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Abstract Are regions poor because they have bad institutions or are they poor because they are disconnected from the social channels through which technology diffuses? This paper tests institutional and technological theories of economic convergence by looking at income convergence across Colombian municipalities. We use formal employment and wage data to estimate growth of income per capita at the municipal level. In Colombia, municipalities are organized into 32 *departamentos* or states. We use cellphone metadata to cluster municipalities into 32 communication clusters, defined as a set of municipalities that are densely connected through phone calls. We show that these two forms of grouping municipalities are very different. We study the effect on municipal income growth of the characteristics of both the state and the communication cluster to which the municipality belongs. We find that belonging to a richer communication cluster accelerates convergence, while belonging to a richer state does not. This result is robust to controlling for state fixed effects when studying the impact of communication clusters and vice versa. The results point to the importance of social interactions rather than formal institutions in the growth process.

Keywords Economic convergence · institutions · technological diffusion · growth · development · Colombia

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1 Introduction

Why are some nations and regions rich and others poor? If all have access to the same technology, the neoclassical growth model predicts that they should all converge to a common income level, a phenomenon called unconditional convergence. Poorer locations should experience higher marginal productivity of capital, resulting in faster growth rates. However, empirical cross-national studies offer little support for the unconditional convergence hypothesis, with no evidence of a systematic tendency for more rapid growth in poor countries compared to rich countries, over long periods. For the last two centuries, the data suggest incomes across nations have experienced significant divergence [39]. The only real exception has been Rodrik (2013) in finding global unconditional convergence in labor productivity in manufacturing [43]. Studies also find weak or no absolute convergence across members of the European Union [35].

By contrast, studies of unconditional convergence within nations have often found positive results. In their seminal work, Barro and Sala-i-Martin (1991) found unconditional convergence between states of the United States [11]. Further studies also found evidence of unconditional convergence mostly in developed countries, including Canada [19], Australia [16], Spain [24], Germany during reunification [15] and Indonesia [41]. Other studies, mostly in less developed countries, found little evidence of convergence including Italy [50], Russia [29], China [32], Mexico [7], and Colombia [14,45]. Shleifer et al (2014) conclude that convergence is faster in developed countries and those with better capital markets, noting, "A calibration of a neoclassical growth model suggests that significant barriers to factor mobility within countries are needed to account for the evidence" [27].

To make sense of the empirical evidence in the context of the neoclassical growth model, it is necessary to drop the assumption that all places have access to the same technology. The question becomes why access to technologies is unequal across or within countries. Starting with the work of Barro (1989) and Mankiw, Romer and Weil (1990), a large literature tried to identify the factors that condition convergence [12,34]. One line of thinking, most notably tied to North (1990) [36], the many works of Acemoglu and Robinson with colleagues [3–6], and Rodrik et al (2004) [44], argues that convergence appears to be conditional on the institutions in place. This explanation points to the role of institutions in defining the rules of the game (e.g. property rights and rule of law) that determine the incentive structure in which individual and collective decisions are made, including the incentives to adopt technology. By extension, state-level institutions within the country shape the local incentive structure, the interaction with national institutions, and the distribution of political power within the country, as argued by Acemoglu and Dell (2010). The authors conclude: "through these channels, local institutions impact important determinants of the efficiency of production, such as the provision of local public goods and the security of local property rights," conditioning convergence [1].

An alternative explanation points to the nature of technology itself and the obstacles to its diffusion, which limit the capacity of different places to utilize similar technologies. In this view, technology is composed of three forms of knowledge: embodied, codified and tacit. Embodied knowledge is contained in the tools and materials used in production. Codified knowledge is readily transmitted and stored, as found in blueprints, patents and documents. As conceptualized by Polanyi (1958), (1966), tacit knowledge, or knowhow, is the often unconscious capacity of the brain to recognize patterns and respond appropriately [37,38]. Knowhow cannot be expressed verbally or written down: as Polanyi put it, "you know more than you can say". Rather, knowhow exists only in brains and can only move from brain to brain through a long process of imitation and repetition, as argued by Arrow (1969) [8].

As a consequence, while tools can be shipped and codes can be shared, knowhow moves with difficulty between brains through social interaction. At any point in time, all three forms of knowledge are complementary, such that a restriction on one reduces the effectiveness of the others. Hence, the slow movement of tacit knowledge limits the speed with which embodied and codified knowledge (i.e. tools and blueprints) can diffuse. Moreover, the diffusion of tacit knowledge requires repeated social contact, which limits its diffusion to communities that interact intensely. Tacit knowledge and its complementarity with embedded knowledge in capital goods may be the hidden variable that explains "the significant barriers to factor mobility within countries [that] are needed to account for the evidence" of the absence of unconditional convergence discussed by Shleifer et al (2014) [27]. It may also explain the Rodrik (2013) finding regarding unconditional convergence of productivity in manufacturing [43]: since manufactured goods are typically tradable, producers from different countries interact with each other through competitive processes. This may create both selection pressures and favor multinational corporations and other forms of cooperation that can diffuse best practices internationally.

The literature on knowledge diffusion has shown very large effects of different dimensions of distance on many aspects of productivity and technology development and diffusion. For example, patents tend to cite other patents that were developed in nearby places (Jaffe et al, 1993) [30]. The effectiveness with which R&D expenditures translate into patent output is geographically clustered (Branstetter, 1999; Bottazzi and Peri, 2003) [46,13]. The productivity of subsidiaries of multinational corporations falls with the distance to headquarters (Keller and Yeaple, 2013) [31]. The ability of countries to develop comparative advantage in a new export product is strongly influenced by having a neighboring country that is a successful producer of that good (Bahar et al, 2014) [10]. All of these examples suggest that intense interaction is key to knowledge diffusion.

The institutional and socio-technological hypotheses have been debated in the context of the interpretation of the impact of white settler mortality in 1750 on subsequent economic development. For Acemoglu, Johnson and Robinson (2001), the institutional choices of white European settlers at the time of colonization set the stage for subsequent paths to development [3]. By contrast, Glaeser et al (2004) argue that the correlation between white settlers and subsequent development may not come from the adoption of institutions but from the movement of knowhow in the brains of the settlers, which could then be transmitted through learning by doing to subsequent generations [28].

This mechanism is consistent with findings in other literatures. Biological anthropologists have studied the slow diffusion of agriculture during the Neolithic Revolution, emphasizing the fact that imitation through cultural channels did not seem to be enough: much of the diffusion happened through the demographic expansion of agriculturalists [22,23,42]. The influential work by Jared Diamond [21] explored how differences in the timing and geographic spread of the Neolithic Revolution explain much of subsequent differential development, while Galor and Moav (2007) [26], Galor (2011) [25] and Ashraf and Galor (2011) [9] study other ways in which variations in the time since the Neolithic transition affect incomes today. Comin, Easterly and Gong [17] argue that the level of technological development today is highly correlated with the levels millennia ago. This could only happen if there are significant obstacles to technological diffusion. Similar obstacles are discussed in Spolaore and Wacziarg (2009, 2013) [49,48], which can explain how the time since two populations share a common ancestor is related to their technological distances from each other. These effects are even starker if one considers the historical origin of the population that now inhabits a certain place, as shown by Putterman and Weil (2010) [40]. This evidence is consistent with the idea that technologies are embedded in people and in social settings, where the adoption of technology by other social groups encounters major challenges.

Telling institutional versus socio-technological interpretations apart has been challenging. This paper tests these two hypotheses by measuring convergence in income across Colombian municipalities along two distinct geospatial divisions: one institutional, one socio-technological. The institutional explanation would emphasize the role that belonging to a particular *departamento*, or state, has on the institutional arrangements and the provision of public goods, thus affecting the incentive structure of agents to operate with better technology.

Although Colombia is a unitary republic, not a federation, states have significant autonomy[1]. Studies on Colombia, including those that take an institutional perspective such as Acemoglu et al (2015) [2], utilize state-level data, as do almost all studies of intra-national unconditional convergence worldwide. Under the institutional assumption, a municipality should tend to converge to the income of the state to which it belongs.

The socio-technological explanation would predict that municipal income convergence should occur within the cluster of municipalities that interact

[1] The country is comprised of 32 states (*departamentos*) and a capital district, each state has a governor and an assembly (*asamblea departamental*). Fiscal resources are distributed from the national level to the *departmentos*, which share part of them with their municipalities. A large part of the administration is conducted by the states and their municipalities. State assemblies can only issue administrative acts, not laws. Legislative power is concentrated at the federal level.

intensely with each other, whether or not they belong to the same state. This is due to the need for intensive social interactions for knowhow to diffuse. To form these socio-technological groupings, we utilize a unique dataset of cellphone calls to group municipalities so that most of the phone calls happen within rather than between these clusters. To facilitate comparison with the 32 states of the institutional state aggregation, we group municipalities into 32 communication clusters (Figure A1). Thus, communication clusters are groups of municipalities that are densely connected through phone calls, meaning that they are significantly more likely to call members of the cluster than they are to call other municipalities.[2] Figure 4a shows the municipalities used grouped into states of Colombia, Figure 4b shows groupings into communication clusters, while Figure 4c depicts the overlap between the two. In general, the two forms of aggregation are very different.

In order to contrast the two hypotheses, our approach requires municipal level data, a level of disaggregation which is seldom used in convergence studies. To obtain such data we use individual data on formal employment and income from the Integrated Report of Payroll Contributions (*Planilla Integrada de Liquidacion de Aportes*, PILA), which we aggregate at the municipal level. While this data only covers formal employment, we show that employment and the wage bill correlate strongly with standard measures of population and GDP at the state level (Figure 1, Table 1).

This paper finds evidence of unconditional convergence across municipalities in Colombia. The speed of convergence is positively influenced by the communication cluster but not by the state. In other words, poor municipalities that share close social interactions with richer municipalities grow faster, regardless of whether they belong to the same state or not. By contrast, we find no evidence of convergence to the state: belonging to a richer state is actually correlated with a slower, rather than a faster, speed of convergence. These results support the socio-technological rather than the institutional interpretation of the obstacles to convergence within countries.

The paper proceeds as follows. Section 2 describes the data and methods used for the estimation. Section 3 presents the results of each of the models and various robustness checks. Section 4 offers concluding remarks.

2 Data and Methods

Our study is based on two pieces of data. First, we develop a measure of municipal income for the period 2010-2014. Second, we use cellphone metadata to develop a dataset of inter-municipal communication in Colombia. Using this data, we measure the intensity of phone calls between the 862 municipalities with at least one cell phone tower (out of 1,122). We then group municipalities

[2] Note that this measure is also a good estimation of face-to-face interactions, as previous studies proved that there is a high correlation between social and mobility networks, both in general [20] and specifically in Colombia [18].

into 32 communication clusters, to be compared to the 32 *departamentos* or states.

2.1 Measuring Income and Growth

We develop a measure of municipal-level income per capita, to allow for two alternative ways of aggregating municipalities. To measure income at the municipal level, we use the PILA data managed by the Ministry of Health. The PILA contains individual-level wage data for all formal employees in Colombia. In this study, the municipality of Bogotá is treated as part of the larger state of Cundinamarca.[3]

Since PILA contains data at the individual level, we can use it to create municipal aggregates. There are two important disadvantages of working with PILA data. First, the period of observation is limited to 2010 to 2014, a time span of four years for which we have the required data. Most convergence studies appropriately use a longer time period. Second, PILA data only cover formal employment, meaning that we do not have data on informal employment and output. In 2014, according to the DANE Integrated Household Survey (*Gran Encuesta Integrada de Hogares*, GEIH), total employment in Colombia reached 21.6 million people. The PILA data captured 13.3 million registered employees, representing 61.6% of employment. The full-time equivalent employment in the PILA totaled 6.7 million in 2013, meaning that the typical formal worker contributed half the time. In what follows, we will keep track of monthly contributions to calculate effective numbers of workers employed.

While formal sector employment and wages are not the whole economy, the question is whether they correlate and co-move with the overall economy. There are good reasons why they should. The formal wage bill in a municipality W_m for a particular year can be calculated as:

$$W_m = \sum_{i \in m} \sum_{t=1}^{12} W_{i,t},$$

where $W_{i,t}$ is the wage income declared by worker i of municipality m in month t. We have suppressed the year subscript here and in what follows. The total effective formal employment in municipality m for a particular year is:

[3] Bogotá is both the capital of the nation, composed of a single municipality, and the capital of the state of Cundinamarca, though not legally a part of it. If we treat Bogotá as a state, it would drop out of the study as it would include a single municipality. However, it would not drop out if we treat it as part of the state of Cundinamarca, which is composed of 87 municipalities. The communication cluster that contains Bogotá is comprised of 4 other municipalities. In our basic results, we treat Bogotá as part of the state of Cundinamarca. However, in Table 6 below, we show that our results are robust to dropping Bogotá, Cundinamarca, and Bogotá's cluster from the sample.

$$L_m = \frac{\sum_{i \in m} \sum_{t=1}^{12} I_{i,t}}{12},$$

where $I_{i,t}$ is equal to 1 if worker i paid payroll contributions in month t and zero otherwise. L_m is the effective number of formal employee-years worked in the municipality. The average effective wage per worker in municipality m is:

$$w_m = \frac{W_m}{L_m}.$$

Our proxy of income per capita in the municipality is the formal wage income per capita, which is equal to:

$$wpc_m = \frac{W_m}{P_m} = w_m \frac{L_m}{P_m}.$$

Log-differentiating this expression we get:

$$\widehat{wpc_m} = \widehat{w_m} + (\widehat{L_m} - \widehat{P_m})$$

where the $\widehat{}$ represents the percentage change over infinitesimal units of time of the variable. The equation shows that growth in wages per capita is driven by growth in two margins: wages per worker and formality rates, or increases in formal effective employment per capita.

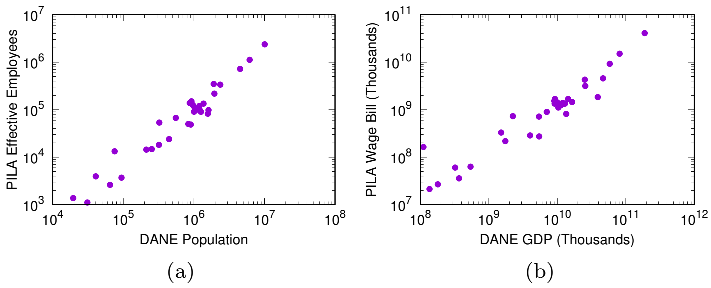

Fig. 1: PILA-DANE relationships (state level).

Table 1: PILA-DANE regressions (state level).

PILA	DANE	β	Std. Err.	R^2
L_m	Population	1.177***	0.0528	0.943
W_m	GDP	0.887***	0.0544	0.899

Figure 1 and Table 1 show that formal employment vs. working age population and the wage bill vs. GDP, highlighting that both are highly correlated. The association between formal employment in the PILA and working age population in DANE shows an elasticity slightly greater than 1, consistent with the fact that richer municipalities create more of their income from formal activities.

Figure 2 presents the distribution of wages reported in the PILA and shows why the formality margin is particularly important in Colombia. Half of all wages reported in the PILA are concentrated at or near the minimum wage. A significant part of the variance in wages per capita comes from changes in effective participation in formal employment rather than from changes in reported wages. A variance decomposition of the growth of the wage bill between the wage per worker, formal employment and population finds 37.1% of the growth is due to growth in formal effective employees, 33.0% is due to growth in average wage per capita, 16.8% is due to growth in population, and the remaining 13.1% is attributed to the interaction between the three.

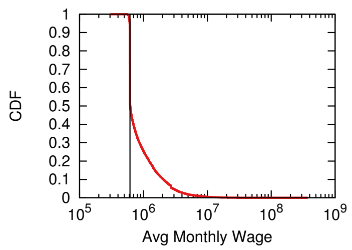

Fig. 2: Monthly wage cumulative distribution in PILA. Black line indicates minimum wage. Plot indicates that 50% of PILA employees earn the minimum wage. Only about 25% earn a million pesos or more.

We use the PILA data to calculate both levels and rates of change of wages per capita, average wages per worker and participation rates. We conduct our convergence analysis using the growth rate in the four years between 2010 and 2014. We convert nominal wages into real wages by using the consumer price index, as published in the World Development Indicators. The appendix presents basic descriptive statistics of the data (Table A1). On average wage per capita in municipalities grew by 11.38% annually over the 2010-2014 period, including an increase in formality by 6.46%, and an increase in wage per employee of 4.06%.

To make sure that our results are not driven by very small municipalities with few PILA contributors, we eliminate all municipalities with fewer than 100 formal workers. This eliminates 110 observations from our sample, leaving us with 752 municipalities. In Table 6 we check that our results are robust to the elimination of all municipalities with fewer than 200 formal workers.

In our regression analysis, we will use the average income of the state and of the communication cluster to which a municipality belongs. We eliminate the municipality in question when calculating these averages to make sure that any correlation is not driven by the direct impact of the municipality on the larger aggregation.

2.2 Cellphone Call Record Metadata

We use metadata of cellphone call origin and destination locations from telecommunication operators in Colombia. The observation period goes from December 1st, 2013 to May 31st, 2014. In total, we observe 2.2 billion calls. We do not possess information on market penetration. However, we observe more than 40 million different cell phone numbers in a country of 46 million inhabitants. We assume that the sample size is large enough so that our sample is representative of Colombia as a whole.

The metadata include a variety of attributes for each call; in this paper, we focus on the following subset:

Originator of the call. The telecommunication operators provided us with a random anonymized ID of the cellphone originating the call. The random IDs in the data are consistent, i.e. the same cellphone is always assigned to the same random ID.

Target of the call. The random ID of the cellphone called by the originator. The same remark applies. Note that the target set is different from the originator set. In fact, the vast majority of phone numbers (82%) are found exclusively in the target set. The target set includes cellphones that are not customers of the same telecommunication operators, or that are not cellphones. Additionally, the set includes any other foreign phone called from a Colombian phone. We do not have the tower through which the phone call connected to the target and hence cannot locate the target phone directly. We can only locate its usual residence by looking at the instances in which the target ID originated calls. For this reason, we can only use IDs that made at least one call. As a consequence, we drop all IDs that never originated a call.

Phone Tower used. To initiate a call, the originator's cellphone has to connect to a cellphone tower. Each cellphone tower is uniquely identified by an ID. We are able to cross this ID with a table assigning the tower ID to the municipality in which the tower is located. A cellphone cannot be very far from the tower through which it connects. This enables us to pinpoint the position of the originator at the moment of the call.

2.3 Detecting Communication Clusters

We use the cell phone dataset to create a matrix of inter-municipal communication. The study utilizes a dataset of 863 municipalities, where each municipality has at least one cellphone tower to present the home municipality of any cellphone[4]. We assign each cell phone to a municipality based on the most frequent point of origination of its calls. Note that there are more sophisticated methods to pinpoint a phone's home location from call metadata [51, 52], but they are not necessary here because they are needed only when the desired spatial granularity is much finer than the municipality (usually the city block).

Once we have associated each cellphone to its home location, we can map the relationships across municipalities. For each pair of municipalities, we count the number of calls made originating from one municipality to a cellphone located in the same or a different municipality. We use the home municipality of the two cellphones, not their current location at the moment of the call, given that we do not have information on the target's phone tower. Hence, we are able to identify the pattern of phone calls between the regular location of each participant and not the one where they happen to be for that particular phone call.

To measure the density of interconnectedness of calls between municipalities, we use a matrix clustering algorithm. Our choice is the k-means algorithm [33] because it is the standard algorithm for this measure–it is well known and well understood. We use the k-means algorithm to detect centroids in the matrix of densities of communication frequency across municipalities. Each municipality is thereby assigned to the cluster of the nearest centroid, such that they are block diagonals. Second, it allows us to specify k, the number of communities. This is important, because we want to fix k equal to the number of states in Colombia (32), so that as to make the results more comparable. The algorithm delivers the 32 communication clusters of intensely socially interconnected municipalities.

The clustering procedure works as follows. The starting point is the matrix M, a municipality-municipality matrix containing the logarithm of the number of calls made from one municipality to another. We apply the k-means algorithm, which partitions the n municipalities into k $(\leq n)$ clusters $S = (S_1; S_2; \ldots; S_k)$ so as to minimize the within-cluster sum of squares (WCSS, or the sum of distance functions of each point in the cluster to the K center). In other words, its objective is to find:

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \left\| \mathbf{x} - \boldsymbol{\mu}_i \right\|^2 ,$$

where μ_i is the mean of points in S_i. In practice, k-means picks k centroids and assigns each municipality to the nearest centroid (using squared Euclidean

[4] The only other municipality excluded from the study is Agua de Dios, due to the unreliability of the data. Agua de Dios is dropped because many self-reported entries erroneously use it for Bogotá. This is due to the fact that its code in PILA is 25001. The "25" prefix indicates the state of Cundinamarca, where Bogotá is also located. But Bogotá contains its own unique department code (11). While this misallocation represents an insignificant share of Bogotá employees in the PILA, they add up to a number of employees in Agua de Dios that far exceeds the total number of inhabitants in the municipality.

distance). The process is repeated with new centroids. The algorithm delivers the set of centroids minimizing the sum of the squared Euclidean distances.

As a quality measure of the clustering achieved we use the Relative Risk (RR) measure, which is the ratio of observed to expected calls, given by the rate of outgoing calls of the originating municipality and the incoming calls of the target municipality:

$$CallRR_{i,i} = \frac{M_{i,i}}{M_{\cdot,i}} \Big/ \frac{M_{i,\cdot}}{M_{\cdot,\cdot}},$$

where $M_{i,i}$ is the number of calls made by municipalities in cluster i to municipalities in the same cluster. The numerator is number of calls from municipalities in cluster i to itself as a share of all calls it received. The denominator is the number of all calls emanating from municipalities in cluster i as a share of all national calls. The ratio indicates how much more than random is the link between the cluster with itself, with Call RR equal to 1 indicating a number of calls proportional to a random draw.

We test the quality of the clustering by measuring how much more likely a caller is to call his or her own cluster rather than any other cluster. We chose k to be 32, to match the number of states. From a clustering perspective, this choice could be quite arbitrary and far from the optimal number of clusters. We check to see whether the choice of 32 is appropriate by looking at the RR measure of calling your own cluster as the number of clusters changes. However, the greater the number of clusters, the less likely one is to call one's own cluster. This probability declines as the square root of the number of clusters – since the k-means algorithm aims to transform the observed matrix into a square block diagonal matrix. Thus, we calculate a normalized relative risk ratio:

$$NormalizedCallRR = \frac{CallRR}{\sqrt{k}}.$$

In Figure 3, we show the value of the Normalized Call RR for each incremental increase in the number of clusters by the cutoff k: although the optimal value is reached when $k = 6$, the quality of the clustering is quite flat after $k = 10$, with a normalized value around two. For $k = 32$ this means that a caller is about 11.3 times more likely than random to call his own cluster rather than a different cluster.

Figure A1 depicts the network view of the communication clusters that results from our methodology. The links represent only the most significant relationships among the municipalities using a disparity filter which compares each cell to a random network where each node has an equal number of incoming and outgoing calls [47]. We set the p-value to 0.001. Each municipality is a node and each link is a directed edge connecting the two nodes. The 863 municipalities are found to hold 9,639 links between themselves. We color the municipalities according to the communication cluster we calculate using the k-means algorithm.

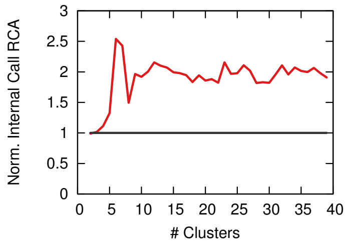

Fig. 3: Cluster quality per different number of clusters.

Figure 4 presents the geographical difference between grouping the municipalities by state and communication cluster. Figure 4a colors each municipality by the state to which it belongs. In Figure 4b we show the communication clusters, which are mostly geographically compact, with few exceptions. Figure 4c provides a visualization of the degree to which there is concordance between the state and the communication cluster classification. For each municipality m, S_m is the set of municipalities in the same state and C_m is the set of municipalities in the same cluster. We calculate the degree of overlap between these two sets using the Jaccard coefficient:

$$J_m = \frac{|S_m \cap C_m|}{|S_m \cup C_m|}.$$

The Jaccard coefficient takes values between 0 (the two sets are completely disjointed) and 1 (the two sets contain the same elements). The colors in Figure 4c follow the J_m value from high (green) to medium (yellow) to low (red). We can see that, even though communication clusters are geographically compact (and thus somewhat correlated with states), they form very different groupings of municipalities.

The example of the municipalities in the state of Antioquia helps illuminate the difference between the two geographic groupings. Home to over six million people, Antioquia holds significant geographic diversity, at the intersection of two major mountain ranges of the Andes, with the lowlands in Bajo Cauca, and a stretch of the Caribbean Sea. The cellphone metadata shows highly fractured socio-economic relationships within the state: the municipalities in Antioquia are divided across nine communication clusters. Along the Caribbean coast of Antioquia, the Apartadó municipality belongs to a communication cluster of coastal municipalities that spans across states. The municipalities along the coffee growing valley of Antioquia form their own communication cluster comprised of only municipalities within the state, centered on the Andes municipality. Despite close geographic proximity of this *Eje Cafetero* (coffee axis) to the capital of the state, Medellin belongs to a distinct communication cluster that spans municipalities across broad geographic distance. Indeed, states and communication clusters are quite different.

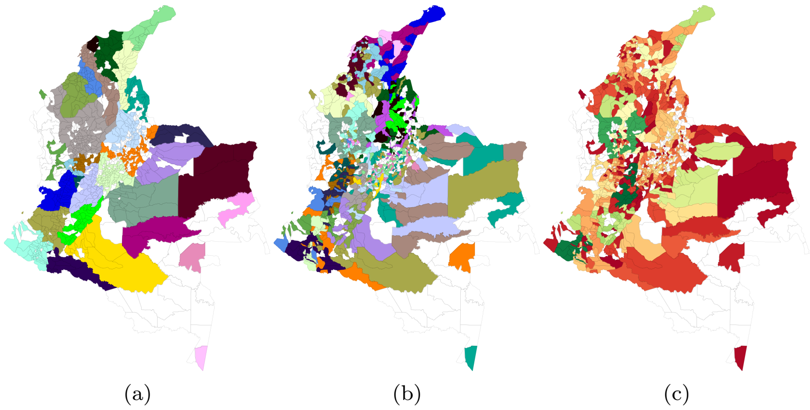

Fig. 4: The geographic distribution of states and communication clusters of Colombia. We color each municipality according to: (a) the state; and (b) the communication cluster to which it belongs. (c) We color each municipality according to the overlap between state and communication clusters, where green (red) municipalities have a high (low) overlap of the state and the communication clusters.

3 Results

We use our data to test for unconditional convergence and to see if the speed of convergence is affected by the characteristics of the state or the communication cluster. As is traditional in the convergence literature, the dependent variable is the economic growth rate of a region, in our case a Colombian municipality. The first regressor is the initial level of income of the municipality. A negative coefficient on the initial income variable indicates convergence, as it implies that the poorer the region, the faster it grows. Here we use formal wage income (according to PILA), divided by the working-age population of the municipality (according to DANE). As discussed earlier, the left-hand side variable includes both growth in average reported wages per worker and growth in formal effective participation rates. To study these two channels of convergence independently, we include separate tables using as dependent variables the average wage per worker and the participation rate. All regressions have clustered standard errors at the communication cluster or state level, as appropriate.

We test two alternative divisions of municipalities: institutional via states, and socio-technological via communication clusters. The question is whether poor municipalities tend to grow faster if they belong to richer states or to richer communication clusters.

Before presenting our main findings, we replicate the typical absolute convergence equation at the state level using both GDP per capita data from DANE and the new wage data from the PILA. We also explore absolute convergence at the level of the communication clusters. The previous literature (Branisa and Cardozo 2009; Royuela 2015) has failed to find evidence of absolute convergence in Colombia at the state level [14, 45].

Table 2: State- and Cluster-level unconditional convergence models (GDPPC and Wage PC).

	Dependent variable:			
	$\widehat{s}$		$\widehat{c}$	
	(1)	(2)	(3)	(4)
Initial GDP PC	0.017*		−0.054**	
	(0.009)		(0.023)	
Initial wpc_m		−0.012		−0.012*
		(0.007)		(0.006)
Constant	−0.201	0.267**	0.570**	0.232***
	(0.145)	(0.104)	(0.218)	(0.082)
Observations	32	32	32	32
R^2	0.106	0.079	0.152	0.116
Adjusted R^2	0.076	0.049	0.124	0.087
Residual Std. Error	37.033	28.142	65.963	34.953
F Statistic	3.565*	2.590	5.394**	3.956*
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 2 reports results of testing for absolute convergence at the state level (columns 1 and 2, $\widehat{s}$ being the growth of the state s either in GDP or wage) and at the communication cluster level (columns 3 and 4, $\widehat{c}$). We find no solid evidence for absolute convergence at the state level, using either measure of initial income. This confirms the previous literature. By contrast, we find some evidence of absolute convergence at the communication cluster level, which is stronger when we use GDP per capita than when we use wage per capita.

The main results of this paper are presented in Table 3. Column 1 tests for absolute convergence in Colombia at the municipal level. We find strong evidence of absolute convergence among municipalities in Colombia in the 2010-2014 period. The speed of convergence is 6.5% per year in our data. This means that poor municipalities were indeed catching up to richer ones.

The remaining columns test the influence of the characteristics of the state (wpc_s) and of the communication cluster (wpc_c) on the speed of convergence. Column (2) controls for the average wage per capita of the state to which the municipality belongs (wpc_s). Convergence would imply a positive coefficient, indicating that, controlling for municipal income, belonging to a richer state makes growth higher. Instead, we find a negative coefficient, indicating that a richer state actually dampens the speed of convergence that a municipality would experience. We say that it dampens convergence because the negative state effect is smaller than the absolute convergence effect. However, the estimated effect is not statistically significant.

Table 3: PILA wage per capita 2010-2014 growth model.

	Dependent variable:					
	$\widehat{wpc_m}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Initial wpc_c			0.022**	0.026***	0.023***	
			(0.009)	(0.009)	(0.006)	
Initial wpc_s		−0.014		−0.021		−0.049*
		(0.034)		(0.019)		(0.027)
Initial wpc_m	−0.065***	−0.063***	−0.073***	−0.073***	−0.050***	−0.077***
	(0.012)	(0.014)	(0.012)	(0.012)	(0.007)	(0.013)
Constant	0.938***	1.121**	0.759***	0.991***	0.482***	1.819***
	(0.153)	(0.559)	(0.182)	(0.329)	(0.099)	(0.405)
State F.E.	N	N	N	N	Y	N
Comm F.E.	N	N	N	N	N	Y
Observations	752	752	752	752	752	752
R^2	0.172	0.176	0.184	0.192	0.582	0.340
Adjusted R^2	0.171	0.174	0.182	0.189	0.565	0.309
Residual Std. Error	0.113	0.112	0.112	0.111	0.082	0.103
F Statistic	156.130***	80.201***	84.379***	59.311***	33.507***	11.186***
Note:						*p<0.1; **p<0.05; ***p<0.01

Column 3 controls instead for the average income of the communication cluster (wpc_c). Communicating closely with rich municipalities helps a poor municipality to grow faster ($p < 0.05$). Column 4 includes both the state and the communication cluster initial level of income. We find that both the communication cluster effect and the state effect survive and become slightly stronger: with a more positive impact of the communication cluster and a more negative impact of the state, strengthening our basic result.

Columns 5 and 6 represent further robustness checks of our basic result. They include alternatively communication cluster fixed effects and state fixed effects when testing for the impact of the other variable. This allows for a non-parametric influence of each grouping on the possible effect of the other variable. For example, Column 5 in Table 3 includes state fixed effects when testing for the impact of the communication cluster. This allows maximum flexibility for a state to influence its municipalities, independent of any parametric measure of income we might assume. We find a similar effect of the communication cluster on growth but with a stronger statistical significance ($p < 0.01$).

Column 6 includes communication cluster fixed effects when testing for the impact of the state income on municipality growth. Doing this strengthens the negative effect of the state on municipal growth, and makes it statistically significant ($p < 0.1$).

We conclude that belonging to a richer state does not accelerate convergence but belonging to a richer communication cluster does.

Tables 4 and 5 study two channels through which the convergence effect takes place: changes in the formal employment rate ($\widehat{frm_m}$) and changes in

Table 4: PILA formality 2010-2014 growth model.

	Dependent variable: $\widehat{frm_m}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Initial frm_c			0.015***	0.014***	0.018***	
			(0.005)	(0.005)	(0.004)	
Initial frm_s		0.009		0.004		−0.013
		(0.021)		(0.011)		(0.017)
Initial frm_m	−0.030***	−0.031***	−0.037***	−0.037***	−0.041***	−0.043***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.005)	(0.009)
Constant	−0.027	−0.009	0.001	0.008	0.006	−0.073
	(0.020)	(0.059)	(0.023)	(0.032)	(0.015)	(0.057)
State F.E.	N	N	N	N	Y	N
Comm F.E.	N	N	N	N	N	Y
Observations	752	752	752	752	752	752
R^2	0.064	0.066	0.074	0.075	0.385	0.168
Adjusted R^2	0.063	0.064	0.072	0.071	0.359	0.129
Residual Std. Error	0.093	0.093	0.092	0.092	0.077	0.089
F Statistic	51.079***	26.643***	30.017***	20.146***	15.018***	4.378***

Note: *p<0.1; **p<0.05; ***p<0.01

wages per formal worker ($\widehat{wpw_m}$), respectively. In Table 4, the dependent variable is the growth in formal employment per capita ($\widehat{frm_m}$). Interestingly, Column 1 shows evidence of unconditional convergence in formal employment rates among municipalities ($p < 0.01$) with an estimated speed of convergence of 3.0% per year. Column 2 includes the average initial formal employment rate of the state (frm_s) and finds a small positive, though not statistically significant coefficient of the state income on the speed of convergence. Column 3 finds a positive and significant impact ($p < 0.01$) of the communication cluster (frm_c) on the speed of formalization with a speed of 1.5%. Including both state and communication cluster effects, to control for each other, reduces the effect of the state, which remains insignificant, while maintaining the size and significance of the effect of the communication cluster on convergence (Column 4). Adding state fixed effects strengthens the impact and the statistical significance ($p < 0.01$) of the communication cluster on the convergence of the formal employment rate (Column 5). Adding communication cluster fixed effects (Column 6) results in a negative, and statistically insignificant effect of the state on formal employment convergence. Highly informal municipalities with close social ties to more formal municipalities are found to achieve faster growth in effective formal workers per capita, but municipalities that belong to more formal states do not.

The final set of regressions tests the wage per worker margin ($\widehat{wpw_m}$, Table 5). The results are similar to overall wage per capita except for two important differences. First, the speed of absolute convergence seems to be much stronger, with an estimated speed of 12.8% per year (Column 1). This effect may be due to the fact that, as shown in Figure 2, about half of all workers in the PILA earn close to the minimum monthly wage, which is set nationally. Column 2 confirms the negative result of the effect of state income (wpw_s) on the speed of convergence with a large negative but statistically insignificant coefficient.

Table 5: PILA wage per employee 2010-2014 growth model.

	Dependent variable:					
	$\widehat{wpw_m}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Initial wpw_c			0.063***	0.065***	0.015	
			(0.019)	(0.018)	(0.014)	
Initial wpw_s		−0.097		−0.100***		−0.073**
		(0.060)		(0.035)		(0.034)
Initial wpw_m	−0.128***	−0.110***	−0.143***	−0.124***	−0.097***	−0.130***
	(0.010)	(0.016)	(0.010)	(0.012)	(0.009)	(0.012)
Constant	2.124***	3.413***	1.341***	2.637***	1.371***	3.361***
	(0.157)	(0.979)	(0.249)	(0.519)	(0.253)	(0.528)
State F.E.	N	N	N	N	Y	N
Comm F.E.	N	N	N	N	N	Y
Observations	752	752	752	752	752	752
R^2	0.440	0.473	0.466	0.501	0.666	0.582
Adjusted R^2	0.439	0.472	0.464	0.499	0.652	0.563
Residual Std. Error	0.042	0.040	0.041	0.039	0.033	0.037
F Statistic	588.758***	336.477***	326.616***	250.338***	47.957***	30.281***
Note:						*p<0.1; **p<0.05; ***p<0.01

By contrast, the communication cluster (wpw_c, Column 3) has a positive effect on the speed of convergence with an estimated coefficient of 6.3% ($p < 0.01$). When both effects are included (Column 4) the effect of the communication cluster becomes slightly stronger and the negative effect of the state becomes a bit larger and is now statistically significant with $p < 0.01$. The main difference with previous tables is that in Column 5, the communication cluster effect becomes weaker and statistically insignificant when controlling for state fixed effects. By contrast, including communication cluster fixed effects causes a slightly smaller negative and significant ($p < 0.05$) effect of state wages on municipal convergence.

To interpret these results, we must remember that our variance decomposition of the growth in wages per capita found that 37.1% is driven by changes in the growth of formal employment and an additional 16.8% by the growth in population, while only 33.0% is driven by changes in wages per employee. This, together with the bunching of monthly wages at the minimum wage may explain why our results are stronger at the level of growth in wages per capita and in formal employment per capita than when we look at wages per worker.

Table 6 shows additional robustness checks on the impact of the communication cluster on the growth of wages per capita. All equations include state fixed effects. Column 1 replicates Column 5 of Table 3. Column 2 excludes Bogotá and Cundinamarca from the sample, thus eliminating 83 municipalities and changing the clustering. Column 3 eliminates all municipalities with fewer than 200 formal workers, this reduces the sample by 172 municipalities. The results are confirmed. In Appendix Table A2 we explore other samples to test the robustness of our main result.

The next set of robustness tests studies whether our results are the consequence of omitted variables. For example, rural municipalities may behave differently from urban ones, and more educated municipalities may differ from

Table 6: PILA wage per capita 2010-2014 growth model – robustness checks.

	Dependent variable:				
	$\widehat{wpc_m}$				
	(1)	(2)	(3)	(4)	(5)
Initial wpc_c	0.023***	0.019***	0.021***	0.016**	0.016***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Initial wpc_m	−0.050***	−0.057***	−0.045***	−0.059***	−0.061***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.010)
Urban				0.010	−0.008
				(0.025)	(0.027)
Secondary				0.131	0.088
				(0.085)	(0.086)
Constant	0.482***	0.608***	0.431***	0.626***	0.666***
	(0.099)	(0.094)	(0.094)	(0.126)	(0.133)
State F.E.	Y	Y	Y	Y	Y
Observations	752	674	580	752	674
R^2	0.582	0.590	0.479	0.588	0.591
Adjusted R^2	0.565	0.571	0.451	0.570	0.572
Residual Std. Error	0.082	0.079	0.081	0.081	0.079
F Statistic	33.507***	31.910***	16.831***	32.086***	29.965***
Note:					*p<0.1; **p<0.05; ***p<0.01

less educated ones. The concern is that the communication clusters may be grouping municipalities according to these characteristics and not through social interactions per se. To address this concern, we control for the rate of urbanization and the proportion of the working age population with a high school education in Columns 4 and 5. The results indicate that the effect of the communications cluster on growth remains strong, if a bit smaller, and significant ($p < 0.05$) while the two additional variables are insignificant.

To get a sense of the magnitude of the estimated effects, we use column 4 of Table 3, and the state and cluster wage distribution of Table A1. Other things equal, a municipality in the 25th percentile of the wage per capita distribution would be expected to grow 6.7% faster than a municipality in the 75th percentile. By contrast, two otherwise identical municipalities that belong to two different communications clusters located at the 25th and 75th percentile of the cluster distribution would find their growth rates differing by 3.5%. In the same vein, two municipalities differing only in the income of the state they belong to, the municipality in the state at the 75th percentile would grow 1.7% more slowly than a municipality in a state at the 25th percentile.

4 Conclusion

Economists tend to agree that the fundamental difference in income across countries and regions is not explained by the difference in factor endowments but mostly by differences in total factor productivity, which they take as the reflection of differences in technology. The question then becomes why would technology vary across places? Two types of causality have been proposed: institutional and socio-technological. Institutions tend to vary more between than within countries and may explain the absence of absolute convergence in cross-country data but the stronger presence of convergence within (mostly advanced) countries. By contrast, the assumption that tacit knowledge moves slowly through networks of intense social interaction would explain why convergence may be slow between places, both within and across countries. While much of the literature cited above on long-run determinants of development is suggestive of socio-cultural channels of technological diffusion, they cannot rule out institutional mechanisms to explain the observed patterns.

To test these two interpretations in a more direct way, we use municipal level data for Colombia, which we aggregate using two different grouping criteria: the *departamento* or state to capture institutional variation; and the communication cluster to which a municipality belongs, to capture the intensity of social interaction. We use formal wages per capita as our measure of income per capita, as it can be measured at the municipal level. We use cellphone data to group municipalities into communication clusters of intense interaction.

In this setting, we find evidence of absolute convergence in Colombia at the municipal level. We find evidence that the process is accelerated when the municipality belongs to a richer communication cluster. However, we do not find evidence of a positive influence of belonging to a richer state. We interpret these results as evidence in favor of the idea that obstacles to technology diffusion may be related to the fact that the use of technology requires tacit knowledge which tends to move slowly between brains through a protracted process of imitation and repetition as occurs in learning by doing. Within communications clusters, there seems to be accelerated convergence. Obstacles to convergence in developing countries may be related to the paucity of social interactions between citizens of the same country.

Our setup suffers from several weaknesses. First, for Colombia, we do not possess a long period with which to measure growth at the municipal level. It would be ideal to replicate our approach with a longer dataset. However, while finding income data for a longer time period may be feasible in other countries, the constraint that will arise is access to cellphone data for the more distant past with which to measure the extent of social interaction between locations during earlier periods.

From a policy perspective, the findings emphasize the fact that economic convergence requires intense social interaction, not just the presence of institutions of a certain quality. Regions that are formally part of the same nation-state but do not really interact with the more advanced parts of the country cannot expect to share similar development outcomes.

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Appendix

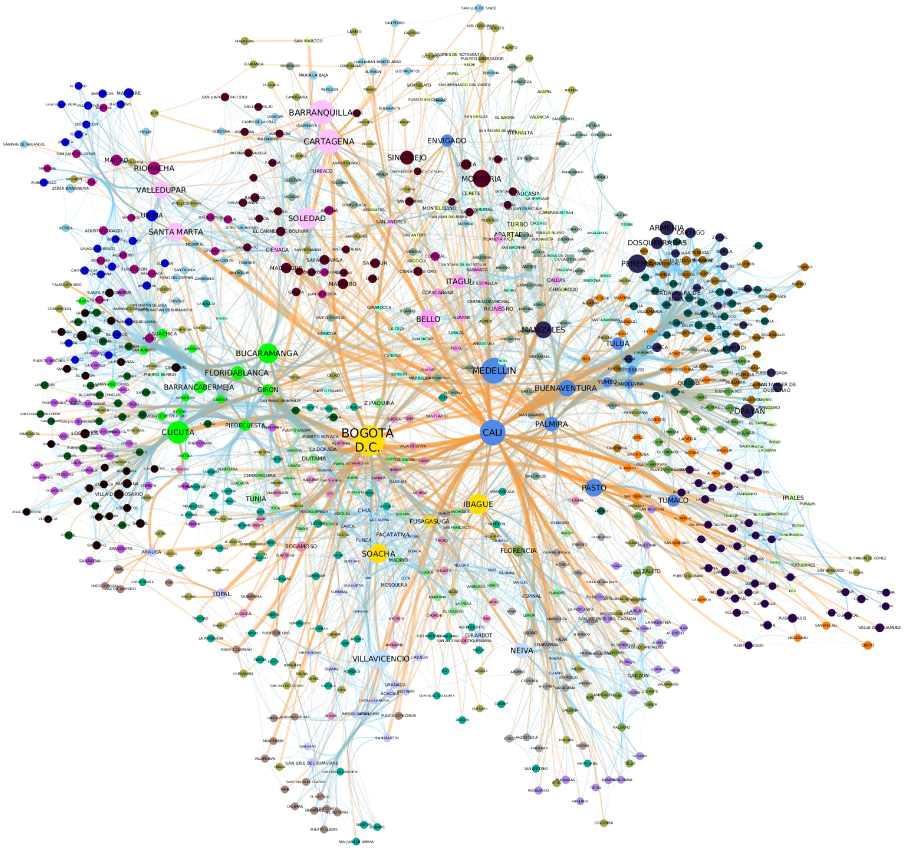

Fig. A1: Communication clusters in Colombia. The graph representing the communication clusters in Colombia across municipalities. Each node is a municipality and directed links connect two municipalities if people from one municipality have a significant amount of phone calls with the other municipality. Node size is proportional to indegree, and node color indicates the node community, as detected by the k-means algorithm. Link size and transparency is proportional to its significance, as is its color: orange links are very significant, blue links are less strong.

Table A2 explores the robustness of our results using different samples of municipalities, to make sure that our results are not driven by a few marginal municipalities with either very few formal workers, very low population or very few phone calls. Column 1 repeats the equation in Table 3 Column 5. Column 2 weighs the observations using the log of the number of formal workers in the

Table A1: Statistics of wage and formality, values and growth, for municipalities, states and social communities.

	Variable	Min	25%	Median	Average	StDev	75%	Max
Muni.	Wage PC 2010	47,414	215,117	327,543	508,075	643,128	535,280	4,134,129
	Wage PC Growth	-0.3279	0.0395	0.1004	0.1138	0.1237	0.1694	0.7829
	Formality 2010	0.0075	0.0273	0.0408	0.0694	0.0750	0.0790	0.5791
	Formality Growth	-0.2281	0.0055	0.0547	0.0646	0.0958	0.1147	0.5258
	Wage PE 2010	6,469,620	9,385,721	11,713,019	12,431,205	3,850,051	14,748,032	32,053,570
	Wage PE Growth	-0.1423	0.0126	0.0402	0.0406	0.0557	0.0746	0.2499
State	Wage PC 2010	399,660	598,315	871,466	102,879	591,289	1,377,251	3,204,184
	Wage PC Growth	0.0580	0.0900	0.0994	0.1128	0.0353	0.1250	0.2070
Comm.	Wage PC 2010	168,225	348,534	519,620	858,673	783,868	1,350,879	3,568,629
	Wage PC Growth	0.0169	0.0504	0.0603	0.0749	0.0464	0.0826	0.2307

municipality. Column 3 includes all municipalities with a population of at least 5,000 (788 municipalities). Column 4 includes the same sample as column 3 and it weighs the observations using the log of the number of formal workers in the municipality. Column 5 includes all municipalities with a population of at least 10,000 (614 municipalities). Column 6 includes all municipalities with at least 5,000 calls made, (642 municipalities). Column 7 includes all municipalities with at least 5,000 calls received (649 municipalities). All errors are clustered at the communications cluster level. The results are consistent across all samples.

Table A2: PILA wage per capita 2010-2014 growth model – additional robustness checks.

	Dependent variable:						
	wagepc.growth						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(social.cluster.wagepc.2010)	0.023^{***}	0.021^{***}	0.022^{***}	0.020^{***}	0.023^{***}	0.019^{***}	0.018^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
log(wagepc.2010)	-0.050^{***}	-0.046^{***}	-0.064^{***}	-0.055^{***}	-0.064^{***}	-0.055^{***}	-0.054^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.482^{***}	0.439^{***}	0.660^{***}	0.565^{***}	0.647^{***}	0.580^{***}	0.579^{***}
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)
State F.E.	Y	Y	Y	Y	Y	Y	Y
Observations	752	752	788	788	614	642	649
R^2	0.582	0.524	0.659	0.589	0.630	0.596	0.598
Adjusted R^2	0.565	0.505	0.646	0.572	0.611	0.576	0.578
Residual Std. Error	0.082	0.210	0.088	0.219	0.090	0.082	0.082
F Statistic	33.507^{***}	26.500^{***}	48.823^{***}	36.109^{***}	33.154^{***}	29.995^{***}	30.645^{***}
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$