Impact of High-Skill Jobs On Commercial Real Estate*

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Abstract

Job vacancies and labor demand are among the most critical drivers behind the value of local commercial properties. Using 4.8 million job advertisements from more than 40,000 career websites from 2010 to 2020, we measure labor demand trends within metro areas and assess their impact on CRE rent levels. We build time-varying measures for the demand of workers of high and low machine replacement risk and achieve identification by relying on the cross-sectional differences of tenants and property types to changes in labor skill demand. We document a positive relationship between employment growth and lease rates. For industrial properties, tenants who seek talents one year before the lease was signed pay 9.1% more than similar tenants who did not advertise any job vacancy. Meanwhile, office tenants who seek talents one year before pay 3.2% higher effective rents than tenants who did not announce any position. Those differences in rent levels are mainly driven by the demand for high-skill laborers that machines cannot replace.

Keywords: Commercial Real Estate, House Price, Labor Market, High-Skill Jobs

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1 Introduction

Commercial real estate is an essential component of the U.S. economy. During economic cycles, some cities show strong growth in commercial real estate (CRE) values while others struggle and decline. Extant studies have pointed out that local employment demands are closely linked to the strength of real estate markets.[1] For example, Molloy et al. (2017) document a simultaneous trend in both the decline in employment changes and the decline of the local real estate market since 1980. Furthermore, Pirinsky and Wang (2006) and Tuzel and Zhang (2017) document the direct linkage between local factors such as employment and real estate prices. Similarly, a large literature in urban economics links employment growth to real estate prices (Glaeser, 2008 and Rosenthal et al. (2022)).

The drastic developments in digitization, artificial intelligence (AI), and automation in the past decade present both opportunities and challenges to the labor markets and CRE markets across the U.S. In 2012, the U.S. Bureau of Labor Statistics (BLS) recognized that some low-skill occupations would shrink in their labor demand due to technical advancements while high-skill occupations that cannot be replaced by machines and computers will thrive. If that is the case, the level of rent for CRE properties may increase or decrease based on changes in tenant demand for low-skill or high-skill workers[2].

A major obstacle in the extant studies on the impact of labor market demand on CRE is that their analyses are limited by aggregated numerical *ex-post* employment data[3]. Having more disaggregated and more detailed *ex-ante* data about the employers' demand for labor skills could go a long way in helping understand the impacts of technology on CRE rents.

[1]See, for example, Schnure and Thompson (2020), Saks (2008), Böheim and Taylor (2002), Eliasson et al. (2003)

[2]See Assessing the Impact of New Technologies on the Labor Market: Key Constructs, Gaps, and Data Collection Strategies for the Bureau of Labor Statistics [Link]

[3]Most of the extant studies focus on *ex post* aggregate measures of employment or unemployment rates. For example, public employment and occupation data published by the Bureau of Labor Statistics (BLS) and the American Community Survey (ACS) are summaries of job matches made available with a considerable lag and thus may not reflect current labor market conditions. As a result, little attention has been paid to employers' labor demand or job vacancies, which are ex ante drivers behind employment and economic growth, and therefore, making them infeasible in CRE investment decision makings.

We bridge this literature gap by focusing on differences in labor skill level to study the extent that labor and real estate (capital) are complements or substitutes (Cobb and Douglas, 1928; Krusell et al., 2000; Karabarbounis and Neiman, 2014; Ohanian et al., 2021; Eisfeldt et al., 2021).

To fix ideas, we rely on the insights obtained from the theoretical model introduced by Eisfeldt et al. (2021) which examines the complementarity and substitutability between firm capital, high skill labor, and low skill labor. In their model, high-skill labor (which they term "human capitalist") earns wage income and equity-based compensation (a share in the firm's capital appreciation). In contrast, low-skill workers only receive wages. By differentiating the compensation packages between high and low skill workers, Eisfeldt et al. (2021) demonstrate that high skill workers and capital are complementary while low skill workers and capital are substitutes. Extending the insights of their model to our commercial real estate setting examined in this study, we would anticipate a stronger link between the low-skill labor demand and the demand for space.

Office and industrial property returns are most likely to respond to changes in high and low-skill worker demand. In this study, we focus on office and industrial properties in three gateway cities across the U.S: Atlanta, GA, Houston, TX, and Miami, FL. We employ information on individual leases from CompStak, an industry-leading data provider on commercial leases. Our data cover the period from 2010 to 2020. The data contains information on the effective rent (contract rent incorporating the effect of lease concessions), property type and quality (building class), lease term, percent of the building represented by the lease, and the signing date of the lease.

We focus on the cross-sectional differences of tenants and property types to changes in labor skill demand. For example, if computers replace low-skill office workers, then office property occupied by tenants with a high fraction of low-skill office workers would decline in value because the space is no longer needed. Meanwhile, returns to office property occupied by tenants with high-skill office workers will show strong growth because those jobs are not machine replaceable. This hypothesis is supported by Schnure and Thompson (2020) who find that metro areas with higher migration of high-skill workers have seen growth in the local office markets. However, MSAs with greater immigration of low-skill laborers in production experienced little to no growth.

Our employment skill demand metric is based on a novel data series from Burning Glass Technologies that contains more than 4.8 million job vacancy advertisements from more than 40,000 online job boards and company websites. Using both the numerical and textual portions of this database, we document labor demand trends from 2011 to 2020, focusing on differences in demand for high or low skilled labor, and assess the impact of these trends on local CRE prices.

We use three approaches to identify the demand for high-skill and low-skill labor in our data. First, we match each job's O*NET ID with the Bureau of Labor Statistics' *Occupational Employment Projections* data on the likelihood machines can replace such occupation. Next, we validate our labor-skill/automation-risk identifications following a list of high-automation-risk and low-automation-risk occupations provided in Frey and Osborne (2017). Finally, we utilize textual analysis techniques to show the differences in the most common skill requirement words found in each type of job vacancy. We document that office administrative support and transportation jobs require fewer skills and are at the highest risk of being replaced by machines. In contrast, jobs at low risk of automation require higher management skills and educational degrees and are concentrated in information technologies and financial industries.

Our numerical analysis support this hypothesis: for both commercial properties and offices, we find a positive relation between employment growth and lease rates the sensitivity of job announcements for industrial leases is larger than for office leases. For industrial properties, tenants experiencing employment growth pay approximately 9.1% higher effective lease rates, on average, than tenants who did not have a position announcement in the year prior to when the lease was signed. Employment demand has a persistent but diminishing impact on lease rates as we see positive, albeit not statistically significant. For offices, tenants with job announcements in the year prior to leasing office space paid effective rents that were 3.2% higher than firms that did not have a job posting online. Again, the effect dissipates to 2.1% (significant at the 10% level) for job postings two-years prior to the lease year and is positive (but not statistically significant) for job announcements three-years prior to the lease year.

In addition, we document several differential impacts of tenant employment demand on effective rents across the demand for laborers of different skill levels. In terms of job automation risk, office tenants pay 2.8% higher effective rents when advertising low automation risk jobs in years prior to the lease year, while industrial tenants pay 14.6% more. Industrial space usage is negatively correlated with job automation – automation reduces the need for space for employees. Firms that are actively expanding their warehouse/industrial operations but employing more workers that cannot be replaced by equipment are willing to pay higher rents for that space. Overall, our analysis of effective rent is consistent with the theoretical predictions outlined in Eisfeldt et al. (2021), which propose a high degree of complementarity between capital and high skilled labor. We demonstrate that firms expanding their high skilled employment base face higher lease costs is consistent with the complementarity of capital and labor. Furthermore, we do not find a significant link between firm demand for lower skilled labor (high risk of automation) and effective lease costs, suggesting landlords recognize the substitutability associated with low skilled labor and capital, and thus do not increase rents in response to greater lower skilled labor demand. This finding is supported by Wang and Zhou (2021) who find landlords are capable of compiling valuable information at granular levels regarding how tenants operate.

To further investigate the potential impact of the cost of space on employers' demand for high-skill and low-skill laborers, we construct monthly quality-adjusted effective rent indexes for both industrial property and office property for Atlanta, GA, Austin, TX, and Miami, FL. We do not see a strong impact of the lagged rent indexes on the change in job announcements for any skill category.

The paper is structured as follows. Section 2 provides a detailed description of the data and identification strategies. The empirical methodology can be found in section 3. The main results are presented in section 4. We also provide a discussion on the impact of CRE costs and labor demand in section 5. Section 6 concludes the paper.

2 Empirical Identification and Data

2.1 Job Vacancy Labor Demand Data

We use daily data on job vacancy postings from Burning Glass Technologies (BGT), an employment analytic and labor market information company. BGT scrapes electronic postings from over 40,000 online job boards and company websites to obtain the "near-universe of jobs that were posted online". The data were first used by Hershbein and Kahn (2018) to show that the Great Recession accelerated adoption of labor-replacing technologies.

We collected and cleaned over 4.8 million real job advertisements covering the period between January 2010 to May 2020 for Atlanta, GA, Houston, TX, and Miami, FL. The data contains over 70 standardized fields providing detailed information about each position, including location (city), employer name, industry, occupation and job functions, and minimum education requirements. As a result, our data set provides rich and timely data on the demand of labor with fine geographic and industry identification for the past decade. Figure 1 plots the monthly number of job advertisements by city. Consistent with the economic expansion during this decade and the growth in on-line job search platforms, we note a positive trend in job postings with a notable upward increase in 2018.

The major downside of the BGT data is that it only covers employers that seek talents from online sources. While online job advertisements have been increasingly common since the late 2000s, there is still a possibility that our data over-represent higher-skilled occupations and industries. The BLS collects establishment-level data on the physical demands, environmental conditions, education, training, and experience of jobs in the U.S. by surveying approximately 25,300 establishments each year, focusing on the requirements of specific occupations from the employer's perspective. This data captures key measures of skill, such as education and pre-employment training. Reassuringly, Dalton et al. (2018) link BGT position advertisements to the *Job Openings and Labor Turnover Survey* released by the BLS at the establishment level and find significant alignment across the two datasets.

2.2 Identify High-Skill and Low Skill Jobs

We use two approaches to identify and validate our categorizations of high-skill and low-skill jobs in our job advertisements data.

First, we match each job's O*NET ID with the Bureau of Labor Statistics' *Occupational Employment Projections* data[4]. O*NET is an online service developed for the US Department of Labor that provides detailed occupation skill requirement information on approximately 600 occupations that can be linked to the Labor Department's Standard Occupational Classification (SOC). For each occupation, O*NET provides answers to more than two hundred standardised and measurable questions that detail the day-to-day functions and requirements of each occupation. It also provides key data on the cognitive and mental requirements for specific occupations. This allows us to: (a) objectively rank occupations according to the mix of knowledge, skills, and abilities they require; and (b) subjectively categorize them based on the variety of tasks they involve.

Next, we validate our labor skill identifications following Frey and Osborne (2017). Frey and Osborne (2017) ranked each O*NET occupation's skill requirements and its likelihood of being replaced with automation by three metrics: perception, creative intelligence, and social intelligence. Those traits create engineering bottlenecks that significantly and practically limit automation. They classified occupations as low-skill if the estimated probability of automation is 70% or higher and high-skill if it is under 30%. For example, they find that

[4] Bureau of Labor Statistics Occupational Employment Projections to 2022 [Link]

many office and administrative support, transportation, and services jobs are at risk.

Table Appendix 1 and Table Appendix 2 list job positions of high-skill/low-risk and low-skill/high-skill requirements, respectively. After carefully reviewing both lists, we found two important patterns worth emphasizing: (1) The majority of O*NET occupations demand high-skill labor. Specifically, 313 occupations fall under the high-skill category, and only 145 occupations are low-skill. (2) The identification strategies rely on detailed skill/education requirements instead of industries or job titles. For example, although "(regular) Driver" is a low-skill job, "Ambulance Drivers and Attendants" is a high-skill job that requires additional knowledge, skills, and abilities.

Figure 2 plots the shares of total jobs that are denoted as being high (low) risk of machine replacement for each city. Mid-risk/Mid-skill jobs are the omitted category. Consistent with Frey and Osborne (2017), we note that the share of total jobs at low risk of automation is above 50% in each city, but the trend in the share of high-skill job postings is slightly declining. Jobs at low risk of automation tend to require higher skills and are concentrated in higher technology, financial, or service sector industries. The large proportion of high-skill jobs online is not surprising given career websites are historically for high-tech positions. On the other hand, the share of jobs noted as being at high risk for machine replacement is relatively stable with slight positive trend across each city – again, consistent with the growth in on-line job position advertisement.

In order to gain more insights into the job advertisements, we utilize machine learning textual analysis techniques to identify high-frequency keywords and phrases used in each type of job advertisement as revealed in the rich job advertisement data[5]. Figure 7, and Figure 8 display the most common requirements employers seek in low automation risk job ads and high automation risk job ads, respectively. The most common qualifications for high-skill jobs are college degrees, two to five years of relevant experience, communication skills, computer programming skills, problem-solving skills, and management skills. In contrast, the level

[5]See Ambrose et al. (2020), Shen and Wilkoff (2020), and Shen and Ross (2021) for discussion of textual analysis using machine learning.

of education requirement for high automation risk jobs is much lower (high school degrees or diploma equivalent) than those of high-skill jobs (bachelor's degree). The required skills for high automation risk jobs are generic, such as basic written/verbal/oral communication skills. Those findings are consistent with Frey and Osborne (2017) who document that office and administrative support, transportation, and services jobs are at the highest risk of being replaced by machines. They are also consistent with our earlier finding that jobs at low risk of automation require higher skills and are concentrated in information technologies and financial industries.

2.3 Commercial Real Estate Leases and Transactions Data

We focus on office and industrial properties in this study. Office and industrial property returns are most likely to respond to changes in high and low-skill worker demand. Thus, we match the employment data to information on individual leases from CompStak, an industry leading provider of data on commercial leases and property sales. We collected detailed data on 39,104 office leases and 10,733 industrial leases covering the period from 2009 to 2020. The data contains information on the effective rent (contract rent incorporating the effect of lease concessions), property type and quality (building class), lease term, percent of building represented by the lease, and the date of the transaction. Figure 3 displays the frequency count of office and industrial leases by lease execution year. Office lease growth increased substantially from 2010 to 2017, however we see substantial heterogeneity in lease counts across markets. For example, Houston saw a dramatic decline in lease activity in 2018 while Atlanta remained relatively flat. We also observe differences in industrial lease activity across markets. For example, the Atlanta market experienced a growing trend in the industrial sector while Houston was relatively flat to declining over the sample period.

We also collected detailed information on industrial and office property sale transactions from CompStak. The data contain information on 9,166 industrial property transactions and 6,203 office building sales. Figure 4 shows the distribution of property sale transactions for Atlanta, Houston, and Miami. Again, we find different patterns in the property sale activity across markets. For example, Atlanta appears to have a growing trend in sales while Houston and Miami experienced a marked decline in sale activity following 2017. Interestingly, in contrast to the lease data we note that Miami has the highest count of property sale transactions. Miami accounts for 56% of all property sale transactions in the sample but only 20% and 11% of industrial and office lease activity, respectively, in the sample. In contrast, Houston represents only 8.7% of the property sale transactions but accounts for 49.7% of the lease activity.

Table 1 provides the summary statistics by property type and location. As expected, office leases command substantially higher effective rents per square foot ($20.51 versus $6.21). In terms of lease size, we note that the average office lease represents approximately 4% of the total building size whereas the typical industrial lease accounts for 31% of the building. We also note that lease terms are about 5-years for both property types. All the findings discussed above are consistent across all three cities in our sample. After merging the lease data with job announcements by tenant/employer names, we note that 7% of the office tenants and 8% of the industrial tenants placed at least one job position advertisement one year before they signed the lease. Furthermore, 5% of office tenants and 6% of industrial tenants had a job announcement two years prior to executing a new lease. The percentage of tenants that made job announcements three years prior to them signing a lease dropped to 4% for offices and 5% for industrial properties. Interestingly, we find little difference in skill levels for the jobs. For example, 3% of the tenants advertised positions classified as high-skill one year before the lease execution while 6% of office tenants and 6% of industrial tenants advertised positions classified as low skill. Finally, we note that about 3% of the office and 4% of the industrial tenants advertised both high-skill and low-skill positions 1 year before the lease was executed.

3 Empirical Methods

We employ the following empirical specifications via ordinary least squares (OLS) to test the link between employment demand (as proxied by job advertisements) and lease rent.

$$y_{it} = \alpha + \beta X_i + \gamma \Sigma_{n=1}^{3} Z_{i,t-n} + \lambda \Gamma + \sigma \Sigma_{k=1}^{3} QE_k + \varepsilon_{it} \quad (1)$$

where y_{it} represents the natural log of effective rent for lease i at time t, X_i is matrix of lease characteristics (e.g. lease size as a % of building size, building size, lease term), $Z_{i,t-n}$ is a set of variables indicating whether the tenant had at least one job announcement n year(s) prior to an observed lease contract, and Γ is a set of fixed effects to control for year-quarter of lease signing, building quality (class), location (city). Since monetary policies might also affect rent, we also control for three monetary policy regimes (quantitative easing) being pursued by the Federal Reserve during our sample period following Luck and Zimmermann (2020). QE_1 is an indicator variable that is set to 1 if the sample is from March 2009 to March 2010, QE_2 is set to 1 from November 2010 to June 2012, and QE_3 is set to 1 if the sample is from January 2013 to October 2014. We cluster standard errors by city and year.

To the extent that labor demand signals greater demand for space, then we would expect positive estimated coefficients for the job announcement variables ($\gamma > 0$).

To further investigate whether a certain type of job vacancies drive space demand, we test the following model specification in which an employer had vacancies for high-risk and low-risk jobs in year t.

$$y_{it} = \alpha + \beta X_i + \gamma \Sigma_{n=1}^{3} Lowrisk_{i,t-n} + \iota \Sigma_{n=1}^{3} Highrisk_{i,t-n} + \lambda \Gamma + \sigma \Sigma_{k=1}^{3} QE_k + \varepsilon_{it} \quad (2)$$

4 Empirical Results

In this section, we formally test the link between employment demand (as proxied by job advertisements) lease rent.

Table 2 shows the estimated coefficients for office and industrial properties separately. Columns (1) and (3) focus on the simple effects of any job announcement regardless of skill level (Equation 1) while columns (2) and (4) focus on the effects of jobs differentiated by skill level (Equation 2). We first note that across both specifications the lease characteristic variables are statistically significant and have the expected sign. For industrial properties, the effective rents are inversely correlated with building size. In addition, industrial leases that account for a larger fraction of the total building have lower effective rents. These results suggest a size discount for industrial space. For example, a 1% increase in the lease as a percent of the building size decreases the effective rent by 0.74%. We also see a discount for longer term industrial leases. We find no significant differences in effect rents on leases entered during periods when the Federal Reserve engaged in Quantitative Easing than during non-QE periods for industrial leases.

Consistent with the office market and space usage being different than the industrial market, we find differences in the pricing of building and lease characteristics. For office space we find that leases in larger buildings command higher effective rents. This is consistent with larger office buildings typically having better locations and offering agglomeration opportunities for tenants. The marginally significant (at the 10% level) and negative coefficient on lease size as a fraction of total building implies a small discount when acquiring a larger percentage of the building. For example, a 1% increase in the lease size relative to the building size corresponds to a 0.03% reduction in the effective rent. In addition, the positive and statistically significant (at the 1% level) coefficient for lease term for office buildings is consistent with an upward sloping lease term structure in the office market. Finally, we note that the effective rents on office leases were significantly lower during the period between November 2010 and June 2012, when the Federal Reserve engaged in its second Quantitative

Easing initiative.

Turning to the variables indicating whether the tenant had job announcements while also seeking new space (*Tenant Job Ad*), we find a positive relation between employment growth and lease rates. For industrial properties, in column (1) we note a positive and statistically significant (at the 1% level) coefficient for the variable indicating that tenants that advertised a job one year prior to when the lease was signed paid significantly higher effective rents than tenants who did not advertise a position. The coefficient indicates that industrial tenants experiencing employment growth pay approximately 9.1% higher effective lease rates, on average, than tenants who did not have a position announcement in the year prior to when the lease was signed. We note that employment demand has a persistent but diminishing impact on lease rates as we see positive, albeit not statistically significant, coefficients for the variable indicating that the tenant had a job ad two and three years prior to the lease year. In column (3), we find similar, albeit a slightly smaller, effects for office properties. The estimated coefficients suggest that firms with job announcements in the year prior to leasing office space paid effective rents that were 3.2% higher than firms that did not have a job posting online. Again, the effect dissipates to 2.1% (significant at the 10% level) for job postings two-years prior to the lease year and is positive (0.5% but not statistically significant) for job announcements three-years prior to the lease year.

In columns (2) and (4) we turn to focus on the type of job announcement, either high or low risk of automation. Again, jobs at high risk of automation tend to be lower skilled while jobs at low risk of being replaced with automation are typically higher skilled. The coefficients measure the effect on rent relative to jobs considered to be at medium risk of automation. Considering industrial properties (column (2)), the coefficients for high-risk/low-skill jobs are not statistically significant. In contrast, the estimated coefficient for the variable indicating whether the firm placed an announcement in the year prior to the lease start for a job at low risk of automation is positive and statistically significant (at the 1% level). The estimated coefficient implies that the effective rent for industrial tenants having growth in low-risk-of-automation jobs is 14.6% higher than tenants that did not advertise such positions. This is consistent with landlords recognising that firms that have greater demand for jobs at low risk of automation have a lower elasticity of substitution between capital (real estate) costs and labor costs. As a result, landlords are able to command higher rents from these firms[6].

We also see that for office properties (column (4)) the estimated coefficient for the variable indicating a firm that advertised in the year prior to leasing a position with a low risk of automation is positive and statistically significant (at the 1% level). The estimated coefficient indicates that firms advertising demand for low automation risk jobs pay effective rents that are 2.8% higher than firms that did not advertise such demand. We note that this effect carries over to firms placing low automation risk ads two years prior to leasing as well.

We note several differential impacts of tenant employment demand on effective rents between office and industrial properties. First, we find that the sensitivity of job announcements for industrial leases is larger than for office leases. The estimated coefficients imply that industrial tenants with job announcements in the year they sign the lease pay 9.1% more than similar tenants while office tenants pay approximately 3.2% more. Turning to the differentiation in job automation risk, we see that office tenants pay 2.8% higher effective rents when advertising low automation risk jobs in the lease year while industrial tenants pay 14.6% more. These results are intuitive. Industrial space usage is negatively correlated with job automation – automation reduces the need for space for employees. Firms that are actively expanding their warehouse/industrial operations but are employing more workers that cannot be replaced by equipment are willing to pay higher rents for that space.

Overall, our micro analysis of effective rent is consistent with the theoretical predictions outlined in Eisfeldt et al. (2021). In calibrating their theoretical model with time series of factor shares data, Eisfeldt et al. (2021) pin down the elasticity of substitution between

[6]The positive coefficient is also consistent with firms having to provide higher quality space to attract and retain employees who perform tasks that are at lower risk from automation. However, the inclusion of building class fixed effects provides a control for building quality.

physical capital and human capital (high skilled labor) to 0.66, which implies a high degree of complementarity between capital and high skilled labor. Thus, our empirical results demonstrating that firms expanding their pool of high skilled workers (those at low risk of automation) face higher lease costs is consistent with the complementarity of capital and labor. Furthermore, we do not find a significant link between firm demand for lower skilled labor (high risk of automation) and effective lease costs. This suggests that landlords recognize the substitutability associated with low skilled labor and capital, and thus do not increase rents in response to greater lower skilled labor demand.

5 Discussion: Commercial Rent Index and Employment Measures

In this section, we investigate the macro level links between lease rates and employment growth in high and low automation risk jobs. Our objective is to determine whether aggregate employment growth responds to changes in physical capital costs.

To begin, we create industrial and office rent indexes for Atlanta, Houston, and Miami using the effective rent per square foot (R) for office and industrial leases contained in the CompStak database that were originated January 2010 and December 2019. As noted in section 2, Compstak reports information on 39,104 office leases and 10,733 industrial leases across the three cities.

We employ a simple hedonic pricing model that conditions the effective rent on lease characteristics to create a monthly index. Following Hill (2011), we estimate the following semi-log model:

$$y = Z\beta + D\delta + \varepsilon \qquad (3)$$

where $y = log(R)$, Z is a matrix of property characteristics (building size, lease size, lease term, and building quality or class), and D is a matrix of year-month dummy variables. In this formulation, β is a vector of shadow prices for the lease characteristics, δ is a vector of year-month prices, and ε is a vector or random errors. From this model, we can compute a property quality and characteristic adjusted rent index for each city by taking the exponential of the respective estimated δ_t coefficients: $\hat{R}_t = exp(\hat{\delta}_t)$.

Figures 5 and 6 show the result industrial property and office property monthly quality-adjusted effective rent indexes, respectively, for each city. We note significant heterogeneity in the rental indexes by property and market. For example, industrial and office effective rents in Atlanta increased substantially between 2010 and 2019. Whereas, we see that Houston experienced less overall rent growth. In particular, the Houston office market is relatively flat with less volatility. On the other hand, Figures 5 and 6 indicate that Miami experienced much greater office rent volatility with a positive upward trend after 2016. Furthermore, we note that the industrial property rent indexes for Atlanta and Houston have greater volatility than their respective office indexes due to the fewer observations.

To focus on the substitution between capital (rent cost) and labor (employment), we estimate the following model of monthly changes in the shares of jobs with low and high risk of automation:

$$\begin{aligned} ln(\Delta S_t^i) &= \alpha + \Sigma_{j=1}^{1} 2\beta_j^I ln(R_{t-j}^I) + \Sigma_{j=1}^{1} 2\beta_j^O ln(R_{t-j}^O) \\ &\quad + \delta_2 QE_2 + \delta_3 QE_3 + \lambda\Gamma + \varepsilon_t \end{aligned} \tag{4}$$

where ΔS_t^i $i = L, H$ represents the month-to-month change in the share of low automation risk jobs or high automation risk jobs, $ln(R_t^I)$ and $ln(R_t^O)$ are the log industrial and office rent indexes, QE_2 and QE_3 are dummy variables denoting the periods associated with the Federal Reserve Quantitative Easing program (November 2010-June 2012 and January 2013-October 2014), Γ is a set of city and year fixed effects, and ε_t is the error term. The specification in equation (4) provides for a flexible response in job announcements to aggregate capital costs of industrial and office property markets with up to a 12-month lag.

We estimate equation (4) separately for the change in the share of low and high automation risk jobs (high skilled and low skilled, respectively) as well as the month-to-month change in total job announcements. Table 3 presents the OLS regression coefficient estimates. Interestingly, we do not see a strong impact of the lagged rent indexes on the change in job announcements. Only the dummy variable denoting the period associated with QE3 is negative and statistically significant (at the 10% level) in the regression of low automation risk job ads and total job ads. Since lagged labor demand across different years might be serially correlated, we propose to use LASSO regression, a machine learning analysis method, to performs variable selection to enhance the accuracy and interpretability of the model in this section.

6 Conclusion

This study represents a first attempt at conducting a micro level analysis focused on the assessing whether firm space usage and labor are complements or substitutes. Motivated by the theoretical insights in Eisfeldt et al. (2021), we examine the trade-off of effective rents in office and industrial property with measures of employment demand for high and low skill workers. To do so, we use data from Burning Glass Technologies that compiles labor demand data classified into categories based on whether the position is at high or low risk of automation.

Consistent with recent findings suggesting that high skilled labor and physical capital are complements, our empirical analysis reveals that firms advertising high skilled jobs face higher effective rents. In contrast, we find no statistically significant link between demand for low skilled labor and the cost of space.

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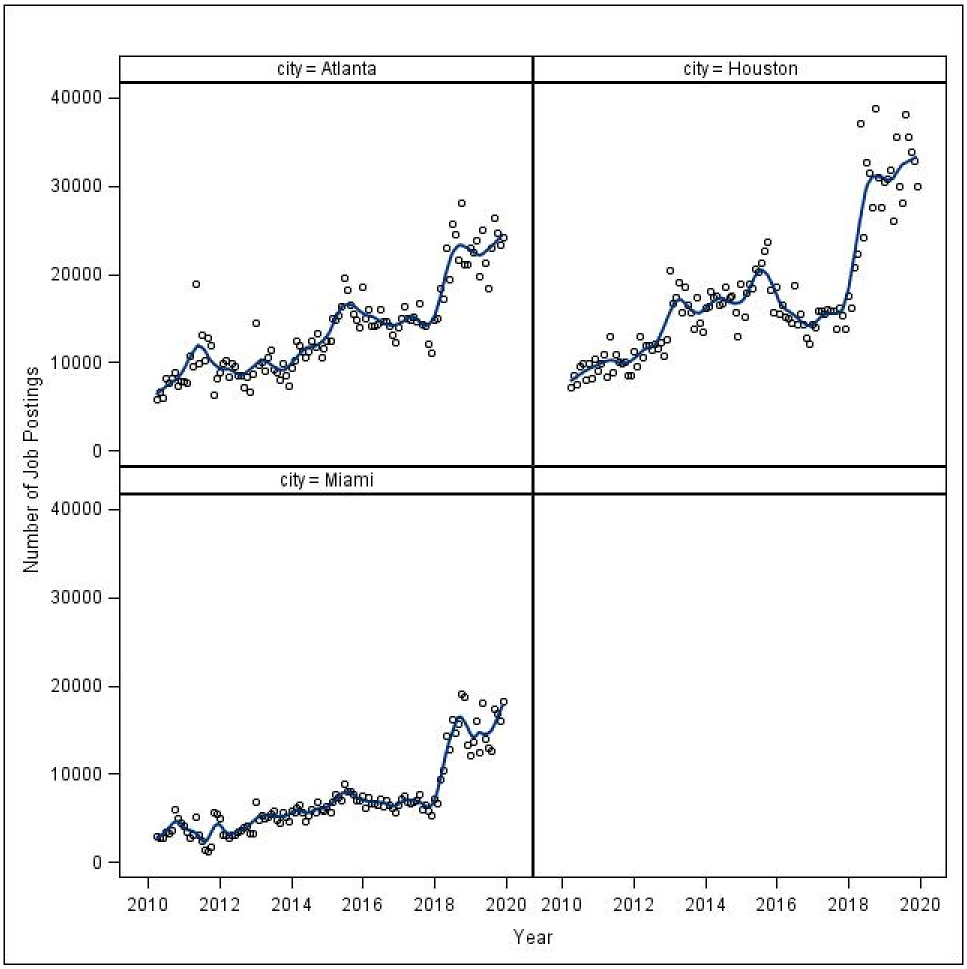
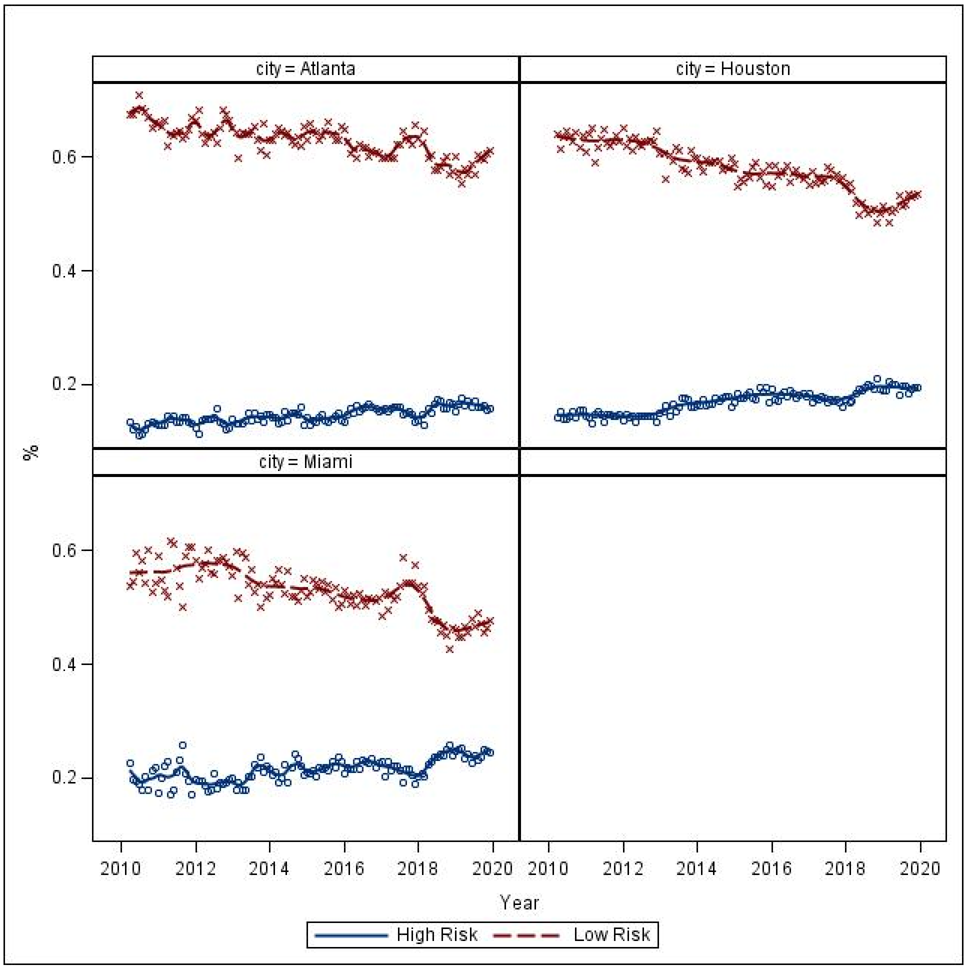
Figure 1: Monthly Number of Job Postings for Atlanta, Houston, and Miami



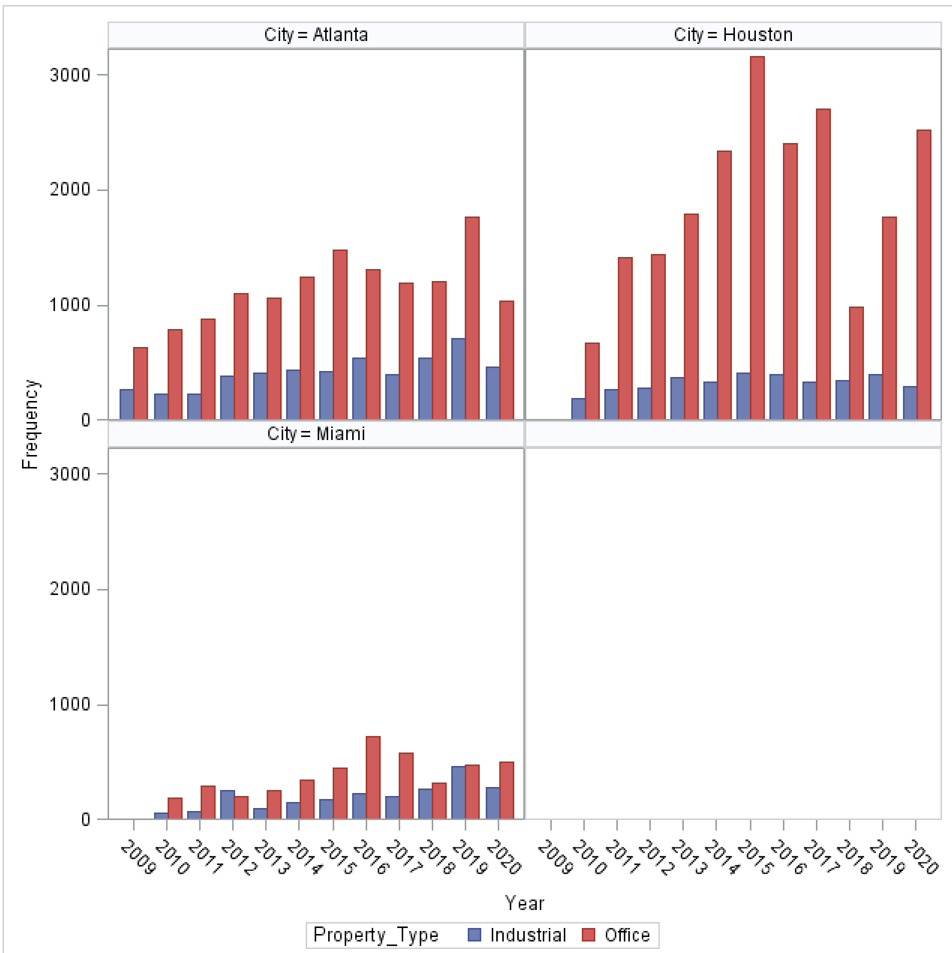
Notes: plots the monthly number of job advertisements by city from 2010 to 2020. Consistent with the economic expansion during this decade and the growth in on-line job search platforms, we note a positive trend in job postings with a notable upward increase in 2018.

Figure 2: Shares of High-Risk (Low-Skill) and Low Risk (High-Skill) Job Postings for Atlanta, Houston, and Miami



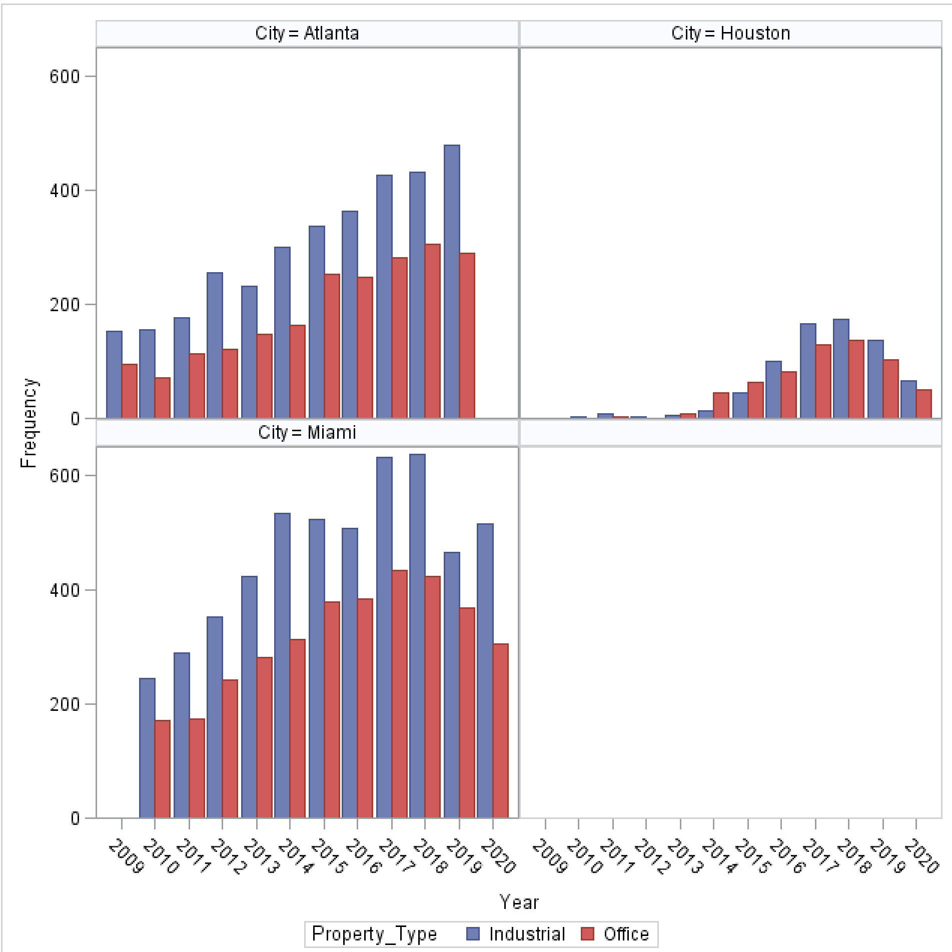
Notes: This Figure plots the shares of total jobs that are denoted as being high (low) risk of machine replacement for each city from 2010 to 2020. The share of total jobs at low risk of automation is above 50% in each city, but the trend in the share of high-skill job postings is slightly declining. Mid-risk/Mid-skill jobs are the omitted category.

Figure 3: Frequency Distribution of Office and Industrial Leases by Lease Origination Year and City



Notes: This Figure displays the frequency count of office and industrial leases by lease execution year from 2010 to 2020. Office lease growth increased substantially from 2010 to 2017, however we see substantial heterogeneity in lease counts across markets. We also observe differences in industrial lease activity across markets.

Figure 4: Frequency Distribution of Office and Industrial Properties Sold by Transaction Year and City



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Notes: This Figure displays the distribution of property sale transactions for Atlanta, Houston, and Miami from 2010 to 2020. Again, we find different patterns in the property sale activity across markets. For example, Atlanta appears to have a growing trend in sales while Houston and Miami experienced a marked decline in sale activity following 2017. Interestingly, in contrast to the lease data we note that Miami has the highest count of property sale transactions. In contrast, Houston represents only 8.7% of the property sale transactions but accounts for 49.7% of the lease activity.

Figure 5: Industrial Property Rent Indexes for Atlanta, Houston, and Miami

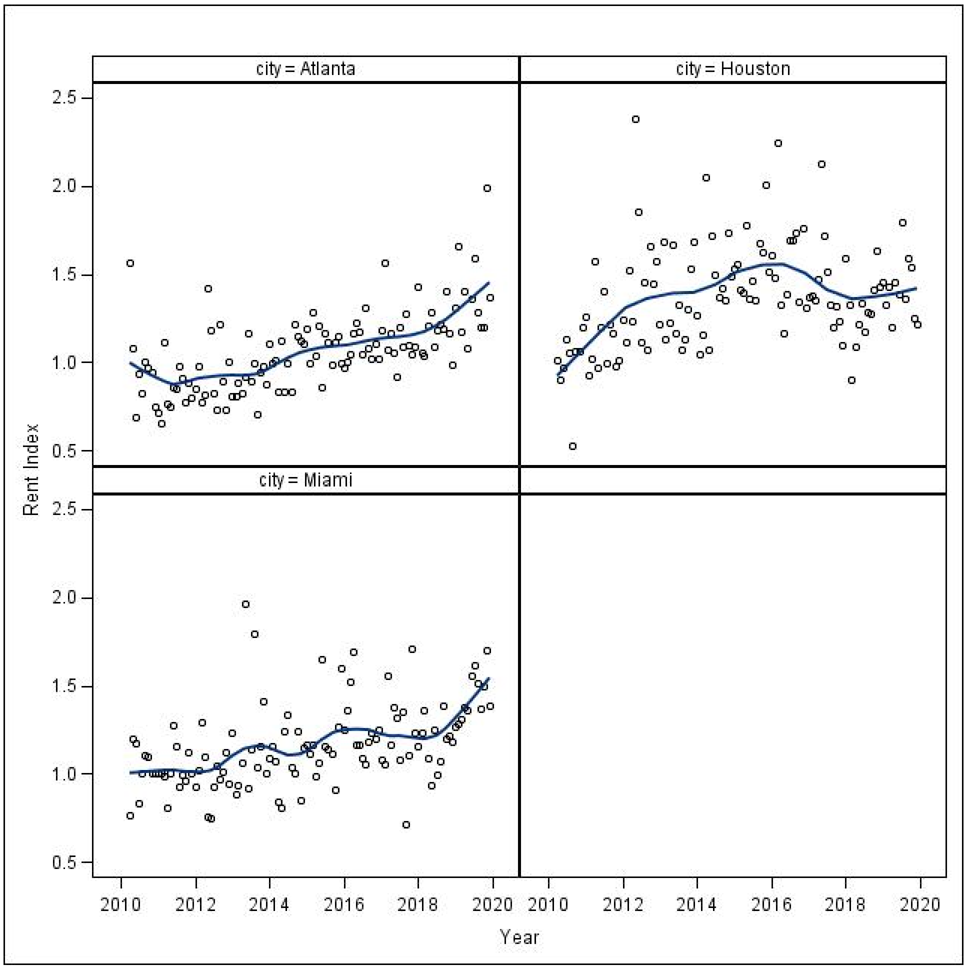


Figure 6: Office Property Rent Indexes for Atlanta, Houston, and Miami

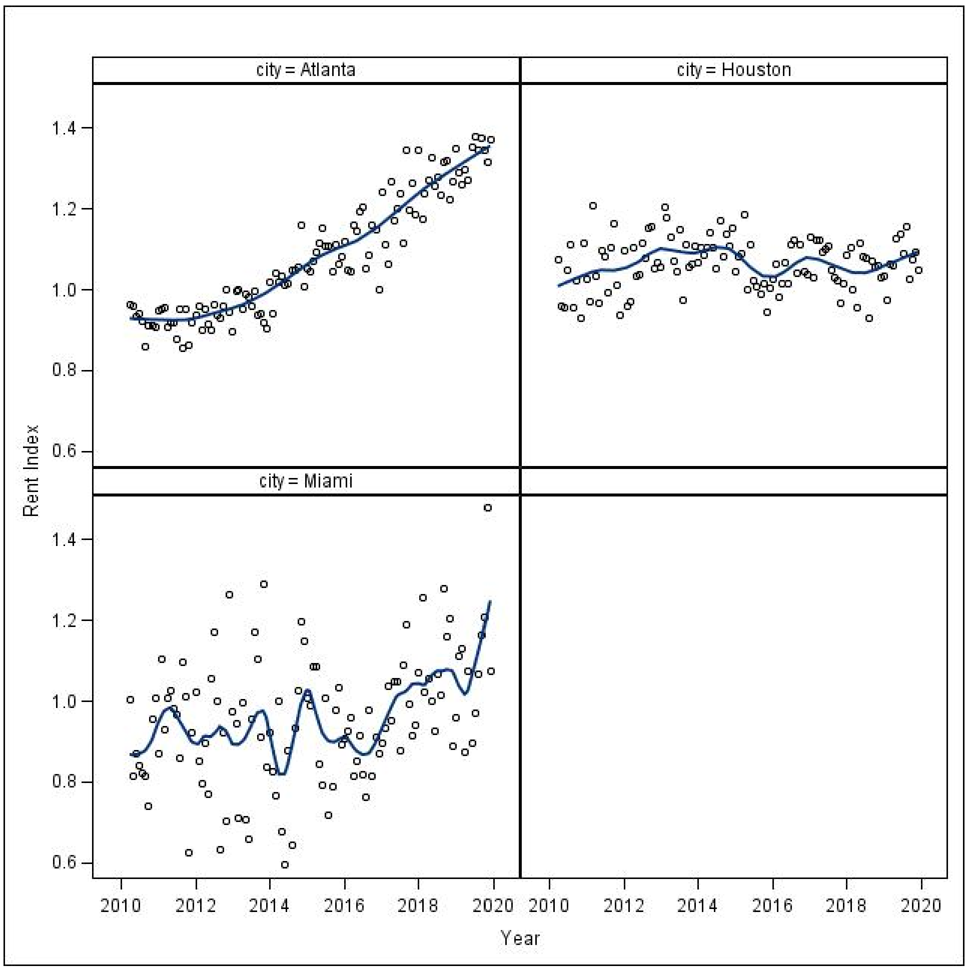
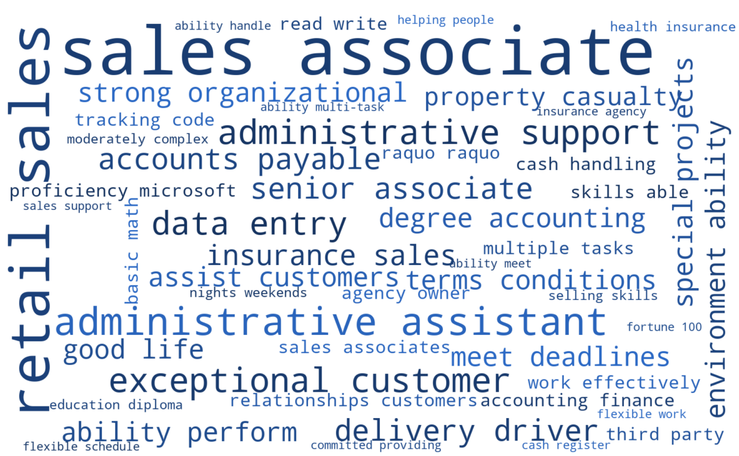


Figure 7: Keywords in Low-Risk Job Advertisements

Notes: This figure displays the most frequent characteristics employers seek in the potential job candidates for high-skill (low automation risk) jobs. The most common qualifications for high-skill jobs are college degrees, two to five years of relevant experience, communication skills, computer programming skills, problem-solving skills, and management skills.

Figure 8: Keywords in High-Risk Job Advertisements



Notes: This figure displays the most frequent characteristics employers seek in the potential job candidates for low-skill (high automation risk) jobs. The level of education requirement for those jobs are much lower (high school degrees or diploma equivalent) than those of high-skill jobs (bachelors degree).

Table 1: Summary Statistics

	Industrial				Office			
	Atlanta	Houston	Miami	All	Atlanta	Houston	Miami	All
Effective Rent	6.21	9.91	9.16	8.11	22.17	18.37	27.50	20.51
	(4.27)	(6.15)	(4.68)	(5.41)	(7.17)	(6.09)	(11.16)	(7.66)
Building Size	173665.33	151054.92	156252.29	162173.29	295520.86	217619.81	242864.41	245555.11
	(361.62)	(691.65)	(50.19)	(499.39)	(517.56)	(483.54)	(890.29)	(22.13)
Lease Size / Building Size (%)	0.34	0.26	0.33	0.31	0.06	0.03	0.06	0.04
	(0.31)	(0.31)	(0.29)	(0.31)	(0.13)	(0.09)	(0.14)	(0.11)
Lease Term (months)	60.18	48.74	58.36	55.57	59.18	32.17	59.59	43.67
	(31.19)	(33.67)	(30.85)	(32.52)	(33.86)	(29.83)	(32.76)	(34.22)
Tenant Job Ad 1 year prior to Lease Year (d)	0.09	0.07	0.08	0.08	0.11	0.04	0.09	0.07
	(0.29)	(0.26)	(0.27)	(0.28)	(0.31)	(0.19)	(0.28)	(0.25)
Tenant Job Ad 2 Years Prior to Lease Year (d)	0.07	0.06	0.06	0.06	0.08	0.03	0.06	0.05
	(0.26)	(0.23)	(0.23)	(0.24)	(0.27)	(0.17)	(0.25)	(0.22)
Tenant Job Ad 3 Years Prior to Lease Year (d)	0.06	0.05	0.05	0.05	0.06	0.02	0.06	0.04
	(0.23)	(0.21)	(0.22)	(0.22)	(0.24)	(0.15)	(0.23)	(0.19)
Tenant High-risk Job Ad 1 year Prior to Lease Year (d)	0.05	0.04	0.04	0.04	0.05	0.02	0.06	0.03
	(0.21)	(0.20)	(0.19)	(0.20)	(0.22)	(0.15)	(0.23)	(0.18)
Tenant High-risk Job Ad 2 Years Prior to Lease Year (d)	0.03	0.03	0.03	0.03	0.04	0.02	0.04	0.03
	(0.18)	(0.18)	(0.18)	(0.18)	(0.19)	(0.12)	(0.20)	(0.16)
Tenant High-risk Job Ad 3 Years Prior to Lease Year (d)	0.03	0.03	0.03	0.03	0.03	0.01	0.04	0.02
	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.11)	(0.19)	(0.14)
Tenant Low-risk Job Ad 1 Year Prior to Lease Year (d)	0.08	0.05	0.06	0.06	0.09	0.03	0.07	0.06
	(0.26)	(0.23)	(0.23)	(0.25)	(0.29)	(0.18)	(0.26)	(0.23)
Tenant Low-risk Job Ad 2 Year Prior to Lease Year (d)	0.06	0.04	0.05	0.05	0.07	0.02	0.06	0.04
	(0.23)	(0.21)	(0.22)	(0.22)	(0.26)	(0.16)	(0.23)	(0.20)
Tenant Low-risk Job Ad 3 Years Prior to Lease Year (d)	0.05	0.04	0.04	0.04	0.06	0.02	0.05	0.03
	(0.21)	(0.19)	(0.19)	(0.20)	(0.23)	(0.14)	(0.21)	(0.18)
Tenant with High and Low-risk Job Ads 1 year prior to Lease Year (d)	0.04	0.03	0.03	0.04	0.04	0.02	0.05	0.03
	(0.20)	(0.18)	(0.18)	(0.19)	(0.21)	(0.13)	(0.21)	(0.17)
Number of Leases	2,937	2,435	1,128	6,500	9,538	16,785	2,854	29,177

Notes: This table presents the summary statistics by property types in Atlanta, Houston, and Miami from 2010 to 2020.

Table 2: OLS Regression of Effective Rent by Property Type

Parameter	Industrial		Office	
	(1)	(2)	(3)	(4)
Lease Size / Building Size (%)	-0.744***	-0.749***	-0.031*	-0.031*
	(0.024)	(0.024)	(0.018)	(0.018)
Log(Building Size) (SF)	-0.172***	-0.173***	0.032***	0.033***
	(0.007)	(0.007)	(0.002)	(0.002)
Log(Lease Term)	-0.036***	-0.036***	0.085***	0.085***
	(0.010)	(0.010)	(0.002)	(0.002)
QE1 (March 2009-March2010)	-0.015	-0.015	0.010	0.010
	(0.061)	(0.061)	(0.018)	(0.018)
QE2 (Nov 2010-June2012)	0.026	0.026	-0.049***	-0.049***
	(0.040)	(0.040)	(0.012)	(0.012)
QE3 (Jan 2013-Oct2014)	-0.019	-0.017	-0.006	-0.006
	(0.044)	(0.044)	(0.013)	(0.013)
Tenant Job Ad 1 Year Prior to Lease Year(d)	0.091***		0.032***	
	(0.031)		(0.009)	
Tenant Job Ad 2 Years Prior to Lease Year(d)	0.045		0.021*	
	(0.038)		(0.011)	
Tenant Job Ad 3 Years Prior to Lease Year(d)	0.028		0.005	
	(0.038)		(0.012)	
Tenant High-risk Job Ad in Year Prior to Lease Year (d)		0.001		0.014
		(0.047)		(0.013)
Tenant High-risk Job Ad Two Years Prior to Lease Year (d)		0.006		-0.012
		(0.056)		(0.016)
Tenant High-risk Job Ad Three Years Prior to Lease Year (d)		-0.073		0.022
		(0.061)		(0.017)
Tenant Low-risk Job Ad 1 Year Prior to Lease Year (d)		0.146***		0.028***
		(0.039)		(0.011)
Tenant Low-risk Job Ad 2 Years Prior to Lease Year (d)		0.052		0.025*
		(0.047)		(0.013)
Tenant Low-risk Job Ad 3 Years Prior to Lease Year (d)		0.060		-0.013
		(0.048)		(0.014)
Building Class Fixed Effects	Yes	Yes	Yes	Yes
Location (City) Fixed Effects	Yes	Yes	Yes	Yes
Lease Year Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.470	0.472	0.369	0.369
Number of Observations	55,070	55,070	29,041	29,041

Notes: This table displays the analysis results of the impact of job advertisements on effective rents for industrial properties and offices. We cluster standard errors by city and year.

Table 3: OLS Regression Testing Link Between Job Announcements and Market Rents

Parameter	High Risk	Low Risk	All Jobs
Industrial Rent (t-1)	-0.08183	-0.08904	-0.09504
	(0.077)	(0.077)	(0.074)
Industrial Rent (t-2)	-0.07574	-0.09719	-0.09179
	(0.106)	(0.105)	(0.102)
Industrial Rent (t-3)	-0.14052	-0.19401	-0.18311
	(0.130)	(0.130)	(0.125)
Industrial Rent (t-4)	-0.08222	-0.07359	-0.08157
	(0.149)	(0.148)	(0.143)
Industrial Rent (t-5)	-0.11892	-0.10228	-0.11185
	(0.162)	(0.161)	(0.156)
Industrial Rent (t-6)	-0.06298	-0.03971	-0.04831
	(0.169)	(0.169)	(0.163)
Industrial Rent (t-7)	-0.06889	-0.05776	-0.06551
	(0.172)	(0.171)	(0.165)
Industrial Rent (t-8)	-0.05760	-0.06658	-0.06757
	(0.164)	(0.163)	(0.157)
Industrial Rent (t-9)	-0.03220	-0.02027	-0.01569
	(0.149)	(0.148)	(0.143)
Industrial Rent (t-10)	0.02508	-0.03707	-0.00632
	(0.129)	(0.128)	(0.124)
Industrial Rent (t-11)	0.01373	0.02616	0.02552
	(0.103)	(0.103)	(0.099)
Industrial Rent (t-12)	0.09044	0.04770	0.07174
	(0.075)	(0.074)	(0.072)
Office Rent (t-1)	-0.02083	-0.08256	-0.06098
	(0.131)	(0.130)	(0.126)
Office Rent (t-2)	-0.02158	-0.02467	-0.01904
	(0.165)	(0.164)	(0.159)
Office Rent (t-3)	-0.02981	0.04805	0.01601
	(0.184)	(0.183)	(0.177)
Office Rent (t-4)	-0.15282	-0.07929	-0.10852
	(0.188)	(0.187)	(0.181)
Office Rent (t-5)	-0.02522	-0.03082	-0.03763
	(0.194)	(0.193)	(0.186)
Office Rent (t-6)	0.07184	0.07776	0.06067
	(0.201)	(0.200)	(0.193)
Office Rent (t-7)	-0.03314	-0.02692	-0.04692
	(0.202)	(0.201)	(0.194)
Office Rent (t-8)	-0.12523	-0.10578	-0.10536
	(0.195)	(0.194)	(0.188)
Office Rent (t-9)	-0.07180	-0.07291	-0.06976
	(0.188)	(0.187)	(0.181)
Office Rent (t-10)	-0.15164	-0.21032	-0.19408
	(0.181)	(0.180)	(0.174)
Office Rent (t-11)	-0.09163	-0.01084	-0.04129
	(0.162)	(0.161)	(0.156)
Office Rent (t-12)	0.17734	0.11887	0.14691
	(0.130)	(0.129)	(0.125)
QE2 (Nov 2020-June2012)	-0.00162	-0.01444	-0.00626
	(0.075)	(0.074)	(0.072)
QE3 (Jan 2013-Oct2014)	-0.11457	-0.14548*	-0.13902*
	(0.081)	(0.081)	(0.078)
R-Sq	0.0825	0.0831	0.0864
Observations	318	318	318
Location (city) Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Note: This table reports the estimated coefficients for the analysis on the impact of CRE rent index on labor demand. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table Appendix 1: High Skill Occupation

Job Code	**Job Title**
11101100	Chief Executives
11101103	Chief Sustainability Officers
11102100	General and Operations Managers
11201100	Advertising and Promotions Managers
11202100	Marketing Managers
11202200	Sales Managers
11302100	Computer and Information Systems Managers
11303101	Treasurers and Controllers
11305100	Industrial Production Managers
11305101	Quality Control Systems Managers
11306100	Purchasing Managers
11312100	Human Resources Managers
11313100	Training and Development Managers
11902100	Construction Managers
11903100	Education and Childcare Administrators, Preschool and Daycare
11903200	Education Administrators, Kindergarten through Secondary
11903300	Education Administrators, Postsecondary
11904100	Architectural and Engineering Managers
11905100	Food Service Managers
11908100	Lodging Managers
11911100	Medical and Health Services Managers
11912100	Natural Sciences Managers
11912101	Clinical Research Coordinators
11912102	Water Resource Specialists
11915100	Social and Community Service Managers
11916100	Emergency Management Directors
11919900	Managers, All Other
11919901	Regulatory Affairs Managers
11919902	Compliance Managers
11919908	Loss Prevention Managers
13101100	Agents and Business Managers of Artists, Performers, and Athletes
13102200	Wholesale and Retail Buyers, Except Farm Products
13104101	Environmental Compliance Inspectors
13104103	Equal Opportunity Representatives and Officers
13104104	Government Property Inspectors and Investigators
13104106	Coroners
13104107	Regulatory Affairs Specialists
13107100	Human Resources Specialists
13107500	Labor Relations Specialists
13108100	Logisticians
13108102	Logistics Analysts
13111100	Management Analysts
13112100	Meeting, Convention, and Event Planners
13113100	Fundraisers
13114100	Compensation, Benefits, and Job Analysis Specialists
13115100	Training and Development Specialists
13119900	Business Operations Specialists, All Other
13119904	Business Continuity Planners
13119905	Sustainability Specialists
13119906	Online Merchants
13205100	Financial and Investment Analysts
13206100	Financial Examiners
13207100	Credit Counselors
13209901	Financial Quantitative Analysts
13209904	Fraud Examiners, Investigators and Analysts
15201100	Actuaries
15203100	Operations Research Analysts
15204100	Statisticians
15204101	Biostatisticians

High Skill Occupation (Continued)

Job Code	Job Title
17101100	Architects, Except Landscape and Naval
17101200	Landscape Architects
17102200	Surveyors
17102201	Geodetic Surveyors
17201100	Aerospace Engineers
17203100	Bioengineers and Biomedical Engineers
17204100	Chemical Engineers
17205100	Civil Engineers
17205101	Transportation Engineers
17206100	Computer Hardware Engineers
17207100	Electrical Engineers
17207200	Electronics Engineers, Except Computer
17207201	Radio Frequency Identification Device Specialists
17208100	Environmental Engineers
17211102	Fire-Prevention and Protection Engineers
17211200	Industrial Engineers
17213100	Materials Engineers
17214100	Mechanical Engineers
17216100	Nuclear Engineers
17217100	Petroleum Engineers
17219900	Engineers, All Other
17219903	Energy Engineers, Except Wind and Solar
17219907	Photonics Engineers
17219908	Robotics Engineers
17219911	Solar Energy Systems Engineers
17302100	Aerospace Engineering and Operations Technologists and Technicians
17302600	Industrial Engineering Technologists and Technicians
17302700	Mechanical Engineering Technologists and Technicians
17302900	Engineering Technologists and Technicians, Except Drafters, All Other
17302901	Non-Destructive Testing Specialists
17302908	Photonics Technicians
19101200	Food Scientists and Technologists
19102100	Biochemists and Biophysicists
19102200	Microbiologists
19102300	Zoologists and Wildlife Biologists
19102900	Biological Scientists, All Other
19102901	Bioinformatics Scientists
19102903	Geneticists
19103102	Range Managers
19104100	Epidemiologists
19104200	Medical Scientists, Except Epidemiologists
19109900	Life Scientists, All Other
19201100	Astronomers
19201200	Physicists
19203100	Chemists
19203200	Materials Scientists
19204100	Environmental Scientists and Specialists, Including Health
19204101	Climate Change Policy Analysts
19204102	Environmental Restoration Planners
19204300	Hydrologists
19209901	Remote Sensing Scientists and Technologists
19301100	Economists
19302200	Survey Researchers
19303200	Industrial-Organizational Psychologists
19303900	Psychologists, All Other
19305100	Urban and Regional Planners
19309300	Historians
19309400	Political Scientists
19309900	Social Scientists and Related Workers, All Other
19309901	Transportation Planners
19402100	Biological Technicians

High Skill Occupation (Continued)

Job Code	Job Title
19409200	Forensic Science Technicians
21101100	Substance Abuse and Behavioral Disorder Counselors
21101200	Educational, Guidance, and Career Counselors and Advisors
21101300	Marriage and Family Therapists
21101400	Mental Health Counselors
21101500	Rehabilitation Counselors
21101900	Counselors, All Other
21102100	Child, Family, and School Social Workers
21102200	Healthcare Social Workers
21102300	Mental Health and Substance Abuse Social Workers
21102900	Social Workers, All Other
21109100	Health Education Specialists
21109200	Probation Officers and Correctional Treatment Specialists
21109300	Social and Human Service Assistants
21109400	Community Health Workers
21109900	Community and Social Service Specialists, All Other
21201100	Clergy
21202100	Directors, Religious Activities and Education
23101100	Lawyers
23101200	Judicial Law Clerks
23102200	Arbitrators, Mediators, and Conciliators
25101100	Business Teachers, Postsecondary
25102100	Computer Science Teachers, Postsecondary
25102200	Mathematical Science Teachers, Postsecondary
25103100	Architecture Teachers, Postsecondary
25103200	Engineering Teachers, Postsecondary
25104200	Biological Science Teachers, Postsecondary
25104300	Forestry and Conservation Science Teachers, Postsecondary
25105200	Chemistry Teachers, Postsecondary
25106200	Area, Ethnic, and Cultural Studies Teachers, Postsecondary
25106300	Economics Teachers, Postsecondary
25106600	Psychology Teachers, Postsecondary
25106700	Sociology Teachers, Postsecondary
25107100	Health Specialties Teachers, Postsecondary
25107200	Nursing Instructors and Teachers, Postsecondary
25108100	Education Teachers, Postsecondary
25111100	Criminal Justice and Law Enforcement Teachers, Postsecondary
25111200	Law Teachers, Postsecondary
25111300	Social Work Teachers, Postsecondary
25112100	Art, Drama, and Music Teachers, Postsecondary
25112200	Communications Teachers, Postsecondary
25112300	English Language and Literature Teachers, Postsecondary
25112400	Foreign Language and Literature Teachers, Postsecondary
25112500	History Teachers, Postsecondary
25112600	Philosophy and Religion Teachers, Postsecondary
25119400	Career/Technical Education Teachers, Postsecondary
25119900	Postsecondary Teachers, All Other
25201100	Preschool Teachers, Except Special Education
25201200	Kindergarten Teachers, Except Special Education
25202100	Elementary School Teachers, Except Special Education
25202200	Middle School Teachers, Except Special and Career/Technical Education
25202300	Career/Technical Education Teachers, Middle School
25203100	Secondary School Teachers, Except Special and Career/Technical Education
25203200	Career/Technical Education Teachers, Secondary School
25205100	Special Education Teachers, Preschool
25205900	Special Education Teachers, All Other
25301100	Adult Basic Education, Adult Secondary Education, and English as a Second Language Instructors
25302100	Self-Enrichment Teachers
25309900	Teachers and Instructors, All Other
25902100	Farm and Home Management Educators
25903100	Instructional Coordinators
25909900	Educational Instruction and Library Workers, All Other

High Skill Occupation (Continued)

Job Code	Job Title
27101100	Art Directors
27101200	Craft Artists
27101300	Fine Artists, Including Painters, Sculptors, and Illustrators
27101400	Special Effects Artists and Animators
27102100	Commercial and Industrial Designers
27102200	Fashion Designers
27102300	Floral Designers
27102400	Graphic Designers
27102500	Interior Designers
27102600	Merchandise Displayers and Window Trimmers
27102700	Set and Exhibit Designers
27102900	Designers, All Other
27201100	Actors
27201203	Media Programming Directors
27201204	Talent Directors
27201205	Media Technical Directors/Managers
27202100	Athletes and Sports Competitors
27202200	Coaches and Scouts
27203100	Dancers
27301100	Broadcast Announcers and Radio Disc Jockeys
27303100	Public Relations Specialists
27304100	Editors
27304305	Poets, Lyricists and Creative Writers
27309100	Interpreters and Translators
27401400	Sound Engineering Technicians
27402100	Photographers
27403200	Film and Video Editors
29101100	Chiropractors
29102100	Dentists, General
29102200	Oral and Maxillofacial Surgeons
29102300	Orthodontists
29102900	Dentists, All Other Specialists
29103100	Dietitians and Nutritionists
29104100	Optometrists
29105100	Pharmacists
29107100	Physician Assistants
29107101	Anesthesiologist Assistants
29112200	Occupational Therapists
29112300	Physical Therapists
29112400	Radiation Therapists
29112500	Recreational Therapists
29112600	Respiratory Therapists
29112700	Speech-Language Pathologists
29112800	Exercise Physiologists
29113100	Veterinarians
29114100	Registered Nurses
29114102	Advanced Practice Psychiatric Nurses
29114103	Critical Care Nurses
29114104	Clinical Nurse Specialists
29115100	Nurse Anesthetists
29116100	Nurse Midwives
29117100	Nurse Practitioners
29118100	Audiologists
29201200	Medical and Clinical Laboratory Technicians
29203100	Cardiovascular Technologists and Technicians
29203200	Diagnostic Medical Sonographers
29203400	Radiologic Technologists and Technicians
29203500	Magnetic Resonance Imaging Technologists
29205100	Dietetic Technicians
29205300	Psychiatric Technicians
29205500	Surgical Technologists

High Skill Occupation (Continued)

Job Code	Job Title
29205600	Veterinary Technologists and Technicians
29205700	Ophthalmic Medical Technicians
29206100	Licensed Practical and Licensed Vocational Nurses
29209100	Orthotists and Prosthetists
29209900	Health Technologists and Technicians, All Other
29209901	Neurodiagnostic Technologists
29909100	Athletic Trainers
29909200	Genetic Counselors
29909900	Healthcare Practitioners and Technical Workers, All Other
31201100	Occupational Therapy Assistants
31201200	Occupational Therapy Aides
31202100	Physical Therapist Assistants
31909200	Medical Assistants
33101200	First-Line Supervisors of Police and Detectives
33109900	First-Line Supervisors of Protective Service Workers, All Other
33302106	Intelligence Analysts
33303100	Fish and Game Wardens
33901100	Animal Control Workers
33902100	Private Detectives and Investigators
33909100	Crossing Guards and Flaggers
35101100	Chefs and Head Cooks
39201100	Animal Trainers
39309300	Locker Room, Coatroom, and Dressing Room Attendants
39402100	Funeral Attendants
39403100	Morticians, Undertakers, and Funeral Arrangers
39501200	Hairdressers, Hairstylists, and Cosmetologists
39509100	Makeup Artists, Theatrical and Performance
39509400	Skincare Specialists
39601200	Concierges
39701200	Travel Guides
39901100	Childcare Workers
39901101	Nannies
39903100	Exercise Trainers and Group Fitness Instructors
39903200	Recreation Workers
39904100	Residential Advisors
39909900	Personal Care and Service Workers, All Other
41101100	First-Line Supervisors of Retail Sales Workers
41101200	First-Line Supervisors of Non-Retail Sales Workers
41304100	Travel Agents
41401100	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products
41401107	Solar Sales Representatives and Assessors
41903100	Sales Engineers
43101100	First-Line Supervisors of Office and Administrative Support Workers
43503100	Public Safety Telecommunicators
45204100	Graders and Sorters, Agricultural Products
47101100	First-Line Supervisors of Construction Trades and Extraction Workers
47101103	Solar Energy Installation Managers
47211100	Electricians
47402100	Elevator and Escalator Installers and Repairers
47508100	Helpers–Extraction Workers
49101100	First-Line Supervisors of Mechanics, Installers, and Repairers
49202200	Telecommunications Equipment Installers and Repairers, Except Line Installers
49209500	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
49304200	Mobile Heavy Equipment Mechanics, Except Engines
49905100	Electrical Power-Line Installers and Repairers
49905200	Telecommunications Line Installers and Repairers
49906200	Medical Equipment Repairers
49909200	Commercial Divers
49909900	Installation, Maintenance, and Repair Workers, All Other

High Skill Occupation (Continued)

Job Code	**Job Title**
49909901	Geothermal Technicians
51101100	First-Line Supervisors of Production and Operating Workers
51204100	Structural Metal Fabricators and Fitters
51609200	Fabric and Apparel Patternmakers
51609300	Upholsterers
51609900	Textile, Apparel, and Furnishings Workers, All Other
53201100	Airline Pilots, Copilots, and Flight Engineers
53202100	Air Traffic Controllers
53301100	Ambulance Drivers and Attendants, Except Emergency Medical Technicians
53706100	Cleaners of Vehicles and Equipment
53706400	Packers and Packagers
Total	**313**

Notes: This table provides a list of high-skill occupations as identified by the U.S. Bureau of Labor Statistics. The BLS suggest that those jobs require high skilled laborers that are unlikely to be replaced by machines. There are 313 distinguish high skill occupations identified by the BLS.

Table Appendix 2: Low Skill Occupation

Job Code	Job Title
11311100	Compensation and Benefits Managers
13102100	Buyers and Purchasing Agents, Farm Products
13103200	Insurance Appraisers, Auto Damage
13203100	Budget Analysts
13204100	Credit Analysts
13205300	Insurance Underwriters
13207200	Loan Officers
13208100	Tax Examiners and Collectors, and Revenue Agents
13208200	Tax Preparers
23201100	Paralegals and Legal Assistants
23209300	Title Examiners, Abstractors, and Searchers
25403100	Library Technicians
27202300	Umpires, Referees, and Other Sports Officials
27304200	Technical Writers
29201100	Medical and Clinical Laboratory Technologists
29201102	Cytotechnologists
29205200	Pharmacy Technicians
31909400	Medical Transcriptionists
31909600	Veterinary Assistants and Laboratory Animal Caretakers
33903100	Gambling Surveillance Officers and Gambling Investigators
35201400	Cooks, Restaurant
35201500	Cooks, Short Order
35202100	Food Preparation Workers
35303100	Waiters and Waitresses
35304100	Food Servers, Nonrestaurant
35901100	Dining Room and Cafeteria Attendants and Bartender Helpers
35903100	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
37101100	First-Line Supervisors of Housekeeping and Janitorial Workers
37301100	Landscaping and Groundskeeping Workers
37301200	Pesticide Handlers, Sprayers, and Applicators, Vegetation
39302100	Motion Picture Projectionists
39303100	Ushers, Lobby Attendants, and Ticket Takers
39509200	Manicurists and Pedicurists
39701100	Tour Guides and Escorts
41201100	Cashiers
41202100	Counter and Rental Clerks
41202200	Parts Salespersons
41203100	Retail Salespersons
41302100	Insurance Sales Agents
41901200	Models
41902100	Real Estate Brokers
41902200	Real Estate Sales Agents
41904100	Telemarketers
41909100	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers
41909900	Sales and Related Workers, All Other
43201100	Switchboard Operators, Including Answering Service
43202100	Telephone Operators
43301100	Bill and Account Collectors
43303100	Bookkeeping, Accounting, and Auditing Clerks
43305100	Payroll and Timekeeping Clerks
43306100	Procurement Clerks
43307100	Tellers
43401100	Brokerage Clerks
43402100	Correspondence Clerks
43407100	File Clerks
43408100	Hotel, Motel, and Resort Desk Clerks
43411100	Interviewers, Except Eligibility and Loan
43412100	Library Assistants, Clerical
43413100	Loan Interviewers and Clerks
Total	313

Low Skill Occupation (Continued)

Job Code	Job Title
43415100	Order Clerks
43416100	Human Resources Assistants, Except Payroll and Timekeeping
43417100	Receptionists and Information Clerks
43501100	Cargo and Freight Agents
43502100	Couriers and Messengers
43503200	Dispatchers, Except Police, Fire, and Ambulance
43505100	Postal Service Clerks
43506100	Production, Planning, and Expediting Clerks
43507100	Shipping, Receiving, and Inventory Clerks
43511100	Weighers, Measurers, Checkers, and Samplers, Recordkeeping
43601100	Executive Secretaries and Executive Administrative Assistants
43601200	Legal Secretaries and Administrative Assistants
43601400	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
43902100	Data Entry Keyers
43905100	Mail Clerks and Mail Machine Operators, Except Postal Service
43906100	Office Clerks, General
43907100	Office Machine Operators, Except Computer
45209300	Farmworkers, Farm, Ranch, and Aquacultural Animals
47204100	Carpet Installers
47205100	Cement Masons and Concrete Finishers
47206100	Construction Laborers
47207300	Operating Engineers and Other Construction Equipment Operators
47218100	Roofers
47301200	Helpers–Carpenters
47405100	Highway Maintenance Workers
47406100	Rail-Track Laying and Maintenance Equipment Operators
49202100	Radio, Cellular, and Tower Equipment Installers and Repairers
49302100	Automotive Body and Related Repairers
49309100	Bicycle Repairers
49901100	Mechanical Door Repairers
49904300	Maintenance Workers, Machinery
49906100	Camera and Photographic Equipment Repairers
49909100	Coin, Vending, and Amusement Machine Servicers and Repairers
49909600	Riggers
51202200	Electrical and Electronic Equipment Assemblers
51202300	Electromechanical Equipment Assemblers
51209200	Team Assemblers
51209900	Assemblers and Fabricators, All Other
51301100	Bakers
51302100	Butchers and Meat Cutters
51302200	Meat, Poultry, and Fish Cutters and Trimmers
51402100	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
51403200	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51403300	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51403500	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic
51406100	Model Makers, Metal and Plastic
51407200	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
51408100	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51419100	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
51419900	Metal Workers and Plastic Workers, All Other
51511100	Prepress Technicians and Workers
51511300	Print Binding and Finishing Workers
51603100	Sewing Machine Operators
51606200	Textile Cutting Machine Setters, Operators, and Tenders
51606400	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders
51609100	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers
51701100	Cabinetmakers and Bench Carpenters
51702100	Furniture Finishers

Low Skill Occupation (Continued)

Job Code	Job Title
51704100	Sawing Machine Setters, Operators, and Tenders
51704200	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
51802100	Stationary Engineers and Boiler Operators
51901200	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
51902100	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
51903200	Cutting and Slicing Machine Setters, Operators, and Tenders
51904100	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
51906100	Inspectors, Testers, Sorters, Samplers, and Weighers
51908100	Dental Laboratory Technicians
51911100	Packaging and Filling Machine Operators and Tenders
51912300	Painting, Coating, and Decorating Workers
51914100	Semiconductor Processing Technicians
51915100	Photographic Process Workers and Processing Machine Operators
51919700	Tire Builders
51919900	Production Workers, All Other
53303100	Driver/Sales Workers
53401100	Locomotive Engineers
53601100	Bridge and Lock Tenders
53602100	Parking Attendants
53604100	Traffic Technicians
53605101	Aviation Inspectors
53605107	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation
53701100	Conveyor Operators and Tenders
53702100	Crane and Tower Operators
53705100	Industrial Truck and Tractor Operators
53706300	Machine Feeders and Offbearers
53707200	Pump Operators, Except Wellhead Pumpers
53708100	Refuse and Recyclable Material Collectors
Total	**145**

Notes: This table provides a list of low-skill occupations as identified by the U.S. Bureau of Labor Statistics. The BLS suggest that those jobs require low skilled laborers that are likely to be replaced by machines. There are 145 distinguish low skill occupations identified by the BLS.