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The Wider Impacts of High-Technology Employment: Evidence from U.S. Cities

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Abstract

Innovative, high-technology industries are commonly described as drivers of regional development. 'Tech' workers earn high wages, but they allegedly generate knock-on effects throughout the local economies that host them, producing new jobs and raising wages in nontradable activities. At the same time, in iconic high-tech agglomerations like the San Francisco Bay Area, the home of Silicon Valley, the success of the tech industry creates tensions, in part as living costs rise beyond the reach of many non-tech workers. Across a large sample of US cities, this paper explores these issues systematically. Combining annual data on wages, employment and prices from the Quarterly Census of Employment and Wages, the Department of Housing and Urban Development and the Consumer Price Index, it estimates how growth in tradable tech employment affects the real, living-cost deflated wages of local workers in nontradable sectors. Results indicate that high-technology employment has significant, positive, but substantively modest effects on the real wages of workers in nontradable sectors. However, in cities with highly price-inelastic housing markets, the relationship is inverted, with tech generating negative externalities for nontradable workers.

Keywords: high-technology, inequality, real wages, nontradable services; housing

JEL codes: J21; J31; O18; R11; R31

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1. Introduction

Innovative, high-technology industries are commonly believed to drive regional development, and it is equally commonplace for policymakers to expend effort to attract them to their localities (Clark, 1972; Duranton, 2011). ‘Tech’ workers command high wages, and as such their presence contributes to regional prosperity. Above and beyond this direct effect, tech industries are thought to generate wider economic benefits in the local economies that host them. Durable employment growth in tech and other tradable sectors raises demand for local nontradable services, such as health care, restaurants and dry cleaners. Higher demand for nontradables can be expressed through job creation as well as higher pay. Since tech work is more highly remunerated than many other tradables, indirect benefits from tech ought to be comparatively large. Still, some dark clouds hang over this sunny-seeming picture. Most notably, cities hosting larger concentrations of skilled workers in tech and other activities have also witnessed faster growth in local prices (Shapiro, 2006; Florida 2017). Studies of the most iconic technology clusters in the U.S. highlight the deleterious effects of rising costs, especially housing, on workers whose jobs support tech and other traded sectors (Schafran, 2013; Hyra, 2015). This work questions the narrative that tech employment generates outcomes that are “unambiguously positive” (Moretti and Thulin, 2013, p.343).

Motivated by this debate, this paper aims to better understand the relationship between tech and the welfare of workers in local nontradable sectors. More specifically, it answers three questions related to the causal effects of local changes in employment in tradable high-technology activities. First, across a large sample of US cities, how do changes in local high-technology employment affect the real (cost-deflated) wages of workers in nontradable sectors? Second, in terms of its association with the real wages earned by nontradable sector employees, is tech employment distinct from other tradable activities? Third, by limiting housing price increases, does the elasticity of local housing supply moderate the relationship between tech employment and nontradable real wages?

To answer these questions, we make use of information from the Quarterly Census of Employment and Wages (QCEW), which offers comprehensive longitudinal data on employment and wages by industry for units as small as counties. We identify our relationship of interest by estimating how annual changes in tradable employment in metropolitan areas are associated with changes in the real wages of local workers in nontradable activities, with locational and time fixed effects absorbing bias from unobserved city-specific, and general dynamic factors, respectively.[1] To enable this approach, we require measures of real income and housing supply elasticity, as well as clean distinctions between tech and other industries. We classify each 4-

[1] Throughout the paper, unless otherwise specified, we use terms like ‘regional,’ ‘urban,’ ‘local,’ and ‘city’ interchangeably to refer to functionally-integrated metropolitan areas, defined by the U.S. Census Bureau as Metropolitan Core-Based Statistical Areas (CBSAs).

digit NAICS industry into one of three categories: tech tradable, non-tech tradable or nontradable. To do so we use locational Gini coefficients to estimate the geographic ubiquity of each industry, on the assumption that tradable sectors will be relatively concentrated in space. Within tradables, we follow the strictest guidance from the Bureau of Labor Statistics (BLS) on what constitutes high-technology. We build annual local consumer price indices that combine median rent information from the Department of Housing and Urban Development (HUD) with non-housing prices from the BLS' CPI-U, and use these as a deflator to capture location-specific real wages. To measure the moderating effect of the elasticity of housing supply, we interact tech employment with Saiz' (2010) index of geographic land availability and, separately, with Gyourko's (2008) CBSA-level estimates of the Wharton Index of Land Use Regulation (WRLURI).

Our paper contributes to three active areas of research. First, and most directly, it engages with a long-running debate about the local development effects of high-technology and other tradable activities. Much of this work has focused on impacts that flow directly from local specialization in tech activities (Malecki, 1981; Glaeser et al, 1992; Kemeny and Storper, 2015). Meanwhile, nearly all studies examining wider, indirect effects consider only job creation as an outcome (i.e., Moretti, 2010, Van Dijk, 2016). Only a few studies consider wage impacts (i.e., Lee and Rodriguez-Pose, 2016), and these ignore variation in local prices. We contribute in a few specific ways. Ours is the first known study that measures the role of tradable sectors in shaping location-specific real wages; that distinguishes between tradable tech, tradable non-tech, and nontradable activities; and that models potential heterogeneity across markets facing different housing constraints. A second stream of related research is concerned with the turn towards growing income inequality within and between cities (Drennan et al, 1996; Moretti, 2012; Breau et al, 2014; Ganong and Shoag, 2017). Recent work shows that tech and other high-skill workers have increasingly sorted into more expensive cities (Shapiro, 2006; Diamond, 2016). While this spatial stratification reduces real wage inequality at a national scale (Moretti, 2013b), it also implies growing precariousness of workers in nontradable activities who have *not* sorted to low-cost locations – precisely the barbers, dry cleaners and health care workers whose services tech workers consume. This paper is the first known attempt to examine the links between tech and the welfare of this population of workers in a direct and systematic way Third, and most loosely, this paper contributes to sociological accounts of the role of tech employment in generating neighborhood change. Existing work has considered themes of displacement, changes in the consumption landscape and other topics, often at a relatively small spatial scale and largely inside iconic hubs of tech activity (Solnit, 2002; Centner, 2008; Stehlin, 2016). The present paper complements this work by adding a more regional perspective, a more systematic approach, and a wider frame in terms of the range of cities considered.

In brief, we find that regional growth in tech tradables is positively related to growth in real wages for workers in nontradable sectors. However, the overall relationship is relatively modest: an increase of one thousand tech workers increases the annual real wages of workers in nontradable activities by approximately $20. By contrast, non-tech tradable employment is unrelated to the real wages of workers in nontradables. Additionally, as theory predicts, we conclude that the real wage effects of tech employment depend on local housing supply, and in those locations where the supply of housing is highly inelastic, the relationship between tech sector growth and nontradable wages is negative. This suggests that, in tight housing markets, the wider benefits of high-tech are reallocated from workers to incumbent landowners.

The remainder of the paper is organized as follows. In Section 2 we review the literature linking high-technology employment to development outcomes, focusing especially on theory and empirics regarding the indirect effects of this relationship on workers in nontradable sectors. Section 3 describes our empirical approach, while Section 4 discusses data and measurement issues. Section 5 presents our findings, and Section 6 concludes.

2. Literature Review

Innovative, high-technology activities have long enjoyed a privileged position in the minds of researchers and policymakers concerned with economic development (Clark, 1972; Malecki, 1981; Scott and Storper, 1987; Duranton and Puga, 2001; Howells, 2005; Block and Keller, 2009; Storper et al., 2015; Feldman et al., 2016). Nonroutine high-technology activities tend to be strongly localized in space, as firms and workers congregate to match with each other and to efficiently produce and exchange tacit knowledge (Storper and Walker, 1989; Glaeser et al, 1992; Saxenian, 1994; Chatterji et al, 2014).

The increasing importance of high-technology goods and services has stimulated job growth in these activities, whether through the expansion of existing firms or the birth of new ventures. The growth of this sector can have direct and indirect effects on the localities that play host to it. First and most obviously, it will expand the local employment base. And as workers in high-technology industries tend to be well paid, growth in tech employment is likely to increase local per capita incomes. Such direct income effects can be large. At the extreme, consider the tech boom of 1994-2000. Over this period, Galbraith and Hale (2004) demonstrate that the California counties of San Mateo, Santa Clara and San Francisco (all in the San Francisco Bay Area that contains Silicon Valley), as well Washington’s Kings County (home to Microsoft and Amazon) together accounted for nearly all the growth in between-county income inequality.

The indirect effects of tech employment are subtler. To understand them, we must first distinguish between tradable and nontradable economic activity. Tradable goods are those produced to serve national, and potentially global markets, and as such face prices that are not defined locally. Many such activities are subject to internal or external increasing returns to scale in production, and consequently will tend towards some degree of geographic concentration. Some are so concentrated that their locations have come to represent them metonymically, such as Hollywood, Wall Street, and of course Silicon Valley. Meanwhile, nontradable activities serve local needs and face local prices. As described in the introduction, these include goods and services like health care, dry cleaning, and restaurants. Nontradables comprise the majority of local employment; in the U.S. context, they are also responsible for the bulk of employment growth in recent years (Spence and Hlatshwayo, 2012).

Using export-base theory and input-output methods, scholars have long considered that local tradable and nontradable employment are linked (North, 1955; Richardson, 1985). Moretti (2010) provides a theoretical update, describing a general equilibrium framework under which the national economy is comprised of a system of cities in which workers choose locations. Each city contains a mix of tradable and nontradable activities. A positive shock to local labor demand in the tradable sector will stimulate greater demand for workers in the nontradable sector. This will lead to new jobs for dry cleaners, medical technicians and chefs, as well as higher pay for workers in these sectors.[2] As Moretti and Thulin (2013) outline, the extent to which expansions of the tradable sector produce job growth as opposed to wage growth in nontradables depends on the supply of housing in a location, as well as on potential migrants' responsiveness to new opportunities. Locations that face strong constraints on housing supply will experience higher wage growth and lower job creation. Meanwhile, all else equal, a greater elasticity of migration will tip the balance towards larger job multipliers and weaker upward pressure on wages (Hsieh and Moretti 2016). On the basis that high-productivity tech work produces a larger expansion in local income relative to other tradables, growth in tech ought to create especially large demand for nontradables.

Evidence on these propositions has been almost entirely focused on measuring job multipliers. A growing literature has documented the existence of multipliers flowing from various kinds of tradable activities in a range of countries (Moretti, 2010; de Blasio and Menon, 2011; Moretti and Thulin, 2013; Fleming and Measham, 2014; van Dijk, 2016, Frocrain and Giraud, 2017). Moretti (2010) finds that the addition of a manufacturing job in a local economy generates 1.6 nontradable jobs, whereas a new tech job generates nearly 5 jobs in nontradable activities.

Surprisingly, given renewed interest in this topic, there is nearly no evidence tracing the effects of tech or other tradable employment on the wages earned by workers in local nontradable activities. In the U.S. context, there is at least one strong reason to explore this channel: internal

[2] There are some other reasons why workers in nontradable will experience pay growth as a consequence of an expansion in tradable employment. One is productivity spillovers, yet logic suggests these effects ought to relatively minor, in that one does not expect barbers to become more productive because they are around computer programmers. Baumol's (1967) 'cost disease' represents another potential channel, though for reasons that are somewhat related to the limits of productivity spillovers, one expects the influence of this to be quite limited in scope in terms of the kinds of nontradable work it affects. In short, physics instructors and classical musicians do not typify work in the nontradable sector. Meanwhile, barbers and retail clerks are not likely to seamlessly switch to computer programming because it pays more. We revisit this empirically later in the paper.

migration has slowed since 1980, a trend that cuts across a wide range of demographic features (Molloy et al, 2011, 2014). As a consequence, at least some of the pressure from rising demand ought to be pushing up the nominal wages of workers in nontradable activities. Only a few studies exist that investigate how high-technology employment affects the wages of workers outside of tech itself. Echeverri-Carroll and Ayala (2009) and Lee and Rodriguez-Pose (2016) show that tech employment in U.S. metropolitan areas is associated with higher nominal wages for workers without college degrees; the latter also finds no association between tech and the share of local residents falling below the national poverty line. Studying the UK, Lee and Clarke (2017) show that tech employment is associated with growth in poorly paid jobs requiring relatively unskilled labor. A little more loosely related, Fowler and Kleit (2013) find ambiguous relationships between concentrations of tradable activity and the local incidence of poverty.

No known work has captured how high-technology or other tradable activities affect the real wages for workers in local nontradable sectors. There are strong reasons why this is necessary. Longstanding patterns of interstate and inter-metropolitan income convergence more or less stopped after 1980 (Drennan et al, 1996; Moretti, 2012; Giannone, 2017). While we lack consensus on the deep causal explanations for this shift, one proximate cause is a skill-biased sorting process, whereby higher- and lower-skilled workers are increasingly concentrating in different locations (Shapiro, 2006, Moretti, 2013). Since 1980, high-skill workers are increasingly concentrated in high-productivity, high-amenity locations, where the already-elevated cost of housing has increased more sharply than in locations with lower shares of college graduates (Diamond, 2016). While living costs in high-productivity locations reduce cost-blind estimates of national income inequality (Moretti, 2013), they also highlight the need to consider effects of high-technology employment on real, not nominal wages. Ganong and Shoag (2017) illustrate the point by showing that while janitors working in New York City in 2010 earned nearly one third more in nominal pay than their counterparts in Deep South States, after adjusting for housing prices they earn six percent less.

This should come as little surprise to a broad range of scholars and advocacy organizations long concerned with processes of gentrification, displacement and neighborhood change (National Urban Coalition, 1978; Clay, 1979; Henig, 1980; Lees et al., 2013, Zuk et al, 2015). This methodologically varied field of research has documented how the renewed urbanization of skilled workers has generated winners and losers. A clear consensus indicates that the housing security of lower-income workers, many of whom work in the nontradable sector of the economy, can be precarious in the face of sudden changes in the nature of urban housing markets.

All of the preceding prompts the three research questions this paper explores:

> Q1: What is the relationship between local high-technology employment and the real wages earned by workers in nontradable industries?

Q2: Is the relationship in Q1 specific to high-technology tradables? How does it compare to growth in non-high-technology tradables?

Q3: Does the relationship between local high-technology employment and real wages for workers in nontradable industries depend on the elasticity of local housing supply?

In the next section we describe our approach to answering these questions.

3. Empirical Approach

We evaluate the relationship between local employment in the high-technology sector and the real wages of workers in nontradable sectors by estimating the following regression equation:

$$RW_{ct}^{NT} = \beta_0 + \beta_1 E_{ct}^{T} + \gamma X'_{ct} + \mu_c + \eta_t + \nu_{ct} \qquad (1)$$

where *RW* describes the real (local cost-deflated) wages of workers in nontradable activities, captured by the superscript *NT*, in city *c* and time *t*. *E*mployment in high-tech tradable sectors is measured by E^T, and *X'* is a vector of relevant time-varying city characteristics. μ is a city-specific fixed effect, whose purpose is to absorb bias from unobserved but relatively stationary regional features, while η is included to capture time-varying but economy-wide shocks, such as the Great Recession. ν is the standard random error term. The key parameter to be estimated is β_1, measuring the effect of high-technology employment.

Applying the fixed effects estimator, Equation (1) measures how the average annual real wages of workers in local nontradable activities respond to changes in the level of high-technology employment around them. It does so while accounting for major sources of spurious correlation that might otherwise bias estimates. However, estimates remain vulnerable to unobserved localized shocks that happen to be correlated with the level of high-technology employment, and that also shape real wages. For a potential example of this issue, consider that several regions in the sample contain municipalities that pass legislation raising the minimum wage (as the cities of Los Angeles and Seattle did in 2015). Let's imagine that cities with growing high-technology sectors are more likely to enact such laws. To the extent that shocks to minimum wages improve the fortunes of workers in nontradable sectors, while coinciding with growth in local high-tech employment, estimates of the wider effects of high-technology employment will be upwardly biased. To account for such bias, we follow standard practice and instrument for our key potentially endogenous regressor using two-stage least squares. Our instrument is a shift-share measure of the kind used by Bartik (1991), Ottaviano and Peri (2006) and others. In general, the value of such measures lies in their ability to capture the component of labor demand that stems from non-local sources, and which is therefore plausibly exogenous to unmeasured local shocks which might generate biased estimates of the relationship of interest. In our case we aim to capture the exogenous component of local demand for high-technology sectors, as follows:

$$\widehat{E^{T}_{c,t}} = E^{T}_{c,t-1}\left[1 + \frac{\left(E^{T}_{US,t} - E^{T}_{c,t}\right) - \left(E^{T}_{US,t-1} - E^{T}_{c,t-1}\right)}{\left(E^{T}_{US,t-1} - E^{T}_{c,t-1}\right)}\right] \qquad (2)$$

where E_{US} denotes national employment levels, and all other variables remain as above. Equation 2 arrives at the 'expected' level of local high-tech employment in period t by multiplying initial local tech tradable employment by the national growth rate for employment in the sector between *t-1* and *t*. Because raw national growth rates include the region in question, and could therefore be driven by them, we follow Faggio and Overman (2014) in subtracting local employment from national employment in order to calculate the truly exogenous component of national growth rates between one period and the next.

4. Data and Measurement

Our primary data comes from the U.S. Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW). QCEW is built from State-submitted Unemployment Insurance (UI) records, which are then linked in order to provide a time series of employment and wages. Since QCEW provides information on the universe of workers covered by State UI programs, as well as Federal employees, its coverage is relatively comprehensive, capturing more than 90 percent of workers in the country. Compared to alternative data sources, QCEW offers several additional advantages. One is that, unlike public-use samples of the Decennial Census and American Community Survey, the data completely identify local areas. This means estimates ought to be considerably more reliable. Furthermore, since they are not self-reported, wage data in QCEW ought to be higher quality than those found in population Census data.

For a given industry and location, the level of coverage in QCEW is determined by confidentiality policy, which seeks to ensure that reported data cannot be used to identify information on firms and individuals. Confidentiality issues arise in jurisdictions with a small number of employers in a given industrial classification. Since we focus on 4-digit NAICS sectors, and relatively densely populated metropolitan regions, our dataset covers in excess of 90% of the population of total employment in our industries of interest. Although QCEW data are available from 1990 to the present, we confine our analysis to the period 2001-2015, since annual data for certain control variables is missing prior to 2000.

The scale of interest in this study is the metropolitan regional scale, defined in terms of economic rather than administrative integration. Researchers define regional economies in different ways; and these choices may have material consequences for the understanding of regional processes.

We mainly use definitions for metropolitan Core-Based Statistical Areas (CBSAs), put forth by the Office of Management and Budget (OMB). A metropolitan CBSA is an area containing at least one core urban center with at least 50,000 residents, around which are arrayed adjacent communities that are strongly economically and socially integrated.[3]

4.1 Distinguishing Tradable and Nontradable Industries

In order to capture the effects of tradable high-technology employment on the wages of workers in nontradable sectors, we must first distinguish tradable from nontradable industries. One key distinction between the two is their spatial presence. Every town needs dry cleaners, barbershops and offices of general practitioners. By contrast, the manufacturing of car engines could occur in a very limited number of locales and still satisfy a much wider geographic scope of demand. This intuition has been operationalized as a means of identifying the distinction between tradable and nontradable activities. Following Krugman (1991), we measure the level of geographical concentration of each 4-digit industry, using a locational Gini coefficient, given by the following formula:

$$G_j = \sum_c \left[{}^{E_c}\!/_{E_{US}} - {}^{E_{c,j}}\!/_{E_{US,j}} \right]^2 \qquad (3)$$

where *E* equals the level of employment in city *c* for industry *j*. Based on this index, an industry which is geographically dispersed would have a Gini coefficient closer to 0, whereas one more concentrated would have a value closer to 1.[4] We estimate Gini coefficients using 4-digit NAICS industries, using industry employment data from 2015.[5] The median level of industry concentration in 2015 is of 0.015.

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[3] The labor market for a given CBSA can overlap with that of nearby CBSAs, and such adjoining CBSAs are combined together into Consolidated Statistical Areas (CSA) by the OMB. Limitations in data coverage for certain variables at the CSA scale helped to determine our focus on CBSAs as our unit of analysis. To ensure that findings are not biased by the exclusion of nontrade workers who may work in, but live outside of a given CBSA, we run our models at the CSA scale as a robustness check, albeit with an incomplete set of control variables

[4] As with Jensen and Kletzer (2010), we opt not to adjust measures for the possibility that concentration reflects the presence of a very small number of large plants – a possibility raised and addressed empirically by Ellison and Glaeser (1997). Because our interest is in measuring tradability, not agglomeration, concentration in any form is equally relevant.

[5] Comparing Ginis produced for 2015 to those built using data from 2002, we confirm that our results are not driven by the year selected.

Table 1. Most- and least-geographically concentrated industries according to Locational Gini coefficients, 2015.

Rank	NAICS	Industry Name	Gini
1	4821	Rail Transportation	0.9756
2	4879	Scenic and Sightseeing Transportation, Other	0.7323
3	3122	Tobacco Manufacturing	0.6918
4	4861	Pipeline Transportation of Crude Oil	0.6576
5	1132	Forest Nurseries and Gathering of Forest Products	0.6528
⋮			
299	8111	Automotive Repair and Maintenance	0.0006
300	4422	Home Furnishings Stores	0.0006
301	6211	Offices of Physicians	0.0005
302	4451	Grocery Stores	0.0005
303	6212	Offices of Dentists	0.0002

Note: Authors' calculations of Gini coefficients based on 4-digit QCEW data for 2015. A full list of classified industries is available from the authors upon request.

Table 1 presents the lowest- and highest-scoring industries, offering the opportunity to check these results against intuition. As is evident, the least geographically concentrated sectors are largely nontradable retail, while the most concentrated represent evidently tradable sectors, mainly those that are dependent on first-nature resource allocations that are geographically uneven. The most concentrated and least concentrated thirds of the distribution of Gini coefficients by sector conforms to basic intuition, with manufacturing sectors being amongst the most geographically concentrated sectors and retail sectors amongst the least. Distinctions in the middle of the distribution, however, are much less clear, with tradable activities sitting cheek-by-jowl with nontradables and a handful of ambiguous cases. To maximize the validity of our categorization scheme, we manually examine the ranking of industries and identify ones whose Gini values do not correspond to expectations regarding tradability. For instance, NAICS 4851 Urban Transit Systems receives a Gini coefficient that places it in the immediate neighborhood of tradable sectors like Lime and Gypsum Product Manufacturing (NAICS 3274). And yet, while urban transit sustains tourism, we believe it is chiefly a locally-consumed service. In clear cases such as these, we follow our intuition regarding industry classification. We additionally flag 18 varieties of wholesale activities, which receive a very wide array of Gini values. Unclear on their tradability, we remove these from our analytical dataset.[6] Out of a total of 302 industries, these procedures leave us with 149 activities that we define as tradable, and 135 sectors defined as nontradable.

4.2 Identifying High-Technology Industries

Next we define the subset of tradable activity that we deem to be high-technology. Just as with the tradability distinction, any categorization scheme will be imperfect and open to criticism.

[6] A full list of classified industries is available from the authors upon request.

Some researchers use subjective or objective judgments about the technological content of industry outputs, while others consider input measures, such as the presence of workers in scientific occupations or shares of spending on R&D.[7]

Table 2. Level 1 High-Technology Industries

NAICS	Industry	Wages (2015)
3254	Pharmaceutical and medicine manufacturing	$123,811
3341	Computer and peripheral equipment manufacturing	164,648
3342	Communications equipment manufacturing	104,034
3344	Semiconductor and other electronic component manufacturing	100,161
3345	Navigational, measuring, electromedical, and control instruments manufacturing	96,558
3364	Aerospace product and parts manufacturing	96,795
5112	Software publishers	147,045
5179	Other telecommunications	88,624
5191	Other information services	166,765
5182	Data processing, hosting, and related services	98,616
5413	Architectural, engineering, and related services	86,405
5415	Computer systems design and related services	106,613
5417	Scientific research-and-development services	129,553

Note: Information drawn from Hecker (2005), Table 1. The table has been updated to reflect 2015 annual wages using data from QCEW. Hecker originally defines high-technology activities as including NAICS codes 5161, Internet Publishing and broadcasting and 5181, Internet service providers and Web search portals. In 2007, the Census Bureau merged these categories into code 5191, 'Other information services,' a category which is predominantly made up of 5-digit NAICS code 51913, Internet Publishing and Broadcasting and Web Search Portals.

We adopt an approach proposed by Hecker (2005), which puts into practice guidance from the BLS on what constitutes high technology industries. It considers both input and output dimensions, capturing the intensity of scientific, technical and engineering occupations; R&D employment; advanced-technology products; and the use of high-technology production methods. More specifically, we use the strictest threshold defined by Hecker (2005), which he labels 'Level 1' high technology activity. Table 2 provides a list of these industries, along with median wages for the year 2015. Level 1 industries are those in which technology-oriented occupations are present at five times the overall economy-wide average – at least 24.7 percent of total industry employment.

This definition contrasts somewhat with that taken by some closely related studies. For instance, Lee and Rodriguez-Pose (2016) include all three levels described by Hecker (2005), and is thus much more inclusive. This looser threshold includes many manufacturing industries that may involve technological products and processes, but that host workers less engaged in high-wage nonroutine work.[8] We believe our stricter threshold is more appropriate given the underlying theory we seek to test. On the other hand, we are more inclusive than Moretti (2010), who considers only components of high-tech industries that involve manufacturing activities, ignoring

[7] For a more detailed review, interested readers are directed to Hecker (2005)

[8] This distinction can be seen from the comparatively higher median wage levels of workers in Level 1 activities.

design, data processing and other industries that form an important component of contemporary high-technology activity in the U.S.

Our key independent variable of interest in Equation (1) is $E^T_{c,t}$, which measures local high-technology employment. Because we are interested in capturing the effects of relatively permanent changes in this variable, as opposed to short-run fluctuations, as in Moretti (2010), throughout our analysis we use 3-year moving averages of tech employment, centered on the current year.

4.3 Measuring Real Wages

As noted above, living costs vary strongly from one regional economy to another in the U.S., making both nominal incomes as well as incomes deflated using a national consumer price index (CPI) inadequate to the task of measuring inter-regional economic welfare. Several recent efforts have been made to construct consumer price indices that reflect subnational differences. Moretti (2013) constructs two such measures, one capturing local differences in the cost of housing, the other additionally reflecting local variation in non-housing costs. Meanwhile, the Federal government has released Regional Price Parities that cover housing and non-housing components for 38 large metropolitan areas in selected years (Bureau of Economic Analysis, 2016). Given the less-than-comprehensive nature of the latter, and given broad consistency across approaches reported in Moretti (2013), we opt to mimic the simpler of Moretti's methods to estimate our own annual local consumer price indices.

According to the BLS methodology, 'housing' includes direct costs like rent, but also indirect expenditures on heating and other utilities. It is the largest single component of the national Consumer Price Index for All Urban Consumers (CPI-U), representing approximately 40 percent of the total expenditures. On this basis, and because housing markets are much more localized than, say, markets for food and clothing, we allow the price of housing to vary from one locality to the next, while our accounting of non-housing costs is derived from the national CPI-U. To account for the role of housing in consumer expenditures, we follow common practice in using rental information rather than the prices faced by home buyers. Home prices combine the value of a consumption good, as well as future investment expectations. As such, it is less suitable than rents in capturing the actual use-value of housing (Poole et al, 2005).

Our local CPI measure combines location-specific information on rents, with national non-housing prices. To measure housing prices, we use annual 50th percentile rent information from the Department of Housing and Urban Development. Specifically, for each county we calculate the average of 50th percentile rents for two- and three-bedroom dwellings. We sum to the regional scale using county population shares as weights. As mentioned, non-housing components are drawn from the CPI-U, as are annual measures of component weights. This allows us to estimate a local CPI as follows:

$$LCPI_{c,t} = w_t^H\left(Housing_{c,t}\right) + w_t^{NH}(Nonhousing) \tag{4}$$

where *w* measures the relative importance in year *t* by the CPI program to either housing (H) or nonhousing (NH) components of the CPI-U.[9] We use our annual LCPI measures as deflators for QCEW-derived annual incomes for workers in nontradable sectors. Hence, we arrive at their real wages as follows:

$$RW_{c,t}^{NT} = {NW_{c,t}^{NT}}\Big/{LCPI_{c,t}} \tag{5}$$

where *NW* captures the average nominal wages for workers in nontradable sectors in a location and year. Though nominal and real wages for workers in nontradable sectors are fairly strongly correlated (r=0.78; p=0.000), high local prices do significantly reduce the real incomes of workers in selected cities. Table 3 presents the five metro CBSAs with the highest nominal and real incomes in 2015; comparison across these measures provides some insights into role of local prices. Cities with high nominal wages for workers in nontradable sectors conform to expectations; at least three out of five cities are heavily specialized in high-technology activities. But none remain at the top in terms of the cost-deflated wages earned by workers in nontradable sectors. Notably, Bay Area metros San Francisco and San Jose fall to 92nd and 93rd, respectively.

Table 3. Cities with the highest nominal and real wages earned by workers in nontradable sectors, 2015

	Workers in Nontradable Industries	
Rank	Nominal Wages	Real Wages
1	San Jose-Sunnyvale-Santa Clara, CA	Bloomsburg-Berwick, PA
2	Bridgeport-Stamford-Norwalk, CT	Houston-The Woodlands-Sugar Land, TX
3	San Francisco-Oakland-Hayward, CA	Pittsburgh, PA
4	Washington-Arlington-Alexandria, DC-VA-MD-WV	Midland, MI
5	Boston-Cambridge-Newton, MA-NH	Hartford-West Hartford-East Hartford, CT

Note: Authors' calculations based on QCEW, HUD and CPI-U data, as described in Equations 4 and 5.

4.4 Measuring housing supply elasticity

We are interested in measuring the elasticity of local housing supply as a means of capturing potential heterogeneity in how demand shocks for high-technology activities shape the fates of workers in nontradable sectors. On the one hand, less elastic housing markets ought to shift the balance in terms of wider effect from tech employment away from new job creation, towards greater pressure on nominal wages in nontradable activities. On the other, it ought to raise the local cost of housing, thereby reducing real wages.

[9] Historical relative component weights of the CPI-U can be obtained from the BLS, using December as the reference month in each year. These weights

We measure the elasticity of local housing supply in two very different ways. First, we use the 2005 Wharton Regulation Index, described in detail in Gyourko et al (2008), which exploits survey data to measure the strength of the local growth regulatory context across a wide range of data on such features as zoning laws, lot requirements, affordable housing requirements and other factors. Cities that feature more onerous regulation, and therefore higher values of the Wharton Index, ought to have a more inelastic housing supply. We use metropolitan aggregates of these municipality-specific measures constructed by Saiz (2010).

Since legislation represents only one potential driver of housing supply elasticity, we deploy a second measure. We consider that the availability of developable land will determine the responsiveness of the local housing market. The supply of locations with greater proportions of undevelopable land will respond more inelastically to demand shocks, whereas those with abundant available land will have more elastic housing supply. To measure this, we use an index created by Saiz (2010), using satellite data to gauge the proportion of land within 50km of an urban center that cannot be developed due to the presence of steep slopes, lakes and other natural geographical features. Since the measure captures the percent of unbuildable land in each metropolitan area, higher values of what we will describe herein as the Saiz Index indicate lower levels of housing supply elasticity.

Neither of these measures perfectly captures housing supply elasticity, but each sheds light on different dimensions of it. Accordingly, at the metropolitan CBSA scale, these two measures are moderately positively correlated (r=0.23, p=0.001). In the analysis that follows, we explore the potential role each has in moderating the effects of changes in tech employment.

4.5 Additional control variables

One of the strengths of Equation (1), estimated on a panel of cities, lies in its ability to account for unmeasured stationary features of cities. Time-varying factors, on the other hand, could bias estimates of the relationship of interest. We include two dynamic control variables in all specifications. First, we measure the year- and region-specific unemployment rate, expressed as a percentage, using data from the BLS Local Area Unemployment Program. High levels of unemployment could put downward pressure on nominal wages as well as on the housing market.

Second, using data from one percent extracts from the American Community Survey, drawn from IPUMS (Ruggles et al, 2015), we measure the share of non-institutional, actively employed workers over the age of 25 with at least a 4-year degree. Because metro-level identifiers in the ACS are not available between 2001 and 2004, we use geometric interpolation to impute educational attainment during these years. Though the existing literature is unclear on whether educational spillovers of the type reported in studies like Rauch (1993) and Moretti (2004) extend to workers in nontradable sectors, we include this measure to ensure that measures of the relationship between tech employment and nontradable wages are not driven instead by productivity spillovers from the presence of highly-educated workers.

5. Results

5.1 Descriptive Results

Table 4 presents descriptive statistics for key variables in the 349 metropolitan CBSAs that constitute our primary analytical sample, with values presented for the year 2015. The average urban worker in nontradable activities earns around $36,000 in nominal terms, and $26,000 in real terms. The average metro CBSA hosts around 14,000 workers in tradable high-technology activities, and 18,000 jobs in non-high-technology tradables. Over the period, which includes the Great Recession, local unemployment rates averaged less than six percent, and about 17 percent of adult workers had attended at least four years of college.

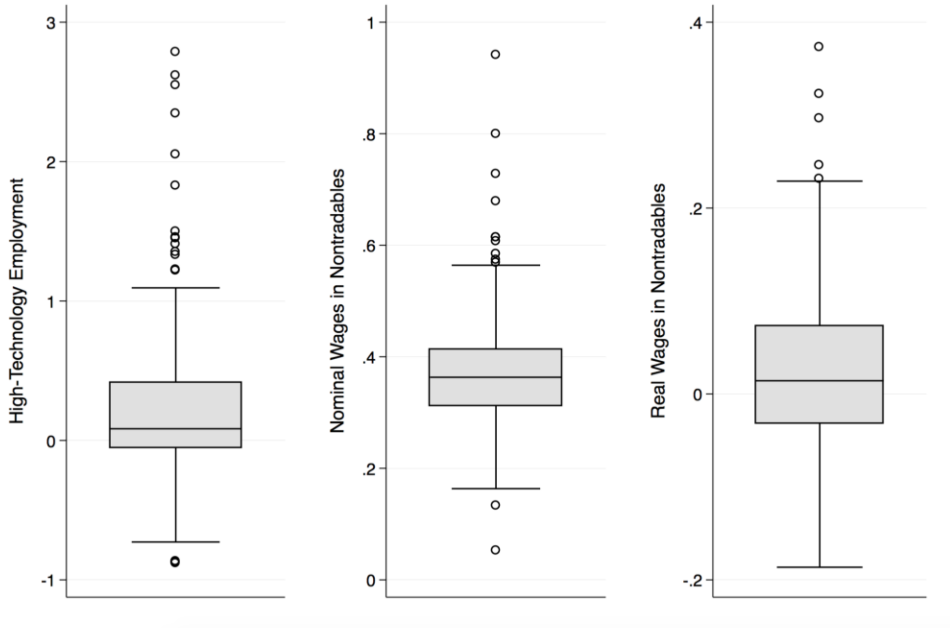
Table 4. Summary Statistics for Key Variables of Interest in Metropolitan CBSAs in 2015

Variable	Mean	Standard Deviation
Nominal wages for workers in nontradable sectors ($)	36,077	6,104
Real wages for workers in nontradable sectors ($)	26,364	3,811
High-technology tradable employment	14,145	39,847
Non-high-technology tradable employment (000s)	18,414	41,459
Unemployment rate (%)	5.48	1.99
Workers over 25 years old with at least 4 years of College (%)	16.98	4.58
Wharton Regulation Index	-0.18	0.72
Saiz Index (% Unbuildable Land)	23.45	20.13
Median Rent for 2 and 3 Bedroom Dwelling	1,029.34	241.17

Note: Authors' calculations based on data described in Section 4. All variables measured over 349 metropolitan CBSAs, except the Wharton and Saiz indices, which are time invariant and measured for 191 CBSAs.

The measure of dispersion indicates considerable variation across cities, especially in terms of employment in tradable activities. This makes sense given the relatively heterogeneous nature of the metro CBSA category: although it has a minimum population threshold, it contains cities like New York and Los Angeles, with populations well over ten million, as well as Hinesville, Georgia, with just over 80,000 residents. Similarly, metropolitan areas hosting the largest agglomerations of high-technology activity, like San Jose, Los Angeles, and New York employ an order of magnitude more workers in such activities than the average city.

Figure 1. Variation in 2001-2015 growth rates in High-Technology Employment, Nominal and Real Wages, N=349 CBSAs



Note: Based on authors' calculations using data described in Section 4.

Crucially for our purposes, over our study period there is also meaningful temporal variation within cities. Figure 1 presents a box plot of growth rates over 2001-2015 for high-technology employment, as well as nominal and real wages. The median city expands its high-technology employment base by just over ten percent, and the interquartile range spans a decline of seven percent to an increase of just over 50 percent. In more concrete terms, the median city added around 200 new jobs in high technology activities over the study period, while the average city added 1,000. A few cities, notably Seattle, San Francisco and Houston, added tens of thousands of new tech jobs, while Los Angeles, Miami and Philadelphia fall considerably short of their boom-era peaks in the early 2000s. Nominal wages for workers in nontradable sectors rise by an average of over 30 percent. Among these workers, real wages increase much more modestly, averaging only 2.4 percent over the study period.[10]

5.2 What is the relationship between local high-technology employment and the real wages of workers in nontradable sectors?

We now present estimates of the main relationship of interest. As described in Sections 3 and 4, the analysis is conducted on a panel of cities, using two estimators: ordinary least squares (OLS), and subsequently two-stage least squares (2SLS). In each model, city fixed effects account for stationary unobserved heterogeneity among regional economies. Year fixed effects are included

[10] This is not a surprise. Stagnant real wages among American workers are a well-documented fact, especially after the recession (for instance, see Daly et al, 2016).

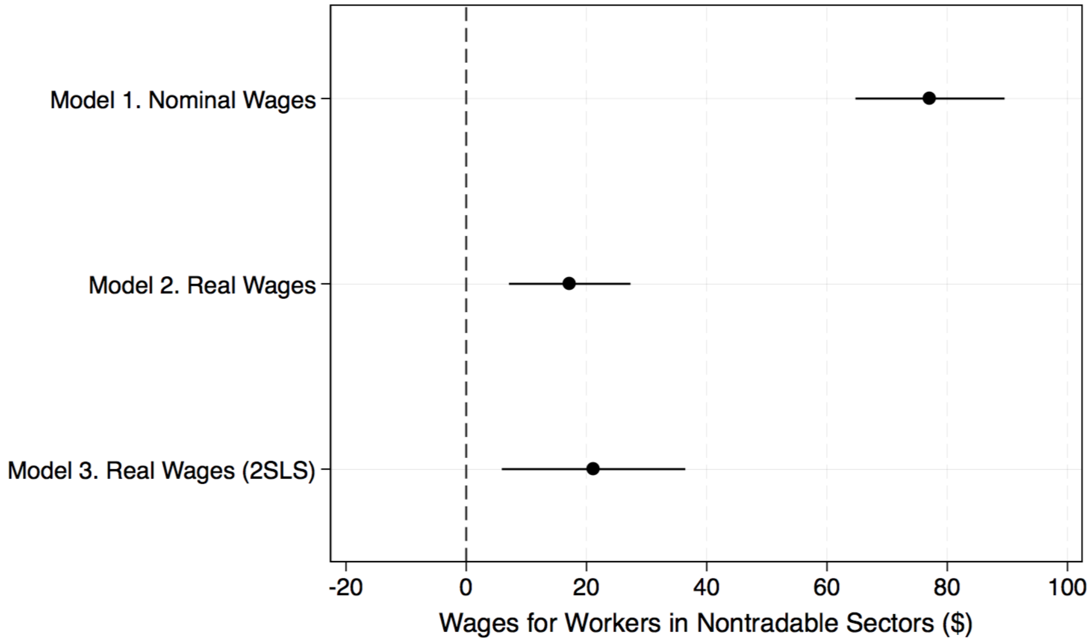
to capture unmeasured shocks that are uniform across cities, but which vary over time.[11] Throughout, we include measures of unemployment and the proportion of workers with at least four years of college education as controls.

The first research question posed in this paper asks: how do changes in local high-technology employment affect the wages of workers in nontradable sectors? Figure 2 summarizes key results regarding this question, with each row of the figure highlighting the relationship between tech employment and wages as estimated in a particular regression model. As long as the span of the 95 percent confidence interval does not cross the zero line, the coefficient of interest is statistically significant at a 5 percent level of confidence.[12] Though our primary interest is in real wages, as an initial exercise, we estimate the relationship between tech employment and nominal wages. Model 1 presents the relationship between local high technology employment and the nominal wages of workers in nontradable sectors. The coefficient on tech employment is positive and statistically significant at a 1 percent level. Its magnitude suggests that an increase in local high-technology employment of 1,000 workers is associated with approximately an $80 increase in the annual wages of workers in nontradable sectors. In other words, though significant in statistical terms, given that a typical metropolitan area in our sample expanded its local tech sector by 200 workers over the full study period, the effect in most cities is substantively modest. Yet in Seattle, where tech employment increased by over 60,0000 over the study period, this models predicts an increase in annual nominal wages of nearly 5,000 dollars.

[11] While a Hausman specification test indicated that a random effects model generated more efficient estimates of the relationship of interest, actual differences between each estimated coefficient in fixed versus random effects models was substantively negligible. This together with the strong need to account for the potential effects of unobserved heterogeneity push for the fixed effects approach described in Equation (1).

[12] Full regression tables from which these figures are drawn are included in the appendix.

Figure 2. Average Marginal Effects (with 95% Confidence Interval) of 1,000-Worker Increase in Local High-Technology Employment on Annual Wages of Workers in Nontradable Sectors, 2001-2015



Note: Each model presents coefficient and 95% confidence interval describing the relationship between high technology employment and the nominal or real wages of workers in nontradable sectors. All models estimated on 2001-2015 panel of metropolitan CBSAs. Each model includes city and year fixed effects, and additionally contains controls for unemployment and the share of workers with at least 4 years of college education. Estimates that cross the zero mark are not statistically significant at a 5% level. Models 1 and 2 are estimated using OLS. Model 3 is estimated using 2SLS using the shift-share instrument (Kleibergen-Paap Wald F=764.04). N for Models 1& 2=4,312; N for Model 3=3,795. Data sourced from QCEW, HUD and ACS as described in Section 4. Full regression table listed in the appendix, Table A1.

Model 2 estimates the same equation, this time with nontradable real wages as the dependent variable. The coefficient on tech employment remains positive and significant at a 1 percent level, but its size has diminished markedly as compared with nominal wages. This fits with the initial intuition, suggesting that although growth in tech employment raises the raw money wages for workers in nontradable activities, their value diminishes as growing demand also prompts expansion in the local cost of living. The coefficient in Model 2 is around 17 dollars – almost one-fifth the size of its counterpart for nominal wages.

To account for potential bias from unobserved shocks to localities that are both correlated with changes in tech employment and also related to the real wages for workers in nontradable sectors, Model 3 instruments for high-tech employment using the shift-share measure described in Equation 2, using the 2SLS estimator. The instrument passes tests of under- and weak-identification. We cannot formally test for its exogeneity, since the equation is exactly identified. Second-stage results closely resemble those reported in Model 2 though the coefficient in Model 3 is slightly larger, as is the confidence interval. The consistency across Models 2 and 3 suggests that the positive relationship between local tech employment and wages for workers in nontradable activities is not driven by unobserved shocks. Since the instrument used in Model 3 strips away location-specific unobserved factors, we are left with an estimate whose causal significance is clearer: it suggests that expansions in local tech employment exert an independent, positive (though modest) effect on the real wages of workers in nontradable sectors.

We confirm the robustness of these findings in a few ways. First, we get meaningfully comparable results when additionally estimating these models in log-log and log-linear functional forms. Results remain consistent when we replace our count-measure of high-technology employment with one that instead describes the proportion of tech jobs in the local economy. To check that results do not depend on our use of 3-year moving averages for both our dependent variable and our key independent variable, we also estimate models using unadjusted single-year values. These results are materially consistent with those we report in the paper. Given that there are a handful of regions whose levels and growth in tech employment over the study period are quite different from the average, we also explore the robustness of our results to the exclusion of these outliers. We estimate a succession of models in which San Jose, San Francisco, Seattle, Los Angeles, as well as all possible combinations of these regions are removed from the analytical sample. Their inclusion does not fundamentally shape estimates of the relationship of interest.

On the intuition that workers in nontradable sectors might be priced out of metropolitan areas into adjacent, and presumably more affordable 'micropolitan' CBSAs, we also re-estimate each of the models discussed thus far defining regional economies according to OMB definitions for Consolidated Statistical Areas (CSAs), where available, and otherwise using metropolitan CBSAs. Perfect analogues of Models 1-3 for this sample are not possible given our inability to perfectly measure unemployment and education levels in micropolitan areas that lie within CSA boundaries. However, for both kinds of samples we can compare estimates of a version of Equation 1 that lacks these controls, but which still includes year and city fixed effects. Doing so, we find that the real wage effects of high-technology employment across these two samples are each positive and statistically significant at a 1 percent level, with magnitudes that are nearly indistinguishable.[13]

As a further robustness check, we explore the likelihood that the relationship of interest is driven by Baumol's 'cost disease' (1967), instead of by derived-demand explanations that form the basis of the hypotheses. Observing that the wages of workers in particular nontradable sectors like education have risen despite major changes in productivity, Baumol suggests that teacher pay must be indexed to rates of wage growth in productive sectors, as a means of ensuring that teachers do not defect to activities where pay and productivity are rising. To the extent that this mechanism is in operation, in the present context it is essential to note that not all workers are

[13] Figure A1 in the appendix presents these results.

equally likely to switch to the productive sector. The average barber, for example, is a lot less likely than a physics teacher to switch to software engineering. To account for potential bias from this source, we recode classic nontradable cost-disease industries – those in education, health care, and the arts – to the ‘indeterminate’ category. Having excluded workers in these industries, we then re-estimate Models 1-3 on our restricted subsample of nontradables.[14] Results strongly resemble those generated for the full complement of nontradable activities, with significant, positive, albeit relatively modest impacts of tech employment on both nominal and real nontradable wages. These results suggest that the cost disease is not the primary explanation of the relationship of interest. Findings remain consistent with the hypothesized derived-demand explanation.

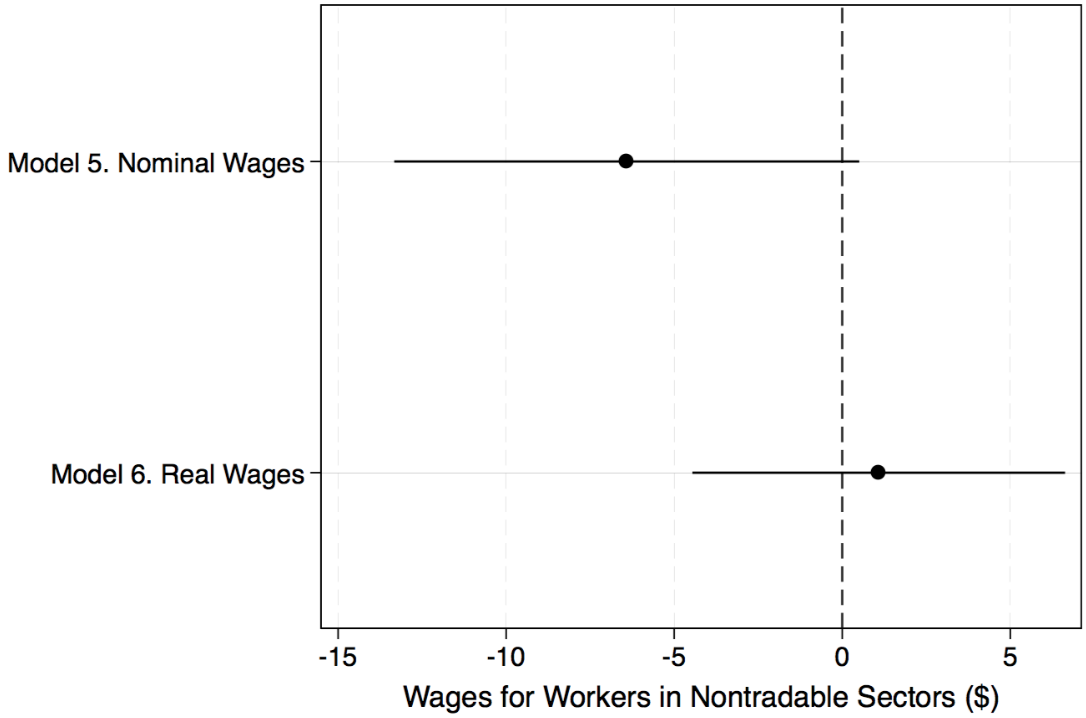
5.3 Is high-technology employment special?

Next we consider the second research question: the extent to which tech has a unique relationship with nontradable real wages when compared with other tradable activities. In 2015, the average worker in tech activities earned 42 percent more than their counterpart in non-tech tradables. This premium is consistent across the full study period. Consequently, one might expect larger benefits for workers in nontradable sectors flowing from tech as opposed to non-tech tradables. To explore whether this is the case, we re-estimate Equation 1, this time substituting high-tech employment for employment among activities that are tradable but not part of the BLS definition of high-technology sectors as described above.

Figure 3 reports coefficients for non-high-technology tradable employment regressed on the nominal and real wages of workers in nontradable sectors, respectively. The estimate for Model 5 indicates that tradable non-high-technology employment is not significantly related to the nominal wages earned by workers in nontradables. Model 6 suggests that employment growth in non-tech tradables is also unrelated to changes in their real wages. We interpret this to mean that high-technology employment is indeed distinct from the average non-tech tradable activity, in terms of its effects on the wages earned in the nontradable sector. While tradable tech activities stimulate growth in nominal and real wages for workers in nontradable activities, tradable non-tech employment does not.

[14] We disinclude all 4-digit NAICS sectors within NAICS 61 (Education services), and 62 (Health care and social assistance), as well as 7111 (Performing arts companies), 7115 (Independent artists, writers, and performers), and 8122 (Death care services). Full regression results for research questions 1-3 on the subsample of nontradable activities in which these sectors are removed are presented in the appendix, Table A2.

Figure 3. Average Marginal Effects (with 95% Confidence Interval) of 1,000-Worker Increase in Local Non-High-Technology Tradable Employment on Annual Wages of Workers in Nontradable Sectors, 2001-2015

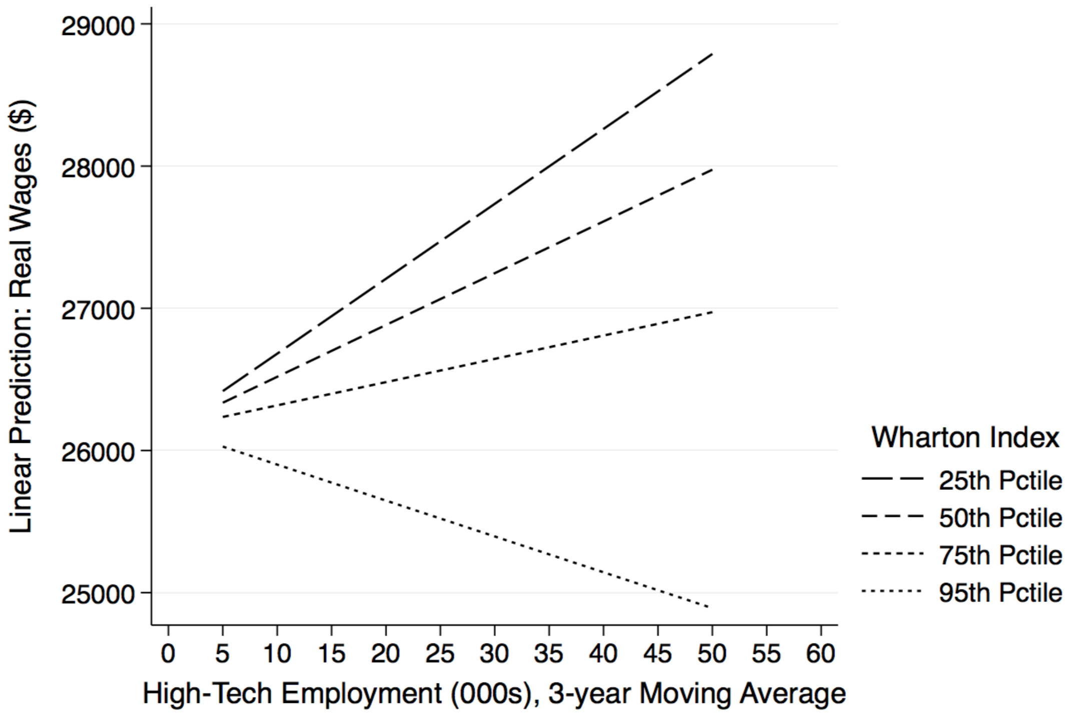


Note: Each model presents coefficient and 95% confidence interval describing the relationship between non-high technology tradable employment and the nominal or real wages of workers in nontradable sectors. All models estimated on 2001-2015 panel of metropolitan CBSAs. Each model includes city and year fixed effects, and additionally contains controls for unemployment and the share of workers with at least 4 years of college education. Estimates that cross the zero mark are not statistically significant at a 5% level. Models 1 and 2 are estimated using OLS. Model 3 is estimated using 2SLS using the shift-share instrument. N for Models 1& 2=4,312. Data sourced from QCEW, HUD and ACS. Full regression table listed in the appendix, Table A1.

5.4 Housing supply elasticity

Our third research question revisits the primary relationship of interest, but considers that estimates for the average city conceal heterogeneity in terms of how wages respond to changes in high tech employment. Specifically, we consider that workers living in cities in which the supply of housing is more inelastic will be more negatively affected by high-technology employment, as nominal wage gains are eroded by growth in local prices. Meanwhile, in cities where the supply of housing reacts more frictionlessly to demand shocks, real gains to workers in nontradable activities are likely to be more substantial. As described above, we test this idea using two different measures of housing supply elasticity: the Wharton index of land use regulation, and Saiz's measure of the proportion of developable land.

Figure 4. Predictive Margins for Real Wages of Workers in Nontradable Sectors in Response to Change in High-Technology Employment, by Levels of Land Use Regulation



Note: Model estimated on a 2001-2015 panel of metropolitan CBSAs (N=2,483). The model includes city and year fixed effects, and additionally contains controls for unemployment and the share of workers with at least 4 years of college education. Interaction term between high-technology employment and the Wharton index is significant at a 1 percent level. Overall adjusted R^2=0.93. Data sourced from QCEW, HUD and ACS. Full regression table listed in the appendix, Table A3.

We re-estimate Equation 1, adding a linear interaction term between high-technology employment and either the Wharton or Saiz index. Since these latter measures are time-invariant, the coefficient on each measure of housing supply elasticity alone drops out of the model. Our interest lies in interpreting the significance of the interaction term, and the joint meaning of the coefficients on tech employment and the linear interaction term.

Table 5. Marginal Effects for Real Wages of Workers in Nontradable Sectors in Response to Change in High-Technology Employment, by Levels of Two Measures of Housing Supply Elasticity

	Marginal Effects			
	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile	95^{th} Percentile
Land Use Restrictiveness Index (Wharton)	52.69***	36.41***	16.39***	-25.26**
	(12.08)	(8.18)	(5.08)	(11.76)
Percent Unbuildable Land (Saiz Index)	35.64***	29.36***	18.06***	-0.14
	(9.39)	(7.61)	(5.30)	(6.83)

Note: Models estimated on 2001-2015 panel of metropolitan CBSAs. Each model includes city and year fixed effects, and additionally contains controls for unemployment and the share of workers with at least 4 years of college education.

N=2,483. The interaction terms using the Wharton and Saiz indices are significant at a 1 and 5 percent level, respectively. Overall adjusted in each model is R^2=0.93. Data sourced from QCEW, HUD and ACS. Full regression table listed in the appendix, Table A3.

Using these two very different indices, estimates produced regarding the moderating role of housing supply elasticity are strongly consistent. Using either the Wharton and Saiz indices, the coefficient on tech employment remains positive, while the interaction term is negative and significant at a minimum of a 5 percent level.[15] Confirming intuition, this suggests that gains from tech employment in the real wages of workers in nontradable activities are eroded more strongly in cities featuring more inelastic housing markets. Figure 4 plots predicted margins at the 25th, 50th, 75th and 95th percentile of the Wharton index. Slopes for levels below the 95th percentile are positive, whereas from the 95th percentile and higher, they turn sharply negative. Table 5 presents marginal effects at the same specific levels of housing supply elasticity for both Wharton and Saiz indices. What is clear from both is that, for the majority of cities, gains in tech employment confer real wage gains for workers in nontradables, and the size of these gains increase with rising elasticity. Using the Wharton index, workers in the most inelastic housing markets experience losses, while with the Saiz index, the relationship is essentially zero. On the other hand, workers in nontradables who live in cities where the housing supply is highly elastic are considerably more strongly rewarded by growth in the tech sector. While each index only imperfectly captures housing supply elasticity, the fact that we see the same relationship in both strongly suggests that housing supply elasticity moderates the wider benefits generated by high-technology employment.

6. Conclusion

This paper set out to explore the relationship between local high-technology employment and the real wages of workers in nontradable sectors. Scholars have long considered the direct impacts of high-technology and other kinds of specialization on regional economic performance. Others have examined indirect effects, but this work has largely concentrated on job creation as an outcome, despite recent theory identifying mechanisms through which tradable jobs in an urban labor market can affect local nontradable wages. Most narrowly, this paper contributes to recent efforts to explore this channel empirically. It does so in several ways, most notably by considering how employment growth in tech might shape not only nominal wages, but wages adjusted for local living costs.

We argue that accounting for living costs is essential to determining the wider economic impacts of high technology employment. While high- and low-skill American workers are increasingly sorting into cities with different cost structures, concentrations of skilled tech workers still depend upon services provided by workers in nontradable sectors. And while the paychecks in the pockets of barbers and phlebotomists in tech agglomerations might be larger as a consequence,

[15] Full regression results for models in Section 5.4 are presented in appendix, Table A3.

housing and other rising costs might make these workers considerable worse off than their counterparts elsewhere.

Based on the estimation approach, high-quality data, and breadth of coverage, we believe this paper offers strong evidence suggesting that, for the average metropolitan area in the United States, growth in high-technology employment offers statistically significant but substantively very modest real wage benefits for workers in nontradable activities. We find that a 1,000 job increase in local high-technology employment is associated with just under a $20 increase in the annual real wages of workers in nontradables. The nature of the relationship is supported by evidence that accounts for potential bias from unobserved shocks. These results must be read against a real experience of high-technology expansion over the study period in which most cities add limited quantities of tech jobs. It should also be compared to our estimate of approximately 2 jobs in nontradables created for each new job in tech, a figure broadly in line with recent evidence from van Dijk (2016). This suggests that tech's local effects are felt more strongly through job creation than through real improvements in the wages of workers in nontradables.

At the same time, the reputed ills of tech do not seem apparent, at least when we do not distinguish between Seattle's tech economy and that found in Muskegon, Michigan. Our results also show that the positive relationship we identify for tech does not extend to the collection of tradable but not high-technology industries. The reason for this is likely that, on average, other tradable activities pay lower salaries. This does not indicate that specific non-tech tradables need not have a similar relationship to real nontradable wages. We also probe the question of heterogeneity hinted at in our main results. Specifically, we find that the association between high-technology employment and nontradable real wages depends on the elasticity of a region's housing supply. In highly elastic markets, workers in nontradables reap higher rewards from tech employment. By contrast, in markets that are strongly constrained by building regulation or natural limits to construction, tech employment actually reduces the real wages of workers in nontradables. The rate of living cost increases in such markets outstrips any benefits accrued through positive nominal wage effects. To put it another way, wider gains from tech employment in such locations are redistributed from workers in nontradables to incumbent landowners.

These differentiated results offer some complement to sociological accounts of the pains of neighborhood change. Results confirm that the wider effects of tech employment in tight housing markets can be negative at the regional scale. But they also suggest that the impact of high-technology employment varies considerably across cities, with evidence of a positive, albeit modest aggregate effect on the real wages of workers in nontradables. These findings also add to a growing body of research identifying a key role for land use regulations in shaping the welfare of communities within regions. While regions can expend great effort both to attract and develop the tech industry within their communities, with the objective of raising local incomes, there should be a greater recognition that real incomes are shaped not only by explicit economic development efforts, but indirect policies, such as land use regulations.

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Appendix

Table A1: Panel Estimates of Relationship between Local Tradable Employment and Annual Wages for Workers in Nontradable Sectors, 2001-2015

	(1) Nominal Wages OLS	(2) Real Wages OLS	(3) Real Wages 2SLS	(5) Nominal Wages	(6) Real Wages (OLS)
High-Technology Employment (000s)	77.13***	17.21***	21.18**		
	(6.32)	(5.156)	(7.787)		
Non-High-Tech Tradable Employment (000s)				-6.412	1.086
				(3.529)	(2.828)
Unemployment Rate (%)	-287.1***	-346.4***	-347.6***	-308.4***	-349.8***
	(18.95)	(15.45)	(18.12)	(19.34)	(15.50)
Workers with at least 4 years College (%)	19.37	-4.904	-5.691	19.26	-4.285
	(17.79)	(14.51)	(13.71)	(18.15)	(14.55)
Kleibergen-Paap Wald F			764.04		
Adjusted R^2	0.96	0.93	--	0.963	0.928
N	4,132	4,132	3,795	4,132	4,132

Note: Standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percentage level, respectively. All models estimated on 2001-2015 panel of metropolitan CBSAs. Each model includes city and year fixed effects.

Table A2. Panel Estimates of Relationship between Local Tradable Employment and Annual Wages for Workers in Nontradable Sectors, excluding cost disease sectors 2001-2015

	(1) Nominal Wages (OLS)	(2) Real Wages (OLS)	(3) Real Wages (2SLS)	(4) Nominal Wages (OLS)	(5) Real Wages (OLS)	(6) Real Wages (OLS)	(7) Real Wages (OLS)
High-Technology Employment (000s)	90.98***	22.84***	24.89**			41.77***	33.30***
	(6.56)	(5.23)	(7.68)			(12.25)	(7.59)
Unemployment Rate (%)	-369***	-402***	-404***	-403***	-406***	-412***	-412***
	(19.65)	(15.66)	(19.45)	(19.34)	(15.67)	(19.15)	(19.14)
Workers with at least 4 years College (%)	27.68	1.872	2.593	27.22	4.716	53.52*	54.16*
	(18.45)	(14.70)	(14.15)	(19.09)	(15.47)	(23.01)	(22.98)
Non-high-technology Tradable Employment (000s)				-14.1***	5.17*		
				(3.08)	(2.49)		
High-Technology Employment (000s) * Saiz Index						-57.23*	
						(26.54)	
High-Technology Employment (000s) * Wharton Index							-28.65**
							(9.67)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4132	4132	3795	3795	3795	2304	2304
adj. R-sq	0.97	0.94	--	0.97	0.94	0.94	0.94

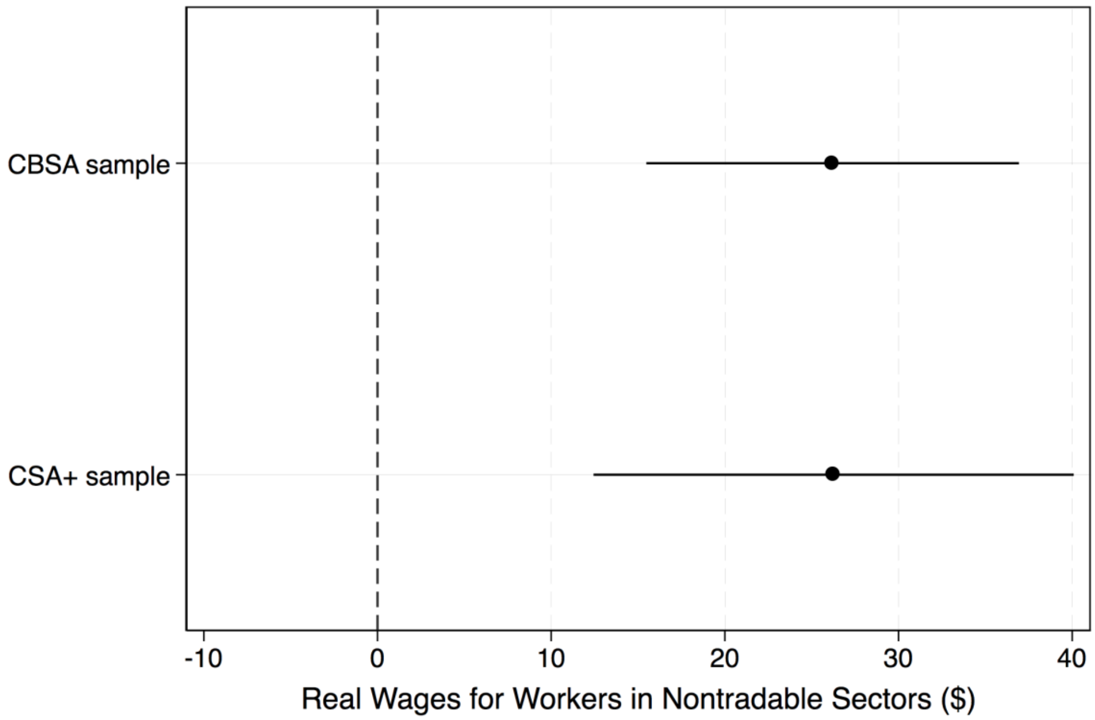
Note: Standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percentage level, respectively. All models estimated on 2001-2015 panel of metropolitan CBSAs.

Table A3: Panel Estimates of Relationship between Local High-Technology Employment, Housing Supply Elasticity, and Annual Wages for Workers in Nontradable Sectors, 2001-2015

	(2) Wharton Interaction	(1) Saiz Interaction
High-Technology Employment (000s)	29.21*** (6.709)	40.67*** (10.93)
High-Technology Employment (000s) * Wharton Index	-31.30*** (8.693)	
High-Technology Employment (000s) * Saiz Index		-62.79** (22.13)
Unemployment Rate (%)	-354.2*** (18.94)	-355.5*** (18.95)
Workers with at least 4 years College (%)	43.98* (21.93)	42.89 (21.95)
N	2,483	2,483
Adjusted R^2	0.929	0.929

Note: Standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percentage level, respectively. All models estimated on 2001-2015 panel of metropolitan CBSAs. Each model includes city and year fixed effects.

Figure A1. Comparing CBSA sample and CSA+ sample: Average Marginal Effects (with 95% Confidence Interval) of 1,000-Worker Increase in Local Non-High-Technology Tradable Employment on Annual Wages of Workers in Nontradable Sectors, 2001-2015;



Note: Each model presents coefficient and 95% confidence interval describing the relationship between high technology employment and the real wages of workers in nontradable sectors. One model estimated on 349 metro CBSAs (N=4,132). The second model estimated on 275 CSAs and metro CBSAs (N=3,207). Each model includes city and year fixed effects. Estimates that cross the zero mark are not statistically significant at a 5% level. Data sourced from QCEW, HUD and ACS.