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Remote Work and High-Proximity Employment in Mexico

Lorenzo Aldeco Leo* † Alejandrina Salcedo †

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 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 are not driven by changing patterns of consumption associated to Internet access during the pandemic. Since high proximity employment tends to locate in places where the propensity to remote work occupations is larger, such as cities, our estimates imply that remote work may have slowed the employment recovery from the pandemic in certain regions. A counterfactual where we reassign remote work potential equally across municipalities results in a more robust recovery in Mexico's service-intensive central region, which faced the steepest, most persistent drop in service employment. Our results suggest that if remote work remains an important feature of labor markets, consumer service sectors in cities in the developing world may face challenges stemming from these new work arrangements in the post-COVID era.

Keywords: Remote work; Consumer services; Middle-income countries; Regional labor markets

JEL Codes: O33, R11, J2

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1 Introduction

At its onset, the COVID-19 pandemic deeply 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 entertainment 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. However, even as rising vaccination rates in many countries of the world lowered the likelihood of contagion, and despite eased government restrictions, formal employment in high proximity sectors had not returned to its pre-pandemic levels by early 2023. Lower formal employment in high proximity sectors is concerning, since these jobs can provide income and access to social security to a large group of generally lower skilled workers in developing countries (Nayyar et al., 2021).[1] Service oriented regions of the developing world have recovered slowly from the pandemic (see e.g. Banco de México, 2022), contrary to 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.

In this paper we show evidence that remote work, likely a common feature of some occupations after the pandemic, is related to enduring lower formal employment in high proximity consumer service sectors in Mexico.[2] High proximity service sectors 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. 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, before and after the pandemic, we find that 1 percentage point more remote employment at the municipal level decreased high proximity employment by as much as 0.6 percent one year into the pandemic, and by a persistent 0.2 percent by early 2023.

To better understand the underlying demand and supply effects related to remote work, we turn to data on wages, individual worker transitions, and prices. We

[1] In our setting, private sector formal employees are usually affiliated to IMSS (Instituto Mexicano del Seguro Social), which provides health, retirement, and other social security benefits.

[2] In 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.

find precise zero wage effects, which suggests that labor supply in these sectors was highly elastic and so lower demand translated directly to lower employment. Concentrated negative employment effects at the bottom end of the wage distribution also imply that remote work may have a negative effect on wage inequality at the local level, as remote workers tend to also be higher earners (Gottlieb et al., 2021).

If workers moved away from high proximity sectors because they could now work remotely, we would expect those workers that exit high proximity jobs in locations with high remote work to switch to other sectors, as opposed to leaving the formal labor market. Individual level data, however, 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 by making remote occupations more attractive to these workers, but instead by decreasing demand for consumer services. 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 opposed to changes in labor supply related to remote work. 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.

To quantify the role of remote work on aggregate employment in service-heavy locations, we show regional counterfactual employment time series assuming that remote work and high proximity services do not co-locate. These illustrate that the remote work mechanism explains some of the muted recovery of employment in Mexico's central region, where relatively large shares of employment were in high proximity sectors and in occupations with remote work potential. Finally, we study price data to check for possible market level effects on services. 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.[3]

Our results are consistent with evidence for the United States, where the pandemic sharply reduced employment in service sectors that involve greater proximity to consumers, with particularly strong effects where a greater proportion of the jobs could be performed remotely at the beginning of the pandemic (Althoff et al., 2022, Chetty et al., 2020). By showing that these mechanisms are also at play in a middle

[3]While 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 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.

income country, our work highlights that cities in the developing world may face a unique set of challenges in the post-COVID era. Many developing countries urbanized quickly over the 20th century, specializing in a broad set of services (Nayyar et al., 2021). As cities grow and their workforces become more skilled, they demand services and amenities, and give rise to important consumer service sectors (Diamond, 2016; Moretti, 2011). Our results stress that to the extent that remote work continues to be a feature of labor markets after 2020, the co-location of consumer service workers and skilled workers (Gottlieb et al., 2021) may impose challenges to some lower skilled workers in the aftermath of the pandemic. As framed by Bryan et al., 2019, the prosperity provided by cities in less-developed countries hinges on the balance between the positive economic spillovers delivered by spatial proximity and the costs associated to density, including congestion. Our work quantifies a channel through which remote work may have weakened these positive agglomerative forces during the pandemic, and contributes to the nascent literature on the challenges that the pandemic poses for cities (Glaeser, 2022). 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 plays into economic development policy after COVID-19 (OECD, 2021).

The rest of the paper proceeds as follows. Section 2 describes high proximity consumer service employment in Mexico during the pandemic, and shows descriptive evidence about its relationship to remote work. Section 3 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 4 shows, through counterfactual regional employment calculations, the effect of remote work on the uneven performance of employment across Mexico in the recovery from the pandemic, and illustrates the role of remote work as a contributor to the muted growth of employment in the service-heavy central region. Section 5 concludes.

2 Remote Work and High Proximity Employment during the COVID-19 pandemic

High proximity sectors 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.[4] We use administrative employment data from the Mexican Social Security Institute (IMSS), which covers over 80% of formal employment in Mexico, and reports employment by municipality and month with a high degree of disaggregation by sector, allowing us to study high proximity employment throughout the course of the pandemic.[5]

Employment has fared worse in high-proximity sectors than in low-proximity sectors throughout the pandemic, as shown in Figure 1. This shows the percentage difference in formal employment with respect to February 2020, in low and high proximity sectors. In low-proximity sectors, employment fell at a more moderate rate than in high-proximity sectors, and by October of 2021 it had returned to its pre-prepandemic level. High-proximity sectors, on the other hand, still showed a gap of 10% two years after the start of the pandemic, and as of the first quarter of 2023 has not fully recovered.

To study whether greater feasibility of remote work influenced the evolution of employment in high-proximity sectors, we calculate the share of employment in a municipality that was in occupations that could potentially be performed remotely before the pandemic using the 2020 Census.[6] For each municipality, we categorized the occupations in the 2020 Population Census using the catalog in Leyva and Mora, 2021. The classification is based on whether the occupations can be performed remotely. In what follows, potential remote work is defined as the percentage of municipal employment that could be performed remotely according to this classification.

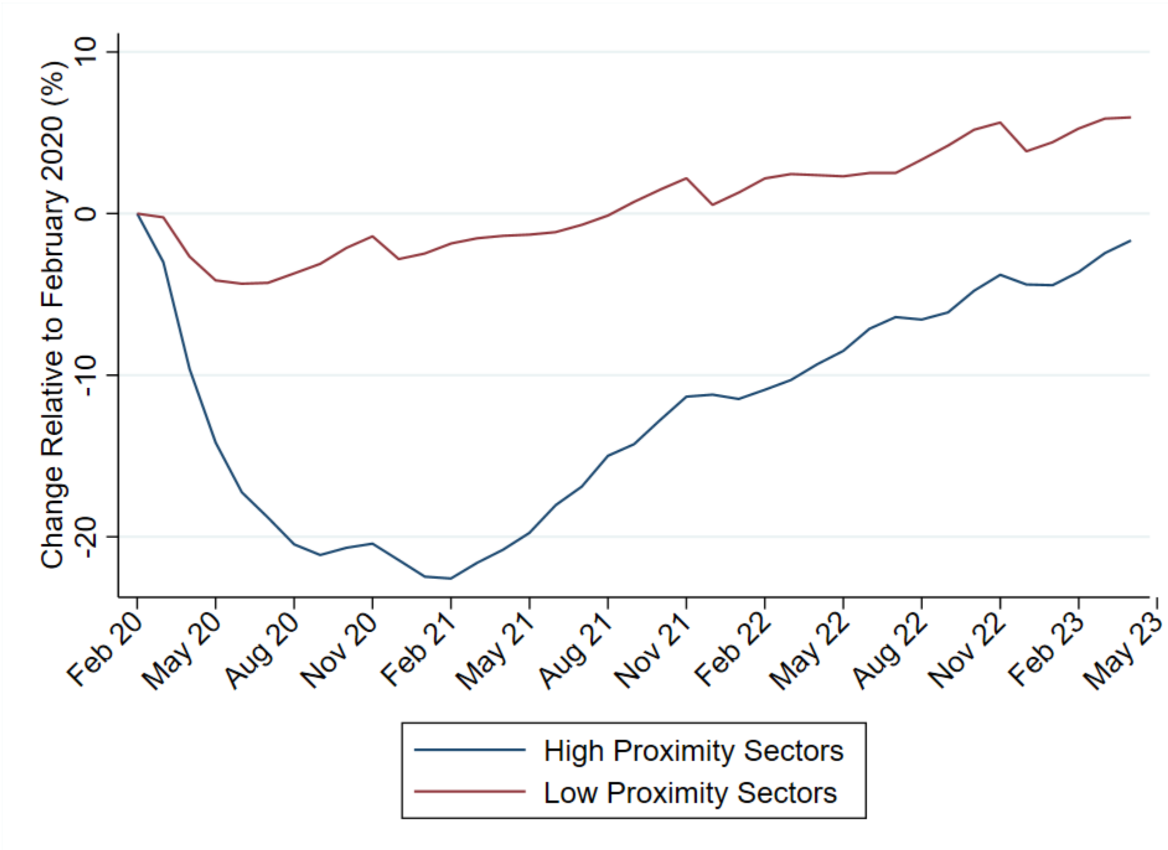
Figure 2 illustrates that, since the beginning of the pandemic, employment in high proximity sectors has been weaker in municipalities where a greater proportion of

[4]While some tourism-related sectors (such as air transport and accommodation) may also be classified 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 has shown 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.

[5]Using the National Survey of Occupation and Employment (ENOE) we find that in the first quarter of 2020, 83.6% of formal workers were affiliated to IMSS.

[6]The 2020 Census was mostly collected before the declararion of the pandemic. It reports two-digit occupations, which do not allow us to directly apply the classification from Leyva and Mora, 2021. They classify the occupations in the SINCO catalog as either feasible to be performed remotely or not, using four digit occupations. Therefore, we consider a two-digit occupation to be remotely realizable if at least one of its four-digit occupations is remotely realizable according to the aforementioned study.

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

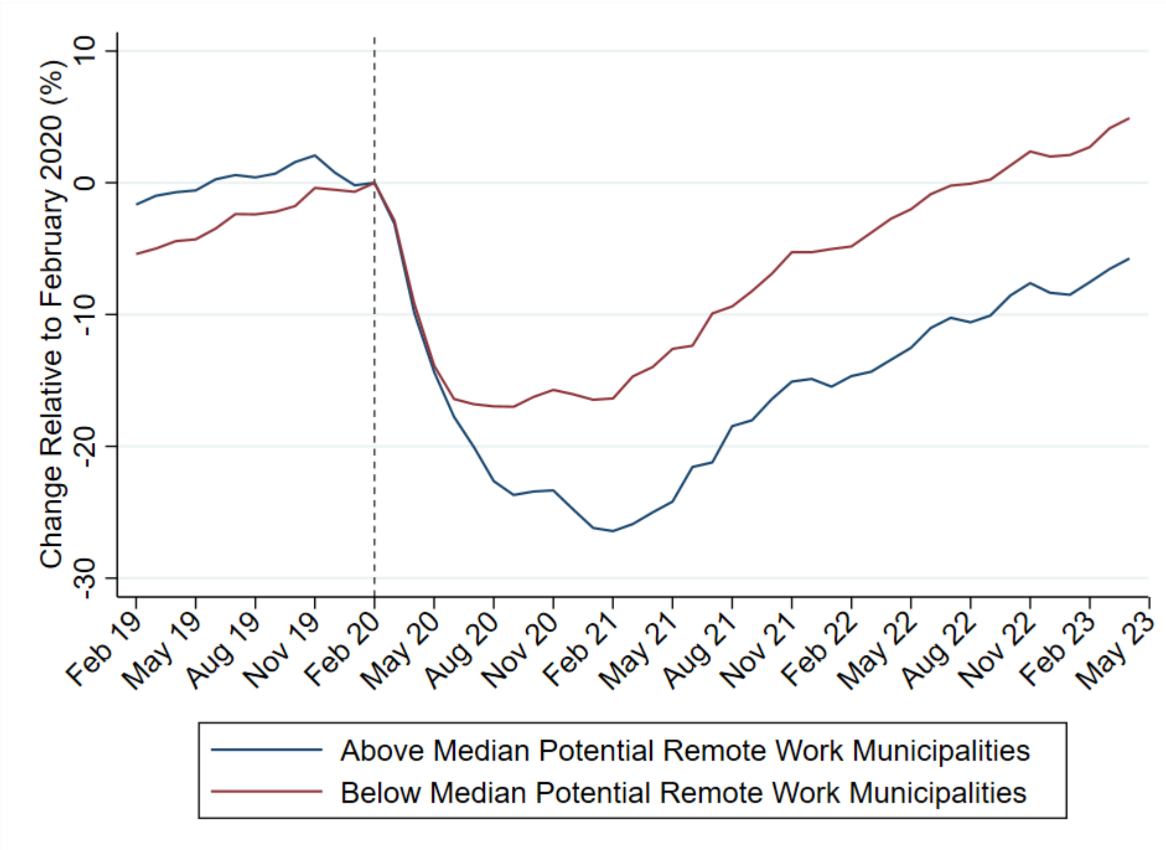


Note: The figure shows the percentage difference in employment with respect to February 2020 in high and low proximity sectors, for the period from February 2020 to April 2023. Employment data are from IMSS records of insured workers. High proximity employment is defined as employment in the food and beverage services and entertainment IMSS 3 digit subsectors, and low proximity employment are all other subsectors excluding air transport and temporary accomodation.

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. At the national level we calculate potential remote work at 25.6%, while Leyva and Mora, 2021 estimate it at 10.6% using their disaggregated occupation data. Our estimates differ because in order to construct a municipality level measure of remote work, we use Census data that is less disaggregated at the occupation level.[7]

[7] In other work using a different classification of occupations, based on Dingel and Neiman, 2020, Monroy-Gomez-Franco, 2020 estimates this national figure at 20%-23%.

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 April 2023. Municipalities are grouped according to whether their share of remote work occupations are above or below the national median, employment weighted. Remote work 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.

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.[8] States with larger shares of workers in occupations that could be performed remotely in 2020 show less 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 remote work reflects to some extent differences in remote work 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

[8]Google Community Mobility Reports provide indexes reflecting how long a population spends in several 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.

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.

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 remote work.

3 Model and Estimation

We aim to estimate the effect of remote work potential, as defined above, on high proximity employment. 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, as shown in Figure 2. Even before the pandemic, in the end of 2019, high proximity services seemed to perform worse in locations with high remote work.[9] To the extent that remote work is associated to differential trends in municipal employment, the difference-in-difference strategy would yield biased estimates (due to time being correlated with differences between the treated and control group, i.e. the existence of non-parallel trends).

We then turn to a triple-differences strategy, also comparing high and low proximity sectors, to quantify the effect of remote work potential on the employment gap in high-proximity sectors during the pandemic. As surveyed and formalized in Olden and Møen, 2022, triple difference estimators are widely used and rely on weaker identification assumptions that difference-in-difference designs. Intuitively, we start by comparing gaps in high-proximity employment in places with greater and lesser remote work (first difference). However, 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 use a monthly employment panel of high and low-proximity sectors at the municipal level, and estimate the following model:

$$
\begin{aligned}
Employment\_Gap_{gjt} = {} & \mu_j + \alpha_1 HiProx_g + \alpha_2 Pandemic_t \\
& + \delta_1 RW_j \times HiProx_g + \delta_2 RW_j \times Pandemic_t + \delta_3 HiProx_g \times Pandemic_t \\
& + \beta \ \mathbf{RW_j} \times \mathbf{HiProx_g} \times \mathbf{Pandemic_t} \\
& + \Theta X_{jt} + \epsilon_{gjt}
\end{aligned} \tag{1}
$$

[9] A possible explanation is that food delivery and on-demand entertainment, which substitute demand away from high proximity employment, and became widespread during the pandemic, were already on the rise in our treated municipalities.

TABLE 1: TRIPLE DIFFERENCE ESTIMATES, EMPLOYMENT

	Employment gap		
$HiProx_g \times RW_j \times Pandemic_t$	-0.365***	-0.365***	-0.366***
	(0.066)	(0.066)	(0.067)
$HiProx_g \times RW_j$	0.131**	0.232	0.234
	(0.044)	(0.132)	(0.137)
$RW_j \times Pandemic_t$	-0.329***	-0.329***	-0.188
	(0.053)	(0.053)	(0.098)
$HiProx_g \times Pandemic_t$	-0.003	-0.003	-0.003
	(0.026)	(0.026)	(0.026)
$HiProx_g$	-0.048***	-0.083	-0.082
	(0.014)	(0.045)	(0.047)
RW_j	0.064***		
	(0.013)		
$Pandemic_t$	0.107***	0.107***	0.104*
	(0.017)	(0.017)	(0.045)
Observations	205,020	205,020	201,000
Municipalities	2010	2010	2010
Months	51	51	50
Municipality FE	No	Yes	Yes
Controls	No	No	Yes

Note: This table shows estimates of equation 1, 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. *p<0.1; **p<0.05; ***p<0.01

In the above, $Employment\_Gap_{gjt}$ 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 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 Fenruary 2020; μ_j is the fixed effect of the municipality j, and X_{jt} is a vector of controls.[10] The above regression is

[10]The vector includes the following variables to control for other factors associated with the course and recovery of the pandemic: interactions of month indicator variables with school-age population

weighted by the number of formal workers in municipality j, in group g, in February 2020. Table 1 shows the main estimates.

A 1 percentage point (pp) increase in remote work potential implies a drop of 0.36 percentage points in employment in high-proximity formal work sectors during the pandemic, robust across specifications with different sets of control variables. The results 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 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.

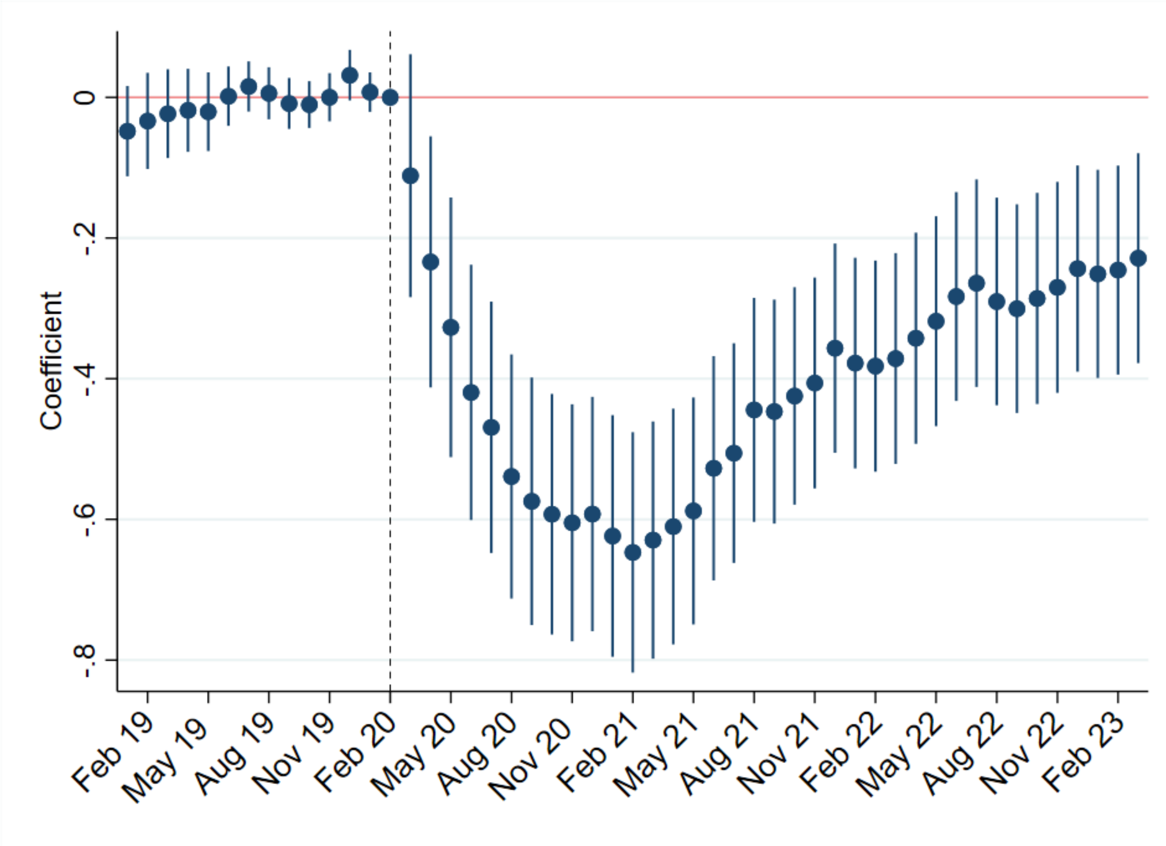
$$\begin{aligned} Employment\_Gap_{gjt} &= \mu_j + \lambda_t + \alpha_1 HiProx_g \\ &+ \delta_1 RW_j \times HiProx_g + \delta_{2t} RW_j \times Pandemic_t + \delta_3 HiProx_g \\ &+ \beta_{\mathbf{gt}}\ \mathbf{RW_j} \times \mathbf{HiProx_g} \times Pandemic_t \\ &+ \Theta X_{jt} + \epsilon_{gjt} \end{aligned} \tag{2}$$

The results of the event study estimation are shown in Figure **??** and are interpreted as the 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 -0.4 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 three 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 2023.

Our results are consistent with other research that finds negative effects of remote

(6 to 24 years), interactions of month indicator variables with the percentage of total employment in the secondary sector (measured in February 2020), interactions of month indicator variables with municipality indicator variables and the number of COVID-19 cases and deaths in the municipality in the previous month.

EVENT STUDY TRIPLE DIFFERENCE ESTIMATES FOR HIGH PROXIMITY EMPLOYMENT



Note: This figure shows estimates of β_{gt} in Equation 2. February 2020 is ommitted and marked by a vertical line. The sample covers the same municipalities and period described in Table 1. 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.

work on consumer service workers, which have mostly studied the US (Dalton et al., 2022, Althoff et al., 2022, Chetty et al., 2020). By showing that remote work relates to lower consumer service employment in Mexico, however, we highlight that cities in middle-income countries may also face challenges due to a lasting shift in the consumption patterns of now-remote workers. If consumer service demand is permanently weaker due to remote work, low-skill workers in developing country cities might be at a disadvantage during the post-pandemic period, posing a challenge to policy makers and potentially increasing inequality.[11] However, it is also possible that the observed negative effect of remote work on high proximity employment is due to consumer service workers shifting to occupations, such as call-center services, which can be performed remotely. We now bring in evidence on other outcomes to

[11] A decrease in demand in services would 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.

shed firther light on the mechanisms behind the effects of remote work.

3.1 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 ask whether this is due to changes in labor demand or supply (or both). While we cannot fully separate them, we can shed some light on these two hypotheses by studying wages: if labor decreased due to lower demand for high-proximity services, then we should observe lower compensation in these sectors after the pandemic. There exists anecdotal and empirical evidence that employment decreased because of a drop in demand for services (for instance Chetty et al., 2020), but in Table 2 we find zero effects of remote work on wages under the triple difference strategy in our setting. We look into two explanations that are consistent with a lower demand for high-proximity employment even in the absence of wage effects. First, it is possible that high-proximity sectors received a negative demand shock that got translated only to employment and not wages due to binding minimum wages or downward rigidities in these sectors. We find evidence of this in Figure 4, 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.[12] Second, 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 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. In this sense, our results suggest that remote work may be increasing inequality at the local level by decreasing the demand for relatively poorer workers in the formal labor market.

3.2 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 remote work on high proximity employment, we turn to using these individual level data to

[12] The large mass at the observed observed lower bound is, incidentally, close to the legal lower bound of wages: approximately equal to 120 MXN daily (or 6 dls) in 2020.

TABLE 2: TRIPLE DIFFERENCE ESTIMATES, WAGES

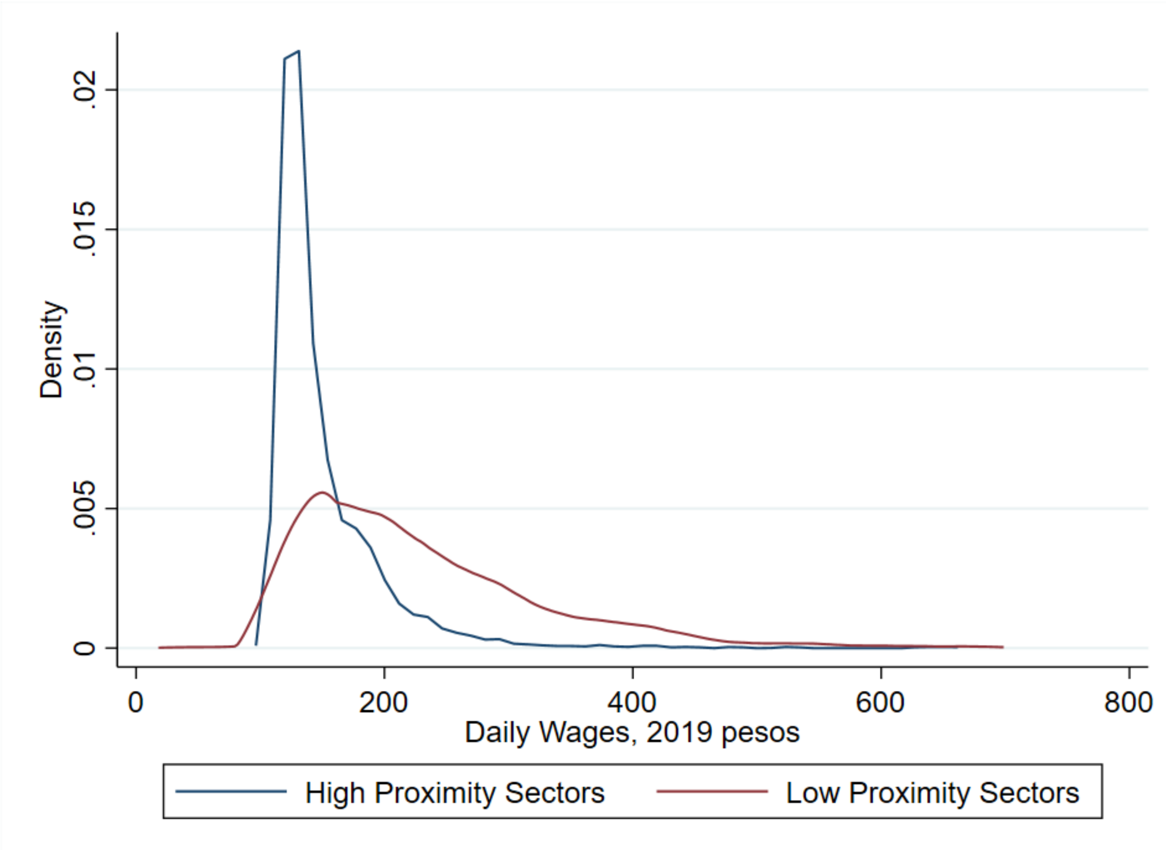
	Wage gap		
$HiProx_g \times RW_j \times Pandemic_t$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
$HiProx_g \times RW_j$	0.001*	0.001	0.000
	(0.000)	(0.000)	(0.000)
$RW_j \times Pandemic_t$	0.000	0.000	-0.001
	(0.000)	(0.000)	(0.001)
$HiProx_g \times Pandemic_t$	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)
$HiProx_g$	-0.000**	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)
RW_j	-0.000**		
	(0.000)		
$Pandemic_t$	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)
Observations	205,020	205,020	201,000
Municipalities	2010	2010	2010
Months	51	51	50
Municipality FE	No	Yes	Yes
Controls	No	No	Yes

Note: This table shows estimates of equation 1, 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. *p<0.1; **p<0.05; ***p<0.01

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 remote work exit the formal workforce, or whether they transition to other sectors, mitigating the negative employment effect.

For this exercise, we restrict attention on the workers that 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 reason-

FIGURE 4: 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.

ably reflect changes in employment dynamics due to the pandemic.[13] 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:

$$\Delta ShareRemain_j = \frac{HP_{Feb\_2022}^{remain}}{HP_{Feb\_2020}} - \frac{HP_{Feb\_2020}^{remain}}{HP_{Feb\_2018}} \tag{3}$$

[13]By comparing February across two different years we also net out possible seasonality effects.

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 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.

$$\Delta ShareRemain_j = \alpha + \beta RW_j + \epsilon_j \tag{4}$$

Columns 1 to 3 of Table 3 show the results. Consistent with our findings on employment, remote work correlates with lower shares of high proximity workers remaining in that sector. A 1 percentage point increase in remote work decreases the share of workers that remain in high proximity sectors by .08 percentage points. Most of the decrease is accounted for by workers that exit the formal labor market, which suggests that remote work is decreasing demand for these workers. This result is also consistent with the existence of costs to switching occupations (see Artuç et al., 2010, Arias et al., 2018, and 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).

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 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 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 remote work made consumer service 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 3 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.

TABLE 3: TRANSITIONS OF WORKERS EMPLOYED IN HIGH PROXIMITY SECTORS AND REMOTE WORK

	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	1,035	1,035	1,035	1,035
R^2	0.0277	0.0365	0.0012	0.0017
Adjusted R^2	0.0268	0.0356	0.0002	0.0007

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. *p<0.1; **p<0.05; ***p<0.01

3.3 Role of Internet Access

Our results so far are in line with existing evidence for the US showing that remote work is negatively related to high proximity employment. 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 service employment at the same time as remote work. In Mexico Internet access and remote work potential are correlated, but not perfectly, which allows us to estimate effects for these two channels separately.[14] We use municipality level shares of household with Internet access as a second triple-difference variable, and repeat the estimation. Table 4 replicates our triple difference specification, including both remote work and Internet triple interaction terms:

[14] It 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 et al., 2021. We abstract from these interaction effects and focus on the direct impact of Internet and remote work separately during the pandemic.

$$
\begin{aligned}
Employment\_Gap_{gjt} = {} & \mu_j + \alpha_1 HiProx_g + \alpha_2 Pandemic_t \\
& + \delta_1 RW_j \times HiProx_g + \lambda_1 Internet_j \times HiProx_g \\
& + \delta_2 RW_j \times Pandemic_t + \lambda_2 Internet_j \times Pandemic_t \\
& + \delta_3 HiProx_g \times Pandemic_t \\
& + \beta_{\mathbf{1}} \ \mathbf{RW_j \times HiProx_g \times Pandemic_t} \\
& + \beta_{\mathbf{2}} \ \mathbf{Internet_j \times HiProx_g \times Pandemic_t} \\
& + \Theta X_{jt} + \epsilon_{gjt} \qquad (5)
\end{aligned}
$$

Table 4 shows estimates of the effects of Internet access and remote work on employment. We find evidence that Internet access had an independent negative effect on high proximity employment, although the effect is noisily estimated and we cannot statistically reject it is zero. The remote work effects are robust to the inclusion of the Internet access triple difference terms, although the coefficients do decrease in size 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 service sectors, Internet access may be an important factor to consider when studying the trajectory of employment in these sectors during the pandemic.[15] In this sense, the independent variation in Internet access and 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 controlling for this important counfounder of the effect of remote work. This is a feature of studying remote work, and communications technology more broadly, in developing countries: due to lower Internet adoption, it is possible to some extent to control for Internet access when studying related outcomes.

3.4 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 remote work. Given our results above, *a priori* it is possible that prices decreased or increased: the lower demand for consumer services may push prices down, but if the

[15] For instance, it is possible that during the pandemic some consumption shifted online, hurting employement in service sectors.

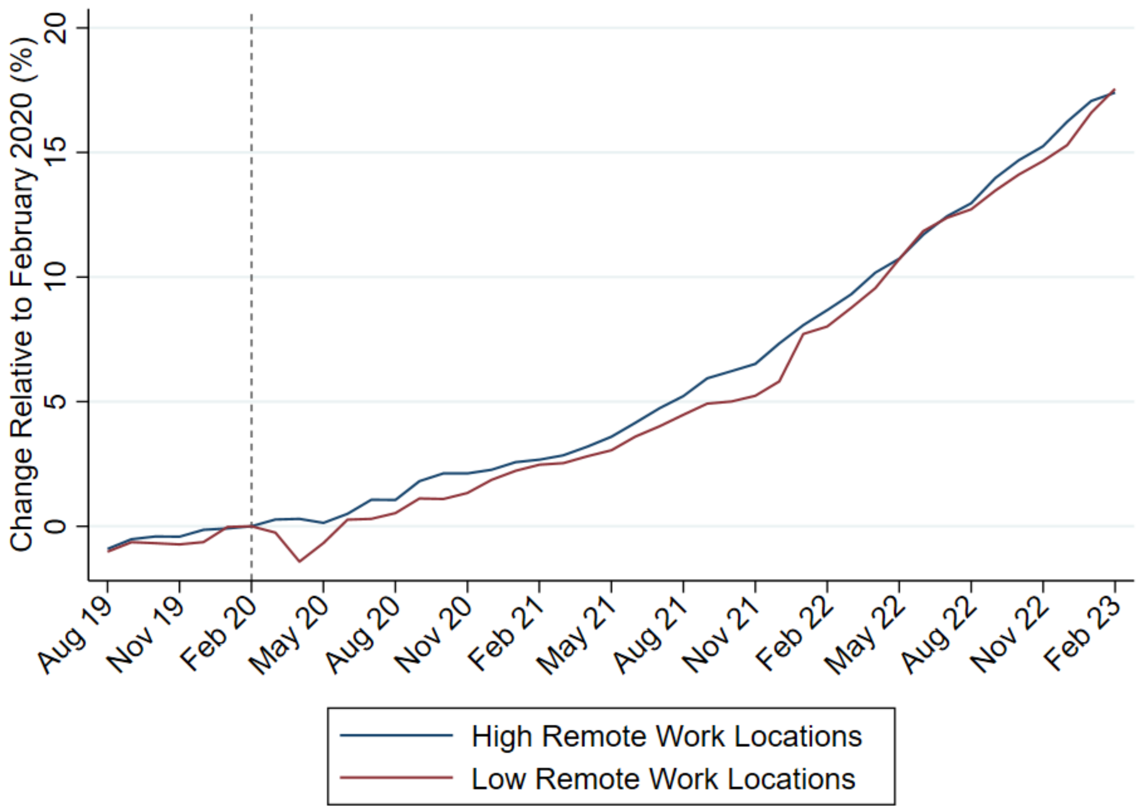
TABLE 4: TRIPLE DIFFERENCE ESTIMATES WITH INTERNET INTERACTIONS

	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

Note: This table shows estimates of Equation 5. 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. *p<0.1; **p<0.05; ***p<0.01.

pandemic caused closures, then we might also expect higher prices due to lower competition or scale in high proximity sectors.

FIGURE 5: LOCAL PRICE OF RESTAURANTS AND ENTERTAINMENT, BY REMOTE WORK POTENTIAL



Note: The figure shows percent change in prices 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 service 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 of housing, relative to February 2020.

In order to study the relationship between prices in high proximity sectors and remote work during the pandemic, we turn to consumer price index data at the city level, from INEGI. Prices 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 prices in these sectors with respect to February 2020, in line with our analysis of employment.[16] In Figure 5 we plot these price gaps. The Figure shows that consumer service prices in high and low potential remote work cities have followed similar trends over time, with prices usually higher

[16]To each city-month level observation of the change in prices relative to February 2020, we substract the percentage difference in housing prices. By netting out housing price changes, we partly account for differences in city-level price trends in other services.

in locations with more remote work. In a two-way fixed effect panel regression, we find no significant effects of remote work on prices after the pandemic, suggesting the absence of price effects of remote work.

4 Counterfactual and regional implications

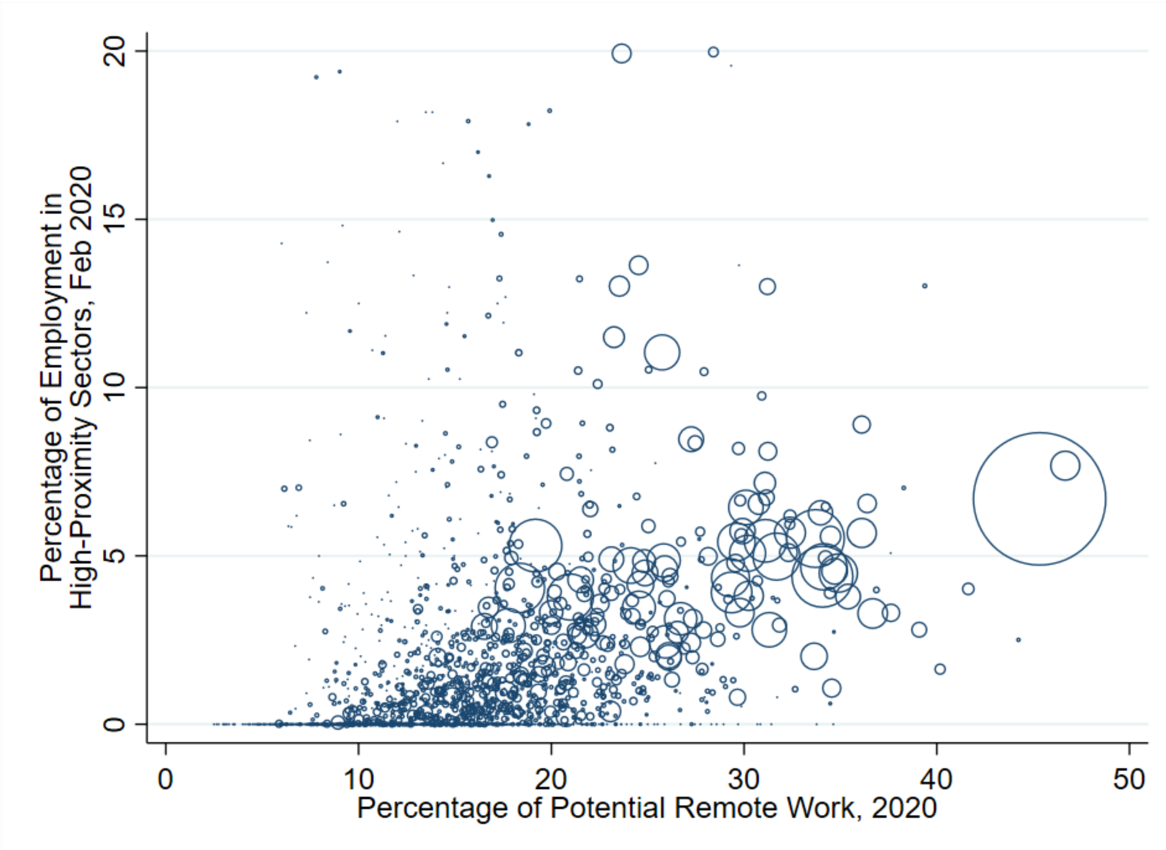
Our previous results show that a larger share of potential remote work is associated with lower employment in high-proximity sectors after the start of the pandemic. However, these two types of employment tend to co-locate: in our setting, in all regions of Mexico the correlation between the remote work 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). Under this logic, it is natural to expect remote work potential and consumer service workers to co-locate across the municipalities of Mexico. Indeed, Figure 6 shows that in general municipalities with larger shares of remote work occupations also have larger shares of consumer service workers. This natural co-location of 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 3.

This suggests that the mechanism we study may be important at more aggregate levels, and may have affected regional patterns of high proximity employment after the pandemic. To illustrate this, in this section we study how the observed distribution of potentially remote work matters for regional employment in high proximity sectors. We use Banco de México's definition of regions.[17] The strongest correlation between both kinds of employment is observed in the central region, where the correlation coefficient between both variables at the municiapality 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. [18]

[17]These 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

[18]The co-location of both kinds of employment can also be summarized by calculating the proportion of remote work at the municipal level to which employees in sectors of high proximity are

FIGURE 6: 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.

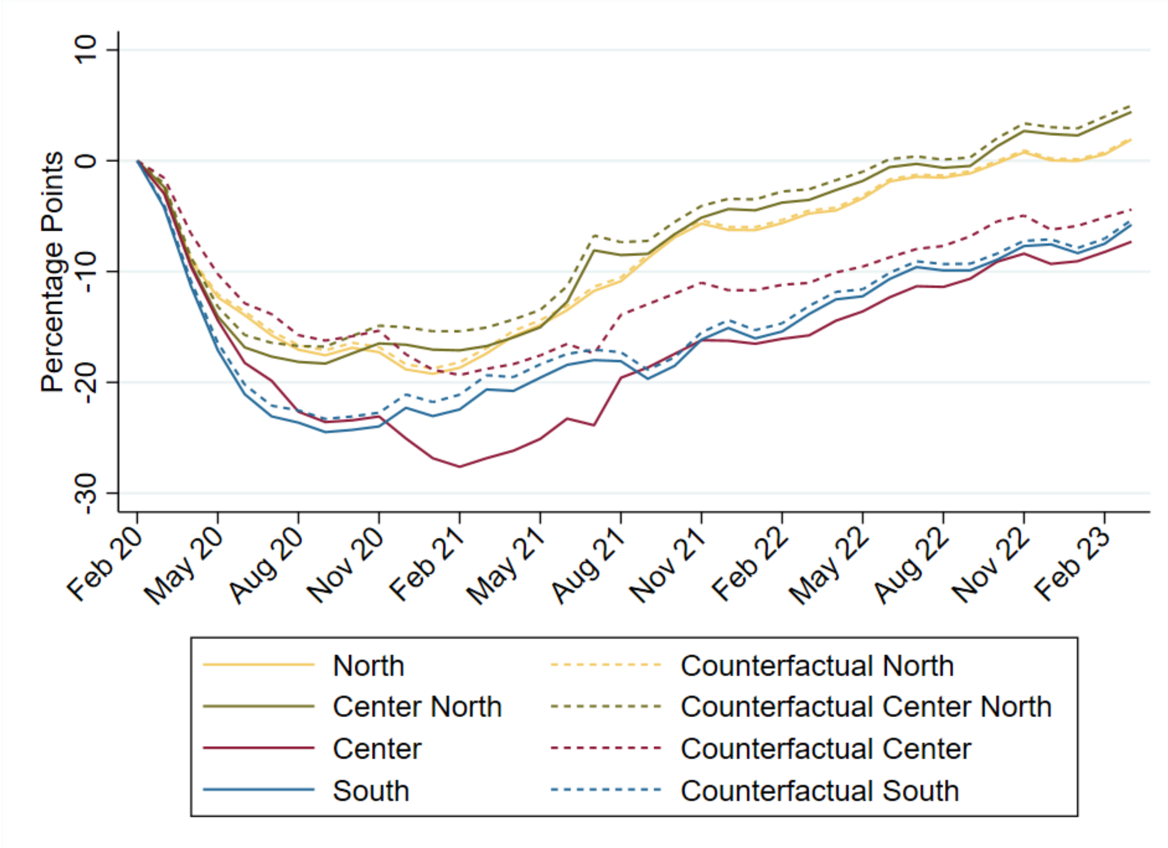
To illustrate the importance of this interaction, we compute a measure of the co-location of remote work and high-proximity sectors by region in February 2020. This measure is the share of high-proximity employment of each region that is found in municipalities where remote work potential was greater than the national median at the time of the 2020 Census.[19] The central region shows a substantially higher proportion than the others, with 83.9% of its high-proximity employment located where remote work potential was high.[20] The second largest value is observed in the north

exposed on average. Under this metric, remote work exposure in high proximity sectors in Center is 38.4%, compared to 28.3% in the Center North, 26.4% in the North, and 27.7% in the South.

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

[20]The 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-

FIGURE 7: OBSERVED AND COUNTERFACTUAL EMPLOYMENT BY REGION



Note: This figure shows observed and counterfactual employment in high proximity sectors for Mexican regions, expressed as gaps with respect to regional totals in February 2020, in percentage points. Counterfactual employment is calculated using estimates from Table 4, and reassigning remote work so that it is equally distributed among municipalities.

central region with 58.7%, followed by the northern region with 41.3% and southern region with 38.7% The central region also has the highest 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 7 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

localization of both variables and confirms that it is stronger in the central region.

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 7 shows the counterfactual trajectory of high proximity employment in the centeral 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 7 displays the counterfactual trajectories of high proximity 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 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 (Nayyar et al., 2021) may impose challenges during the post-COVID period, and that their role as promoters of growth (Bryan et al., 2019) may be weaker now.

5 Conclusion

In this paper we find, through a triple difference design, that a larger share of employment in occupations that can be performed remotely implied a decrease in high proximity employment during the COVID-19 pandemic in Mexico. Since high proximity employment and 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. In particular, our results suggest that to the extent that remote work continues to be a characteristic of cities in developing countries, these may face slower recoveries in some lower skilled service sectors. As an illustration of the strength of this channel, we show that if potential remote work and high proximity employment did not co-locate, the most sector-intensive region in Mexico would have displayed a substantially stronger recovery in high proximity employment.

We find a persistent contraction of employment in a specific sector of services, while at the same time, three years after the start of the pandemic, the overall labor market shows signs of tightness. To the extent that our results reflect shifting patterns of consumer demand in the aftermath of the pandemic, they may also point to imbalances in supply and demand within segments of the labor market. In the context of the sectoral reallocation observed since the start of the pandemic, 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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