In Service of Affluence?

High-income multipliers, wages, and occupational restructuring in the US

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0. Preface

Ich bin ein Esel, der erstens keine *deadline* einhalten kann und zweitens etwas in Überlänge produziert hat. Zur Beruhigung: Es sind ein paar bunte Grafiken und ein paar mehr graue Tabellen dabei. *Ich hoffe*, es ist nicht *zu* schlimm… Leid tut es mir aber…

1. Introduction

Since the 1980s, the US labor market has undergone major changes emblematic of broader shifts in the American economy (Scott 2011, 2012). The decline of manufacturing as the primary engine of growth and employment as well as the expansion of service industries (Wessel, 2005; Gatta et al., 2009; Autor & Dorn, 2013; Dwyer & Wright, 2019; Charles et al., 2019) were accompanied by increasing social, economic, and spatial disparities (Evenhuis et al., 2021). Inequalities have increased within (Piketty & Saez, 2003; Atkinson & Piketty, 2007; Piketty, 2014) and between regions (Yamamoto, 2008; Manduca, 2019; Buchholz et al., 2020). While economically less prosperous places seem to bear the negative consequences of automation, financialization, and globalization, a set of innovative regions and upper segments of the labor force have reaped large gains from the economic change in recent decades (Feldman et al., 2021).

Much attention has been directed to these upper strata of the labor force. Here, a new core of highly educated professional, managerial, and technical workers has emerged in cutting-edge industries such as finance, biotech, and information technology (Reich, 1992; Sassen, 2001; Florida, 2004; Scott, 2012; Storper et al., 2015). Firms in these highly tradable sectors often exercise monopoly power and exert global influence while their headquarters and well-paying jobs are highly concentrated in a few selected places (Feldman et al., 2021). However, these upper strata of the labor force do not operate in a social, economic, or spatial vacuum. While they ultimately serve international markets, they require and build upon local infrastructures and services provided by an increasing share of low-wage service workers such as childcare workers, janitors, housekeepers, salesclerks, and taxi drivers (DeFilippis et al., 2009; Storper & Scott, 2009; Scott, 2011, 2012, 2017).

This paper attempts to shed light on the spatially structured interdependencies between high-income earners and low-wage service workers. It examines how changes at the top of the income distribution affect the volume, composition, and living conditions of lower-tier segments of the labor market. For this, the paper draws on the local employment multiplier framework (Moretti, 2010; Moretti & Thulin, 2013; Faggio & Overman, 2014; van Dijk, 2017, 2018; Goos et al., 2018; Bartik & Sotherland, 2019; Lee & Clarke, 2019; Gutierrez-Posada, 2022; Osman & Kemeny, 2022). The literature on local multipliers is certainly extensive. So far, however, it has paid limited attention to issues of inequality. This paper attempts to venture into this underexplored area. It modifies the multiplier approach to investigate the distinct effects of *high-income* workers in tradable industries on employment growth in non-tradable services.

The scope of this study's examination into inequality extends beyond high-income workers in tradable industries. The distributional implications of the growth in non-tradable service employment are explored as well. In general, multiplier studies provide estimates of the number of jobs created by exogenous changes in the tradable industries. However, by focusing on total job creation, these studies tend to paint an overly rosy picture. What kinds of jobs are created garners less attention. Noticeably, though, not all jobs are created equal (Kalleberg, 2011; Scott, 2012; Feldman et al., 2016). Additionally, the local employment multiplier literature also tends to leave wider impacts on wages, affordable housing, and living conditions largely unaddressed (Kemeny & Osman, 2018; Lee & Clarke, 2019).

This study attempts to paint a more complete picture. I provide evidence on the types of jobs created by the expansion of well-paying tradable jobs. In addition, this paper also presents methodological refinements to the local multiplier literature. It incorporates recent improvements to the local employment multiplier approach (Osman & Kemeny, 2021) and implements novel techniques for assessing the robustness of instrumental variables in two-stage least-squares models with multiple endogenous regressors (Lewis & Mertens, 2022). This paper covers developments in US commuting zones from 1980 to 2018, using data from the Decennial Census and the American Community Survey.

The study has four main findings. First, affluent workers in tradable industries substantially affect the size of the non-tradable sector. One new high-income job creates more than six non-tradable jobs in the local economy. Second, high-income workers exert a modest influence on the size of the lower-tier service sector, as one new high-income jobs creates only 0.6 jobs in low-wage, low-education services. Third, affluent workers exert a compositional effect on

lower tiers of the service sector. Especially services geared towards domestic care needs, such as childcare and housekeeping, but also sales-related services in retail, increase when the number of high-income workers increases. The positive employment effects on other occupational groups are less pronounced. For some service occupations, high-income earners appear to cause crowding-out. These findings indicate that consumption by affluent households is a relevant driver of both job growth and occupational restructuring. The findings also indicate that consumption by affluent households is not a strong driver of occupational polarization. Nevertheless, high-income earners shape livelihoods at the bottom of the income distribution by heterogeneously affecting demand for services and goods provided by lower-tier service workers.

2. Theoretical Overview

2.1. Occupational change and income inequality

Different strands of literature have investigated the simultaneous expansion of occupations at both the top and the bottom of the wage distribution. Scott (2012), for example, sketches the emergence of a new class bifurcation. Drawing on Reich (1992) and Florida (2004), he identifies the formation of a group of highly qualified cognitive and cultural workers. The rise of these upper-tier workers is contrasted with an increasingly large group of service workers characterized by low wages, few formal qualifications, and often precarious working conditions. Scott (2011, 2012, 2017) refers to the latter group as the "service underclass" or "new servile class." According to Scott (2012: 120, 2017: 123), these low-wage, low-education workers serve the direct and indirect demands of higher-income workers, either by maintaining infrastructures or supporting domestic and personal needs.

Sassen (2001, 2012) marshals a similar argument and draws attention to the emergence of global cities and their distinct industrial and occupational structure. Global cities feature a disproportionate share of corporate headquarters, producer services, and financial activities. The workforce in these sectors serves global markets and commands high wages, but – according to Sassen (2012: 268-270) – also requires the labor of low-wage, low-skill service workers. For Sassen, this results in a bifurcated earnings structure. Indeed, global city regions are characterized by high levels of inequality (Boschken, 2022), although claims of social polarization and a disappearing middle remain contested (Fainstein, 2001).

One prominent research avenue emphasizes the role of technology. Here, a series of influential studies (among them: Autor et al., 2003; Autor & Dorn, 2013; Goos et al., 2014) have argued that recent technological change has been routine-biased. According to Autor and Dorn's

(2013) framework, new technologies displace routine-intensive occupations. Crucially, these routine-intensive occupations tend to be found in the middle of the wage distribution. Higher-tier occupations, on the other hand, involve non-routine, abstract, and creative tasks that are complemented by technology. Finally, lower-tier service occupations at the bottom of the wage distribution also involve a higher share of non-routine tasks. Thus, they are less prone to automation and even tend to expand. The interaction of these trends results in a pattern of employment change that has been termed job polarization. This literature is not without its critics. The timing and extent of job polarization postulated in the literature have been questioned (Lefter & Sand, 2011; Hunt & Nunn, 2022). Similarly, the apparent link between job polarization and rising wage inequality has been contested (Mishel *et al*., 2013; Hunt & Nunn, 2022). Finally, technology's role as the primary explanatory factor has also been subject to criticism (Fernández-Macías, 2012), with Dwyer (2013), for example, drawing attention to alternative explanations such as changes in demographics, women's labor market participation, and the care economy.

In order to explain the expansion of low-wage service employment, models of routine-biased technological change tend to rely on consumption spending as a mechanism. Interestingly, the models tend to apply relatively restrictive assumptions about consumption. As Goos *et al*. (2014: 2518) themselves point out, both their own framework and that of Autor and Dorn (2013) assume homothetic consumer preferences. Consumers with high spending power demand commodities in the same proportions as consumers with low spending power. A hypothetical change in the distribution of income that is not accompanied by a change in aggregate income would therefore have no effect on the types and quantities of goods demanded.

A few selected empirical studies – that have examined the consumption behavior of high-income households – break with this assumption. Mazzolari and Ragusa (2013), for example, find evidence for so-called "consumption spillovers", where an increase in the income shares of the top 10% increases demand for services that act as substitutes for domestic tasks. They theorize that as a household's income rises, so too do its opportunity costs. The higher the income, the greater the incentive to outsource time-intensive domestic work to low-skilled, low-wage workers. Analyzing consumption expenditure data, Leonardi (2015) presents complementary evidence. He finds that more educated households tend to consume disproportionately large shares of services that are characterized by a very low skill-intensity. Interestingly though, Leonardi (2015) also reports that educated households are inclined to

consume larger shares of high-skill-intensive services. Mid-skill-intensive services are – relatively speaking – less important.

The – by now – recurring theme of an increasing share of affluent individuals driving demand for low-wage service occupations has a distinct spatial dimension. Personal service occupations tend to be non-tradable and place-bound. That is, they require physical proximity between service workers and their customers. Waiters, hairdressers, and personal care aides do not operate through the ether. Similarly, gardeners and cleaners require access to their customers' premises. This spatial dimension is at the conceptual core of the employment multiplier framework that informs the empirical approach of this study. The underlying concepts are explored in the following subsection.

2.2 Tradability and local employment multipliers

This study relies on the local employment multiplier framework to investigate the impact of high-income workers on lower tiers of the occupational structure. The framework draws on export-base theory (Tiebout, 1956a, 1956b; Thulin, 2015) and divides the economy into two sectors: a tradable sector that primarily serves *non-local* markets and a non-tradable sector serving *local* markets[1]. A crucial assumption here is that the size of the non-tradable sector depends on its tradable counterpart. When a firm producing tradable goods expands its workforce, parts of the wages of the newly employed workers find their way into the local non-tradable sector, increasing income and employment there (Lee & Clarke, 2019: 2). The relationship between employment growth in the tradable and employment growth in the non-tradable sectors can be measured as a so-called local employment multiplier.

The size of the multiplier depends on several factors. These include the overall health of the economy, cultural preferences regarding consumption (Osman & Kemeny, 2021), industry-specific differences in supply chains (Moretti & Thulin, 2013), agglomeration effects, and congestion effects (Bartik & Sotherland, 2019). For the latter, constraints on the housing supply play a key role (Moretti & Thulin, 2013). Finally, the literature also draws attention to income levels in the newly created jobs in the tradable sector. Quite intuitively, workers that command

[1] As pointed out by Van Dijk (2017: 487), the classification as tradable or non-tradable is sensitive to the geographical unit. At a large enough scale – for example *the world* (Tiebout, 1956a: 161) – the 'nonlocal' disappears and the framework becomes *somewhat* less helpful.

higher wages have more money to spend on local services, thus leading to higher employment multipliers (Moretti & Thulin, 2013; Van Dijk 2017; Lee & Clarke, 2019: 2).

The literature provides employment multipliers for the tradable sector, the public sector, manufacturing, and individual industrial subsectors. In his seminal study on the US economy, Moretti (2010) found that one additional job in manufacturing created 1.59 jobs in the non-tradable sector, whereas one additional job in high-technology industries created 4.9 jobs in the non-tradable sector. Goos *et al.* (2018) found similarly large high-technology multipliers for Europe. Other studies (Van Dijk 2017, 2018; Wang & Chanda 2018; Bartik & Sotherland, 2019; Lee & Clarke, 2019; Osman & Kemeny, 2021) find evidence that the employment effects of high-technology industries are comparatively larger too, but their multiplier estimates tend to be substantially lower in magnitude than those suggested by Moretti (2010).

It is indeed common for multiplier studies to compare employment effects of industries with different average wage levels. Multiplier effects are generally larger in industries with higher average wage levels. However, these industry averages mask substantial variation in incomes. To understand the distinct effects of changes at the top of the income distribution, the study at hand takes a more granular approach and estimates the multiplier effects of high-income *individuals.*

To investigate the distributional implications of changes in the number of high-income workers, this study introduces other conceptual refinements too. For the most part, multiplier studies provide estimates on the overall number of non-tradable jobs created. Less attention is directed at *what* kind of jobs are created. This study, on the other hand, provides estimates of employment effects for different types of workers and occupations. Specifically, the increasing share of low-education, low-wage services is investigated.

3. Empirical strategy

4.1 Models

In this study, I estimate employment multipliers using the following equation:

$$\Delta EMP_{i,t}^{Non-tradables} = \alpha + \beta \Delta EMP_{i,t}^{Rich\ tradables} + X_{i,t,k}\gamma_k + \mu_i + \eta_t + \varepsilon_{i,t} \qquad (1)$$

Drawing on Faggio and Overman (2014), the growth rate on the left-hand side describes the contribution of non-tradable jobs to the total employment growth in commuting zone *i* between the years *t* and *t-10*. Specifically, it is defined as:

$$\Delta EMP_{i,t}^{Non-tradables} \equiv \frac{\left(EMP_{i,t}^{Service} - EMP_{i,t-10}^{Service}\right)}{EMP_{i,t-10}^{Total}} \qquad (2)$$

Similarly, the term $\Delta EMP_{i,t}^{Rich\ tradables}$ on the right-hand side describes the contribution of high-income individuals in the tradable sector to total employment growth. With this setup, the key parameter β offers a rather intuitive interpretation: When the number of high-income tradable jobs in a given commuting zone increases by 100, the number of non-tradable service jobs is expected to increase by $100 \times \beta$. X is a matrix of *k* control variables. μ_i is a location-specific fixed effect included to capture bias from unobserved but relatively constant local features. η_t is a period fixed effect, included to capture time-varying, but economy-wide shocks.

While my primary aim is to assess the relevance of consumption by high-income individuals to the occupational restructuring and wages in the non-tradable sector, I also consider other explanatory variables. I control for women's labor market participation, demographic structure, unemployment, and agglomeration effects. Factors such as the overall health of the economy and consumption preferences should be absorbed by the fixed effects (Osman & Kemeny 2021: 160).

Still, reservations regarding omitted variable bias remain. This study analyzes the impact of high-income jobs in tradable industries. However, high-income jobs represent only a fraction of all tradable jobs. The remaining employment consists, unsurprisingly, of non-high-income workers. The problem is that changes in the high-income segment may be correlated with changes in the remaining and unobserved parts of the tradable sector. As recommended by Osman and Kemeny (2021: 157), I therefore control for changes in non-high-income tradable employment. This control variable is specified analogously to the changes in high-income tradable employment.

Although changes over time, the set of control variables, and the fixed effects in the model remove some bias, endogeneity still poses a challenge. Unobserved time-varying region-specific shocks – such as changes in amenities, tax regimes, and subsidies – could affect *both* the non-tradable sector *and* the high-income tradable sector at the same time. Hence, β is potentially biased in either direction.

There is a remedy though. In line with the vast majority of the multiplier literature (for an overview, see Osman & Kemeny, 2021: 154-155), I employ a Bartik-style shift-share

instrument to isolate the exogenous variation in the change of tradable, high-income employment. The instrument is constructed as follows:

$$Z_{i,t}^{Rich\ tradables} = \sum_{j=1}^{J} \frac{EMP_{i,t-1}^{j}}{EMP_{i,t-1}^{Tradable}} \times \left(\frac{EMP_{i',t}^{j,rich} - EMP_{i',t-1}^{j,rich}}{EMP_{i',t-1}^{j}} \right) \qquad (4)$$

The first term on the right-hand side represents local exposure shares that vary from region to region. In practice, I compute them by dividing employment in tradable industry *j* in region *i* by the total tradable employment in region *i*. The second term on the right-hand side represents nationwide employment growth rates of high-income workers in tradable industry *j*. Following current common practice (e.g., Moretti & Thulin, 2013; Faggio & Overman, 2014; Van Dijk, 2018; Osman & Kemeny, 2021), a "leave-one-out" twist is added to these growth rates. That is to say, the instrument for region *i* is computed using employment changes in *all* regions *except* for those in region *i* itself. The rationale for this exclusion is to further minimize endogeneity concerns, which could be an issue for sectors with high spatial concentration (Osman & Kemeny, 2021: 158). Put simply, the instruments substitute the observed – and potentially endogenous – change in regional high-income tradable employment with a locally weighted national average.

Unfortunately, this single instrument only removes some of the endogeneity concerns. Since I follow Osman and Kemeny's (2021: 157) suggestion to control for employment changes of non-high-income workers in the tradable sector, endogeneity enters the picture yet again. Consequently, there might be unobserved time-varying shocks that simultaneously affect the non-high-income tradable sector and the non-tradable sector. As an additional remedy, I follow Van Dijk's (2018: 285) suggestion to introduce a second shift-share instrument. This second instrument is constructed analogously to the first instrument in *Eq. (4)* and captures the exogenous effect of changes in non-high-income tradable employment.

While Bartik shift-share instruments are widely applied in the literature, scholars have identified conceptual challenges to this method (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2018; Jaeger et al., 2018; Broxterman & Larson, 2020). Reviewing the local multiplier literature, Osman & Kemeny (2021: 158, 164-165) find that results from a range of studies should be treated with caution since conventional criteria for weak instruments are often not met, diagnostics are applied inappropriately or rather opaquely. Osman and Kemeny (2021) improve on this situation by applying new and rigorous testing strategies, such as the non-homoskedastic-robust Montiel-Pflueger test for weak instruments (Montiel Olea & Pflueger,

2013). The study at hand would like to follow suit, however, the Montiel-Pflueger test statistic only applies to models containing a single endogenous regressor. Controlling for employment changes of non-high-income workers introduces a second endogenous regressor though. Fortunately, Lewis and Mertens (2022) have recently proposed a generalized version of the Montiel-Pflueger test that can be applied to regressions with multiple endogenous variables. As an improvement to the extant multiplier literature, this study incorporates the Lewis-Mertens test to assess instrument strength.

3.2 Data, measurement, and operationalizations

The primary data source is the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2022), covering roughly four ten-year periods from 1980 to 2018. Census data are used for 1980, 1990, and 2000, whereas 2010 and 2018 are covered by the American Community Survey (ACS). The data are aggregated at the commuting zone level with the help of crosswalks constructed and provided by Autor and Dorn (2013). Commuting zones offer a good approximation of local labor markets (Bartik & Sotherland 2019: 21). In contrast to the more limited samples in other multiplier studies, commuting zones include larger parts of the US, particularly less urbanized regions. Still, restrictions apply to the sample in this study. I only consider commuting zones within the contiguous United States. In addition, the sample is restricted to employed individuals aged between 18 and 64 years.

Another recurring conceptual problem in multiplier studies is the classification of industries into tradable and non-tradable sectors. The study relies on 3-digit industry codes provided by IPUMS, with slight modifications to establish consistency for the sample period from 1980 to 2018. Following Jensen and Kletzer (2006) and Kemeny and Osman (2018), locational Gini coefficients are computed to assess the spatial concentration of each industry. Since non-tradable industries primarily serve local markets, they should, in principle, be distributed relatively evenly across regions and hence feature low locational Ginis. Industries that produce tradable goods, on the other hand, are more likely to cluster in space. Using locational Ginis, I first sort industries and then refine the classification by hand (Thulin, 2015). Furthermore, occupational information is used to adjust the tradability classification. For example, the oil and gas extraction sector is highly tradable and spatially concentrated. However, within this industry, a small number of workers provide services that are clearly non-tradable, such as childcare and housekeeping. For consistency, workers in such non-tradable service occupations are removed from otherwise tradable industries.

The study not only distinguishes between non-tradable and tradable sectors, but also splits the tradable-sector workforce along income lines. A range of multiplier studies distinguish – implicitly or explicitly – between higher-income and lower-income tradable multipliers. However, for the most part, they base this distinction on industry averages. This study takes a different approach. It does not look at industry averages but at individual high-income workers. As a demarcation line for high incomes, I choose the national 90th income percentile in a given year. I categorize anyone employed in tradable industries with an income above this threshold as a high-income tradable worker. Of course, such a cut-off point implies a degree of arbitrariness.

Capturing the lower tail of the workforce also poses measurement challenges. To assess the impact of high-income earners on the lower tiers of the labor market, I focus on occupations rather than on individuals. For this, I draw on Scott's work (2012, 2014, 2017) on low-tier service labor. Scott (2012: 97-101) formulates three criteria an occupation must meet to belong to – what he somewhat polemically calls – the "service underclass." The occupational median wage must be below two-thirds of the national median wage, the occupation's median education level must be below any college education, and the occupation in question must be a service occupation.

4. Main findings

4.1 Descriptive analysis

To set the scene, Table 1 provides a descriptive overview of employment changes in key occupational groups. From 1980 to 2018, the workforce has expanded by 52%, adding 50 million workers. These gains are not distributed evenly. Occupations in production and resource extraction declined by more

than 30% since 1980. This is in stark contrast to service occupations, such as personal care and healthcare support occupations, which tripled in the same period.

Table 1: Employment figures for selected occupational classes in the US, all figures in thousands

	1980	1990	2000	2010	2018	Change 1980 to 2018
Total workforce	96,428	114,145	127,068	138,155	146,603	52%
Production and extraction occupations:						
Production	14,133	12,480	11,512	9,637	9,116	-35%
Extraction	353	216	146	214	239	-32%
Selected service occupations:						

Sales-related occupations	9,854	13,918	14,925	16,690	15,957	62%
Food preparation & serving	4,718	5,638	6,793	8,464	9,430	100%
Personal care services	2,112	2,705	3,811	5,510	6,407	203%
Healthcare support	1,781	2,209	2,967	4,281	5,020	182%
Maids and housekeepers	1,033	1,038	1,164	1,496	1,613	56%
Appearance services	807	993	1,073	1,283	1,473	83%
Childcare services	740	781	1,345	1,413	1,340	81%
„Service underclass“ workforce	14,454	17,676	22,305	26,851	29,924	107%

The “service underclass,” defined as service occupations in non-tradable industries with low formal qualifications and median incomes, doubled over the last four decades. In 2018, about 30 million workers made up the “service underclass.” This amounts to more than a fifth of the total workforce in the US.

Table 2 shifts the focus to high-income workers, i.e. workers with incomes above the 90th percentile. In 2018, approximately 5 million high-income workers were employed in tradable industries. This number increased by 65% since 1980, slightly outpacing the increase in the overall workforce. The table also highlights the 15 most important tradable industries based on the number of high-income workers in 2018. The distribution is rather skewed towards certain industries: In 2018, computer and data processing industries employed around 890,000 high-income workers. Public relations, finance, and legal services also feature prominently. Alongside these producer services, a number of – mostly high-tech – manufacturing industries still provide high-income jobs. However, the growth rates of these industries tend to be modest.

Table 2: Distribution of high-income workers across tradable industries, top-15 industries by employment in 2018. All employment figures in thousands.

	1980	1990	2000	2010	2018	CHANGE 1980 TO 2018
Computer and data processing services	61	159	459	584	890	1359%
Management and public relations services	61	142	303	345	423	593%
Legal services	191	365	410	461	417	118%
Security, commodity brokerage, and investment companies	36	100	263	360	379	953%
Electrical machinery, equipment, and supplies, n.e.c.	138	170	229	214	208	51%
Credit agencies, n.e.c.	28	57	119	161	175	525%
Real estate, including real estate-insurance offices	70	137	134	169	171	144%
Research, development, and testing services	79	108	107	151	170	115%
Accounting, auditing, and bookkeeping services	77	119	138	161	160	108%
Drugs	35	53	85	127	154	340%
Aircraft and parts	105	113	76	77	150	43%

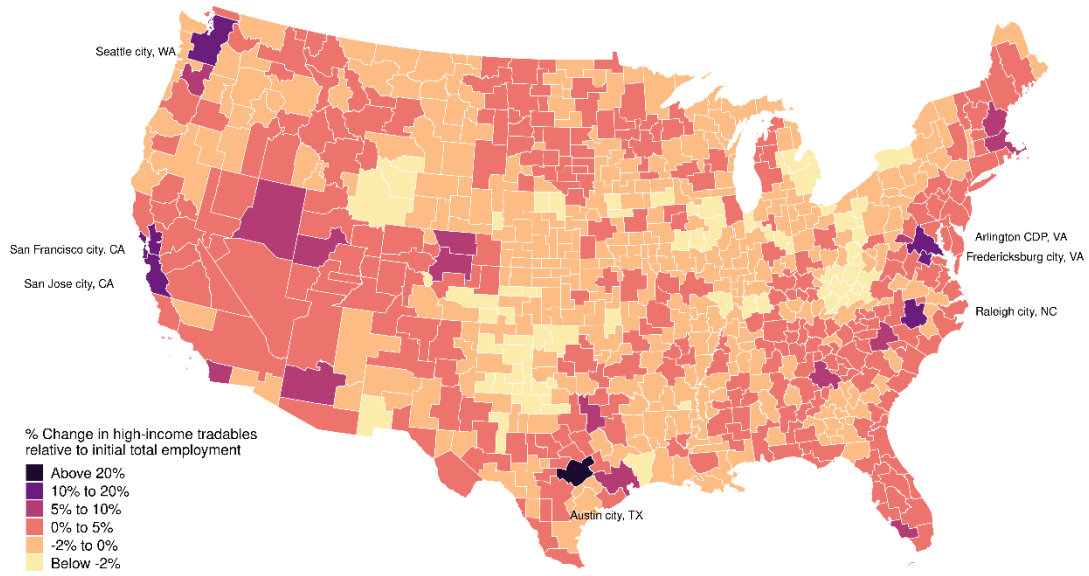
Oil and gas extraction	99	76	52	95	142	43%
Motor vehicles and motor vehicle equipment	209	159	205	121	128	-39%
Radio and television broadcasting and cable	32	52	76	81	121	278%
Medical, dental, and optical instruments and supplies	22	31	56	77	103	368%
Total high-income tradable employment - including industries outside the top 15	3,256	3,761	4,448	4,809	5,357	65%

The fate of motor vehicles and related equipment manufacturing is noteworthy. In 1980, this sector was the single largest employer of high-income workers[2]. Since then, the sector has not only lost in relative shares, but also in absolute terms, decreasing from 209,000 high-income workers in 1980 to approximately 121,000 in 2018. Overall, the "typical" tradable industries employing high-income workers have changed quite drastically, shifting from manufacturing sectors to service provision.

Geographical shifts accompany these sectoral shifts. Figure 1 shows the contribution of high-income tradable jobs to total employment growth between 1980 and 2018. The tech clusters on the West Coast, such as Seattle and the Bay area, feature strong growth in this category. Similarly, East Coast commuting zones around Washington, D.C., and – somewhat more inland – in Raleigh City, North Carolina also experienced substantial increases. In these regions, tradable high-income jobs contributed between 10% and 15% to total employment growth. However, it is Austin, Texas, that saw the strongest gains – with an increase of just over 20% between 1980 and 2018.

[2] However, in 1980 the distribution was far less skewed. The 200,000 or so workers in motor vehicle industries comprised "only" 6% of all high-income workers in the tradable sector. In 2018, the 890,000 workers in computer and data-processing services accounted for 16% of the high-income tradable workforce.

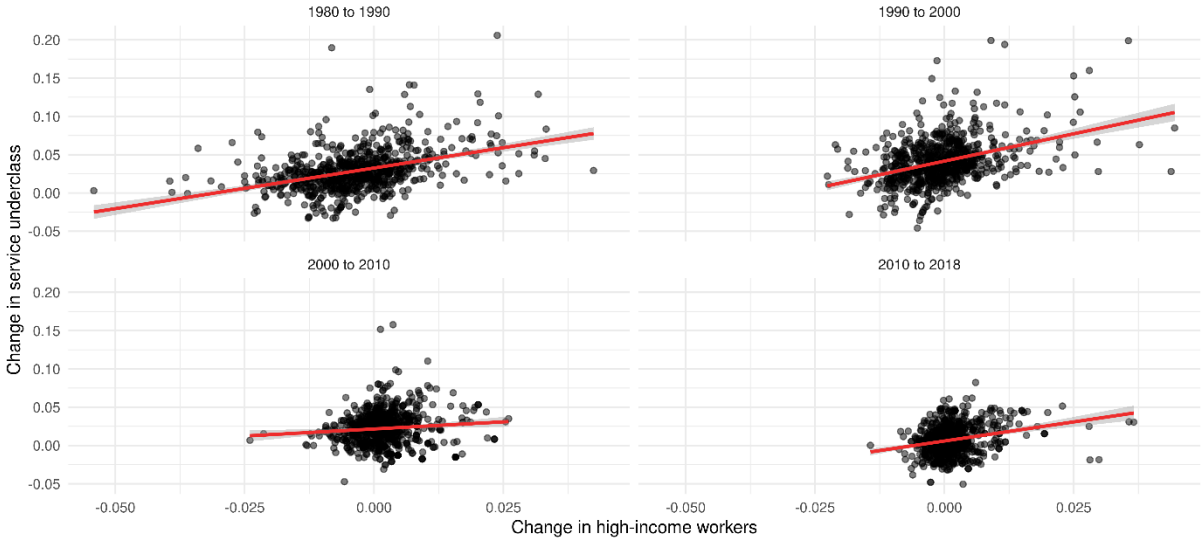
Figure 1: Contribution of high-income tradable employment to total employment change, 1980 to 2018



In most US commuting zones, the number of tradable high-income jobs has stagnated or declined slightly. Among the larger agglomerations that lost out the most are commuting zones in or near the so-called Rustbelt. Several regions in Indiana (i.e., Gary, Muncie, and Waterloo) report losses between 3% and 4.9%. Similarly, Youngtown in Ohio and Detroit lost 3.6% and 3.3%, respectively.

The changing spatial distribution of high-income workers in tradable industries seems to be associated with shifts in low-tier non-tradable employment. Figure 2 depicts the association between changes in affluent tradable workers and the "service underclass" for different decades. This first – and unconditional – lineup reveals a positive correlation between high- and low-income workers over the four decades shown. Between 2000 and 2010, a period of considerable economic turmoil, the correlation is much more modest.

Figure 2: Employment change of high-income tradable workers and service underclass in US commuting zones. Changes are measured relative to initial total employment



4.2 Baseline results

This study uses a series of regression models to identify the relationship between high-income job growth and labor market conditions for low-tier workers. In Table 3, I estimate the impact of high-income workers in tradable industries on employment in *all* non-tradable industries. While the study focuses on lower-tier service employment, this first set of regressions presents results for the entire non-tradable sector to allow for a better comparison with the existing local multiplier literature. I use two types of estimators: ordinary least squares (OLS) and instrumental variables (IV).

The first five columns show the OLS estimation results. Controls are introduced step by step. All models include regional and time-fixed effects. The OLS models show a significant and positive correlation between high-income tradable workers and non-tradable employment. However, the multiplier weakens substantially with the addition of controls. The impact of non-high-income tradable employment on non-tradable jobs is more of a mixed bag. While some scenarios (OLS II and OLS III) indicate a significant and positive relationship, the results become insignificant in the fully specified case (OLS V).

Columns 6-10 present the instrumental variable (IV) estimation results. To reiterate, I instrument for changes in both high-income and non-high-income tradable employment. The instruments pass the Lewis-Mertens weak instrument test in all cases. As in the OLS models, the coefficients of high-income tradable employment are significant. However, in most IV

models the magnitudes for high-income employment increased substantially, suggesting that the OLS results are biased downwards.

The results of the fully specified IV model (i.e., IV V) imply that one new high-income tradable job creates more than six new non-tradable jobs in the same commuting zone. The coefficient of non-high-income employment only becomes positive, when the high-income employment variable is excluded. In all other IV models that include *both* high-income and non-high-income tradable employment change, the coefficients of the latter turn negative.

Table 3: Impact of high-income employment in tradable industries on non-tradables, 1980 -2018

	OLS I	OLS II	OLS III	OLS IV	OLS V	IV I	IV II	IV III	IV IV	IV V
Δ High-income tradables	3.218***		2.477***	1.251***	1.775***	2.654***		8.716***	4.971***	6.685***
	(0.284)		(0.282)	(0.270)	(0.277)	(0.427)		(1.407)	(1.220)	(1.361)
Δ Non-high-income tradables		0.694***	0.396***	0.021	-0.035		0.323**	-1.977***	-2.171***	-2.455***
		(0.090)	(0.091)	(0.077)	(0.077)		(0.124)	(0.396)	(0.355)	(0.388)
log population				-0.272***	-0.327***				-0.398***	-0.474***
				(0.015)	(0.016)				(0.025)	(0.029)
Unemployment %					-0.578***					-0.378+
					(0.123)					(0.201)
Share age 65 and above					0.235+					0.108
					(0.142)					(0.200)
Share employed women					-0.612***					-0.835***
					(0.054)					(0.099)
Num.Obs.	2888	2888	2888	2888	2888	2888	2888	2888	2888	2888
R^2	0.684	0.674	0.691	0.751	0.768	-	-	-	-	-
R^2 Adj.	0.578	0.565	0.587	0.668	0.689	-	-	-	-	-
Fixed Effect: commuting zones	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect: decade	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lewis-Mertens test / threshold value	-	-	-	-	-	316.19 / 23.06	296.40 / 23.06	22.07 / 20.83	24.35 / 19.95	23.36 / 20.32

*Note: Dependent variable is the change in non-tradable employment. Standard errors reported in parentheses, clustered on commuting zone level. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001*

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4.3 High-income multipliers and occupational restructuring

The previous models considered employment in the non-tradable sector but largely abstracted from concrete economic functions that workers perform there. In Table 5, I change perspective by examining the impact of high-income workers on employment in different lower-tier service occupations. I present results for the rise in lower-tier service employment, drawing on Scott's concept of a "service underclass". Since this service underclass combines a range of heterogeneous service activities, I also present results for occupational subgroups of the service underclass.

Column 1 of Table 4 illustrates that growth in high-income tradable employment positively affects overall employment in service underclass occupations. For every 100 high-income tradable jobs, 67 low-skill, low-wage service jobs are created. The result is significant at a 5% level. Columns 2 through 9 present evidence for selected lower-tier service occupations. Taken together, these categories account for over 80% of all workers in the service underclass. As can be seen, the magnitudes and significances of the estimated high-income multipliers vary. In absolute terms, the greatest multiplier effects on low-wage, low-education jobs are observed for sales-related occupations, such as cashiers and retail clerks. In other words, the occupations facilitating other people's consumption respond quite strongly to the expansion of affluent households. There is also a significant response in the number of childcare workers and housekeepers. Personal appearance service workers such as barbers, hairdressers, and cosmetologists also seem to benefit, but this result is statistically significant at the 10% level only.

There is also no significant effect on workers who prepare and serve food, janitors, groundkeepers, chauffeurs, and taxi drivers. Finally, the effect on packers and packagers is significantly negative. This may be because packers provide their services in different contexts. Some directly assist customers in settings akin to the sales-related occupations mentioned earlier. Others are involved in preparing shipments in more industrial or even tradable contexts.

Table 4: IV estimates of the impact of high-income employment in tradable industries on different occupational classes

	SERVICE UNDERCLASS	SALES RELATED	CHILDCARE	HOUSEKEEPING	PERSONAL APPEARANCE	FOODPREP	JANITORS & GROUNDKEEPERS	CHAUFFEURS & TAXI DRIVER	PACKERS & PACKAGERS
Δ High-income tradables	0.667*	0.452***	0.217***	0.128**	0.073+	0.069	-0.001	-0.009	-0.099***
	(0.329)	(0.125)	(0.059)	(0.047)	(0.040)	(0.149)	(0.072)	(0.012)	(0.028)
Δ Non-high-income tradables	-0.449***	-0.138***	-0.076***	-0.042**	-0.032*	-0.144**	-0.007	0.002	0.037***
	(0.098)	(0.037)	(0.017)	(0.015)	(0.014)	(0.046)	(0.021)	(0.004)	(0.009)
log population	-0.104***	-0.027***	-0.008***	-0.006***	-0.005***	-0.033***	-0.012***	0.000	0.002**
	(0.008)	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.000)	(0.001)
Unemployment %	-0.059	0.014	-0.023**	-0.021**	-0.006	-0.011	-0.045***	0.000	-0.009*
	(0.049)	(0.018)	(0.008)	(0.007)	(0.006)	(0.022)	(0.012)	(0.002)	(0.004)
Share age 65 and above	0.016	0.004	0.014+	-0.007	-0.011+	0.010	-0.007	0.000	0.000
	(0.046)	(0.016)	(0.008)	(0.007)	(0.006)	(0.020)	(0.012)	(0.002)	(0.004)
Share employed women	-0.248***	-0.044***	-0.032***	-0.028***	-0.012***	-0.069***	-0.019**	-0.003**	-0.004+
	(0.026)	(0.009)	(0.005)	(0.004)	(0.003)	(0.012)	(0.006)	(0.001)	(0.002)
Num.Obs.	2888	2888	2888	2888	2888	2888	2888	2888	2888
Fixed Effect: commuting zones	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect: decade	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lewis-Mertens test / threshold value	23.36 / 20.32	23.36 / 20.32	23.36 / 20.32	23.36 / 20.32	23.36 / 20.32	23.36 / 20.32	23.36 / 20.32	23.36 / 20.32	23.36 / 20.32

*Note: Dependent variable is the change in employment for the group reported in the column title. Standard errors reported in parentheses, clustered on commuting zone level. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001*

5. Conclusion and Discussion

One new high-income job in tradable industries creates six jobs in the non-tradable part of the economy. At first sight, these estimates seem plausible, since they are in a similar ballpark to the multipliers for high-technology industries estimated by Moretti (2010) and Goos *et al.* (2018). At second sight, there is reason for caution as more recent studies (e.g., Van Dijk, 2018; Bartik & Sotherland 2019; Lee & Clarke 2019; Osman & Kemeny, 2021) have found substantially lower high-tech multipliers, thus casting a shadow of doubt on any large multiplier effect. However, the comparison between high-tech multipliers in prior studies and high-income multipliers in this study is somewhat misleading. The estimates in the literature rely on industry averages, and while high-tech industries offer higher incomes on average, not all high-tech workers command high incomes. In contrast, my high-income category is much more restrictive since it consists exclusively of workers earning more than the 90th income percentile. Consequently, the substantial multipliers presented here do not contradict the findings in the recent multiplier literature.

Compared with the overall employment multiplier, the impact on service underclass employment is significant but modest, as it only explains a fraction of the actual increase in low-wage, low-education services. Other factors drive occupational restructuring as well.[3] To some extent, this evidence runs counter to common narratives of polarization (e.g., Sassen, 2001, 2012). Still, the results do not imply that affluent workers do not require substantial amounts of labor from lower-tier service workers for their reproduction. Affluent workers might create demand for low-wage services while at the same time crowding out similar classes of service workers that cater to a mid- or lower-tier customer base. The occupational data used in this study might still be too coarse to allow for precise conclusions. Additionally, analysis of lower-tier services revealed that high-income workers cause occupational restructuring. In

[3] As can be seen in the results, changes in gender relations seem to offer one such complementary explanation. In most employment models, the initial share of women's labor market participation exerts a negative influence on the growth of non-tradable jobs. There appear to be two mechanisms at work. On the one hand, non-employed women offer an untapped pool of labor for expanding service industries. On the other hand, women entering the labor market must rely more strongly on the market for the provisioning of certain services such as personal care.

particular, an increase in high-income workers positively affects sales-related occupations, childcare, and housekeeping services. What is rather surprising is the insignificant impact on workers who prepare and serve food. I would have expected a positive employment response similar to the other services that provide market substitutes for domestic activities.

Some concerns remain regarding the methodology. The modest impact on service underclass employment might be caused by the spatial unit chosen to approximate local labor markets. In their study on high-tech multipliers in British Travel to Work Areas, Lee and Clarke (2019: 7) discuss a potential "leaky buckets" dynamic, where the positive employment effects leak into other regions. Similarly, high-income workers might induce even more considerable demand for service underclass workers – but this demand may primarily affect workers in neighboring areas. This could be the case if the rising cost of living or other factors prohibit co-location. However, I consider this somewhat improbable since commuting zones already cover large land areas (Bartik & Sotherland, 2019). Still, using even larger units of analysis, such as states or explicitly modeling spatial spillovers (Gerolimetto & Magrini, 2016), could offer further insights. Either way, the relatively modest impact of affluence on the service underclass reported here invites additional investigation into the causes behind the expansion of lower-tier services.

Lower-tier services also warrant further conceptual reflection. The so-called service underclass provides various services: some may primarily cater to the demand of affluent households, while others are more foundational. It is worthwhile to consider alternative specifications of lower-tier service work to better understand its relationship with affluent strata.

An issue that remains puzzling is the consistently negative impact of low- and medium-income workers on non-tradable service occupations. In the literature, negative multipliers are associated with crowding-out effects (Faggio & Overman, 2014). Arguably, non-high-income workers in tradable industries exert pressure on housing markets that their additional spending on local activities may not offset. Another aspect less explicitly explored in the multiplier literature might be driving the negative multipliers. Low- and mid-wage jobs in tradable industries are likely to bear the brunt of automation and offshoring. Since 1980, the number of tradable-industry jobs with incomes below the 90th percentile has stagnated nationally. On a regional scale, approximately 70% of commuting zones have seen declining non-high-income tradable employment. To some extent, the adverse employment multipliers found in this study seem to indicate not a strict crowding-out, but rather workers transitioning from the manufacturing sector to employment in service industries. As low- to mid-pay manufacturing

jobs disappear in many regions, service jobs and service underclass jobs may offer the only suitable alternatives for large swaths of the workforce.

Lastly, the study has identified potential avenues for future research. First, the article focuses on the commuting-zone level to approximate local labor markets. Adopting other spatial scales – for example, concentrating on smaller areas – might offer further insights into the spatial interdependencies between top-income and bottom-income workers. Second, this study has applied an intra-regional lens to understand the growth of low-wage services, placing inter-regional aspects largely outside its brackets. However, inter-regional aspects might be an important factor driving changes in the occupational structure. Third, the compositional effects of affluent workers on the lower-wage segments of the labor market call for further conceptualization of the service underclass. Somewhat contradictory, the service underclass in its current operationalization includes both activities primarily geared to serve the needs of an affluent few and activities that provide "foundational" services and infrastructures for society at large (Hansen, 2022; Novy, 2022). Finally, the analysis could be advanced by a deeper analysis of the underlying changes in the gendered and racialized structure of lower-tier occupations (Dwyer, 2013; Dwyer & Wright, 2019).

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