	336,724
R-squared	0.623	0.557	0.658	0.171	0.125	0.250
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.009***	0.007***	0.001	0.001	-0.003	
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	
Observations	330,612	330,612	330,612	330,612	330,612	
R-squared	0.077	0.065	0.051	0.143	0.110	

Note: This table reports local-disruption estimates with standard errors two-way clustered at the prefecture and two-digit-industry level. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture (city), year-month, and two-digit industry fixed effects. Two-way-clustered standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B5: Local Disruptions and Export Growth in Cells with Positive Postings

Variables	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count
	Panel A: Baseline		
Local disruption	-0.066***	-0.067***	-0.050***
	(0.004)	(0.006)	(0.004)
Observations	337,298	337,298	337,298
R-squared	0.606	0.520	0.688
	Panel B: Export Growth and Local Disruptions		
Local disruption	-0.050***	-0.042***	-0.046***
	(0.006)	(0.008)	(0.005)
Δ Log Export Value	0.010***	0.014***	0.007***
	(0.003)	(0.005)	(0.002)
Local disruption	0.007***	0.009***	0.005***
$\times \Delta$ Log Export Value	(0.003)	(0.004)	(0.002)
Observations	111,254	111,254	111,254
R-squared	0.545	0.451	0.652

Note: This table examines the effects of mobility disruption on labor market and the buffering effect of exports, by excluding city-industry-monthly observations with zero job-postings. Panel A checks the robustness of baseline, Panel B checks the buffering effect of export. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. All columns control for prefecture fixed effects, year-month fixed effects, two-digit industry fixed effects, and province-by-year fixed effects. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.2 Additional Heterogeneity and Trade Specifications

Table B6: Local Disruptions and Recruiting, by Work-from-Home Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	IHS Job Postings	IHS Vacancies	IHS Firm Count	Years of Education	Min Work Experience	Log Wage
Local disruption	-0.063***	-0.064***	-0.044***	0.087***	0.019***	-0.011
	(0.004)	(0.005)	(0.003)	(0.018)	(0.005)	(0.011)
Local disruption	-0.023***	-0.035***	-0.017***	-0.004	-0.012***	-0.003
× WFH Intensity	(0.004)	(0.005)	(0.003)	(0.013)	(0.004)	(0.003)
Observations	899,481	899,481	899,481	337,294	326,710	336,724
R-squared	0.623	0.557	0.658	0.171	0.125	0.227
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Local disruption	0.009***	0.008***	0.001	0.002	-0.003	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Local disruption	-0.000	-0.007***	-0.004***	-0.006***	-0.000	
× WFH Intensity	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	
Observations	330,612	330,612	330,612	330,612	330,612	
R-squared	0.077	0.065	0.051	0.143	0.110	

Note: This table examines whether the effects of the COVID-19 mobility disruption vary with the work-from-home (WFH) feasibility of the occupation/industry. WFH Intensity is standardized (z-score) across all industries. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, year-month fixed effects, two-digit industry fixed effects, and province-by-year fixed effects. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B7: Local Disruptions and Recruiting: Firms Registered after 2020

Dep. Var.	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.071***	-0.077***	-0.047***	0.103***	0.012	-0.002
	(0.008)	(0.009)	(0.005)	(0.032)	(0.008)	(0.007)
Observations	971,136	971,136	971,136	135,758	127,636	135,606
R-squared	0.416	0.343	0.442	0.161	0.159	0.285
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.010***	0.007*	-0.003	-0.001	-0.005	
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	
Observations	132,188	132,188	132,188	132,188	132,188	
R-squared	0.097	0.082	0.065	0.135	0.123	

Note: This table examines the relationship between local mobility disruptions and recruiting outcomes, using the subsample of firms newly registered after 2020 (based on firm registry data). Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, year-month fixed effects, and two-digit industry fixed effects; province-by-year fixed effects are not included. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B8: Local Disruptions and Recruiting: Firms Registered before 2020

Dep. Var.	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Local disruption	-0.054***	-0.050***	-0.035***	0.082***	0.019***	0.001
	(0.004)	(0.005)	(0.003)	(0.017)	(0.005)	(0.005)
Observations	981,252	981,252	981,252	348,598	338,851	347,971
R-squared	0.611	0.554	0.644	0.125	0.116	0.248
Dep. Var.	(7) NRCA	(8) NRCI	(9) RC	(10) RM	(11) NRMP	
Local disruption	0.008***	0.007***	-0.000	0.002	-0.002	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Observations	341,517	341,517	341,517	341,517	341,517	
R-squared	0.071	0.061	0.048	0.149	0.113	

Note: This table examines the relationship between local mobility disruptions and recruiting outcomes, using the subsample of incumbent firms registered before 2020 (based on firm registry data). Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, year-month fixed effects, and two-digit industry fixed effects; province-by-year fixed effects are not included. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B9: Alternative Measures of Export Growth and Importer Demand

Variables	(1) IHS Job Postings	(2) IHS Vacancies	(3) IHS Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Panel A: Own-Province Industry Export Growth						
Local disruption	-0.061***	-0.059***	-0.044***	0.110***	0.019**	-0.003
	(0.006)	(0.006)	(0.004)	(0.026)	(0.008)	(0.004)
Export growth (own)	0.010***	0.014***	0.007***	0.014	-0.009	0.001
	(0.003)	(0.003)	(0.002)	(0.019)	(0.008)	(0.003)
Local disruption	0.010***	0.012***	0.008***	0.007	-0.001	0.002
× Export growth (own)	(0.002)	(0.003)	(0.001)	(0.014)	(0.005)	(0.002)
Observations	261,330	261,330	261,330	111,252	109,368	111,037
R-squared	0.608	0.531	0.656	0.098	0.073	0.184
Panel B: Trading-Partner Import Demand						
Local disruption	-0.061***	-0.054***	-0.044***	0.112***	0.020**	-0.002
	(0.006)	(0.006)	(0.004)	(0.025)	(0.008)	(0.004)
Importer demand	0.006***	0.006***	0.005***	0.004	-0.006*	0.001
	(0.001)	(0.001)	(0.001)	(0.010)	(0.004)	(0.001)
Local disruption	0.008***	0.006***	0.006***	0.005	-0.004**	-0.000
× Importer demand	(0.001)	(0.001)	(0.001)	(0.005)	(0.002)	(0.001)
Observations	277,530	277,530	277,530	117,616	115,706	117,388
R-squared	0.605	0.530	0.654	0.097	0.072	0.182

Note: This table reports recruiting relationships using alternative measures of external market conditions. Panel A uses the year-over-year change in log export value of the focal province at the two-digit industry level. Panel B uses annual log import growth in trading-partner countries at the two-digit industry level, weighted by the province's 2019 export-destination shares. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wage, and are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture (city), year-month, and two-digit industry fixed effects; province-by-year fixed effects are not included. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.3 Pre-Pandemic Outcome Comparisons

Table B10: Pre-Pandemic Recruiting Outcomes and Subsequent Mobility Disruptions

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	IHS Job Postings	IHS Vacancies	IHS Firm Count	Years of Education	Min Work Experience	Log Wage
Local disruption	-0.001	-0.002	-0.002	0.0012	0.010**	0.002
	(0.004)	(0.005)	(0.003)	(0.015)	(0.005)	(0.003)
Mean (s.d.) of Y	1.2 (1.9)	1.5 (2.4)	0.8 (1.3)	10.1 (4.5)	1.4 (1.2)	8.8 (0.7)
Observations	899,481	899,481	899,481	321,870	321,870	321,870
R-squared	0.624	0.599	0.660	0.097	0.107	0.187
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Local disruption	-0.000	0.001	-0.000	0.000	0.001	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Mean (s.d.) of Y	0.2 (0.5)	0.3 (0.6)	-0.1 (0.5)	-0.5 (0.5)	-0.5 (0.5)	
Observations	316,678	316,678	316,678	316,678	316,678	
R-squared	0.065	0.057	0.061	0.132	0.084	

Note: This table compares recruiting outcomes from 2016–2018 with subsequent mobility disruptions measured in 2020–2022. Columns (1-3) outcomes are the inverse hyperbolic sine transformations of the total number of job postings, vacancies and firms. Columns (4-6) outcomes are the average required years of education, minimum work experience, and log wages. Columns (7-11) outcomes are skill contents in terms of non-routine cognitive analytical (NRCA), non-routine cognitive interactive (NRCI), routine cognitive (RC), routine manual (RM), and non-routine manual physical (NRMP) tasks. Columns (4-11) are restricted to prefecture–industry–month cells with at least one job posting. All columns control for prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects. The mean (s.d.) of mobility disruption is -0.8 (1.0) in Columns (1)-(3), -1.0 (1.0) in Columns (4)-(6), -1.0 (1.0) in Columns (7)-(11). Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.