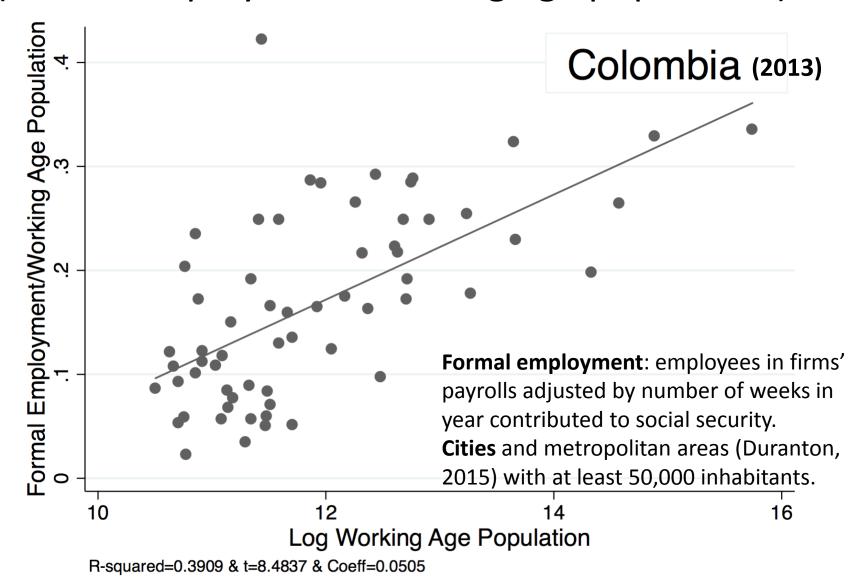
# Formal Employment is a Consequence of Skill Diversity in Cities

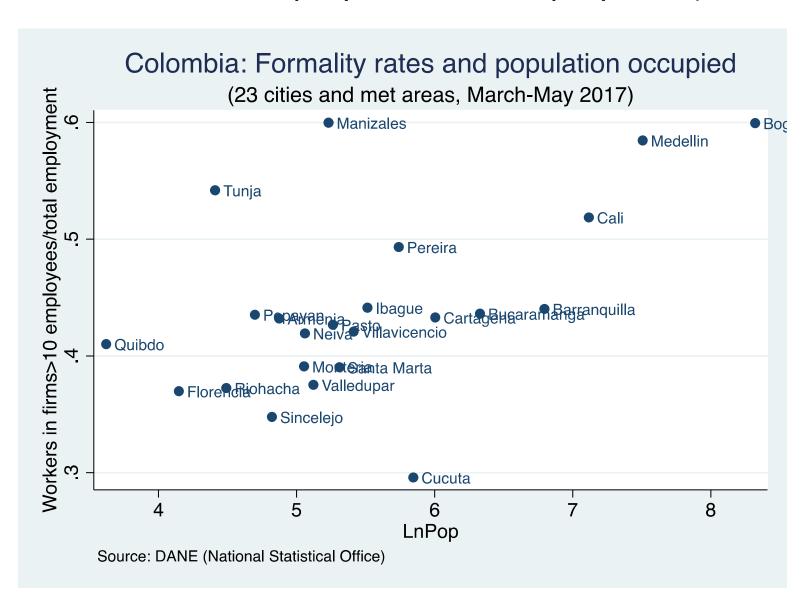
Neave O'Clery, Juan Camilo Chaparro, Andrés Gómez-Liévano and Eduardo Lora

The Economics of Informality Conference 2018
Universidad del Rosario
Bogotá, May 2018

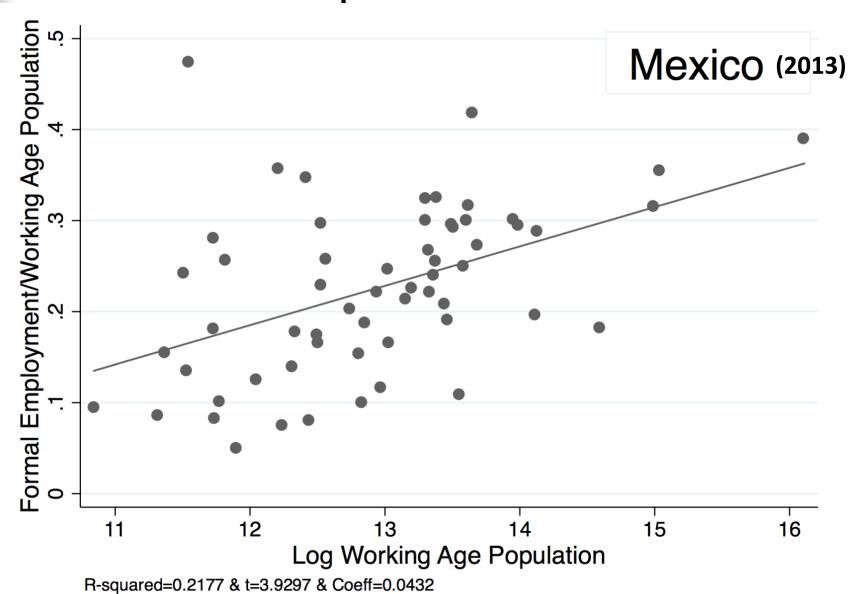
## Larger cities have higher formal occupation rates (formal employment/working age population)



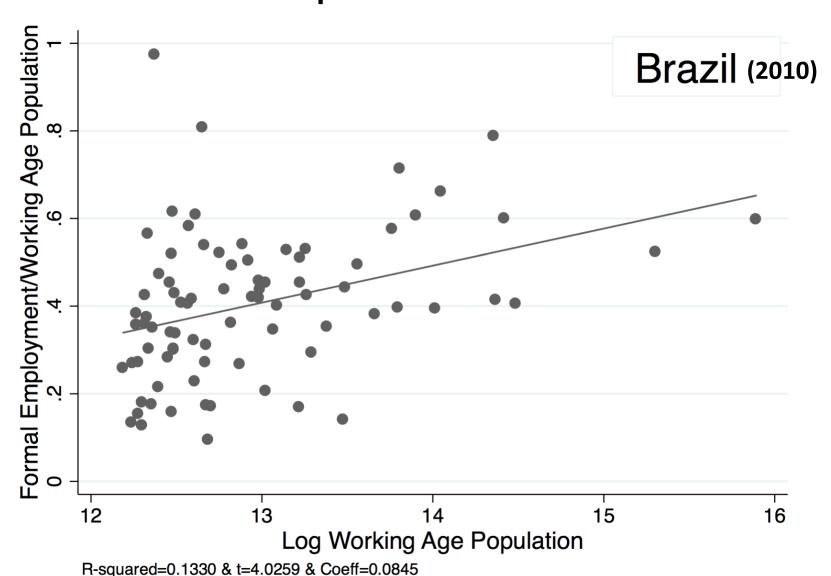
### Larger cities have higher "formality rates" (employees in firms > 10 employees/total employment)



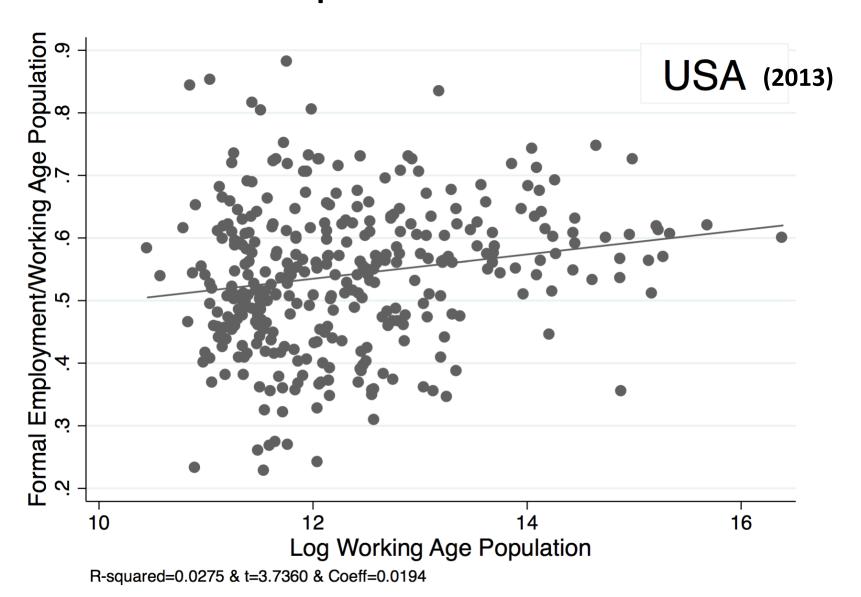
# Larger cities have higher formal occupation rates



# Larger cities have higher formal occupation rates

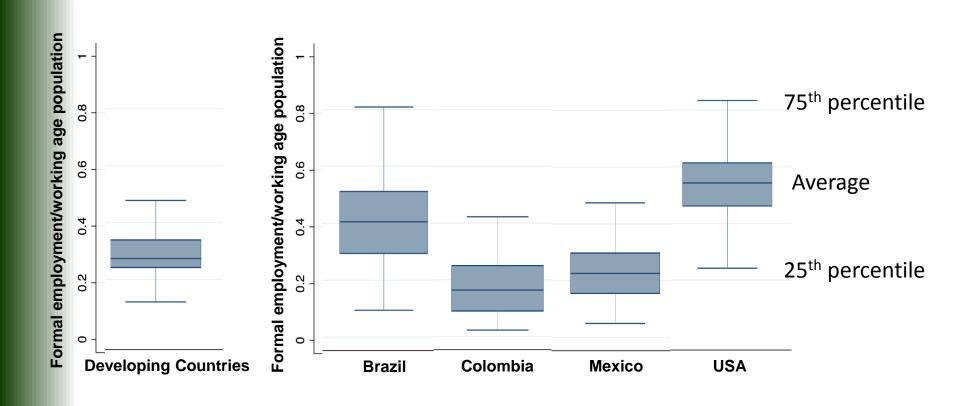


# Larger cities have higher formal occupation rates



### Cities have a lot to tell us on (in)formality

Formal occupation rates: formal employment/working age population



#### This talk

- Motivation
- Main ideas in our theory of (in)formality
- Theoretical model
- Measuring complexity when skills are unobservable
- Testing model predictions
- Further evidence
- Concluding remarks.

# Main ideas in our theory of labor (in)formality

- Focus on cities, rather than countries:
  - Cities are the actual places where labor markets operate. Cities exist because they give firms access to pools of workers, and give workers access to alternative employment sources (Glaeser, 2011)

- Focus on cities, rather than countries
- Emphasis in skill diversity (in cities), rather than skill or education attainment:
  - Agglomeration economies result (in part) from the interaction between individuals with different skills (Marshall 1890; Lucas 1978; Duranton and Puga 2004, 2010; Glaeser 1999; Glaeser & Resseger 2010)

- Focus on cities, rather than countries
- Emphasis in skill diversity (in cities)
- Firms exist because of tacit knowledge:

Firms exist to solve incomplete contracting problems (Coase 1937). Firms solve the incomplete contracting problem that results from the inability of markets to contract over tacit knowledge (Grant 1996)

- Focus on cities, rather than countries
- Emphasis in skill diversity (in cities)
- Firms exist because of tacit knowledge
- Informal labor (i.e not in organized firms) exists because some goods can be produced with few (non-specialized) skills
  - Not denying that labor taxes, minimum wages and other interventions may curtail formal employment creation (Levy 2008, 2010; Kugler & Kugler, 2009; Kugler, Kugler & Prada, 2017).

- Focus on cities, rather than countries
- Emphasis in skill diversity (in cities)
- Firms exist because of tacit knowledge
- Informal labor in productions with few skills
- Firms evolve by tinkering with skills:
  - The set of feasible technologies (products) is not known in advance, but discovered by recombining skills (Beinhoker 2006, Ch. 11)

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### Theoretical Model (1)

Workers:  $i \in \{1, ..., N_t\}$  Skills:  $Z = \{0, 1, ..., S\}$ 

Skill Complexity:  $\delta(S) > \delta(S-1) \dots \delta(1) > \delta(0)$ 

Some skills are harder to learn than others

Worker's skill endowment:  $K(i) \in Z$ 

Supply of workers with skill k:  $S_t(k)$   $\sum_{k=0}^{S} S_t(k) = N_t$ 

Output of informal work:  $y_t^i = h(A_t^i, K(i))$ 

### Theoretical Model (2)

Industries: *J*the set of all possible and meaningful subsets of Z

Skills:  $Z = \{0, 1, ..., S\}$ 

A firm's industry:  $j_t(r) \in J$  An industry is a subset of skills.

$$y_t^r = A_t^r \left[ \sum_{k \in j_t(r)} l_t^r(k)^{\rho} \right]^{\frac{1}{\rho}}$$

Firms combine skills to produce output, but the relevant set of skills depends on the firm's industry.

Elasticity of substitution between skills:

$$1/(1-\rho)$$

### Theoretical Model (3)

$$\sum_{t \in j_t(r)}$$

Labor costs: 
$$\sum \quad \theta_t(k) \ * \ \overline{\overline{w}}_t \ * \ l_t^r(k)$$

**Minimum** 

 $k \in j_t(r)$   $\theta_t(k)$  proportional to skill complexity,  $\delta(k)$ .

Labor demand

Industry complexity:

$$C_t^j = \sum_{k \in j} \theta_t(k)^{\frac{\rho}{\rho - 1}}$$

It measures the portfolio of skills which must be combined in order to produce output.

**Optimal** labor demand:

$$l_t^r(k)^* = \left(\frac{y_t^r}{A_t^r}\right) \left(\theta_t(k)\right)^{\frac{1}{\rho-1}} \left(C_t^{j_t(r)}\right)^{\frac{-1}{\rho}}$$

### Theoretical Model (4)

The probability that a firm which currently operates in industry j transitions into industry j'

$$E_t \left( C_{t+1}^j \mid j_t(r) = j \right) = p \ C_t^j + (1-p) \underbrace{\left[ \sum_{j' \in J} \beta_t(j,j') \ C_t^{j'} \right]}_{\text{The industry in which a firm operates follows an evolutionary process.} \mathcal{E}_{t} \left[ C_{t+1}^j \mid j_t(r) = j \right] = p \ C_t^j + (1-p) \underbrace{\left[ \sum_{j' \in J} \beta_t(j,j') \ C_t^{j'} \right]}_{\text{Complexity Potential}}$$

$$F_{t+1} = \sum_{r} \sum_{k \in j_{t+1}(r)} l_{t+1}^{r}(k)^{*}$$

$$= \sum_{r} \left[ \left( \frac{y_{t+1}^{r}}{A_{t+1}^{r}} \right) \left( C_{t+1}^{j} \right)^{\frac{-1}{\rho}} \sum_{k \in j_{t+1}(r)} \left( \theta_{t+1}(k) \right)^{\frac{1}{\rho - 1}} \right]$$

Aggregate formal employment in a city depends on current complexity of all its firms, which in turn depend on past complexity potential

#### Theoretical Model: Main Predictions

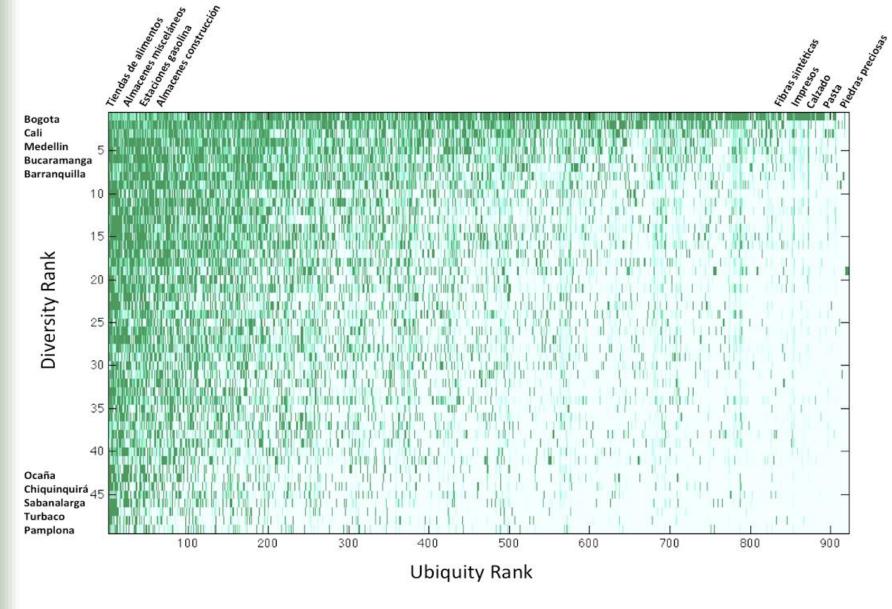
- (1) The entry rate of firms is higher among low-complexity industries.
- (2) Average wages are higher in more complex industries.
- (3) A positive correlation between the size of cities and total formal employment.
  - City-wide skill accumulation should follow a "geological layers process".
- (4) City-wide formal employment creation at t + 1 depends on complexity potential at t

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## Measuring complexity when skills are unobservable

- Complexity: "A measure of the amount of productive capabilities that an industry requires to operate (...).
   Industries are complex when they require a sophisticated level of productive knowledge (...) with many individuals with distinct specialized knowledge interacting in a large organization".
- We adapt a method developed by Hidalgo and Hausmann (2009) that employs international trade data to estimate the complexity of products and nations.
- We use employment by city and industry contained in the social security data for Colombia (PILA) to compute a proxy for industry and city complexity.
- First we compute a matrix of city x industry presences (RCA>1), and sort the rows (cities) and columns (industries) by the number of presences.



The complexity of an industry is measured by calculating the average diversity of locations that have the industry, and the average ubiquity of the industries that those locations have.

### Most and least complex industries

IT and related activities

**Automotive vehicles** 

**Clothing and leather products** 

Office machinery

**Textile products** 

Machinery and electrical appliances

**Rubber and plastic products** 

Paper and paperboard

**Chemicals** 

**Machinery and equipment** 

•••

**Public administration** 

Retail

**Social services** 

**Hotels and restaurants** 

**Electricity and gas** 

Coal

Crude oil and natural gas

Associations n.s.e.

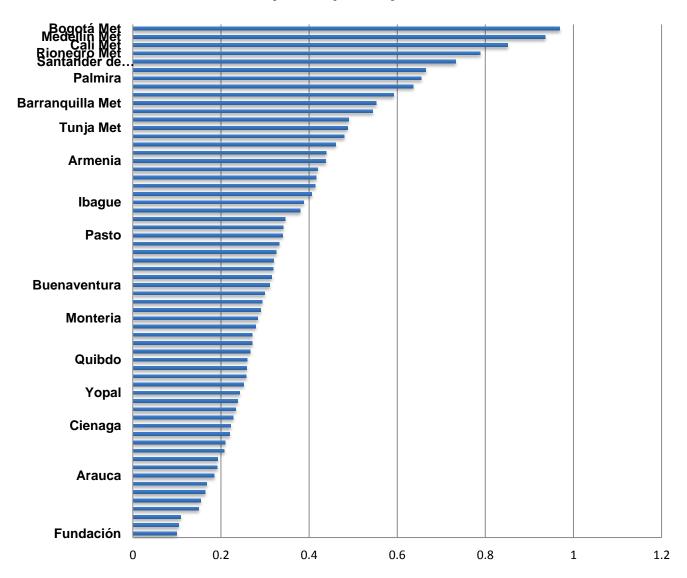
Waste disposal

**Aquatic transport** 

10 most complex industries, 2-digit ISIC

10 least complex industries, 2-digit ISIC

#### City Complexity, 2015



Note: cities with at least 50,000 inhabitants in 2008.

## How close is a city to new complex industries?

- We need to define 'close': we compute the skill relatedness between industries (Neffke et al, 2013) using labour transitions. Industries are proximate if many workers switch jobs between them.
- A<sub>i,i</sub> is the skill-proximity between industries i and j
- For each industry i in city c: we compute

$$d_{c,i} = \frac{\sum_{j \in N_c} A_{i,j}}{\sum_j A_{i,j}}.$$

where N<sub>c</sub> is the set of industries that is present in city c.

 This can be seen as the likelihood industry i is in city c (given the know-how already embedded in industries N<sub>c</sub>).

## How close is a city to new complex industries?

 For each missing industry in a city, we compute industry complexity times density

$$CP_c = \frac{1}{|M_c|} \sum_{i \in M_c} d_{c,i} C_i,$$

where  $M_c$  denotes the set of 'missing' industries for city c, and the  $C_i \in [0, 1]$  is the normalized complexity of industry i.

 Complexity potential is a measure of the aggregate potential of a city to move to new complex industries.

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## Prediction 1. Entry of firms is lower in high complexity industries

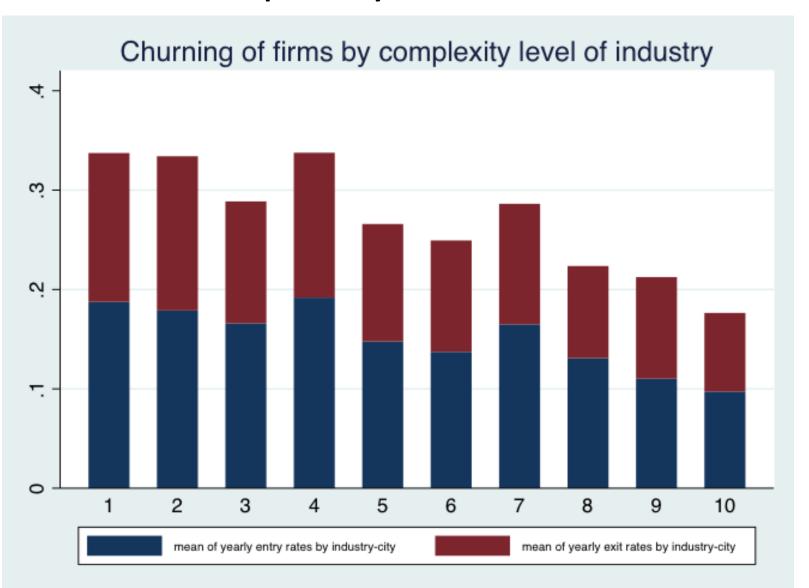


Table 1. Regressions on industry complexity of entry, exit and churning rates of firms

	Entry	y rate	Exit	rate	Churn	ing rate
Industry complexity	-0.186***	-0.266***	-0.171*	-0.136***	-0.357	-0.402***
industry complexity	(0.033)	(0.034)	(0.029)	(0.023)	(0.057)	(0.050)
Constant	0.283*** 0.084***	0.220***	0.045***	0.503***	0.129***	
Constant	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Small establishments included	Yes	No	Yes	No	Yes	No
Adjusted R-squared	0.101	0.067	0.104	0.089	0.109	0.089
Number of observations	7882	2825	7882	2825	7882	2825

Each observation is an industry in a city (with at least three establishments in city every year). Small establishments are those with 10 or less employees on average during their years in operation. All rates are averages over 2008-2015 by industry (SIC 4 digits).

<sup>\*\*\*:</sup> significant with 99% confidence, \*\*: significant with 95% confidence; \*: significant with 90% confidence.

## Prediction 2. Higher wages in more complex industries

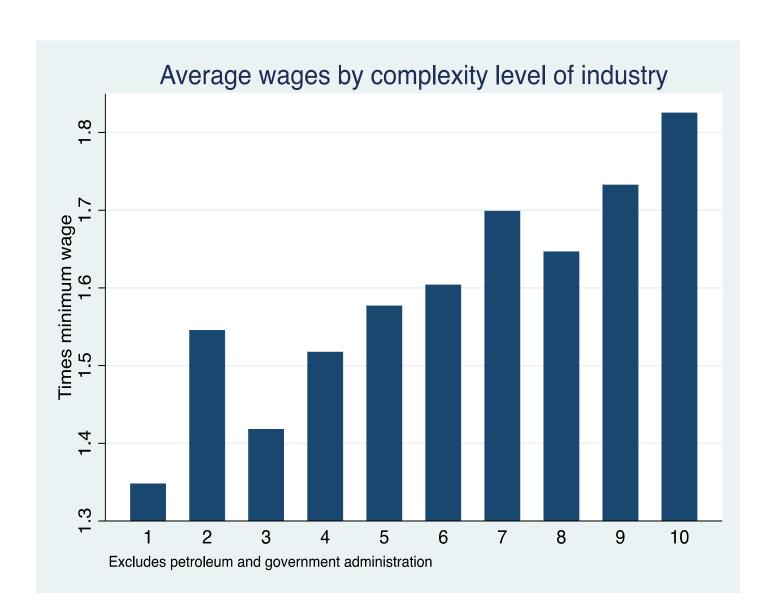


Table 2. Regressions of industry wages on industry complexity

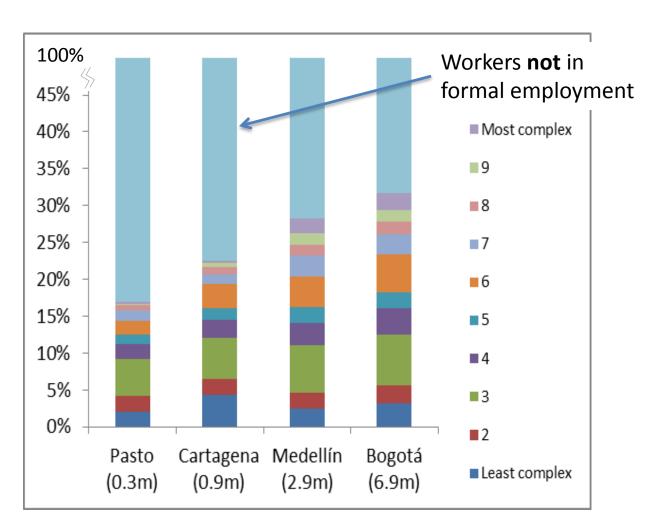
	Dependent variable: log of (average wage in industry/minimum					
	wage)					
Industry complexity	0.445***	0.059	1.347***	0.577***	1.247***	0.643***
madati y complexity	(0.094)	(0.090)	(0.137)	(0.135)	(0.133)	(0.132)
Number of employees per					0.135***	0.098***
establishment (log)					(0.006)	(0.007)
Constant	6.199***	6.205***	6.292***	6.299***	5.819***	5.953***
Constant	(0.004)	(0.004)	(0.005)	(0.005)	(0.022)	(0.024)
City fixed effects	No	Yes	No	Yes	No	Yes
With small establishments	Yes	Yes	No	No	No	No
Adjusted R-squared	0.001	0.109	0.012	0.125	0.069	0.153
Number of observations	15513	15513	8131	8131	8131	8131

Each observation is an industry (four-digit SIC) in a city in 2015. Oil and government sectors are excluded (SIC 11-, and 75- respectively). Small establishments are those with 10 or less employees.

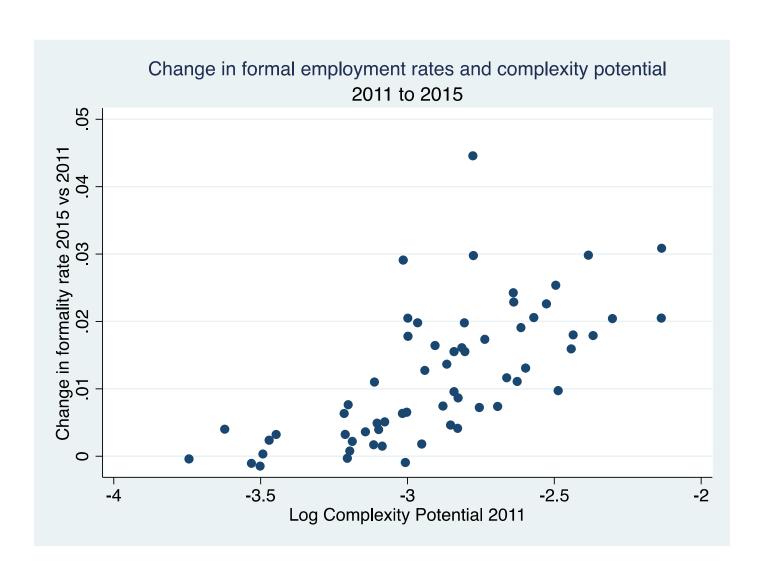
<sup>\*\*\*:</sup> significant with 99% confidence, \*\*: significant with 95% confidence; \*: significant with 90% confidence.

## Prediction 3. Employment creation follows a pattern of "geological layers"

Composition of formal employment by complexity level of industries in cities of different sizes



## Prediction 4. Change in formal employment is faster in cities with higher initial complexity potential



### Prediction 4. Change in formal employment is faster in cities with higher initial complexity potential

Table 3. Regression results for annual change of formal occupation rates (2008-2015)

	2008-2015			
	All sectors	All sectors	Low complexity sectors	High complexity sectors
Log complexity potential (at t0)	0.007** (0.003)	0.012*** (0.003)	0.008*** (0.003)	0.003** (0.001)
Log working age population (at t0)		-0.002** (0.001)	-0.001 (0.001)	-0.000 (0.000)
Dummy for oil producing cities		0.013*** (0.004)	0.009** (0.004)	0.002** (0.001)
Growth government spending per capita		0.002	0.002 (0.002)	0.000 (0.001)
Sectoral demand shocks (Bartik)		-0.188* (0.103)	-0.075 (0.057)	0.000 (0.011)
Formal occupation rate (at t0)	0.036** (0.018)	0.125** (0.052)	0.093* (0.054)	0.016 (0.014)
Constant	0.029*** (0.011)	0.069*** (0.018)	0.051** (0.021)	0.008
Number of cities	62	61	61	61
R squared	0.28	0.638	0.605	0.556

<sup>\*\*\*:</sup> significant with 99% confidence, \*\*: significant with 95% confidence; \*: significant with 90% confidence.

## Results robust to "competitiveness" indicators of infrastructure, institutions, and education

Table 5. Regression results for annual change of formal occupation rates (2011-2015)

	2011-2015		
	All sectors	All sectors	
Log complexity potential (at t0)	0.015***	0.0153***	
	(0.004)	(0.004)	
Infrastructure quality (at t0) 1/		0.0015	
		(0.001)	
Quality of institutions (at t0) $^{1/}$		0.0007	
		(0.0008)	
Higher education quality (at t0) <sup>1/</sup>		-0.0023***	
		(0.0007)	
Constant	0.054**	0.0558**	
	(0.025)	(0.0247)	
Number of cities	54	54	
R squared	0.654	0.719	

Other controls: Log working age population (at t0), dummy for oil producing cities, growth government spending per capita, sectoral demand shocks (Bartik), formal occupation rate (at t0).

1/ Data by department of city from Consejo Privado de Competitividad & Universidad del Rosario (2013), which uses the same methodologies of the *Global Competitiveness Report*.

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### Concluding remarks

- Possible extensions
  - Labor market rigidities
  - Labor migration
  - Non-tradable goods
- Relation to endogenous growth models
  - Supply model (externality from skill diversity)
  - Role of knowledge (by-product of evolutionary rule of firm survival)
  - Convergence vs divergence.

### The building blocks of a formal employment strategy

- "Intelligent diversification" (instead of spe
  - Identify missing industries technological **ar** to those already successful
  - Identify the barriers facing those ip
- Training focused on those indu education in general)
- A Policies are about active labor policies Infrastructure investment times within and between reducing freight trap
- Coordination acre
  - Training
  - Zone plap
  - urban ✓astructure Transp
  - elocation.

# Thank you for your time and your comments

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