Economic Downturns, Skill Upgrading, and Export-Led Resilience

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Abstract

Economic downturns reshape labour markets by altering both the quantity and composition of labour demand. Using 122 million online vacancy postings and mobility data from China during the COVID-19 pandemic, we study medium-term labour market adjustment. Reduced mobility led to fewer vacancies, higher education and experience requirements, and increased demand for non-routine cognitive skills, particularly in the service sector and second-tier prefectures. Export demand mitigated these effects, stabilising employment and enabling incumbent firms, especially in manufacturing, to offer competitive wages. These findings reveal how recessions accelerate shifts in skill demand and highlight the role of global trade in buffering domestic economic shocks.

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Non-Technical Summary

Economic downturns exert a profound and multifaceted influence on labour markets, reshaping both the quantity and composition of labour demand. In this paper, we leverage an extensive dataset, 122 million online vacancy postings combined with high-frequency geographic mobility data, to analyse medium-term labour market adjustment in China during the COVID-19 pandemic. Our study is among the first to explore these dynamics in a developing country context, where reliable administrative labour market data is often scarce, and where economic structures and adjustment patterns may differ markedly from those observed in developed economies.

We construct our dataset using vacancy postings from three major job boards in China, which are particularly popular among high-skilled job seekers in the service sector. These postings contain detailed information on wages, education requirements, and work experience. We measure skill requirements, mapping occupations to associated skill demands. We further conduct text analysis of job descriptions to extract within-occupation skill content. To ensure representativeness, we compare the geographic, industry, and occupational distributions in our dataset with census and yearbook data, finding strong alignment with broader labour market patterns.

To capture the severity of the recession at the prefecture level, we employ changes in within-prefecture mobility derived from the Baidu Mobility Map. Baidu, a leading provider of mapping and navigation services in China, collects mobility data through mobile phone location services. This allows us to track human movement both between and within cities. During the pandemic, stringent mobility restrictions, including the national lockdown in early 2020 and the Shanghai lockdown in April 2022, sharply curtailed within-prefecture movement. We find that higher local COVID-19 case numbers and more restrictive government policies are strongly associated with greater reductions in mobility. These mobility changes provide us with a reliable proxy for the intensity of economic disruption across regions.

Our analysis documents clear shifts in labour market conditions from 2020 to 2022. In harder-hit prefectures, we observe fewer vacancy postings, fewer firms recruiting, and fewer job opportunities overall. Job requirements became more stringent, with employers demanding higher educational attainment and longer prior work experience. There is also a notable shift toward non-routine cognitive skills, particularly analytical and interactive tasks, accompanied by a decline in demand for routine cognitive skills. This skill upgrading was driven primarily by service sector firms and was most pronounced in second-tier prefectures, which likely possess greater potential for both technological adoption and skill-related advancement compared to Tier-1 urban centers.

The impacts of mobility shocks were uneven across firm types. We find that new entrant firms were disproportionately affected, with hiring activity significantly suppressed during periods of high mobility restriction. Incumbent firms displayed greater adaptability and resilience, maintaining recruitment more effectively under adverse conditions.

We then examine the role of export growth as a buffer during the pandemic-induced recession. Our findings show that rising export demand mitigated the negative impact of mobility shocks on labour markets. Export-driven prefectures experienced more stable aggregate labour demand, with increases in vacancies, postings, and hiring firms. Incumbent firms in the manufacturing sector were able to leverage expanding international markets to offer competitive wages and attract higher-skilled workers.

Our results diverge from those reported in developed economy contexts that have found recessions often facilitate routine-biased technological change through machinery adoption. In contrast, within China during COVID-19, skill upgrading was concentrated in the service sector, and manufacturing exhibited minimal technological change. These differences underscore the importance of considering structural economic distinctions between developing and developed countries when interpreting labour market responses to recessions.

Overall, our study demonstrates that online vacancy posting data, combined with fine-grained mobility information, provides new opportunities to examine labour market dynamics where traditional administrative sources are limited. Our findings reveal that recessions accelerate shifts in skill demand, while export-led growth plays a critical role in cushioning labour demand and stabilising wages.

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Abstract

Economic downturns reshape labor markets by altering both the quantity and composition of labor demand. Using 122 million online vacancy postings and mobility data from China during the COVID-19 pandemic, we study medium-term labor market adjustment. Reduced mobility led to fewer vacancies, higher education and experience requirements, and increased demand for non-routine cognitive skills, particularly in the service sector and second-tier prefectures. Export demand mitigated these effects, stabilizing employment and enabling incumbent firms, especially in manufacturing, to offer competitive wages. These findings reveal how recessions accelerate shifts in skill demand and highlight the role of global trade in buffering domestic economic shocks.

Keywords: Recession, Skills, Within-Prefecture Mobility, Export, Covid-19 Pandemic.
JEL codes: J21, J23, J61, O33, R12, I18.

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1 Introduction

Economic recessions have significant impacts on labor markets, both in the short and long term. In the short term, labor supply is influenced by changes in household income and the opportunity costs of pursuing education, while labor demand is shaped by fluctuations in consumer demand for goods and the cost of production inputs. In the medium to long term, firms may adopt new technologies in response to shifting opportunity costs, which can lead to changes in skill requirements (Hershbein and Kahn 2018). Additionally, cohorts entering the labor market during recessions face both immediate and lasting consequences, including reduced career opportunities and lifetime income losses (Oreopoulos et al. 2012; Schwandt and Von Wachter 2019). These dynamics highlight the far-reaching effects of economic downturns on individual workers and broader labor market structures.

In this paper, we examine the medium-run impact of a recession on labor market conditions in a developing country context, using job vacancy postings during the COVID-19 pandemic as a case study. To measure the severity of the recession across Chinese prefectures, we use reductions in within-prefecture mobility as a proxy. Our findings show that in harder-hit prefectures, there were fewer job vacancy postings, fewer firms recruiting, and fewer overall vacancies. Additionally, posted job vacancies exhibited higher requirements for education and minimum years of work experience. We also observe an increased demand for non-routine cognitive analytical and interactive skills. These shifts were primarily driven by service sector firms and were most pronounced in second-tier prefectures. Lastly, we find that export demand growth counteracted the effects of the recession by stabilizing aggregate labor demand and contributing to wage improvements in the manufacturing sector.

We construct a comprehensive dataset on labor market conditions by utilizing online vacancy postings from three major job boards in China. These platforms are particularly popular among high-skilled job seekers in the service sector. The dataset includes detailed information on wages, education requirements, and work experience. To analyze skill requirements, we develop a concordance between job titles in the postings and the ONET dataset, enabling us to map occupations to their associated skill demands. Additionally, we perform text analysis on a subsample of job postings, focusing on verbs to extract within-occupation skill content. To assess the representativeness of the dataset, we compare the geographic, industry, and occupational distribution of the job postings with census and yearbook data, demonstrating alignment with broader labor market patterns.

We use changes in within-prefecture mobility, derived from the Baidu Mobility Map, to measure the severity of the recession. Baidu, a leading map service provider in China, collects mobility data through mobile phone location services, allowing it to track human movement both between and within cities. During the study period, China implemented strict within-prefecture mobility restrictions, such as the national lockdown in February and March 2020 and the Shanghai lockdown in April 2022. Our analysis shows that higher case numbers and more restrictive government policies are strongly associated with significant reductions in within-prefecture mobility, providing a reliable proxy for the intensity of the economic disruption.

We begin by documenting time trends in vacancy characteristics from 2020 to 2022. During this period, we observe an increase in experience requirements and education requirements and a sharp decline in wages. These patterns align with existing literature, which highlights the disadvantages faced by fresh graduates entering the labor market during a recession. Additionally, there is a notable rise in demand for non-routine cognitive skills, particularly analytical and interactive skills, accompanied by a decline in demand for routine cognitive skills. These trends reflect a shift in labor market preferences toward higher-skill tasks during the recession.

We then use the cross-sectional variation in within-prefecture mobility changes to investigate the impact of recessions on labor demand. Our findings reveal that mobility shocks during the COVID-19 pandemic had a significant negative impact on aggregate labor demand, leading to fewer vacancy postings, fewer overall vacancies, and a decline in the number of hiring firms. Job requirements became more stringent, with increased demand for education and work experience, alongside a shift toward non-routine cognitive skills, particularly analytical and interactive tasks. These effects were most pronounced in the service sector, which played a central role in driving skill upgrading during the crisis. Geographic heterogeneity was evident, with Tier-2 prefectures experiencing the most pronounced skill shifts, likely reflecting their greater potential for technological and skill-related advancements compared to Tier-1 prefectures. Additionally, mobility shocks disproportionately suppressed hiring among new entrant firms, highlighting their vulnerability during economic uncertainty, while incumbent firms demonstrated greater adaptability and resilience. These findings underscore the uneven impact of mobility shocks across sectors, regions, and firm types.

Finally, we examine the buffering effects of international trade growth on labor markets during the pandemic-induced recession. Export growth played a critical role in mitigating the negative impact of mobility shocks, directly boosting labor demand through increased job postings, vacancies, and hiring firms. It also moderated the recession-driven acceleration in skill upgrading, with regions experiencing stronger export growth showing a less pronounced shift toward non-routine cognitive skills, such as analytical and interactive tasks. Instead, these regions exhibited higher demand for non-routine manual physical labor, reflecting the characteristics of export-oriented industries. While export growth provided a demand buffer for both new entrants and incumbent firms, only incumbents were able to leverage this advantage to raise wages, likely due to their greater resilience and ability to attract higher-skilled workers. Overall, these results emphasize the stabilizing role of external demand in offsetting domestic economic disruptions and reveal the uneven capacity of firms to adapt to such shocks.

Our paper contributes to several strands of literature, with the most significant contribution being to research on the impact of recessions on labor market conditions. Prior studies have documented the large and persistent effects of recessions on labor market outcomes, particularly for cohorts entering the labor market during economic downturns (Kahn 2010; Oreopoulos et al. 2012; Schwandt and Von Wachter 2019). For instance, Hershbein and Kahn (2018) examine how recessions accelerate skill-biased technological change, while Kroft et al. (2016) investigate long-term unemployment during the Great Recession, focusing on composition, duration dependence, and nonparticipation. A key contribution of our paper is that it is among the first to examine labor market conditions in developing countries, where reliable administrative labor market data is often scarce. By utilizing major online job posting data from China, we conduct high-frequency analysis of labor market dynamics in a developing country context during the medium run, a period when policy interventions are particularly relevant. Our findings also diverge from studies in developed economies, such as Hershbein and Kahn (2018), who show that machinery adoption facilitates routine-biased technological change. In contrast, we find that skill upgrading during the recession was concentrated in the service sector, while the manufacturing sector experienced minimal technological change. Additionally, we connect to the literature on export dynamics during recessions by leveraging the specific context of international trade as a buffer against economic shocks. Unlike Almunia et al. (2021), who demonstrate that negative domestic demand shocks lead firms to redirect output to international markets, our findings show that positive international demand shocks can offset the adverse effects of domestic recessions on labor markets. This highlights the stabilizing role of external demand in supporting employment and moderating skill shifts during economic downturns.

Our work also contributes to the literature on technological change, particularly studies that utilize job vacancy postings (Atalay et al. 2018; Atalay et al. 2020; Bloom et al. 2021; Acemoglu et al. 2022; Atalay et al. forthcoming), as well as the growing use of high-frequency data to analyze recession dynamics in real time (Forsythe et al. 2020; Chetty et al. 2024; Graziano and Tian 2024). Our study demonstrates that online vacancy posting data, combined with geographic mobility data, offers new opportunities to explore these questions in the context of developing countries, where economic dynamics and labor market structures differ significantly from those in developed economies.

The rest of the paper is organized as follows. In Section 2, we describe the vacancy data. Section 3 describes the nature of the COVID-19-induced recession and how we measure it. Section 4 presents the empirical specification and main results. Section 5 discusses the role of export growth. Section 6 concludes.

2 Vacancy Data

2.1 Overview

We use online vacancy posting data to measure job market performance across prefectures on a monthly basis. We collected data on online job vacancy postings from the three largest online recruitment platforms in China: 51job.com, Zhaopin.com, and Liepin.com. Using a web-scraping algorithm, we obtained the universe of job postings from these platforms spanning the period from January 1, 2015, to December 31, 2022, resulting in a dataset of 165.36 million job vacancy entries. For each entry, the dataset includes information such as the date of the posting, job title, occupation code, number of positions available, wage, education requirements, work experience requirements, firm name, job location, and the full text of the job description.

These three platforms are the largest online recruitment platforms in China, characterized by their early establishment in the market, substantial market share, high web traffic, broad geographic coverage, and comprehensive range of services. Similar to international platforms such as Indeed.com and LinkedIn.com, they provide a wide array of services, including job postings, resume searches, career advice, and HR solutions, catering to both job seekers and employers. For example, the largest platform, 51job.com, was founded in 1998 and currently holds 34.2% of the market share, with 11 million monthly mobile device visits in 2020 and job vacancy listings spanning almost all prefectures across China. Collectively, the three platforms account for approximately two-thirds of the market share in China's online recruitment industry, with a combined monthly mobile device traffic exceeding 24 million.[1]

The primary quality improvement applied to the web-scraped data is the removal of duplicate job postings. Employers often repost the same job ad multiple times or across different locations to increase visibility. While each platform independently checks for and removes false information and duplicate postings, we further eliminate duplicates when consolidating data from the three platforms. Duplicate postings across platforms are identified if they share the same firm name, job title, occupation code, work location, and number of positions available. Since all three platforms require a minimum of one week for firms to update job postings, we identify duplicates across platforms on a weekly basis.

2.2 Vacancy Data Cleaning

Linking with firm registration records We link job vacancy posting entries with firm registration records using firm names to identify firm entry dates, locations, and industries. The

[1] Data source: "2021 China Online Recruitment Industry Market Development Research Report" by iResearch, a leading market consulting firm founded in 2002. Additional details on the history and performance of the three platforms are provided in Appendix A.1.

Firm Registration Database, maintained by China's State Administration for Market Regulation, contains administrative information for the universe of firms in China. This includes the initial registration date, business location, industry code, registered capital, ownership type, and demographic details of the owner. Additionally, the database provides complete shareholding structures and, if applicable, the dates when registrations are revoked or canceled. To merge firm registration data with job vacancy data, we standardized firm names in the vacancy postings to enable a one-to-one match. For entries that initially failed to match, we manually corrected them and cross-referenced historical name-change records to ensure data consistency. Ultimately, we successfully matched 122 million of the 165 million job postings, corresponding to 4.2 million enterprises. This set of entries constitutes the final sample of vacancy postings used in this paper.

Constructing standardized occupation codes First, we construct standardized occupation codes by mapping the platform-specific occupation codes and job titles to the 6-digit Standard Occupational Classification (SOC) codes developed by the U.S. Bureau of Labor Statistics. The SOC codes are widely used in labor market research in the U.S. (e.g., Atalay et al. (forthcoming)) and offer additional advantages, such as integration with the ONET-SOC taxonomy. This taxonomy provides a rich set of variables describing work and worker characteristics, including skill requirements.[2] In total, we obtain 763 unique SOC-6 codes.

A subset of our job posting entries includes occupation classifications assigned by the platforms themselves. These platforms provide approximately 1,360 unique occupations, and we manually construct a mapping between these occupation classifications and the 6-digit SOC codes. This subset accounts for 70.74% of our entries, which we refer to as the labeled entries. For the remaining 29.26% of unlabeled entries, we employ a supervised machine learning approach using a Long Short-Term Memory (LSTM) network to assign SOC codes based on unstructured job titles in the dataset.[3] The labeled entries are used to train the classification model, enabling it to predict SOC codes for the unlabeled postings. The variables used in training the model include text of the job title, firm name, prefecture, year and month. The LSTM model is particularly effective at capturing contextual dependencies and hierarchical structures in professional titles. For instance, it can differentiate between a project manager in construction and one in information technology by analyzing the sequential context of the title.[4]

Through this process, we assign a 6-digit SOC code to all job posting entries, resulting in a total of 383 unique SOC codes.

[2]Details on the ONET-SOC taxonomy can be found at: https://www.onetcenter.org/taxonomy.html#latest.

[3]The likelihood of an entry being labeled is largely influenced by the platform design in specific years. For instance, the share of unlabeled entries is notably higher after 2020.

[4]While more complex large language models face practical constraints when applied to large datasets, the LSTM model achieves high classification accuracy while remaining computationally efficient. Our algorithm achieves a prediction accuracy of 71.9% on the training set.

Measuring job task content We then measure the task content of job using the nature of tasks involved. Following Acemoglu and Autor (2011), we characterize occupations along task intensities along five dimensions: non-routine cognitive analytical (NRCA), non-routine cognitive interpersonal (NRCI), routine cognitive (RC), routine manual (RM), non-routine manual physical (NRMP). To construct task intensities across five dimensions for each occupation, we use occupation-level data on work activities, work context, and abilities importance from the O*NET database, following the methodology outlined by Acemoglu and Autor (2011). For instance, to measure an occupation's intensity in non-routine cognitive analytical tasks, we extract the intensities of three specific items from the work activities: analyzing data/information, thinking creatively, and interpreting information for others. Each occupation is rated on these three activities using a scale from 1 to 5, and we sum these ratings to create an occupation-level composite intensity measure for non-routine cognitive analytical tasks. Finally, we standardize this measure to have a mean of 0 and a standard deviation of 1, allowing for easy comparison of task intensities across occupations. Details of information used to construct the five measures can be found in Appendix Table A1.

Text analysis of job descriptions To further identify the key job activities driving changes in task content, we perform text analysis on the full job descriptions to extract words corresponding to the five composite task dimensions on a subsample of the vacancy postings. We draw a random sample of approximately 2% from the universe of posting entries between January 2019 and December 2022. This random sample includes 770,102 online job postings and is representative of the overall job posting population.[5] Following Spitz-Oener (2006) and further expanded by Atalay et al. (2020), we construct a list of words corresponding to each task intensity dimension: (1) nonroutine analytic (e.g., analyze, design, research), (2) nonroutine interactive (e.g., advise, coordinate, negotiate), (3) nonroutine manual (e.g., repair, serve), (4) routine cognitive (e.g., calculate, measure), and (5) routine manual (e.g., operate, equip). Using vacancy description texts, we extract verbs (and verb-noun combinations in case of ambiguity) and select the top 500 most frequent ones. These top verbs are then mapped to the predefined word lists for the five task categories. At the posting entry level, we count the frequency of words from each of the five dimensions appearing in the job descriptions. To account for variations in document length, we normalize the word frequencies by dividing the raw counts by the logarithm of the total word count of each advertisement.

2.3 Supplementary Datasets

We use two supplementary datasets to assess the representativeness of the online vacancy posting data in relation to overall labor market conditions. The first dataset consists of prefecture statistical

[5]As shown in Panel B of Appendix Table A2, the key descriptive statistics of this subsample are highly consistent with those of the aggregate data presented in Panel A of Appendix Table A2.

yearbooks for 2015, 2017, and 2019, which provide aggregate employment numbers and average wages at the prefecture level. The second dataset is the 1% random sample of individual-level records from the 2015 Mini Population Census, which contain detailed information on education level, employment status, industry, occupation, and geographic location (i.e., prefecture). We restrict the sample to 1 million individuals aged between 15 and 70, with non-missing industry and occupation information. To validate the online vacancy posting data, we aggregate the individual-level census records across these dimensions for comparison.

2.4 Descriptives on Vacancies

Representativeness in terms of region, industry, and occupation A key limitation of the data is its exclusive coverage of online job postings, which, while increasingly widespread, tend to over-represent higher-skilled occupations and industries. However, Bai et al. (2021) linked Burning Glass Technologies (BGT) online job ads to the Job Openings and Labor Turnover Survey at the establishment level and found strong alignment between the two datasets. In China, online platforms are widely used due to their low search costs. For example, Zhaopin.com had 230 million individual subscribers and 6.3 million daily active users by late 2020.[6] The platform's large user base and low recruitment costs have made it a major channel for employers. Job seekers can submit their information online, and the platform automatically generates standardized resumes for desired positions. To validate the representativeness of online job postings, we compared them to labor market variables from population censuses and city yearbooks, finding significant alignment across datasets.

Figure 1 evaluates the representativeness of the vacancy posting data in terms of geographic coverage using data from prefecture yearbooks. Panel (a) compares the aggregated prefecture-level total number of job postings with urban employment data from Prefecture Yearbooks for 2015, 2017, and 2019. Panel (b) compares average wages from the vacancy posting data with average urban wages reported in the Prefecture Yearbooks. Both employment and wage measures from the two datasets exhibit very high correlations, with consistent patterns observed across all years.[7]

Figure 2 evaluates the representativeness of the vacancy posting data in terms of industry and occupation using census data. Panel (a) compares employment composition at the two-digit industry level across 97 industries, grouped by sector. We observe a strong correlation between the number of job postings and employment numbers across all three sectors: agriculture, manufacturing, and services. Panel (b) analyzes employment composition at the broad occupational level (i.e., SOC-2 level), excluding agricultural occupations. The results highlight the tendency of online re-

[6]Data source: "2021 China Online Recruitment Industry Market Development Research Report" by iResearch, a leading market consulting firm founded in 2002.

[7]Corresponding regression results are shown in Table A3.

cruitment platforms to over-represent high-skill industries, such as management, computer science, and finance.

We provide additional evidence on the representativeness of the job vacancy data at the prefecture level in Appendix A.3. Specifically, we analyze the data by: (1) distinguishing provincial capital prefectures from other prefectures in Figure A1, (2) grouping prefectures by average education level (above vs. below the median) in Figure A2, and (3) grouping prefectures by the share of manufacturing GDP (above vs. below the median) in Figure A3.

Trends Figure 3 presents the evolution of labor market outcomes and skill requirements during the 2019–2022 period using the vacancy posting data, encompassing both the onset and recovery phases of the COVID-19 pandemic. Key labor market indicators, including the number of job postings (Panel a), vacancies (Panel b), and number of firms (Panel c), indicate a sharp contraction in early 2020, followed by a gradual yet incomplete recovery through 2022. During this period, wages (Panel d) show a notable decline. Concurrently, minimum work experience and education requirements increase, suggesting a contraction in labor market demand.

Focusing on skill requirements and task content, we observe a rise in demand for non-routine cognitive skills, such as analytic and interactive abilities, alongside a decline in demand for routine cognitive skills. Additionally, demand for manual jobs experienced a modest increase.

Aggregation To examine the impact of the COVID-19 pandemic on labor market conditions in China, we aggregate vacancy posting data at the prefecture-industry-month level. Appendix Table A2 Panel A provides the summary statistics. The sample consists of 281 prefectures, 97 two-digit industries, and 33 months spanning January 2020 to December 2022, resulting in 899,481 prefecture-industry-month observations.[8] On average, the data show 8 firms, 227 vacancies, and 38 job postings per prefecture-industry-month triplet.

For years of education, minimum work experience, and wages, prefecture-industry-month observations with zero job postings are excluded. Regarding task requirements for occupations, the data indicate, on average, a neutral demand for non-routine cognitive interactive skills (mean of -0.07), a bias toward non-routine cognitive analytic-intensive jobs (mean of 0.15), and a negative bias against routine cognitive and manual jobs.[9]

Panel B presents the summary statistics for a random sample consisting of 770,102 online job postings. The analysis indicates that the sample is representative of the overall job posting population, as shown in Panel A, with respect to education, experience requirements, and skill content.

[8] June, July, and August 2020 are excluded from the analysis due to the lack of available mobility data.

[9] The number of observations is smaller for the task requirements, (330,612 compared to 337,294), due to a small number of prefecture-industry cells containing only 1–2 postings with no matching occupancy codes in the O*NET task database.

3 Covid-19 Recession: Background and Measurement

3.1 Background

The COVID-19 pandemic has profoundly impacted global economic development and caused significant loss of life. In response, governments worldwide have implemented nonpharmaceutical interventions to mitigate the spread of the virus (Hsiang et al. 2020; Maier and Brockmann 2020; Chen et al. 2025). These measures, ranging from social distancing to complete lockdowns, have inevitably restricted economic activities, including international trade (Graziano and Tian 2024) and commuting flows (Fajgelbaum et al. 2021).

China was particularly affected by the initial outbreak of COVID-19, prompting the Chinese government to implement stringent top-down lockdowns and other social distancing policies across numerous cities (Fang et al. 2020). The Chinese government rapidly implemented top-down lockdown policies and other social distancing measures across numerous cities. The speed of disease transmission, the severity of the pandemic, and the strictness and duration of lockdown measures varied significantly across Chinese cities. This variation provides an opportunity to analyze geographical differences in the presence and intensity of lockdown policies. In particular, we focus on the pandemic's impact on the labor market, including shifts in firm recruitment behavior, fluctuations in wage levels, and changes in job requirements for workers.

3.2 Using Baidu Mobility Data to Measure Recession

To quantify the extent of recession induced by the COVID-19 pandemic, we use anonymized, aggregated human mobility data from Baidu Maps, the largest map service provider and leading search engine in China. This dataset tracks daily population movements at the prefecture level, including inflow, outflow, and within-prefecture movements, offering valuable insights into shifts in travel patterns during the pandemic.

Our analysis focuses on reductions in within-prefecture mobility as a measure of the recession induced by the COVID-19 pandemic, measured using the indexation of the share of people who leave home for at least 500 meters for more than 30 minutes. Within-prefecture mobility reduction is particularly relevant in the Chinese context because pandemic containment measures, such as "stay-at-home" orders, neighborhood lockdowns, and the suspension of local public transport, were predominantly implemented at the within-prefecture level (Fang et al. 2020; Hale et al. 2021). These measures, combined with the strict enforcement of digital health codes required for accessing workplaces and public spaces, significantly curtailed intra-city movement, as evidenced by the sharp decline in mobility observed in early 2020.[10]

[10]Some background on the digital health code: `https://www.csis.org/blogs/trustee-china-hand/chinas-`

Figure 4 shows the monthly evolution of the within-prefecture mobility index averaged across Chinese prefectures from January 2019 to May 2023. Figure 5 illustrates the spatial heterogeneity of within-prefecture mobility shocks across Chinese prefectures during different phases of the pandemic. These figures show substantial variation both over time and across space in local mobility disruptions.

We construct a "mobility shock" for each prefecture i and month t as the negative of the difference in Baidu Map's within-prefecture mobility index relative to a pre-pandemic baseline at the city-month level. This measure captures the reduction in the intensity of high-frequency population flows before and after the COVID-19 shock, where larger positive values indicate greater declines in mobility. The mobility index from January 2019 ($t = 0$) is used as the baseline for pre-COVID mobility levels.

$$MobilityShock_{i,t} = -(MobilityIndex_{it} - MobilityIndex_{i0}) \tag{1}$$

3.3 Validation of the Mobility Measures

We validate the connection between the mobility shock and pandemic severity, measured by the number of COVID-19 cases and the stringency of policy restrictions. The *Oxford COVID-19 Government Response Tracker* (*OxCGRT*; Hale et al. 2021) compiles data on COVID-19 containment policies globally at both national and sub-national levels. Using the OxCGRT dataset, we obtained information on eight policy measures at the provincial level in China under the containment and closure policies category (C1–C8 in Appendix Table A5). These measures include school and university closures, workplace closures, public transport suspensions, cancellations of public events, stay-at-home orders (C1–C6), restrictions on internal movement between cities or regions (C7), and restrictions on international travel (C8).

We construct a composite stringency measure at the provincial level using these eight policy measures. Each policy measure is assigned a numerical value to reflect its stringency. For example, the mobility restriction indicator is set to 0 if no restrictions are implemented, 1 if the government recommends against traveling across regions, and 2 if cross-region movement is restricted. Following Hale et al. (2021), we construct provincial-level policy indexes by re-scaling each policy measure to its maximum value, creating a score between 0 and 100. Composite policy indicators for each province are then calculated by averaging the re-scaled scores across the C1–C8 sub-policy indexes.

We investigate the relationship between the mobility shock, number of cases, and policy stringency using the following equation:

$$MobilityShock_{i,t} = a_0 + a_1 Log(Cases)_{i,t-1} + a_2 Stringency_{i,t-1} + d_t + S_i + \nu_{i,t} \tag{2}$$

`novel-health-tracker-green-public-health-red-data-surveillance`.

where $Log(Cases)_{i,t-1}$ are confirmed COVID-19 cases in prefecture i in the previous period $t-1$. Lagging accounts for the time between infection spread and policy/mobility responses. $Stringency_{i,t-1}$ measures the stringency of locally enacted containment policies in prefecture i at time $t-1$. Note that since the policy data is at the provincial level, we assume that all prefectures within a province share the same stringency. We control for year-month fixed effects d_t and prefecture fixed effects S_i through all specifications.

Appendix Table A4 presents the correlation between local containment policies, the number of confirmed cases, and the mobility shock. The results indicate that stricter local containment policies are associated with greater reductions in within-prefecture mobility. Additionally, the significant positive coefficient on confirmed cases suggests that higher local caseloads in the preceding period contribute to reduced mobility in the current period. This relationship likely reflects a combination of government-imposed restrictions and voluntary behavioral changes driven by health concerns.

3.4 International Trade During the COVID-19 Pandemic

COVID-19 caused significant contractions in international trade during 2020 and 2021, driven by reductions in both demand and supply, as well as disruptions to transportation networks. Gross exports only returned to pre-pandemic levels from 2019 in 2022.[11] However, exports from China experienced substantial growth during this period, as illustrated in Figure 6, and supported by evidence of an increased share of containership departures from China (Graziano and Tian 2024). China's export growth during the pandemic was driven by a combination of demand and supply factors. On the supply side, policies supporting export production activities allowed manufacturing to continue despite domestic mobility restrictions.[12] On the demand side, larger waves of lockdowns and reduced production capacities in other parts of the world, coupled with a shift in consumer demand from services to manufactured goods, especially in developed countries, contributed to the surge in exports from China.

To measure the significance of China's trade growth during the COVID-19 period, we use province-product-month-level export value data from Chinese Customs.[13] We hypothesize that trade growth may have had a buffering effect on the labor market by acting as a positive external demand shock. While aggregate trade flow data cannot fully disentangle demand and supply factors, we employ several methods to isolate the demand-driven components of trade growth.

[11] Source: Exports of goods and services in constant 2015 USD from `https://data.worldbank.org/indicator/NE.EXP.GNFS.KD`.

[12] See for example, measures taken at the Tesla plant in Shanghai during lockdown that supported production: `https://www.scmp.com/business/companies/article/3179043/beds-factory-floor-and-mobile-toilets-peek-teslas-closed-loop`.

[13] We map HS6 product classifications to 2-digit industries to align with the level of aggregation used in the vacancy posting data.

4 Effects of Recession on Labor market

4.1 Econometric Framework and Identification

We first analyze how the labor market responds to the COVID-19 shock at the prefecture level, using the previously aggregated posting-level records at the prefecture-industry and year-month levels. The empirical specification is:

$$Y_{i,k,t} = \alpha + \beta \,\text{MobilityShock}_{i,t} + \delta_t + \lambda_i + \theta_k + \phi_{p(i),y(t)} + \varepsilon_{ikt}, \tag{3}$$

where $Y_{i,k,t}$ 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. We include time fixed effects δ_t, prefecture fixed effects λ_i, industry fixed effects θ_k, and province-by-year fixed effects $\phi_{p(i),y(t)}$ in all specifications to account for unobserved heterogeneity and temporal trends. Standard errors are clustered at the prefecture level.

We examine three sets of outcomes. First, to evaluate the overall performance of the labor market, we focus on three key indicators: the total number of job postings, the number of personnel in job postings, and the total number of unique firms. These results are based on a balanced prefecture-industry-time sample. We take the logarithm of the dependent variables and impute observations with zero job postings as 1 in the baseline specification.[14]

Second, to examine changes in job characteristics, we analyze requirements related to years of education, minimum work experience, and log wages. These observations are restricted to prefecture-industry-time instances with at least one job posting.

Third, we assess task content using O*NET-based measures of intensity in non-routine cognitive analytical, non-routine cognitive interactive, routine cognitive, routine manual, and non-routine manual physical tasks. Similar to the job characteristics analysis, these observations are restricted to prefecture-industry-time instances with at least one job posting.

Our key identification assumption is that, in the absence of shocks to the mobility index, prefectures would exhibit similar changes in labor market performance, conditional on the fixed effects. While this assumption is not directly testable, we provide evidence consistent with the absence of pre-trends by regressing changes in the outcome variables during the 2016–2018 period, rather than the 2020–2022 period. Specifically, instead of using labor market outcomes from 2020 to 2022 as in the baseline results, we regress labor market outcomes from 2016 to 2018, four years prior to the shock, on mobility shocks calculated for the 2020–2022 period. The results of this analysis are presented in Table 1. We find no statistically significant evidence of pre-trends in almost all

[14] In the empirical results section, we demonstrate the robustness of the results by employing alternative treatments for zero posting observations, including dropping them and using inverse hyperbolic sine transformations.

outcome variables.[15]

4.2 Main Empirical Results

Aggregate labor demand Columns (1) to (3) of Table 2 examine the effect of mobility shocks on labor market outcomes, specifically the number of job postings, the number of vacancies, and the number of firms. The results indicate that mobility shocks significantly reduce labor demand. Column (1) shows a statistically significant impact of mobility shocks on the number of job postings, where a one-standard-deviation increase in within-prefecture mobility shock (0.95) leads to a 5.7% larger reduction in job postings. Similar effects are observed in Columns (2) and (3): a one-standard-deviation increase in the mobility shock reduces the number of vacancies by 5.9% and the number of hiring firms by 3.8%. These consistent patterns, both in magnitude and statistical significance, suggest that the demand side of the labor market is more adversely affected in prefectures experiencing larger within-prefecture mobility shocks.

Job requirements and compensation Columns 4 to 6 of Table 2 presents the effect on job requirements and wages. In Column (4), education requirements increase by 0.087 years for a prefecture-industry-month observation experiencing a one-standard-deviation larger mobility shock, compared to an average education requirement of 11 years. Similarly, in Column (5), a one-standard-deviation increase in the mobility shock leads to an additional 0.018 years of work experience required, relative to an average experience requirement of approximately 1.9 years in the sample. These findings suggest a shift toward hiring more educated and experienced workers. During economic recessions, firms may prefer experienced workers to minimize training costs and reduce production disruptions. These results highlight significant upskilling effects in firms' hiring behavior during economic downturns, providing evidence that firms become more selective when labor, particularly skilled labor, becomes more abundant.

The effect on log wages, as shown in Column (6), is not statistically significant. The net effect on wages reflects the interplay between a decline in labor supply, as proxied by the mobility shock, and a reduction in labor demand, as captured in the first three columns. Overall, wages remain similar in locations experiencing large supply shocks, suggesting that the supply and demand effects may offset each other. It is worth noting that the overall wage level during this period was lower compared to the pre-pandemic period.

[15] This holds across Columns 1 to 11, except for Column 5, where minimum work experience is used as the outcome variable. The coefficient of minimum work experience with respect to mobility shocks in column 5 is 0.010 in Table 1, compared to 0.018 in Table 2. This suggests that, even if some level of pre-trend effects exists, the requirements for minimum work experience increased further following the mobility shock.

Task contents Columns (7) to (11) of Table 2 examine the effect of mobility shocks on skill-specific requirements. The results indicate that mobility shocks significantly increase the demand for non-routine cognitive analytical skills and non-routine cognitive interactive skills. Specifically, as shown in Columns (7) and (8), a one-standard-deviation increase in the mobility shock leads to a 0.009-standard-deviation increase in the intensity of non-routine cognitive analytical skills and a 0.007-standard-deviation increase in the intensity of non-routine cognitive interactive skills.

In contrast, we find no significant effects on the demand for routine cognitive, routine manual, or non-routine manual physical skills. These findings on skill upgrading differ from those in Hershbein and Kahn (2018), where routine cognitive demand increased substantially due to the complementary adoption of capital. However, our data does not directly capture capital adoption, preventing us from explicitly examining the complementarity between labor skills and capital. One possible explanation for the decreased demand for routine cognitive skills is that these skills are highly complementary to machines and automation. During the pandemic, however, firms may have faced financial constraints that limited their ability to invest in machinery upgrades. Additionally, we find that the observed changes in skill demand are primarily driven by the service sector rather than the manufacturing sector in the later section.

We complement the aggregate analysis with posting-level evidence based on keyword analysis. Instead of relying on the full sample of job postings, we use text analysis results from a subsample of postings, focusing on verbs in the text to identify skill requirements. Table 3 examines the effect of mobility shocks on specific skill requirements by decomposing the five broad skill categories into their most representative high-frequency verbs. The dependent variable is the verb frequency per posting multiplied by 1,000, normalized by $\log(1 + \text{text length})$. Taking "analyze" as an example, given an average job posting length of 253 characters, a one-unit increase in the mobility shock leads to a 1.3% increase (0.687/53.3) in its frequency relative to the mean.

This granular analysis confirms that the demand for non-routine cognitive analytical skills increased across the board (Panel A). Specifically, mobility shocks led to higher demand for tasks such as "analyze," "design," and "develop," suggesting that firms responded to the shock by seeking workers capable of re-evaluating and redesigning business processes.

In contrast, the results for interactive skills reveal a clear shift (Panel B). While the demand for tasks like "sell" and "communicate" decreased, there was a significant rise in demand for tasks such as "recruit" and "operate." This indicates that firms moved away from traditional face-to-face sales activities and instead prioritized internal restructuring and digital operations.

For routine and manual tasks, the effects are predominantly negative or insignificant (Panels C, D, and E). Tasks such as "calculate," "equipment operation," and "maintain" experienced declines. These findings confirm that mobility shocks triggered a genuine shift in labor demand, favoring high-level analytical skills over routine or physical labor.

4.3 Heterogeneity

We further investigate the heterogeneity of effects by sectors, across prefectures of different sizes, and by firm tenure.

Sector We divide all job posting observations into manufacturing and service sectors and separately aggregate them to the prefecture-industry-month level. The results reveal notable differences in how the two sectors responded to the mobility shock (Table 4 and Table 5). The service sector experienced a more pronounced decline in labor demand compared to manufacturing. Specifically, a one-standard-deviation increase in the mobility shock led to a 6.7% reduction in job postings and a 7.2% reduction in vacancies in the service sector, compared to 5.3% and 4.8% in manufacturing, respectively. Similarly, the number of hiring firms fell more sharply in the service sector (-4.4%) than in manufacturing (-3.7%).

In terms of job requirements, both sectors exhibited significant increases in hiring criteria, with higher requirements for years of education and work experience. The magnitude of these adjustments was slightly larger in manufacturing for both education and work experience.

The two sectors also diverged in terms of skill demand. The service sector showed a clear shift toward non-routine cognitive skills. The demand for non-routine cognitive analytical and non-routine cognitive interactive skills increased significantly (with coefficients of 0.009 and 0.007, respectively, both significant at the 1% level, Table 5 Columns 7 and 8). In contrast, the manufacturing sector showed no statistically significant changes in demand for any of the five skill categories (Table 4 Columns 7 to 11).

This sectoral heterogeneity suggests that the pandemic-induced recession primarily accelerated skill-biased changes within the service sector. The increased necessity for remote work, digital customer interactions, and analytical problem-solving in a disrupted environment likely drove this heightened demand for non-routine cognitive skills. In contrast, the absence of a similar shift in manufacturing may reflect its differing exposure to lockdowns, since some plants remained operational, or, as hypothesized earlier, constraints on firms' ability to simultaneously invest in physical capital and high-skill labor during the crisis.

Prefecture size The impact of the mobility shock also varied systematically with the size of the prefecture and its level of economic development, as shown by interactions with prefecture-tier dummies in Table 6. Prefectures are classified into tiers by the National Bureau of Statistics, with four tier-1 prefectures and 31 tier-2 prefectures.[16] The negative impact on aggregate labor demand

[16]Tier 1 cities include Beijing, Shanghai, Guangzhou, and Shenzhen, and tier 2 cities include 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.

was most pronounced in tier-1 prefectures. The coefficients for tier-1 prefectures are large and negative, indicating that these major metropolitan hubs, which are likely characterized by denser service economies, were hit hardest by the demand shock. Tier-2 prefectures also experienced significant contractions, though the magnitude was smaller. Prefectures with smaller populations and less economic activity experienced the least severe impacts.

The pattern of skill demand changes, however, is inversely related to prefecture tier. As shown in Columns 7 to 11 of Table 6, despite experiencing the largest demand shock, tier-1 prefectures did not exhibit significant changes in demand for any of the five skill types. This may suggest that their labor markets were already highly skill-intensive, leaving limited room for further within-crisis upgrading, or that the shock affected all skill groups uniformly. In contrast, tier-2 and smaller prefectures were the primary drivers of the aggregate skill shift. Both Tier-2 and smaller prefectures showed significant increases in demand for non-routine cognitive analytical and non-routine cognitive interactive skills.

This heterogeneity across prefecture tiers highlights that the recession's impact on labor markets was not geographically uniform. Tier-1 prefectures experienced the deepest cuts in labor demand, while tier-2 and smaller prefectures were the main sites where the recession catalyzed a shift in labor demand toward non-routine cognitive skills. This may reflect a process of catch-up or adaptation in these smaller prefectures, where firms used the crisis as an opportunity to restructure toward more skill-intensive technologies that had already been widely adopted in tier-1 prefectures.

Firm tenure We further investigate whether the impact of the recession differed between new firms entering the job market during the crisis and established firms operating prior to the crisis (Tables 7 and 8). Incumbents are defined as firms that posted job vacancies on the online platforms prior to 2020, while new entrants are those that began posting only after 2020. We find that new entrant firms were significantly more vulnerable to the mobility shock, experiencing larger declines in job postings, vacancies, and hiring activity compared to incumbents. While both groups raised their education requirements, only incumbents significantly increased their demand for work experience. Notably, both new entrants and incumbents contributed to the shift toward non-routine cognitive skills, suggesting that skill upgrading was a widespread response among hiring firms, regardless of their tenure in the market.

4.4 Robustness Check

We conduct several robustness checks using alternative specifications.

First, we test whether our results are sensitive to the choice of fixed effects used to capture local time trends. In Appendix Table B1, we replace the baseline province-by-year fixed effects with more stringent prefecture-by-year fixed effects. This specification accounts for any prefecture-specific annual shocks that could be correlated with both mobility changes and labor market outcomes. The results remain qualitatively unchanged and statistically significant. The mobility shock continues to negatively affect labor demand, increase education requirements, and raise demand for non-routine cognitive skills. The coefficients are of similar magnitude to those in Table 2, confirming that our main estimates are not driven by unobserved provincial-level annual trends.

Second, we adopt an alternative approach to define the dependent variables by using the difference in outcome levels relative to the pre-pandemic baseline period (January–March 2019), rather than directly using the logarithm of outcome variable levels. Appendix Table B2 presents the results. It is important to note that the number of observations in these regressions is smaller than those in Table 2 for Columns (4)–(11), as these columns require the baseline period to have at least one job posting in the prefecture-industry pair. The coefficient estimates for the mobility shock on differences in labor market outcome levels remain qualitatively unchanged and statistically significant compared to the baseline estimates in Table 2. For skill measures, the mobility shock continues to lead to a significant increase in demand for non-routine cognitive analytical (NRCA) and interactive (NRCI) skills, with no systematic changes observed for routine or manual skills. These findings confirm that our main conclusions are robust to using differences relative to the pre-COVID benchmark, rather than relying solely on levels of the outcome variables.

Third, we explore alternative approaches to address zero observations in our aggregated prefecture-industry-month panels. In our baseline approach, we add 1 to count variables before taking the logarithm. In Appendix Table B3 Columns (1)-(3), we employ two alternative methods. In Panel A, we exclude all observations with zero job postings. In Panel B, we apply the inverse hyperbolic sine transformation to the dependent variables, a common method for handling zero values in log-linear models. The results from both panels are consistent with our main findings, and confirm that our conclusions are robust to the functional forms used to handle zeros in the data.

4.5 Summary of main results

In sum, our findings indicate that mobility shocks had a significant adverse impact on aggregate labor demand. A substantial reduction in within-prefecture mobility led to fewer vacancy postings, fewer overall vacancies, and a decline in the number of firms hiring on the platform. At the same time, job requirements became more stringent, with increases in the demand for years of education and work experience.

In terms of task content, the demand for skills shifted toward non-routine cognitive tasks, particularly analytical and interactive skills. This suggests that firms responded to the crisis by prioritizing higher-order cognitive skills, likely reflecting a shift toward more skill-intensive production processes or technologies. Notably, the negative effects on aggregate labor demand were more pronounced in the service sector, which is likely due to its reliance on face-to-face interactions and its greater exposure to mobility restrictions. Furthermore, the observed skill upgrading in non-routine cognitive tasks was entirely driven by the service sector, underscoring the sector's role as a key driver of labor market adjustments during the crisis.

Our results also reveal important geographic heterogeneity. Tier-2 prefectures were the most affected by the mobility shocks, with these areas showing the most pronounced skill upgrading. This pattern suggests that Tier-2 prefectures, which may have had more room for technological and skill-related advancements compared to Tier-1 prefectures, used the crisis as an opportunity to catch up by adopting more skill-intensive production methods. In contrast, Tier-1 prefectures, which already had highly skill-intensive labor markets, exhibited less room for further upgrading.

Finally, we find that the mobility shocks disproportionately suppressed hiring activity among new entrant firms compared to incumbent firms. This result highlights the heightened vulnerability of new entrants during periods of economic uncertainty, as they may lack the resources, networks, or resilience to weather such shocks. Incumbent firms, on the other hand, were better positioned to adapt, as evidenced by their ability to increase job requirements and participate in the shift toward non-routine cognitive skills.

Overall, these findings underscore the uneven impact of mobility shocks across sectors, geographic regions, and firm types, while also highlighting the role of the service sector and mid-tier prefectures in driving skill upgrading during the crisis. In the next section, we delve deeper into the role of international trade in enhancing the resilience of manufacturing labor markets. Specifically, we examine how trade dynamics may have mitigated the adverse effects of mobility shocks, supported labor demand, and influenced skill requirements within the manufacturing sector.

5 The Buffering Effects of Export

A distinct feature of the pandemic-induced economic recession in China was the substantial growth in Chinese exports during periods of domestic mobility disruption. As illustrated in Figure 6, the total value of exports increased significantly, rising from 200 billion USD in January 2019 to 300 billion USD in January 2023. This remarkable growth was partly driven by a global trade substitution effect, as production capacity in other parts of the world declined substantially, leading to increased reliance on Chinese exports. Consequently, regions within China that experienced faster export growth may have been less severely affected by the pandemic's economic disruptions, as the export sector likely provided a buffer against the adverse effects of reduced domestic mobility and demand.

It is important to separate the demand-side drivers of export growth from the supply-side drivers. On the supply side, as noted by Almunia et al. (2021), regions may increase exports when domestic demand falls. Additionally, regions less affected by the pandemic may have more capacity to produce and export goods. To isolate the demand-side shock to exports, we measure industry-specific export growth in all provinces except the one where the prefecture is located. This ensures the measure reflects external demand rather than local supply conditions.

We use customs records at the HS8-month-province level and aggregate them to the prefecture-industry-month level. The export demand shock is measured as the year-over-year difference in exports for the same month. We then interact this export demand shock with the local mobility shock to examine whether strong external demand lessened the impact of the local recession on labor market outcomes. This method allows us to assess whether external demand helped mitigate the effects of the pandemic on local labor markets.

Table 9 presents evidence of the buffering effect of exports on labor market outcomes. Consistent with the broader recessionary impact, the mobility shock significantly reduces labor demand, as reflected in declines in job postings, vacancies, and the number of hiring firms (Columns 1–3). Additionally, the mobility shock increases job requirements for education and experience (Columns 4–5).

Export growth, on the other hand, has a direct and positive effect on labor demand, leading to increases in job postings, vacancies, and hiring firms. Importantly, the positive and statistically significant interaction term between the mobility shock and export growth in Columns (1)–(3) indicates that export demand helped mitigate the negative effects of the domestic recession on employment. Specifically, for every additional unit of export growth, the adverse impact of the mobility shock on job postings, vacancies, and hiring firms is significantly reduced. This suggests that strong external demand provided a stabilizing force for local labor markets during the pandemic.

Columns (7)–(11) of Table 9 examine the impact of the export demand shock on skill requirements. The results show that for non-routine cognitive interactive and non-routine cognitive analytical skills, the interaction term between the mobility shock and export growth is negative and significant. This suggests that export growth not only acted as a demand buffer but also moderated the recession-induced acceleration in skill upgrading. In regions with stronger export demand, the shift toward high-skill cognitive tasks was less pronounced, indicating that external demand helped stabilize skill requirements during the crisis. Furthermore, we observe a positive effect of the mobility shock on the demand for non-routine manual physical labor, which is primarily driven by regions with strong export growth. This finding highlights that export-driven regions may have relied more on manual physical tasks, potentially reflecting the nature of industries tied to export production during the pandemic.

The buffering effect of export demand described above is robust to alternative measures of external demand shocks. As shown in Appendix Table B4, we re-estimate the model using two alternative constructs for the export shock. In Panel B, we construct a more direct demand-side measure: the growth in imports by China's major trading partners at the industry-year level, weighted by each province's initial export destination composition. This measure combines aggregate annual trade data from China's trading partners at the product level with 2019 Chinese customs data, which details export destinations and product-level trade by province. The results in both panels remain consistent with our main findings, both qualitatively and quantitatively. The interaction term between the mobility shock and Δ Log Export Value continues to be positive and statistically significant for key labor demand outcomes, including job postings, vacancies, and firm count. These findings confirm that external export demand mitigated the negative employment effects of the domestic pandemic recession. Importantly, the robustness of the results across different measures of export shocks indicates that our conclusions are not sensitive to the specific construction of the primary export shock variable.

We further investigate whether the buffering effect of exports varied between new firms that entered the job market during the crisis and established firms that were active prior to the crisis. Table 10 explores the heterogeneous buffering effect of exports by firm entry status. Export growth provided a significant demand buffer for both new entrants and incumbents, mitigating the negative impact of the mobility shock on labor demand, as evidenced by the positive interaction terms in Columns (1)–(3) of both Panels A and B. However, a notable difference emerges in wage outcomes. Comparing the coefficients on the wage variable in Column (6) of Panel A and Panel B, we find that for incumbent firms, export growth not only buffered employment but also led to a significant positive effect on wages during the recession. In contrast, this wage effect is absent for new entrants. This suggests that incumbent firms, with greater resilience to mobility shocks, were better positioned to offer higher wages to attract employees with higher education and work experience. While new entrants benefited from the employment buffer provided by export growth, they lacked the capacity to adjust wages in a similar manner.

Overall, our findings highlight the critical role of export growth in mitigating the economic impact of the pandemic-induced recession. The substitution of international demand for weakened domestic demand enhanced economic resilience by directly increasing labor demand and significantly offsetting employment losses caused by domestic mobility restrictions. Additionally, export growth moderated the accelerated pace of skill-biased technological change driven by the recession, particularly the shift toward non-routine cognitive skills. Importantly, the buffering effect of exports benefited both new entrants and established firms; however, only incumbent firms were able to leverage this advantage to support wage growth, reflecting their greater capacity to attract and retain higher-skilled workers during the crisis.

6 Conclusion

Economic recessions can reshape labor demand and supply while accelerating technological changes. In the context of the COVID-19 pandemic in China, we analyze medium-term labor market responses using data on online vacancy postings and within-prefecture human mobility changes. Our findings show that reduced mobility within prefectures led to fewer vacancy postings, fewer firms hiring, and increased education and experience requirements. The demand for non-routine cognitive skills rose significantly, driven by service sector firms and most pronounced in second-tier prefectures. Additionally, export demand played a key role in mitigating the adverse effects of mobility restrictions on labor markets. Incumbent firms, particularly in the manufacturing sector, experienced smaller declines in aggregate demand and leveraged export growth to offer competitive wages, further enhancing their resilience during the recession.

These findings shed light on the broader economic dynamics of recessions and their impact on labor markets. The buffering role of export demand underscores the importance of external demand in stabilizing employment and mitigating the adverse effects of domestic economic shocks. This highlights the interconnectedness of global trade and local labor markets, where shifts in international demand can offset domestic disruptions. The pronounced skill upgrading in second-tier prefectures suggests that regions with greater room for technological and skill advancements are more likely to experience accelerated structural changes during economic downturns. Furthermore, the ability of incumbent firms, particularly in the manufacturing sector, to leverage export growth for wage increases reflects their relative resilience and capacity to adapt to external shocks. In contrast, new entrants, while benefiting from the employment buffer provided by export growth, lacked the same ability to adjust wages, highlighting the uneven effects of recessions across firm types. More broadly, the findings illustrate how recessions can act as catalysts for structural shifts in labor markets, including increased demand for cognitive skills and higher job requirements, particularly in sectors and regions with the capacity to adapt to changing economic conditions.

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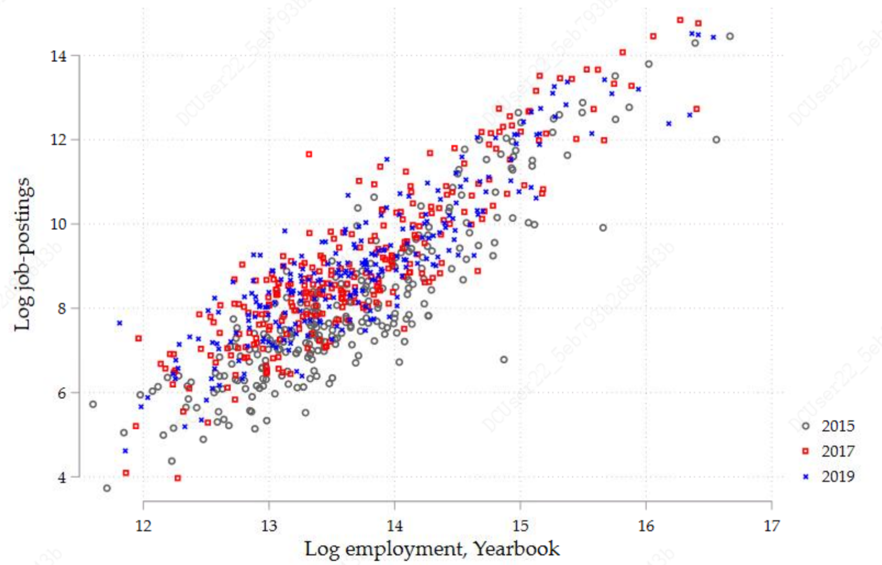
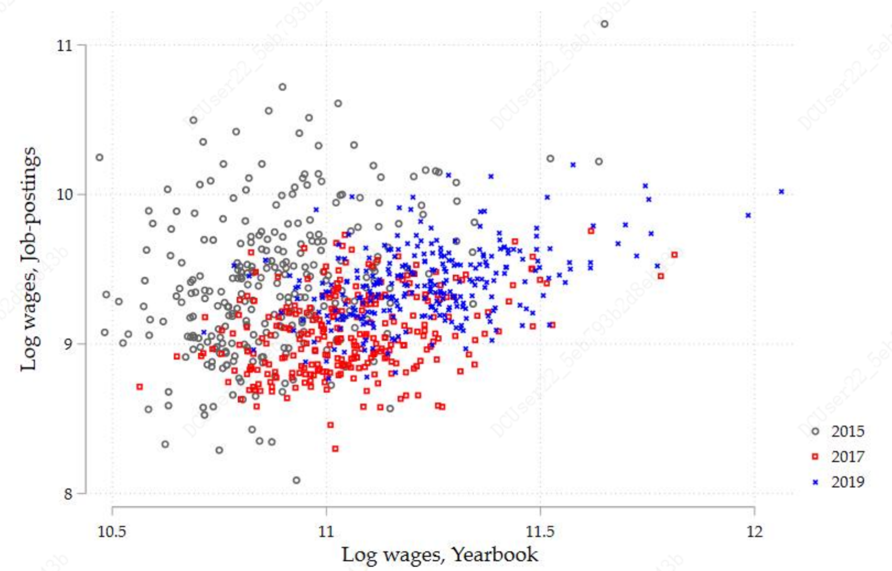
Figures and Tables

Figure 1: Representativeness of vacancy posting data at the prefecture level, employment and wages, compared to data from prefecture yearbooks

(a) Aggregated prefecture-level employment, vacancy posting data vs. yearbooks



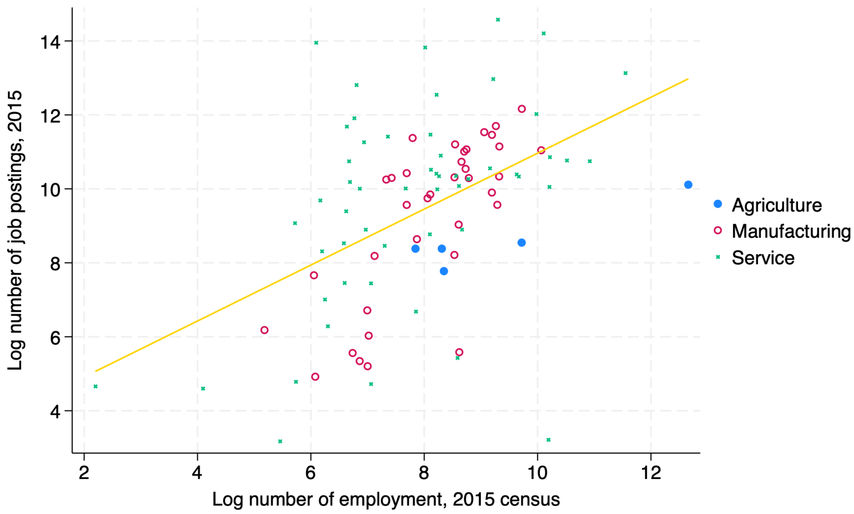
(b) Average prefecture-level wage, vacancy posting data vs. yearbooks



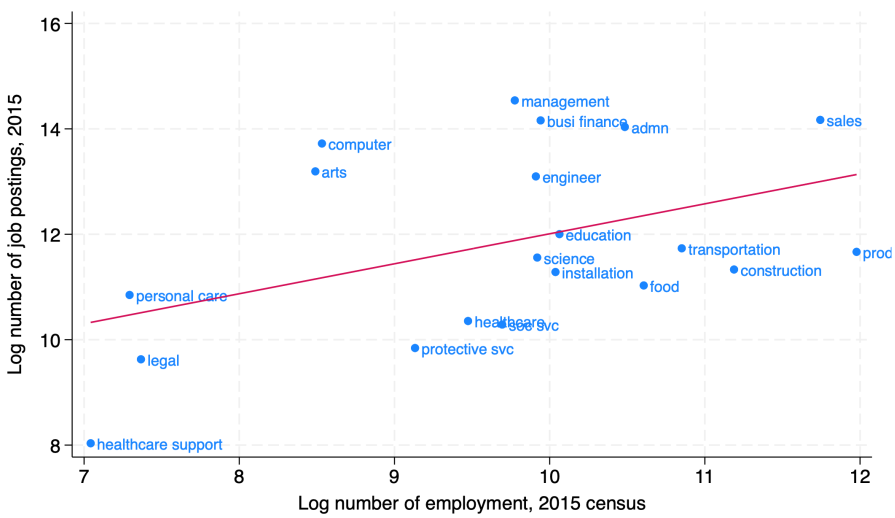
Note: This figure shows the representativeness of the vacancy posting data at the prefecture level. Panel (a) plots the log number of postings aggregated from vacancy postings (vertical axis) against the log number of employment from Prefecture Statistical Yearbooks (horizontal axis) in 2015, 2017 and 2019. The fitted line is: $log(postings) = 1.9\ log(employment) - 18$. Panel (b) plots the average wages from vacancy postings (vertical axis) against wages from Prefecture Statistical Yearbooks (horizontal axis) in 2015, 2017 and 2019. The fitted line is: $log(wages, posting) = 0.6\ log(wages, Yearbook) + 2.4$. In both regressions, year fixed effects are controlled. Details of the regression results can be found in Table A3.

Figure 2: Representativeness of job-posting data, compared to Census by industry and occupation

(a) Aggregated industry-level employment of job-posting vs census



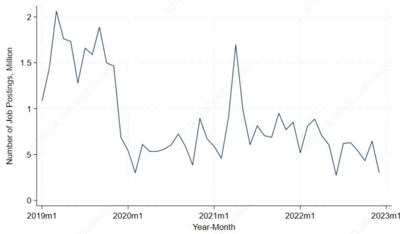
(b) Aggregated occupational-level employment of job-posting vs census



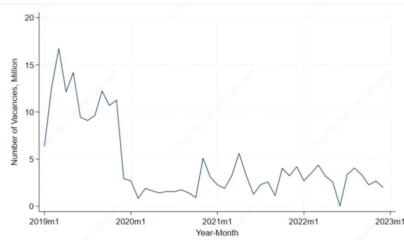
Note: This figure shows the representativeness of the job-posting data in terms of industry and occupation composition. Panel A shows the correlation of log number of employment from 2015 census, and log number of total vacancies from job postings, aggregated to two-digit industry level. Panel B shows the correlation of log number of employment from 2015 census, and log number of total vacancies from job postings, aggregated to one-digit occupation level.

Figure 3: Trends in labor market demand and task contents, 2019-2022

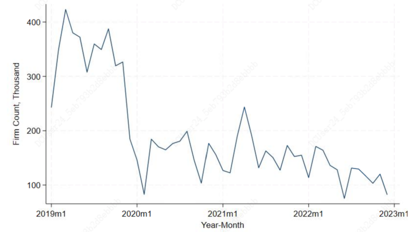
(a) Number of job postings



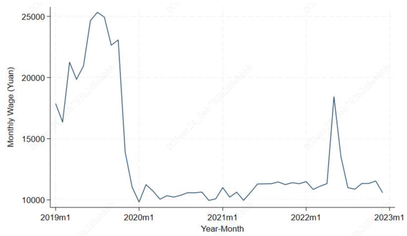
(b) Vacancies



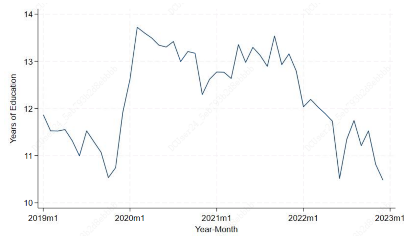
(c) Number of firms



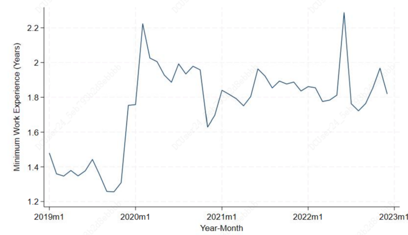
(d) Wage



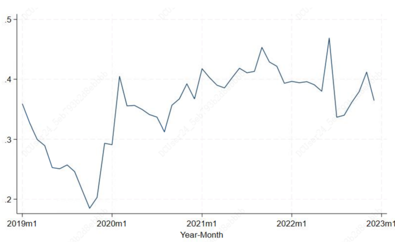
(e) Years of education



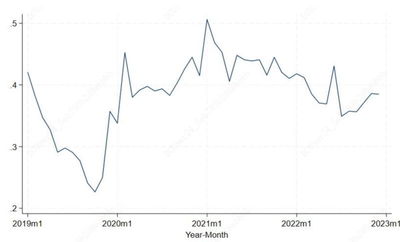
(f) Minimum work experience



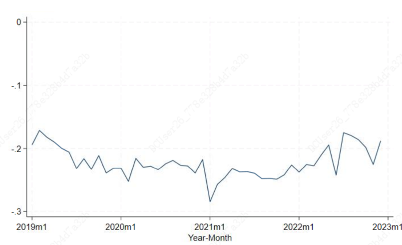
(g) Non-routine cognitive analytic



(h) Non-routine cognitive interactive



(i) Routine cognitive

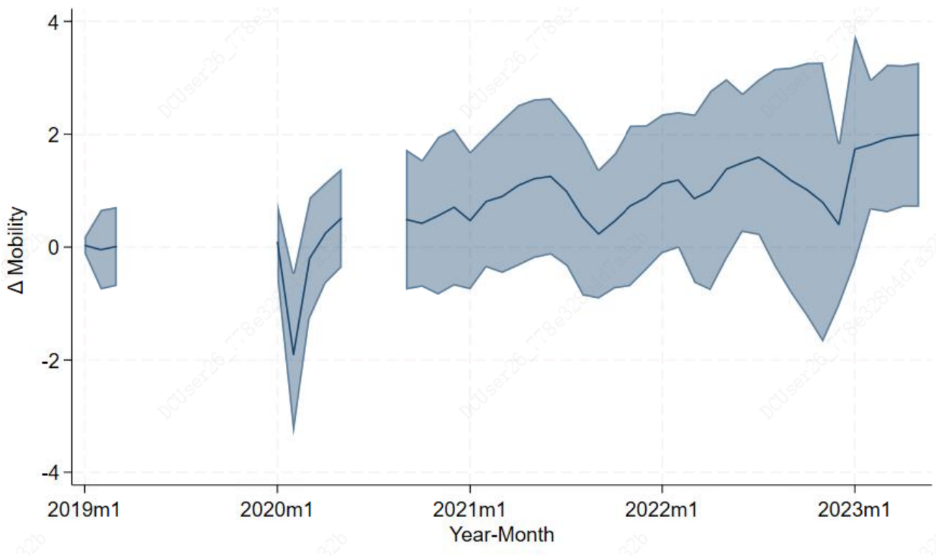


(j) Routine manual

(k) Non-routine manual physical

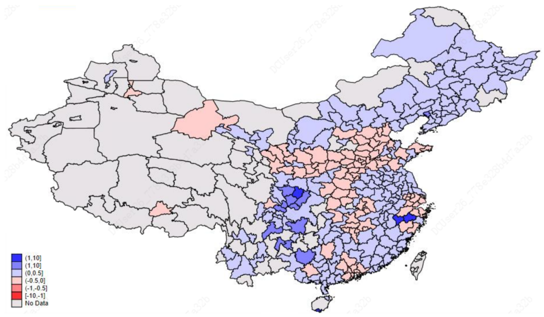
Note: This figure presents the trends in labor market outcomes and skill requirements from 2019 to 2022. Subfigures (a)-(f) depict labor market outcomes: (a) Number of job postings, (b) Number of vacancies, (c) Number of firms, and (d) Wage. Subfigures (e)-(k) depict skill requirements: (e) Years of 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.

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

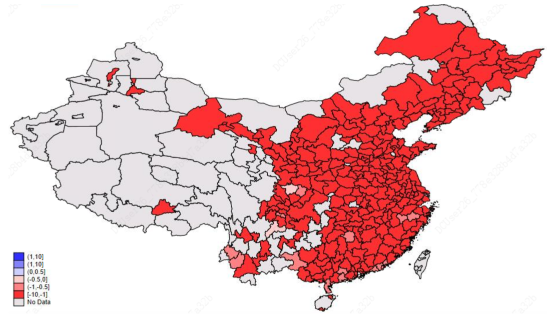


Note: This figure shows the average mobility index across Chinese prefectures from January 2019 to May 2023, derived from the Baidu Migration Index. The shaded area represents the 95% confidence interval.

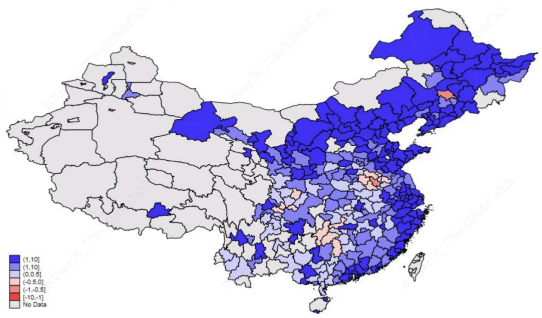
Figure 5: Distribution of Mobility Shock in China



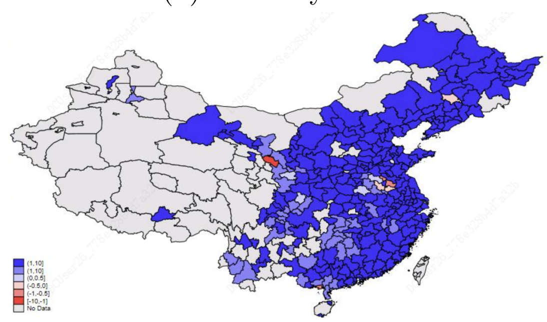
(a) January 2020



(b) February 2020



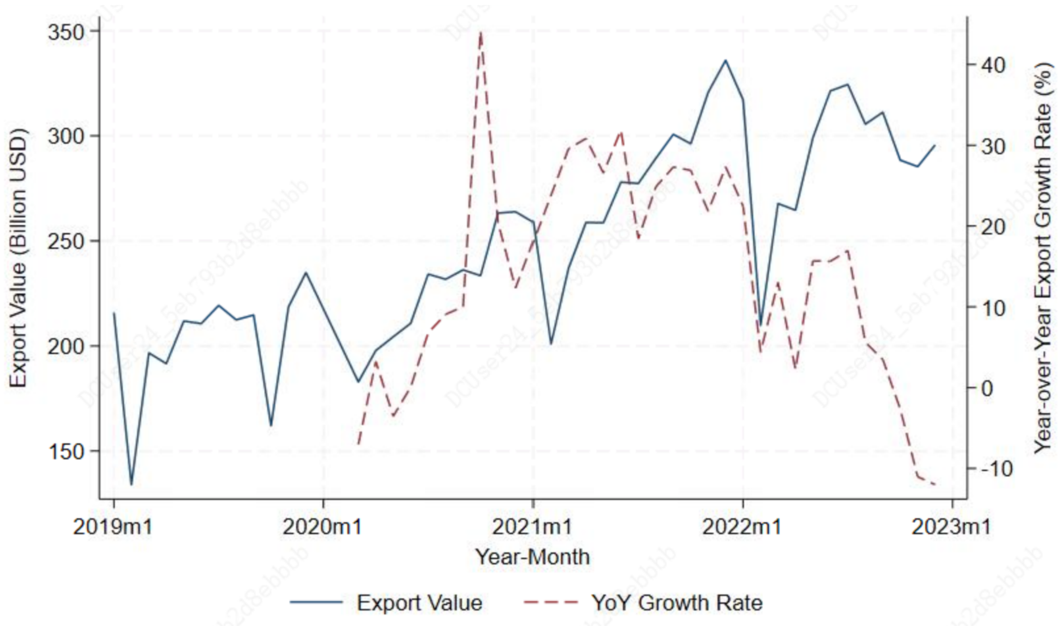
(c) July 2021



(d) July 2022

Note: This figure shows the spatial distribution of mobility index across Chinese prefectures for January 2020, February 2020, July 2021 and July 2022, based on the Baidu Migration Index. Blue areas indicate higher mobility levels, while red areas signify mobility contractions.

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.

Table 1: Pre-trend Test of Effects of Mobility Shock on Labor Market

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Job Postings	Log Vacancies	Log Firm Count	Years of Education	Min Work Experi-ence	Log Wage
Mobility Shock	-0.002	-0.003	-0.003	0.0012	0.010**	0.002
	(0.004)	(0.005)	(0.002)	(0.015)	(0.005)	(0.003)
Mean (s.d.) of Y	1.0 (1.6)	1.3 (2.1)	0.6 (1.1)	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	0.625	0.599	0.655	0.097	0.107	0.187
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	-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 presents the pre-trends test of the effect of mobility shocks on labor market outcomes. We regress the corresponding changes in the outcome variables in the 2016-2018 period, four years prior to the COVID-19 shock, to mobility shocks calculated in 2020-2022 period. 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. 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 shock 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: Effects of Mobility Shock on Labor Market Outcomes and Task Contents

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Job Postings	Log Vacancies	Log Firm Count	Years of Education	Min Work Experi-ence	Log Wage
Mobility Shock	-0.057***	-0.059***	-0.038***	0.087***	0.018***	0.000
	(0.004)	(0.004)	(0.003)	(0.018)	(0.005)	(0.005)
Mean (s.d.) of Y	1.0 (1.6)	1.0 (1.9)	0.6 (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	0.553	0.653	0.171	0.125	0.250
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	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 effects of COVID-19 mobility shocks with labor market outcomes and skill requirements. 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. 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 shock 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 3: Effects of Mobility Shock on Text-Derived Task Contents

	(1)	(2)	(3)	(4)	(5)
Panel A: non-routine cognitive analytical					
	Analyze	Design	Develop	Predict	Research
Mobility Shock	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
Mobility Shock	-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
Mobility Shock	-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
Mobility Shock	-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
Mobility Shock	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 COVID-19 Mobility Shocks on skill-specific requirements extracted from online job advertisement texts. The dependent variables are normalized word frequencies, calculated as (word counts per posting $\times$ 1000) divided by log(1+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 4: Effect of Mobility Shock on Labor Demand and Task Contents: Manufacturing Sector

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Job Postings	Log Vacancies	Log Firm Count	Years of Education	Min Work Experi-ence	Log Wage
Mobility Shock	-0.053***	-0.048***	-0.037***	0.094***	0.020***	0.007*
	(0.005)	(0.005)	(0.004)	(0.025)	(0.008)	(0.004)
Mean (s.d.) of Y	1.1 (1.6)	1.1 (1.8)	0.7 (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	0.613	0.532	0.659	0.088	0.063	0.171
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	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 heterogeneous effects of COVID-19 Mobility Shocks on labor demand and skill requirements, using subsample of manufacturing sector. 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. 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 shock 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 5: Effect of Mobility Shock on Labor Demand and Task Contents: Service Sector

Dep. Var.	(1) Log Job Postings	(2) Log Vacancies	(3) Log Firm Count	(4) Years of Education	(5) Min Work Experience	(6) Log Wage
Mobility Shock	-0.067***	-0.072***	-0.044***	0.079***	0.017***	-0.002
	(0.004)	(0.005)	(0.003)	(0.023)	(0.006)	(0.006)
Mean (s.d.) of Y	1.0 (1.7)	1.2 (2.1)	0.7 (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	0.687	0.611	0.709	0.198	0.161	0.308
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	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 heterogeneous effects of COVID-19 Mobility Shocks on labor demand and skill requirements, using subsample of service sector. 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. 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 shock 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: Effect of Mobility Shock on Labor Demand and Task Contents, Prefecture Heterogeneity

Variables	(1) Log Job Postings	(2) Log Vacancies	(3) Log Firm Count	(4) Years of Education	(5) Min Experience	(6) Log Wage
Mobility Shock	-0.122***	-0.086***	-0.096***	-0.018	0.016*	0.008
× Tier-1 prefecture	(0.017)	(0.022)	(0.006)	(0.023)	(0.009)	(0.018)
Mobility Shock	-0.115***	-0.110***	-0.080***	0.108***	0.027***	-0.001
× Tier-2 prefecture	(0.009)	(0.007)	(0.007)	(0.021)	(0.006)	(0.006)
Mobility Shock	-0.030***	-0.037***	-0.018***	0.088***	0.011**	0.000
× other prefecture	(0.004)	(0.005)	(0.003)	(0.022)	(0.006)	(0.005)
Mean (s.d.) of Y	1.0 (1.6)	1.0 (1.9)	0.6 (1.1)	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	0.554	0.653	0.171	0.125	0.250
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	-0.001	0.002	-0.000	0.009	0.009	
× Tier-1 prefecture	(0.004)	(0.003)	(0.003)	(0.007)	(0.006)	
Mobility Shock	0.008***	0.005***	0.001	0.005*	-0.002	
× Tier-2 prefecture	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	
Mobility Shock	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 effect of mobility shock on labor demand and skill requirement, by prefecture tier. 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. 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 shock 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: Effect of Mobility Shock on Labor Demand and Task Contents: New Entrants

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Job Postings	Log Vacancies	Log Firm Count	Years of Education	Min Work Experi-ence	Log Wage
Mobility Shock	-0.067***	-0.072***	-0.045***	0.095***	0.009	-0.001
	(0.006)	(0.007)	(0.004)	(0.025)	(0.006)	(0.006)
Mean (s.d.) of Y	0.6 (1.2)	0.6 (1.6)	0.4 (0.8)	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	0.532	0.447	0.564	0.142	0.120	0.279
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	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 COVID-19 Mobility Shocks on labor demand and skill requirements, using subsample of new entrant firms. 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. 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 shock 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: Effect of Mobility Shock on Labor Demand and Task Contents: Incumbents

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Job Postings	Log Vacancies	Log Firm Count	Years of Education	Min Work Experi-ence	Log Wage
Mobility Shock	-0.039***	-0.036***	-0.022***	0.081***	0.024***	0.002
	(0.003)	(0.004)	(0.002)	(0.016)	(0.005)	(0.004)
Mean (s.d.) of Y	0.8 (1.5)	0.9 (1.7)	0.5 (1.0)	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	0.586	0.533	0.612	0.01	0.116	0.197
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	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 heterogeneous effects of COVID-19 mobility shocks on labor demand and skill requirements, using subsample of incumbent firms. 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. 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 shock 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: Effect of Mobility Shock on Labor Demand and Task Contents, Export Buffers

Variables	(1) Log Job Postings	(2) Log Vacancies	(3) Log Firm Count	(4) Years of Education	(5) Min Experience	(6) Log Wage
Mobility Shock	-0.054***	-0.052***	-0.037***	0.088***	0.020**	0.006
	(0.005)	(0.006)	(0.004)	(0.026)	(0.009)	(0.004)
Δ Log Export Value	0.007***	0.009***	0.005***	-0.007	-0.008	0.002
	(0.001)	(0.001)	(0.001)	(0.017)	(0.006)	(0.003)
Mobility Shock	0.004***	0.004***	0.003***	-0.005	-0.002	0.002
× Δ Log Export Value	(0.001)	(0.001)	(0.001)	(0.014)	(0.004)	(0.002)
Mean (s.d.) of Y	1.0 (1.5)	1.1 (1.8)	0.7 (1.0)	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	0.611	0.528	0.656	0.090	0.064	0.173
	(7)	(8)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	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)	
Mobility Shock	-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 the year-over-year difference in export value, for all other provinces at the two-digit industry level for the current month. The sample is restricted to prefecture-industry-month observations where export data are available. 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. 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 shock 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 10: The Buffering Effect of Export, by Entrants and Incumbents

Variables	(1) Log Job Postings	(2) Log Vacancies	(3) Log Firm Count	(4) Years of Education	(5) Min Experience	(6) Log Wage
Panel A: Subsample of New Entrants						
Mobility Shock	-0.051***	-0.050***	-0.032***	0.120**	0.006	-0.001
	(0.006)	(0.006)	(0.004)	(0.042)	(0.011)	(0.006)
Δ Log Export Value	0.004***	0.005***	0.002***	-0.051	-0.006	0.004
	(0.001)	(0.001)	(0.001)	(0.034)	(0.011)	(0.005)
Mobility Shock	0.003***	0.003***	0.002***	-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	0.5 (1.0)	0.5 (1.2)	0.3 (0.6)	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	0.422	0.320	0.471	0.072	0.058	0.200
Panel B: Subsample of Incumbents						
Mobility Shock	-0.044***	-0.034***	-0.026***	0.069***	0.019**	0.007**
	(0.005)	(0.005)	(0.003)	(0.023)	(0.008)	(0.004)
Δ Log Export Value	0.004***	0.009***	0.003***	-0.000	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.012)	(0.004)	(0.002)
Mobility Shock	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	0.9 (1.5)	1.0 (1.7)	0.6 (0.9)	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	0.598	0.527	0.647	0.083	0.076	0.151

Note: This table examines the heterogeneous buffering effect of export demand growth for new entrant and incumbent firms. Panel A uses the subsample of new entrants, and Panel B uses the subsample of incumbents. The key explanatory variable Δ Log Export Value is constructed as the year-over-year difference in export value, for all other provinces at the two-digit industry level for the current month. The sample is restricted to prefecture-industry-month observations where export data are available. All regressions include prefecture, year-month, two-digit industry, and province-by-year fixed effects. The mean (s.d.) of mobility shock 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)

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

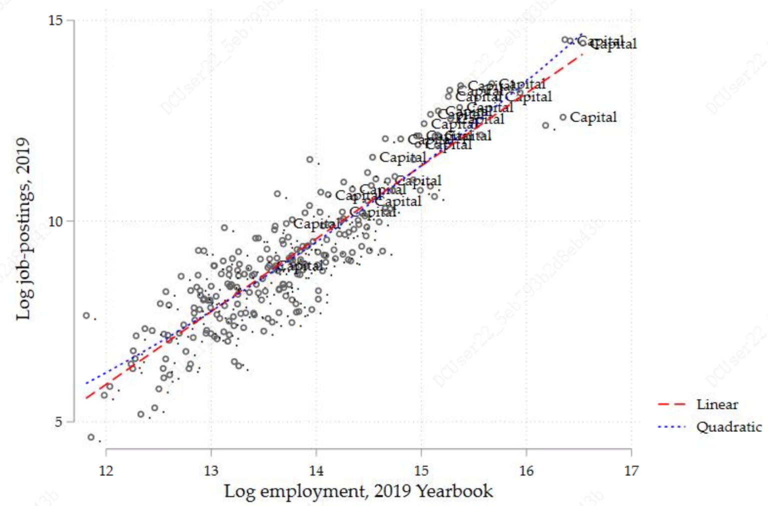
Item	Category	Variable in O*NET
Non-routine cognitive: analytical (NRCA)		
Analyzing data/information	activities	analyzing
Thinking creatively	activities	thinking
Interpreting information for others	activities	interpreting
Non-routine cognitive: interactive (NRCI)		
Establishing and maintaining personal 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.

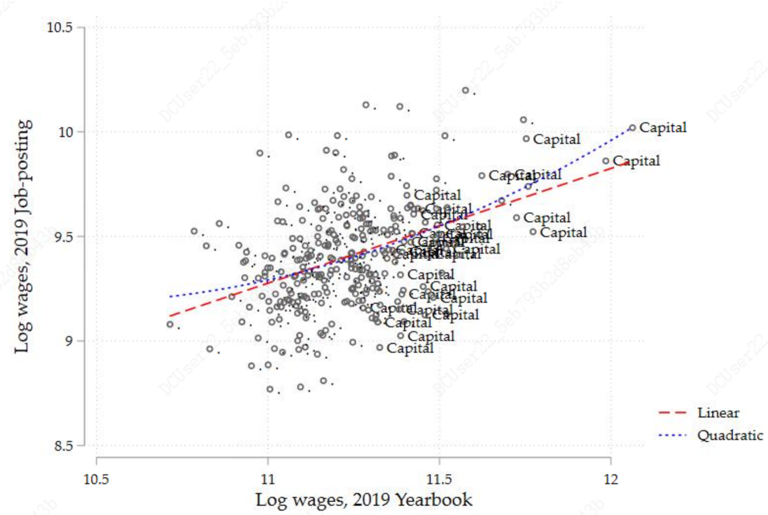
A.3 Additional Evidence on Representativeness

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

(a) Log employment



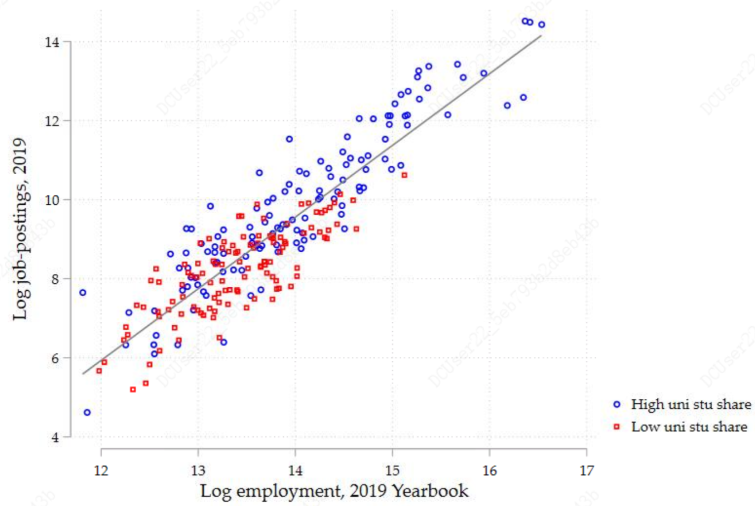
(b) Log wages



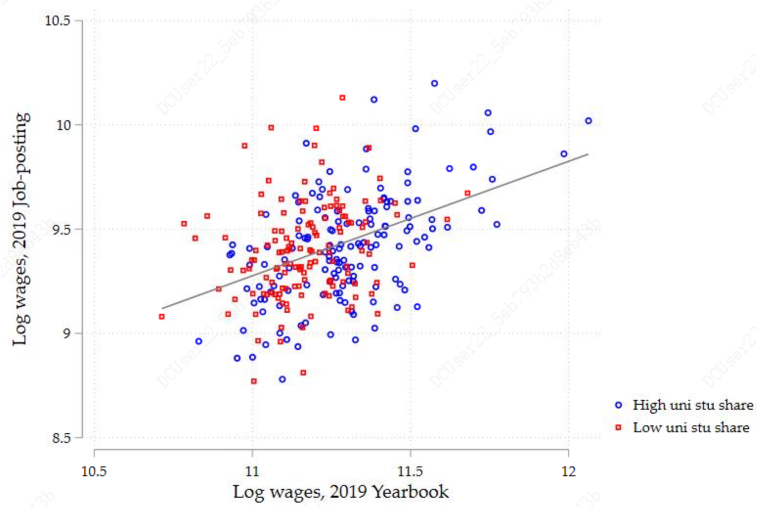
Note: This figure shows the representativeness of the vacancy posting data at the prefecture level distinguishing provincial capital prefectures from other prefectures. Prefectures are divided into two groups: provincial capitals and non-capitals. Panel (a) plots the log of total employment from job 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 fit lines are shown for each group.

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

(a) Log employment



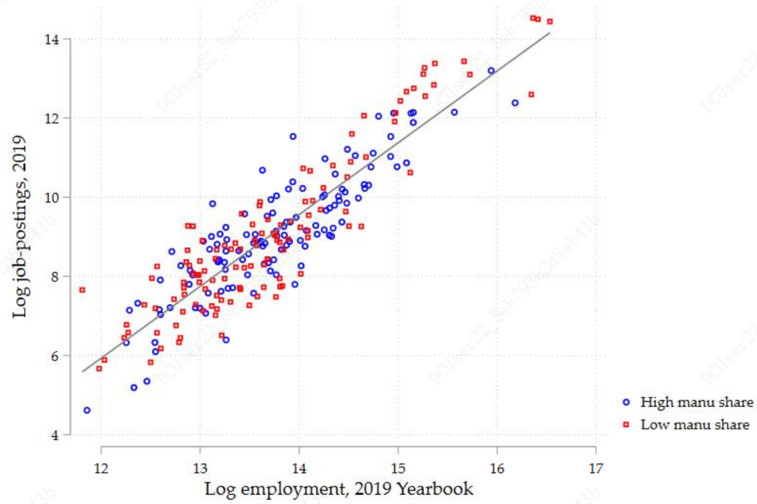
(b) Log wages



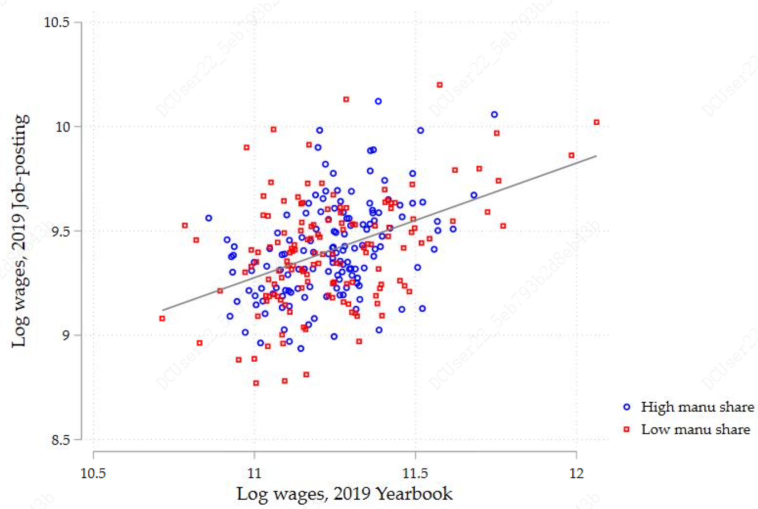
Note: This figure shows the representativeness of the vacancy posting data at the prefecture level by average education level. Prefectures are split into two groups based on the share of university students in the population (above vs. below the median), using data from the Prefecture Yearbooks. Each point represents a prefecture, with blue points shown for high-share groups, and red points for low-share groups.

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

(a) Log employment



(b) Log wages



Note: This figure shows the representativeness of the vacancy posting data 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
Vacanies	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				
	(1)	(2)	(3)	(4)
Variables	All three years	2015	2017	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				
	(1)	(2)	(3)	(4)
Variables	All three years	2015	2017	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 shows the corresponding regression results of Figure 1, showing the representativeness of the vacancy posting data at the prefecture level. Panel (a) regress the log number of postings aggregated from vacancy postings on log number of employment from Prefecture Statistical Yearbooks. Panel (b) regress the average wages from vacancy postings on wages from Prefecture Statistical Yearbooks. 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-19 Policies

Dep. Var.	Mobility Shock			In-Migration Shock		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Confirmed Cases	0.109***		0.091***	0.041***		0.033***
	(0.009)		(0.009)	(0.007)		(0.007)
Stringency Index		0.015***	0.014***		0.006***	0.006***
		(0.001)	(0.001)		(0.000)	(0.000)
Observations	11,088	11,088	11,088	11,088	11,088	11,088
R-squared	0.702	0.714	0.716	0.559	0.565	0.566
Prefecture FE	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y
Mean of Dep. Var.	-0.669	-0.669	-0.669	0.215	0.215	0.215

Note: This table presents regression results of mobility shocks on government policies and confirmed cases. Mobility Shock and In-Migration Shock are calculated as the difference between post-COVID and pre-COVID migration indices, derived from the Baidu Migration Index. Stringency Index is sourced from the Oxford COVID-19 Government Response Tracker. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: COVID-19 Containment Policies

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

Notes. This table lists policies that are classified as containment policies in the Oxford COVID-19 Government Response Tracker (Hale et al., 2021).

B Additional Empirical Results

B.1 Robustness of the effect of mobility shocks on labor market outcomes

Table B1: Robustness of Table 2 results, using alternative fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log Job Postings	Log Vacancies	Log Firm Count	Years of Education	Min Work Experi-ence	Log Wage
Mobility Shock	-0.060***	-0.059***	-0.039***	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	0.623	0.555	0.654	0.174	0.128	0.260
	(7)	(9)	(9)	(10)	(11)	
Dep. Var.	NRCA	NRCI	RC	RM	NRMP	
Mobility Shock	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 shocks with labor market outcomes and task contents, using an alternative fixed effects specification. 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. All columns control for industry fixed effects and prefecture-by-year fixed effects, instead of prefecture fixed effects, time fixed effects, industry fixed effects, and province-by-year fixed effects in Table 2. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2: Robustness of Table 2 results, using outcome variables in changes instead of levels

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Δ Log Job Postings	Δ Log Vacancies	Δ Log Firm Count	Δ Years of Education	Δ Min Work Experience	Δ Log Wage
Mobility Shock	-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
	(7)	(9)	(9)	(10)	(11)	
Dep. Var.	Δ NRCA	Δ NRCI	Δ RC	Δ RM	Δ NRMP	
Mobility Shock	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 COVID-19 Mobility Shocks 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. 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 B3: Robustness of Table 2 and Table 9 results, using alternative treatment of zero posting observations

Variables	(1) Log Job Postings	(2) Log Vacancies	(3) Log Firm Count	(4) Log Job Postings	(5) Log Vacancies	(6) Log Firm Count
Panel A: Excluding Zero observations						
Mobility Shock	-0.066***	-0.067***	-0.050***	-0.050***	-0.042***	-0.046***
	(0.004)	(0.006)	(0.004)	(0.006)	(0.008)	(0.005)
Δ Log Export Value				0.010***	0.014***	0.007***
				(0.003)	(0.005)	(0.002)
Mobility Shock				0.007**	0.009**	0.005***
× Δ Log Export Value				(0.003)	(0.004)	(0.002)
Observations	337,298	337,298	337,298	111,254	111,254	111,254
R-squared	0.606	0.520	0.688	0.545	0.451	0.652
Panel B: Using hyperbolic sine transformation of outcome variables						
Mobility Shock	-0.057***	-0.059***	-0.038***	-0.054***	-0.052***	-0.037**
	(0.004)	(0.004)	(0.003)	(0.005)	(0.006)	(0.004)
Δ Log Export Value				0.007***	0.010***	0.005***
				(0.001)	(0.001)	(0.001)
Mobility Shock				0.004***	0.004***	0.003***
× Δ Log Export Value				(0.001)	(0.001)	(0.001)
Observations	899,481	899,481	899,481	261,330	261,330	261,330
R-squared	0.613	0.546	0.637	0.602	0.520	0.646

Note: This table examines the effects of mobility shock on labor market and the buffering effect of exports, using alternative approach to deal with zero observations. Panel A exclude city-industry-monthly observations with zero job-postings. Panel B use hyperbolic sine transformation, i.e. to deal with zero observations instead of $log(1 + x)$ transformation used in the baseline specifications in Table 2 and Table 9. 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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.2 Robustness of the effect of export effects

Table B4: Robustness of Table 9 results, using alternative measure of export shocks

Variables	(1) Log Job Postings	(2) Log Vacancies	(3) Log Firm Count	(4) Years of Education	(5) Min Experience	(6) Log Wage
Panel A: Using change in export of own province as shock						
Mobility Shock	-0.055***	-0.053***	-0.038***	0.110***	0.019**	-0.003
	(0.005)	(0.006)	(0.004)	(0.026)	(0.008)	(0.004)
Δ Log Export Value	0.009***	0.013***	0.006***	0.014	-0.009	0.001
	(0.002)	(0.003)	(0.001)	(0.019)	(0.003)	(0.003)
Mobility Shock	0.009***	0.011***	0.007***	0.007	-0.001	0.002
$\times$ Δ Log Export Value	(0.002)	(0.003)	(0.001)	(0.014)	(0.005)	(0.002)
Observations	261,330	261,330	261,330	111,252	111,252	111,252
R-squared	0.611	0.528	0.656	0.098	0.073	0.184
Panel B: Using change of importer country aggregate demand as shock						
Mobility Shock	-0.055***	-0.050***	-0.038***	0.112***	0.020**	-0.002
	(0.005)	(0.006)	(0.004)	(0.025)	(0.008)	(0.004)
Δ Log Export Value	0.006***	0.005***	0.004***	0.004	-0.006*	0.001
	(0.001)	(0.001)	(0.001)	(0.010)	(0.004)	(0.001)
Mobility Shock	0.008***	0.006***	0.005***	0.005	-0.004**	-0.000
$\times$ Δ Log Export Value	(0.001)	(0.001)	(0.001)	(0.005)	(0.002)	(0.001)
Observations	277,530	277,530	277,530	117,616	117,616	117,616
R-squared	0.608	0.526	0.654	0.097	0.072	0.182

Note: This table examines the robustness of the buffering effect of export demand using alternative measures of the export shock. Panel A uses the year-over-year growth in a prefecture's own province's total export value (ΔLog Export Value) as the shock measure. Panel B constructs an alternative demand-side shock by using the year-over-year change in imports by China's export destination countries at the two-digit industry level, weighted by the initial export destination share by province and industry. All other specifications, including fixed effects and standard error clustering, are identical to the main analysis in Table 9. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.