Telework and internal migration in Latin America*

Jeanne Lafortune[1], Matías Gutiérrez[1], and Hugo E. Silva†[1,2,3,4]

[1]Instituto de Economía, Pontificia Universidad Católica de Chile, Santiago, Chile
[2]Departamento de Ingeniería de Transporte y Logística, Pontificia Universidad Católica de Chile, Santiago, Chile
[3]Center for Advanced Transportation, Logistics, and Economic Competitiveness (CATLEC), ANID/CIN250061, Chile
[4]Millennium Nucleus in Just Transport, ANID/NCS2025_71, Chile

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Abstract

Remote work decentralizes by letting workers hold city jobs from rural places and centralizes by removing commuting from cities. We show it decentralizes only if a job's rural feasibility clears a threshold set by commuting cost and the telework productivity gain against the urban-rural wage gap. Using a differences-in-differences design around COVID-19, we compare teleworkable and non-teleworkable occupations before, during and after the pandemic in Chile, Peru, Mexico, Brazil and Colombia. We find no lasting migration; instead, urban-rural income gaps widened or stayed flat. This points to a productivity gain that favored cities.

Keywords: telework; internal migration; commuting costs; spatial equilibrium

JEL classification: R23; R12; J61; O18

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†Corresponding author: husilva@uc.cl.

1 Introduction

The COVID-19 pandemic made working from home a permanent feature of labor markets, and in the United States, it visibly reorganized where people live. Even three years after the pandemic started, work from home accounted for nearly one-third of paid work days in the US (Delventhal and Parkhomenko, 2023). The mean distance from employee residence to employer location rose from 10 to 27 miles between 2019 and 2023 in the payroll data (Akan et al., 2024). Central business districts lost population and businesses to lower-density areas (Ramani and Bloom, 2022), and house prices flattened with distance to the center (Brueckner et al., 2023; Artigue, 2024).

This paper asks whether Latin American cities followed a similar trend by comparing the behavior of occupations that were teleworkable and those that were not, before, during and after the pandemic in five countries (Chile, Peru, Mexico, Colombia and Brazil). Our empirical conclusions differ from the pattern described for the United States. Remote work itself arrived: in Brazil, the one country in our data that records where people actually worked, work-from-home in teleworkable occupations rose from 26% of workers in 2018 to 49–50% by 2022–2023, against a move from 17% to 20% in other occupations. However, the migration that accompanied telework in the US is almost absent. Across the five countries we study, we find no evidence of a lasting shift of teleworkable occupations toward rural areas nor of an increase in distance from the main urban centers. While teleworking occurred, migration did not.

Why would there be a difference between the patterns observed in the United States and those documented in Latin America? We suggest that the benefits of being in a large city may be much larger in Latin America than in the United States with amenities usually concentrated in a few urban centers. Commuting costs are also relatively high in Latin America making the main city centers attractive for dwellers, particularly if technological change reduces the need to commute daily.

We formalize this argument by extending the intercity spatial equilibrium of Brueckner et al. (2023) with a new primitive: a share $\varphi \in [0, 1]$ of a teleworkable job's tasks that can be performed from a rural location. Telework simultaneously releases two forces. It lets workers hold city jobs from rural addresses, which decentralizes, but at the same time removes commuting from urban life, making the city a better place to live. The second force is the commuting dividend of Duranton and Handbury (2023), who named it in a within-city setting. We show that the net direction of migration depends on whether φ is larger than the threshold φ^* that the commuting dividend sets. A closed form bounds the threshold from above in terms of the commuting cost, the urban-rural wage gap, and the telework productivity gain. The first two are measurable and the gain is not, so we ask how large a gain the data require. We also show that worse commuting makes rural decentralization harder because it raises the dividend that telework gives to cities.

We calibrate the threshold for all five countries. With commuting time valued at half the hourly wage and no productivity gain, the closed form puts Chile's bound at 0.099, against a pre-pandemic rural employment share of teleworkable occupations of 0.094. The bound is loose. Telework moves part of rural residents' work to the city labor market, so rural employment falls, the rural wage

rises, and rural living becomes more attractive. With local labor demand of unit elasticity, the exact threshold at zero gain is 0.020 to 0.034, below observed rural feasibility in every country. Without a productivity gain, the model therefore predicts movement toward rural areas in all five countries. The null we find requires a gain that favors the city: 3.6 percent of the urban wage in Peru and Colombia, 5.9 percent in Brazil, and 9.2 percent in Chile. Mexico would need a third of its urban wage.

The empirical design compares teleworkable and non-teleworkable occupations, classified following Dingel and Neiman (2020), before, during, and after the pandemic, using household survey data from Chile, Peru, Mexico, Brazil, and Colombia. Teleworkable occupations are at the top of the education distribution, so any education-specific trend in urbanization would load onto the treatment. Therefore, our primary specification includes education-decile-by-year fixed effects, which absorb such trends nonparametrically; a stricter variant adds region-by-year fixed effects to absorb local shocks. We show no pre-trends in the migration pattern before COVID in any of the five countries.

The event-study and pooled difference-in-differences estimates are small in every country, and none shows a significant shift toward rural areas after the pandemic. The survey in Brazil also measures telework take-up directly, which we find rose by 8 to 12 percentage points in teleworkable occupations, while the urban share stayed flat.

The model also links migration to wages. Both labor demand curves slope down, so migration alone must move the urban-rural wage gap against the flow; only a telework productivity gain g can widen the gap without migration. In Peru, Mexico, and Brazil, the gap in teleworkable occupations widened, while in Chile and Colombia, it moved little. While compositional shifts could explain part of this pattern, it suggests a productivity gain that made telework more valuable in cities. The migration null and the wage evidence therefore point the same way.

We also estimate both results separately by gender. Women may value the option to work from home and a shorter commute more than men do, so telework could move the two groups differently. The split mostly returns the aggregate answer: neither gender moved persistently away from cities in any country, and where the income gap widened, the widening does not differ significantly between women and men. The female-male differences are at most two percentage points and do not share a sign.

We contribute to the literature on telework and the spatial structure of cities. For the United States, Ramani and Bloom (2022), Delventhal and Parkhomenko (2023), Brueckner et al. (2023), and Duranton and Handbury (2023) document and model large spatial reallocations. A growing body of work links telework to residential locations in other high-income settings: relocation in France, the UK, and the US (Motte-Baumvol and Porcher, 2025), residential mobility in metropolitan Madrid (Sánchez-Moral et al., 2026), and stated location preferences in Lisbon (Colação and de Abreu e Silva, 2026). Evidence from the Global South is scarce. We provide, to our knowledge, the first comparative evidence on telework and internal migration for Latin America, and a reason, written in observables, why the same shock moved Americans and left Latin Americans in place. The design also carries a portable lesson: teleworkable occupations sit at the top of the education

distribution, so where educational urbanization trends are strong, spatial difference-in-differences without education-by-year controls attributes those trends to telework, as would be the case for Peru and Mexico.

On the theory side, Brueckner and Sayantani (2023), Behrens et al. (2024), and Gokan et al. (2022) model remote work and city structure with telework that is uniform in space or all-or-nothing across locations. Our model adds a continuous rural-feasibility parameter and what follows from it: the commuting dividend recast as a migration force and a threshold at which the sign of migration flips. It also converts a reduced-form null into the size of the productivity gain that the null requires. That number can be checked against estimates produced outside the paper.

A separate literature ties telework and commuting to gender. Women give up more of the wage for the option to work from home (Mas and Pallais, 2017) and for a shorter commute (Le Barbanchon et al., 2021); both differences widen with children (Borghorst et al., 2024). The pandemic shifted childcare toward mothers (Alon et al., 2020), and in Chile the first child moves working mothers into informal jobs (Berniell et al., 2021). This work concerns labor supply and job choice within a city. Our model carries the same differences across locations: a higher value of commuting time raises the commuting dividend, so telework raises the value of an urban address by more for women than for men. The by-gender estimates test that prediction in the region for the first time. The female-male difference has the predicted sign in Peru and the opposite sign in Mexico.

Section 2 presents the model and its calibration, Section 3 the data and empirical strategy, Sections 4 and 5 the migration and income results, and Section 6 the split by gender; Section 7 concludes.

2 The model

This section sets out a model that organizes the empirical work. It extends the intercity spatial equilibrium of Brueckner et al. (2023) in one respect: telework is not all-or-nothing in space. We let a share $\varphi \in [0, 1]$ of a teleworkable job's tasks be doable from a rural location. Appendix A contains the formal setup and proofs.

2.1 The setting

The economy has a rural area and one city with two locations: the center and suburbs. Both urban locations share the city's amenities and wages, but suburban residents pay commuting cost t to reach the center. We assume that housing becomes more expensive as a location becomes more populated, labor demand slopes down in both markets, city wages exceed rural wages, and rural amenities are higher: rural areas trade wages for amenities and cheaper housing. Before telework, workers arbitrage utility across the three locations, which pins down the rural population and the split of the city between the center and suburbs. In this equilibrium, the center holds more people at higher housing prices because central living avoids commuting.

The first change due to telework is that an urban teleworker no longer commutes, so the center's

commuting advantage disappears, and the center's housing premium decreases until the two urban locations hold equal populations. Importantly, this makes the city a better place to live: housing in the center is no longer bid up by the desire to avoid commuting, and nobody pays t. Following Duranton and Handbury (2023), we call the resulting gain in urban living standards the commuting dividend, D. Where housing costs are locally linear in population, it takes a simple form (see Appendix A).

$$D \simeq \frac{t}{2}. \tag{1}$$

The dividend is a *centralizing* force that operates at every value of φ. Telework makes cities more attractive than rural areas because it removes the commuting cost from urban life.

The second change is the one the literature has emphasized more. A worker living in a rural area can now remotely perform a share φ of a city job's tasks. She supplies φ efficiency units to the city labor market and the rest to the rural market, so her income is $\varphi\, w_C + (1-\varphi)\, w_R$, where w_C and w_R are the city and rural wages, respectively. Rural living no longer carries the full wage penalty, which is a *decentralizing* force. We also allow a productivity gain $g \geq 0$ from telework that accrues to the city labor market, as documented in the literature (Delventhal and Parkhomenko, 2023; Davis et al., 2024).

2.2 Migration

Which force wins is an empirical question, but our model provides a closed-form approximation. Let $N_R(\varphi)$ be the equilibrium rural population when rural feasibility is φ, N_R^{pre} be its pre-COVID level, and $\Delta_{pre} = w_R - w_C < 0$ be the pre-COVID wage gap. Appendix A shows that the equilibrium is unique and $N_R(\varphi)$ is strictly increasing (Lemma 1).

Proposition 1 (Threshold for rural feasibility)**.** *(a) If telework cannot be performed at all from rural locations, it causes migration from rural areas to the city; $N_R(0) < N_R^{pre}$.*

(b) If $D < |\Delta_{pre}|$, there exists a unique $\varphi^* \in (0,1)$ such that telework decentralizes, $N_R(\varphi) > N_R^{pre}$, if and only if $\varphi > \varphi^*$. Holding the wage gap fixed at Δ_{pre}, the threshold is

$$\varphi^* = \frac{D+g}{|\Delta_{pre}|+g} \simeq \frac{t/2+g}{(w_C - w_R)+g}. \tag{2}$$

If, instead, $D > |\Delta_{pre}|$, telework centralizes at every φ; at $D = |\Delta_{pre}|$ it centralizes for every $\varphi < 1$ and leaves N_R unchanged at $\varphi = 1$.

Appendix A proves both parts. The existence, uniqueness, and sign crossing are exact; the closed form is not. It evaluates the wage gap at the pre-telework level of rural employment. Telework lowers that level, so the closed form is an upper bound on the exact threshold. Section 2.4 shows that the bound is loose.

Part (a) of the proposition does not require $g > 0$. The commuting dividend alone centralizes, so in the case in which city jobs cannot be held from the countryside, telework moves people to the city.

A first and arguably counterintuitive result is that worse commuting makes rural decentralization *harder* ($\partial\varphi^*/\partial t > 0$): a large t makes the commuting dividend large, so telework does more for keeping workers within city than pushing them out. The presumption that congested cities are those that telework will empty out has it backwards. Next, a wider urban-rural wage gap lowers the threshold because telework removes a larger penalty from rural living. Finally, a productivity gain that accrues to the city labor market raises the bar that rural feasibility must clear, $\partial\varphi^*/\partial g > 0$. Whether a threshold exists is decided by the commuting cost against the wage gap and does not involve g.

2.3 Wages

Both labor demand curves slope down, so the urban-rural wage gap is governed by rural *employment*; workers moving toward the city raise the rural wage and lower the city wage, so the gap closes. Migration cannot widen the gap it is responding to. Telework, however, changes rural employment even when nobody moves; at an unchanged rural population, a share φ of rural residents' tasks is now supplied to the city labor market, which raises rural wages.

Proposition 2. *Without an increase in productivity due to telework ($g = 0$), the change in the urban-rural wage gap has the same sign as the change in rural employment, and a productivity gain $g > 0$ widens the gap. Two consequences follow. Holding φ fixed, migration always moves the gap against the direction of the flow. And at unchanged rural population, the arrival of telework lowers rural employment by φN_R, so at $g = 0$ the gap narrows in a country with no residential response.*

Appendix A provides the proofs.

Corollary 1. *An urban-rural wage gap that widens with telework when the residential response is zero requires $g > 0$.*

Proposition 2 is the sharpest empirical test that the model delivers: the migration prediction and the wage prediction are tied together by the slopes of the labor demand curves. Section 5 discusses the measurement channels that could mimic $g > 0$.

2.4 Calibrating the threshold

Equation (2) can be evaluated for all five countries. Chile is the cleanest case, because CASEN records commuting time; we present it first and then carry the same conventions to the rest. CASEN provides a mean monthly labor income of 567,015 CLP among urban workers and 395,822 CLP among rural workers in the pre-pandemic cross-sections. Converted at the 2019 average official exchange rate of 702.9 CLP per US dollar, as in Table 1, these are US$807 and US$563, so $|\Delta_{pre}| =$ 243.6 US dollars per month (the gap of the unrounded means). The 2015 and 2017 waves record commuting time: among urban workers the travel time to work averages 31.5 minutes, which is 63.0 minutes a day, or 22.0 commuting hours a month at 21 working days.

We value commuting time at half the hourly wage, which is the standard convention for travel in a worker's own time (Small, 2012) and is US$2.2 per hour in our sample, half of the mean monthly income over the mean monthly hours of urban workers (42.6 hours a week).[1] At half the wage, $t = 48.2$ US dollars per month; thus, by Eq. (1) the commuting dividend is $D = 24.1$ US dollars per month. The existence condition $D < |\Delta_{pre}|$ holds comfortably; therefore, a threshold exists.

At $g = 0$ the threshold is

$$\varphi^* = \frac{24.1}{243.6} = 0.099. \tag{3}$$

The empirical counterpart of φ is the pre-pandemic rural employment share of teleworkable occupations, which is 0.094 in Chile, just below the bound of Eq. (3). The logic of that mapping is revealed feasibility: a teleworkable job already being performed from a rural address before the pandemic demonstrates that its tasks can be performed there. These two objects are not the same. The model's φ is a share of a job's *tasks*, while the proxy is a share of its *workers*, records where people live, and is an equilibrium outcome reflecting industry composition, infrastructure, sorting, and feasibility.[2] Furthermore, this feasibility is exactly what was potentially modified in the pandemic through technological change. Thus, it is possible that the share of tasks that can be performed in a rural area increased after the pandemic.

The same conventions extend to the other four countries. Wage gaps, hourly wages, and the feasibility proxies come from the estimation samples in Section 3, measured per month and converted to US dollars at each country's 2019 average official exchange rate (Table 1). The missing input is the commuting time. Colombia's GEIH asks it directly: urban workers in the pre-pandemic estimation sample report 27.0 minutes one way. Brazil, Mexico and Peru have no commuting question, so we use the mean one-way work-trip times of the metropolitan origin-destination surveys of São Paulo (41.5 minutes; Companhia do Metropolitano de São Paulo, 2019), Mexico City (57.0; INEGI, 2018) and Lima (44.6; JICA, 2013).[3] A metropolitan commute overstates the national urban mean, so for these three countries D is an upper bound and the gain required in Table 1 is a lower bound.

Table 1 presents the results. At $g = 0$, φ sits on the closed-form bound in Chile (0.094 against 0.099) and Colombia (0.049 against 0.048) and below it in Brazil, Mexico, and Peru. The bound is loose, because it holds the wage gap at its pre-telework level. Telework moves a share φ of rural residents' work to the city labor market. Rural employment falls, the rural wage rises, and rural living becomes more attractive (Proposition 2). Appendix D solves for the exact threshold with constant-elasticity local labor demands. The central case is unit elasticity, close to the local wage response measured in Latin America: across 79 Colombian metropolitan areas, a rise of one

[1] The Chilean state's appraisal prices bracket that choice: 0.39 of the gross wage in the 2016 price list (Ministerio de Desarrollo Social, 2016), and 0.58 in the 2026 list, which made the commute a category of its own (Ministerio de Desarrollo Social y Familia, 2026).

[2] Infrastructure deserves emphasis in this region: rural internet quality caps the share of tasks performable from a rural address regardless of the job's task content, and an OECD assessment placed Colombia second to last among 51 OECD and G20 countries in rural fixed network speed (Caldas et al., 2023). Poor rural connectivity is a physical ceiling that can hold φ below φ^* on its own.

[3] The São Paulo and Mexico City means are computed from the surveys' trip microdata and reproduce their published aggregates. Appendix D details the sources and conventions.

Table 1: The threshold, rural feasibility, and the gain a null requires

	Commute	D	$\lvert\Delta_{pre}\rvert$	φ^* at $g=0$		φ	Gain required
	(min)	(US$)	(US$)	Eq. (2)	Exact		(% of w_C)
Chile	31.5	24.1	243.6	0.099	0.024	0.094	9.2
Peru	44.6	15.4	196.3	0.078	0.027	0.050	3.6
Mexico	57.0	13.3	44.0	0.303	0.034	0.224	34.0
Brazil	41.5	23.4	245.0	0.095	0.033	0.076	5.9
Colombia	27.0	8.7	182.5	0.048	0.020	0.049	3.6

Note: Commute is the mean one-way travel time to work of urban workers, from the household survey where it asks one (CASEN in Chile, GEIH in Colombia) and from the largest metropolitan origin-destination survey otherwise (Lima 2012, Mexico City 2017, São Paulo 2017). D is the monthly commuting dividend in Eq. (1), and $|\Delta_{pre}|$ is the pre-pandemic urban-rural gap in mean monthly labor income, both measured in local currency in the estimation samples and converted to US dollars at the 2019 period-average official exchange rates (702.9 CLP, 3.34 PEN, 19.26 MXN, 3.94 BRL, and 3,281.6 COP per dollar; World Bank). The thresholds are unit-free and unaffected by the conversion. The first φ^* column is the closed form of Eq. (2) at $g = 0$, an upper bound; the second is the exact threshold at $g = 0$ with local labor demands of unit elasticity. φ is the pre-pandemic rural employment share of teleworkable occupations. The gain required is the smallest g, in percent of mean urban monthly labor income, at which the exact threshold reaches φ. Appendix D details the sources and conventions and reports other elasticities.

percentage point in the Venezuelan migrant share lowered native hourly wages by about 1 percent (Lebow, 2022). At unit elasticity the exact threshold is 0.020 to 0.034 at $g = 0$, and for elasticities from 0.5 to 2 it stays between 0.013 and 0.062. It lies below φ in every country, so without a productivity gain the model predicts movement toward rural areas in all five. A gain that accrues to the city raises the threshold. The last column of Table 1 reports the gain at which the exact threshold reaches φ: 3.6 percent of the urban wage in Peru and Colombia, 5.9 percent in Brazil, and 9.2 percent in Chile. An elasticity of 2 cuts these numbers by half or more, and one of 0.5 at least doubles them (Figure 1). Mexico requires 34 percent. Its survey, ENOE, counts as rural everything outside the 39 cities it samples separately, so 22 percent of Mexican teleworkable workers are rural. At that share, the fall in rural employment is large.

The calibration therefore does not predict a null. It states what a null requires: a productivity gain of a few percent of the urban wage that favors the city, and a much larger one in Mexico.

2.5 Caveats

An important caveat of the model and its implications is that the pandemic was not only a telework shock. This may have raised the value of rural amenities directly through the fear of contagion and looser distancing rules. Such a shock does not interact with teleworkability at first order, and it reverts when the fear does, while the telework channel is monotone in φ and persists (Remark 2). The two channels are separated by timing, provided that the amenity shock reverts; therefore, we report event-study estimates by year instead of a single during-versus-after contrast. What is not differenced out is an amenity shock that teleworkable workers were better placed to act on, since they could move without giving up city earnings.

A second caveat is that the threshold predicts a sign, not a size. How large a population movement follows from a given distance to the threshold also depends on how housing costs rise

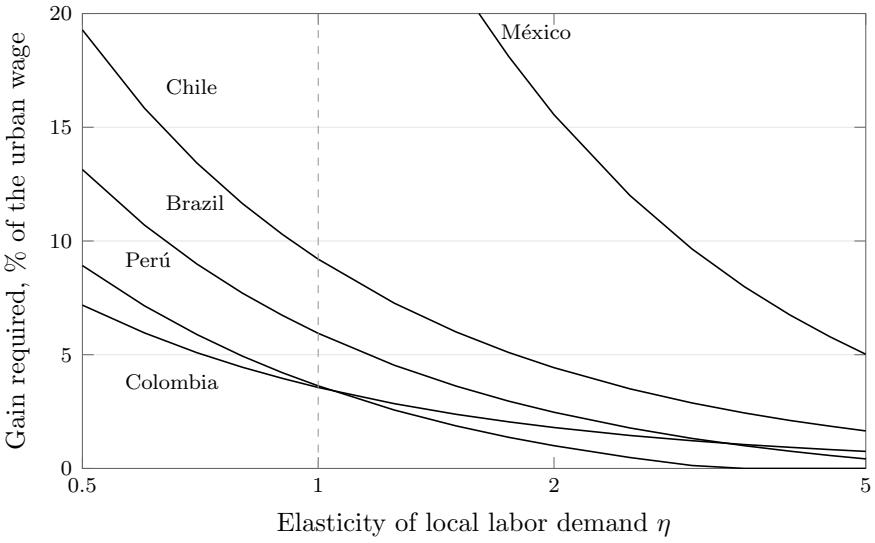


Figure 1: The productivity gain that a null requires

Note: Each line is the smallest telework productivity gain g, in percent of mean urban monthly labor income (US$807, 363, 249, 546, and 360 for Chile, Peru, Mexico, Brazil, and Colombia), at which the exact threshold reaches the country's observed rural feasibility φ (Table 1). Local labor demands have constant elasticity η in both markets (Appendix D); the dashed line marks unit elasticity. Below a country's line, the model predicts movement toward rural areas. México's line lies above the plotted range for $\eta < 1.6$ (34 percent at $\eta = 1$). As η grows, the exact threshold approaches Eq. (2) and the gain required falls toward zero.

with population. We do not calibrate that slope. Our regressions also compare teleworkable with non-teleworkable occupations, not teleworkers with commuters, so the reduced-form coefficients are roughly the per-teleworker effect scaled by the take-up differential.

3 Data and empirical strategy

3.1 Data and telework classification

We use repeated cross-sections from the main household surveys of Chile, Peru, Mexico, Brazil and Colombia, harmonized so that each country has a consistent set of occupations over the entire period. Table 2 lists the survey, wave, and period definitions. Each survey classifies the respondent's area of residence as urban or rural,[4] records labor income, and codes occupation in a classification that we can map to ISCO-08.[5] Four surveys also locate the respondent in a geographic unit, the comuna in Chile, the province in Peru, the state in Mexico, and the department in Colombia, to which we attach the distance in kilometers to the nearest major city: Santiago, Valparaíso, or Concepción in Chile; Lima, Callao, or Arequipa in Peru; Mexico City, Ecatepec, or Tijuana in Mexico; and Bogotá, Medellín, or Cali in Colombia. We use this distance as a second location outcome in Section 4.3.

[4]Mexico's ENOE records as urban the 39 cities it samples as separate domains and as rural the rest of the country. Its rural category therefore includes towns and smaller cities.

[5]Chile uses CIUO-88/CIUO-08 at three digits; Mexico's SINCO 2019 categories are merged to guarantee a balanced panel of occupations and converted through the SOC to ISCO-08; Peru and Brazil use ISCO-08 directly. Colombia's classification is specific to the country; its two-digit CNO-70 groups are the occupation unit, and the 2022 and 2023 waves are bridged to that basis as described below.

Brazil's PNADC has no geographic identifier fine enough, but it additionally asks where the person was, in general, while working (at home, at an office, on the street), which allows us to measure telework take-up directly in Section 4.1.

Table 2: Surveys, waves and period definitions

Country	Survey	Pre	Base year	During	After
Chile	CASEN	2015	2017	2020	2022, 2024
Peru	ENAHO	2018	2019	2020	2022, 2024
Mexico	ENOE	2017–2018	2019	2020, 2021	2022, 2023, 2024
Brazil	PNADC	2017–2018	2019	2020, 2021	2022, 2023, 2024
Colombia	GEIH	2018	2019	2020, 2021	2022, 2023

Note: The base year is the omitted category in the event studies and the last pre-pandemic wave. Chile, Peru, and Colombia each contribute one identified pre-period coefficient (2015, 2018, and 2018); Mexico and Brazil contribute two (2017 and 2018). Waves verified against the estimation extracts.

We classify occupations as teleworkable following Dingel and Neiman (2020), applied at the ONET-code level through crosswalks from each country's classification. Classifying by occupation avoids the endogeneity of individual telework status to location. The teleworkable share of workers is 27% in Chile, 11% in Peru, 21% in Mexico, 23% in Brazil, and 29% in Colombia. Table 3 shows the composition: in all five countries, roughly half of teleworkable employment consists of professionals and technicians. Administrative support workers and managers come next in the first four countries; in Colombia, personal service workers and machine operators take those places. For robustness, we replace the indicator with the occupation's teleworkability probability; for México, we also replace the classification with the one built by the Central Bank of Mexico from 2019 employment data (Leyva and Mora, 2021), which is 40% narrower. The second rule is Mexican by construction; therefore, we do not apply it to the other four countries.

One feature of the Chilean data requires a repair. CASEN coded occupation in CIUO-88 through 2020 and in CIUO-08 from 2022. Crosswalking the earlier waves forward with the ILO correspondence table coarsens them: 2015 to 2020 carry 277 codes between them against 426 in 2022 and 2024, of which 160 have no pre-pandemic rows, and the measured teleworkable share would drop from 0.30 in 2020 to 0.22 in 2022. We therefore put all five waves on one basis. CASEN 2020 codes every employed respondent in both classifications, so each CIUO-08 code can be assigned its CIUO-88 code in that wave. The 2022 and 2024 codes take that step and then the same ILO correspondence as the earlier waves. The harmonized waves carry 257 to 276 codes each, fewer than 1% of post-2020 workers sit in codes without pre-pandemic presence, and the teleworkable share is between 0.25 and 0.30 in every wave. Appendix OA-B documents the harmonization and shows that the results hold when all five waves are kept in CIUO-88 instead. The other three countries need no such step: the number of occupations available to the primary specification falls by six in Peru, one in Brazil, and none in Mexico across their waves.

Colombia needs a bridge of its own. The GEIH codes occupation in the two-digit CNO-70 through 2021 and in the four-digit CIUO-08 from 2022, and no wave carries both. We put the 2022 and 2023 waves on the CNO-70 basis. Each CIUO-08 code is linked to its CIUO-88 candidates by

the ILO correspondence and each candidate to a CNO-70 group by DANE's own correspondence table (DANE, 2005). The group with the most links receives the code, with ties broken by the group's 2021 employment. The bridge assigns a group to 95% of workers in 2022 and 2023, and the teleworkable share is between 0.28 and 0.30 in every wave. The two-digit CNO-70 group is the occupation unit for fixed effects and clustering in Colombia, 82 groups in the estimation sample. Appendix OA-C documents the bridge.

Table 3: Remote-workable occupations by country (Dingel and Neiman, 2020)

Occupations by SINCO11 (1-digit level)	**Chile**		**Peru**		**Mexico**		**Brazil**		**Colombia**	
	N	%	N	%	N	%	N	%	N	%
Officials, directors, and managers	23,163	19.45	920	3.16	133,448	13.17	158,730	12.67	28,053	8.84
Professionals and technicians	53,343	44.78	15,924	54.75	459,471	45.33	623,935	49.81	126,086	39.73
Auxiliary workers in administrative activities	31,050	26.07	11,860	40.78	235,417	23.23	297,384	23.74	5,703	1.80
Merchants, sales employees, and sales agents	4,219	3.54	345	1.19	119,693	11.81	56,409	4.50	90,258	28.44
Personal service and security workers	6,634	5.57	37	0.13	12,272	1.21	66,905	5.34	16,382	5.16
Agricultural, livestock, forestry, and fishing workers	0	0.00	0	0.00	0	0.00	0	0.00	1,516	0.48
Craftsmen workers	99	0.08	0	0.00	0	0.00	892	0.07	10,092	3.18
Industrial machinery operators, assemblers, drivers	527	0.44	0	0.00	27,153	2.68	43,877	3.50	28,749	9.06
Elementary and support workers	80	0.07	0	0.00	26,068	2.57	4,596	0.37	10,493	3.31
Total	119,115	100.00	29,086	100.00	1,013,522	100.00	1,252,728	100.00	317,332	100.00

Note: Workers in occupations classified as teleworkable, pooled over all waves of the estimation sample, grouped by the 1-digit SINCO11 category. Agricultural occupations include no teleworkable employment outside Colombia, where 0.5% of teleworkable workers sit in that category. Each country's occupation codes are crosswalked to SINCO11, and each column is computed over the workers classified by the crosswalk. It misses 0.4% of teleworkable workers in Chile (500 of 119,615), 17% in Perú (5,924 of 35,010), 2% in Brazil (31,974 of 1,284,702), and 15% in Colombia (55,106 of 372,438). México's occupation codes are SINCO, so its column loses none.

Table 4 summarizes the outcomes by period and occupation group. Before the pandemic, teleworkable occupations were already overwhelmingly urban: 91% in Chile, 95% in Peru, 78% in Mexico, 92% in Brazil, and 95% in Colombia. They also sit far above non-teleworkable occupations in income and, as the composition table suggests, in education. Any education-specific trend in urbanization would therefore load onto a teleworkability contrast. We use education × year fixed effects to address this potential problem.

3.2 Empirical strategy

Our primary specification is the event study:

$$Y_{i,o,t} = \sum_{\tau \neq b} \gamma_\tau \cdot WFH_o \cdot \mathbf{1}\{t = \tau\} + \phi_o + \theta_{d(o),t} + X'_{i,o,t}\beta + \eta_{i,o,t}, \tag{4}$$

where $Y_{i,o,t}$ is the outcome for person i in occupation o in year t, WFH_o indicates a teleworkable occupation, and the sum runs over the survey years in Table 2, omitting the base year b. The specification includes occupation fixed effects ϕ_o, education-decile-by-year fixed effects $\theta_{d(o),t}$, where $d(o)$ is the decile of the occupation's pre-pandemic mean education, and individual controls (education, gender, and age). Standard errors are clustered at the occupation level, the level of treatment. A stricter variant adds region-by-year fixed effects $\psi_{r(i),t}$ to absorb local shocks, as we report in the robustness analysis in Appendix B.

We make the event study primary and leave the pooled version to Appendix B's tables, where

Table 4: Summary statistics

	Urban share (%)			Log (income)		
	Pre	During	After	Pre	During	After
			Panel A: Chile			
Not teleworkable	77.8	82.7	80.6	12.643	12.721	13.132
Observations	149,725	47,189	130,023	140,580	40,050	124,937
Teleworkable	90.6	92.1	90.2	13.188	13.325	13.608
Observations	50,684	20,403	48,528	46,939	17,663	46,761
			Panel B: Perú			
Not teleworkable	59.4	56.5	64.0	5.842	6.461	6.392
Observations	127,056	53,904	113,502	90,844	39,706	86,757
Teleworkable	95.0	94.4	95.2	6.996	7.260	7.270
Observations	15,661	6,137	13,212	15,038	6,033	12,808
			Panel C: México			
Not teleworkable	57.8	61.3	59.7	8.398	8.539	8.749
Observations	1,407,817	778,087	1,540,674	1,005,495	558,222	1,067,924
Teleworkable	77.6	79.7	78.6	8.879	9.014	9.208
Observations	383,800	215,041	414,681	237,503	137,541	250,049
			Panel D: Brazil			
Not teleworkable	71.4	72.3	72.6	6.959	7.087	7.305
Observations	1,855,548	829,090	1,607,280	1,778,308	795,942	1,559,555
Teleworkable	92.4	92.8	92.3	7.685	7.792	7.956
Observations	530,934	254,518	499,250	527,396	253,107	496,897
			Panel E: Colombia			
Not teleworkable	78.6	87.3	85.0	13.388	13.302	13.552
Observations	143,925	256,784	505,493	126,142	232,546	478,569
Teleworkable	95.1	96.2	96.1	13.823	13.976	14.246
Observations	61,951	108,456	202,031	54,785	97,586	190,104

Note: Urban share is the percentage of workers whose area of residence the survey classifies as urban. Income is the log of labor income. Periods as defined in Table 2. The urban-share and income cells partition the estimation samples of column (1) of Tables B.1 and B.2.

the year interactions are replaced with a single term $\gamma \cdot WFH_o \cdot T_t$, where T_t indexes the During and After periods of Table 2.

Teleworkable and non-teleworkable occupations differ in many dimensions, most of which are correlated with education. The decile-by-year terms absorb, nonparametrically, any trend common to occupations of similar education. What they leave is the within-decile contrast between teleworkable and non-teleworkable occupations. For comparison, we also estimate a naive specification with only occupation and year fixed effects and controls, which is the standard difference-in-differences in the literature, and report it alongside the primary specification in the Appendices.

Equation (4) does not follow individuals. These are repeated cross-sections, so the coefficient is the change in the urban share among people observed working in each occupation, not migration by incumbents; occupational switching, employment selection, and labor-force entry could move it with nobody changing address. We read the estimates as changes in the residential composition of teleworkable occupations and use decentralization as a shorthand for that object, without claiming identified flows.

Identification requires parallel trends within education deciles, and the pre-pandemic coefficients of Eq. (4) are natural checks. The results of these checks are summarized in the Online Appendix OA-A, Tables OA.1 to OA.5. Under the primary specification, they are small and insignificant in all five countries: Chile's 2015 coefficient is -0.0006 with a standard error of 0.0057, Peru's 2018 coefficient is -0.0098 with a standard error of 0.0062, Colombia's 2018 coefficient is -0.003 with a standard error of 0.003, and the four pre-period coefficients of Mexico and Brazil lie within 0.003 of zero.

The model disciplines what to expect from Eq. (4). Teleworkable occupations become less urban when $\varphi > \varphi^*$ and more urban when $\varphi < \varphi^*$. At $g = 0$ the calibration in Section 2.4 puts every country above its exact threshold, so a null is informative about the productivity gain. The usable predictions are that effects persist only through the telework channel and that the income response of Section 5 must be consistent with the migration response through Proposition 2. Neither requires measuring telework at the individual level, which would be endogenous to location. Both operate through occupation-level feasibility interacted with the timing of the pandemic.

4 Results: telework and the urban-rural margin

4.1 Telework take-up: the first stage

Before the migration estimates, we establish that telework arrived in these countries. Brazil is the only country in our sample that records where people actually worked, so we estimate the first stage there. Figure 2 shows the event study for an indicator of working primarily from home. The indicator counts any work done at the worker's own home, including home-based businesses, so we call it home working. Workers in teleworkable occupations became 4.8 percentage points more likely to work from home in 2020, and 11 to 12 percentage points more likely from 2021 onward, relative to non-teleworkable occupations, with a 2018 pre-period coefficient of -0.004. In levels,

home work in teleworkable occupations rises from 26% in 2018 to 49–50% by 2022–2023, against a move from 17% to 20% in the rest. Under the primary specification with education-decile × year effects, the During and After coefficients fall to 0.016 and 0.026 and lose significance (Table OA.6). The reason is that teleworkability is close to a function of education at the occupation level, so the decile × year effects absorb most of the first stage. Inside the education overlap band, where teleworkable and non-teleworkable occupations coexist at the same education level, the first stage returns: 0.048 during and 0.085 after, both significant. The within-decile first stage is weaker than the raw contrast, and we read the residential estimates with that in mind. Telework did arrive in Latin America. The rest of this section asks whether migration followed.

The other four surveys do not record where people worked, but outside evidence indicates that the shock was region-wide. The ILO estimates that 23 million workers in Latin America and the Caribbean moved to working from home in the second quarter of 2020, and that 20–30 percent of wage earners still at work did so from home during the lockdowns, against less than 3 percent before the pandemic (International Labour Organization, 2021). The survey evidence for Brazil, Peru, and Argentina shows the same jump (Conesa Martinez et al., 2023). Moreover, telework persists: in 2024–2025, college-educated employees in Latin America still worked from home about one day per week (Aksoy et al., 2025). Therefore, we read the Brazilian first stage as the measured case of a shared regional shock.

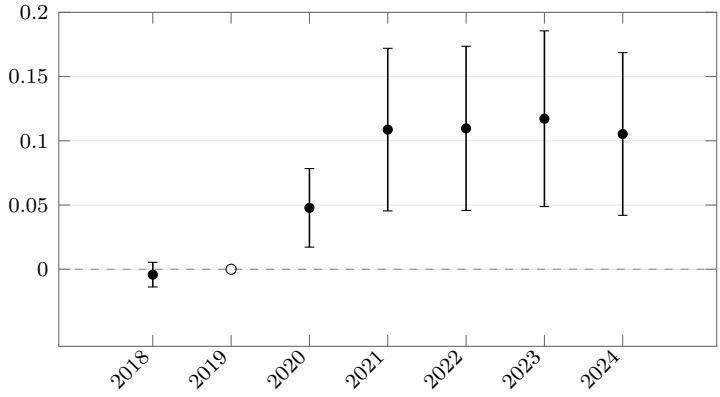


Figure 2: Brazil: working from home (self-reported), the first stage

Note: Coefficients on Telework × year for an indicator of working primarily from one's own home, with occupation fixed effects and controls (recorded for about a fifth of the Brazilian sample each year from 2018). The indicator counts work done at home for an outside employer and home-based businesses alike. 95% confidence intervals, occupation-level clustering, and base year 2019 (open circle). The full specification ladder and coefficient table are in Appendix OA-A.

4.2 Migration

Figure 3 shows the migration event studies under the primary specification, with one panel per country. Appendix Table B.1 reports the pooled During and After estimates on a ladder that runs from the basic covariate specification to the primary specification. The main result is a null: no country shows a lasting shift of teleworkable occupations toward rural areas, and the largest

movements are about one percentage point.

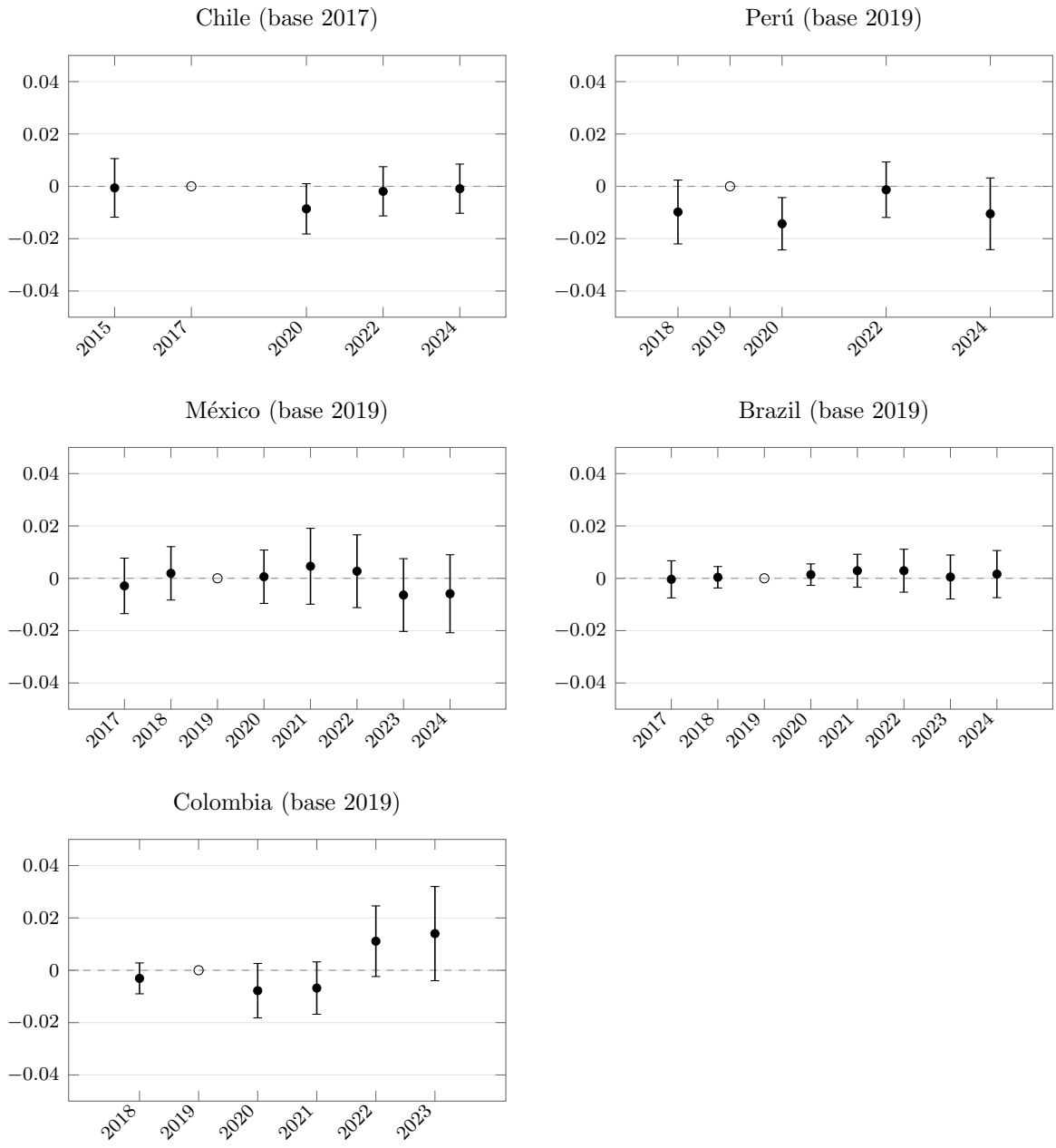


Figure 3: Event studies: telework and urban residence under the primary specification

Note: Coefficients on Telework × year with 95% confidence intervals, under occupation fixed effects, education-decile × year fixed effects, individual controls, and occupation-level clustering. Open circles indicate omitted base years. The vertical scale is the same for all panels. Colombia's survey runs from 2018 to 2023; its occupation unit is the two-digit CNO-70 group (Section 3). Full coefficient tables are in Appendix OA-A.

The clearest results are in Brazil and Mexico, where no coefficient is distinguishable from zero. The pooled After coefficients are +0.002 (0.005) in Brazil and −0.003 (0.007) in Mexico (Table B.1), so the 95% intervals exclude rural shifts above 0.8 and 1.7 percentage points, 11% and 7% of their rural teleworkable shares (Table 1). Chile shows a small movement confined to the pandemic year.

Chile's During estimate is −0.008 under education-decile-by-year fixed effects and −0.011 when region-by-year shocks are absorbed as well, small and barely significant, and its After coefficients are −0.002 in 2022 and −0.001 in 2024 (standard errors 0.005), so the movement does not persist. Peru looks like Chile during the pandemic and like zero afterward. Its 2020 coefficient is −0.014, against −0.010 in 2018 (Table OA.2); its 2024 coefficient is −0.011, significant at 10% only once region × year effects are added.

Colombia's pre-period coefficient is also zero: −0.003 with a standard error of 0.003 under the primary specification. Its pandemic coefficients are small and negative, −0.008 and −0.007, and its 2022 and 2023 coefficients are +0.011 and +0.014, with standard errors of 0.007 and 0.009. The post-pandemic movement is toward the cities. It is not a between-region pattern: region × year effects leave the 2022 and 2023 coefficients at +0.009 and +0.012 (Table OA.5).

Across the five countries, we find no evidence of a significant and persistent urban-rural migration response to telework. Mexico and Brazil show no movement that the confidence intervals can distinguish from zero; Chile and Peru show movements of one to 1.4 percentage points, concentrated in the pandemic year, and the distance to the main urban centers rises nowhere (Section 4.3). Colombia shows no difference from 2019 during the pandemic and a small move toward cities afterward, significant at 10%. At $g = 0$ the model predicts a move toward rural areas in every country (Section 2.4). Within the model, the null is therefore evidence of a productivity gain that favored cities. Such a gain must also show up in wages. Section 5 turns to that evidence.

4.3 Robustness

Appendices B and C collect the robustness exercises, and their message is that, once education-decile × year effects are included, no specification produces a significant and persistent shift toward rural areas in any country. Adding survey weights or region-by-year fixed effects leaves every conclusion in place. So does replacing the binary indicator with the Dingel and Neiman (2020) teleworkability probability. Mexico's own central-bank classification (Leyva and Mora, 2021) is the one exercise that moves a point estimate, turning Mexico's During coefficient negative, but the movement comes from the relabeling and the added observations rather than from the design: on a fixed sample with the paper's labels the engine returns Table B.1 exactly, and neither estimate is significant once the sample is held fixed (Appendix C). The naive specification also shows why the decile terms matter. Without them, Peru's During and After estimates are −0.024 and −0.025, both significant at 1%, weighted or not; with them, the During estimate falls to −0.009 and the After estimate to −0.001.

The urban indicator is an extensive margin: a worker who moves from a large city to a town stays urban. Table B.3 therefore repeats the event study with the log of the distance to the nearest major city as the outcome, for the four countries whose surveys locate respondents geographically (Section 3). Nowhere does the distance rise. Mexico's coefficients are within 0.02 of zero under the primary specification. Peru's coefficients are within 0.05 of zero, but their standard errors are near 0.1 under the primary specification and shrink to about 0.02 only once region-by-year shocks are absorbed. Colombia is the one country with a significant move. Its pre-period coefficient is

0.03 (0.04), and from 2020 onward its teleworkable occupations sit about 20 log points closer to a major city, significant at 5%. Distance is measured by department, so this is a shift across departments. Chile's coefficients are negative in every post-pandemic year, between −0.03 and −0.06, and significant only when region-by-year shocks are absorbed, so teleworkable occupations moved, if anything, about 3% closer to Santiago, Valparaíso, and Concepción. Two caveats apply. Distance varies at the comuna level in Chile but at the province, state, and department level elsewhere, so Mexico's zero counts only moves across states. Moreover, in Mexico and Colombia the distance is constant within the region variable, so the region-by-year variant cannot be estimated.

Chile's During estimate carries three specific concerns, none of which overturns it. First, support: the estimate is −0.0081 on the propensity-score common support, significant at 10%, and −0.006 inside the education overlap band, where two-thirds of the sample drops and precision goes with it ($p = 0.39$), so the estimate does not depend on extrapolation across education levels, although the band cannot independently confirm it. Second, survey mode: CASEN 2020 was fielded 99.6% by telephone and under-represents rural households by 2.9 percentage points. Placebo outcomes do not move; post-stratifying the 2020 wave to the 2017 composition moves the estimate only from −0.011 to −0.009, fieldwork-stage restrictions and reweighting toward the hard-to-reach households leave it between −0.005 and −0.018 with no drift, and the effect is weaker among proxy responses (−0.008) than among self-reports (−0.014). Third, the occupation classification changes after 2020, and the post-pandemic waves are harmonized through the CASEN 2020 double coding (Section 3). The During estimate never crosses the change, since 2015, 2017, and 2020 lie on one side of it, and stays between −0.006 and −0.011 under every restriction we impose. The After coefficients depend on the harmonization. They are zero under it and zero when all five waves are kept in CIUO-88 instead; the two codings differ only in the During estimate, which is −0.005 to −0.007 under native CIUO-88 codes (Appendix OA-B). Even at its peak, the movement is about one percentage point on an urban share of 92%, measured under maximal lockdown pressure, so the telework component alone is, if anything, smaller.

5 Results: telework and the urban-rural income gap

Proposition 2 (Appendix A) ties the urban-rural wage gap to rural employment, and rural employment falls with the arrival of telework itself, by φN_R, even if nobody moves. With $g = 0$ the gap must therefore narrow wherever the residential response is zero. A gap that widens instead is direct evidence of a productivity gain.

The surveys measure resident income rather than the wage per efficiency unit, so we estimate the change in the income gap by interacting the teleworkability indicator with the period indicators and urban residence, under the same set of controls and fixed effects as the migration regressions.[6]

Figure 4 shows the event studies of the change in the income gap, one panel per country.

[6]The model abstracts from general-equilibrium spillovers across worker types: if teleworkers relocate, local demand for non-teleworkable labor may fall, partly offsetting the wage effects. Gokan et al. (2022) study this channel explicitly; we regard our estimates as reduced-form averages that conflate the direct telework effect with any such spillovers.

Appendix Table B.2 reports the pooled During and After estimates on a ladder that runs from the basic covariate specification to the primary one. The main result is that the gap narrows nowhere. Peru, Mexico, and Brazil show that the urban incomes of teleworkable occupations rise relative to rural ones, and Chile and Colombia show movements that are small and not significant. Section 4 places the residential response at or near zero everywhere, so the proposition has content: at $g = 0$ those zeros imply a narrowing gap. A gap that instead holds or widens points to a productivity gain that raised urban wages relative to rural ones and worked against telework's decentralizing pull.

Brazil is the best-measured of the three widening cases. While its residential response is zero, that does not mean the model predicts an unchanged gap. With the rural population unchanged, rural employment still falls by φN_R, and the measured resident gap compresses by a further factor $(1 - \varphi)$, so at $g = 0$ the model predicts a gap that narrows. Instead, it widened by 5 log points during the pandemic (+0.048 under the primary specification, +0.049 with region-by-year effects added), significant at 1% on 5.4 million observations. The Brazilian panel in Figure 4 puts the widening at +0.039 in 2020 and +0.070 in 2021, fading to +0.037 in 2022 and 2023, and +0.026 in 2024, with non-significant pre-period coefficients of +0.001 and +0.017. The timing matches the first stage of Figure 2, which also builds through 2021.

Mexico and Peru complete the widening group. The event study shows positive coefficients but statistically significant only at the 10% level. Pooling the periods, our main specification gives a statistically significant coefficient of 0.02 for the During and After period (Table B.2). Mexico's 2017 pre-period coefficient is −0.022, significant at 5% (Table OA.10), so part of its post-pandemic widening may be recovery from a pre-period dip. Peru's widening is the largest and the least precise: +0.19 under the primary specification, peaking at +0.36 in 2022. It is identified from a few rural teleworkable workers, 1,719 in total, against 10,422 in Chile and 105,599 in Brazil.

Chile and Colombia show nothing comparable. Chile's estimated change in the gap during the pandemic is positive in every specification but never significant (+0.040 under the primary specification, standard error 0.036), and the After coefficient is negative in three of the four columns of Table B.2. Its panel in Figure 4 puts the coefficient at +0.048 in the pandemic year with a near-zero 2015 pre-period coefficient. The 2022 and 2024 coefficients are negative, indistinguishable from zero. Colombia's estimates are positive but imprecise: the change in the gap is +0.08 during and +0.10 after the pandemic under the primary specification, with standard errors of 0.08 and 0.12. Region × year effects leave them at +0.08 and +0.09 (Table B.2).

Read through the lens of Proposition 2, the pattern indicates a productivity gain, $g > 0$, that made telework more valuable in cities. Measurement is why we do not put a point estimate on the gain. The proposition signs the gap in wages per efficiency unit, while the regression coefficient is the change in the measured urban-rural gap in *resident income*, and three channels widen that object at any level of productivity. Urban teleworkers stopped commuting, and any part of the freed hour that went into work raises measured monthly income at an unchanged wage. Employment selection moves it too, since income is observed only for those working. Composition inside teleworkable occupations moves it in the same direction, because urban teleworkable work is concentrated in

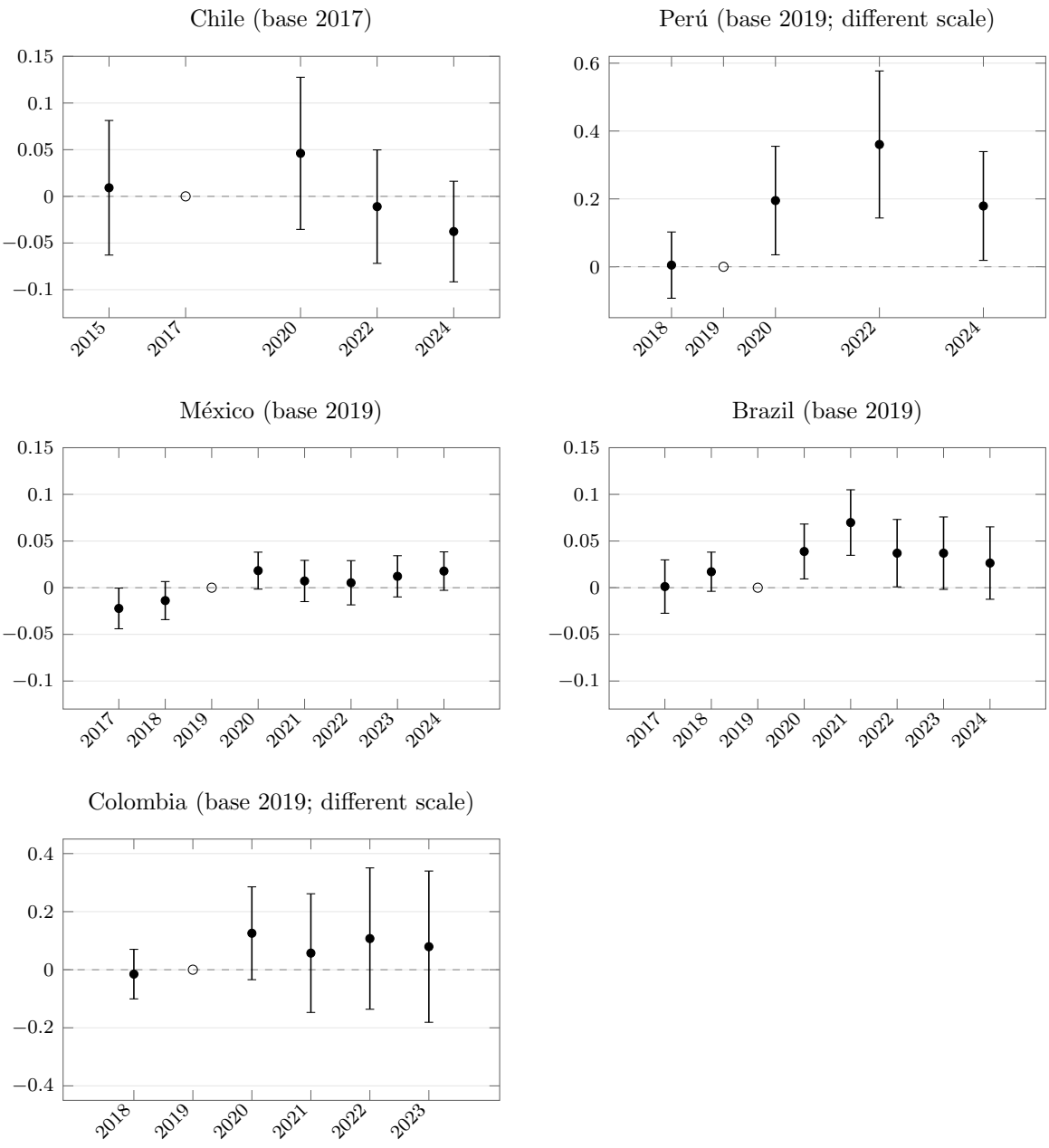


Figure 4: Event studies: the urban-rural income gap of teleworkable occupations

Note: Coefficients on Telework × Urban × year for log income with 95% confidence intervals under the primary specification: the constituent double interactions, occupation fixed effects, education-decile × year fixed effects, individual controls, and occupation-level clustering. Open circles indicate omitted base years. The Peruvian and Colombian panels carry different vertical scales, several times as wide as the others because their coefficients are an order of magnitude larger; the Chilean, Mexican, and Brazilian panels share one scale. Colombia's survey runs from 2018 to 2023, and its occupation unit is the two-digit CNO-70 group, 82 clusters (Section 3). Full coefficient tables are in Appendix OA-A.

finance, information technology, and professional services, while rural teleworkable work is concentrated in local public administration, education, and health. All three push the coefficient above the gain. The model's own compression pushes the other way: at an unchanged rural population, the fall in rural employment and the factor $(1-\varphi)$ narrow the measured gap, so a modest widening can coexist with a larger gain. The coefficient therefore bounds the gain in neither direction.

The income evidence therefore agrees in sign with the migration null of Section 4. At $g = 0$ the model cannot produce that null. A design caveat applies as urban residence is a chosen outcome sitting on the right-hand side of the wage regression, so mover composition could, in principle, move the estimated change in the gap. The estimated flows are about one percentage point, a fifth of Peru's rural teleworkable share and an eighth of Brazil's (Table 1), so mover composition cannot be ruled out where the rural cell is thin, in particular in Peru.

5.1 Robustness

Appendices B and C collect the income robustness exercises, and their message matches the migration one: no specification produces a significant narrowing in any country, and the widening in Brazil and Peru survives every exercise. Mexico's After coefficient survives as well; its During coefficient loses significance in three of its four alternative-classification cells (Tables C.2 and C.3). On the covariate ladder of Table B.2, Brazil's During coefficient moves between +0.044 and +0.061 and keeps 1% significance in every column, ending at +0.049 with region × year effects added. Mexico's During and After coefficients stay between +0.019 and +0.049, significant in every column, at 10% in the During cell once region × year effects are added. Chile and Colombia are never significant in any column.

The ladder also shows why the decile terms matter, just as it does for migration. Peru's During coefficient falls from +0.66 under the naive specification to +0.19 under the primary one, and its After coefficient from +0.64 to +0.28. Most of the naive widening was an education-specific trend. Adding survey weights moves no conclusion.

The classification exercises leave the picture unchanged. Replacing the indicator with the Dingel and Neiman (2020) remote-work probability reproduces the widening in Brazil (+0.046 during, significant at 1%), Peru (+0.19 during and +0.28 after), and Mexico (+0.023 after); Colombia stays negative and not significant, and Chile's During coefficient is significant at 10% in both columns of Table C.2, with and without region × year effects. Under Mexico's central-bank classification (Leyva and Mora, 2021), the narrower rule discussed in Section 4, the During widening shrinks to +0.009 and loses significance, while the After widening holds at +0.026, significant at 5% (Table C.3). Table OA.10 reports the Peruvian, Mexican, and Colombian income event studies in full.

6 Migration and income gap by gender

Gender is a natural margin for heterogeneity in these estimates. As the introduction reviews, women value working from home and a shorter commute more than men do, and school closures shifted

childcare toward mothers. In the model, a higher value of commuting time raises the commuting dividend and with it the threshold, so telework raises the value of an urban address by more for women than for men. The aggregate estimates could therefore hide responses by gender that differ in size or sign.

Table 5: Telework, urban residence and the income gap, by gender

	Chile	Peru	Mexico	Brazil	Colombia
Panel A. Urban residence					
During	−0.004	−0.021**	0.012	0.002	−0.008
	(0.007)	(0.008)	(0.008)	(0.003)	(0.005)
After	−0.001	−0.003	0.002	0.006	0.018**
	(0.008)	(0.005)	(0.008)	(0.006)	(0.008)
During × Female	−0.005	0.021*	−0.017***	0.000	0.007
	(0.008)	(0.011)	(0.005)	(0.003)	(0.007)
After × Female	0.001	0.004	−0.010*	−0.008*	−0.010
	(0.010)	(0.006)	(0.006)	(0.004)	(0.008)
Observations	446,552	329,412	4,740,100	5,576,617	1,278,640
Panel B. Urban-rural income gap of teleworkable occupations					
During	0.105	0.068	0.026**	0.048**	0.094
	(0.070)	(0.123)	(0.012)	(0.021)	(0.066)
After	−0.009	0.116	0.031**	0.045*	0.115
	(0.027)	(0.112)	(0.014)	(0.023)	(0.090)
During × Female	−0.101	0.301	0.004	0.000	−0.047
	(0.077)	(0.267)	(0.012)	(0.025)	(0.097)
After × Female	−0.024	0.385*	−0.005	−0.014	−0.047
	(0.038)	(0.228)	(0.015)	(0.027)	(0.150)
Observations	416,930	251,128	3,256,734	5,411,202	1,179,732

Note: All estimates use the primary specification (occupation fixed effects, education-decile × year fixed effects, age and education controls, occupation-level clustering). Panel A is the urban-residence regression of Section 4 with the female level and its interactions with Telework, During, and After added: the During and After rows report the responses of the male base group, and the rows interacted with Female the female-minus-male difference in each response. Adding region × year fixed effects leaves Mexico's differences at −0.016*** and −0.009** and raises Peru's During difference to 0.022**. The implied female responses (male plus difference) are not significant at 5% in any country under the primary specification. Panel B is the income regression of Section 5 with the female level and its interactions with every term added, so the rows report the same objects as Panel A: the male base response in the change in the urban-rural income gap of teleworkable occupations, and the female-minus-male difference. Adding region × year fixed effects leaves Peru's After difference at 0.373*. The implied female responses (male plus difference) are 0.030*** and 0.027** in Mexico, 0.048*** and 0.031* in Brazil, and 0.369* and 0.502*** in Peru. Standard errors clustered at the occupation level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The split mostly returns the aggregate answer. Panel A of Table 5 allows the During and After responses in the primary specification to differ between women and men, and Appendix E re-estimates the event studies of Figure 3 separately by gender (Figure E.1). Neither gender traces a persistent path away from cities in any country. The male During and After coefficients are small and not significant in Chile, Mexico, and Brazil, and the implied female responses (the male coefficient plus the interaction) are not significant at 5% in any country. Two differences between women and men stand out, with opposite signs. In Peru, men in teleworkable occupations became

less urban during the pandemic, by −0.021, while women did not move; the difference of +0.021 is significant at 10%, and at 5% with region × year effects. In Mexico, the During difference is −0.017 and significant at 1%: women in teleworkable occupations moved toward cities by less than men did, but neither gender's own response is significant. Brazil's After difference is −0.008, significant at 10%, against male and female responses that are both within one percentage point of zero. Colombia's differences are within one percentage point of zero and not significant. Each movement is at most two percentage points against urban shares near 80 to 95%. The largest movement in the split event studies, Peru's male 2020 coefficient of −0.026, sits 0.006 below that group's own 2018 coefficient. Commutes, telework take-up, and labor-force attachment all differ by gender in these countries, so the design cannot attribute these differences to one channel, and we report the split without claiming a mechanism.

For the same reasons, we also split the income estimates by gender. Panel B of Table 5 adds the female dummy and its interactions to the income regression, with the split event studies in Figure E.2. The female-minus-male difference is not significant at 5% in any country, so the split does not reject a common widening. Mexico's and Brazil's male During and After coefficients are positive, three of the four significant at 5%, and the implied female responses are of the same size and significant. Peru's widening is larger for women, +0.30 during and +0.39 after relative to men, the latter at 10%; the implied female responses are +0.37 and +0.50, while the male coefficients, +0.07 and +0.12, are not significant on their own. Chile's and Colombia's differences are small and insignificant. No country shows a significant narrowing for either gender at 5%. In particular, the pooled widening does not come from a change in the gender composition of urban and rural teleworkable workers.

7 Conclusion

Telework was expected to spread people out, and in the United States, it did. This paper asked whether it did the same in Latin America, and the answer is no. Across harmonized household surveys from Chile, Peru, Mexico, Brazil, and Colombia, teleworkable occupations became far more remote in practice but no more rural in residence. We find no evidence of a lasting urban-rural migration response: at most one percentage point in Chile in 2020, and none at all in Brazil, while take-up rose by 12 points.

The explanation we offer does not rest on Latin American exceptionalism. Telework frees some workers from the city, but it also frees the city from commuting, and the second force is worth about half of the commuting cost. Migration turns on whether rural feasibility clears the threshold the two forces define. Without a productivity gain, rural feasibility clears the exact threshold in every country, so the model predicts a move toward rural areas that did not happen. The null requires a gain that favors the city, of about 4 to 9 percent of the urban wage outside Mexico. The wage evidence points the same way. At zero gain, the income gap of teleworkable occupations should have narrowed; instead, it widened in Peru, Mexico, and Brazil and moved little in Chile and Colombia.

Both results indicate a productivity gain that favored cities and raised the threshold above rural feasibility. Mexico is the exception: its null would require a gain of a third of the urban wage.

The policy implication, if the mechanism is right, concerns infrastructure. The margin that decides whether remote work decentralizes cities in the region is not adoption, which arrived, but rural feasibility, which has not. Rural internet quality is the ceiling on φ that Section 2 discusses, although we do not measure whether connectivity, hybrid attendance requirements, or amenities bind first. The threshold also says the most congested cities are the hardest to decentralize, because a long average commute makes the commuting dividend large; transport improvements that shorten commutes also lower the threshold by shrinking the dividend that telework would otherwise hand the city.

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Appendix

Appendix A formally describes the model and proves the results in Section 2. Appendix B reports the migration and income estimates on a common ladder of covariate specifications, and the distance to the nearest major city as a second location outcome. Appendix C re-estimates both under the two alternative definitions of teleworkable occupations. Appendix D details the sources and conventions behind the threshold calibration described in Section 2.4. Appendix E reports the event studies by gender. The Online Appendix reports the coefficients of the three figures.

A The model

A.1 Setup

The model features a rural area R and one city with two locations, a center and suburbs, denoted "C" and "S". Both locations share the city amenities A, but living in the suburbs entails a commuting cost t to reach the center, while rural jobs have negligible commuting costs. As in Brueckner et al. (2023), the amount of land at each location is fixed, so the land supply elasticity is zero, and total population is constant at N. The city wage is $w(L, \alpha)$, where L is employment and α is a productivity shifter; without telework $L = N_C + N_S$. Labor productivity is higher in the city than in rural places, $\alpha > \alpha_R$, and amenities differ between rural (A_R) and urban areas (A).

Consumers have identical quasi-linear preferences over non-housing consumption, housing and amenities. As Brueckner et al. (2023) show, net housing utility (the value of housing consumption minus its cost) can then be written as a decreasing function $H(\cdot)$ of local population, so the utility of living and working at location i is

$$U_i = A_i + w_i + H(N_i) - t\,\mathbf{1}\{i = S\}\ \forall i \in \{C, S, R\}, \tag{5}$$

where the last term is the commuting cost borne by suburban residents.

The equilibrium in the absence of telework equates utility across the three locations. Within the city, both locations share amenities and wages; therefore, the commuting disadvantage of the suburbs must be compensated by more net housing utility:

$$H(N_S) - H(N_C) = t. \tag{6}$$

Since $H(\cdot)$ decreases in population, $N_S < N_C$: the center holds more people at higher housing prices, which is the standard monocentric prediction adapted to two locations. Across the urban-rural margin, indifference requires

$$A + w_C(N_C + N_S, \alpha) + H(N_C) = A_R + w_R(N_R, \alpha_R) + H(N_R), \tag{7}$$

which replicates the intercity analysis of Brueckner et al. (2023). We consider the case where rural

amenities are higher ($A < A_R$),[7] more people live in the city than in rural areas ($N_C + N_S > N_R$), and the wage is higher in the city ($w_C > w_R$). Rural areas trade wages for amenities and cheaper housing.

It is convenient to summarize the city using a single state variable. Let $N_U \equiv N_C + N_S = N - N_R$ denote the total city population. For a given N_U and commuting cost t, Eq. (6), together with the adding-up condition, pins down the split between the center and suburbs, so we can write $N_C = N_C(N_U; t)$. Define the *commuting-adjusted housing index*

$$G(N_U; t) \equiv H\big(N_C(N_U; t)\big), \tag{8}$$

which is the net housing utility a city resident obtains once the internal allocation has adjusted to commuting cost t. With this notation, and writing $\Delta(m) \equiv w_R(m, \alpha_R) - w_C(N - m, \alpha) < 0$ for the rural-urban wage gap when rural employment is m, the pre-telework equilibrium condition becomes

$$F^{\text{pre}}(N_R) \equiv (A - A_R) + G(N - N_R; t) - H(N_R) - \Delta(N_R) = 0. \tag{9}$$

Two of the three terms are rural advantages: $A - A_R < 0$ because rural amenities are higher and $G - H = H(N_C) - H(N_R) < 0$ because the city center holds more people and its housing is therefore more expensive. These are offset by the urban wage advantage: $-\Delta > 0$. This is the standard spatial equilibrium, written so that telework enters through exactly two places: the commuting cost t inside G, and the share of the population that faces the rural wage inside Δ.

A.2 Telework and the commuting dividend

A teleworker no longer commutes; therefore, t decreases to zero for her. Substituting $t = 0$ into Eq. (6) gives $H(\tilde{N}_S) = H(\tilde{N}_C)$, so the center and the suburbs must hold equal populations, $\tilde{N}_C = \tilde{N}_S = N_U/2$. Because the pre-telework equilibrium had $N_C > N_U/2$, this is a move of the population away from the center, and it occurs for any value of φ, including $\varphi = 0$. In terms of the index defined in Eq. (8), city residents move from $G(N_U; t)$ to $G(N_U; 0)$. We define the difference as the commuting dividend:

$$D(N_U) \;\equiv\; G(N_U; 0) - G(N_U; t) \;=\; H\Big(\tfrac{N_U}{2}\Big) - H\big(N_C(N_U, t)\big) \;>\; 0, \tag{10}$$

which is strictly positive because $N_C(N_U; t) > N_U/2$ and H decreases. If H is locally linear over the relevant range, N_C and N_S are symmetric about $N_U/2$ and the dividend takes the form $D \simeq t/2$ of Eq. (1).

A worker living in a rural area remotely performs a share φ of a city job's tasks. She supplies φ efficiency units to the city labor market and the remaining $1 - \varphi$ units to the rural market, so her income is $\varphi\, w_C + (1 - \varphi)\, w_R$. Therefore, rural employment is $(1 - \varphi)N_R$, and city employment is

[7] This is not necessarily the case, but altering it would require another source of attraction for rural areas: if they offer worse wages and worse amenities, and housing is not cheap enough to compensate, nobody should select that location.

$N-(1-\varphi)N_R$. Let $g \geq 0$ denote any productivity gain from telework accruing to the city labor market. Combining these two changes, the post-telework spatial equilibrium requires

$$F(N_R;\varphi) \;\equiv\; (A-A_R)+G(N-N_R;0)-H(N_R)-(1-\varphi)\big[\Delta\big((1-\varphi)N_R\big)-g\big] \;=\; 0. \qquad (11)$$

Comparing Eq. (11) with Eq. (9) shows the whole model in one line. Telework replaces $G(\cdot\,;t)$ with $G(\cdot\,;0)$, which adds the dividend D. It scales the wage penalty of rural living by $(1-\varphi)$, because only the non-teleworkable share of a rural resident's tasks is paid at the rural wage. Finally, it adds g to the city wage.

A.3 Remarks

Remark 1 (Two margins). Setting $t=0$ implies $\tilde{N}_C = \tilde{N}_S$ for every $\varphi \in [0,1]$, whereas the pre-telework equilibrium has $N_C > N_S$. Therefore, the center loses population share at every value of φ, including values below φ^*, at which the city as a whole *gains* population.

Remark 2 (Amenity confound). A shock $\epsilon > 0$ to A_R enters Eq. (11) additively and independently of φ, so it does not interact with teleworkability at first order (the equilibrium response does depend on φ through the slope of F; see the note below) and reverts when ϵ does. The telework channel is strictly monotone in φ by Lemma 1 and persists after the shock.

On Remark 2: the equilibrium response $dN_R/d\epsilon = 1/F_{N_R}$ does depend on φ through the slope F_{N_R}, so the differencing holds only to first order.

A.4 Proofs

Lemma 1 (Regularity and monotonicity)**.** *Assume that $F(\cdot;\varphi)$ of Eq.* (11) *changes sign on $(0,N)$ for every $\varphi \in [0,1]$, that is, an interior equilibrium exists before and after telework. Then $F(\cdot;\varphi)$ is strictly increasing in N_R, so the post-telework equilibrium rural population $N_R(\varphi)$ exists, is unique, and satisfies $dN_R/d\varphi > 0$.*

Proof. Both inverse labor demands slope down, so $\Delta'(m) = \partial[w_R(m,\alpha_R) - w_C(N-m,\alpha)]/\partial m < 0$: a rise in rural employment lowers the rural wage and raises the city wage. Equivalently, $|\Delta|$ increases in m, as stated in Section 2. Each term of $\partial F/\partial N_R$ then contributes positively: $\partial G(N-N_R;0)/\partial N_R = -\frac{1}{2}H'\Big(\frac{N-N_R}{2}\Big) > 0$, because the city shrinks and city housing becomes cheaper; $-H'(N_R) > 0$, because rural housing becomes more expensive; and $-(1-\varphi)^2\Delta' > 0$. Hence, F is strictly increasing in N_R; with the assumed sign change and continuity, its root exists and is unique. For the comparative static, $\partial F/\partial\varphi = [\Delta - g] + (1-\varphi)N_R\Delta' < 0$, since $\Delta < 0$, $g \geq 0$ and $\Delta' < 0$. The implicit function theorem then yields $dN_R/d\varphi = -(\partial F/\partial\varphi)/(\partial F/\partial N_R) > 0$. □

Proof of Proposition 1. For part (a), setting $\varphi = 0$ in Eq. (11) and subtracting Eq. (9) term by term gives $F(N_R;0) - F^{\text{pre}}(N_R) = D + g$ at every N_R, because the wage terms cancel exactly when no rural resident holds a city job. Evaluated at the pre-telework equilibrium, $F(N_R^{\text{pre}};0) = D + g >$

$0 = F^{\text{pre}}(N_R^{\text{pre}})$. By Lemma 1, $F(\cdot;0)$ is strictly increasing; therefore, its root lies strictly below N_R^{pre}. The argument uses only $D > 0$, so it holds at $g = 0$.

For part (b), the same difference at an arbitrary φ is

$$\Phi(\varphi) \;\equiv\; F(N_R^{\text{pre}};\varphi) - F^{\text{pre}}(N_R^{\text{pre}}) \;=\; D + \Delta_{pre} - (1-\varphi)\Delta\big((1-\varphi)N_R^{\text{pre}}\big) + (1-\varphi)g, \tag{12}$$

which is continuous and strictly decreasing in φ, as $\Delta < 0$, $\Delta' < 0$ and $g \geq 0$. It is positive at $\varphi = 0$ by part (a), where it equals $D + g$, and at $\varphi = 1$ it equals $D - |\Delta_{pre}|$, which is negative if and only if $D < |\Delta_{pre}|$. Under this condition, Φ has a unique root, $\varphi^* \in (0,1)$. For $\varphi > \varphi^*$ the difference is negative, so the root of $F(\cdot;\varphi)$ lies above N_R^{pre} by Lemma 1, which is decentralization; for $\varphi < \varphi^*$ it lies below N_R^{pre}. If, instead, $D > |\Delta_{pre}|$, the difference is positive at every $\varphi \in [0,1]$, telework centralizes throughout, and no threshold exists; at $D = |\Delta_{pre}|$ it is positive on $[0,1)$ and zero at $\varphi = 1$, so the threshold sits at the boundary. This establishes the existence, uniqueness, and sign crossing without any approximations.

Equation (2) is the root of Φ under one further restriction, namely, that the wage gap is evaluated at the pre-telework level of rural employment rather than at the post-telework level: setting $\Delta((1-\varphi)N_R^{\text{pre}}) = \Delta_{pre}$ in Eq. (12) gives $D + \varphi\Delta_{pre} + (1-\varphi)g$, whose root is $\varphi^* = (D+g)/(|\Delta_{pre}| + g)$. This restriction is not innocuous, but its direction is known. Post-telework rural employment is $(1-\varphi)N_R^{\text{pre}} < N_R^{\text{pre}}$, and $|\Delta|$ is increasing in rural employment, so $|\Delta((1-\varphi)N_R^{\text{pre}})| < |\Delta_{pre}|$ at every $\varphi > 0$. Hence, $\Phi(\varphi) < D + \varphi\Delta_{pre} + (1-\varphi)g$ for all $\varphi \in (0,1]$, and because both are decreasing, the exact root lies *below* the closed-form one. Equation (2) is therefore an upper bound on the true threshold. The gap between the two depends on how strongly the wage gap responds to rural employment. Appendix D calibrates that response and solves $\Phi(\varphi) = 0$ exactly. □

Proof of Proposition 2. Rural employment is $m = (1-\varphi)N_R$ and city employment is $N - m$. Both inverse labor demands slope down, so $|\Delta(m)| = w_C(N-m,\alpha) - w_R(m,\alpha_R)$ is strictly increasing in m: a rise in rural employment lowers w_R and raises w_C. When $g = 0$ the gap moves with m. A gain $g > 0$ enters the measured gap additively as $|\Delta| + g$ in Eq. (11), and so widens it at any m. Rural employment moves for two reasons simultaneously. Holding φ fixed, $dm = (1-\varphi)dN_R$ has the sign of the residential flow, so migration moves the gap against its own direction. Holding N_R fixed, m decreases by φN_R when telework arrives. In a country whose residential response is zero, the second channel operates alone: m falls; therefore, at $g = 0$ the gap must narrow. A gap that widens cannot be produced by any $g = 0$ configuration of the model, which is the overidentifying restriction. □

B Robustness to covariates

This appendix reports the migration and income estimates on a common ladder of specifications. Column (1) uses occupation and year fixed effects with individual controls (education, gender, and age); column (2) adds each country's survey weights; column (3) adds education-decile × year fixed

effects, which makes it the primary specification; and column (4) adds region × year fixed effects. Standard errors are clustered at the occupation level throughout. Table B.1 reports the migration estimates, Table B.2 the income-gap estimates, and Table B.3 the distance outcome of Section 4.3.

Table B.1: Robustness to covariates: telework and urban residence

	(1) Base	(2) (1) + weights	(3) (1) + educ-dec × yr	(4) (3) + region × yr
Panel A: Chile				
Telework × During	−0.0132**	−0.0088	−0.0083*	−0.0106**
	(0.0051)	(0.0059)	(0.0045)	(0.0042)
Telework × After	−0.0052	−0.0051	−0.0010	−0.0021
	(0.0050)	(0.0057)	(0.0041)	(0.0032)
Observations	446,552	446,552	446,552	446,552
Panel B: Perú				
Telework × During	−0.0242***	−0.0266***	−0.0092**	−0.0057
	(0.0038)	(0.0060)	(0.0043)	(0.0050)
Telework × After	−0.0251***	−0.0202**	−0.0007	−0.0005
	(0.0056)	(0.0084)	(0.0048)	(0.0040)
Observations	329,472	329,472	329,412	328,713
Panel C: México				
Telework × During	−0.0099**	−0.0071	0.0033	0.0034
	(0.0039)	(0.0052)	(0.0064)	(0.0061)
Telework × After	−0.0047	0.0042	−0.0028	−0.0023
	(0.0037)	(0.0061)	(0.0070)	(0.0068)
Observations	4,740,100	4,740,100	4,740,100	4,740,100
Panel D: Brazil				
Telework × During	−0.0023	0.0024	0.0021	0.0018
	(0.0032)	(0.0020)	(0.0026)	(0.0022)
Telework × After	0.0020	−0.0009	0.0016	0.0018
	(0.0028)	(0.0019)	(0.0051)	(0.0047)
Observations	5,576,620	5,576,620	5,576,617	5,576,617
Panel E: Colombia				
Telework × During	−0.0201***	−0.0141*	−0.0055	−0.0060
	(0.0069)	(0.0074)	(0.0048)	(0.0049)
Telework × After	0.0019	0.0205**	0.0140*	0.0119
	(0.0083)	(0.0082)	(0.0080)	(0.0076)
Observations	1,278,640	1,278,640	1,278,640	1,278,640

Note: The outcome is an indicator for urban residence and the reported coefficient is Telework × Period, so a negative value means teleworkable occupations became less urban relative to non-teleworkable occupations. Every column includes occupation fixed effects and individual controls (education, gender, and age) with standard errors clustered at the occupation level. Column (1) uses occupation and year fixed effects; column (2) adds each country's survey weights; column (3) adds education-decile × year fixed effects, the primary specification; column (4) adds region × year fixed effects. The clusters in columns (1) and (2) are 276, 415, 363, 429, and 82 for Chile, Perú, México, Brazil, and Colombia; under the decile fixed effects, they are 276, 409, 363, 428, and 82. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Robustness to covariates: the urban-rural income gap of teleworkable occupations

	(1) Base	(2) (1) + weights	(3) (1) + educ-dec × yr	(4) (3) + region × yr
Panel A: Chile				
Telework × During × Urban	0.0295	0.0169	0.0410	0.0454
	(0.0351)	(0.0525)	(0.0356)	(0.0352)
Telework × After × Urban	−0.0351	0.0475	−0.0306	−0.0188
	(0.0235)	(0.0291)	(0.0207)	(0.0200)
Observations	416,930	416,930	416,930	416,930
Panel B: Perú				
Telework × During × Urban	0.6568***	0.7873***	0.1921**	0.1572*
	(0.2479)	(0.2760)	(0.0899)	(0.0906)
Telework × After × Urban	0.6429***	0.7617***	0.2777***	0.2612***
	(0.1804)	(0.2194)	(0.0649)	(0.0673)
Observations	251,186	251,186	251,128	250,698
Panel C: México				
Telework × During × Urban	0.0250**	0.0458***	0.0236**	0.0188*
	(0.0105)	(0.0117)	(0.0106)	(0.0100)
Telework × After × Urban	0.0250**	0.0486***	0.0242**	0.0241**
	(0.0109)	(0.0112)	(0.0111)	(0.0103)
Observations	3,256,734	3,256,734	3,256,734	3,256,734
Panel D: Brazil				
Telework × During × Urban	0.0437***	0.0611***	0.0482***	0.0490***
	(0.0127)	(0.0155)	(0.0132)	(0.0118)
Telework × After × Urban	0.0265	0.0200	0.0273	0.0287*
	(0.0174)	(0.0169)	(0.0166)	(0.0159)
Observations	5,411,205	5,411,205	5,411,202	5,411,202
Panel E: Colombia				
Telework × During × Urban	0.0857	0.0323	0.0827	0.0777
	(0.0761)	(0.0787)	(0.0796)	(0.0701)
Telework × After × Urban	0.0045	−0.0434	0.1016	0.0930
	(0.1295)	(0.1647)	(0.1167)	(0.1083)
Observations	1,179,732	1,179,732	1,179,732	1,179,732

Note: The outcome is log income and the reported coefficient is on Telework × Period × Urban, so a positive value means that the urban-rural income gap of teleworkable occupations widened relative to non-teleworkable ones. Every column includes the constituent double interactions, occupation fixed effects, and individual controls (education, gender, and age) with standard errors clustered at the occupation level. Column (1) uses occupation and year fixed effects; column (2) adds each country's survey weights; column (3) adds education-decile × year fixed effects, the primary specification; column (4) adds region × year fixed effects. The clusters in columns (1) and (2) are 275, 414, 363, 429, and 82 for Chile, Perú, México, Brazil, and Colombia; under the decile fixed effects, they are 275, 408, 363, 428, and 82. Perú's estimate is identified off a few rural teleworkable workers and is read with caution (Section 5). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Robustness to the location outcome: telework and distance to the nearest major city

	Chile (base 2017)	Perú (base 2019)	México (base 2019)	Colombia (base 2019)
Panel A: primary specification				
Telework × pre-period year	0.002	0.009	0.009	0.032
	(0.053)	(0.083)	(0.013)	(0.044)
Telework × 2020	−0.056	0.016	0.002	−0.197*
	(0.062)	(0.105)	(0.013)	(0.101)
Telework × last post-pandemic year	−0.026	0.018	−0.017	−0.198**
	(0.046)	(0.106)	(0.018)	(0.090)
Panel B: adding region × year fixed effects				
Telework × pre-period year	−0.012	0.013	n.e.	n.e.
	(0.014)	(0.020)		
Telework × 2020	−0.034*	−0.001	n.e.	n.e.
	(0.018)	(0.018)		
Telework × last post-pandemic year	−0.032***	0.009	n.e.	n.e.
	(0.010)	(0.014)		
Panel C: pooled, primary specification				
Telework × During	−0.057	0.011	−0.008	−0.226**
	(0.045)	(0.096)	(0.012)	(0.106)
Telework × After	−0.042	−0.020	−0.014	−0.234**
	(0.033)	(0.078)	(0.014)	(0.108)
Observations	443,773	328,713	4,740,100	1,278,640

Note: The outcome is $\ln(1+d)$, where d is the distance in kilometers from the respondent's geographic unit to the nearest major city (Section 3), so a negative coefficient means that teleworkable occupations moved closer to the major cities relative to other occupations. Brazil has no geographic identifier fine enough for this outcome. Every column includes occupation fixed effects, education-decile × year fixed effects, and individual controls (education, gender, and age), with standard errors clustered at the occupation level; Panel B adds region × year fixed effects. The pre-period year is 2015 in Chile and 2018 elsewhere; México's 2017 coefficient is +0.002 (0.017). The last post-pandemic year is 2024 in Chile, Perú, and México and 2023 in Colombia. In México and Colombia distance is measured at the state and department level and is therefore constant within the region variable, so Panel B cannot be estimated (n.e.) there. Observations are those of Panel A. The Chilean sample is smaller than in Table B.1 because three comunas have no distance (2,779 workers). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Alternative definitions of a teleworkable occupation

The teleworkability of an occupation is assigned, not observed; therefore, the assignment rule is a candidate explanation for everything in Section 4. This appendix re-estimates the migration and income tables in Appendix B under two alternatives to the Dingel and Neiman (2020) indicator, and the two have different reach.

The first maintains that classification but uses the underlying probability of remote work in place of the indicator built from it. The treatment becomes continuous on $[0, 1]$, so the coefficient is the effect of moving an occupation from fully non-teleworkable to fully teleworkable. Tables C.1 and C.2 report the results for these five countries. Colombia's probability inherits its coarse occupation groups, so it takes only nine distinct values and is missing for some occupations, which shrinks its sample.

The second replaces the classification outright with the one the Central Bank of Mexico built from the 2019 employment data (Leyva and Mora, 2021). We apply it to México only. It is defined on México's own occupational classification, so taking it to the other four countries would insert a crosswalk between the definition and the data and confound a change of classification with a change in crosswalk. On México's estimation sample, it is the narrower rule by a wide margin: it labels 12.8% of workers teleworkable against 21.4% under Dingel–Neiman, or 60 for every 100. Table C.3 reports it.

Both run through the estimation engine that produces Tables B.1 and B.2. Fed the paper's own classification, the engine returns every coefficient, standard error, and sample size in those two tables exactly; therefore, a difference here is a difference in the classification and not in the pipeline. Samples move with the classification, however, because the rules leave different occupations unclassified, and for México, that must be separated from the relabeling itself.

The two results the argument rests on survive. Brazil's migration estimate stays at zero, +0.0018 against +0.0021 in Table B.1, on 5.5 million observations, and its income gap continues to widen during the pandemic, at +0.046 against +0.048 and significant at 1%. Chile's decentralization also survives, and is slightly larger under the continuous measure (−0.0092 against −0.0083), holding its significance when region × year effects are added. Perú remains negative and México remains null under the continuous measure. Colombia repeats the indicator's residence pattern: a small negative During coefficient (−0.0090) and a positive After coefficient (+0.0239, significant at 5%). Region × year effects leave the After coefficient at +0.0213, also significant at 5%. Its income estimates stay negative and imprecise. Therefore, the pattern that Section 4 reports is not an artifact of the indicator.

What does move is México under its own central bank's definition, and it moves against this paper. The During estimate on urban residence turns negative, −0.0073, and significant at 10%, where Table B.1 reports a well-measured +0.0033, and it does not survive the addition of region × year fixed effects, falling to −0.0045 with a standard error of 0.0037. The income gap moves the same way: the During widening falls from +0.024 to an insignificant +0.009, though the After widening holds at +0.026.

The weight that the movement can carry depends first on the sample. The Banco de México rule classifies every worker the Dingel and Neiman (2020) indicator classifies and 753,028 more, so one sample contains the other exactly, and the two can be compared on the intersection, which is the 4,740,100 observations in Table B.1. (The estimation drops 38 of the added observations as singletons, so Table C.3 reports 5,493,090.) Holding the sample fixed, along with the controls and the education deciles, leaves only the relabeling, and the relabeling is substantial: it moves 524,016 observations, 11% of the sample, and takes the teleworkable share from 21.4% to 12.8%. Fed the paper's own labels on those observations, the engine returns Tables B.1 and B.2. Using the Banco de México labels on the same observations, the During estimate for urban residence is −0.0048 with a standard error of 0.0039, and the income-gap During estimate is +0.0064 with a standard error of 0.0119. Neither is significant. The relabeling, therefore, produces about three-quarters of the movement in the point estimate and none of its significance; the remainder comes from the observations that the second rule adds.

The pre-period coefficients determine the weight the estimate can carry. A classification that reassigns treatment also changes the event study; therefore, Figure 3, which is estimated under the Dingel and Neiman (2020) indicator, cannot speak for this one. Re-estimated under the Banco de México rule, México's event study shows a clear pre-pandemic drift. The 2017 pre-period coefficient is +0.0156, significant at 1%, and the 2018 coefficient is +0.0089, while every coefficient from 2020 onwards lies within 0.003 of zero and none is significant. Adding region × year effects leaves the pattern intact, at +0.0138 in 2017. What this classification isolates in México is a pre-pandemic drift toward urban residence, with nothing at the shock itself, and that, rather than the region × year result, is the qualification the During estimate carries. The income-gap pre-period coefficients run the other way: they are near zero under this classification, at −0.010 and −0.013, and are not significant, whereas the Dingel–Neiman version has −0.022 in 2017.

We report the exercise because México's point estimates are plainly not classification-free, and the reader is entitled to see that. We do not read this as evidence against Table B.1. An estimate that loses its significance once the sample is held fixed, and that comes from a classification whose 2017 coefficient is significant at 1%, cannot carry much weight.

Table C.1: Telework and urban residence under the Dingel–Neiman remote-work probability

	(1) Educ-dec × yr	(2) + region × yr
Panel A: Chile		
Telework × During	−0.0092*	−0.0119***
	(0.0049)	(0.0044)
Telework × After	−0.0008	−0.0021
	(0.0042)	(0.0034)
Observations	446,552	
Panel B: Perú		
Telework × During	−0.0088**	−0.0056
	(0.0044)	(0.0050)
Telework × After	−0.0010	−0.0009
	(0.0048)	(0.0040)
Observations	329,575	328,876
Panel C: México		
Telework × During	0.0040	0.0042
	(0.0065)	(0.0063)
Telework × After	−0.0024	−0.0019
	(0.0072)	(0.0070)
Observations	4,740,100	
Panel D: Brazil		
Telework × During	0.0018	0.0016
	(0.0028)	(0.0023)
Telework × After	0.0018	0.0020
	(0.0053)	(0.0048)
Observations	5,534,611	
Panel E: Colombia		
Telework × During	−0.0090	−0.0091
	(0.0063)	(0.0064)
Telework × After	0.0239**	0.0213**
	(0.0100)	(0.0092)
Observations	1,278,640	

Note: The teleworkability indicator is replaced by the occupation's Dingel and Neiman (2020) probability of remote work, a continuous measure on $[0, 1]$, so a coefficient is the effect of moving an occupation from fully non-teleworkable to fully teleworkable. The outcome is an indicator for urban residence and the layout follows the tables of Appendix B: one panel per country, occupation fixed effects, education-decile × year fixed effects and individual controls in every column, standard errors clustered on occupation, and column (2) adding region × year fixed effects. Observations are those of column (1). For Colombia the continuous measure is the share of teleworkable CIUO-08 codes within the CNO-70 group (Appendix OA-C). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: The urban-rural income gap under the Dingel–Neiman remote-work probability

	(1) Educ-dec × yr	(2) + region × yr
Panel A: Chile		
Telework × During × Urban	0.0556*	0.0592*
	(0.0337)	(0.0339)
Telework × After × Urban	−0.0266	−0.0151
	(0.0201)	(0.0198)
Observations	416,930	
Panel B: Perú		
Telework × During × Urban	0.1907**	0.1560*
	(0.0903)	(0.0910)
Telework × After × Urban	0.2779***	0.2621***
	(0.0652)	(0.0675)
Observations	251,290	250,860
Panel C: México		
Telework × During × Urban	0.0203*	0.0158
	(0.0108)	(0.0103)
Telework × After × Urban	0.0226**	0.0228**
	(0.0110)	(0.0103)
Observations	3,256,734	
Panel D: Brazil		
Telework × During × Urban	0.0462***	0.0475***
	(0.0131)	(0.0119)
Telework × After × Urban	0.0253	0.0270*
	(0.0167)	(0.0161)
Observations	5,369,542	
Panel E: Colombia		
Telework × During × Urban	−0.0514	−0.0469
	(0.1324)	(0.1254)
Telework × After × Urban	−0.0623	−0.0527
	(0.1814)	(0.1670)
Observations	1,179,732	

Note: The outcome is log income and the reported coefficient is on Telework × Period × Urban, so a positive value means that the urban-rural income gap of teleworkable occupations widened. The classification is the one used in Table C.1 and the layout follows the tables in Appendix B: one panel per country, the constituent double interactions, occupation fixed effects, education-decile × year fixed effects, and individual controls in every column; standard errors clustered on occupation; and column (2) adding region × year fixed effects. The observations are those in column (1). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: México under the Banco de México telework classification

	(1) Educ-dec × yr	(2) + region × yr
Panel A: urban residence		
Telework × During	−0.0073*	−0.0045
	(0.0038)	(0.0037)
Telework × After	−0.0056	−0.0049
	(0.0040)	(0.0037)
Observations	5,493,090	
Panel B: income gap		
Telework × During × Urban	0.0087	0.0056
	(0.0117)	(0.0112)
Telework × After × Urban	0.0262**	0.0267**
	(0.0122)	(0.0117)
Observations	3,807,219	

Note: The teleworkability indicator is replaced by the one the Central Bank of Mexico built from 2019 Mexican employment data (Leyva and Mora, 2021). It is applied to México alone, because it is defined on México's own occupational classification and carrying it to the other four countries would put a crosswalk between the definition and the data. The layout follows the tables of Appendix B, with one panel per outcome: Panel A is the urban-residence regression in Table B.1 and Panel B the income-gap regression of Table B.2, each with occupation fixed effects, education-decile × year fixed effects, individual controls, and occupation-level clustering, and column (2) adding region × year fixed effects. Observations are those in column (1). The samples are larger than those in Tables B.1 and B.2 because this classification is missing for fewer workers. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Inputs for the five-country threshold

Table 1 applies the conventions of Section 2.4 to all five countries. Commuting minutes are doubled, multiplied by 21 working days, and valued at half the urban hourly wage (Small, 2012); the hourly wage is mean monthly labor income over mean monthly hours (52/12 times weekly hours) among urban workers; D is half the resulting monthly cost, by Eq. (1). Wage gaps, urban hours, and the feasibility proxy φ are unweighted means on the estimation samples of the paper's regressions, pre-pandemic waves; the samples exactly reproduce the observation counts in column (1) of Table B.1. Three inputs come from outside the extracts. Peru's income levels use ENAHO's annualized net labor income divided by twelve because the survey records amounts per payment period, which do not compare in levels. Brazil's hours are the usual weekly hours of urban workers in the PNADC, 2017–2019. Colombia's hours are the usual weekly hours of the urban employed in the GEIH April 2018 and 2019 waves. Currency amounts are converted to US dollars at the 2019 period-average official exchange rates listed in the note to Table 1.

Commuting times come from four sources. Chile: CASEN 2015 and 2017, urban workers, 31.5 minutes one way. Colombia: the GEIH commute question, urban workers in the 2018–2019 estimation sample, 27.0 minutes. Brazil, Mexico and Peru have no commuting question in the household survey, so the input is the mean one-way work-trip time of the main metropolitan origin-destination survey: São Paulo (41.5 minutes, computed from the trip microdata, which reproduce the survey's published all-trip mean; Companhia do Metropolitano de São Paulo, 2019), Mexico

City (57.0 minutes, computed from the trip microdata, which reproduce the published duration distribution; INEGI, 2018), and Lima–Callao (44.6 minutes, the published mean; JICA, 2013). These are the largest metropolitan areas of each country, where commutes are longest, so the corresponding thresholds are upper bounds.

The exact threshold

Equation (2) holds the wage gap at its pre-telework level, so it is an upper bound on the root of Eq. (12) (Appendix A). To find the root, we use constant-elasticity inverse labor demands calibrated to the pre-pandemic levels, $w_R(m) = w_R^{pre}(m/s)^{-1/\eta}$ and $w_C(L) = w_C^{pre}[L/(1-s)]^{-1/\eta}$. Total employment is normalized to one, s is the pre-pandemic rural share of employment in the estimation sample, and η is the same in both markets. The central value, $\eta = 1$, follows the local wage response to the Venezuelan inflow in Colombia. Across 79 metropolitan areas, a rise of one percentage point in the migrant share lowered native hourly wages by 1.05 percent, or 0.59 percent with regional trends, with little effect on native employment (Lebow, 2022). These estimates imply elasticities of about 1 and 1.7. Across Mexican schooling and experience groups, a 10 percent fall in labor supply through emigration raised wages by about 4 percent (Mishra, 2007), an elasticity of 2.5. The wages, D, and φ are those of Table 1, and g is measured as a share of w_C. Table D.1 reports the exact threshold at $g = 0$ and the smallest gain at which it reaches φ. As η grows, the root approaches Eq. (2), the case of perfectly elastic local demand. Setting s to the rural share of teleworkable employment moves the threshold by less than 0.01 at $\eta \leq 2$. The rural elasticity matters more than the city one. An inelastic rural market ($\eta = 0.5$) with an elastic city market ($\eta = 2$) gives thresholds between the two symmetric cases and closer to the rural one, because rural employment falls by the share φ while city employment rises by only $\varphi s/(1-s)$.

Table D.1: The exact threshold and the gain a null requires

	Chile	Peru	Mexico	Brazil	Colombia
Panel A. Exact threshold at $g = 0$					
$\eta = 0.5$	0.014	0.016	0.018	0.020	0.013
$\eta = 1$	0.024	0.027	0.034	0.033	0.020
$\eta = 2$	0.039	0.041	0.062	0.049	0.029
$\eta = 5$	0.062	0.058	0.123	0.070	0.038
Eq. (2) ($\eta \to \infty$)	0.099	0.078	0.303	0.095	0.048
Observed φ	0.094	0.050	0.224	0.076	0.049
Rural share of employment, s	0.190	0.367	0.380	0.239	0.164
Panel B. Gain required, percent of the urban wage					
$\eta = 0.5$	19.3	8.9	75.3	13.1	7.2
$\eta = 1$	9.2	3.6	34.0	5.9	3.6
$\eta = 2$	4.4	1.0	15.6	2.5	1.8
$\eta = 5$	1.7	0.0	5.0	0.4	0.8
Eq. (2) ($\eta \to \infty$)	0.0	0.0	0.0	0.0	0.1

Note: Panel A reports the root of Eq. (12) at $g = 0$ with constant-elasticity local labor demands of elasticity η in both markets, calibrated to the pre-pandemic wages of Table 1 and the rural share of employment s in the pre-pandemic estimation sample. Panel B reports the smallest gain g, in percent of mean urban monthly labor income, at which that root reaches the observed φ. A zero means that φ is already at or below the threshold at $g = 0$.

E Migration and income by gender

This appendix reports the event studies behind Table 5. Figures E.1 and E.2 re-estimate the event studies of Figures 3 and 4 separately by gender, under the primary specification; the gender control drops out of the split regressions, and the age and education controls remain.

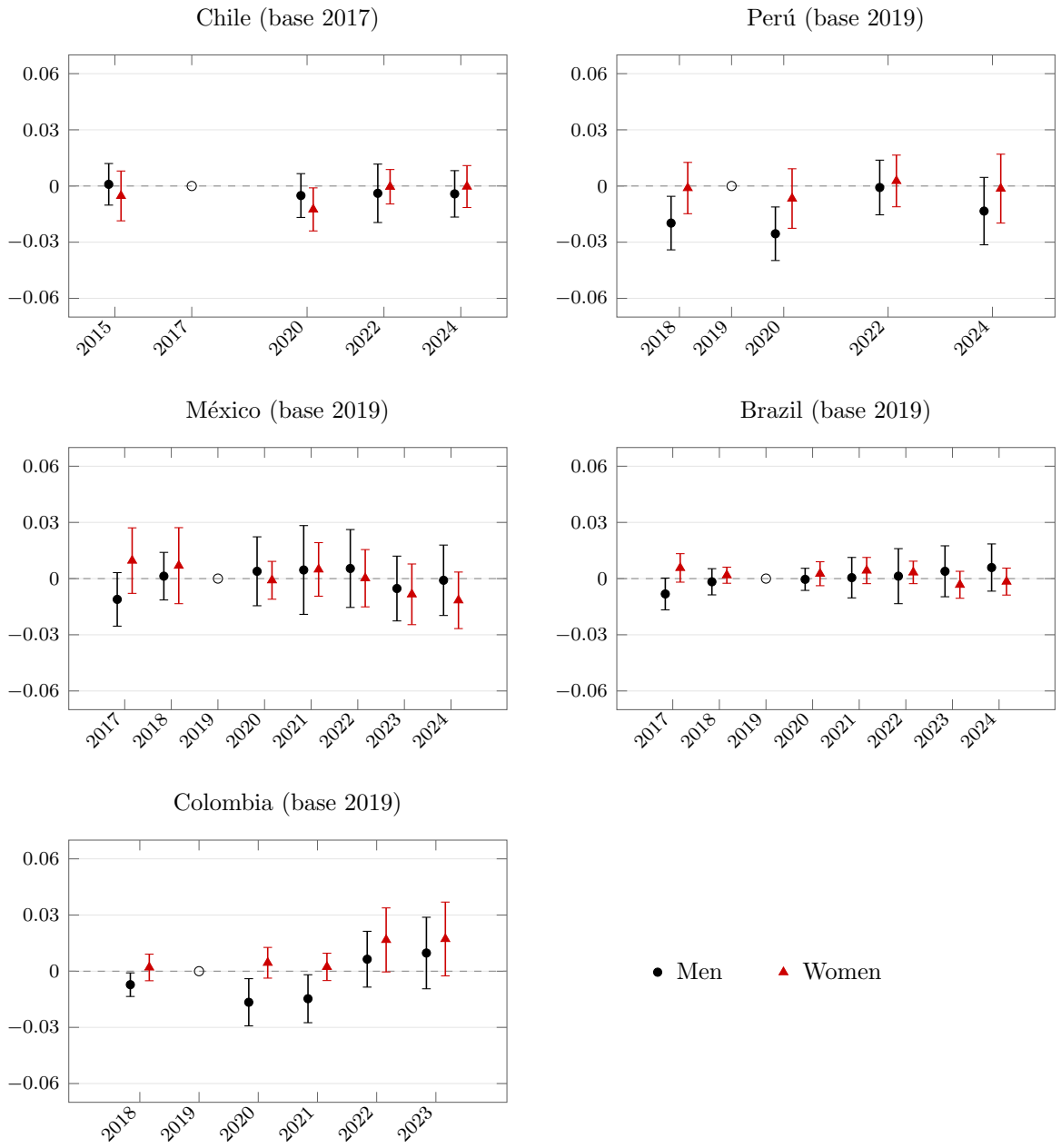


Figure E.1: Event studies by gender: telework and urban residence

Note: Coefficients on Telework × year with 95% confidence intervals, estimated separately for men (black circles, shifted left) and women (dark-red triangles, shifted right), under the primary specification. Open circles indicate omitted base years. The vertical scale is the same for all panels. Estimation samples (men, women): Chile 252,960 and 193,585; Perú 172,294 and 157,086; México 2,783,662 and 1,956,438; Brazil 3,174,621 and 2,401,995; Colombia 715,914 and 562,726.

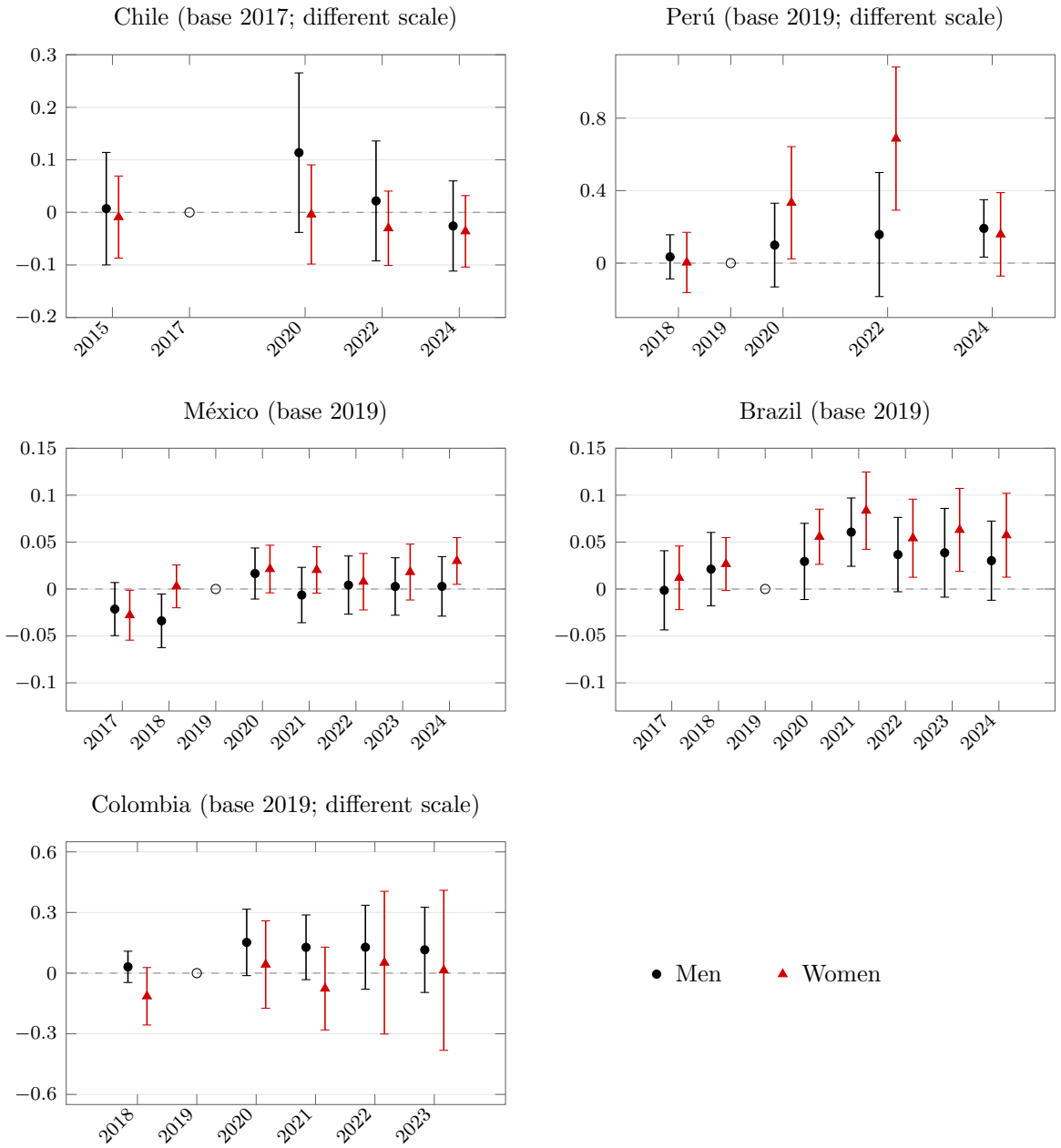


Figure E.2: Event studies by gender: the urban-rural income gap of teleworkable occupations

Note: Coefficients on Telework × Urban × year for log income with 95% confidence intervals, estimated separately for men (black circles, shifted left) and women (dark-red triangles, shifted right), with all lower-order interactions, under the primary specification. Open circles indicate omitted base years. México and Brazil share one vertical scale; Chile, Perú, and Colombia carry their own. Estimation samples as in Panel B of Table 5.