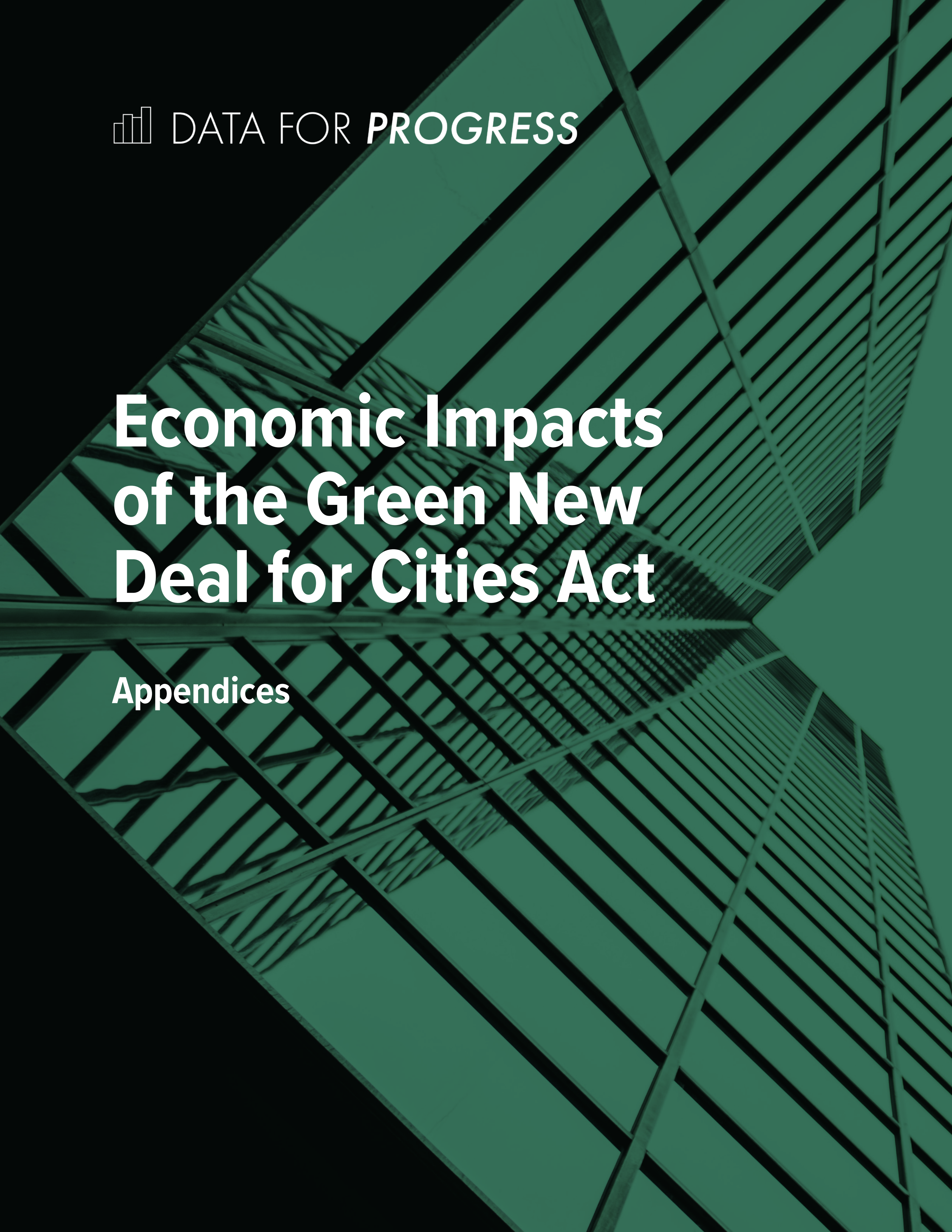

DATA FOR *PROGRESS*

Economic Impacts of the Green New Deal for Cities Act

Appendices

Appendix A: Background on Input-Output Modeling

In this section, we describe the basics of the I-O framework used to generate our estimates, as well as some of the assumptions and methodological choices that are specific to our analysis. Appendix B contains even more detail about the mathematics underlying the model.[1]

An I-O model is a simplified representation of an economy that uses data on the inputs that various industries require to produce their final outputs in order to illustrate the linkages among different sectors.[2] Knowing what these linkages look like allows policy analysts to understand how an initial increase or decrease in spending by governments, firms, or consumers — what economists would refer to as a change in *autonomous spending* — will filter through the economy, and what will be its ultimate effect on certain macroeconomic indicators of interest, such as GDP or aggregate employment.

Input-output modeling assumes that such a change in autonomous spending has three types of effects on output and employment:

- Direct effects — the incremental economic activity and jobs created by the production of *final* goods and services brought about by the new spending;
- Indirect effects — the incremental economic activity and jobs created by the production of the *intermediate inputs* to those final goods and services; and
- Induced effects — the incremental economic activity and jobs created by the expenditures of workers who are paid to produce these final and intermediate goods and services.

To model direct and indirect effects, we can make use of data on industry-level input requirements made available by the Bureau of Economic Analysis (BEA), which publishes a variety of different tables that can be used to construct an I-O model.[3] One of these tables is known as the *direct requirements matrix*, which shows, for each of a specified set of industries, how many dollars of inputs are required to be purchased from each of the other industries in order to produce one dollar of its output.

Another is known as the *total requirements matrix* or the *Leontief inverse matrix*, after the economist Wassily Leontief, a pioneer of I-O analysis. This shows, for each industry, how many dollars of goods each of the other industries must ultimately produce in order for the initial industry to produce one dollar of its output, taking into account the production of intermediate inputs. Thus, the total requirements matrix allows one to isolate *indirect effects* by comparing to estimates that would be obtained from calculations based on the direct requirements matrix alone.

Induced effects result from the fact that a portion of the income earned by firms in a given industry when selling their outputs will be paid out as labor income for workers, who will then spend some of that income on purchases of consumer goods. The question of how best to model induced effects is itself a potentially complicated one, but for the sake of simplicity, in our baseline model run we choose to follow the approach of Pollin, Garrett-Peltier, Heintz, and Hendricks (2014),[4] who assume on the basis of relevant macroeconomic research that consumer spending has a multiplier of approximately 1.4. That is, each dollar of economic activity associated with the direct and indirect effects of a change in autonomous spending by governments or firms will ultimately generate total economic activity of $1.40.

The requirements matrices allow us to assess the impact of a change in autonomous spending on the *gross output* of every industry, including both intermediate goods sold to other producers and final goods sold to consumers. If we are interested in computing the total impact of an initial stimulus on GDP, we need estimates of *value added* in each industry, which subtract off the costs of intermediate outputs.

To that end, we obtain measures of both gross output and value added by industry from the BEA for each year, and use these to calculate industry-specific ratios of value added to output. Thus, we can take the gross output figures derived from our model and convert them into estimates of value added, which we can then sum across industries in order to obtain an estimate of the total impact on GDP in that year.

Appendix B: Matrix Algebra of I-O Modeling

In algebraic terms, we let the direct requirements matrix be denoted by A, the dimension of which is 71-by-71. The entry in the ith row and the jth column of A indicates how many dollars of industry i's output need to be purchased by industry j in order to produce one dollar of j's output.

Suppose we want to consider the direct economic effect of spending a certain amount of money on purchasing the product of industry j. We can model this spending with a vector X consisting of a single column and 71 rows, where the entry in the jth row, which we denote by x_j, is the amount that we want to spend on product j (and the entries in every other row are zero, if we are not purchasing anything else).

Premultiplying X by the matrix A gives us the product vector AX, which shows how much input we require (in dollars) from each of the industries in order to produce x_j dollars of industry j's output. (Simple matrix algebra shows that the entries of AX will be equal to the entries in the jth column of A multiplied by the scalar x_j.)

However, this calculation only provides us with a partial picture of the total impact that the initial influx of autonomous spending represented by vector X will have on the economy. This is because each of the industries that provide the inputs to allow industry j to produce its output will itself have to purchase inputs from other industries, and each of *those* industries will have to purchase *its* own inputs, and so on. The *direct* effect of the spending represented by vector X will be AX, but the inputs needed to produce AX will be given by A^2X, the inputs needed to produce A^2X by A^3X, and so on.

Therefore, the total effect on the economy, *direct* effects plus *indirect* effects, will be given by the infinite sum:

$$AX + A^2X + A^3X + A^4X + \ldots$$

Through algebraic manipulation, it can be shown that this sum is equal to:

$$(I-A)^{-1}X$$

where the matrix $(I-A)^{-1}$ is known as the *total requirements matrix* or the *Leontief inverse matrix*. The entry in the ith row and jth column of the total requirements matrix gives the total amount of production (in dollars) by industry i that is brought about when industry j produces one dollar of final output. Thus, multiplying this matrix by the spending vector X gives the total economic impact of that initial stimulus.

Appendix C: Methodology for Determining GND for Cities Funding Allocations With Data on American Rescue Plan Act

For purposes of allocating employment effects across states and metro areas, we make use of data from the U.S. Treasury Department on the allocation of funds from the American Rescue Plan Act (ARPA) to predict how the GND for Cities appropriations would be distributed. As mentioned above, we omit U.S. territories from our modeling exercise because the American Community Survey data that we use to measure the industrial composition of employment in different states and metro areas only covers the 50 states and District of Columbia. However, we estimate from the ARPA data that territories received only 1.3 percent of total ARPA funding, so we assume that our analysis covers 98.7 percent of planned spending on the GND for Cities.

To calculate the share of ARPA funds flowing to a particular *state*, we sum up the monies allocated to:

1. The state government;
2. All of that state's county governments;
3. All of that state's metro city and "non-entitlement unit" (NEU, i.e., nonmetro) local governments; and
4. All of the Tribal governments located within the geographic boundaries of the state. Our source for details on the allocation of ARPA funds across tribes is the Harvard Project on American Indian Economic Development.[5]

To calculate the share of ARPA funds flowing to a particular *metro area*, we sum up the monies allocated to:

1. The governments of all states that contain all or part of the metro area, weighted by the fraction of state employment in the metro area as calculated from the ACS;
2. The governments of all counties contained in the metro area (metropolitan statistical areas (MSA) are composed of collections of adjacent counties);
3. The governments of all metro cities contained in the metro area; and
4. The governments of all NEUs in states that contain all or part of the metro area, weighted by the fraction of state employment in the metro area as calculated from the ACS. (The Treasury only reports NEU ARPA allocations at the state level, so we cannot directly observe funds flowing to NEUs at a finer geography.)

These shares are then used to allocate our aggregate estimates of direct employment across states and metro areas.

Appendix D: Average Employment Effects by Industry (2024-2027)[6]

Industry	**Jobs Created or Preserved**	**Jobs Created or Preserved as a Percentage of Recent Industry Employment**
Manufacturing	345,522	2.27
Administrative, Support, Waste Management, and Remediation Services	217,607	3.09
Public Administration	214,057	2.20
Professional, Scientific, and Technical Services	192,259	1.37
Construction	171,051	1.45
Healthcare and Social Assistance	161,888	0.67
Educational Services	147,167	0.91
Agriculture, Forestry, Fishing, and Hunting	137,718	6.68
Transportation and Warehousing	87,054	1.39

Wholesale Trade	43,470	1.24
Accommodation and Food Services	30,445	0.28
Other Services	29,748	0.39
Finance and Insurance	28,232	0.53
Management of Companies and Enterprises	26,140	12.78
Retail Trade	20,496	0.15
Real Estate and Rental and Leasing	17,904	0.58
Utilities	12,241	0.84
Information	10,669	0.41
Mining, Quarrying, and Oil and Gas Extraction	4,208	0.66
Arts, Entertainment, and Recreation	3,375	0.13
TOTAL:	**1,901,251**	—

Appendix E: Average Estimated Employment Effects for All 50 States/District of Columbia (2024-2027)[7]

State	Cumulative Number of Jobs Created or Preserved (Direct)	Cumulative Number of Jobs Created or Preserved (Indirect)	Cumulative Number of Jobs Created or Preserved (Induced)	Cumulative Number of Jobs Created or Preserved (Total)
AL	2,805	16,368	8,104	27,277
AK	1,899	3,511	1,628	7,038
AZ	7,167	22,609	11,017	40,793

AR	1,824	9,818	4,831	16,473
CA	31,418	139,860	67,308	238,586
CO	4,106	20,580	9,961	34,647
CT	3,293	12,646	6,093	22,032
DE	895	3,137	1,526	5,558
DC	1,632	3,253	1,504	6,389
FL	11,525	65,555	32,087	109,167
GA	5,901	35,380	17,406	58,687
HI	1,524	4,408	2,070	8,002
ID	1,270	7,540	3,633	12,443
IL	9,919	43,760	21,560	75,239
IN	3,993	22,623	11,344	37,960
IA	1,892	12,995	6,295	21,182
KS	1,879	10,264	4,951	17,094
KY	2,661	13,758	6,791	23,210
LA	3,474	13,101	6,327	22,902
ME	1,100	6,285	2,986	10,371
MD	4,262	24,271	11,322	39,855
MA	6,139	25,022	11,999	43,160

MI	8,190	33,405	16,579	58,174
MN	3,940	20,794	10,209	34,943
MS	2,033	8,936	4,347	15,316
MO	3,640	19,908	9,784	33,332
MT	1,249	4,497	2,126	7,872
NE	1,308	7,149	3,451	11,908
NV	2,789	8,686	4,250	15,725
NH	1,028	5,436	2,616	9,080
NJ	6,943	28,296	13,844	49,083
NM	2,157	7,061	3,299	12,517
NY	16,781	63,794	30,227	110,802
NC	6,358	34,132	16,695	57,185
ND	1,192	3,012	1,423	5,627
OH	7,520	39,402	19,698	66,620
OK	6,185	12,252	5,987	24,424
OR	3,130	16,530	8,018	27,678
PA	9,490	43,007	21,228	73,725
RI	1,190	3,944	1,904	7,038
SC	2,924	17,989	8,808	29,721

SD	1,430	3,244	1,559	6,233
TN	4,239	21,795	10,890	36,924
TX	18,590	90,731	44,791	154,112
UT	1,788	10,764	5,290	17,842
VT	882	2,484	1,171	4,537
VA	5,114	31,271	14,874	51,259
WA	5,676	29,822	14,355	49,853
WV	1,435	4,698	2,294	8,427
WI	3,850	23,537	11,739	39,126
WY	950	2,138	1,016	4,104
Total:	**242,579**	**1,115,458**	**543,215**	**1,901,251**

Appendix F: Estimated Employment Effects for Top 250 Metro Areas, 2024-2027

Rank	**Metro Area**	**Average Number of Jobs Created/Preserved (Total)**
1	New York-Newark-Jersey City, NY-NJ-PA	110,569
2	Los Angeles-Long Beach-Anaheim, CA	76,952
3	Chicago-Naperville-Elgin, IL-IN-WI	56,678

4	Washington-Arlington-Alexandria, DC-VA-MD-WV	44,168
5	Dallas-Fort Worth-Arlington, TX	41,843
6	Houston-The Woodlands-Sugar Land, TX	39,003
7	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	35,602
8	Atlanta-Sandy Springs-Roswell, GA	33,967
9	Miami-Fort Lauderdale-West Palm Beach, FL	31,470
10	Boston-Cambridge-Newton, MA-NH	31,026
11	San Francisco-Oakland-Hayward, CA	27,760
12	Phoenix-Mesa-Scottsdale, AZ	27,295
13	Detroit-Warren-Dearborn, MI	25,723
14	Riverside-San Bernardino-Ontario, CA	25,576
15	Seattle-Tacoma-Bellevue, WA	25,233
16	Minneapolis-St. Paul-Bloomington, MN-WI	23,977
17	San Diego-Carlsbad, CA	19,812
18	Denver-Aurora-Lakewood, CO	19,224
19	Baltimore-Columbia-Towson, MD	17,202
20	Portland-Vancouver-Hillsboro, OR-WA	16,768
21	St. Louis, MO-IL	16,478

22	Tampa-St. Petersburg-Clearwater, FL	16,335
23	Charlotte-Concord-Gastonia, NC-SC	15,236
24	Sacramento--Roseville--Arden-Arcade, CA	15,073
25	Austin-Round Rock, TX	14,366
26	Pittsburgh, PA	13,343
27	Orlando-Kissimmee-Sanford, FL	13,066
28	Kansas City, MO-KS	12,932
29	San Antonio-New Braunfels, TX	12,669
30	Nashville-Davidson--Murfreesboro--Franklin, TN	12,494
31	Cincinnati, OH-KY-IN	12,397
32	Cleveland-Elyria, OH	12,172
33	Columbus, OH	12,057
34	San Jose-Sunnyvale-Santa Clara, CA	12,026
35	Indianapolis-Carmel-Anderson, IN	11,989
36	Milwaukee-Waukesha-West Allis, WI	11,460
37	Providence-Warwick, RI-MA	11,328
38	Las Vegas-Henderson-Paradise, NV	10,343
39	Virginia Beach-Norfolk-Newport News, VA-NC	9,780

40	Fresno, CA	9,192
41	Raleigh, NC	8,818
42	Bakersfield, CA	8,589
43	Jacksonville, FL	8,467
44	Oklahoma City, OK	8,188
45	Louisville/Jefferson County, KY-IN	7,488
46	Hartford-West Hartford-East Hartford, CT	7,223
47	Richmond, VA	7,217
48	Salt Lake City, UT	7,133
49	New Orleans-Metairie, LA	6,988
50	Buffalo-Cheektowaga-Niagara Falls, NY	6,854
51	Rochester, NY	6,460
52	Oxnard-Thousand Oaks-Ventura, CA	6,363
53	Birmingham-Hoover, AL	6,321
54	Grand Rapids-Wyoming, MI	6,310
55	Omaha-Council Bluffs, NE-IA	6,249
56	Worcester, MA-CT	6,235

57	Memphis, TN-MS-AR	6,101
58	Knoxville, TN	6,013
59	Greenville-Anderson-Mauldin, SC	5,922
60	Albuquerque, NM	5,828
61	Tucson, AZ	5,810
62	Albany-Schenectady-Troy, NY	5,748
63	Bridgeport-Stamford-Norwalk, CT	5,680
64	Des Moines-West Des Moines, IA	5,658
65	Visalia-Porterville, CA	5,501
66	Urban Honolulu, HI	5,475
67	Charleston-North Charleston, SC	5,437
68	New Haven-Milford, CT	5,426
69	Boise City, ID	5,219
70	Dayton, OH	5,135
71	Salinas, CA	5,108
72	Columbia, SC	4,979
73	Baton Rouge, LA	4,633

74	El Paso, TX	4,569
75	Allentown-Bethlehem-Easton, PA-NJ	4,459
76	Stockton-Lodi, CA	4,452
77	Greensboro-High Point, NC	4,436
78	Santa Maria-Santa Barbara, CA	4,199
79	Spokane-Spokane Valley, WA	4,125
80	Portland-South Portland, ME	4,119
81	Akron, OH	4,067
82	Wichita, KS	4,065
83	Colorado Springs, CO	3,983
84	North Port-Sarasota-Bradenton, FL	3,885
85	Toledo, OH	3,821
86	Ogden-Clearfield, UT	3,798
87	Lakeland-Winter Haven, FL	3,733
88	Winston-Salem, NC	3,696
89	Syracuse, NY	3,666
90	McAllen-Edinburg-Mission, TX	3,622

91	Harrisburg-Carlisle, PA	3,585
92	Anchorage, AK	3,576
93	Little Rock-North Little Rock-Conway, AR	3,543
94	Lancaster, PA	3,494
95	Cape Coral-Fort Myers, FL	3,442
96	Provo-Orem, UT	3,429
97	Springfield, MA	3,388
98	Deltona-Daytona Beach-Ormond Beach, FL	3,344
99	Modesto, CA	3,294
100	Palm Bay-Melbourne-Titusville, FL	3,278
101	Fayetteville-Springdale-Rogers, AR-MO	3,232
102	Reno, NV	3,206
103	Chattanooga, TN-GA	3,135
104	Jackson, MS	3,094
105	Reading, PA	3,046
106	Huntsville, AL	3,041
107	York-Hanover, PA	3,016

108	Augusta-Richmond County, GA-SC	3,015
109	Port St. Lucie, FL	2,964
110	Asheville, NC	2,958
111	Santa Rosa, CA	2,922
112	Lansing-East Lansing, MI	2,870
113	Youngstown-Warren-Boardman, OH-PA	2,769
114	Scranton--Wilkes-Barre--Hazleton, PA	2,732
115	Lafayette, LA	2,680
116	Hickory-Lenoir-Morganton, NC	2,612
117	Pensacola-Ferry Pass-Brent, FL	2,588
118	Corpus Christi, TX	2,570
119	Ann Arbor, MI	2,550
120	Eugene, OR	2,538
121	Vallejo-Fairfield, CA	2,520
122	Manchester-Nashua, NH	2,422
123	Fort Collins, CO	2,334
124	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	2,318

125	Canton-Massillon, OH	2,300
126	Salisbury, MD-DE	2,296
127	Fort Wayne, IN	2,287
128	Trenton, NJ	2,193
129	Mobile, AL	2,191
130	Ocala, FL	2,184
131	Montgomery, AL	2,179
132	Beaumont-Port Arthur, TX	2,160
133	Lincoln, NE	2,151
134	Kalamazoo-Portage, MI	2,120
135	Gulfport-Biloxi-Pascagoula, MS	2,087
136	Springfield, MO	2,081
137	Yakima, WA	2,018
138	Madera, CA	1,977
139	Brownsville-Harlingen, TX	1,973
140	Spartanburg, SC	1,972
141	Rockford, IL	1,957

142	Clarksville, TN-KY	1,874
143	Wilmington, NC	1,833
144	Olympia-Tumwater, WA	1,831
145	San Luis Obispo-Paso Robles-Arroyo Grande, CA	1,804
146	Barnstable Town, MA	1,804
147	Bremerton-Silverdale, WA	1,778
148	Shreveport-Bossier City, LA	1,778
149	Norwich-New London, CT	1,735
150	Erie, PA	1,728
151	Roanoke, VA	1,711
152	Naples-Immokalee-Marco Island, FL	1,692
153	Las Cruces, NM	1,634
154	Bellingham, WA	1,619
155	Santa Cruz-Watsonville, CA	1,587
156	Tuscaloosa, AL	1,549
157	Racine, WI	1,541
158	Fayetteville, NC	1,527

159	Gainesville, FL	1,507
160	Utica-Rome, NY	1,486
161	Hanford-Corcoran, CA	1,481
162	Lubbock, TX	1,455
163	College Station-Bryan, TX	1,430
164	Waco, TX	1,417
165	Amarillo, TX	1,408
166	Merced, CA	1,382
167	Binghamton, NY	1,381
168	Lynchburg, VA	1,375
169	Topeka, KS	1,374
170	Burlington-South Burlington, VT	1,363
171	El Centro, CA	1,336
172	Bend-Redmond, OR	1,335
173	Wenatchee, WA	1,323
174	Yuma, AZ	1,292
175	Laredo, TX	1,286

176	Medford, OR	1,284
177	Champaign-Urbana, IL	1,279
178	Springfield, IL	1,278
179	Coeur d'Alene, ID	1,265
180	Janesville-Beloit, WI	1,260
181	Blacksburg-Christiansburg-Radford, VA	1,258
182	Yuba City, CA	1,247
183	Houma-Thibodaux, LA	1,242
184	Elkhart-Goshen, IN	1,218
185	Daphne-Fairhope-Foley, AL	1,211
186	Tyler, TX	1,210
187	Atlantic City-Hammonton, NJ	1,199
188	Niles-Benton Harbor, MI	1,193
189	Redding, CA	1,186
190	Burlington, NC	1,183
191	Gainesville, GA	1,149
192	Dover, DE	1,145

193	Saginaw, MI	1,141
194	Chico, CA	1,101
195	Santa Fe, NM	1,092
196	Lafayette-West Lafayette, IN	1,082
197	Bloomington, IL	1,073
198	Hilton Head Island-Bluffton-Beaufort, SC	1,072
199	Oshkosh-Neenah, WI	1,066
200	Muskegon, MI	1,058
201	Decatur, AL	1,051
202	Florence, SC	1,044
203	Columbia, MO	1,039
204	Prescott, AZ	1,033
205	Bangor, ME	1,008
206	Jefferson City, MO	1,005
207	Midland, TX	1,004
208	Rocky Mount, NC	959
209	Jackson, MI	942

210	Wausau, WI	938
211	Bismarck, ND	926
212	East Stroudsburg, PA	925
213	Eau Claire, WI	907
214	Lake Havasu City-Kingman, AZ	895
215	Sebastian-Vero Beach, FL	891
216	Charleston, WV	878
217	Greenville, NC	877
218	Sheboygan, WI	871
219	State College, PA	867
220	Flagstaff, AZ	853
221	Joplin, MO	853
222	Auburn-Opelika, AL	833
223	Pueblo, CO	828
224	St. George, UT	811
225	Monroe, MI	803
226	Lebanon, PA	800

227	Odessa, TX	778
228	Springfield, OH	753
229	Napa, CA	749
230	Iowa City, IA	744
231	Mansfield, OH	736
232	Wichita Falls, TX	723
233	Morgantown, WV	722
234	Monroe, LA	721
235	Bloomington, IN	710
236	Pittsfield, MA	696
237	Lewiston-Auburn, ME	693
238	La Crosse-Onalaska, WI-MN	692
239	Ocean City, NJ	690
240	Lawrence, KS	687
241	Punta Gorda, FL	683
242	Grand Junction, CO	681
243	Glens Falls, NY	672

244	Harrisonburg, VA	667
245	Michigan City-La Porte, IN	646
246	San Angelo, TX	606
247	Johnstown, PA	604
248	Kankakee, IL	603
249	Goldsboro, NC	599
250	Owensboro, KY	597

Endnotes

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[1] Even more background and a case study can be found in "Introduction to the Data for Progress Jobs Model," available at https://www.dataforprogress.org/memos/2022/2/28/introduction-to-the-data-for-progress-jobs-model.

[2] For further background on I-O modeling, see Ronald E. Miller and Peter D. Blair (2009), *Input-Output Analysis: Foundations and Extensions*, 2nd Ed. Cambridge, U.K.: Cambridge University Press.

[3] Robert Pollin, Heidi Garrett-Peltier, James Heintz, and Bracken Hendricks (2014), "Green Growth: A U.S. Program for Controlling Climate Change and Expanding Job Opportunities," available at https://peri.umass.edu/fileadmin/pdf/Green_Growth_2014/GreenGrowthReport-PERI-Sept2014.pdf.

[4] For our purposes here, all of the BEA tables that we use rely on an industry classification scheme involving 71 industries based on the North American Industry Classification System (NAICS). To access these tables, see the Bureau of Economic Analysis webpage on "Input-Output Accounts Data," available at https://www.bea.gov/industry/input-output-accounts-data.

[5] Harvard Project on American Indian Economic Development, COVID-19 Response and Recovery Policy Brief No. 7 (November 3, 2021), “Assessing the U.S. Treasury Department’s Allocations of Funding for Tribal Governments under the American Rescue Plan Act of 2021.” Available at https://ash.harvard.edu/files/ash/files/assessing_the_u.s._treasury_departments_allocations_of_funding_for_tribal_governments.pdf?m=1635972521.

[6] The third column reports jobs created or preserved as a percentage of total employment in the respective sector as calculated from the 2021 American Community Survey (ACS). As of the time of writing, ACS data are not yet available for 2022.

[7] Note that state figures may not exactly sum to national totals due to rounding.