

# Occupation Demand Shocks and Mismatch in Local Labor Markets

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## Focus of project: What are effects of local labor demand shocks to different occupation types? Variation by group, and by local characteristics?

- **My initial motivation:** What should industry targets be for state/local economic development policies? Should we consider what jobs are “well-matched” to local residents we want to help most? (For ex., will attracting Amazon HQII high-skill jobs help local residents?)
- **Author hypothesis:** Local data may shed light on Autor (2019) hypothesis that “occupational polarization” explains declining relative wages of non-college grads, particularly in largest cities.
- **Main finding:** Consistent with Autor hypotheses, mid jobs by far the most important in explaining local labor market outcomes, particularly for non-college-grads.
- **Policy Implications:** Local econ dev policies should target “mid jobs” – to extent this is feasible. But limitations of growth potential of mid-jobs suggests need to also increase occ mobility to “high jobs”, & boost wages of “low jobs”.

## Model and Data: Effects on long-run (2000 to 2015-19) change in labor market outcomes for different groups of demand shocks to high-, middle-, or low-occupations, interacted w/ local characteristics

$$\begin{aligned} \ln(Y_{jz9}) - \ln(Y_{jz0}) = & B_0 + B_e \times \ln(E_{z0}) + B_c \times [\ln(C_{z0}) - \ln(C_{n0})] + \\ & B_l \times (D_{lz}) + B_{le} \times [(\ln(E_{z0})) (D_{lz}) + B_{lc} \times [\ln(C_{z0}) - \ln(C_{n0})] (D_{lz}) + \\ & B_m \times (D_{mz}) + B_{me} \times [(\ln(E_{z0})) (D_{mz}) + B_{mc} \times [\ln(C_{z0}) - \ln(C_{n0})] (D_{mz}) + \\ & B_h \times (D_{hz}) + B_{he} \times [(\ln(E_{z0})) (D_{hz}) + B_{hc} \times [\ln(C_{z0}) - \ln(C_{n0})] (D_{hz}) \end{aligned}$$

$Y_{jz9}$  and  $Y_{jz0}$  are demographically-adjusted real labor market outcomes for group  $j$  in CZ  $z$  at years 2015–2019 (from ACS) or year 2000 (Census).  $(E_{z0})$  is CZ  $z$ 's overall adjusted employment rate relative to the U.S. in the year 2000.  $(C_{z0})$  and  $(C_{n0})$  are the college grad percent of adults ages 25–64 in the year 2000 in either the CZ or the nation (subscript  $n$ ).  $(D_{lz})$ ,  $(D_{mz})$ , and  $(D_{hz})$  are the demand shocks to low-, mid- and high-occupations in CZ  $z$  from the former to the latter period.

Model is estimated on 371 “commuting zones” (CZs), all > 100K in pop, which comprise 96% of U.S. pop.

For presentation, focus on change in real earnings for different education groups (less than BA, BA+). Real earnings controls for local prices.

CZ population	Most populous county in CZ	Change from 2000 to 2015-19 in relative real earnings index for <BA	Change for BA plus
16,372,860	<b>Los Angeles CA</b>	<b>-11.9%</b>	<b>-7.6%</b>
10,762,079	Kings NY	-7.2%	1.1%
8,610,555	Cook IL	-8.5%	-1.2%
6,661,455	Bergen NJ	-3.8%	-5.0%
5,100,708	<b>Alameda CA</b>	<b>2.4%</b>	<b>11.8%</b>
5,077,106	<b>Wayne MI</b>	<b>-14.7%</b>	<b>-8.3%</b>
4,770,018	Harris TX	-1.2%	0.1%
4,751,998	Middlesex MA	-0.1%	4.2%
4,435,552	Philadelphia PA	-6.7%	2.7%
4,414,255	Fairfax VA	0.6%	1.2%
3,955,878	<b>Miami-Dade FL</b>	<b>-11.8%</b>	<b>-10.9%</b>
3,942,141	<b>King WA</b>	<b>8.1%</b>	<b>12.0%</b>
3,797,219	Fulton GA	1.1%	3.3%
3,469,660	Maricopa AZ	-0.1%	7.8%
3,405,239	Fairfield CT	-1.3%	3.1%
3,029,141	Dallas TX	2.5%	-2.3%
2,955,948	San Diego CA	-7.0%	-0.6%
2,945,557	<b>Hennepin MN</b>	<b>8.8%</b>	<b>7.7%</b>
2,945,432	Cuyahoga OH	5.7%	3.6%
2,880,863	Denver CO	4.9%	3.9%
2,665,798	Baltimore MD	0.7%	0.4%
2,603,382	<b>Allegheny PA</b>	<b>21.2%</b>	<b>1.4%</b>

**Occ types based on Autor: high** (managers/execs; professionals + sales in finance/ads; technicians+fire/police); **middle** (retail sales except fin/ads; clerical/admin support; production/operative); **low** (transport; construction;laborers; mechanics;services; farming/mining)

**Table 5: Growth in employment, 2000 to 2015-2019, by high, mid, and low occupations**

		Total	High	Mid	Low
<b>2000</b>	<b>Employment(in millions)</b>	130.9	50.3	40.7	39.8
	<b>Percent of total employment</b>	100.0%	38.4%	31.1%	30.4%
<b>2015-2019</b>	<b>Employment(in millions)</b>	155.9	66.7	38.9	50.3
	<b>Percent of total employment</b>	100.0%	42.8%	25.0%	32.3%
	<b>2000 to 2015-19 % growth, as percent of total base in 2000</b>	19.1%	12.5%	-1.4%	8.0%

Occ growth at national level can be divided into 3 components: (1) National growth; (2) Differential growth of industries w/ diverse occ shares; (3) w/i industry shifts across occ groups. Negative share effect for mid-occ is driven a lot by manufacturing's below-average growth. Positive share effect for low-occ driven in part by above average growth of restaurants. Shift effect from mid to high occurs across MANY industries.

	Total	High	Mid	Low
<b>2000 to 2015-19 % growth, as percent of total base in 2000</b>	19.10%	12.54%	-1.41%	7.97%
<b>National growth effect</b>		8.08%	5.22%	5.80%
<b>Industry Share effect</b>		0.56%	-2.80%	2.24%
<b>Occ Shift effect</b>		3.90%	-3.83%	-0.07%

## Definition of a CZ's occupation demand shocks

- $\sum_i (1/E_{z0}) \times [E_{izo} \times (E_{in9}/E_{in0}) \times P_{oi9} - E_{izo} \times P_{oi0}]$
- The summation is over all industries  $i$  for each CZ  $z$ .  $E_{iz0}$  is employment in industry  $i$  in CZ  $z$  at the base time period (1999),  $E_{z0}$  is total employment in the CZ in 1999,  $E_{in9}$  is national employment in industry  $i$  in 2016,  $E_{in0}$  is national employment in industry  $i$  in 1999,  $P_{oi9}$  and  $P_{oi0}$  are the national proportion of industry  $i$ 's employment in occupation group  $o$  at the final time period (subscript 9), and the base time period (subscript 0). Intuition: change in occ jobs in CZ as % of total base jobs if all industries grew at national rate & followed national ind/occ shares.
- Sum of this expression over three occ groups = geographic share effect from geographic shift-share analysis = total percent job growth predicted if all industries in CZ grew at national average = Bartik instrument = proxy for demand-driven increase in jobs if all export-base industries kept their national market share.

**Descriptive stats for 371 CZs for growth and various components, 1999 to 2016, based on Upjohn Institute's WholeData (County Business Patterns with suppressions estimated) for over 1,000 industries, and industry/occ shares from Census/ACS**

		Mean	Median	Standard Deviation
<b>Overall growth</b>		8.97%	6.14%	17.75%
<b>Share effect (Bartik shock)</b>		9.23%	10.39%	6.90%
	<b>High group Demand shock</b>	8.03%	8.13%	<b>2.30%</b>
	<b>Differential industry growth component</b>	4.22%	4.50%	<b>2.45%</b>
	<b>Within-industry shift component</b>	3.81%	3.85%	<b>0.46%</b>
	<b>Mid group Demand shock</b>	-4.15%	-3.64%	<b>3.21%</b>
	<b>Differential industry growth component</b>	-0.40%	0.15%	<b>2.94%</b>
	<b>Within-industry shift component</b>	-3.75%	-3.72%	<b>0.60%</b>
	<b>Low group Demand Shock</b>	5.35%	5.41%	<b>2.03%</b>
	<b>Differential industry growth component</b>	5.41%	5.52%	<b>1.98%</b>
	<b>Within-industry shift component</b>	-0.06%	-0.07%	<b>0.31%</b>
<b>Competitive Shift Effect</b>		-0.26%	-2.25%	15.03%



Demand shock to occ types, 1999 to 2016		Effect on 2000 to 2015-19 change in ln(earnings) for those w/ < BA	Effect on 2000 to 2015-19 change in ln(earnings) for those w/ BA+
<b>High-occ</b>	<b>At means</b>	-0.8396 (0.5112)	-0.1523 (0.3215)
	<b>Interacted w/ ln(EmpRate index, 2000)</b>	-17.65 (10.94)	-4.10 (5.28)
	<b>Interacted w/ diff of ln(CollGradRate) from U.S. mean</b>	0.572 (1.319)	-0.060 (0.798)
<b>Mid-occ</b>	<b>At means</b>	<b>1.951</b> (0.633)	<b>0.728</b> (0.354)
	<b>Interacted w/ ln(EmpRate index, 2000)</b>	4.06 (6.45)	<b>6.80</b> (2.78)
	<b>Interacted w/ diff of ln(CollGradRate) from U.S. mean</b>	1.327 (1.656)	-0.648 (0.709)
<b>Low-occ</b>	<b>At means</b>	0.112 (1.005)	-0.079 (0.534)
	<b>Interacted w/ ln(EmpRate index, 2000)</b>	<b>26.33</b> (9.20)	<b>-8.57</b> (3.67)
	<b>Interacted w/ diff of ln(CollGradRate) from U.S. mean</b>	<b>-4.966</b> (2.567)	1.619 (1.195)

**Table 19: How Effects of Labor Demand Shocks on Earnings of Non-College & College Grads Vary at Different Levels of CZ Characteristics (Erate holding grad rate at median; Grad rate holding Erate constant at median)**

	Non-college graduates			College graduates		
	Panel A: With CZ employment rate					
	10th pctile	50th pctile	90th percentile	10th pctile	50th pctile	90th percentile
<b>High</b>	0.317	-0.923	<b>-1.856</b>	0.168	-0.119	-0.336
	(1.109)	(0.623)	(0.731)	(0.566)	(0.386)	(0.450)
<b>Mid</b>	1.289	<b>1.575</b>	<b>1.789</b>	0.399	<b>0.876</b>	<b>1.236</b>
	(0.676)	(0.427)	(0.497)	(0.339)	(0.247)	(0.266)
<b>Low</b>	-0.498	1.351	<b>2.744</b>	0.119	-0.483	-0.936
	(0.850)	(0.778)	(1.033)	(0.415)	(0.385)	(0.467)
<b>"Average" shock</b>	<b>0.5266</b>	<b>0.7765</b>	<b>0.9646</b>	<b>0.2564</b>	<b>0.2206</b>	<b>0.1936</b>
<b>30%H,44%M,27%L</b>	(0.2643)	(0.1528)	(0.2122)	(0.1070)	(0.0669)	(0.0950)
	Panel B: With college grad rate					
	10th pctile	50th pctile	90th percentile	10th pctile	50th pctile	90th percentile
<b>High</b>	-1.161	-0.923	-0.685	-0.094	-0.119	-0.144
	(1.027)	(0.623)	(0.572)	(0.630)	(0.386)	(0.350)
<b>Mid</b>	1.021	<b>1.575</b>	<b>2.125</b>	1.147	0.876	0.607
	(0.788)	(0.427)	(0.833)	(0.320)	(0.247)	(0.439)
<b>Low</b>	<b>3.424</b>	1.351	-0.710	<b>-1.158</b>	-0.483	0.189
	(1.359)	(0.778)	(1.283)	(0.585)	(0.385)	(0.670)
<b>"Average" shock</b>	<b>1.0140</b>	<b>0.7765</b>	<b>0.5403</b>	<b>0.1670</b>	<b>0.2206</b>	<b>0.2739</b>
<b>30%H,44%M,27%L</b>	(0.1856)	(0.1528)	(0.2573)	(0.0820)	(0.0669)	(0.1136)

CZ population	Most populous county in CZ	Emp rate relative to nation, 2015-2019	College % of pop 25-64, 2015-2019	High effect for <CG	Mid effect for <CG	Low effect for <CG
16,372,860	Los Angeles CA	0.993	31.7%	-0.74	1.86	0.16
10,762,079	Kings NY	1.005	41.4%	-0.80	2.26	-0.83
8,610,555	Cook IL	1.018	40.9%	-1.03	2.30	-0.44
6,661,455	Bergen NJ	1.027	44.7%	-1.14	2.45	-0.65
5,100,708	Alameda CA	1.023	48.3%	-1.04	2.54	-1.12
5,077,106	Wayne MI	0.981	34.0%	-0.49	1.90	-0.50
4,770,018	Harris TX	1.001	32.8%	-0.86	1.93	0.20
4,751,998	Middlesex MA	1.031	50.0%	-1.14	2.61	-1.10
4,435,552	Philadelphia PA	1.000	41.0%	-0.73	2.23	-0.90
4,414,255	Fairfax VA	1.058	52.1%	-1.59	2.78	-0.61
3,955,878	Miami-Dade FL	1.021	32.3%	-1.22	1.99	0.82
3,942,141	King WA	1.007	41.1%	-0.84	2.26	-0.75
3,797,219	Fulton GA	1.028	40.5%	-1.22	2.32	-0.12
3,469,660	Maricopa AZ	0.978	30.6%	-0.50	1.75	-0.05
3,405,239	Fairfield CT	1.024	41.1%	-1.15	2.33	-0.30
3,029,141	Dallas TX	1.034	35.8%	-1.39	2.18	0.65
2,955,948	San Diego CA	0.988	37.8%	-0.55	2.07	-0.84
2,945,557	Hennepin MN	1.073	43.9%	-1.93	2.61	0.61
2,945,432	Cuyahoga OH	1.013	32.7%	-1.09	1.98	0.57
2,880,863	Denver CO	1.032	45.4%	-1.21	2.49	-0.60
2,665,798	Baltimore MD	1.038	41.6%	-1.36	2.40	-0.02
2,603,382	Allegheny PA	0.999	37.7%	-0.74	2.11	-0.54

Industry	Description	Employment	LQ SD	Low%	Mid%	High%
3116	Animal slaughtering, processing, and seafood	421,202	4.37	28.0%	<b>58.4%</b>	13.6%
337	Furniture and related products manufacturing	359,933	4.04	18.0%	<b>62.8%</b>	19.2%
313-315	Fabric and textile mills & apparel	302,633	3.50	12.7%	<b>66.3%</b>	21.0%
321	Miscellaneous wood product manufacturing	351,448	3.34	29.9%	53.5%	16.6%
322	Paper and pulp mills and products	334,672	3.24	23.9%	54.6%	21.5%
335	Electrical machinery and equipment manufacturing	333,844	2.92	12.3%	52.6%	35.0%
3361-3363	Motor vehicles and motor vehicle equipment manufacturing	861,870	2.86	16.9%	<b>56.1%</b>	27.0%
3391	Medical equipment and supplies	275,880	2.82	7.7%	48.1%	44.2%
5111	Newspapers and book publishing	350,552	2.65	5.5%	24.7%	69.8%
all other 325	Industrial and miscellaneous chemicals	225,219	2.38	16.1%	41.3%	42.6%
3254	Pharmaceuticals and medicines	246,051	2.36	7.8%	32.1%	<b>60.2%</b>
3364	Aircraft and aerospace manufacturing	395,524	2.23	11.6%	34.2%	54.2%
all other 311	Dairy, animal foods specialty foods	668,250	1.69	30.0%	47.9%	22.2%
all other 339	Miscellaneous manufacturing	252,227	1.66	18.8%	<b>55.4%</b>	25.8%
3261	Plastics products	598,596	1.51	18.6%	<b>59.6%</b>	21.8%
333	Machinery manufacturing	979,932	1.46	13.8%	51.4%	34.8%
all other 334	Other electronic components and products.	736,040	1.44	6.5%	34.1%	<b>59.4%</b>
all other 327	Cement, concrete, & other non-metallic mineral products	245,001	1.36	37.1%	40.3%	22.6%
3118	Bakeries	289,434	1.29	22.1%	<b>64.4%</b>	13.5%
493	Warehousing and storage	812,620	1.19	<b>54.2%</b>	36.6%	9.3%
332	Fabricated metal products manufacturing	1,367,201	1.17	15.5%	<b>61.3%</b>	23.2%
488	Services incidental to transportation	677,864	1.16	<b>53.3%</b>	25.7%	21.1%
323	Printing and related support activities	437,522	1.09	9.0%	<b>64.8%</b>	26.2%
721	Traveler accommodations	1,971,617	1.07	<b>59.5%</b>	20.5%	20.0%
5614	Business support services	751,639	1.04	5.5%	<b>67.6%</b>	26.9%
562	Waste management and remediation services	375,310	0.87	<b>63.7%</b>	19.3%	17.0%
22	Utilities	604,385	0.85	29.1%	35.7%	35.3%
5112	Software publishers	516,621	0.85	1.0%	18.4%	<b>80.6%</b>

# Conclusions

- Mid job shocks tend to have greater effects overall in most CZs, particularly for less-educated groups.
- What happens to less-educated groups will depend in part on post-pandemic trends in mid jobs: will occupational polarization continue at same pace, or slow down? Whither U.S. manufacturing?
- State/local economic development policies should consider mix of mid jobs in chosen industrial targets – if such industries are growing.
- But due to issues w/ mid jobs potentially lagging, policymakers should also consider how to increase mobility to high jobs, and how to improve wages for low jobs.