Federal Reserve Bank of New York
Staff Reports

Labor Market Pooling and Occupational Agglomeration

Todd M. Gabe
Jaison R. Abel

Staff Report no. 393
September 2009
Revised January 2010

This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in the paper are those of the authors and are not necessarily reflective of views at the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.

Labor Market Pooling and Occupational Agglomeration
Todd M. Gabe and Jaison R. Abel
Federal Reserve Bank of New York Staff Reports, no. 392
September 2009; revised January 2010
JEL classification: R12, J24, R20

Abstract

This paper examines the micro-foundations of occupational agglomeration in U.S. metropolitan areas, with an emphasis on labor market pooling. Controlling for a wide range of occupational attributes, including proxies for the use of specialized machinery and for the importance of knowledge spillovers, we find that jobs characterized by a unique knowledge base exhibit higher levels of geographic concentration than do occupations with generic knowledge requirements. Further, by analyzing co-agglomeration patterns, we find that occupations with similar knowledge requirements tend to co-agglomerate. Both results provide new evidence on the importance of labor market pooling as a determinant of occupational agglomeration.

Key words: agglomeration, occupations, labor market pooling, knowledge

---

Gabe: University of Maine (e-mail: todd.gabe@umit.maine.edu). Abel: Federal Reserve Bank of New York (e-mail: jaison.abel@ny.frb.org). The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

I. INTRODUCTION

Alfred Marshall's ideas provide a conceptual foundation for contemporary research on the determinants of agglomeration: labor market pooling, sharing of specialized inputs, and knowledge spillovers.[1] One important aspect of labor market pooling is that a high agglomeration of activity provides workers and businesses with a wide range of options if they possess or require a unique skill set. In their study of co-agglomeration patterns, Ellison, Glaeser and Kerr (2009) found that industries employing the same types of workers tend to co-agglomerate. This behavior is advantageous to workers and firms: people can move among employers without retooling and businesses have access to a deep pool of labor with the skills they need.

This paper examines the micro-foundations of occupational agglomeration in U.S. metropolitan areas. Here, we emphasize the importance of labor market pooling as measured by the extent to which workers possess a specialized knowledge base covering a wide range of topics. People in jobs with generic knowledge requirements are not expected to benefit from labor market pooling, whereas individuals in occupations that need a specialized base of knowledge are apt to seek out a place with a high agglomeration of activity. With respect to co-agglomeration, we expect occupations with similar knowledge profiles to co-locate. Such behavior facilitates movement among jobs with similar types of knowledge and helps to ensure Marshall's (1920) "constant market for skill."

Our analysis of the geographic concentration of occupations provides a new way to look at the forces of agglomeration. Industry-centric studies focus on where similar

---

[1] For surveys of the literature on agglomeration, see Duranton and Puga (2004) and Rosenthal and Strange (2004).

types of goods and services are made, since sectors are assigned based on a firm's primary output. In contrast, recent occupational-based approaches to urban and regional analysis emphasize what people do in their jobs (Feser 2003; Markusen 2004; Florida, Mellander and Stolarick 2008; Gabe 2009; Scott 2009; Bacolod, Blum and Strange 2009a, 2009b). For example, Markusen (2004, p. 254) suggests the use of occupational-level data to examine the "skills and activities of those in a particular neighborhood." Here, we use occupations to understand the knowledge required to perform a job, as well as a worker's use of specialized equipment and the importance of keeping current with new information and trends.

For at least two of Marshall's (1920) micro-foundations of agglomeration, the benefits of a geographic concentration of activity seem to be more relevant for occupations (i.e., tasks and activities people perform in their jobs) than industries (i.e., goods and services provided). Agglomeration facilitates knowledge spillovers because it allows individuals to share ideas and tacit knowledge (Kloosterman 2008; Ibrahim, Fallah and Reilly 2009). A computer programmer, for example, presumably benefits more from proximity to others involved in similar day-to-day activities (e.g., interacting with computers, using technology) than he or she gains from working next to others in the same industry (e.g., a software company's receptionist, human resources specialist, or chief executive).

Likewise, the basic idea behind labor market pooling—that agglomeration provides a thick labor market for those who possess or require a particular skill set—seems to apply more readily to occupations than industries. In an analysis of industry agglomeration, Rosenthal and Strange (2001, p. 205) suggest that labor market pooling is the most problematic of the Marshallian micro-foundations to measure because "it is difficult to identify industry characteristics that are related to the specialization of the industry's labor force."[2] This is not the case with occupations. Some jobs require a very specific knowledge and skill set that is specialized to the task at hand, while other occupations call for a more generic set of knowledge and skills.

II. AGGLOMERATION OF U.S. OCCUPATIONS

Following Krugman (1991) and Audretsch and Feldman (1996), we begin our analysis using locational Gini coefficients to measure occupational agglomeration across U.S. metropolitan areas. The locational Gini coefficient (*LGINI*) for U.S. Census occupations, indexed by k, is calculated as (Kim, Barkley and Henry 2000):

(1) $LGINI_k = \Delta / 4\, u,$

where $\Delta = \{1 / [n\,(n\text{-}1)]\} \sum_{i=1}^{n} \sum_{j=1}^{n} | x_i - x_j |$

$i, j =$ U.S. metropolitan areas ($i \neq j$)

$u =$ mean of x_i

$x_{i(j)} =$ (metro area i's (j's) share of employment in k / metro area i's (j's) share of total employment)

and, $n = 324$, the number of U.S. metropolitan areas included in the analysis.

Locational Gini values close to zero suggest that employment in the occupation is widely dispersed across U.S. metropolitan areas and spread out in a manner similar to the distribution of overall employment. Values close to 0.5 suggest that workers in the

[2] Rosenthal and Strange (2001) use three measures (e.g., net productivity, an indicator of "brains to brawn," and the percentage of workers with advanced degrees) as proxies for the importance of labor market pooling. Overman and Puga (2009) point out the limitations of these indicators and, instead, focus on the effects of idiosyncratic firm-level employment shocks on industry agglomeration. Their results suggest establishments that expand while the overall industry declines (or vice versa) benefit more from agglomeration than plants in sectors with homogeneous employment shocks.

occupation are geographically concentrated in a single metropolitan area, or a very few places.

A limitation of the locational Gini, when studying industries, is that it could suggest high levels of concentration in cases where sectors comprised of a few large companies locate in a dispersed, random pattern (Ellison and Glaeser 1997). The Ellison-Glaeser concentration measure overcomes this limitation by incorporating information about the size distribution of firms in the industry (i.e., the Herfindahl index). In the case of occupations, information needed to calculate Herfindahl indices—namely, firm-level employment data—is not readily available. Thus, as an alternative measure of occupational agglomeration, we propose a modified version of the Ellison-Glaeser index that is based on the distribution of workers in an occupation across major industrial sectors, relative to total occupational employment, instead of the Herfindahl index. Our modified Ellison-Glaeser index (*INDEX*) for U.S. occupations is calculated as:

$$(2) \qquad INDEX_k = [G - (1 - \sum_{i=1}^{n} t_i^2)\, I] \,/\, [(1 - \sum_{i=1}^{n} t_i^2)\,(1 - I)]$$

where, $G = \sum_{i=1}^{n} (s_i - t_i)^2$

$I = \sum_{j=1}^{m} y_j / e_k$

t_i = metro area's share of total employment

s_i = metro area's share of occupational employment

y_j = industry's share of occupational employment

e_k = total occupational employment in U.S. metropolitan areas

and, $m = 19$, the number of major NAICS industrial categories.

The expression G is a measure of an occupation's geographic concentration, adjusted to account for differences in total employment across U.S. metropolitan areas, represented by $(1 - \sum_{i=1}^{n} t_i^2)$, as well as the distribution of occupational employment across major NAICS industrial sectors, represented by $I = \sum_{j=1}^{m} y_j / e_k$. Our modified version of the Ellison-Glaeser concentration index is constructed such that occupations present in only one (or a few) major industrial categories have lower values than occupations that are more evenly spread across major NAICS sectors. Likewise, occupations with smaller numbers of workers exhibit lower concentration index values than those that are more abundant in U.S. metropolitan areas.

The original Ellison-Glaeser index, as an alternative to measures such as the locational Gini, is based on the logic that industries with an uneven size distribution of plants (i.e., large Herfindahl indices) have artificially high levels of geographic concentration. Thus, the Ellison-Glaeser measure downwardly adjusts the level of concentration in cases where industries are dominated by a few large plants.[3] Our agglomeration measure is based on the idea that occupations with an uneven distribution of employment across industrial sectors, or a low number of workers overall, have overstated concentration levels. Thus, as noted previously, our modified Ellison-Glaeser measure adjusts the occupational concentration index value using the expression I, which would have a maximum value of 1.0 in the extreme case where an occupation is made up

3 The Ellison and Glaeser (1997, p. 890) measure is constructed such that positive index values, found in 446 of 459 (97 percent) 4-digit SIC manufacturing industries, indicate that geographic concentration is higher than would be expected if plants had randomly chosen locations by merely "throwing darts at a map." The sign of our modified occupational agglomeration index, which exceeds zero in all cases, has no such interpretation.

of one worker. The Herfindahl index, used in the Ellison-Glaeser industry concentration measure, would have a maximum value of 1.0 in the extreme case where an industry consists of a single plant.

Table 1 presents information on the average agglomeration of U.S. occupations, summarized by major Standard Occupational Classification (SOC) category. Agglomeration figures are based on an occupation's location across 324 U.S. metropolitan areas, included in the Special EEO Tabulation of the 2000 U.S. Census. Information on the share of occupational employment by major NAICS industrial category, used to examine the distribution of employment across industrial sectors, is from the one-percent sample of the 2000 U.S. Census (Ruggles et al. 2008). Using either measure of agglomeration, we find that the most geographically concentrated jobs are in the broad categories of Farming, Fishing, and Forestry Occupations; and Life, Physical, and Social Science Occupations. Other broad categories that exhibit high average levels of agglomeration include Computer and Mathematical Occupations (third highest ranking based on locational Gini, sixth highest ranking based on concentration index); Arts, Design, Entertainment, Sports, and Media Occupations (third highest ranking based on concentration index, seventh highest ranking based on locational Gini); and Production Occupations (fourth highest ranking based on locational Gini, fifth highest ranking based on concentration index).

We ranked the average scores for the broad occupational categories from the most to least geographically concentrated and found that these rankings exhibit a high correlation (r = 0.897; Spearman Rank Correlation) between the two measures of agglomeration. Similarly, the correlation between the actual locational Gini coefficients and agglomeration index values shown in Table 1 is quite high (r = 0.903). Using information on the 468 individual occupational categories that underlie the aggregate figures presented in Table 1, we find a lower—although still positive—correlation (r = 0.512) between the two measures of occupational agglomeration.

Tables 2a and 2b show the twenty most-agglomerated U.S. occupations based on the locational Gini coefficients and concentration index values, respectively. Ten occupations appear in the top twenty lists as determined by both measures of agglomeration. Jobs that involve aspects of textile manufacturing (e.g., SOC 51-6064, SOC 51-6061, and SOC 51-6063) exhibit high levels of geographic concentration, similar to the ranking of textiles among the most agglomerated manufacturing industries reported by Krugman (1991), Ellison and Glaeser (1997), and Duranton and Overman (2005). Other occupations that are highly geographically concentrated as ranked by both agglomeration measures include gaming workers (e.g., SOC 43-3041 and SOC 39-3010), aircraft assemblers (e.g., SOC 51-2011) and specialized engineers (e.g., SOC 17-2121 and SOC 17-21XX).

It is interesting to note that the two occupations with the high concentration index values—Economists and Actors—are not included in the list of the most geographically concentrated jobs based on the locational Gini coefficients. Two other entertainment-related occupations—Television, Video, and Motion Picture Camera Operators and Editors; and Producers and Directors—are also among the most agglomerated occupations based on the concentration indices (but not the locational Gini coefficients). On the other hand, several marine-related occupations (e.g., SOC 53-5031, SOC 53-5011 and SOC 45-3000) are included in the top twenty list according to locational Gini coefficients, but are not counted among the most agglomerated based on the concentration indices.

Tables 3a and 3b show the twenty least-agglomerated U.S. occupations. Ten occupations appear on the lists based on the locational Gini coefficients and concentration indices. These include retail salespersons, cashiers, secretaries, retail managers and school teachers. Other jobs that appear to be widely dispersed across U.S. metropolitan areas include several clerical- (e.g., SOC 43-9061, SOC 43-4071, SOC 43-9199 and SOC 43-4071), healthcare- (e.g., SOC 29-1111 and SOC 31-909X) and maintenance-related (e.g., SOC 49-3023 and SOC 49-2011) occupations.

III. WHY PEOPLE AGGLOMERATE

Equation 3 shows the regression model that provides a foundation for our empirical analysis of the determinants of occupational agglomeration.

$$\text{(3)} \quad \textit{Occupational Agglomeration} = \beta_0 + \beta_1\, \textit{Specialized Knowledge} + \beta_2\, \textit{Specialized Equipment} + \beta_3\, \textit{Update Knowledge} + \beta_4\, \textit{Interaction with Public} + \beta_5\, \textit{Average Establishment Size} + \beta_6\, \textit{Agriculture} + \beta_7\, \textit{Mining}$$

This is the same general approach used by Rosenthal and Strange (2001) to examine the agglomeration of manufacturing industries. Summary statistics of the variables used in the empirical analysis are presented in Table 4.

As described in the previous section, *Occupational Agglomeration* is measured using locational Gini coefficients (*LGINI*) and concentration index values (*INDEX*). The explanatory variable of key interest, used as a proxy for the importance of labor market pooling, is the extent to which an occupation's knowledge profile differs from the average U.S. job. This variable, *Specialized Knowledge*, is constructed using information from the U.S. Department of Labor's Occupational Information Network (O*NET) on the importance and level of knowledge required in 33 subjects (see Table 5).[4] The O*NET, based on employee surveys and input from professional occupational analysts, asks respondents to rate on a scale of 1 to 5 the importance of these knowledge areas to a person's job. For topics that are rated as at least "somewhat important" (i.e., a score of 2 or higher), the respondent is asked to rate on a scale of 1 to 7 the level of knowledge required.

For each of the 33 areas, we use information on the importance and level to construct, as the product of the two, a knowledge index (Feser 2003). With these indices for 468 occupations and 2000 U.S Census data on occupational employment, we calculated the (weighted) average U.S. occupation's knowledge requirement in each of the 33 topics.[5] To measure the extent to which an occupation's knowledge profile differs from the average U.S. job, we constructed the *Specialized Knowledge* variable as:

$$(4) \qquad \textit{Specialized Knowledge}_k = \sum_{z=1}^{33} (KI_{k,z} - KI_{ave,z})^2$$

where the subscript z indicates the knowledge area, KI is the knowledge index, the subscript k indicates the occupation, and the subscript ave indicates the average U.S. occupation. Low values of this variable indicate that the occupation's knowledge profile is similar to the average U.S. job, while high values suggest that the occupation requires specialized knowledge.

---

4 See Peterson et al. (2001) for a detailed discussion of O*NET.

5 Occupational employment information is from the Special Equal Employment Opportunity (EEO) Tabulation of the 2000 U.S. Census. It includes employment figures for 471 occupations, three of which were removed from our analysis due to incomplete data.

Along with the importance of labor market pooling, Marshall (1920) suggested that agglomeration facilitates the sharing of intermediate inputs and the flow of knowledge spillovers. Specialized machinery and equipment, especially items that exhibit increasing returns to scale in their use, are examples of inputs that workers and firms may agglomerate around. We use the variable *Specialized Equipment* as a proxy for the use of specialized machinery and equipment. It is constructed as an index, similar to the knowledge variables, using information from O*NET on the importance and level of an occupational activity titled “Operating Vehicles, Mechanized Devices, or Equipment.”

Of Marshall’s three micro-foundations of agglomeration, knowledge spillovers have received the most attention in the literature (Jaffe, Trajtenberg and Henderson 1993; Audretsch and Feldman 1996; Kloosterman 2008; Ibrahim, Fallah and Reilly 2009). The idea here is that agglomeration allows workers to learn job-specific tasks and stay current with new developments as if they were “in the air.” The variable *Update Knowledge* is used as a proxy for the importance of knowledge spillovers. Constructed as an index using information from O*NET on the importance and level of an occupational activity titled “Updating and Using Relevant Information,” this variable captures the idea that knowledge spillovers are more important in occupations that require workers to keep up with current information and trends.

In addition to the variable *Update Knowledge*, we investigate (in separate regression models) the effects of two other proxies for the importance of knowledge spillovers (not shown in equation 3). The first variable, *Creativity*, is an O*NET occupational-based activity (calculated as an index, similar to the other variables) that measures the extent to which a job requires creative thinking (McGranahan and Wojan

2007). Florida's (2002, 2008) extensive work on the topic suggests that creative workers seek out places where they can collaborate and share ideas with others. The second variable, *Years of Education*, is the average number of years of education for those in an occupation, calculated using data from the one-percent sample of the 2000 U.S. Census. Although Rosenthal and Strange (2001) used the share of industry employment with advanced degrees as proxies for labor market pooling, Kolko (2009) suggests that educational attainment is also a suitable proxy for the importance of knowledge spillovers.

The explanatory variable *Interaction with Public* represents a sort of transport cost that is expected to affect agglomeration. Kolko (2009), in an analysis of the agglomeration of service industries, suggests that transport costs dictate that low-value services delivered through face-to-face contact should be geographically dispersed. Moreover, jobs characterized by heavy interaction with the general public typically require face-to-face contact, which limits an occupation's tendency to agglomerate (Storper and Venables 2004). We constructed the *Interaction with Public* variable as an index using information from O*NET on the importance and level of an occupational activity titled "Performing for or Working Directly with the Public."

To account for the importance of establishment-level economies of scale, the regression model includes the variable *Average Establishment Size*. It is constructed by matching occupations to industries using the one-percent sample of the 2000 U.S. Census (Ruggles et al. 2008). After determining the sectors that correspond to each of the 468 occupations, we calculated an average employment size using data from County Business Patterns. The final two explanatory variables, *Agriculture* and *Mining*, were also constructed using information from the one-percent sample of the 2000 U.S. Census. These variables, which measure the percentage of occupational employment in agricultural- or mining-related industries, account for the importance of natural advantages and raw material use in the agglomeration process (Kim 1995; Ellison and Glaeser 1999).

IV. REGRESSION RESULTS

Table 6 presents OLS regression results on the determinants of occupational agglomeration. The first three models examine locational Gini coefficients (*LGINI*) as the measure of geographic concentration, but differ in terms of the variable used to control for the importance of knowledge spillovers (e.g., *Update Knowledge*, *Creativity* or *Years of Education*). The final three sets of results focus on agglomeration indices (*INDEX*) to represent occupational agglomeration.

Across all six models, the results provide strong evidence on the importance of labor market pooling to occupational agglomeration. Since the dependent variable and *Specialized Knowledge* both enter into the regressions as natural logs, the estimated coefficients can be interpreted as elasticities. They suggest that a doubling of the *Specialized Knowledge* variable, roughly equivalent to a one and one-half standard deviation increase, is associated with over a 10-percent increase in the locational Gini coefficient. A doubling of this proxy for the importance of labor market pooling is associated with about a 40-percent increase in the agglomeration index.

Other regression results shown in Table 6 are generally consistent with expectations based on Marshall's ideas and other studies of industry agglomeration. Two of the three variables used to measure the importance of knowledge spillovers—*Update*

Knowledge and *Creativity*—have a positive and significant effect on occupational agglomeration in at least one of the two regression models. These results suggest occupations that require workers to keep current with new information, and jobs that involve creative thinking are associated with high levels of geographic concentration. Empirical results also show that jobs requiring the use of machinery and equipment (*Specialized Equipment*), as well as occupations steeped in agriculture- and mining-related industries (*Agriculture* and *Mining*) exhibit a high level of agglomeration. On the other hand, jobs that involve heavy interaction with the public (*Interaction with Public*) tend to be more geographically dispersed.

With respect to variable *Average Establishment Size*, our results suggest that establishment-level internal economies of scale do not appear to influence the geographic concentration of occupations. To explain this somewhat counterintuitive finding, we note that many of the jobs characterized by the largest average employment size fall in the major SOC categories of Healthcare Practitioners and Technical Occupations (SOC 29-0000) and Healthcare Support Occupations (SOC 31-0000). Hospitals—which employ a large proportion of workers in these occupations—tend to be large in size and geographically dispersed across metropolitan areas.

V. CO-AGGLOMERATION OF OCCUPATIONS

Another implication of labor market pooling is that workers are likely to seek out places where they can easily move among jobs that use the same general types of knowledge. This would result in a high co-agglomeration of occupations with similar knowledge profiles (or, conversely, a low co-agglomeration of occupations that require different types of knowledge). Following Ellison and Glaeser (1997) and Ellison, Glaeser and Kerr (2009), we constructed a co-agglomeration index for occupations *k* and *l* as:

$$(5) \qquad \textit{Occupational Co-Agglomeration}_{k,l} = \Omega \,/\, (1 - \sum_{i=1}^{n} t_n^2)$$

where, $\Omega = \sum_{i=1}^{n} (s_{i,k} - t_i)\,(s_{i,l} - t_i)$

i = U.S. metropolitan areas (n=324)

$s_{k(l)}$ = metro area's share of employment in occupation k (l)

t = metro area's share of total employment.

Table 7 shows the occupational pairs with the highest levels of co-agglomeration in U.S. metropolitan areas.[6] Occupations that are involved in aspects of casino gaming (e.g., Gaming Service and Cage Workers) and film / television (e.g., Actors, Editors, Agents and Directors) tend to co-agglomerate, as well as jobs related to textiles (e.g., Knitting, Weaving and Machine Operators) and the dismal science (e.g., Economists, Social Scientists and Budget Analysts). Similarly, in their analysis of the co-location of manufacturing industries, Ellison, Glaeser and Kerr (2009) report several textile-related sectors (e.g., Yarn and Thread Mills, Knitting Mills, Textile Finishing) at the top of the list of the highest pair-wise agglomerations.

We measured the dissimilarity of knowledge profiles for occupations *k* and *l* as:

$$(6) \qquad \textit{Dissimilar Knowledge}_{k,l} = \sum_{z=1}^{33} (KI_{k,z} - KI_{l,z})^2$$

6 Consistent with the findings of Ellison, Glaeser and Kerr (2009), the mean value of the co-agglomeration index we calculated is "approximately zero."

where the subscript z indicates the knowledge area and KI is the knowledge index. Low values of this variable suggest that the knowledge profiles of the two occupations are similar, whereas high values indicate that the jobs are quite distinct in terms of knowledge requirements. Along with the (dis)similarity of knowledge requirements, the (dis)similarity of goods and services that workers produce is expected to affect occupational co-agglomeration patterns. Ellison, Glaeser and Kerr (2009) found that industries employing workers in the same occupations tend to co-agglomerate. Here, as it appears to be the case in Table 7, we expect occupations involved in the same industries to co-agglomerate as well. To measure the extent to which occupations k and l contribute to (dis)similar types of goods and services, we constructed the *Dissimilar Output* variable as:

$$(7) \qquad \textit{Dissimilar Output}_{\mathrm{k,l}} = \sum_{z=1}^{19} |IS_{k,z} - IS_{l,z}|$$

where IS represents the occupation's share of employment by industry, and z is a subscript indicating the major NAICS industrial category.[7] Low values of this variable, constructed using information from the one-percent sample of the 2000 U.S. Census, suggest that workers in the two occupations make similar goods and services. On the other hand, high values of *Dissimilar Output* indicate that workers in the occupations contribute to different sectors.

Table 8 presents OLS regression results on the relationship between the co-agglomeration of occupations and the extent to which the knowledge requirements are similar between the two selected jobs. The dependent variable is the Ellison-Glaeser

[7] Krugman (1991) used a similar variable to measure the divergence of industrial structures across regions.

(1997) index of co-agglomeration, calculated for 109,278 occupation pairs (using the same 468 occupations analyzed in Table 6). Logs are not used, as in the previous analysis, because the Ellison-Glaeser co-agglomeration index can have non-positive values. Instead, we normalize the variables to have a mean of zero and a standard deviation of one, consistent with the approach used by Ellison, Glaeser and Kerr (2009).

The two regression models are the same, with the exception of a set of 22 dummy variables that indicate whether or not the two occupations are part of the same major SOC category. The r-squared values shown in Table 8 are close to those reported by Ellison, Glaeser and Kerr (2009). In univariate regressions that examine the Ellison-Glaeser co-agglomeration index applied to manufacturing industries, the model goodness of fit ranges from 0.005 to 0.049 in that study. In multivariate models (with between three and five explanatory variables), the r-squared values reported by Ellison, Glaeser and Kerr (2009) range from 0.059 to 0.110.

Our empirical results from both models reveal a negative relationship between the co-agglomeration of occupations and the variable *Dissimilar Knowledge*. Specifically, a one-standard deviation increase in the value of *Dissimilar Knowledge* is associated with about a 0.10-standard deviation decrease in the co-agglomeration index. This suggests that the co-agglomeration measure decreases as the difference in knowledge profiles among two occupations increases. Put another way, people in jobs with similar knowledge requirements tend to co-agglomerate. Results also show a negative relationship between the co-agglomeration index and the variable *Dissimilar Output*. A one-standard deviation increase in *Disimilar Output* is associated with about a 0.13- to 0.16-standard deviation decrease in the co-agglomeration measure. This indicates, as expected, that people in occupations involved in similar industries have higher levels of co-agglomeration than those in jobs that contribute to different sectors.

VI. CONCLUSIONS

Researchers have long been interested in the causes of agglomeration. Alfred Marshall's (1920, p. 225) ideas about labor market pooling, which suggest employers locate around "workers with the skills which they require" and workers seek out places "where there are many employers who need such skill as theirs," emphasize the strong connection between agglomeration and the specialization of work-related tasks. Focusing on the knowledge requirements of a wide variety of jobs, this paper presents new evidence on the importance of labor market pooling as a determinant of occupational agglomeration. Specifically, our findings suggest jobs that draw from a specialized knowledge base are geographically concentrated, and occupations with similar knowledge requirements tend to co-agglomerate.

This first key result—that specialized knowledge requirements lead to an increase in agglomeration—gets at the heart of Marshall's argument about the benefits of labor market pooling. Such behavior is advantageous if firms need and workers possess a specialized knowledge base, whereas agglomeration is less important in occupations with generic knowledge requirements where suitable workers and jobs are easy to find. Our second key result—that co-agglomeration patterns are enhanced by the similarity of knowledge requirements among two jobs—also suggests that occupational agglomeration can help ensure Marshall's (1920) "constant market for skill."

A limitation of our analysis of occupational co-agglomeration is that the negative relationship found between the Ellison-Glaeser co-agglomeration index and the similarity of knowledge requirements is consistent with our explanation related to labor market pooling (as described previously), but also lends support for the importance of knowledge spillovers. On the one hand, a person might seek out a place where jobs are available that require similar types of knowledge as a way to minimize the prospects of being out of work (i.e., a thick labor market argument). However, it is also plausible that a person would locate in such a place to collaborate and share ideas with others that possess similar types of knowledge (i.e., a knowledge spillover argument).

The availability of cross-industry information allowed Ellison, Glaeser and Kerr (2009) to construct different proxies for the importance of labor market pooling (e.g., "the extent to which different industries hire the same occupations") and knowledge spillovers (e.g., measures of technology flows among industries) as determinants of industry co-agglomeration. In our analysis of occupations, however, information on the extent to which knowledge created in a particular occupation is used by individuals in other jobs is not readily available. This inability to distinguish between labor market pooling and knowledge spillovers, which is of less concern in our analysis of occupational agglomeration because we use three proxies to measure the importance of knowledge spillovers, is hardly new to the literature on agglomeration. As noted previously, Rosenthal and Strange (2001) used data related to formal education (e.g., share of industry workers with a college degree) as a proxy for the importance of labor market pooling, while Kolko (2009) suggests that education-based variables are equally well suited to represent the importance of knowledge spillovers.

Despite this caveat, the paper represents what we believe to be one of the first attempts to examine the agglomeration and co-agglomeration of occupations. As noted throughout, numerous studies have looked at both the causes and consequences of industry agglomeration. Thus, we have a developed a pretty good understanding about why similar goods and services are produced within a close geographic proximity, and what this type of agglomeration means for regional economic growth. What has been missing is an empirical analysis of the agglomeration patterns of workers involved in similar job-related tasks and activities. Our work on this topic has helped to illuminate the importance of labor market pooling as a key determinant of agglomeration, which has been an illusive task in many past studies focusing on industries.

REFERENCES

Audretsch, David and Maryann Feldman. 1996. "R&D Spillovers and the Geography of Innovation and Production," *American Economic Review*, 86, 630-640.

Bacolod, Marigee, Bernardo Blum, and William Strange. 2009a. "Skills in the City," *Journal of Urban Economics*, 65, 136-153.

Bacolod, Marigee, Bernardo Blum, and William Strange. 2009b. "Urban Interactions: Soft Skills vs. Specialization," *Journal of Economic Geography*, 9, 227-262.

Duranton, Gilles and Henry Overman. 2005. "Testing for Localization Using Micro-Geographic Data," *Review of Economic Studies*, 72, 1077-1106.

Duranton, Gilles and Diego Puga. 2004. "Micro-Foundations of Urban Agglomeration Economies," Chapter 48 in Henderson, J.V., Thisse, J.F. (eds.), *Handbook of Regional and Urban Economics*, Vol. 4, Amsterdam: Elsevier/North-Holland, pp. 2063-2117.

Ellison, Glenn and Edward Glaeser. 1997. "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach," *Journal of Political Economy*, 105, 889-927.

Ellison, Glenn and Edward Glaeser. 1999. "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration," *American Economic Review*, 89, 311-316.

Ellison, Glenn, Edward Glaeser, and William Kerr. 2009. "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns," *American Economic Review*, forthcoming.

Feser, Edward. 2003. "What Regions Do Rather than Make: A Proposed Set of Knowledge-Based Occupation Clusters," *Urban Studies*, 40, 1937-1958.

Florida, Richard. 2002. *The Rise of the Creative Class*, New York: Basic Books.

Florida, Richard. 2008. *Who's Your City?* New York: Basic Books.

Gabe, Todd. 2009. "Knowledge and Earnings," *Journal of Regional Science*, 49, 439-457.

Ibrahim, Sherwat, M. Hosein Fallah, and Richard Reilly. 2009. "Localized Sources of Knowledge and the Effect of Knowledge Spillovers: An Empirical Study of Inventors in the Telecommunications Industry," *Journal of Economic Geography*, 9, 405-431.

Jaffe, Adam, Manuel Trajtenberg, and Rebecca Henderson. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *Quarterly Journal of Economics*, 108, 577-598.

Kim, Sukkoo. 1995. "Expansion of Markets and the Geographic Distribution of Economic Activities: The Trends in U.S. Regional Manufacturing Structure, 1860-1987," *Quarterly Journal of Economics*, 110, 881-908.

Kim, Yunsoo, David Barkley, and Mark Henry. 2000. "Industry Characteristics Linked to Establishment Concentrations in Nonmetropolitan Areas," *Journal of Regional Science*, 40, 231-259.

Kloosterman, Robert. 2008. "Walls and Bridges: Knowledge Spillover between 'Superdutch' Architectural Firms," *Journal of Economic Geography*, 8, 545-563.

Kolko, Jed. 2009. "Urbanization, Agglomeration, and Co-Agglomeration of Service Industries," Chapter 5 in Glaeser, E.L. (ed.), *The Economics of Agglomeration*, Chicago: University of Chicago Press for the NBER, forthcoming.

Krugman, Paul. 1991. *Geography and Trade*, Cambridge, MA: The MIT Press.

Marshall, Alfred. 1920. *Principles of Economics*, London: Macmillan.

Markusen, Ann. 2004. "Targeting Occupations in Regional and Community Economic Development," *Journal of the American Planning Association*, 70, 253-268.

McGranahan, David and Timothy Wojan. 2007. "Recasting the Creative Class to Examine Growth Processes in Rural and Urban Counties," *Regional Studies*, 41, 197-216.

Overman, Henry and Diego Puga. 2009. "Labour Pooling as a Source of Agglomeration: An Empirical Investigation," Chapter 4 in Glaeser, E.L. (ed.), *The Economics of Agglomeration*, Chicago: University of Chicago Press for the NBER, forthcoming.

Peterson, Norman, Michael Mumford, Walter Borman, Richard Jeanneret, Edwin Fleishman, Kerry Levin, Michael Campion, Melinda Mayfield, Frederick Morgeson, Kenneth Pearlman, Marilyn Gowing, Anita Lancaster, Marilyn Silver, and Donna Dye. 2001. “Understanding Work Using the Occupational Information Network (O*NET): Implications for Practice and Research,” *Personnel Psychology*, 54, 451-492.

Rosenthal, Stuart and William Strange. 2001. “The Determinants of Agglomeration,” *Journal of Urban Economics*, 50, 191-229.

Rosenthal, Stuart and William Strange. 2004. “Evidence on the Nature and Sources of Agglomeration Economies,” Chapter 49 in Henderson, J.V., Thisse, J.F. (eds.), *Handbook of Regional and Urban Economics*, Vol. 4, Amsterdam: Elsevier/North-Holland, pp. 2119-2171.

Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. 2008. *Integrated Public Use Microdata Series: Version 4.0* [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].

Scott, Allen. 2009. “Human Capital Resources and Requirements across the Metropolitan Hierarchy of the USA,” *Journal of Economic Geography*, 9, 207-226.

Storper, Michael and Anthony Venables. 2004. “Buzz: Face-to-Face Contact and the Urban Economy,” *Journal of Economic Geography*, 4, 351-370.

Table 1. Agglomeration of Major Occupational Categories

SOC Category	Description	Average *LGINI*	Average *INDEX*
11-0000	Management Occupations	0.1045	0.0013
13-0000	Business and Financial Operations Occupations	0.1187	0.0018
15-0000	Computer and Mathematical Occupations	0.1937	0.0043
17-0000	Architecture and Engineering Occupations	0.1731	0.0067
19-0000	Life, Physical, and Social Science Occupations	0.2464	0.0092
21-0000	Community and Social Services Occupations	0.0889	0.0010
23-0000	Legal Occupations	0.1371	0.0032
25-0000	Education, Training, and Library Occupations	0.0874	0.0006
27-0000	Arts, Design, Entertainment, Sports, and Media Occupations	0.1468	0.0083
29-0000	Healthcare Practitioners and Technical Occupations	0.0973	0.0008
31-0000	Healthcare Support Occupations	0.0909	0.0030
33-0000	Protective Service Occupations	0.1767	0.0021
35-0000	Food Preparation and Serving Related Occupations	0.0798	0.0006
37-0000	Building and Grounds Cleaning and Maintenance Occupations	0.0820	0.0009
39-0000	Personal Care and Service Occupations	0.1170	0.0042
41-0000	Sales and Related Occupations	0.0661	0.0006
43-0000	Office and Administrative Support Occupations	0.0832	0.0006
45-0000	Farming, Fishing, and Forestry Occupations	0.3192	0.0171
47-0000	Construction and Extraction Occupations	0.1009	0.0013
49-0000	Installation, Maintenance, and Repair Occupations	0.1162	0.0015
51-0000	Production Occupations	0.1786	0.0051
53-0000	Transportation and Material Moving Occupations	0.1058	0.0022

Table 2a. 20 Most-Agglomerated Occupations, by Locational Gini

Occupation	Locational Gini
Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders, SOC 51-6064	0.4544
Marine Engineers and Naval Architects, SOC 17-2121	0.4542
Miscellaneous Extraction Workers, Including Roof Bolters and Helpers, SOC 47-50XX	0.4507
Shoe Machine Operators and Tenders, SOC 51-6042	0.4494
Tire Builders, SOC 51-9197	0.4430
Textile Bleaching and Dyeing Machine Operators and Tenders, SOC 51-6061	0.4418
Gaming Cage Workers, SOC 43-3041	0.4372
Textile Knitting and Weaving Machine Setters, Operators, and Tenders, SOC 51-6063	0.4325
Lay-Out Workers, Metal and Plastic, SOC 51-4192	0.4236
Petroleum, Mining and Geological Engineers, Including Mining Safety Engineers, SOC 17-21XX	0.4225
Nuclear Engineers, SOC 17-2161	0.4132
Aircraft Structure, Surfaces, Rigging, and Systems Assemblers, SOC 51-2011	0.4102
Fishing and Hunting Workers, SOC 45-3000	0.4095
Ship Engineers, SOC 53-5031	0.4065
Graders and Sorters, Agricultural Products, SOC 45-2041	0.4018
Mining Machine Operators, SOC 47-5040	0.3967
Gaming Services Workers, SOC 39-3010	0.3953
Sailors and Marine Oilers, SOC 53-5011	0.3924
Explosives Workers, Ordnance Handling Experts, and Blasters, SOC 47-5031	0.3914
Riggers, SOC 49-9096	0.3904

Table 2b. 20 Most-Agglomerated Occupations, by Concentration Index

Occupation	Concentration Index
Economists, SOC 19-3011	0.1620
Actors, SOC 27-2011	0.1569
Gaming Cage Workers, SOC 43-3041	0.1031
Petroleum, Mining and Geological Engineers, Including Mining Safety Engineers, SOC 17-21XX	0.0990
Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders, SOC 51-6064	0.0870
Gaming Services Workers, SOC 39-3010	0.0869
Marine Engineers and Naval Architects, SOC 17-2121	0.0533
Textile Knitting and Weaving Machine Setters, Operators, and Tenders, SOC 51-6063	0.0456
Derrick, Rotary Drill, and Service Unit Operators, and Roustabouts, Oil, Gas, and Mining, SOC 47-50YY	0.0420
First-Line Supervisors/Managers of Gaming Workers, SOC 39-1010	0.0417
Textile Bleaching and Dyeing Machine Operators and Tenders, SOC 51-6061	0.0363
Television, Video, and Motion Picture Camera Operators and Editors, SOC 27-4030	0.0360
Lay-Out Workers, Metal and Plastic, SOC 51-4192	0.0343
Sewing Machine Operators, SOC 51-6031	0.0334
Forging Machine Setters, Operators, and Tenders, Metal and Plastic, SOC 51-4022	0.0320
Aircraft Structure, Surfaces, Rigging, and Systems Assemblers, SOC 51-2011	0.0313
Graders and Sorters, Agricultural Products, SOC 45-2041	0.0311
Taxi Drivers and Chauffeurs, SOC 53-3041	0.0285
Textile Cutting Machine Setters, Operators, and Tenders, SOC 51-6062	0.0282
Producers and Directors, SOC 27-2012	0.0280

Table 3a. 20 Least-Agglomerated Occupations, by Locational Gini

Occupation	Locational Gini
Retail Salespersons, SOC 41-2031	0.0369
Secretaries and Administrative Assistants, SOC 43-6010	0.0409
First-Line Supervisors/Managers of Retail Sales Workers, SOC 41-1011	0.0418
Elementary and Middle School Teachers, SOC 25-2020	0.0465
First-Line Supervisors/Managers of Office and Administrative Support Workers, SOC 43-1011	0.0477
Bookkeeping, Accounting, and Auditing Clerks, SOC 43-3031	0.0484
Human Resources Assistants, Except Payroll and Timekeeping, SOC 43-4161	0.0498
Hairdressers, Hairstylists, and Cosmetologists, SOC 39-5012	0.0509
Maids and Housekeeping Cleaners, SOC 37-2012	0.0521
Cashiers, SOC 41-2010	0.0530
Stock Clerks and Order Fillers, SOC 43-5081	0.0536
Food Service Managers, SOC 11-9051	0.0542
Automotive Service Technicians and Mechanics, SOC 49-3023	0.0542
Office Clerks, General, SOC 43-9061	0.0555
Secondary School Teachers, SOC 25-2030	0.0601
Registered Nurses, SOC 29-1111	0.0636
Cooks, SOC 35-2010	0.0637
General and Operations Managers, SOC 11-1021	0.0641
Medical Assistants and Other Healthcare Support Occupations, SOC 31-909X	0.0648
Carpenters, SOC 47-2031	0.0654

Table 3b. 20 Least-Agglomerated Occupations, by Concentration Index

Occupation	Concentration Index
Retail Salespersons, SOC 41-2031	0.0001
Hairdressers, Hairstylists, and Cosmetologists, SOC 39-5012	0.0001
Bookkeeping, Accounting, and Auditing Clerks, SOC 43-3031	0.0001
Receptionists and Information Clerks, SOC 43-4171	0.0001
First-Line Supervisors/Managers of Office and Administrative Support Workers, SOC 43-1011	0.0001
Food Service Managers, SOC 11-9051	0.0001
Elementary and Middle School Teachers, SOC 25-2020	0.0002
Cashiers, SOC 41-2010	0.0002
Office and Administrative Support Workers, All Other, SOC 43-9199	0.0002
Payroll and Timekeeping Clerks, SOC 43-3051	0.0002
First-Line Supervisors/Managers of Retail Sales Workers, SOC 41-1011	0.0002
Postal Service Mail Carriers, SOC 43-5052	0.0002
File Clerks, SOC 43-4071	0.0002
Secretaries and Administrative Assistants, SOC 43-6010	0.0003
Dispatchers, SOC 43-5030	0.0003
First-Line Supervisors/Managers of Personal Service Workers, SOC 39-1021	0.0003
Computer, Automated Teller, and Office Machine Repairers, SOC 49-2011	0.0003
First-Line Supervisors/Managers of Non-Retail Sales Workers, SOC 41-1012	0.0003
Child Care Workers, SOC 39-9011	0.0003
Stock Clerks and Order Fillers, SOC 43-5081	0.0003

Table 4. Descriptive Statistics (n=468)

Variable	Description	Mean	Standard Deviation
LGINI	Locational Gini coefficient calculated across 324 U.S. metropolitan areas	0.1872	0.0962
INDEX	Modified Ellison-Glaeser concentration index calculated across 324 U.S. metropolitan areas	0.0064	0.0150
Specialized Knowledge	Variable measuring the difference between an occupation's knowledge profile and the knowledge profile of the average U.S. occupation	684.5	412.6
Specialized Equipment	Index value that measures the importance (scale of 1 to 5) and level (scale of 1 to 7) of occupational activity titled "Operating Vehicles, Mechanized Devices, or Equipment"	5.479	5.738
Update Knowledge	Index value that measures the importance (scale of 1 to 5) and level (scale of 1 to 7) of occupational activity titled "Updating and Using Relevant Knowledge"	14.87	5.701
Creativity	Index value that measures the importance (scale of 1 to 5) and level (scale of 1 to 7) of occupational activity titled "Thinking Creatively"	11.24	5.742
Years of Education	Average years of education of those in occupation	13.18	1.885

Table is continued on the following page.

Table 4. Descriptive Statistics (n=468), continued

Variable	Description	Mean	Standard Deviation
Interaction with Public	Index value that measures the importance (scale of 1 to 5) and level (scale of 1 to 7) of occupational activity titled "Performing for or Working Directly with the Public"	10.12	7.150
Average Establishment Size	Average size of businesses that employ workers in the occupation	74.47	77.83
Agriculture	Share of people in occupation who work in agricultural-related industry	0.0207	NA
Mining	Share of people in occupation who work in mining-related industry	0.0154	NA

Table 5. Knowledge Areas

Administration and Management	Building and Construction	Education and Training
Clerical	Mechanical	English Language
Economics and Accounting	Mathematics	Foreign Language
Sales and Marketing	Physics	Fine Arts
Customer and Personal Service	Chemistry	History and Archeology
Personnel and Human Resources	Biology	Philosophy and Theology
Production and Processing	Psychology	Public Safety and Security
Food Production	Sociology and Anthropology	Law and Government
Computers and Electronics	Geography	Telecommunications
Engineering and Technology	Medicine and Dentistry	Communications and Media
Design	Therapy and Counseling	Transportation

Table 6. Regression Results on the Agglomeration of Occupations (n = 468)

Variable	Estimated Coefficients (t-stats in parentheses) Dependent Variable: *LGINI*			Dependent Variable: *INDEX*		
Constant	-2.570*** (-9.79)	-2.524*** (-9.55)	-3.093*** (-6.74)	-8.373*** (-12.32)	-8.172*** (-12.18)	-9.025*** (-7.52)
Specialized Knowledge	0.117*** (2.69)	0.107** (2.38)	0.116** (2.35)	0.474*** (4.16)	0.362*** (3.22)	0.446*** (3.49)
Specialized Equipment	0.054*** (3.05)	0.054*** (3.13)	0.063*** (3.20)	0.084* (1.85)	0.088** (1.98)	0.097* (1.95)
Update Knowledge	0.108** (2.07)	NA	NA	0.061 (0.47)	NA	NA
Creativity	NA	0.102** (2.25)	NA	NA	0.287** (2.42)	NA
Years of Education	NA	NA	0.301 (1.34)	NA	NA	0.388 (0.65)
Interaction with Public	-0.179*** (-8.75)	-0.177*** (-9.14)	-0.176*** (-8.57)	-0.406*** (-7.57)	-0.435*** (-8.63)	-0.413*** (-7.69)

Table is continued on the following page.

Table 6. Regression Results on the Agglomeration of Occupations (n = 468), continued

	Estimated Coefficients (t-stats in parentheses)					
Variable	Dependent Variable: *LGINI*			Dependent Variable: *INDEX*		
Average Establishment Size	-0.001 (-0.04)	0.015 (0.51)	0.004 (0.14)	-0.065 (-0.89)	-0.049 (-0.70)	-0.067 (-0.93)
Agriculture	0.719*** (5.04)	0.739*** (5.37)	0.749*** (5.44)	1.698*** (5.17)	1.721*** (5.21)	1.726*** (5.27)
Mining	0.701*** (4.12)	0.716*** (4.34)	0.683*** (4.04)	2.219*** (4.26)	2.276*** (4.88)	2.200*** (4.21)
r-squared	0.228	0.231	0.224	0.214	0.225	0.214
Adjusted r-squared	0.216	0.219	0.213	0.202	0.213	0.202

Notes: All variables except *Agriculture* and *Mining* are measured in logs. ***, ** and * denote significance at the .01, .05 and .10 levels, respectively. *t*-statistics in parentheses; computed using robust standard errors.

Table 7. 20 Highest Co-Agglomeration Pairs

Occupation 1	Occupation 2	Co-Agglomeration
Gaming Services Workers	Gaming Cage Workers	0.09
Actors	Television, Video, and Motion Picture Camera Operators and Editors	0.07
Budget Analysts	Economists	0.06
First-Line Supervisors/Managers of Gaming Workers	Gaming Cage Workers	0.06
Actors	Sewing Machine Operators	0.06
Actors	Producers and Directors	0.06
Agents and Business Managers of Artists, Performers, and Athletes	Actors	0.06
First-Line Supervisors/Managers of Gaming Workers	Gaming Services Workers	0.05
Textile Knitting and Weaving Machine Setters, Operators, and Tenders	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	0.05
Operations Research Analysts	Economists	0.05
Miscellaneous Mathematical Science Occupations, Including Mathematicians and Statisticians	Economists	0.05
Economists	Miscellaneous Social Scientists, Including Sociologists	0.05
Petroleum, Mining and Geological Engineers, Including Mining Safety Engineers	Geological and Petroleum Technicians	0.04
Actors	Textile Cutting Machine Setters, Operators, and Tenders	0.04
Actors	Jewelers and Precious Stone and Metal Workers	0.04
Astronomers and Physicists	Economists	0.04
Meeting and Convention Planners	Economists	0.04
Petroleum, Mining and Geological Engineers, Including Mining Safety Engineers	Derrick, Rotary Drill, and Service Unit Operators, and Roustabouts, Oil, Gas, and Mining	0.04
Textile Bleaching and Dyeing Machine Operators and Tenders	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	0.03
Textile Bleaching and Dyeing Machine Operators and Tenders	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	0.03

Table 8. Regression Results on the Co-Agglomeration of Occupations (n = 109,278)

Variable	Estimated Coefficients	
Constant	$-1.40e^{-10}$ (0.000)	-0.0152*** (-4.89)
Dissimilar Knowledge	-0.108*** (-38.31)	-0.099*** (-34.55)
Dissimilar Output	-0.157*** (-33.38)	-0.132*** (-26.89)
Controls for Major SOCs	No	Yes
r-squared	0.043	0.061
Adjusted r-squared	0.043	0.061

Notes: All of the variables are normalized to have a mean of zero and a standard deviation of one. *** denotes significance at the .01 level. *t*-statistics in parentheses; computed using robust standard errors.