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Working Paper Remote work and high proximity employment in Mexico

Working Papers, No. 2024-17

Provided in Cooperation with: Bank of Mexico, Mexico City

Suggested Citation: Aldeco Leo, Lorenzo; Salcedo, Alejandrina (2024) : Remote work and high proximity employment in Mexico, Working Papers, No. 2024-17, Banco de México, Ciudad de México

This Version is available at: https://hdl.handle.net/10419/310400

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Banco de México

Working Papers

N° 2024-17

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December 2024

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Documento de Investigación 2024-17

Working Paper 2024-17

Remote Work and High Proximity Employment in Mexico*

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Abstract: We show that in Mexico larger shares of potential remote work at the municipality level are related to lower post-pandemic employment in high-proximity consumer services, a relatively large sector that mainly employs low-income workers. We use a triple difference event study design where we compare employment in high and low proximity sectors across municipalities with different levels of remote work potential, before and after the pandemic. Our results contribute to explain the relatively weak recovery in high proximity employment in the central region of the country, where at the start of the pandemic a larger proportion of high-proximity services located where remote work potential was high, relative to other regions. The analysis highlights that with the pandemic the sectoral distribution of employment has changed, and that the effects on workers depend on their capacity to adjust to the new labor market.

Keywords: Remote work, Consumer services, Middle-income, Triple-differences **JEL Classification:** O33, R11, J20

Resumen: Mostramos que en México una mayor proporción de empleo realizable a distancia a nivel municipal se asocia con un menor nivel de empleo pospandemia en servicios de consumo de alta proximidad, un sector importante que tiende a emplear trabajadores de salarios bajos. Usamos un estudio de evento de panel de triples diferencias en el que se compara el empleo en sectores de alta y baja proximidad entre municipalidades con distintos niveles de potencial para el trabajo remoto, antes y después del inicio de la pandemia. Los resultados contribuyen a explicar la recuperación relativamente débil del empleo en servicios de alta proximidad en la región centro del país, pues ahí al inicio de la pandemia una mayor proporción del empleo en servicios de alta proximidad se encontraba donde el potencial para el trabajo a distancia era alto, con respecto a otras regiones. El análisis resalta que con la pandemia ha cambiado la distribución sectorial del empleo, y que los efectos sobre los trabajadores dependen de su capacidad de ajustarse al nuevo mercado laboral.

Palabras Clave: Trabajo remoto, Servicios al consumo, Países de ingreso medio, Triples diferencias

^{*}We thank Giulia Buccione, Jorge Pérez, Daniela Puggioni, and seminar participants at the 2022 ITAM Alumni Conference and the 2022 BIS XII CCA Research Conference for valuable comments. A previous version was published as BIS Working Paper, No. 1133, Oct 23. Horacio Reyes provided superb research assistance. Data accessed through Banxico's EconLab, which promotes evidence-based research and fosters ties between Banxico and the academic community. For data inquiries email econlab@banxico.org.

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1 Introduction

In this paper we show that locations where larger shares of employment could be performed remotely at the start of the COVID-19 pandemic registered weaker employment recoveries in consumer services sectors in Mexico in the years after 2020.¹ Mexico is a middle income country where between 10% and 25% percent of jobs that existed at the start of the pandemic could be performed remotely. Service sectors that require high proximity with consumers include restaurants, bars, and other consumer services, and faced one of the steepest, most persistent drops in formal employment after the start of the pandemic (in what follows we call these sectors high-proximity or consumer services exchangeably). A nascent literature in urban and labor economics has drawn a link between remote work and consumer service employment, positing that as some workers begin to perform some of their tasks remotely, demand for service workers near workplaces can decrease (Gokan et al., 2022; Althoff et al., 2022; Monte, Porcher, and Rossi-Hansberg, 2023). Through a triple difference event study design where we compare employment in high and low proximity sectors across municipalities with different levels of potential remote work as a percentage of total employment, before and after the pandemic, we find that 1 percentage point (pp) more potential for remote work (as a percentage of overall employment) at the municipal level implied a gap in formal employment in high-proximity sectors, relative to February 2020, 0.6pp larger one year into the pandemic, and a persistent 0.2pp by early 2024. Our results are evidence that the advent and persistence of remote work has had consequences for lower-skill service work in cities, and more generally that the pandemic may have had lasting effects on cities, as suggested by Glaeser (2022).

At its onset, the COVID-19 pandemic severely affected service sectors that require high physical proximity between consumers. In an attempt to curb the spread of the coronavirus, many governments imposed restrictions to the capacity at which restaurants, bars, and entertain-

¹In a setting where informality is high, a fall in formal employment may not reflect an overall drop in the employment in a given sector. However, as Leyva and Urrutia (2020) show, informality rates decreased strongly in Mexico during the pandemic, implying that the informal sector tended not to cushion the pandemic shock, and lending support to our study of the labor market through formal employment data.

ment venues could operate - and, simultaneously, consumers lowered demand for services that involved crowds in order to decrease their risk of infection. As a consequence, employment in these sectors decreased strongly during the first months of the pandemic. This dramatic drop in consumer services employment happened both in the developed world and outside it: in Mexico, formal employment in these high-proximity sectors fell over 20% from its pre-pandemic level, and recovered slowly, reaching its February 2020 level only by mid-2023.² Consumer services employment remained below pre-pandemic levels even as eased capacity restrictions and high vaccination rates lowered the likelihood of contagion. By contrast, overall formal employment had reached prepandemic levels by the first quarter of 2022. Lower formal employment in high-proximity sectors is concerning, especially in developing economies such as Mexico, where these consumer services jobs can provide income and access to social security to a large group of generally lower skilled workers (Nayyar, Hallward-Driemeier, and Davies, 2021). The slow recovery from the pandemic in service-intensive regions of the developing world (e.g. see Banco de México, 2022c) is important especially given their historical roles as engines for development (Glaeser, 2022), raising the question of which economic mechanisms are operating differently in the aftermath of the pandemic. Our work suggests that remote work, which was widespread during the COVID-19 pandemic and remained a feature of many occupations after the recovery, may contribute to explain some of the persisting shifts in sectoral and regional employment patterns.

We find precise zero wage effects, which are consistent with a negative demand shock to these workers that could not be accommodated along the wage margin possibly due to binding nominal restrictions.³ Concentrated negative employment effects at the bottom end of the wage distribution also imply that potential remote work may have a negative effect on income inequality at the local level.⁴

²In this setting, we define formal work as that which provides social security benefits to the worker, including health insurance and a retirement saving plan. Notwithstanding that there exists a large informal sector that may absorb workers from the formal sector, changes in the level of formal employment imply shifts in the quality of the jobs workers hold, and can reflect overall trends in the labor market.

³In Mexico, the law prevents nominal decreases in wages, inducing wage rigidities. See Castellanos, García-Verdú, and Kaplan (2004).

⁴A large share of consumer services workers earned close to the minimum wage at the start of the pandemic in our data: 39% of workers earned below 1.1 times the minimum wage in these sectors, relative to 19% in

Individual-level data shows that workers who exited high-proximity jobs tended to leave the formal labor market entirely, suggesting that remote work affected high-proximity employment not because workers moved to other sectors willingly, but instead because demand for consumer services decreased. This result is in line with the idea that our measured effects reflect a drop in demand for services near workplaces as some work interactions shifted online (as predicted by Monte, Porcher, and Rossi-Hansberg, 2023 and Gokan et al., 2022). Consistent with this hypothesis, mobility data shows that in locations with more capacity for remote work, both trips to retail locations and workplaces are persistently lower. However, we do not find strong evidence that the prices of consumer services such as restaurants behaved differently in cities with larger shares of potential remote work after the pandemic.⁵

Finally, we provide evidence that in our setting potentially remote employment co-located with the consumer service sectors across space. This sorting of higher skill work with consumption services has been documented for the case of the U.S. in Diamond and Gaubert (2022), and given our results, suggests that locations with high concentrations of remote work potential may be especially affected by the channel we study. To quantify the role of potential remote work on aggregate employment in service-heavy locations, we show regional counterfactual employment time series assuming that remote work potential and high-proximity services do not co-locate. These illustrate that the potential remote work mechanism explains some of the muted recovery of employment in Mexico's consumer service sectors, and especially in the central region where larger shares of high-proximity sectors were exposed to high levels of potential remote work, relative to other regions.

Our results contribute to the emerging literature on the effects of remote work and the con-

the rest. Further, there exists some evidence that remote workers tend to be higher earners (Gottlieb et al., 2021) and that they were less likely to be unemployed after the initial pandemic shock (Dey et al., 2020). As a consequence, to the extent that the negative employment effects we find translated to lower income for affected households, our results raise the possibility that remote work potential may have effects on inequality.

⁵While we find that the price levels of consumer services such as restaurants follow similar paths in locations with high and low potential remote work after the start of the pandemic, this does not rule out that the availability of remote work occupations may have broader effects on the labor market and on prices. Barrero, Bloom, Davis, et al. (2022) show that remote work jobs are subject to lower wage-growth pressures after the pandemic than those with a lower remote component. On the other hand, it is also possible, as suggested by Fulford (2023), that after the pandemic some workers expect to be compensated for work arrangements that allow for less flexibility, pressuring wages.

sequences of the COVID-19 pandemic. While Althoff et al. (2022) show that the potential for remote employment correlates with lower employment in some consumer services, we take advantage of rich administrative data and a triple-difference panel event study to provide evidence in favor of a causal channel. Our work also provides empirical evidence in line with existing theoretical work on the effects of remote work. Monte, Porcher, and Rossi-Hansberg (2023) show that in a model of internal city structure, a positive shock to the number of remote workers can result in a permanent decrease in foot traffic to central business districts in cities, consistent with a drop in demand for consumer services in those areas. The model in Gokan et al. (2022) shows that a larger incidence of remote work in a city implies a lower level of employment in consumption service sectors, because remote work substitutes commuting and decreases demand for these services. Our results show an enduring decrease in consumer services jobs where the potential for remote work was larger at the start of the pandemic, providing well-identified empirical evidence in favor of both of these models. In addition, our work shows that the effects of remote work on city employment are likely to be at work outside of the developed-country settings that previous work has focused on. Given that Aksoy et al. (2022) find that remote work was adopted to some degree in many countries at varying levels of development, our results point to effects of remote work on consumer services employment that may also be present in many other settings.

Our results also stress that to the extent that remote work continues to be a feature of labor markets, the co-location of consumer services workers and skilled workers (Gottlieb et al., 2021) may impose challenges to some lower skilled workers in the aftermath of the pandemic. While the persistent decrease in consumer services employment we find can be read as a slow recovery following the large pandemic shock, it is also possible that our results reflect a structural shift in the demand for consumer services. Under this light, our work contributes to the nascent literature aiming to understand the effects of the pandemic on cities (Glaeser, 2022). As framed by Bryan, Glaeser, and Tsivanidis (2019), cities (including those in less-developed countries) generate positive spillovers thanks to the spatial proximity they provide at the same time as they impose costs associated to density. Consistent with the former, we find that in Mexico workers that could perform their work remotely tended to co-locate with

consumer service workers in larger cities at the start of the pandemic, suggesting that as in other settings the higher-income workers in potentially-remote occupations helped sustain demand for other lower-skilled services (Althoff et al., 2022). Our work quantifies a channel through which the adoption of remote work may have weakened these positive spillovers in cities, in particular by decreasing employment in consumer service sectors. In the light of a secular increase in remote work across the world (Gottlieb et al., 2021), we also contribute to the discussion on how remote work can play into economic development policy after COVID-19 (OECD, 2021).

The rest of the paper proceeds as follows. Section 3 describes the dynamics of high-proximity consumer services employment in Mexico during the pandemic, and shows descriptive evidence about its relationship with the local potential for remote work. Section 2 describes our data. Section 4 lays out the econometric model and shows results for employment and wages, as well as other evidence about the market for consumer services, and the role of Internet access. Section 5 shows, through counterfactual regional employment calculations, the effect of potential remote work on the uneven performance of employment across Mexico in the recovery from the pandemic, and illustrates it as a contributor to the muted growth of employment in the service-heavy central region. Section 6 concludes.

2 Data

2.1 Employment and Wages

We aim to test that as workers adopt remote schemes the employment in consumer services sectors decreases. Our main source of monthly employment data are the administrative records from the Mexican social security institute (*Instituto Mexicano del Seguro Social*, IMSS). The IMSS records provide us with monthly formal employment records including anonymized employeer and employee identifiers, sector and municipality. For our main analysis, we aggregate these to the sector-municipality-month-level, which allow us to study geographical and time variation in consumer services employment, as well as to compare

it to employment in other sectors. Since it is rare for employment surveys to be representative of specific sectors, administrative data like these are particularly well suited to study sectoral employment. IMSS covers a large share of formal work in Mexico, as private firms are required by law to register their salaried workers to IMSS each month, for the calculation of contributions and benefits within the social security system.⁶ In 2020 over 80% of formal workers in Mexico were covered by IMSS.⁷ We classify as high-proximity sectors (or equivalently, consumer services) those IMSS sectors covering food and beverage services and entertainment, and the rest as low-proximity. We exclude touristic sectors from the sample, as shifts in demand for travel after the start of the pandemic could act as a confounder.⁸ The employment records include data on individual monthly compensation, as well as firm identifiers, which allow us to observe the number of firms in each sector too. We study both of these variables as outcomes as well.

Our data allow us to follow individual workers over time, so we can also construct outcomes that reflect different employment paths. In particular, we are interested in whether individuals who lose their jobs in consumer services sectors shift to other sectors or leave the formal workforce. We describe these outcomes in the corresponding results sections.

2.2 **Remote Work Potential**

We generate a measure of the potential for remote work in early 2020 at the municipal level using occupation data from the Mexican 2020 Census.⁹ We calculate potential remote work as the percentage of Census employment in occupations that could be performed remotely,

⁶There exist other social security institutions that cover, for instance government employees under *Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado* (ISSSTE) or those in the state oil company, PEMEX.

⁷According to National Employment and Occupation Survey (*Encuesta Nacional de Ocupación y Empleo*) data indexed to the first quarter of 2020, 83.6% of formal workers were affiliated to IMSS.

⁸We aim to use non-consumer services sectors as a comparison group. Given this, and that employment in tourism could take different trends after the arrival of remote work, means that the inclusion of tourism employment in the sample would threaten the identification strategy. For instance, there are journalistic accounts of locations that were amenable for remote work and may have received inflows of remote workers from other locations (Drillinger, 2022). Our data does not allow us to observe if remote workers demand more services related to tourism, and if so where. As a consequence, we opt these sectors from the analysis completely.

⁹The 2020 Census was collected before the declaration of the pandemic.

using the Mexican occupation classifications from Leyva and Mora (2021). The occupation classification in the Census is coarser than the one provided by these authors, so we coarsen the latter one to match them. To do this, we reclassify a 2-digit occupation as potentially remote if any of its 4-digit components is classified as potentially remote. Using our coarsened measure, we calculate potential remote work at 25.6%, while Leyva and Mora (2021) estimate it at 10.6% using a more disaggregated cross section of occupation data (from ENOE, the national labor survey). While these two measures differ, our estimated total potential remote work is similar to the one based on the classification of Dingel and Neiman (2020) for Mexico, which stands at 20%-23% (Monroy-Gomez-Franco, 2020). Being based on Census data, our measure has the advantage of providing municipal-level variation of potential remote work, which allows us to bring in all of our preferred IMSS employment data to the analysis. Table 1 shows some descriptives of our measures of potential remote work at the municipal-level and high-proximity employment.

TABLE 1: SUMMARY STATISTICS: POTENTIAL REMOTE WORK AND HIGH-PROXIMITY

 EMPLOYMENT

	No. of Municipalities	Mean	S.D.	25th perc.	Median	75th perc.	Max.
Potential remote work, pct	2010	15.33	6.30	10.93	14.47	18.55	47
High proximity employment, pct	2010	2.34	6.60	0.00	0.33	2.23	100

Note: This table shows summary statistics of our measure of potential remote work and high-proximity employment at the municipal level. Potential remote work is expressed as the percentage of all workers in the Census that could perform work remotely according to our measure. High-proximity employment is the percentage of formal employment in consumer services sectors in our classification. The sample of municipalities is restricted to those that have positive high-proximity employment in February 2020.

2.3 Other outcomes and control variables

To study price responses, we use data at the city level for 55 cities in Mexico, reported by Mexico's statistical agency, *Instituto Nacional de Geografía y Estadística* (INEGI). We focus on price indexes of consumer services, in particular service at restaurants and cinemas. As a comparison group within the city, we use the price index of the rest of the components of core inflation.

The 2020 Census provides other variables at the municipality level that we use to construct

controls. These data are indexed to the first quarter of 2020, so they reflect the characteristics of municipalities at the start of the pandemic. In particular, we calculate the share of households with Internet access, the share of overall employment (including informal employment) by sectors, and the share of population in school age. Finally, we use the number of COVID-19 cases and deaths at the municipality level by month from Mexico's health ministry, *Secretaría de Salud*.

3 Context

High-proximity sectors including consumer services such as restaurants, bars, and cafés, compose a substantial part of the workforce in Mexico, accounting for over 910 thousand jobs before the pandemic. This small group of sectors accounted for approximately 4.5% of total formal jobs in February of 2020. For our purposes, we consider a job to be high-proximity if it belongs to the food and drink preparation and service subsectors, to entertainment, or recreation, and collectively refer to these as consumer services or high-proximity services, indistinctly.¹⁰ Employment has fared worse in high-proximity sectors relative to the rest of the sectors in the economy (which we call low-proximity as shorthand) after the start of the pandemic, as shown in Figure 1. The plot shows the percentage difference in formal employment with respect to February 2020, in low and high-proximity sectors. Low-proximity employment fell at a more moderate rate than high-proximity employment, and by October of 2021 had again breached its pre-pandemic level. In contrast, in October 2021 high-proximity sectors still lagged 10% below their pre-pandemic level.

Recent work in urban economics suggests that as high-income workers adopt remote work, their demand for consumer services decreases, leading to drops in employment in these sectors (Althoff et al., 2022; Monte, Porcher, and Rossi-Hansberg, 2023; Gokan et al., 2022;

¹⁰While some tourism-related sectors (such as air transport and accommodation) may also be though of as high-proximity, we do not include them in the analysis because we take them to be less sensitive to our measure of local remote work. However, business tourism also showed a slow pandemic recovery (see Banco de México, 2022a), and it is plausible that the transition towards remote interactions in the workplace may have contributed to this fact. By February 2020, following the above groupings, 4.5% of national formal employment was high-proximity, 93.2% low proximity, and 2.3% was in tourism-related subsectors.



FIGURE 1: FORMAL EMPLOYMENT IN HIGH AND LOW PROXIMITY SECTORS AFTER THE START OF THE COVID-19 PANDEMIC

Note: The figure shows the percentage difference in employment with respect to February 2020 in high and low proximity sectors, for the period from February 2020 to February 2024. Employment data are from IMSS records of insured workers. High-proximity employment is defined as employment in the food and beverage services and entertainment IMSS 3 digit subsectors, and low proximity employment are all other subsectors excluding air transport and temporary accommodation.

Chetty et al., 2020). At the same time, there is evidence that remote work arrangements have persisted after the COVID-19 health emergency and that some managers expect similar levels of remote work in the future (Barrero, Bloom, and Davis, 2023). Then, continued remote work is a likely explanation to the still-lagging employment in consumer services sectors, as well as a factor likely to weigh against its growth in the future. We study the effects of the potential for remote work on employment in Mexico. Mexico is a middle income country with an important service sector: as of the last quarter of 2023, 63.4% of workers were employed



FIGURE 2: FORMAL EMPLOYMENT IN HIGH-PROXIMITY SECTORS, BY MUNICIPAL-LEVEL REMOTE WORK POTENTIAL

Note: The figure shows percentage differences in formal employment in high-proximity sectors with respect to February 2020 for the period February 2019 to February 2024. Municipalities are grouped according to whether their share of remote work occupations is above or below the national median, employment weighted. Remote work potential is measured as the percentage of employment that could perform work remotely before the pandemic, constructed using occupation data from the 2020 Census, and the remote work classification of occupations from Leyva and Mora (2021).

in the tertiary sector (including formal and informal).

Figure 2 illustrates that, since the beginning of the pandemic, employment in high-proximity sectors has been weaker in municipalities where a greater proportion of local jobs could be performed remotely at the beginning of the pandemic than in municipalities with a lower feasibility of implementing remote work. A municipality is classified in the high remote work group if its level of remote work potential in February 2020 was above the national median (weighted by total employment). This suggests that remote work may be influencing

the muted recovery in high-proximity sectors.

FIGURE 3: GOOGLE MOBILITY TRENDS: WORKPLACES, RESIDENCIAL STAY, AND RETAIL & RECREATION BY REMOTE WORK



Note: The figure shows Google mobility data by place categories for the period from February 2020 to October 2022 in Mexico. States are grouped together according to whether their share of remote work occupations in February 2020 was above or below the national median, employment weighted. Occupation shares are measured in the 2020 Census, and remote work occupations are classified following Leyva and Mora (2021). Data are shown at the weekly level and expressed as percent deviations with respect to the average mobility index between February 15 and February 27, 2020. According to the data documentation, residential stay measures the share of time spent at home, workplaces are places of work, and retail and recreation includes places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.

Figure 3 shows Google's region mobility trends from early 2020 to late 2022, in states above and below the median remote work potential in 2020.¹¹ States with larger shares of workers

¹¹Google Community Mobility Reports provide indexes reflecting how long a population spends in several

in occupations that could be performed remotely in 2020 show fewer trips to workplaces, relative to states with lower potential for remote work, from the start of the pandemic and until the end of the period covered by the data. We take this as evidence that our cross-sectional measure of potential remote work reflects to some extent differences in actual remote work across municipalities over time. Interestingly, by 2022 Google's index of residential stay has converged between high and low remote work states, while trips to work remain lower in high remote work states, suggesting that remote work has been an enduring feature of post-pandemic behavior in places that allow it. Consistent with what we show in Figure 1, trips to retail locations, which include restaurants, cafeterias, cinemas, and other entertainment, are also lower in locations with more potential remote work by our measure.

4 Model and Estimation

We aim to capture the effects of remote work on consumer services employment due to the reduction of the demand of these services as workers adopt remote work (this relationship is described and modelled in e.g. Althoff et al. (2022), Gokan et al. (2022), Monte, Porcher, and Rossi-Hansberg (2023). While we could compare high-proximity employment before and after the pandemic across municipalities with more and less remote work potential in a difference-in-difference strategy, employment in high-proximity services did not follow the same trends across municipalities with high and low remote work potential before the pandemic. To show this, we first estimate a panel event study model of the effect of potential remote work on employment of group $g = \{\text{High-Proximity}, \text{Low-Proximity}\}$, from the following equation, where t indexes months.

$$EmploymentGap_{jt} = \lambda_t + \beta_{2t} \ \mathbf{RW}_{j} + \Theta X_{jt} + \epsilon_{jt}$$
(1)

Our outcome is the municipality-level employment gap in percent with respect to February 2020. We pick this outcome for this exercise as well as for the rest of the paper, since we find

location types, including workplaces, residences, retail & recreation, parks, transport, and pharmacies. These are generated using cell-phone location data. Data is provided from February 2020 until November 2022.

it eases the interpretation of the estimates. Each coefficient represents the estimated effect on the employment gap with respect to the start of the pandemic, in percentage points, of a 1 percentage point increase in potential remote work - in other words, the effect of potential remote work on the level of employment relative to before the pandemic started. Since we use the employment gap with respect to February 2020 as an outcome, any time-invariant differences across municipalities j are already differenced out. For this reason, we omit municipality fixed effects from the estimation.

Figure 4 shows the results of the difference-in-difference event study estimates for high and low proximity employment. Panel 4a shows that high-proximity employment was trending differently in locations that had higher potential for remote work before the pandemic, relative to locations with lower potential for remote work. This check suggests the difference-in-difference design may be inadequate in this setting. However, Panel 4b shows that low proximity employment was also on differential trends across the distribution of potential remote work before February 2020. As Olden and Møen (2022) show, when two groups have similar deviations from the parallel trend assumption, triple-difference designs can result in consistent estimates of treatment effects. In our case, both high-promixity and other employment were on more downward trends in locations with higher remote work potential in the months before the start of the pandemic. We implement a triple-difference strategy next.

Intuitively, in our triple-difference design we start by comparing gaps in high-proximity employment in places with greater and lesser potential remote work (first difference). However, as we have seen, municipal employment trends may be different where there is more remote work potential, even in the absence of the pandemic. These trends may be adjusted for by using low proximity sectors as a control group, because these occupations capture the differential behavior of employment in municipalities with high and low remote work potential (second difference). Finally, the effect of the pandemic is obtained by comparing this double difference (high-proximity employment in locations with greater and lesser remote work potential versus low-proximity employment in locations with greater and lesser remote work potential) before and after the onset of the pandemic (resulting in the triple difference). We

FIGURE 4: DIFFERENCE-IN-DIFFERENCE PANEL EVENT STUDY ESTIMATES OF EFFECT OF 1PP POTENTIAL REMOTE WORK ON EMPLOYMENT



Note: This figure shows estimates of β_t in Equation 1. February 2020 is omitted and marked by a vertical line. The sample covers the same municipalities and period described in Table 2. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.

construct a database at the group $g = \{\text{High-proximity}, \text{Low Proximity}\}\$ by month m by municipality j level, and estimate the following model.¹²

$$EmploymentGap_{gjt} = \alpha_1 HiProx_g + \alpha_2 Pandemic_t + \delta_1 RW_j \times HiProx_g + \delta_2 RW_j \times Pandemic_t + \delta_3 HiProx_g \times Pandemic_t + \beta \mathbf{RW_j} \times \mathbf{HiProx_g} \times \mathbf{Pandemic_t} + \Theta X_{jt} + \epsilon_{qjt}$$
(2)

In the above, $EmploymentGap_{gjt}$ is the percentage difference in employment in municipality j, in month t, in group g (high or low proximity sectors) relative to February 2020; RW_j is the percentage of remote work potential from municipality j in February 2020 as

¹²Appendix A details our reasoning for choosing this specific profile of fixed and time-varying effects.

defined in the previous section; $HiProx_g$ is an indicator variable equal to one for the group of high-proximity employment sectors; $Pandemic_t$ is an indicator variable equal to one for the months after February 2020; and X_{jt} is a vector of controls.¹³ The above regression is

		Dep	var. Employmen	n gap	
$HiProx_g \times RW_j \times Pandemic_t$	-0.350*** (0.075)	-0.383*** (0.088)	-0.381*** (0.088)	-0.384*** (0.088)	-0.382*** (0.088)
$HiProx_g \times RW_j$	0.131** (0.044)	0.152*** (0.046)	0.292 (0.179)	0.152*** (0.046)	0.292 (0.179)
$RW_j \times Pandemic_t$	-0.379*** (0.062)	-0.038 (0.147)	-0.035 (0.148)	-0.037 (0.146)	-0.034 (0.147)
$HiProx_g \times Pandemic_t$	0.008 (0.029)	0.021 (0.034)	0.020 (0.034)	0.021 (0.034)	0.020 (0.034)
$HiProx_g$	-0.048*** (0.014)	-0.055*** (0.014)	-0.105 (0.062)	-0.055*** (0.014)	-0.105 (0.062)
RW_j	0.064*** (0.013)	0.054 (0.028)		0.054 (0.028)	
$Pandemic_t$	0.137*** (0.019)	0.268** (0.092)	0.279** (0.092)		
Observations	1,238,793,294	1,238,793,294	1,238,793,294	1,238,793,294	1,238,793,294
TimeFE	No	No	No	Yes	Yes
MunFE	No	No	Yes	No	Yes
Controls	No	Yes	Yes	Yes	Yes

TABLE 2: TRIPLE DIFFERENCE ESTIMATES, EMPLOYMENT

Don Ver: Employment gen

Note: This table shows estimates of equation 2, with percentage differences in employment with respect to February 2020 as an outcome variable. Regressions are at the municipal, month, group level, and are weighted by the IMSS-affiliated employment in each municipality group in February 2020. The sample covers municipalities with positive high and low proximity employment in February 2020. Controls are one month-lagged COVID cases and deaths and interactions of school aged population and February 2020 one digit sectoral shares with time dummies. Standard errors are clustered at the municipality level. *p<0.1; *p<0.05; ***p<0.01

weighted by the number of formal workers in municipality j, in group g, in February 2020.¹⁴

Table 1 shows the main estimates.

¹³The vector includes variables associated with the course and recovery of the pandemic. Interactions of month indicator variables with school-age population (6 to 24 years) controls for differential demand for consumer services coming from students, given pandemic-induced school closures. Interactions of month indicator variables with the percentage of total employment in the secondary sector (measured in February 2020) adjust for differential demand for services from manufacturing workers, also given government-mandated restrictions to operations. The number of COVID-19 cases and deaths in the municipality in the previous month control for differential direct effects of the pandemic, which could have affected both consumer services labor supply and demand.

¹⁴This weighting reflects that some locations are more important in terms of total employment and therefore the changes in employment gap are due to larger shifts in overall employment.

A 1 percentage point (pp) increase in remote work potential implies a gap 0.38 percentage points greater in employment in high-proximity formal work sectors during the pandemic relative to the start of the pandemic, robust across specifications with different sets of control variables. For reference, and as we show in Table 1, a standard deviation in the distribution of remote work potential is around 6pp. Then, an increase of 1 standard deviation in potential remote work at the start of the pandemic translates to a 2.28 pp larger gap in high-proximity employment after the pandemic start. This effect is economically significant as well. In the absence of our estimated negative effect of potential remote work on consumer service employment, we estimate total formal consumer service employment after the pandemic total formal consumer service also indicate that high-proximity employment tended to be higher, prepandemic, in municipalities where remote work potential was higher.

It is possible to estimate the effects of remote work potential on high-proximity formal employment in each month of the study period, using an event study design. The estimating equation in this case is the following, where the notation corresponds to the one used in the main equation and λ are time fixed effects.

$$EmploymentGap_{gjt} = \lambda_t + \alpha_1 HiProx_g + \delta_1 RW_j \times HiProx_g + \delta_2 RW_j \times Pandemic_t + \delta_3 HiProx_g \times Pandemic_t + \beta_{gt} \mathbf{RW_j} \times \mathbf{HiProx_g} + \Theta X_{jt} + \epsilon_{gjt}$$
(3)

The results of the event study estimation are shown in Figure 5 and are interpreted as the

¹⁵Using the estimates shown in Table 1, we can calculate how many more high-proximity jobs would have been observed in the post-pandemic period in the absence of the potential remote work effect. Under the baseline estimates, we find an additional 110, 448 jobs on average in the post-pandemic period, while under the more conservative estimates that control for the inclusion of controls for internet access, shown in Table 3, this figure is instead 84, 965.

effect, at month t, of a 1 pp increase in the percentage of potential remote work on the gap in formal high-proximity employment. The estimated coefficients for the months prior to the pandemic are small and not statistically significant, indicating that the estimate is not affected by secular trends in unobserved variables. During the first two years of the pandemic, a higher proportion of potential remote work is associated with a larger gap in high-proximity employment with respect to low-proximity employment, with effects from -0.6 pp to -0.2 pp for every 1 pp increase in the percentage of potential remote work. The effects were more negative month-on-month through February 2021. By March 2021, the effects are slightly lower, although remote work potential is still associated with larger gaps in high-proximity employment four years after the start of the pandemic. While the extent of remote work in the labor market may continue to change, our results indicate that its effects were still perceptible in service sectors as of early 2024.

Our results are consistent with other work that relates remote work occupations to negative effects on consumer services workers, which have mostly studied the US (Dalton, Dey, and Loewenstein, 2022; Althoff et al., 2022; Chetty et al., 2020). We causally estimate the effects of the potential for remote work at the local level on consumer services employment using event study techniques. Thus our results constitute strong direct evidence in favor of the models that relate remote work to changes in the structure of urban employment (in particular Monte, Porcher, and Rossi-Hansberg (2023) and Gokan et al. (2022)). Further, by showing that potential remote work relates to lower consumer services employment in Mexico, we highlight that remote work can have effects outside of the developed countries that have so far been the focus of the literature. Our results suggest that cities in middle-income countries may also face challenges due to a lasting shift in the consumption patterns of now-remote workers. If demand for consumer services is permanently weaker due to remote work, low-skilled workers in these sectors in developing country cities might be at a disadvantage during the post-pandemic period, posing a challenge to policy makers.¹⁶ We bring in evidence on other outcomes in sections 4.2 and 4.3 to shed further light on the mechanisms behind the

¹⁶A decrease in demand in services may imply that workers may face more difficulty in finding employment, or have to pay costs to change sectors. See Banco de México (2022b) on adjustment costs.



FIGURE 5: EVENT STUDY TRIPLE DIFFERENCE ESTIMATES FOR HIGH-PROXIMITY EMPLOYMENT

Note: Estimates correspond to the effect of a 1 percentage point increase in potential remote work on the gap in formal consumer service employment relative to February 2020 and are estimated using a triple difference panel event study, corresponding to β_{gt} in Equation 7. February 2020 is omitted and marked by a vertical line. The sample covers the same municipalities and period described in Table 2. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.

effects of remote work, and find some evidence of a negative labor demand effect on workers in high-proximity sectors. For now we turn to validity and robustness tests in the next section.

4.1 Pretrend Tests and Robustness

We now evaluate the possible threat of pretrends to the estimation as well as perform some robustness checks. Adapting the recommendations of Freyaldenhoven et al. (2021) to our triple difference event study setting, we first test whether the pre-period coefficients are jointly equal to zero in equation 7. Wald tests reject that all pre-period coefficients are jointly zero at standard levels of significance (p < 0.01). However, we do not take this rejection of the no parallel trend assumption to threaten the validity of the empirical design or the interpretability of the results. As can be seen in Figure 5, the pre-treatment coefficients are precisely estimated but much smaller than the post-treatment ones. For this reason, the violation of no-parallel trends is not likely to be large enough to confound the estimates in a qualitatively meaningful way.

To formally check for the relevance of pre-trends to the results, we performed sensitivity tests to violations in the no pre-trend assumption (following Rambachan and Roth, 2023). These tests check how large the violations of the no pre-trends assumption would need to be in order to explain the treatment estimates from a given event study. One way to implement these empirical checks is to pick bounds to how large the post-treatment deviations from the parallel trend assumption can be, expressed in multiples of the pre-treatment deviations from parallel trends, and calculate adjusted confidence bounds for the treatment effects assuming confounders of the chosen magnitude are present in the estimation. We next show the confidence intervals of our average treatment effects under different assumptions over how large the violations of parallel trends can be. In the horizontal axis we show the values of M, the assumed size of the post-treatment confounder. The first estimation, labeled "Original" assumes there are no deviations from parallel trends, corresponding to usual OLS estimation. The confidence interval (CI) labeled "1" assumes that the post-treatment confounder is at most of the same magnitude as the largest deviation from parallel trends observed in the pre period. This assumption does not meaningfully alter the statistical significance of our estimates, meaning that the pretrend we find is not large enough to explain our results. The CI labeled "2" assumes a confounder twice as large in the postperiod as in the preperiod, and so forth.

The graph shows that the trends found in our pre-period would need to be magnified by a factor of eight to break down the statistical significance of our results - a magnitude so large that the size of the pre-trends themselves seems of relatively small concern. However,

FIGURE 6: ROTH & RAMBACHAN CONFIDENCE INTERVALS FOR POST-TREATMENT EFFECT



Note: This figure shows the Roth & Rambachan confidence intervals of the main triple difference effects under different assumptions about the magnitude of the confounders. The horizontal axis shows the size of the confounder, expressed as multiples of the estimated pre-trend. The main specification's confidence interval (without the Roth & Rambachan adjustment) is labeled "Original".

variables that were correlated to the potential for remote work at the start of the pandemic and could have had independent effects on employment as the pandemic took hold can still threaten the identification of our effects of interest. Internet access constitutes one of these likely threats, since it is closely related to the potential for remote work and locations with larger internet access may have displayed differences in demand for consumer services. Next we analyze the robustness of our results to the inclusion of internet access terms in the triple difference strategy.

4.1.1 Role of Internet Access

Our main results are in line with existing evidence for the US showing that remote work is negatively related to high-proximity employment (Althoff et al., 2022; Chetty et al., 2020).

However, our setting is different in one important dimension. Internet access is much lower in Mexico than in the US: in 2019, over 96% of US working age adults (aged 18 to 64) had Internet access, compared to only 63% of Mexicans (Pew Research Center, 2021; INEGI, 2020). The pandemic may have changed how consumers use the Internet e.g. increasing demand for online food orders and entertainment, suggesting that Internet use may have affected consumer services employment at the same time as remote work, and thus possibly posing a challenge to identification. In Mexico Internet access and remote work potential are correlated, but not perfectly, which allows us to estimate effects for these two channels separately.¹⁷ We use municipality-level shares of households with Internet access as a second triple-difference variable, and repeat the estimation. Table 3 replicates our triple difference specification, including both remote work and Internet triple interaction terms:

$$Employment_Gap_{gjt} = \mu_j + \alpha_1 HiProx_g + \alpha_2 Pandemic_t + \delta_1 RW_j \times HiProx_g + \lambda_1 Internet_j \times HiProx_g + \delta_2 RW_j \times Pandemic_t + \lambda_2 Internet_j \times Pandemic_t + \delta_3 HiProx_g \times Pandemic_t + \beta_1 \mathbf{RW_j} \times \mathbf{HiProx_g} \times \mathbf{Pandemic_t} + \beta_2 \mathbf{Internet_j} \times \mathbf{HiProx_g} \times \mathbf{Pandemic_t} + \Theta X_{jt} + \epsilon_{gjt}$$
(4)

Table 3 shows estimates of the effects of Internet access and potential remote work on employment. We find evidence that Internet access had an independent negative effect on highproximity employment, although the effect is noisily estimated and we cannot statistically reject it is zero. The potential remote work effects are robust to the inclusion of the Internet

¹⁷It is possible that Internet access interacts with remote work potential at the municipality level, for instance by allowing certain tasks to be performed remotely with more ease, as pointed out by Barrero, Bloom, and Davis (2021). We abstract from these interaction effects and focus on the direct impact of Internet and remote work separately during the pandemic.

access triple difference terms, although the coefficients do decrease in absolute terms moderately, from -0.36 to -0.29pp per 1pp of remote work potential. This exercise suggests that, due to the possible effect of shifts in consumption over the Internet on consumer services sectors, Internet access may be an important factor to consider when studying the trajectory of employment in these sectors during the pandemic.¹⁸ In this sense, the independent variation in Internet access and potential remote work in our setting allows us to control for both variables and identify the effect of remote work net of the effect of changes in how consumers use the Internet after the pandemic. In settings with very high Internet penetration, such as the US as studied by Althoff et al. (2022), the almost total access to Internet among American households precludes separately studying the effects of potential remote work and those of internet access. In developing country settings, due to lower Internet adoption, it is possible to some extent to control for the effects of Internet access when studying related outcomes.

4.1.2 Urban and regional trends

Finally, it may be a concern that our potential remote work variable may simply be picking up differential trends in consumer services employment across regions or between more and less urbanized locations after the pandemic. For instance, if after the pandemic started, consumers in more urbanized locations shifted away from restaurants or entertainment venues due to the health risks associated to larger crowds, our estimations may simply be reflecting this fact. On the regional side, it is possible that certain regions were more affected by the pandemic and became persistently discouraged from consumption in denser locales. To rule this out, we replicate our baseline triple difference estimation in separate samples for each of Mexico's regions, following Banco de México's regional classification, as well as in the subsamples of municipalities above and below the median urbanization rate. We show these results in appendix tables A2 and A3. Our results hold in magnitude and level of statistical significance within the urban subsample, as well as within the sample of municipalities

¹⁸For instance, it is possible that during the pandemic some consumption shifted online, changing the composition of employment in service sectors.

in the dense central region.¹⁹ This is evidence in favor of our estimates not reflecting only cross-regional differences in pandemic responses.

¹⁹The estimated triple difference coefficients are negative in all regions, although the disaggregation results in noisier estimates.

	Dep. Var: Employment gap				
$HiProx_g \times RW_j \times Pandemic_t$	-0.298**	-0.298**	-0.291**		
	(0.100)	(0.100)	(0.099)		
$HiProx_g \times Internet_j \times Pandemic_t$	-0.075	-0.075	-0.121		
	(0.117)	(0.117)	(0.126)		
$HiProx_g \times RW_j$	0.165**	0.044	0.039		
	(0.050)	(0.151)	(0.154)		
$HiProx_g \times Internet_j$	-0.027	0.210	0.244		
	(0.048)	(0.259)	(0.267)		
$RW_j \times Pandemic_t$	-0.323***	-0.323***	-0.020		
	(0.088)	(0.088)	(0.156)		
$Internet_j \times Pandemic_t$	-0.006	-0.006	0.008		
	(0.067)	(0.067)	(0.074)		
$HiProx_g \times Pandemic_t$	0.020	0.020	0.046		
	(0.051)	(0.051)	(0.056)		
$HiProx_g$	-0.043*	-0.145	-0.164		
	(0.021)	(0.117)	(0.121)		
RW_j	0.012 (0.017)				
$Pandemic_t$	0.109***	0.109***	0.247***		
	(0.023)	(0.023)	(0.073)		
$Internet_j$	0.048*** (0.014)				
Observations	205,020	205,020	205,020		
Municipalities	2010	2010	2010		
Months	51	51	51		
Municipality FE	No	Yes	Yes		
Controls	No	No	Yes		

TABLE 3: TRIPLE DIFFERENCE ESTIMATES WITH INTERNET INTERACTIONS

Note: This table shows estimates of Equation 4. Regressions are at the municipal, month, group level, and are weighted by the IMSS-affiliated employment in each municipality group in February 2020. The sample covers municipalities with positive high and low proximity employment in February 2020. Internet access at the municipal level is measured from the 2020 Census as the share of households with Internet access. Controls are one month-lagged COVID cases and deaths and interactions of school aged population and February 2020 one digit sectoral shares with time dummies. Standard errors are clustered at the municipality level.*p<0.1; **p<0.05; ***p<0.01.

4.2 Worker transitions

The administrative formal employment records from IMSS allow us to follow individual workers over time. Having found negative effects of the presence of potential remote work on high-proximity employment, we turn to using this individual-level data to study how workers in high-proximity sectors adjusted to the effects of remote work. In particular, we can test whether the workers that leave high-proximity sectors in locations with high potential remote work exit the formal workforce, or whether they transition to other sectors, mitigating the negative employment effect.

For this exercise, we restrict attention to the workers who were employed in high-proximity sectors in February 2020 and observe their formal employment status and sector in February 2022. By February 2022 total formal labor employment in Mexico had returned to its pre-pandemic level, so changes over this two-year period reasonably reflect changes in employment dynamics due to the pandemic.²⁰ We calculate the share of workers in a municipality that two years into the pandemic were still in a formal high-proximity sector job, in the formal sector but in a low proximity sector, and outside the formal sector. To isolate the changes in worker transitions related to the pandemic from those that would be observed due to the usual churn in the labor market over a two-year period, we difference the shares of two-year transitions using the observed 2018-2020 transition shares. Formally, if HP_t is employment in high-proximity sectors in February of year *t*, and HP_{t+2}^{remain} , HP_{t+2}^{switch} , and H_{t+2}^{exit} are the totals of high-proximity employment that remained in high-proximity formal sectors, switched away to other formal sectors, and exited formality two years later, respectively, then we calculate for each municipality:

$$\Delta ShareRemain_j = \frac{HP_{Feb.2022}^{remain}}{HP_{Feb.2020}} - \frac{HP_{Feb.2020}^{remain}}{HP_{Feb.2018}}$$
(5)

This variable measures the changes in transitions from high-proximity sectors observed during the first two years of the pandemic with respect to the previous two year period. We calculate the analogous variable for the shares that switch formal sectors and exit the formal

²⁰By comparing February across two different years we also net out possible seasonality effects.

labor market, and estimate a simple OLS model on the sample of municipalities that had high-proximity employment in each of 2018, 2020, and 2022.²¹

$$\Delta ShareRemain_{j} = \alpha + \beta RW_{j} + \epsilon_{j} \tag{6}$$

Columns 1 to 3 of Table 4 show the results. Consistent with our findings on employment, potential remote work correlates with lower shares of high-proximity workers remaining in that sector. A 1 percentage point increase in potential remote work decreases the share of workers that remain in high-proximity sectors by .08 percentage points. Comparing columns 1 and 2, we see that most of the decrease is accounted for by workers that exit the formal labor market, which suggests that potential remote work is decreasing demand for these workers. This result is also consistent with the existence of costs to switching occupations (Artuç, Chaudhuri, and McLaren, 2010; Arias et al., 2018; Banco de México, 2022b). If workers find it difficult to switch sectors, then sector-specific shocks such as the shift away from service consumption associated to the pandemic will tend to push negatively affected workers out of employment (see Banco de México, 2022c). Incidentally, that we find little switching across sectors in response to our shock also serves to validate the main empirical strategy, since it is evidence that the non-consumer services sector employment we use as a comparison group is not contaminated by the treatment.

Thus, these results also are at odds with the hypothesis that remote work affects high-proximity employment by allowing these service employees to work remotely. If potential remote work decreased high-proximity employment by making employment in sectors with remote work more attractive than high-proximity jobs, we would observe more employment shifting to low proximity sectors. As an additional check for the possible role of potential remote work on labor supply to high-proximity sectors, we calculate the average share of remote work occupations in the sectors that high-proximity workers transition to in each municipality. If

²¹For the worker transitions a triple difference design as we have shown so far is less suitable, given that one of the main outcomes of interest is the switch away from high-proximity sectors and into what would be the "untreated" group in a triple difference design. This rules out using the low-proximity sectors in the estimation, since they could also be affected by the treatment.

remote work made consumer services workers shift towards remote occupations, we would expect to see an increase in the share of employees in sectors that allow for remote work. Column 4 of Table 4 shows that the destination sectors of high-proximity workers do not have a significantly larger content of remote work occupations where remote work was more feasible, serving as further evidence that remote work is not operating mainly through changes in the labor supply decisions of workers.

	Dependent variable:					
	Still in HP Sector	Outside Formality	Non HP Formal Job	Share of RW in Dest. Sector		
	(1)	(2)	(3)	(4)		
RW_j	-0.0808^{***}	0.0696***	0.0091	0.0021		
	(0.0296)	(0.0169)	(0.0182)	(0.0044)		
Constant	-2.9663^{***}	2.0357***	0.7549	0.1757		
	(0.9264)	(0.6123)	(0.5959)	(0.1444)		
Observations	1.025	1.025	1.025	1.025		
Observations	1,055	1,055	1,055	1,055		
\mathbb{R}^2	0.0277	0.0365	0.0012	0.0017		
Adjusted R ²	0.0268	0.0356	0.0002	0.0007		

TABLE 4: TRANSITIONS OF WORKERS EMPLOYED IN HIGH-PROXIMITY SECTORS ANDREMOTE WORK POTENTIAL

Note: This table shows OLS estimates of the effect of remote work on the job outcomes of workers that were in high-proximity sectors in February 2020, measured two years later. "Still in HP sector" is the share of high-proximity workers that remained in high-proximity sectors; "Outside Formality" is the share that was no longer in the formal labor market; "Non HP Formal Job" is the share that was in a non HP sector of the formal labor market, and "Share RW in Dest Sector" is the average share of remote work in the destination sectors of workers, measured from INEGI's ECOVID survey. Regressions are at the municipal level. All outcomes are expressed as first differences, netting out the observed values of each outcome between 2018 and 2020 to account for usual churn in the labor market. Regressions are at the municipal level. The sample consists of all municipalities that had high-proximity employment in 2018, 2020, and 2022. Standard errors are clustered at the municipality level. *p<0.1; **p<0.05; ***p<0.01

4.3 Wages

Having found negative effects of the presence of occupations that can be performed remotely on high-proximity employment during the pandemic, it is natural to study wages. There exists theoretical work and some empirical evidence that consumer services employment decreased because of a drop in demand for services (Chetty et al., 2020; Althoff et al., 2022; Monte, Porcher, and Rossi-Hansberg, 2023; Gokan et al., 2022), which could influence wages. However, in our setting we find zero effects of remote work on wages under the triple difference strategy, as shown in Table 2. Difference-in-difference panel event studies also show no effects of remote work potential on wages, as shown in Appendix Table A5.

Binding minimum wages or nominal rigidities can decrease the margin for downward adjustments in wages in the face of shocks. We find suggestive evidence of this in Figure 7, which shows wage distributions by high- and low- proximity sectors, and confirms that a large mass of wages paid pre-pandemic in high-proximity sectors were close to the lower bound of the distribution.²² These bounds, along with restrictions to nominal decreases, can account for wages in this setting being relatively rigid in the face of a negative shock (Castellanos, García-Verdú, and Kaplan, 2004). It is also possible that lower demand for high-proximity employment was offset by a reduction in labor supply, resulting in positive and negative wage effects that tend to cancel out, along with the observed negative employment effects.

The effects we find, along with the mass of high-proximity employment wages on the left tail of the distribution shown in Figure 7 also have some distributional implications. Importantly, the concentration of high-proximity employment in the lower tail of the wage distribution implies that decreases in these sectors' employment are likely affecting low-income workers the most. While it is possible that remote work allowed some firms and workers to weather the pandemic shock, this result suggests that the sectoral shift implied by remote work may have had some distributional effects, which is one of the predictions in Gokan et al. (2022).

4.4 Prices

As suggested above, a closely related question is whether prices in sectors that involve high physical proximity evolved differently due to the influence of potential remote work. The lower demand for consumer services may induce prices to grow more slowly, but if the pandemic caused closures of consumer service establishments, then prices may have grown faster

²²The large mass at the observed lower bound is near the minimum wage in 2020, equal to 123.22 MXN daily (or approximately 6 USD) for most of the country. In Mexico, municipalities bordering the US have a higher minimum wage, which in 2020 was equal to 185.56 MXN daily.

	Dep. Var: Wage gap				
$HiProx_g \times RW_j \times Pandemic_t$	0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$HiProx_g \times RW_j$	0.001*	0.001*	0.001	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$RW_j \times Pandemic_t$	-0.000	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$HiProx_g \times Pandemic_t$	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$HiProx_g$	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RW_j	-0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(.)	(0.000)	(.)
Pandemic _t	0.001***	0.001***	0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(.)	(.)
Observations	1238753671	1238753671	1238753671	1238753671	1238753671
TimeFE	No	No	No	Yes	Yes
MunFE	No	No	Yes	No	Yes
Controls	No	Yes	Yes	Yes	Yes

TABLE 5: TRIPLE DIFFERENCE ESTIMATES, WAGES

Note: This table shows estimates of equation 2, with percentage differences in wages with respect to February 2020 as the outcome variable. Regressions are at the municipal, month, group level, and are weighted by the IMSS employment in each municipality group in February 2020. The sample covers municipalities with positive high and low proximity employment in February 2020. Controls are one month-lagged COVID cases and deaths and interactions of school aged population and February 2020 one digit sectoral shares with pandemic period dummies. Standard errors are clustered at the municipality level. *p<0.1; **p<0.05; ***p<0.01

due to lower competition or scale in high-proximity sectors.

In order to study the relationship between prices in high-proximity sectors and potential remote work after the start of the pandemic, we turn to consumer price index data at the city level, from INEGI. Price indexes are measured at the city level for 55 cities, which we then group together according to whether their level of remote work potential is above or below the weighted median for the sample of cities, using total employment as weights. We calculate percentage changes in price indexes in these sectors with respect to February 2020, in line with our analysis of employment.²³ In Figure 8 we plot these price gaps. The Figure shows that consumer services price indexes in high and low potential remote work cities have

²³To each city-month level observation of the change in consumer service price indexes relative to February 2020, we substract the percentage difference in the price index of other services. By netting out these other services price changes, we partly account for differences in city-level price trends in services.

FIGURE 7: WAGE DISTRIBUTION FOR HIGH AND LOW PROXIMITY SECTORS, FEBRUARY 2020



Note: This figure shows the kernel density of daily wages in February 2020 for high-proximity and low proximity workers using IMSS data.

followed similar trends over time, with price changes relative to 2020 being slightly higher in locations with more remote work. To test formally for price effects of potential remote work in consumer services sectors, we use the price gap measure as an outcome in a panel event study triple difference. The estimation equation is as follows.

$$PriceGap_{gjt} = \lambda_t + \alpha_1 HiProx_g + \delta_1 RW_j \times HiProx_g + \delta_2 RW_j \times Pandemic_t + \delta_3 HiProx_g \times Pandemic_t + \beta_{gt} RW_j \times HiProx_g + \Theta X_{jt} + \epsilon_{qjt}$$
(7)



FIGURE 8: LOCAL PRICE INDEXES OF RESTAURANTS AND ENTERTAINMENT, BY REMOTE WORK POTENTIAL

Note: The figure shows percentage change in price indexes of restaurants and entertainment with respect to February 2020, grouping together cities with potential remote work above and below the employment-weighted median across cities in the price sample. The consumer services categories are aggregated together using INPC expenditure weights. City-level price changes are aggregated into high and low remote work city averages using total city population as weights. To each of the city-month price percentage changes we use to construct these aggregates, we substract the city-month level percentage change in the price index of other services, relative to February 2020.

Figure 9 plots our estimates. Previous to the start of the pandemic, consumer services price indexes in locations with higher and lower potential for remote work followed similar trends. Upon the start of the pandemic, price index growth was larger in locations with more potential remote work, but these differences are not statistically distinguishable from zero at 95% confidence. We conclude that there is no strong statistical evidence in our data of the effect of remote work on consumer services price gaps with respect to February 2020. While there exists evidence for prices in the Mexican setting that points to a decreased price growth

in high-proximity (in-person) food services after 2020 relative to food delivery (Solórzano, 2024), our data do not allow us to provide strong evidence that remote work contributed to a lower growth of high-proximity services. In this same sense, in Figure A4 of the Appendix we show that a panel event study design cannot reject that there are null effects on the number of firms in high-proximity sectors. These null effects suggest that the main margin in which firms adjusted to the likely drop in demand from remote workers was to decrease their scale.

FIGURE 9: EVENT STUDY TRIPLE DIFFERENCE ESTIMATES FOR PRICES



Note: This figure shows estimates of β_{gt} in Equation 7. February 2020 is omitted and marked by a vertical line. The sample covers the same municipalities and period described in Table 2. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.

5 Counterfactual and regional implications

Our previous results show that a larger share of potential remote work is associated with a weaker recovery in high-proximity sectors after the start of the pandemic. In fact, these two types of employment tend to co-locate: in our setting, in all regions of Mexico the correlation between the remote work potential and share of high-proximity employment is positive. Indeed, the urban economics literature points out that high skilled workers, whose tasks can more frequently be performed remotely, tend to demand amenities and services that require lower skilled workers to locate close to them (Moretti, 2011; Diamond, 2016; Althoff et al., 2022 among others). Under this logic, it is natural to expect remote work potential and consumer services workers to co-locate across the municipalities of Mexico as well. This co-location of our independent and dependent variable suggests that the effect we find may contribute to explain variation in consumer services employment at more aggregate levels. Indeed, Figure 10 shows that in general municipalities with larger shares of remote work occupations also have larger shares of consumer services workers. This natural co-location of potentially-remote workers and high-proximity workers before the pandemic meant that locations with more remote work potential were subject to a larger, more lasting negative shock to employment, through the effects that we estimate in Section 4.

This suggests that the effects we estimate, together with the co-location of potential remote work and consumer services employment, may have affected regional patterns of highproximity employment after the pandemic. To illustrate how regional patterns in consumer services employment may be influenced by the joint location of potentially remote- and consumer service- employment, in this section we perform a counterfactual where we calculate employment under the assumption that the location of potential remote work is independent from that of consumer services employment at the start of the pandemic. We use Banco de México's definition of regions for Mexico.²⁴ The strongest correlation between both kinds

²⁴These are: i) North: Baja California, Chihuahua, Coahuila, Nuevo León, Sonora y Tamaulipas; ii) Center North: Aguascalientes, Baja California Sur, Colima, Durango, Jalisco, Michoacán, Nayarit, San Luis Potosí, Sinaloa y Zacatecas; iii) Center: Ciudad de México, Estado de México, Guanajuato, Hidalgo, Morelos, Puebla, Querétaro y Tlaxcala; and iv) South: Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz y Yucatán

FIGURE 10: MUNICIPAL REMOTE WORK POTENTIAL AND HIGH-PROXIMITY EMPLOYMENT, 2020



Note: The figure shows the percentage of employment in remote work occupations and the percentage of employment in high-proximity sectors in February 2020 for municipalities in Mexico. Potential remote work is measured from the 2020 Census and the catalog of remote work occupations in Leyva and Mora (2021). High-proximity employment is from IMSS affiliation records in February 2020. Marker size is proportional to total municipal IMSS-affiliated employment in February 2020. The employment weighted correlation between these two variables is 0.51.

of employment is observed in the central region, where the correlation coefficient between both variables at the municipality level is 0.76. This region includes Mexico City, a megalopolis specialized in services and that has recovered slowly from the pandemic's negative employment shock. The northern region's correlation between remote work potential and high-proximity is 0.65; 0.49 in the north-central, and 0.17 in the southern region.

To illustrate the importance of this interaction, we compute a measure of the co-location of remote work and high-proximity sectors by region in February 2020. This measure is the

FIGURE 11: OBSERVED AND COUNTERFACTUAL EMPLOYMENT BY REGION





share of high-proximity employment of each region that is found in municipalities where remote work potential was greater than the national median at the time of the 2020 Census.²⁵ The central region shows a substantially higher proportion than the others, with 83.3% of its high-proximity employment located where remote work potential was high.²⁶ The second largest value is observed in the north central region with 58.8%, followed by the northern region with 41.3% and southern region with 38.8% The central region also has the highest

²⁵The national median of remote work potential is calculated by weighting the total formal employment at the municipal level.

²⁶The linear correlation weighted between the percentage of remote work potential and high-proximity employment at the municipal level by region serves as an alternative measure of this co-localization of both variables and confirms that it is stronger in the central region.

		Percentage		Spearman	Correlation
	(1)	(2)	(3)	(4)	(5)
Region	High- Proximity Empl.	Potential Remote Work	HP exposed to High RW	RW vs HP Employ- ment	RW vs HP Share
Center	4.8	23.0	83.3	0.54	0.45
Center-North	4.1	23.5	58.8	0.53	0.38
North	4.3	22.8	41.3	0.61	0.51
South	5.4	21.0	38.8	0.56	0.49

TABLE 6: REGION STATISTICS: REMOTE WORK AND HIGH-PROXIMITY EMPLOYMENT

Note: Columns 1-3 show, for each region, the percentage of formal employment in high-proximity sectors in February 2020; the percentage of total regional employment that could potentially be performed remotely according to our measure; and the percentage of the region's high-proximity employment in municipalities with remote work above the national median. Column 4 shows the within-region across-municipality Spearman correlation coefficient between remote work potential and the level of high-proximity employment; and column 5 shows the Spearman correlation between remote work potential and the share of formal employment that is high-proximity.

level of remote work potential, with 30.3% under our definition. Remote work potential in the northern region is 22.7%; 23.2% at the north-central, and 20.6% in the south. This pattern and our previous results suggest that employment in high-proximity sectors would decline more sharply in the central region after February 2020, and would show a slower recovery compared to the rest of the country. Indeed, Figure 11 shows that the central region suffered the largest and most enduring gap in high-proximity employment. The southern region presents the second largest gap, possibly due to high-proximity sectors also reflecting low demand due to low tourism.

To quantify the role of remote work in the relatively weak recovery of high-proximity sectors in the central region throughout the pandemic period, we carried out the following counterfactual. We construct a hypothetical geographical distribution of potential remote work such that each municipality in the country has the same potential remote work, equal to the national share. Thus, the spatial distribution of remote work potential is independent of high-proximity employment and therefore the co-location of both variables does not affect the employment trajectory in high-proximity sectors. By equalizing remote work potential between regions, this counterfactual also incorporates the role of regional differences in remote work potential on the trajectory of formal employment in sectors of high-proximity. The dashed line in Figure 11 shows the counterfactual trajectory of high-proximity employment in the central region, using the estimates in the previous section and the assumptions described above. This trajectory is more similar to that observed in the other regions, indicating that regional differences in remote work potential, and the co-location of remote work potential and high-proximity sectors, contribute to explain the modest relative recovery of these sectors in the central region. Figure 11 displays the counterfactual trajectories of highproximity employment resulting from an equivalent exercise for non-center regions as well. In all cases, counterfactual employment is higher, although the counterfactual trajectories are more similar to the observed time series in these regions than in the center.

Overall, this exercise illustrates that employment in regions that were specialized in services before the pandemic was negatively affected by the interaction between potential remote work and high-proximity employment. While this mechanism does not completely explain the lagging employment gap observed in Mexico's central region, we show it is a quantitatively important factor that is likely slowing the recovery of the region. More generally, this result suggests that the growth in services that marked many developing country cities (Nay-yar, Hallward-Driemeier, and Davies, 2021) may impose challenges during the post-COVID period, and that their role as promoters of growth (Bryan, Glaeser, and Tsivanidis, 2019) may be weaker now.

6 Conclusion

In this paper we find, through a triple difference design, that locations with a larger share of employment in occupations that can be performed remotely registered larger and persistent decreases in high-proximity employment during the COVID-19 pandemic in Mexico, relative to locations with lower potential remote work. Since high-proximity employment and potentially-remote work occupations tend to co-locate, our results suggest a challenge for locations that showed a larger share of employment in occupations that could be performed

remotely at the beginning of the pandemic.

We find a persistently weaker recovery of employment in consumer services, while at the same time, four years after the start of the pandemic, the overall labor market shows signs of tightness. Our results then reflect that the pandemic's effect varied importantly by sector and location. Sector-specific shocks like this one point to that the persisting effects of the pandemic on workers will depend on their capacity to adjust to this reallocation. Our work then highlights that cities in the developing world may benefit from policies that ease workers' shifts towards the sectors and geographical locations with more dynamic labor markets.

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Appendix

A Choice of degree of flexibility in main and binary effects

This section discusses our choice of main and alternative specifications. Given the prominence of triple difference designs in empirical micro and the explosion of recent work in applied econometrics analyzing panel event studies, there is a remarkable lack of papers that guide practitioners to apply triple difference event study designs. Olden and Møen, 2022 discuss the identifying assumption of a triple difference estimator, but not in the context of a panel event study. Strezhnev (2023) is the only manuscript to our knowledge that studies triple difference event studies, and focuses on the issues raised by staggered adoption, which would seem to not apply in our setting as all our treated units (high-proximity employment groups) are exposed simultaneously to the potential remote work shock. No explicit discussion is provided about the implications of different levels of flexibility in fixed effects and their interactions, which is a central issue when deciding how to implement a triple difference estimator in a panel event study framework.

However, there is a substantial body of work in theoretical and applied econometrics that aims to estimate treatment effects in the presence of flexible unobserved heterogeneity of a form that can be implemented in triple difference event study designs: the literature on interactive fixed effects (in particular the articles following Bai, 2009 and Pesaran, 2006). In the interactive fixed effects setting, unobserved heterogeneity is allowed to take a relatively flexible form subject to it having a factor-loading structure, that is, where outcomes at time t for a unit i (which we take to be a municipality j - group g pair), can be expressed as follows (Λ_i and f_t are unobserved).

$$Y_{it} = \beta X_{it} + \Lambda_i f_t + \epsilon_{it}.$$

As we will show, this form of heterogeneity is more restrictive than a fully flexible triple difference event study design, but it still suffers from biases originating in the large amount of parameters to be estimated. These known downsides of a highly flexible model will suggest some limits to the degree of unobserved heterogeneity to implement in our setting. Consider an interactive fixed effect triple difference event study design, where time period dummies and municipality indicators are present in main and binary effects. Factoring the time and

municipal variation into the binary coefficients, the estimation equation is as follows.

$$Y_{gjt} = \mu_j + \lambda_t + \alpha_1 Hi Prox_g$$
$$+ \delta_{1j} Hi Prox_g + \delta_{2t} \mu_j + \delta_{3t} Hi Prox_g$$
$$+ \beta_{gt} \mathbf{RW}_{j} \times \mathbf{Hi} \mathbf{Prox}_{g}$$
$$+ \Theta X_{jt} + \epsilon_{gjt}$$

For clarity, in this model, the differences in outcomes across each municipality and group over time are determined by time effects (the factors, indexed by t) that affect each observation differently. This equation can be rewritten by factoring the unobserved heterogeneity terms into a factor-loading form.

$$Y_{gjt} = \underbrace{\begin{bmatrix} 1 & HiProx_g & \mu_j & \delta_{1j}HiProx_g \end{bmatrix}}_{\Lambda_{gj}} \underbrace{\begin{bmatrix} \lambda_t \\ \alpha_1 + \delta_{3t} \\ 1 + \delta_{2t} \\ 1 \end{bmatrix}}_{f_t} + \beta_{\mathbf{gt}} \mathbf{RW_j} \times \mathbf{HiProx_g} + \Theta X_{jt} + \epsilon_{gjt}$$

This form is exactly the interactive fixed effect specification, given that the elements of Λ_{gj} and f_t are in general unobserved. The observation that a flexible triple difference specification fits within the interactive fixed effects framework allows us to translate some insights from the literature into guidance for our setting.²⁷ A central finding of the interactive fixed effects literature is that these designs, while flexible, are subject to the incidental parameter problem (see e.g. Lancaster, 2000, and the literature review and discussion in Bai, 2009). This problem arises when there is a large number of parameters to be estimated relative to the size of the sample, and can result in inconsistent estimates of the main treatment effect (see Bai, 2009; Higgins, 2022). In our case, given that there are two groups, J municipalities, and T time periods, notice that dim $(\Lambda_{gj}) = 1+1+J+J = 2J+2$, and dim $(f_t) = T+T+T+1 = 3T+1$.

²⁷This observation also suggests interactive fixed effects estimation methods can be applied to discipline the unobserved heterogeneity in triple difference specifications, although we do not attempt to do that here.

In both the time and panel dimension, as the sample grows, the set of parameters to estimate grows at a multiple of that rate. This well known problem has spurred a large amount of work proposing solutions that we belive are outside of the scope of our paper (Pesaran, 2006; Bai, 2009; more recently, Callaway and Karami, 2023; Higgins, 2022). In settings like ours, where the time dimension (in the order of 50 periods) is small relative to the panel dimension (in the order of 2000 units), Higgins (2022) shows that the incidental parameter problem in interactive fixed effects models can be particularly acute, especially relative to cases where T tends to infinity at a faster rate. If we considered fully flexible interactions of time, group, and municipality effects, the number of incidental parameters would be even larger, further worsening the problem: the interaction between municipality and group effects would be a term of the form δ_{1jg} , municipality and time effects would be a term of the form δ_{2jt} , and those between group and time δ_{3gt} . Given we consider two groups (high and low proximity sectors), the dimension of these binary effects would total $2J + J \times T + 2T = J(T+2) + 2T$, meaning that in a completely flexible model, as we increase the number of panel units, the number of parameters would increase at a similar rate as the number of data points (in our setting each additional panel unit we observe allows us to see two groups for T periods, 2T more data points).

Our reading then is that the degree of flexibility afforded by interactive fixed effects models is likely to be "too much" for our setting, threatening the estimation of our main effects due to incidental parameter bias. This, plus the fact that flexible triple difference panel event study designs can involve calculating an even larger number of interaction terms, push us away from fixed effects specifications that are too flexible, particularly in the binary interactions. This comparison instead suggests it is more reasonable to use whatever we observe to control for some of the unobserved heterogeneity, and to select carefully the dimensions in which we want to be more flexible. In our setting, the main cross-sectional variable to control for is the potential for remote work at the municipality level at the start of the pandemic (RW_j) , and the main time variable is the period covering the pandemic $(Pandemic_t)$. Since we know these two variables are likely to matter, we control for them directly in the main and binary interactions. We then settle for an intermediate level of flexibility in modelling unobserved heterogeneity, allowing flexible effects in the main effects as is typical in panel event studies, but not in the binary ones, to skirt the issue of possible incidental parameter bias. Then, our main specification is as follows in the baseline triple difference.

$$\begin{split} Y_{gjt} &= \mu_j + \lambda_t + \alpha_1 Hi Prox_g \\ &+ \delta_1 RW_j Hi Prox_g + \delta_2 Pandemic_t RW_j + \delta_3 Pandemic_t Hi Prox_g \\ &+ \beta \ \mathbf{RW_j} \times \mathbf{HiProx_g} \times \mathbf{Pandemic_t} \\ &+ \Theta X_{jt} + \epsilon_{gjt} \end{split}$$

In this specification, as the sample grows in the panel dimension, the number of extra parameters to estimate grows at that same rate, as in usual two-way fixed effect designs, suggesting that incidental parameters are less likely to be a source of bias. One downside of not using a fully flexible specification is that unobserved confounders that correlate with remote work at the municipality level and induce differential trends for consumer services employment could bias the estimated coefficient. An example of this is internet access, which is correlated with remote work. As discussed above, changing patterns in online ordering may have induced drops in consumer services employment after the pandemic, which under the less flexible specification could be picked up by the triple interaction term. The inclusion of fully flexible municipality trends would account for this confounder - we instead opt to control for it directly as shown above. In any case, for robustness our main tables now include time dummies instead of the pandemic period dummy in one specification and municipality dummies instead of the potential remote work measure in another.

In order to show our estimated effects over time, we preserve the flexibility in the time dimension of our main parameter of interest, the triple difference, in our event-study specification. This allows us to visualize whether the difference in the outcomes between the high and the low proximity groups was similar in locations with high and low remote work before the pandemic. This corresponds to the usual pre-trend check in panel event studies in our setting, consistent with the identification condition stated by Olden and Møen (2022). In this case, our estimation equation is the following.

$$\begin{split} Y_{gjt} &= \mu_j + \lambda_t + \alpha_1 Hi Prox_g \\ &+ \delta_1 R W_j Hi Prox_g + \delta_2 Pandemic_t R W_j + \delta_3 Pandemic_t Hi Prox_g \\ &+ \beta_{\mathbf{gt}} \ \mathbf{RW_j} \times \mathbf{Hi Prox_g} \\ &+ \Theta X_{jt} + \epsilon_{gjt} \end{split}$$

B Additional Tables

	Dep. Var: Log Employment				
$HiProx_g \times RW_j \times Pandemic_t$	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$HiProx_g \times RW_j$	0.011	0.015***	0.020***	0.015***	0.020***
	(0.008)	(0.004)	(0.003)	(0.004)	(0.003)
$RW_j \times Pandemic_t$	-0.003***	0.001	0.000	0.001	0.000
	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
$HiProx_g \times Pandemic_t$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$HiProx_g$	-0.031***	-0.034***	-0.035***	-0.034***	-0.035***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)
RW_j	0.156***	0.051***	0.000	0.051***	0.000
	(0.018)	(0.011)	(.)	(0.011)	(.)
$Pandemic_t$	0.001***	0.003***	0.001*	0.000	0.000
	(0.000)	(0.001)	(0.001)	(.)	(.)
Observations	1238793294	1238793294	1238793294	1238793294	1238793294
TimeFE	No	No	No	Yes	Yes
MunFE	No	No	Yes	No	Yes
Controls	No	Yes	Yes	Yes	Yes

TABLE A1: TRIPLE DIFFERENCE ESTIMATES: LOG EMPLOYMENT

Note: This table shows estimates of Equation 2 using log employment as an outcome. Regressions are at the municipal, month, group level, and are weighted by the IMSS-affiliated employment in each municipality group in February 2020. The sample covers municipalities with positive high and low proximity employment in February 2020. Internet access at the municipal level is measured from the 2020 Census as the share of households with Internet access. Controls are one month-lagged COVID cases and deaths and interactions of school aged population and February 2020 one digit sectoral shares with time dummies. Standard errors are clustered at the municipality level. *p<0.1; **p<0.05; ***p<0.01.

		Dep. Var: Employment gap				
	All	North	Center North	Center	South	
$HiProx_g \times RW_j \times Pandemic_t$	-0.384***	-0.278	-1.093	-0.331**	-1.021*	
	(0.088)	(0.163)	(0.856)	(0.107)	(0.477)	
$HiProx_g \times RW_j$	0.152***	0.419**	0.449*	0.188**	0.107	
	(0.046)	(0.145)	(0.193)	(0.065)	(0.091)	
$RW_j \times Pandemic_t$	-0.037	-0.484*	-0.488	0.306	-0.446	
	(0.146)	(0.214)	(0.363)	(0.222)	(0.458)	
$HiProx_g \times Pandemic_t$	0.021	-0.023	0.266	0.001	0.162	
	(0.034)	(0.046)	(0.254)	(0.047)	(0.147)	
$HiProx_g$	-0.055***	-0.109**	-0.133*	-0.086**	-0.030	
	(0.014)	(0.035)	(0.052)	(0.028)	(0.028)	
RW_j	0.054	0.080	0.085	-0.007	0.105	
	(0.028)	(0.057)	(0.093)	(0.046)	(0.074)	
Observations	1238793294	342376728	270241125	483722655	142423572	
TimeFE	Yes	Yes	Yes	Yes	Yes	
MunFE	No	No	No	No	No	
Controls	Yes	Yes	Yes	Yes	Yes	

TABLE A2: TRIPLE DIFFERENCE ESTIMATES BY REGION

Note: This table shows estimates of Equation 2 for each of the four regions in Mexico following Banco de México's classification. Regressions are at the municipal, month, group level, and are weighted by the IMSS-affiliated employment in each municipality group in February 2020. The sample covers municipalities with positive high and low proximity employment in February 2020. Internet access at the municipal level is measured from the 2020 Census as the share of households with Internet access. Controls are one month-lagged COVID cases and deaths and interactions of school aged population and February 2020 one digit sectoral shares with time dummies. Standard errors are clustered at the municipality level. *p < 0.1; **p < 0.05; ***p < 0.01.

	Dep. Var: Employment gap		
	Rural	Urban	
$HiProx_q \times RW_j \times Pandemic_t$	-3.497	-0.319***	
	(3.840)	(0.068)	
$HiProx_g \times RW_j$	0.862*	0.158***	
	(0.405)	(0.047)	
$RW_i \times Pandemic_t$	0.794	-0.057	
	(1.737)	(0.145)	
$HiProx_q \times Pandemic_t$	0.774	-0.003	
	(0.817)	(0.026)	
$HiProx_q$	-0.125	-0.058***	
2	(0.068)	(0.015)	
RW_i	-0.107	0.046	
	(0.353)	(0.028)	
Observations	25300278	1213493016	
TimeFE	Yes	Yes	
MunFE	No	No	
Controls	Yes	Yes	

TABLE A3: TRIPLE DIFFERENCE ESTIMATES BY URBAN AND RURAL

Note: This table shows estimates of Equation 2 for the subsamples of municipalities above and below the median urbanization rate. Regressions are at the municipal, month, group level, and are weighted by the IMSS-affiliated employment in each municipality group in February 2020. The sample covers municipalities with positive high and low proximity employment in February 2020. Internet access at the municipal level is measured from the 2020 Census as the share of households with Internet access. Controls are one month-lagged COVID cases and deaths and interactions of school aged population and February 2020 one digit sectoral shares with time dummies. Standard errors are clustered at the municipality level. *p<0.1; **p<0.05; ***p<0.01.

C Additional Figures

FIGURE A1: EVENT STUDY TRIPLE DIFFERENCE ESTIMATES FOR HIGH-PROXIMITY EMPLOYMENT, LOG EMPLOYMENT



Note: This figure shows estimates of β_{gt} in Equation 7, using log employment as an outcome and including municipality fixed effects. February 2020 is omitted and marked by a vertical line. The sample covers the same municipalities and period described in Table 2. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.

FIGURE A2: EVENT STUDY TRIPLE DIFFERENCE ESTIMATES FOR HIGH-PROXIMITY EMPLOYMENT, FLEXIBLE MUNICIPALITY INTERACTIONS



Note: This figure shows estimates of β_{gt} in Equation 7. The outcome are employment gaps with respect to February 2020. Municipality dummies are included in the binary interaction terms instead of the observed remote work variable at the municipality level. February 2020 is omitted and marked by a vertical line. The sample covers the same municipalities and period described in Table 2. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.

FIGURE A3: EVENT STUDY TRIPLE DIFFERENCE ESTIMATES FOR HIGH-PROXIMITY EMPLOYMENT, FLEXIBLE TIME INTERACTIONS



Note: This figure shows estimates of β_{gt} in Equation 7. Month dummies are included in the binary interaction terms instead of the pandemic dummy variables. February 2020 is omitted and marked by a vertical line. The sample covers the same municipalities and period described in Table 2. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.





This figure shows panel event study estimates of the effect of potential remote work on the percentage gap, relative to February 2020, in the number of firms in consumer services sectors. The estimation equation is $FirmGap_{jt} = \lambda_t + \beta_t RW_j + \Theta X_{jt} + \epsilon_{jt}$ where notation is as in Equation 7. February 2020 is omitted and marked by a vertical line. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.





This figure shows panel event study estimates of the effect of potential remote work on the percentage gap, relative to February 2020, in wages in consumer services sectors. The estimation equation is $WageGap_{jt} = \lambda_t + \beta_t RW_j + \Theta X_{jt} + \epsilon_{jt}$ where notation is as in Equation 7. February 2020 is omitted and marked by a vertical line. Controls are lagged COVID-19 cases and deaths, and interactions of February 2020 one digit employment sector shares and school age population with month dummies. Confidence intervals are shown at 95%, constructed from standard errors clustered at the municipality level.