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ORIGINAL ARTICLE

The impact of skill mismatch on unemployment, informality, and labour turnover

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Abstract

The objective of this paper is to analyse the impact of *skill mismatch* on labour turnover, unemployment, and informality, in the case of Colombia. We study Colombia because it is a developing country with one of the highest levels of unemployment and informality in Latin America, along with very restrictive institutions, such as the minimum wage. We found that skill mismatch can explain the high turnover of workers in the Colombian labour market, evident in the increase in hirings and also in separations. Additionally, we find a positive significant effect of skill mismatch on the levels of informality, but no significant effect on unemployment. This evidence remains even once we consider the role of labour market institutions such as minimum wage and non-wage labour costs.

Keywords: informality; overqualification; skill mismatch; unemployment; underqualification; worker reallocation

JEL Codes: I25; J46; J63; J64

Introduction

In the literature, skill mismatch is defined as the disparity between the skills demanded by firms and those possessed by workers (McGuinness et al 2018; Van der Velden and Verhaest 2017). Optimal labour market allocation occurs when workers are employed in jobs that match their training and skill set. Evidence suggests that skill mismatch has adverse effects on both firms and workers in developed economies (Brunello and Wruuck 2021; McGowan and Andrews 2017), and this is even more pronounced in developing countries with limited resources (Cárdenas-Rubio, 2020; Ferreyra et al 2021).

For workers, skill mismatch leads to lower wages, inadequate skill development, reduced training opportunities, and lower job satisfaction (Alba-Ramirez 1993; Allen and Van der Velden 2001; Badillo-Amador and Vila 2013; Di Pietro and Urwin 2006; Verhaest and Omey 2006). For firms, it results in lower productivity and increased hiring and training costs due to higher job turnover (Hersch 1991; McGowan and Andrews 2017; Verhaest and Omey 2006). On a macro level, skill mismatch contributes to efficiency losses, manifested as lower average productivity, elevated equilibrium unemployment, and slower GDP growth due to suboptimal resource allocation (Brunello and Wruuck 2021; Garibaldi et al 2020; Lucifora and Origo 2002; Manacorda and Petrongolo 1999; Olitsky 2008; Quintini 2011).

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Over recent decades, educational attainment has increased considerably in Latin America and Colombia. For example, the proportion of workers with at least a secondary level of education rose from 40% to 60% between 1990 and 2010 (Acosta et al 2015). To meet this surge in secondary education, the supply of tertiary education also expanded during the same period (Camacho et al 2017). In Colombia, there was a 26% increase in the number of institutions offering tertiary education between 2000 and 2010 (Morales et al 2021).

However, the substantial growth in tertiary education institutions did not yield the expected benefits. Returns on secondary and tertiary education decreased in most Latin American countries during the same period (Gasparini et al 2011), including Colombia, where 20% of college students and 41% of technical and technological students experienced negative returns (Gonzalez-Velosa et al 2015; Ferreyra et al 2021). These negative returns can be attributed to the low quality of secondary education and the poor relevance of degrees (Ferreyra et al 2021), contributing to high levels of skill mismatch in Latin America and especially in Colombia (Bassi et al 2012; Levy and Schady 2013; Sevilla and Farias 2020).

The primary contribution of this paper is to investigate the relationship between skill mismatch on various labour market outcomes, including unemployment, informality, and labour turnover, in an economy with stringent institutions like the minimum wage. Most studies focus on the individual costs of skill mismatch, such as lower wage returns and reduced productivity, training, and job satisfaction (Hersch 1995; McGuinness and Wooden 2007; Robst 1995; Rubb 2013; Verhaest and Omey 2006; Alba-Ramirez 1993; Alba-Ramírez and Blázquez 2003; Sloane et al 1999, Di Pietro and Urwin 2006; Groot and Maassen van den Brink 2003). This paper, in contrast, concentrates on the collective effects of skill mismatch, particularly its relationship with informality, which is a significant feature of employment in developing countries. While some studies explore the link between skill mismatch and institutions in developed countries (Brunello and Wruuck 2021), there is limited evidence on the relationship between skill mismatch and informality, especially in the context of developing countries.

To fill this gap, we use the theoretical model of Baley et al (2022) to guide our empirical results. Their model shows a direct interaction between job mobility and skill mismatch. Depending on their skill beliefs and the skill requirements, workers decide whether to search for a better job or even change career paths, which results in increased worker reallocation. Moreover, we also explore the relationship between other aggregate labour market outcomes, such as the unemployment and informality rate. Since all these variables are endogenous in equilibrium, we estimate a dynamic panel fixed effect model following Arellano and Bover (1995) and Blundell and Bond (1998) based on generalised method of moments (GMM) estimator, which is more efficient and with a small bias under finite samples.

Our main findings indicate a positive correlation between the proportion of skill mismatched workers and various measures of labour turnover, such as worker reallocation (WR), separations (S), and hirings (H), as suggested by the theoretical model of Baley et al (2022). Additionally, we find a significant increase in the informality rate, suggesting that workers who are in a skill mismatch situation would probably separate from firms and transition directly to the informal employment, particularly those who are underqualified. Consequently, with fewer flows into unemployment, there is a possible reduction in the unemployment rate, although not statistically significant. The positive relationship between skill mismatched and labour mobility has also been identified by other authors such as Castillo (2007), Mora (2008), and Quejada and Ávila (2017), using individual micro data from Colombia. However, these studies do not explore the impact on different labour outcomes such as informality or unemployment. Furthermore, our results hold even after considering the influence of labour market institutions such as minimum wage and non-wage labour costs.

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The rest of the paper is organised as follows: the next section provides a literature review on the effects of skill mismatch followed by a brief overview of the Colombian labour market defining the key variables such as unemployment, informality, labour reallocation (following Davis and Haltiwanger 1999; Davis et al 1996), and skill mismatch. The next section presents the intuition of the model proposed by Baley et al (2022), connecting skill mismatch with worker reallocation after which we discuss our empirical strategy and present our main findings. Finally, we summarise the key findings and offer some policy implications.

Literature review

Empirical evidence regarding the impact of skill mismatch is extensive, particularly in developed economies. The primary focus of the literature has been on studying the individual costs of mismatch, such as wage returns, poor skill development, lower productivity, reduced training, and diminished job satisfaction. In general, research in this field has revealed that overqualified workers typically face wage penalties, earning less than those with the same level of education who are employed in positions that align with their skill set[1] (see Hartog 2000; Allen and Van der Velden 2001; Badillo-Amador and Vila 2013; Dolton and Vignoles 2000; McGuinness 2006; Rumberger 1987; Verdugo and Verdugo 1989). Hartog (2000) conducted a study across five countries (the Netherlands, Spain, Portugal, the United Kingdom, and the United States) and found that wage returns for overeducated workers are typically about half to two-thirds of the returns received by those who are adequately educated. Some authors explain this negative return as temporary, as workers often accept overqualified positions with the expectation of gaining experience and securing better job opportunities and wages in the future (Rosen 1972; Sicherman and Galor 1990; Sicherman 1991). Few papers have also studied the effect of mismatch on labour productivity although the results are less conclusive; McGowan and Andrews (2017) found that an increase of one standard deviation in the overqualification measure is associated with a 4% reduction in overall labour productivity, while Kampelmann and Rycx (2012) found a positive relationship between overeducation and firm´s productivity.

Another individual cost of skill mismatch widely studied in the literature is related to other job characteristics, including training, job satisfaction, and labour turnover. For Spain, Alba-Ramirez (1993) and Alba-Ramírez and Blázquez (2003) found that overqualified workers tend to be younger, less experienced, more educated, and have shorter on-the-job training compared to those who are adequately educated. Furthermore, the authors discovered that overqualified workers are 4.7 times more likely to change jobs compared to their adequately educated counterparts, which supports the hypothesis of higher labour mobility among overqualified individuals (similar findings were reported by Frei and Sousa-Poza 2012, as well as Verhaest and Omey 2006; Sloane et al 1999; McCall 1990; Miller 1984; Rubb 2013; Di Pietro and Urwin 2006; Groot and Maassen van den Brink 2003). Contrary to these findings, there are some authors that do not find empirical evidence on the relationship between mismatch and labour mobility (Serrano and Malo 1996; Wen and Maani 2019; and Büchel and Mertens 2004). Some of this evidence aligns with the predictions of job matching models (Jovanovic 1979a; 1979b; 1984), which suggest that overqualified workers will actively seek better job positions in line with their educational level, increasing their likelihood of voluntarily leaving their current job. Conversely, underqualified workers, despite lacking an incentive to quit, are more likely to be dismissed by the firm. Therefore, the job matching model implies that skill mismatch (under- and overqualified) may lead to higher labour turnover.

At the aggregate level, McGowan and Andrews (2015) explore the relationship between skill mismatch and public institutions in developed economies.[2] The authors found that skill mismatch is lower in countries with well-designed framework conditions that promote efficient reallocation and has a direct relationship with industry-level labour productivity (McGowan and Andrews 2017).[3] There has also been an ongoing debate about the cyclical nature of workers' skill mismatch. Some studies suggest a procyclical relationship due to an increase in the separation of underqualified workers during recessions, known as the '*cleansing effect*' (Mortensen and Pissarides 1994; Lise and Robin 2017; Pissarides 2000). On the other hand, others argue that skill mismatch is countercyclical, as there is an increase in the hiring of overqualified workers during recessions, referred to as the '*sullying effect*' (Moscarini 2001; Barlevy 2002; Barnichon and Zylberberg 2019). However, more recently, Baley et al (2022) concluded that in the case of the USA, the '*cleansing effect*' unambiguously dominates the '*sullying effect*', indicating a procyclical relationship.

Evidence for developing countries is very limited. Recently, for the case of Chile and Colombia, some authors have explored the individual cost of mismatch, such as the inflationary effect of credentials due to high competition for access to the best positions (Sevilla and Farias 2020; Domínguez 2009; Herrera-Idárraga et al 2013) and lower returns and higher labour mobility of overqualified workers for the case of Colombia (Castillo 2007; Mora 2008; Quejada and Ávila 2017). However, none of these studies explored the aggregate relation of skill mismatch with labour market outcomes such as unemployment, informality, and labour reallocation in a developing country with strict institutions such as Colombia. The only recent study that has examined the role of labour institutions in labour market dynamics in Colombia is Flórez et al (2021). However, they did not investigate the impact of skill mismatch on workers' labour dynamics.

The data and the Colombian labour market context

This section presents the definitions of the main variables used in our empirical exercise. To construct a measure of labour turnover, we use the Integrated Record of Contributions to Social Security (PILA). PILA is a panel that links information about employers and employees. These administrative records contain data on all hirings and separations made by formal firms, which are firms that report social payments such as health and pension contributions of their workers, as required by law (the information is reported directly by each firm to the Ministry of Health). Consequently, we do not cover informal firms, and also we cannot distinguish between voluntary or involuntary separations. To focus exclusively on formal firms, we exclude self-employed individuals, who constitute approximately 16.2% of the total employment in PILA. By using PILA, we can track approximately 369,000 firms and 9,420,000 workers in recent years. This measure includes workers of both full- or part-time jobs, as long as they contribute to the pension or health system. This data enables us to calculate the hiring, separation, and worker reallocation rate for the 23 main cities (Bogotá, Medellín and its metropolitan area, Cali and its metropolitan area, Barranquilla and its metropolitan area, Bucaramanga and its metropolitan area, Pasto, Cartagena, Cúcuta and its metropolitan area, Neiva, Pereira and its metropolitan area, Montería, Villavicencio, Tunja, Quibdó, Popayán, Ibagué, Valledupar, Sincelejo, Riohacha, Florencia, Santa Marta, and Armenia) in Colombia on a quarterly basis for the period 2010–2019. We use information until the last quarter of 2019 so we don't contaminate our exercise with the pandemic shock.

However, since PILA does not provide information about the level of qualification required for each position in each firm, and we lack data on the education level of each worker to measure skill mismatch, we turn to the official Colombian Household Survey (GEIH by its Spanish initials, Departamento Nacional de Estadística (DANE) 2015). To ensure

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comparability with PILA, using GEIH, we retain only individuals who contribute to the social security system payments and work in firms with two or more employees. To have a representative database at the city level, we compile our database on a quarterly basis, using data from both PILA and GEIH.

In the literature, skill mismatch is defined as the disparity between the skills demanded by firms and those possessed by workers (McGuinness et al 2018; Van der Velden and Verhaest 2017). According to McGuinness et al (2018), this definition differs from those related to skill gaps or skill shortages, as it does not account for employer beliefs about worker skills or the difficulty firms face in filling vacancies due to a lack of suitably qualified candidates. Empirically, we approximate our definition as the disparity between an individual's years of education and the years of education required by the firms at any occupation. There are three methods for measuring the educational level required by an occupation (Dolton and Vignoles 2000; Madrigal 2003; Mora 2008; Ramos and Sanromá 2013). The first method is known as '*job analysis*', which involves determining the educational level required based on international occupational classifications created by professionals. The second approach is the '*self-assessment*' method, which assumes that individuals currently in the job are best suited to determine the required level of education. Finally, the '*realised matches*' method uses information on the educational level of individuals working in a particular occupation as a measure of educational requirements, using statistics such as the mode and mean, among others (Leuven and Oosterbeek 2011).

Due to the limitations of our data, this paper employs the '*realised matches*' method. We group individuals with the same occupation and calculate the mode of their years of education. This serves as a proxy for the education requirements in each occupation. A person is considered to be in a mismatch situation when their level of education differs from the mode of the educational level of those in the same occupation. Furthermore, a person is categorised as overqualified when their education level exceeds the mode and underqualified when it falls below (Kiker et al 1997). However, one of the limitations of our mismatch measure is that we lack information on job requirements as specified by employers, the quality of the qualifications, and other multidimensional skill mismatches as suggested by Guvenen et al (2020).[4]

To construct the skill mismatch by occupation in various cities, we aggregate occupations into seven groups for each city, following the ISO-CNO-70 classification defined by DANE in 2015: (a) professionals, technicians, and assimilated workers; (b) directors and senior public officials; (c) administrative staff and assimilated workers; (d) merchants and sellers; (e) service workers; (f) agricultural and forestry workers, fishermen and hunters; and (g) nonagricultural workers, drivers of machines and vehicles of transport and assimilated workers. Therefore, for each city, we calculate the level of skill mismatch as the proportion of individuals whose educational level does not match the level required by their occupation. However, as mentioned by Solon et al (1994), these measures can be affected by a composition effect since during recessions, the pool of employed workers may shift towards higher-skilled occupations. To mitigate this potential bias, we calculate the skill mismatch only for workers aged 26–46 years, a group that are more attached to the labour market and potentially less affected by the cyclical changes of the labour market.

As mentioned earlier, Colombia is a particularly compelling case for study, as it exhibits one of the highest levels of skill mismatch compared to other similar developing countries. In Figure 1(a), we present the skill mismatch level divided into overqualified and underqualified workers. A worker is considered overqualified when their level of education surpasses the requirements of their job and underqualified in the opposite case. In Colombia, the level of skill mismatch is twice the average observed in the Organisation for Economic Co-operation and Development (OECD) countries and more than double that of the USA. Furthermore, Colombia's skill mismatch surpasses that of similar Latin American

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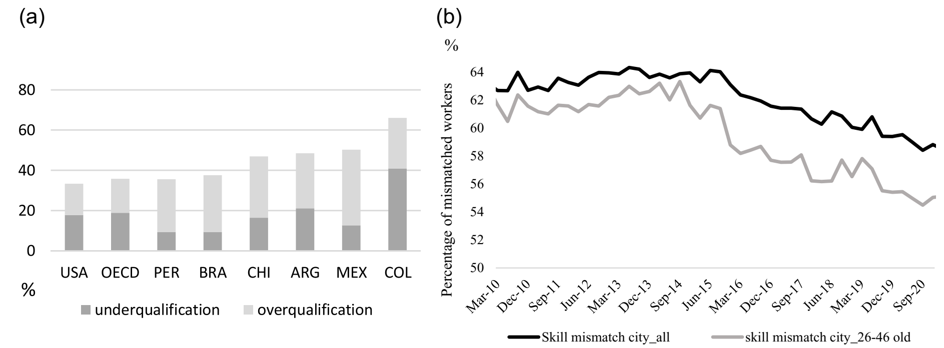

Figure 1. (a) *Skill mismatch* in developed and developing countries (percentage of total workers, 2016). *Source*: OECD (2017), Skills for Jobs Database and author's calculations based on the Colombian household survey – GEIH. Note: A worker is overqualified if his/her level of education exceeds his job requirements and underqualified in the contrary case. (b) *Skill mismatch* in Colombia (2010–2019). *Source*: Author's calculations based on the household survey GEIH.

countries, including Peru, Chile, Brazil, Argentina, and Mexico. In Figure 1(b), we illustrate the evolution of skill mismatch within cities across time in Colombia, revealing a reduction in levels since 2015.

Another important variable used in the paper is the worker reallocation measure, constructed following the framework of Davis and Haltiwanger (1999) and Davis et al (1996). In this case, we use PILA, which matches employer–employee information, enabling us to compute the rates of hirings (H), separations (S), worker reallocation (WR), at the city level (refer to Appendix A for details on the construction of these measures).

In Figure 2(a), we present the dynamics of WR rates over time for the average of the 23 main cities in Colombia. The WR is approximately 30% across time, peaking at 31% in 2015, after which it begins to decline. In Figure 2(b), we depict the dynamics of hiring and separation rates over time. As observed, both hiring and separation rates have been on a declining trend since 2015. However, the hiring rate consistently exceeds the separation rate, implying a positive employment growth rate.

Finally, we aim to analyse whether skill mismatch has an impact on labour market outcomes such as the unemployment rate and the informality rate. To define informality, we use a criterion related to the social protection of workers: in this case, an informal worker is defined as someone who does not make contributions to the health or pension systems. Another measure, used for international comparisons, is the definition of informality based on firm size, as recommended by the International Labour Organization (ILO 2013). According to this definition, all workers employed in firms with fewer than five employees are considered informal. In Figure 3, we present the evolution of the national unemployment rate and the informality rate over time. Panel A depicts the dynamics of the unemployment rate, while Panel B illustrates the dynamics of the informality rate, using both definitions. These definitions are closely related; for that reason, our empirical estimations only present the results using the informality measure based on firm size (commonly used by the ILO). Over this period, we have observed different trends between the unemployment rate and the informality rate. While the unemployment rate has been on the rise, especially since 2015 (with a significant peak during the pandemic), the informality rate has been decreasing. Furthermore, Colombia is particularly interesting due to its high levels of unemployment and informality rates (as seen in Figure B1 in Appendix B). According to the ILO in 2019, Colombia had an unemployment rate of 10% and

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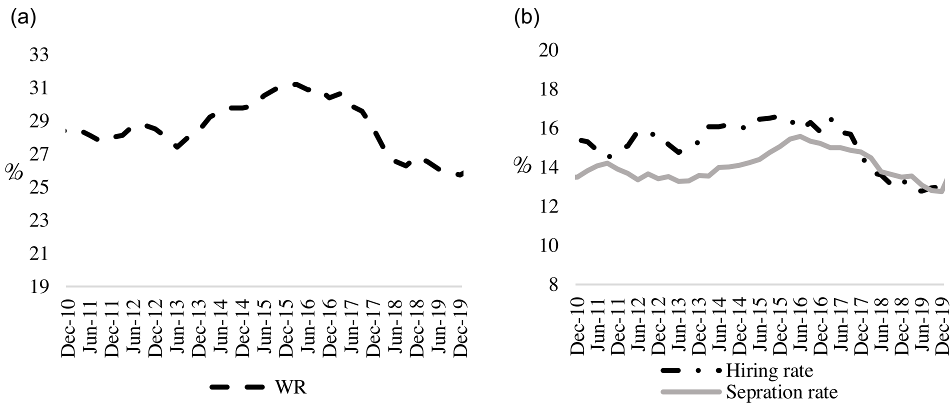

Figure 2. (a) Labour turnover measures (average 23 cities, 2010–2019). (b) Hiring and separation rates. Source: Author's calculations based on PILA.

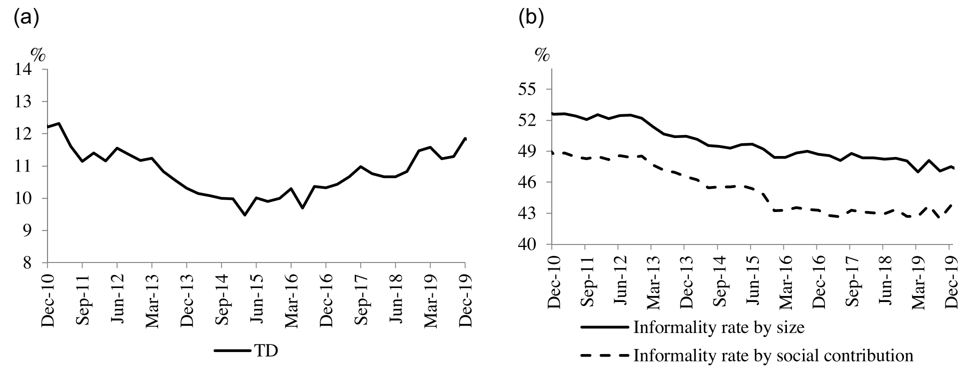

Figure 3. Labour market indicators – average 23 cities (2010–2019). (a) Unemployment rate. (b) Informality rate. *Source*: Author's calculations based on the household survey GEIH.

an informality rate of 62%, significantly above the average levels observed in Latin American countries. These high rates could also be reflective of the high levels of skill mismatch (Cárdenas-Rubio 2020; Schioppa 1991).

Furthermore, the Colombian labour market is characterised by weak and restrictive institutions, such as the minimum wage. For instance, in Figure 4, you can see the minimum wage as a percentage of the median wage in Colombia compared to other countries. While this ratio was around 55% for OECD countries in 2019, in Colombia, it was approximately 92%. This ratio is even higher than that of Latin American countries similar to Colombia, such as Chile, Mexico, and Costa Rica, among others. This evidence indicates that, in the case of Colombia, the minimum wage is highly restrictive (also see Maloney and Mendez 2004; Arango and Rivera 2020; Arango and Flórez 2021; Arango et al 2020; Bell 1997). In accordance with Brunello and Wruuck (2021), the skill mismatch can also be linked to differences in institutions and policy environments. The authors show that countries with strong institutions that facilitate the efficient reallocation of resources tend to have a lower skill mismatch. Policies that promote greater flexibility in wage negotiations, strict regulations on firings, increased mobility in housing markets, greater job training, and higher managerial quality are also associated with lower skill mismatch (McGowan and Andrews 2015, and Di Pietro 2002).

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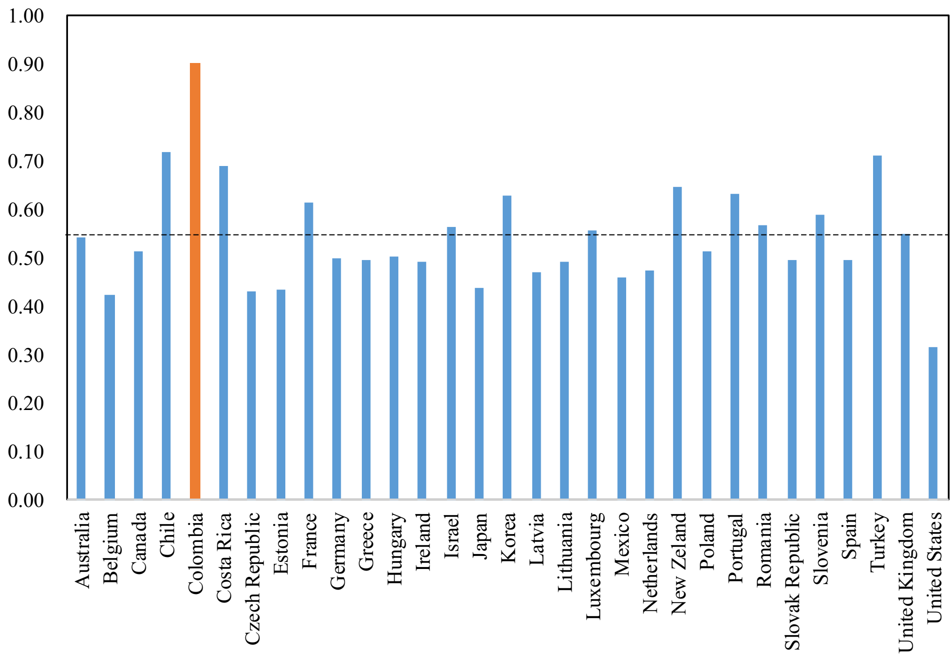

Figure 4. Minimum wage relative to median wage in 2019. *Source*: Data extracted on 9 June 2022 from OECD.Stat.

Theoretical relation of skill mismatch and labour outcomes

The present model shows a relationship between the skill mismatch and different labour flows such as hirings, separations, and worker reallocation. We use this model as a theoretical guide for our empirical results. Baley et al (2022) presented a model where they discussed the relationship between skill mismatch, job mobility, and worker reallocation. Their model is a variation of the directed search model of Menzio and Shi (2010, 2011) with two distinctive features. First, workers differ along multiple skill dimensions and sort into jobs with heterogeneous skill requirements across those dimensions. Second, workers and firms have incomplete information about workers' skills, which leads to a skill mismatch in equilibrium (Jovanovic, 1979a; 1979b; 1984).

As a result, workers are characterised by a high-dimensional vector of different skill types. Based on their skills, workers sort into jobs characterised by the type of skill they employ. Information about workers' skills is imperfect and needs to be inferred from noisy signals (Jovanovic, 1979; 1984). Consequently, given their initial belief about their skills, workers direct their job search towards a particular job type. Once a match is made, they start revising their beliefs. Over time, these revisions lead to job reallocation through on-the-job search, job separations, and career changes.

The model predicts that unemployed workers switch careers when their expected ability is low. Otherwise, they search for jobs in their current career, with a job-finding rate that increases with their expected ability. Employed workers actively search for a better match if their desired job differs from their current job in terms of skill requirements. This means they can decide to move up the ladder (to a job with higher skill requirements or task complexity within the same career) if their expected ability increases, or they can move down the job ladder (to a job with lower skill requirements within the same career) if their expected ability decreases. Therefore, expected ability or beliefs are crucial: workers pursuing a new career search for jobs with the lowest

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complexity or skill requirements, while workers who are more optimistic about their skills in their current career apply to more complex jobs. In equilibrium, workers reallocate both upwards and downwards on job ladders within a given career path and across different career paths.

The model demonstrates a direct interaction between job mobility and skill mismatch. Depending on their skill beliefs and the skill requirements, workers decide whether to search for a better job or even change career paths, which results in increased worker reallocation. Following the theoretical guidance provided by Baley, Figueiredo, and Ulbricht (2022), we assess how skill mismatch increases workers' turnover measures such as worker reallocation, hirings, and separations. We also explore the relationship between other aggregate labour market outcomes, such as the unemployment rate and informality. Moreover, since all these variables are endogenous in equilibrium, in the next section, we estimate a dynamic panel fixed effects model following Arellano and Bover (1995) and Blundell and Bond (1998), which allows us to use lags of dependent and independent variables as instruments to deal with the potential endogeneity of our explanatory variables.

Empirical strategy and results

Following the relationships between the skill mismatch and the workers' reallocation presented by Baley et al (2022), we estimate dynamic panel fixed effects regression by cities as:

$$Y_{it} = \alpha Y_{it-1} + \beta Mismatch_{it} + X_{it}'\theta + \omega ISE_t + \gamma_i + \varepsilon_{it} \quad (1)$$

where Y_{it} represents any of the labour outcomes such as WR_{it} worker reallocation rate, H_{it} hiring rate, S_{it} separation rate, UR_{it} unemployment rate, or IR_{it} informality rate, in a city i at period t. Vector X_{it} contains demographic characteristics of each city, including the share of workers who are males and heads of households and with higher education. Table C1 in the appendix presents the summary of the statistics for the variables that capture the demographic characteristics during the period 2009–2019. The variable sex takes the value 1 if the worker is a man and 0 otherwise, household head status takes the value 1 if the worker is the head of the household and 0 otherwise, the variable age is divided into categories (25 or less, 26–40, 41–50, 51 or more) and takes the value 1 if the worker belongs to a particular category and 0 otherwise, and the variable educational level takes the value 1 if the worker has at least 1 year of university or technical education. Additionally, we also include the variable index of economic activity, which does not change across cities but does change across time. γ_i is a city-specific fixed effect, and ε_{it} is the error term.

We estimate the dynamic panel following Arellano and Bover (1995) and Blundell and Bond (1998), based on the first-differenced GMM estimator.[5] Blundell and Bond (1998) propose a most efficient method by using lagged differences of the dependent variable as instruments for the equations in levels and lagged levels of the dependent variable as instruments for equations in first differences. This approach constitutes a system GMM estimator, known for its efficiency and minimal bias under finite samples and weak instruments. Following Blundell and Bond (1998), we use lags and differences of (Y_{it} *and* $Mismatch_{it}$) as instruments. Additionally, we incorporate exogenous instruments X_{it} such as the demographic age composition of labour force population, share of male workers, and head of households, among others. To ensure model appropriateness, we conduct the *Hansen test* for overidentification restrictions and the *Arellano-Bond test* for serial correlation.

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Table 1. Dynamic panel with fixed effects by cities

	Skill mismatch				
Variables	(1) WR	(2) H	(3) S	(4) UR	(5) IR
Labour market characteristics					
Lag of dependent variable	0.982***	0.936***	0.951***	0.440***	1.052***
	(0.031)	(0.027)	(0.026)	(0.116)	(0.023)
Skill mismatched workers	0.063**	0.093***	0.120**	–0.109	0.026*
	(0.025)	(0.030)	(0.044)	(0.185)	(0.013)
Males	0.115	0.168*	0.080	0.540***	–0.039
	(0.074)	(0.093)	(0.047)	(0.123)	(0.066)
Head of household	0.005	0.010	0.011	0.342***	–0.014
	(0.021)	(0.027)	(0.023)	(0.116)	(0.013)
Higher education	–0.018	–0.025	–0.034	0.084	–0.068**
	(0.030)	(0.032)	(0.041)	(0.228)	(0.031)
Economic activity	0.045**	0.070**	0.048*	–0.090	0.019
	(0.019)	(0.026)	(0.027)	(0.157)	(0.015)
Arellano–Bond (2) *p*-value	0.977	0.000847	0.506	0.150	0.0594
Hansen J χ^2 *p*-value	0.140	0.233	0.272	0.199	0.173
Observations	897	897	897	897	897

Notes. Standard error in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All independent variables represent proportions or means by city. Error term is cluster by cities. We use lags of dependent and independent variables as instruments.

General effects

Table 1 presents the results of the estimation of equation (1). To simplify the interpretation of the coefficients, all variables are standardised; therefore, the effects are interpreted as changes of Y_{it}, expressed in terms of standard deviations, as a result of an increment in one standard deviation (SD) of the independent variable. Moreover, to guarantee that our mismatch measures are representative at the occupational levels explored in this study, we eliminate all occupations with less than 100 individuals by cities in each quarter (Verbeek & Nijman, 1992). This correction eliminates any possible bias in our mismatch estimates. However, Table D1 from Appendix D also presents the results with the whole sample, without eliminating occupations with less than 100 individuals, as we can see these results are like those presented in Table 1. Following Blundell and Bond (1998), we use lags of dependent and independent variables as instruments for $Mismatch_{it}$ and Y_{it-1}. Our *Hansen test* suggests that we cannot reject the null that all instruments are identifying the same parameter (all our *p-values* are higher than 0.05), so our instruments are valid, and the *Arellano–Bond test* also indicates that we cannot reject the null of no serial correlation, except for column (2) where our *p-value* is lower than 5%.

Our results show that all our dependent variables are very persistent, with all lags statistically significant. Moreover, the proportion of mismatched workers has a positive and significant effect on workers' reallocation (*WR*), hirings (*H*), separations (*S*), and informality rate *(IR).* The effect on the unemployment rate (*UR*) is negative but not statistically significant. The results indicate that an increase in mismatched workers

Table 2. Dynamic panel with fixed effects by cities

	Skill mismatch				
Variables	(1) WR	(2) H	(3) S	(4) UR	(5) IR
Overqualified mismatched	**0.102*** **	**0.151*** **	**0.046**	**–0.203**	**–0.000**
	(0.034)	(0.051)	(0.040)	(0.209)	(0.031)
Underqualified mismatched	**0.121*** **	**0.138*** **	**0.101*** **	**–0.319**	**–0.003**
	(0.024)	(0.045)	(0.028)	(0.237)	(0.018)
Arellano–Bond (2) *p*-value	0.808	0.001	0.509	0.180	0.065
Hansen J χ^2 *p*-value	0.507	0.642	0.701	0.739	0.585
Observations	897	897	897	897	897

Notes. Standard error in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All independent variables represent proportions or means by city. Error term is cluster by cities. We use lags of dependent and independent variables as instruments.

increases the workers' reallocation as suggested by the theoretical model of Baley et al (2022). Additionally, we observe a significant increase in the informality rate. This suggests that workers in a skills mismatch situation are likely to leave the firm and transition directly into informal employment, rather than remaining unemployed. Due to lower flows into unemployment, we expect a negative effect on the unemployment rate, although these effects are not statistically significant.

Table 2 shows the panel estimation when we separate the mismatched measure between overqualified and underqualified workers (we include the same controls as in Table 1, but we only present the coefficients for the mismatched measure). The results show that workers' reallocation (*WR*) and hirings (*H*) are explained through both underqualified and overqualified workers, while separations (*S*) are explained mainly by underqualified workers. Notice that the positive relationship between underqualified workers and separations can be related to the '*cleansing effect*' defined in the literature and the positive relationship between overqualified workers and hirings can be related to the '*sullying effect*'. However, it seems that under the cycle, these two effects cancel out since the relationship between the skill mismatch and unemployment rate is not significant. This result contrasts with the finding of Baley et al (2022) for the case of the USA, where the authors found that the '*cleansing effect*' unambiguously dominates the '*sullying effect*', indicating a procyclical behaviour of skill mismatch.

Moreover, we do not find any significant effect of overqualified and underqualified workers on informality, unlike in Table 1, where we find a significant effect. These results can be explained by our imperfect measure of mismatch. We are only using the qualifications as a proxy of skills, but we are not accounting for other dimensions of skill mismatch, such as measures of noncognitive skills and quality of education, among others. The positive increase in labour mobility is also found by other authors such as Castillo (2007), Mora (2008), and Quejada and Ávila (2017), using individual micro data in the case of Colombia. However, they do not analyse the effect on other different labour outcomes such as informality or unemployment rate.

To consider the role that institutions in the dynamics of the labour markets, we include as controls the ratio of the minimum wage (as a proportion of the average wage) and the non-wage labour cost. Even though, the minimum wage is determined at the national level, its level of restrictiveness can be different across cities (Arango and Flórez 2021). Given the potential endogeneity of the minimum wage ratio, we include also lags of minimum wage

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Table 3. Dynamic panel with fixed effects by cities

	Skill mismatch – city				
Variables	(1) WR	(2) H	(3) S	(4) UR	(5) IR
Labour market characteristics					
Lag of dependent variable	0.992***	0.940***	0.957***	0.166**	0.990***
	(0.022)	(0.024)	(0.024)	(0.075)	(0.037)
Skill mismatched workers	**0.059****	**0.100*****	**0.034**	**–0.076**	**0.042****
	(0.025)	(0.032)	(0.033)	(0.177)	(0.017)
Controlling by institutions					
Minimum wage ratio	0.015	0.023	0.011	0.340**	0.092***
	(0.020)	(0.037)	(0.024)	(0.156)	(0.020)
Non-wage labour cost	–0.041**	–0.016	–0.086***	0.139	–0.001
	(0.017)	(0.025)	(0.029)	(0.093)	(0.021)
Arellano–Bond (2) *p*-value	0.601	0.00219	0.424	0.871	0.0622
Hansen J χ^2 *p*-value	0.233	0.435	0.559	0.586	0.278
Observations	897	897	897	897	897

Notes. Standard error in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All independent variables represent proportions or means by city. Error term is cluster by cities. We use lags of dependent and independent variables and some demographic variables as instruments. This regression also includes the control included in Table 1.

as instruments. The results in Table 3 show that after controlling for institutions the effect of skill mismatch remains significant in explaining the dynamics of workers' reallocation (*WR*), hirings (*H*), and informality rate *(IR).* Even though the effect on separation rate (*WR*) is positive this is no longer significant, as in the case of the unemployment rate (*UR*). Our results are also in line with other authors that show that the minimum wage is one of the main determinants of the higher unemployment and informality in the case of Colombia (Arango and Florez 2021; Arango and Rivera 2020; Flórez et al 2021).

In general, we find that skill mismatch can explain the excess of reallocation of workers in the Colombian case, inducing an increase in separations and also in hirings. Additionally, even controlling by the labour institutions such as the minimum wage and non-wage labour cost, these results remain significant. Even though we do not find a significant effect of skill mismatch on the unemployment rate, we do find a positive and significant effect on the levels of informality. Since flows to unemployment are low, the effect on the unemployment rate is potentially negative but not significant.

Final remarks and policy implications

In this paper, we show that there exists a relationship between skill mismatch and labour market outcomes. Using an aggregate panel data at the city level (23 main cities in Colombia), with a quarterly frequency for the period 2010–2019, we find that the increase in the proportion of mismatched workers has a positive and significant effect on the workers' reallocation (*WR*), hirings (*H*), and separations (*S*). We also find that the higher proportion of mismatched workers increase the level of informality. This evidence

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remains even once we consider the role of labour market institutions such as minimum wage and non-wage labour cost.

In summary, we have explored the effects of skill mismatch on different labour market outcomes such as informality and different measures of labour market dynamics such as worker reallocation. We found that in the case of a developing country like Colombia, the mismatch can explain an important increase in the informality rate and also in the rotation of workers. It seems that those workers who are in a skill mismatch have a higher probability of being separated from the firm and moving directly to the informal sector. In this term, skill mismatch is very costly for developing countries such as Colombia, where the skill mismatch introduces more inefficiency in the economy through a more informal economy, negatively affecting the productivity (McGowan and Andrews 2015) and the long-term economic growth. Therefore, we need to develop strategies that improve the adequate qualification of workers, as well as the search process for both workers and firms to reduce the level of mismatch and therefore the level of informality in a developing country like Colombia.

Additionally, in line with the previous finding (Arango and Florez 2021; Arango and Rivera 2020; Flórez et al 2021), the high level of informality rate and unemployment rate is also explained mainly by institutional factors such as the minimum wage and the non-wage labour cost. Therefore, policies oriented to reduce these rigidities should be implemented.

There are some different policies we can implement in order to reduce the mismatch and improve the performance of the labour market. The first policy for countries like Colombia is to invest more in the quality of the human capital they are providing. For example, the quality of the vocational education and training programmes can, in the short term, help to reduce any skill shortages induced by the technological changes (Ferreyra et al 2021; Brunello and Wruuck 2021; Brunello and Rocco 2017; Sevilla and Farías 2020). Moreover, implementing a better-designed apprenticeship system that keeps firms involved in training apprentices is also a very important policy. Employers can respond to skill shortages by activating several measures, including training and recruitment abroad (Brunello and Wruuck 2021).

We know that technological changes are affecting the skills required by employers; therefore, the educational systems need to consider these future needs to offer the skills required by the employers (McGuiness et al 2018; Brunello and Wruuck 2021). In this case, the education system needs to be updated with the private information from the firm's side and improve the existing information system to have a better match between the employers and employees. In Colombia, there is a public vacancy information system called '*Servicio Publico de Empleo*', where all firms report the vacancies with the specific requirements they need for the job. They also help the employers to find the person they need, but in some cases, they can find workers with the skills required. Therefore, this information can be used by other public training institutions such as 'SENA' to improve their training programmes and offer courses that accomplish the firm's requirements and fulfil the employer's needs. Moreover, all this useful information can be used to improve the career guidance and counselling services of secondary education to avoid future mismatch (McGuiness et al 2018).

Notes

1 The returns on wages of those individuals who are in mismatch contradict the prediction of the human capital theory (Becker 1964; Mincer 1974), which predicts that higher education levels imply higher productivity and, therefore, higher wages.

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2 Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, Slovak Republic, Spain, the United Kingdom, and the United States.

3 In general, the existing evidence infer the direct effect of mismatch on productivity indirectly from wages rather than using productivity indicators. Schioppa (1991) explores the effect of mismatch (using different measures such as variance of relative unemployment rates or the difference between unemployment and vacancies, among others) on the unemployment rate for developed economies.

4 Guvenen et al (2020) propose an empirical measure of multidimensional skill mismatch that is based on discrepancy between the portfolio of skills required by an occupation and the portfolio of abilities possessed by a worker for learning those skills. To build this new measure, the authors use the 1979 Longitudinal Survey of Youth (NLSY79), which contains information of the occupation and wage histories of individuals. It also contains test scores from an occupational placement test (Armed Services Vocational Aptitude Battery – ASVAB) and several measures of noncognitive skills. On the occupation side, the authors use O*NET project for data on skill requirements. Unfortunately, given the limitation of this type of information for the case of Colombia, we are not able to build such a multidimensional measure.

5 We perform the estimation using the command xtabond2 from Stata (Roodman 2009).

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Appendix A

Measure of worker reallocation

To build our measures of worker reallocation, we follow the literature of labour market flows (Davis & Haltiwanger, 1999; Davis, Haltiwanger & Schuh, 1996). We present these definitions using the notation presented in Flórez et al (2021). First, let's assume firm j_t is a set of business establishments with at least two employees. An individual i_{jt} is an employee observed in the payroll of firm j at period t. Given that we have employer–employee information, we can compute hirings (h_{jt}) as the set of particular employees observed in a given time that were not observed before. Similarly, separations (s_{jt}) are generated as the specific employees found in the previous periods that were not observed in the current one. Then the set of hirings, separations, and stayers (k_{jt}) in a firm j in the period t is defined as:

$$h_{jt} = \{i: \; i_t \in j_t \;\; \text{and} \;\; i_t \notin j_{t-1}\}$$

$$s_{jt} = \{i: \; i_t \notin j_t \;\; \text{and} \;\; i_t \in j_{t-1}\}$$

$$k_{jt} = \{i: \; i_t \in j_t \;\; \text{and} \;\; i_t \in j_{t-1}\}$$

We can calculate aggregate measures by cities, taking summations of all these previous sets. Therefore, the aggregate flows of hirings ($H_{A,t}$) and separations ($S_{A,t}$) for city A are represented as:

$$H_{A,t} = \sum_{j\varepsilon A} h_{jt}; \; S_{A,t} = \sum_{j\varepsilon A} s_{jt}$$

To simplify the exposition, we omit the subindex A. To build our measure of workers' reallocation, we use two measures defined by Laing, 2011, chapter 23:

$$WR_t \equiv H_t + S_t$$

The first measure is worker reallocation (*WR*) that refers to the number of workers who change their labour status during a period of time, caused by a separation of a hiring. All the measures discussed can be expressed as rates, in which case following Davis, Haltiwanger, and Schuh (1996), we divide by a measure of the employment level of firm *j* at time *t* defined as the average employment in *t* and *t-1*.

Appendix B

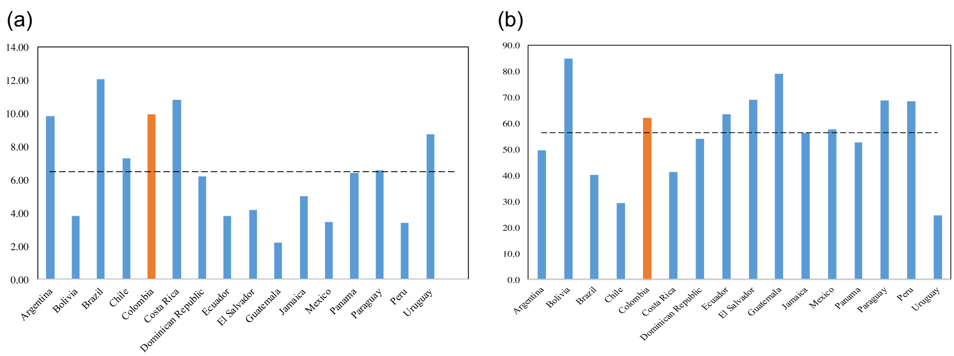

Figure B1. Informality and unemployment rate in Latin American Countries – 2019. *Source*: ILO – International Labour Organization – dash line represents the average for all Latin American. Countries in 2019. Data extracted on 7 July 2022 from OITSTAT.

Appendix C

Table C1. Summary statistics average 2010–2019

Variable	Obs	Mean	Std. dev.	Min	Max
Labour market characteristics					
Worker reallocation rate	920	0.30	0.06	0.15	0.55
Unemployment rate	920	0.13	0.04	0.06	0.29
Informality rate	920	0.55	0.11	0.25	0.75
Hiring rate	920	0.15	0.04	0.05	0.36
Separation rate	920	0.15	0.03	0.06	0.35
% mismatched workers	920	0.59	0.05	0.31	0.70
% overqualified workers	920	0.32	0.06	0.12	0.51
% underqualified workers	920	0.27	0.06	0.13	0.52
% workers with higher education	920	0.45	0.07	0.24	0.68
Demographic characteristics					
% male workers	920	0.58	0.03	0.49	0.65
% household head	920	0.47	0.02	0.40	0.56
% workers under 18 years of age	920	0.02	0.01	0.00	0.07
% workers under 25 years of age	920	0.17	0.03	0.10	0.26
% workers between 26–40 years of age	920	0.44	0.02	0.36	0.53
% workers between 41–50 years of age	920	0.20	0.02	0.12	0.28
% worker over 51 years of age	920	0.16	0.02	0.11	0.25

Source: Author's calculations based on the household survey GEIH.

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Appendix D

Table D1. Dynamic panel with fixed effects by cities *(with all sample)*

Variables	(1) WR	(2) H	(3) S	(4) UR	(5) IR
Labour market characteristics					
Lag of dependent variable	0.984***	0.919***	0.949***	0.422***	1.060***
	(0.023)	(0.022)	(0.028)	(0.073)	(0.030)
Skill mismatched workers	**0.058****	**0.098*****	**0.125*****	**–0.062**	**0.019**
	(0.023)	(0.028)	(0.042)	(0.127)	(0.013)
Males	0.100*	0.136**	0.084*	0.522***	–0.062
	(0.053)	(0.065)	(0.046)	(0.114)	(0.080)
Head of household	–0.007	–0.008	0.005	0.357***	–0.020
	(0.013)	(0.020)	(0.024)	(0.115)	(0.017)
Higher education	–0.013	–0.035	–0.043	0.019	–0.057*
	(0.026)	(0.034)	(0.047)	(0.181)	(0.030)
Economic activity	0.030**	0.055***	0.047**	–0.068	0.016
	(0.014)	(0.018)	(0.023)	(0.092)	(0.011)
Arellano–Bond (2) *p*-value	0.875	0.000850	0.540	0.120	0.0504
Hansen J χ^2 *p*-value	0.132	0.261	0.288	0.162	0.140
Observations	897	897	897	897	897

Notes. Standard error in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All independent variables represent proportions or means by city. Error term is cluster by cities. We use lags of dependent and independent variables as instruments.

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