Workplace Social Interaction and Wage Premium

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Abstract: Many existing studies use employment density to measure labor market agglomeration economies and find that agglomeration economies raise wages in employment clusters. We argue that social interaction is the channel through which agglomeration economies take place and are captured by workers. Using the 2000 U.S. census data and occupation attributes data, we construct variables to measure a worker's face-to-face communication, non-face-to-face communication, and overall social interaction skills. We find that social interaction skills contribute to wages, consistent with the studies on the returns to skills in urban labor markets. More importantly, we find that a worker with little social interaction skills cannot benefit from agglomeration economies and workers with higher social interaction skills benefit more from agglomeration economies. The findings are robust to many specifications and support the idea that the fundamental role of cities is to promote social interactions.

Key Words: Agglomeration; Social interaction; Wage premium
JEL Codes: J24, J31, R13, R30

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** This is a preliminary draft of an ongoing project. Comments are very welcome. Please do not quote or circulate without either author's permission.

1. Introduction

Many existing studies use employment density to measure urban labor market agglomeration economies and find significant, robust wage premia due to agglomeration（Glaeser and Mare, 2001; Wheeler, 2001; Rosenthal and Strange, 2006; Fu, 2007). The main interpretation is that workers interact with each other in workplace and such interaction generates knowledge spillovers or information exchange, leading to higher productivity. However, employment density cannot capture the actual degree of social interactions in workplace: if workers are segregated or isolated due to discrimination or lack of inter-personal communication skills, they may not gain from agglomeration economies even in a high employment density workplace.

Many empirical studies also find human capital externalities in labor market meaning that workers can learn from the concentration of high-skilled or high-human-capital workers (Moretti, 2004). Such learning process takes place also through social interactions. Again, inter-personal communication skills may also affect a worker's capacity for obtaining benefit from human capital externalities.

Few studies directly test how workplace social interaction affects labor market agglomeration economies. Bacolod, Blum, and Strange (2009) use occupation attributes to proxy for worker skills and find that the returns to people skills and cognitive skills are higher in big cities suggesting that people skills may be helpful for workers to gain from thick labor markets. Charlot and Duranton (2004) use survey data in French cities and find that workers communicate more in large and more educated cities and communication directly contributes to wages.

This paper uses occupational work context attributes to measure social interaction skills and tests how social interaction skills affect a worker's ability to reap benefit from labor market agglomeration. We assume that if a worker's occupation requires a high degree of social interaction, then the worker most probably has good social interaction skills, a premise also used in Bacolod, Blum, and Strange (2009). We add the individual social interaction skill variable to the standard wage model for testing agglomeration economies, and also interact the social interaction skill variables with workplace employment density. Using the 5% Public Use Microdata Sample (PUMS) from the 2000 U.S. Decennial Census and O*NET occupation attributes data, we find that social interaction skills contribute to wages; the traditional estimates of agglomeration economies (the coefficient of employment density) attenuates a lot and becomes insignificant; however, the coefficients of the interaction terms are positive and significant, suggesting that social interaction skills is crucial for a worker to gain benefit from concentrated employment. These findings hold for human capital externalities and for Whites and Asians but not for Blacks and Hispanics. We also find that given individual social interaction skills and employment density, a more racially segregated workplace generates less agglomeration benefit because segregation reduces opportunities for social interactions. This suggests the cross-racial difference in agglomeration economies might be explained by reduced social interaction due to segregation or discrimination against minorities.

Our paper is different from Bacolod, Blum, and Strange (2009) and Charlot and Duranton (2004) because they focus on the contributions of different types of skills to wages but not on agglomeration economies. We focus on how social interaction skills affect benefit from agglomeration economies. We also address worker sorting issue by including residential fixed effects based on the idea of Fu and Ross (2010). Our study provides empirical evidence for the argument that the primary function of cities is promoting social interactions among urban population.

The next section presents the basic econometric model and methodology. Section 3 describes the data and Section 4 reports results. Section 5 concludes.

1. Model and Methodology

We use the hedonic wage model with a set of standard individual observable characteristics and workplace agglomeration measures as in the literature. The basic idea is that if firms pay workers their marginal revenue product, higher productivity due to labor market agglomeration economies can, at least partly, be captured by nominal wage. The novelty of our study is to add a worker’s social interaction skill variable and its interaction with agglomeration variables to the wage model. The interaction term captures the role of social interaction in reaping the agglomeration benefit in labor markets. Social interaction skills are identified by work context attributes of a worker's occupation, which will be explained in detail in the next section.

The standard wage model for testing agglomeration economies is specified as follows:

$$y_{ij} = \beta X_i + \gamma_1 Z_j + \varepsilon_{ij}, \qquad (1)$$

where y_{ij} is logarithm of hourly wage of worker i in workplace *j*; X_i is a vector of standard individual observable attributes; Z_j is agglomeration measure of workplace j, usually measured by employment density; ε_{ij} generally captures the unobserved ability of a worker that could influence his wage rate. Besides, industry, occupation dummies are included.

Our model extends model (1) by including individual social interaction skill and its interaction with agglomeration variables:

$$y_{ij} = \beta X_i + \gamma_1 Z_j + \gamma_2 S_i + \gamma_3 Z_j S_i + \varepsilon_{ij}, \qquad (2)$$

where S_i measures individual social interaction skill and $Z_j S_i$ is the interaction of agglomeration variable with individual social interaction skill. If γ_3 is positive and significant, this means for a given level of employment concentration, a worker with stronger social interaction skills can receive higher wage premium. In some extended models we also include human capital externalities variable, defined by the share of college graduates in a workplace.

Two major identification issues arise in estimating equation (2). First, due to workers' sorting across workplaces, such as high ability workers sorting into highly concentrated employment clusters, it is possible that $cov(Z_i, \varepsilon_{ij}) > 0$, biasing estimate of agglomeration economies. Following Fu and Ross (2010), we use a worker's residential location to proxy for unobserved worker ability. The basic idea is that workers also sort into different residential locations based on labor market outcomes and tastes for amenities and workers with the same observable attributes and residing in the same location should have similar unobservable ability.

Second, even after we include many observable individual attributes and residential location fixed effects, it is still possible that the error term contains unobservable skills that are correlated with social interaction skills, making $cov(S_i, \varepsilon_{ij}) > 0$, biasing the estimate of γ_2 and γ_3. Specifically, the occupation categories that are included in model (2) in general are not many, say about 20. Let's call this occupation classification two-digit occupation codes. But an occupation may require hundreds of different skills and many of which can be correlated with social interaction skills but may not be captured by two-digit occupation codes. To deal with this issue, we replace two-digit occupation codes by more disaggregated occupation classifications that we call three-digit occupation codes. There are about 500 three-digit occupation codes, which should better control for detailed skill requirements. Unfortunately, these occupation codes absorb individual social interaction skills (each occupation has a requirement for social interaction skills), and we have to drop the individual social interaction skills variable S_i. When estimating model (2) including three-digit occupation codes, we adjust the standard errors by clustering at the three-digit occupation code cells. This should provide a very conservative statistical inference.

2. Data

The individual demographic data come from the 5% Public Use Microdata Sample (PUMS) from the 2000 U.S. We construct a benchmark sample including male workers of prime-age (30-59 years of age), full time (usual hours worked per week 35 or greater), working in the 33 Consolidated Metropolitan and Metropolitan Statistical areas (MSA) with at least one million residents and at least three workplace Public Use Microdata Areas (WPUMA). This benchmark sample is similar to Fu and Ross (2010) for purpose of comparison. For robustness check, we construct another sample using the same criteria but also include female workers.

The dependent variable, logarithm of wage rate, is based on a wage that is calculated by dividing an individual's 1999 labor market earnings by the product of number of weeks worked in 1999 and usual number of hours worked per week in 1999. The wage rate model includes a standard set of labor market controls including variables capturing age, race/ethnicity, educational attainment, marital status, presence of children in household, immigration status. The census data provides detailed geography information for the workers' work and residential location: workplace PUMA and residential PUMA. A residential PUMA includes at least 100,000 persons; if a place contains 200,000 persons or more, it is split into as many PUMAs as possible. A WPUMA is generally greater than a PUMA and often includes a few PUMAs. The agglomeration economies variable is measured by employment density in a WPUMA; the residential PUMA fixed effects are added to the models to control for unobserved worker ability to reduce the potential bias due to worker sorting.

The occupation attributes data come from the Occupational Information Network (O*NET). O*NET is developed under the sponsorship of the US Department of Labor/Employment and Training Administration (USDOL/ETA) through a grant to the North Carolina Employment Security Commission. It is the most important occupation information source in the U.S., providing information on more than 200 attributes for 873 occupations. Bacolod et al (2009) use the predecessor of O*NET, the Dictionary of Occupational Titles (DOT), to identify workers' skills by skill and ability requirements for each occupation, which is also a part of the occupation attributes data. They argue that, if the labor market is competitive and frictionless, skill requirements of an occupation can be a good measurement of the skill level of the workers who do that job (Roy, 1951). For instance, if an occupation requires a high degree of "face to face discussion", we can infer safely that the worker with that occupation has excellent face-to-face discussion ability or the job gives the worker more opportunity to talk to other people face to face. Although these two situations cannot be distinguished from the data, it is possible that workers taking occupations requiring frequent face-to-face discussion will strengthen their face-to-face discussion skills through working experience or learning by doing.

Following this idea, we use work context indices to proxy for workers' social interaction ability and environment. Specifically, the work context attributes of an occupation describes the required social interaction contents: face to face discussion; electronic email; letters, memos, and telephone. Each of them is given a value from 0 to 100 for every occupation[1]. To distinguish the role of face-to-face communication versus non-face-to-face communication, we construct two variables:

Face-to-face communication: the score of "face-to-face discussion" attribute of each occupation;

Non-face-to-face communication: the average value of "electronic email" and "letters, memos, and telephone" attributes of each occupation.

In addition, we calculate the average value of face-to-face communication and non-face-to-face communication and define it as *total social interaction* variable.

The 5% sample of the 2000 U.S. census data contains 475 occupation categories, which we call them 3-digit occupation categories. We merge the census data and O*NET data by the 3-digit occupation code and 457 occupations in the census data are matched.[2] Because O*NET occupation classification is more finely defined, there are some O*NET occupation codes that can be matched to the same 3-digit occupation code in the census data; in these cases we calculate the average attributes values of these occupation and match them with the same occupation code in the census data.

We also aggregate the occupations in the census data into 19 categories which we call 2-digit occupation code. In some models, we include these 2-digit occupation code dummies. Table 1 provides the summary statistics for key variables.

3. Results

4.1 *Basic results of workplace social interaction*

Table 2 presents the results from estimating the benchmark models. In panel A all models include 19 two-digit occupation code dummies, residential PUMA fixed effects,

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[1] The detailed information about work context data is in the appendix.

[2] In the census data 4 military occupations have no attributes information in the O*NET data, so they are dropped. Also 14 occupations in the census data cannot be matched to any O*NET occupations, so we replace their codes with the closest codes and match them to corresponding O*NET occupations.

and the standard errors are clustered by the workplace PUMA level. Column 1 of panel A replicates the wage-agglomeration model in Fu and Ross (2010), showing that a ten thousand per square kilometers increase in a workplace PUMA will enhance the wage about 0.9%. In column 2 we add two variables to the column 1 model: individual face-to-face communication skill and its interaction with employment density. A ten points increase in the face-to-face communication skill level is associated with a 6.4% increase in hourly wage rates, consistent with the return to people skill evidence found in Bacolod, Blum, and Strange (2009). The coefficient of the interaction term suggests that for a given employment density in a workplace, a ten point increase in face-to-face communication skill level can help the worker gain 14% increase in hourly wage rate. The most striking result is that the coefficient of employment density becomes negative and significant: the benefit of employment agglomeration disappears if a worker has zero face-to-face communication skills. This implies that while employment concentration generates external economies and raises wages, how much of the agglomeration benefit a worker can reap depends on his or her face-to-face communication skills. Columns 3 and 4 replace face-to-face communication skill variable by non-face-to-face communication skill and total social interaction skill variables, respectively, and the results are remarkably consistent.

Since an occupation may have hundreds of skill requirements, the two-digit occupation codes may not capture omitted occupation skill requirements, biasing the estimates of social interaction skill variables upward. To address this concern, we replace the two-digit occupation codes by three-digit occupation codes, but we have to drop the main effect of social interaction skill variables since they are collinear with the occupation dummies. Now the standard errors are clustered by three-digit occupation code cells, providing a more conservative statistical inference. [3] The results are shown in panel B of Table 2. The coefficients of social interaction variables interacting with

[3] We are unable to control for residential PUMA fixed effects in these models due to computation capacity of STATA software, so we include MSA fixed effects. This should not affect the results because Fu and Ross (2010) have confirmed that although residential location controls for unobserved ability well the agglomeration economies estimates are stable and robust, meaning that workers' sorting hardly biases the estimates of agglomeration economies.

employment density are still positive and significant, and slightly larger in magnitude, suggesting that the positive, significant effect of interaction terms should not come from any other unobserved occupation characteristics. These results further confirm that it is social interaction ability that help workers enjoy the agglomeration benefit.

Existing studies on testing labor market agglomeration economies focus on only agglomeration measures such as city size or employment density, and do not pay attention to social interaction environment and skills. Our findings show that only people who own good social interaction skills and work in a good social interaction environment can enjoy agglomeration economies. On the other hand, people who lack of social interaction skills can obtain little benefits from agglomeration even if working in a high employment density workplace.

3.2 *Estimate basic models by race*

Ananat, Fu, and Ross (2012) document the fact that minorities, especially blacks, benefit much less from agglomeration economies compared with whites. The interpretation is that racial-specific social network plays an important role in reaping the agglomeration benefit. We explore an alternative interpretation for the same fact. We estimate model (2) by race. Table 3 report the results for models using total social interaction variable, but results for models using either face-to-face communication or non-face-to-face communication variables are pretty similar.

Panel A of Table 3 shows that the coefficients of total social interaction skill variable are positive, significant and of similar magnitude for all workers of different races, but the coefficient of interaction term is significant only for whites. This implies that although social interaction skills contribute to wages for workers of all races, they are helpful only for whites to gain the benefit from agglomeration economies. Panel B shows a similar pattern but social interaction skills are helpful to Asians too. These results are consistent with Ananat, Fu, and Ross (2012). The underlying idea is that for people of different races with same social interaction skills working in the same workplace, there exist some forces that prevent minorities gaining from employment concentration. This could be due to racial segregation, discrimination, racial-specific social network, or other factors. Identifying all these factors is beyond the purpose of the current paper, but we can test if segregation is a reasonable explanation.

4.3 *Racial segregation effect*

We construct a workplace racial segregation index which is one minus the Herfindahl index in terms of employment by race. We add this variable to model (2) and also interact it with social interaction skill variable and employment density. Table 4 shows that our previous findings still hold: social interactions skills help a worker to capture the benefit from agglomeration economies. However, the coefficient of racial segregation interacting with social interaction skill and employment density is always negative and significant in most cases, suggesting that a more racially segregated workplace prevent workers from reaping agglomeration benefit.

4.4 *Social interaction skills and human capital externalities*

Many studies on labor market agglomeration economies also consider human capital externalities. In general, human externalities are measured by the share or the total number of workers with a college degree or above in a workplace. Most of the studies also find that human capital externalities exist (Moretti (2004) provides a good survey). We add the college share in a workplace PUMA to model (2) and also interact this variable with social interaction skill variables. Table 5 reports the results.

As expected, similar to Table 2, significant human capital externalities exist in concentrated workplace. However, for a worker to capture the benefit from human capital externalities, he or she needs to possess a good skill of social interaction: the coefficients of human capital externalities interacting with social interaction skills are positive and significant in most cases while the coefficients of college share variable attenuate much and become insignificant.

4.5 More extensions

The models can be extended in many directions to check the robustness of previous results or to test channels that prevent workers of same social interaction skills from capturing benefit from agglomeration economies differently. These extensions are being carried on now:

(1) Add same-race employment share to model (2) to check how racial specific social network affects returns to social interaction skills;

(2) A sample including female workers;

(3) A sample including all workers age between 18 to 65.

5 Conclusion

Many existing studies use employment density to measure labor market agglomeration economies and find that workers benefit from agglomeration economies in terms of wage premium in employment clusters. We argue that social interaction is the channel through which agglomeration benefit takes place and is captured by workers. Using the standard census data and occupation attributes data, we construct variables to measure a worker's face-to-face communication skill, non-face-to-face communication skill, and overall social interaction skills. We confirm that social interaction skills contribute to wages, consistent with the studies on the returns to skills in urban labor markets. More importantly, we find that a worker with little social interaction skills cannot benefit from agglomeration economies and workers with higher social interaction skills benefit more from agglomeration economies. This finding is robust to many different specifications. Our findings can shed light on understanding why minorities benefit less from agglomeration economies and understanding the fundamental role of cities that cities promote social interactions.

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Appendix

Different from Bacolod, Blum, and Strange (2009) who use skill requirements in the occupation attributes to measure workers' skills level, we consider work context of each occupation. Specifically, we consider four kinds of work context and construct variables to measure social interaction skills. We use four work context attributes from the O*NET data:

- **Face-to-Face Discussions —** How often do you have to have face-to-face discussions with individuals or teams in this job?
- **Electronic Mail —** How often do you use electronic mail in this job?
- **Letters and Memos —** How often does the job require written letters and memos?
- **Telephone —** How often do you have telephone conversations in this job?

Each work context variable is measure by a score between 0 and 100. We construct three variables to measure social interaction skills of a worker:

- ***Face-to-face communication skill*:** the values are the same as the Face-to-Face Discussions attribute.
- ***Non-face-to-face communication skill*:** the values are the average of Electronic Mail, Letters and Memos, and Telephone attributes.
- ***Total social interaction skills*:** the values are the average of face-to-face communication skill and non-face-to-face communication skill.

Table 1： Descriptive statistics

Variable Name	Mean	Standard Deviation	Min	Max
		Dependent Variable		
Average hourly wage	26.308	40.517	0.001	7466.667
		Workplace PUMA Controls		
PUMA employment density in 100,000’s/square KM	0.012	0.040	0.00004	0.219
Share of college educated workers in PUMA	0.366	0.085	0.139	0.637
		Individual Work Context (Social interaction skills)		
Face-to-face communication	89.8	7.2	39	100
Non-face-to-face communication	67.6	23.4	7	98.3
Total social interaction	78.7	14.2	28.7	99.2
		Individual Worker Controls		
Age of worker	42.7	8.0	30	59
Non-Hispanic white worker	0.778	0.416	0	1
African-American worker	0.101	0.301	0	1
Hispanic worker	0.053	0.224	0	1
Asian and Pacific Islander worker	0.063	0.242	0	1
High school degree	0.440	0.496	0	1
Associate degree	0.071	0.258	0	1
Four years college	0.225	0.418	0	1
Master degree	0.096	0.294	0	1
Degree beyond Masters	0.054	0.226	0	1
Worker single	0.259	0.438	0	1
Presence of own children in household	0.553	0.497	0	1
Born in the United States	0.803	0.397	0	1
Quality of spoken English	0.164	0.370	0	1
Sample size		830259		

Table 2: Results of social interaction and agglomeration for logarithm of hourly wage

	(1)	(2)	(3)	(4)
Independent variables		Panel A		
Employment density	0.914***	-0.392	0.478***	0.0850
	(18.74)	(-1.11)	(3.57)	(0.36)
Face to face communication *employment density		0.0144***		
		(3.60)		
Face to face communication		0.0064***		
		(49.67)		
Non-face-to-face communication *employment density			0.0056**	
			(3.05)	
Non-face-to-face communication			0.0046***	
			(67.28)	
Total social interaction *employment density				0.0098***
				(3.36)
Total social interaction				0.0074***
				(71.22)
R^2	0.299	0.302	0.306	0.306
Independent variables		Panel B		
Employment density		-1.528*	-0.0733	-0.679*
		(-2.22)	(-0.41)	(-2.02)
Face-to-face communication *employment density		0.0235**		
		(2.94)		
Non-face-to-face communication *employment density			0.0091***	
			(3.40)	
Total social interaction *employment density				0.0156***
				(3.52)
R^2		0.317	0.317	0.317

Note: Models in panel A use 2-digit occupational and residential PUMA fixed effects. The standard errors are clustered ate workplace PUMA level. Models in panel B use 3-digit occupational and metropolitan statistical area fixed effects; the standard errors are clustered at 3-digit occupation code level. Individual demographic variables are included but coefficients are not reported here. t statistics are in parentheses. "***", "**", and "*" indicate the significance at the 1%, 5%, and 10% levels, respectively. Sample size: 830,259.

Table 3: Basic results using total social interaction by race

	White	Black	Hispanic	Asian
Independent variables		Panel A		
Employment density	0.434	0.401	0.721*	-0.0975
	(1.54)	(1.50)	(2.02)	(-0.20)
Total social interaction	0.0072*	0.0009	-0.0016	0.0079
*employment density	(2.14)	(0.27)	(-0.33)	(1.30)
Total social interaction	0.0078***	0.0054***	0.0058***	0.0066***
	(65.25)	(23.32)	(17.79)	(18.29)
R^2	0.284	0.226	0.253	0.366
Sample size	645656	83639	43854	52020
Independent variables		Panel B		
Employment density	-0.0564	0.535	0.333	-1.539**
	(-0.15)	(1.61)	(0.86)	(-2.81)
Total social interaction	0.0102*	-0.0029	-0.0005	0.0221***
*employment density	(2.05)	(-0.71)	(-0.09)	(3.32)
R^2	0.296	0.234	0.249	0.366
Sample size	645656	83639	43854	52020

Note: Models in panel A use 2-digit occupational and residential PUMA fixed effects. The standard errors are clustered ate workplace PUMA level. Models in panel B use 3-digit occupational and metropolitan statistical area fixed effects; the standard errors are clustered at 3-digit occupation code level. Individual demographic variables are included but coefficients are not reported here. t statistics are in parentheses. "***", "**", and "*" indicate the significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Add race segregation to basic models

	(1)	(2)	(3)
Independent variables		Panel A	
Employment density	-0.397	0.361**	-0.0001
	(-1.08)	(2.62)	(-0.00)
Race segregation	0.321***	0.303***	0.304***
	(23.29)	(22.25)	(22.42)
Face-to-face communication	0.0064***		
	(49.67)		
Face-to-face communication	0.0309**		
*employment density	(3.25)		
Face-to-face communication	-0.0331*		
*employment density*race segregation	(-2.10)		
Non-face-to-face communication		0.0046***	
		(66.77)	
Non-face-to-face communication		0.0080	
*employment density		(0.72)	
Non-face-to-face communication		-0.0052	
*employment density*race segregation		(-0.26)	
Total social interaction			0.0074***
			(70.84)
Total social interaction			0.0218*
*employment density			(2.15)
Total social interaction			-0.0232
*employment density*race segregation			(-1.32)
R^2	0.303	0.307	0.307
Independent variables		Panel B	
Employment density	-1.693*	-0.238	-0.871*
	(-2.40)	(-1.30)	(-2.54)
Race segregation	0.147***	0.149***	0.148***
	(7.07)	(7.12)	(7.10)
Face-to-face communication	0.108***		
*employment density	(8.20)		
Face-to-face communication	-0.151***		
*employment density*race segregation	(-9.28)		
Non-face-to-face communication		0.0826***	
*employment density		(6.75)	
Non-face-to-face communication		-0.131***	
*employment density*race segregation		(-6.32)	
Total social interaction			0.0989***
*employment density			(8.45)
Total social interaction			-0.148***
*employment density*race segregation			(-8.12)
R^2	0.318	0.318	0.318

Note: Models in panel A use 2-digit occupational and residential PUMA fixed effects. The standard errors are clustered ate workplace PUMA level. Models in panel B use 3-digit occupational and metropolitan statistical area fixed effects; the standard errors are clustered at 3-digit occupation code level. Individual demographic variables are included but coefficients are not reported here. t statistics are in parentheses. "***", "**", and "*" indicate the significance at the 1%, 5%, and 10% levels, respectively. Sample size: 830,259.

Table 5: Add college share to basic models

	(1)	(2)	(3)	(4)
Independent variables		Panel A		
Employment density	0.658***	-0.455	0.421**	0.0850
	(11.09)	(-1.18)	(2.87)	(0.36)
College share	0.315***	-0.0674	-0.00001	-0.229*
	(12.63)	(-0.45)	(-0.00)	(-2.47)
Face-to-face communication		0.0122**		
*employment density		(2.78)		
Face-to-face communication		0.0043**		
*college share		(2.65)		
Face-to-face communication		0.0049***		
		(8.51)		
Non-face-to-face communication			0.0029	
*employment density			(1.42)	
Non-face-to-face communication			0.0045***	
*college share			(6.49)	
Non-face-to-face communication			0.0030***	
			(12.91)	
Total social interaction				0.0057
*employment density				(1.77)
Total social interaction				0.0068***
*college share				(6.07)
Total social interaction				0.0050***
				(13.18)
R^2	0.299	0.302	0.306	0.307

Independent variables		Panel B	
Employment density	-1.678**	-0.0733	-0.679*
	(-2.22)	(-0.41)	(-2.02)
College share	0.0863	0.211***	0.0101
	(0.28)	(3.31)	(0.07)
Face-to-face communication	0.0214**		
*employment density	(2.83)		
Face-to-face communication	0.0042		
*college share	(1.18)		
Non-face-to-face communication		0.0073**	
*employment density		(2.66)	
Non-face-to-face communication		0.0039***	
*college share		(3.45)	
Total social interaction			0.0128**
*employment density			(2.85)
Total social interaction			0.0059**
*college share			(3.03)
R^2	0.319	0.319	0.319

Note: Models in panel A use 2-digit occupational and residential PUMA fixed effects. The standard errors are clustered ate workplace PUMA level. Models in panel B use 3-digit occupational and metropolitan statistical area fixed effects; the standard errors are clustered at 3-digit occupation code level. Individual demographic variables are included but coefficients are not reported here. t statistics are in parentheses. "***", "**", and "*" indicate the significance at the 1%, 5%, and 10% levels, respectively. Sample size: 830,259.