Digital Infrastructure, the Economy and Online Microbusinesses: Evidence from GoDaddy's Microbusiness Data

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Summary

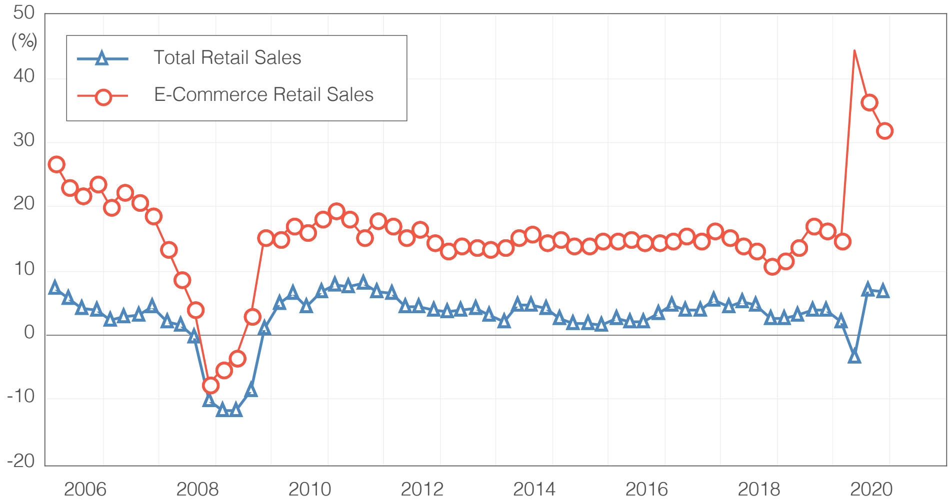
- In this article, we explore the relationship between digital infrastructure, economic activity, and small businesses with an online presence (online microbusinesses).
- We first investigate whether there is a relationship between digital infrastructure and economic outcomes. We find that counties with a higher fraction of residents that have broadband access tend to have stronger labor market outcomes.
- There are a number of reasons why this may be the case. We explore one possibility: that broadband facilitates the formation, and enhances the success, of new businesses and specifically online microbusinesses.
- Using a novel dataset, we find that counties with a higher fraction of residents that have broadband access tend to have more online microbusinesses and that the presence of these businesses correlates with better labor market outcomes.
- In addition, we find that this relationship between online microbusinesses and local labor markets holds when using measures of the intensity of online microbusiness activity (intensive margin), not just their prevalence (extensive margin).

In the 21st century, more and more activities are either replaced or augmented by digital technology and Internet connectivity. During the pandemic as face-to-face interactions have been curtailed, we have seen an acceleration of e-commerce. Figure 1 shows the year-over-year growth of total and e-commerce retail sales. E-commerce sales, which already had a higher growth rate than did total sales prior to March 2020, skyrocketed during the pandemic.

E-commerce is just one example of why infrastructure for broadband and computer access is increasingly important in the digital age. One lesson we learn from the pandemic is that having broadband and computer access might become even more important in the fields of education, public health and medical care. For instance, Yu (2021)[1] finds that, after controlling for various demographic, age, socioeconomic, education, and health factors, a county with a higher percentage of computer and broadband access had a significantly lower cumulative COVID-19 mortality rate and confirmed case rate. One possible explanation is that people with computer and broadband access can more easily access COVID-19 information, make appointments with doctors or use telehealth services, order groceries online for delivery, and work from home. Especially in light of the pandemic, it should not be surprising that we hypothesize that computer and broadband access is associated with local economic prosperity, a relationship we address later in this report.

1. *William Yu, "Health in America: What Explains the Variation in COVID-19 Mortality Rate Across the United States," Anderson Forecast Quarterly Report, March 2021. Link:* https://anderson-review.ucla.edu/wp-content/uploads/2021/05/UCLA-Forecast-March-Yu.pdf

Figure 1 Year-over-year Growth Rates of Total U.S. Retail Sales and E-Commerce Sales



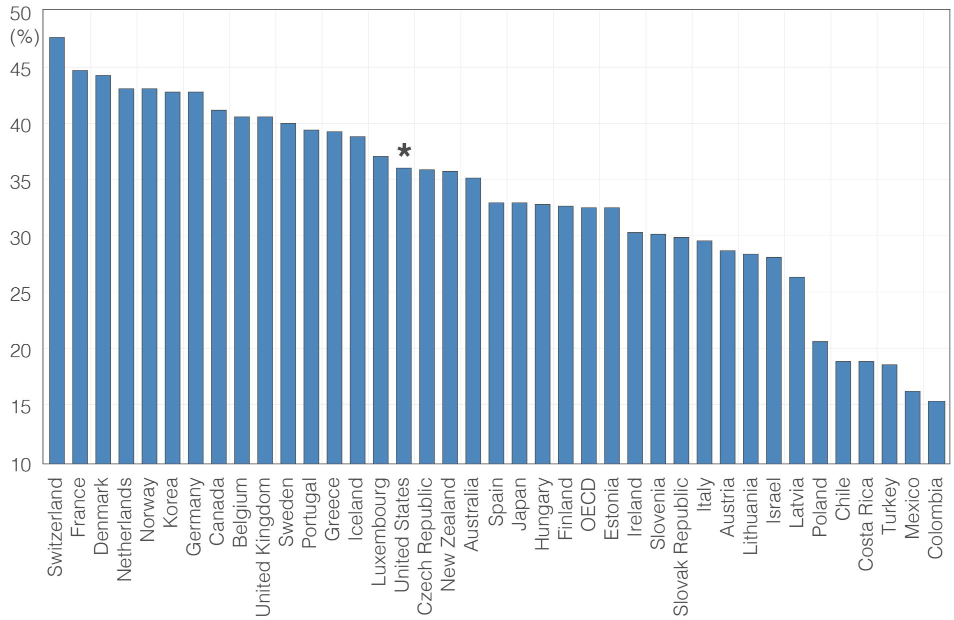
Source: U.S. Census Bureau

Among 37 OECD countries, the fixed broadband subscription rate in the U.S. (36%, or 36 subscriptions per 100 people) ranked 18, lower than Switzerland (47.6%), South Korea (42.8%), and Canada (41.2%) (Figure 2). This is one of the reasons that the Biden Administration's initial proposal called for spending \$100 billion to expand U.S. broadband access as part of the infrastructure plan and why the May Revision to Governor Newsom's budget proposes investing \$7 billion in broadband infrastructure in California. The White House website describing the infrastructure plan expresses the view that "[b]roadband internet is the new electricity," conveying the position that internet access has become an essential utility.[2]

Based on the American Community Survey in 2019, 82.7% of American households have a broadband Internet subscription[3] and 90.3% of households have a computer.[4] Figure 3 and Figure 4 show broadband penetration (the fraction of residents with broadband connectivity) and computer access rates by county. We can see a disparity of digital infrastructure across the country. There is higher usage and availability of computers and broadband in coastal regions but lower connectivity in the South and in some (though not all) more rural areas. Figure 5 displays the correlation between broadband subscription and computer ownership. There is a strong and positive association – counties with higher computer ownership rates also tend to be counties with higher broadband penetration rates. For example, in Los Angeles County, 92% of households have a computer and 84.3% of households have a broadband subscription.

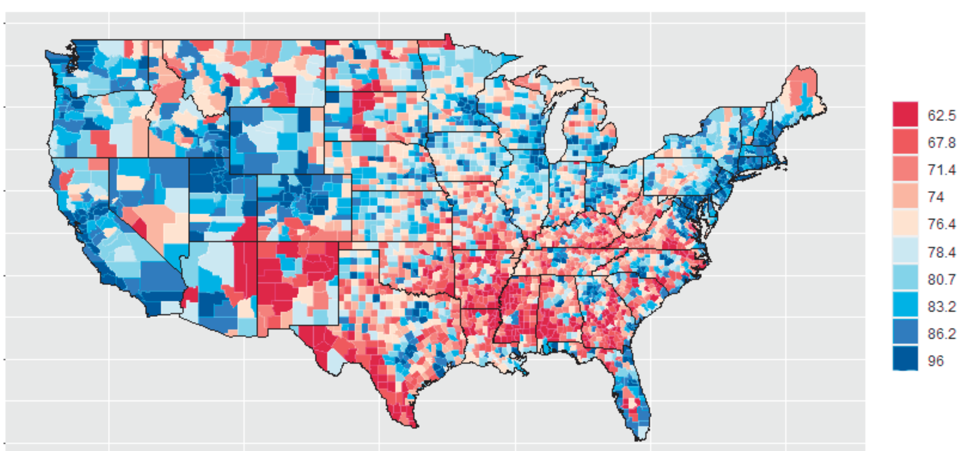
2. See https://www.whitehouse.gov/briefing-room/statements-releases/2021/03/31/fact-sheet-the-american-jobs-plan/. And for California: http://www.ebudget.ca.gov/FullBudgetSummary.pdf.
3. The subscription includes both fixed and mobile broadband.
4. The definition of a computer includes desktops, laptops, smartphones, and tablets. Note that the American Community Survey statistic essentially divides the number of subscriptions by the number of households, whereas the OECD statistics divide by the number of people.

Figure 2 Fixed Broadband Subscription Rate (% of People with a Subscription)



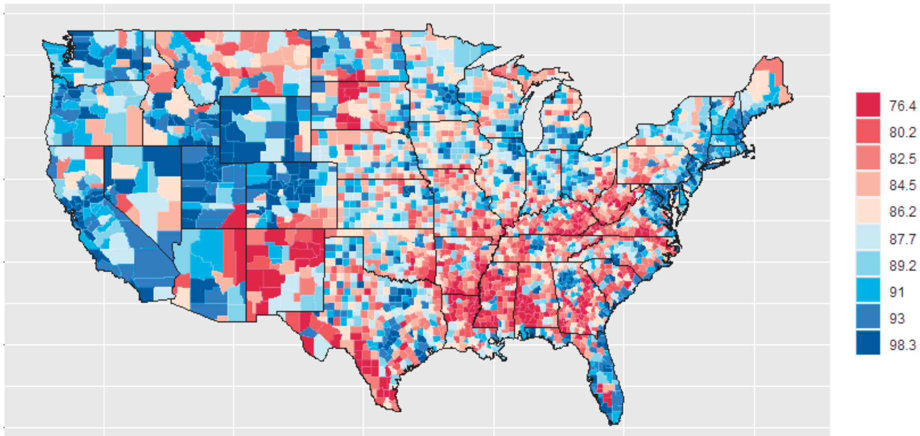
Source: OECD source in June 2020: https://www.oecd.org/sti/broadband/broadband-statistics/

Figure 3 Fraction of Households with A Broadband Internet Subscription (%)



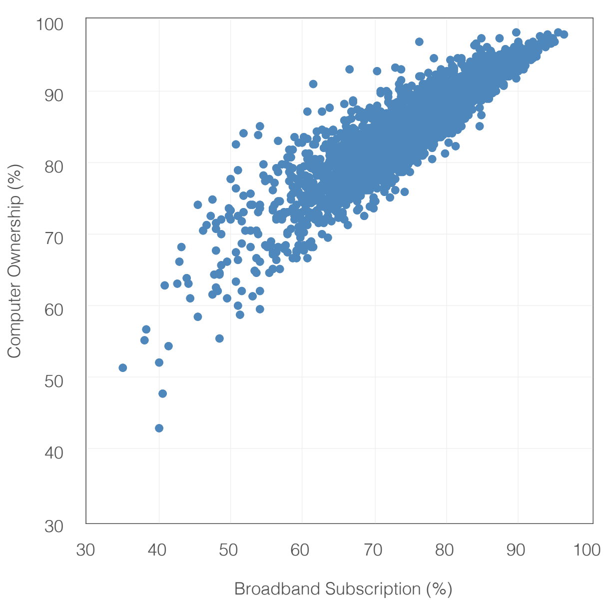
Source: Blue colors indicate higher percentages. The subscription includes both fixed and mobile broadband.
Source: 2019 Five-year American Community Survey

Figure 4 Fraction of Households with A Computer (%)



Source: Blue colors indicate higher percentages. A computer includes desktops, laptops, smartphones, and tablets.
Source: 2019 Five-year American Community Survey

Figure 5 Correlation Between Broadband Subscription and Computer Ownership



Source: 2019 Five-year American Community Survey

Digital Infrastructure and the Local Economy

We now turn to assessing the evidence for whether digital infrastructure penetration, e.g. broadband subscriptions and computer ownership, helps the local economy. The answer seems to be yes. Figure 6 presents the correlation between the percent of households with a broadband subscription in 2019 and the unemployment rate in March 2021 across counties. We can see a slightly negative correlation (the simple correlation is -0.22), suggesting that a county with a higher broadband penetration rate tends to have a lower unemployment rate.[5]

Let's take a deeper look at how broadband is associated with the unemployment rate. We test various specifications of linear regression models where the dependent variable is the county's unemployment rate in March 2021. These specifications are shown in the following summary table and the detailed regression results are presented in the appendices. Equation 1 is a univariate regression where the only explanatory variable is the broadband subscription rate.

5. The negative correlations between a broadband subscription in 2019 and unemployment rates in months of 2019 and 2020 are stronger than those in months in 2021.

Figure 6 Correlation Between Broadband Subscriptions and the Unemployment Rate in March 2021 by County

Source: 2019 Five-year American Community Survey and Bureau of Labor Statistics

In Equations 2 to 7, we ran several multivariate regressions by including additional reasonable predictors (listed in the table) of county unemployment rates to explain the variation in the cross section. Across all specifications, the broadband variable is statistically significant and inversely related to the unemployment rate. In other words, after controlling for these other variables, a county with a higher broadband subscription rate has a lower unemployment rate.

Focusing specifically on the results of Equation 6, the broadband subscription rate is statistically significant at the 0.1% level. Its coefficient is -0.016, meaning that a 10 percentage point increase in a county's broadband subscription rate is associated with a 0.16 percentage point decline in the unemployment rate. Here we control for the unemployment rate in February 2020, before the pandemic. This variable (urate2002) could account for unique characteristics related to job markets of the county that cannot be directly observed in our regressions. We also control for the unemployment rate in April 2020 (urate2004), which was the worst month of the COVID-19 pandemic for labor markets, at least as measured by the unemployment rate. The variable (urate2004) can address the differentiated impact of the pandemic on

Dependent Variable: Unemployment Rate (Urate) in March 2021

Eq.	Main Explanatory Variable	Other Explanatory Variables	Adj. R-Squared	Appendix Number
1	Broadband***		0.050	1
2	Broadband***	CHCI (Human capital), Median income	0.058	1
3	Broadband*	CHCI, Median income, Urate in Feb. 2020	0.446	1
4	Broadband***	CHCI, Median income, Urate in Feb. 2020, Urate in Apr. 2020	0.474	1
5	Broadband***	CHCI, Median income, Urate in Feb. 2020, Urate in Apr. 2020, Population, Population density	0.521	2
6	Broadband***	CHCI, Median income, Urate in Feb. 2020, Urate in Apr. 2020, Population, Population density, COVID case rate, COVID death rate	0.533	2
7	Broadband*	CHCI, Median income, Urate in Feb. 2020, Urate in Apr. 2020, Population, Population density, COVID case rate, COVID death rate, State fixed effect	0.826	3
8	Computer***		0.048	4
9	Computer	CHCI, Median income, Urate in Feb. 2020, Urate in Apr. 2020, Population, Population density, COVID case rate, COVID death rate	0.532	4

Note: *** denotes statistical significance at the 0.1% level, ** at the 1% level, * at the 5% level.

each county. Both variables are highly significant and positively correlated with the latest unemployment rate. We also include measures of human capital (chci; the City Human Capital Index, an index[6] of educational attainment developed by the UCLA Anderson Forecast and based on American Community Survey data) and median household income (mincome) as unemployment rates are known to vary by education and income. The variables for county population in 2019 (population19) and population density (pdensity) are highly significant and positive, suggesting that larger metros and metro cores are facing a slower recovery. One possible reason is that some urban residents moved (either temporarily or permanently) to suburban or rural counties to get away from the pandemic since urban amenities were curtailed by mitigation policies and since remote work is available.

In Equations 8 and 9, we switch the digital infrastructure variable to computer ownership from broadband. We have a clear significant and negative simple correlation between computers and the unemployment rate in Equation 8, but in the multivariate regression setting, the computer variable is not significant anymore. That said, in terms of digital infrastructure, the results suggest that broadband access is more important than computer access. One explanation is that without broadband connectivity, a computer is less productive to foster business and the economy. We will discuss this in the next section.

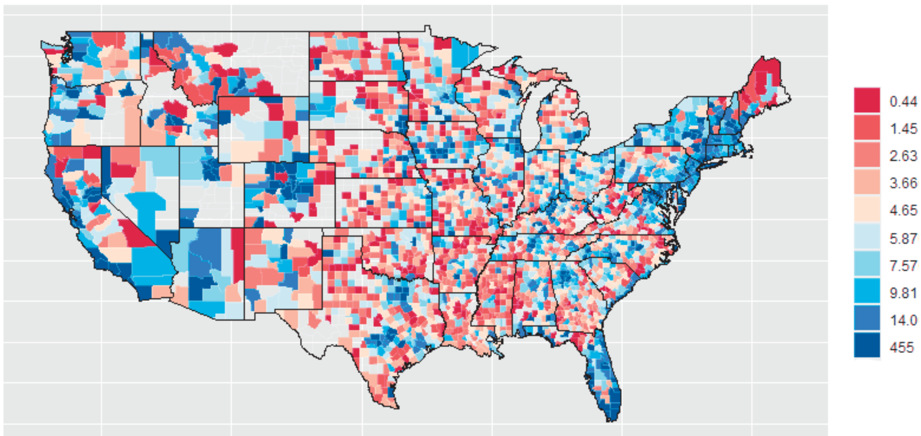
Broadband, Online Microbusinesses, and the Local Economy

Now the question is, why is higher broadband access positively associated with local economic activity, e.g. a lower unemployment rate? One possible channel is that broadband access enables more residents to engage in virtual business, e-commerce, and non-profit activity. In particular, in the pandemic, having broadband access and an online business presence was crucial when brick-and-mortar shopping was curtailed.

Here we analyze data from GoDaddy, one of the leading providers of Internet domain names with a market share of about 40% in the U.S. and over 11 million customers who have over 40 million online microbusinesses in the U.S. The data from GoDaddy are based on information about all individuals who have purchased a domain name from GoDaddy. We use data that are not restricted by how that domain name is used (e.g. for online retail, for informational purposes, for email) or whether the domain name is linked to a publicly accessible website at the time the data were pulled from the database. This is because we do not want to impose subjective judgement on how different individuals use domains for business purposes and because domains may not initially be linked to a public website at the time they are first recorded in the data. Given the size of their business, GoDaddy's data provide a comprehensive picture

6. *For details, see:* *https://www.anderson.ucla.edu/centers/ucla-anderson-forecast/projects-and-partnerships/city-human-capital-index*

Figure 7 Density of GoDaddy's Online Microbusinesses by County, March 2021



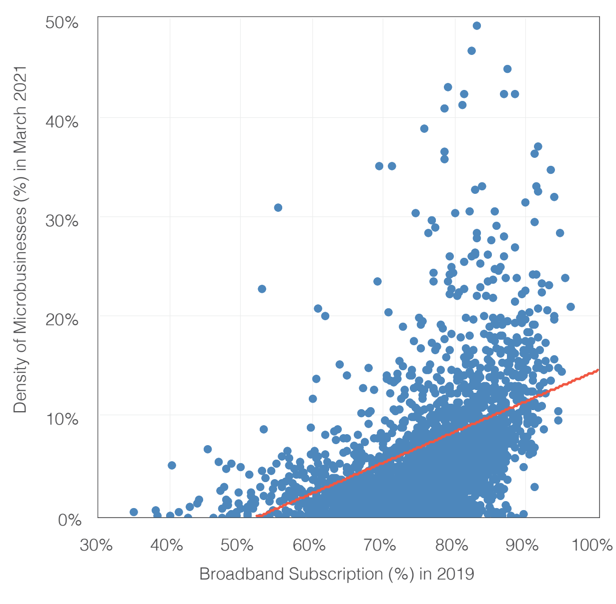
Note: Blue colors indicate higher values.
Source: GoDaddy and UCLA Anderson Forecast.

of online microbusinesses. Figure 7 shows the density of online microbusinesses, which is calculated as the number of active Internet domain names purchased from GoDaddy divided by the county's population. The reason we call them microbusinesses is because GoDaddy's business customers are mostly small businesses or non-profits (55% are sole proprietorships and an additional 37% are small businesses with one to ten employees).[7]

Figure 8 reveals a clearly positive association between broadband access and the density of GoDaddy's online microbusinesses. Equation 10 in Appendix 4 also presents the statistically significant relationship between digital infrastructure and online microbusinesses.

Now let's see if there is a correlation between GoDaddy's online microbusinesses and the local economy. In Equation 11 in Appendix 5, we run a panel regression using data from June 2018 until March 2021 of county unemployment rates on a set of variables that control for specific time and state characteristics, the density of microbusinesses, and COVID-19 new cases and deaths per capita. We find that the

Figure 8 Correlation Between Broadband Subscriptions and the Density of Online Microbusinesses by County



Source: GoDaddy, UCLA Anderson Forecast, and the 2019 Five-year American Community Survey

7. *This is based on a survey conducted by GoDaddy in July 2020 that was sent to a randomly selected subset of its customers. The number of respondents is 2,330.*

density of microbusinesses is significantly negatively correlated with the unemployment rate. In other words, a county with a higher concentration of online microbusinesses tends to also have a lower unemployment rate.

In Equation 12 in Appendix 6, we change the dependent variable to the employment to population ratio, which is another measure of labor market strength. We again see evidence that there is a significantly positive association between online microbusiness density and the employment rate. Note that these two equations cannot necessarily prove that there is a causal relationship from online microbusinesses to local economic activity. In Equation 13, we try to investigate this possibility with a dynamic relationship. The dependent variable is the change in a county's employment between two time periods and the explanatory variable of interest is the change in the number of microbusinesses. In order to control for the variation in county size, we add county population and replace COVID-19 new cases and deaths per capita with the simple count of new cases and deaths in a county. We also control for trends and persistence in employment by including a lag of the employment change. We find a significant and positive relationship between changes in the number of online microbusinesses and changes in local employment. We view this as stronger, though not irrefutable, evidence that online microbusinesses contribute to employment growth and strengthen local labor markets.

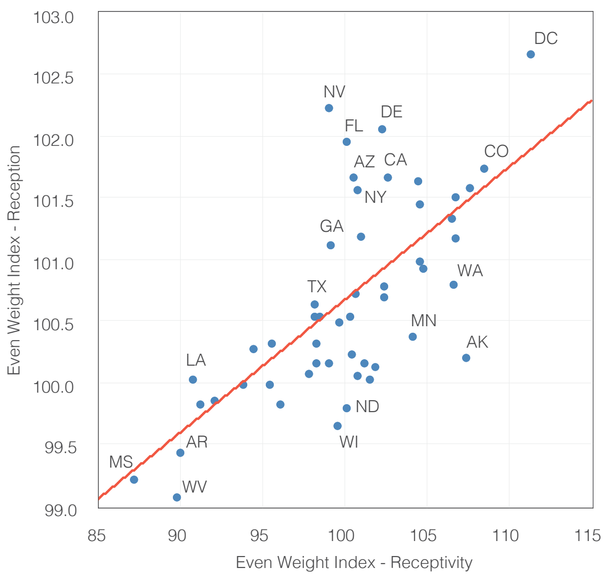
An Index for Online Microbusinesses

We want to take this link between online microbusinesses, broadband, and the local economy a step further with a few considerations. First, the broadband penetration rate does not fully explain everything about online microbusinesses. Broadband access is necessary, but not sufficient. For example, entrepreneurship may also require access to capital (such as loans or grants) and certain types of human capital (such as business management and computer skills) that increase the entrepreneur's ability to use computers and broadband connectivity to create and support their online business activities. Second, the number of microbusinesses per capita is just one aspect of online microbusinesses and only captures the extensive margin – how many there are – not the intensive margin – how active or successful they are. It is reasonable to think that the intensive margin matters for the link between online microbusinesses and local economies. In order to capture all the aspects of microbusinesses, we create an index of online microbusinesses.

Our index incorporates variables that capture various facets of online microbusinesses. These variables come from a subset of GoDaddy's data (April 2020 through March 2021). The data contain characteristics about GoDaddy's customers (individuals who buy domain names and business website services from GoDaddy) and their customer's websites. Our index aims to capture three facets of online microbusinesses: receptivity, reception, and activity. (1) Receptivity is the physical and intellectual infrastructure needed to access and use the Internet. (2) Reception (which captures the extensive margin) is the number of GoDaddy customers and microbusinesses as a percentage of the population of each locale. (3) Activity (which captures the intensive margin) is the frequency and intensity with which those microbusiness websites are updated by the microbusiness owners and used by their customers. To capture receptivity, we use data from the most recent American Community Survey (2019 five-year estimates). The variables include the City Human Capital Index, the fraction of residents with broadband internet subscriptions, and the fraction of residents with computer access. For reception and activity, we map the variables from GoDaddy into these categories. For reception, we use measures of the number of GoDaddy customers and microbusinesses. To capture activity, we use variables that reflect the intensity of website use by the business owner (such as measures of website complexity and update frequency) and the business's customers (such as measures of website traffic). We create a composite index ('even-weight index') which is comprised of all three components and we also create three sub-indices, one each of receptivity, reception, and activity.[8]

8. See Appendix A for details and a discussion of the time series patterns of the index. A complete discussion of the index is in a forthcoming special report about online microbusinesses from the UCLA Anderson Forecast.

Figure 9 Correlation Between Receptivity and Reception of Even-Weight Microbusiness Index by State, March 2021

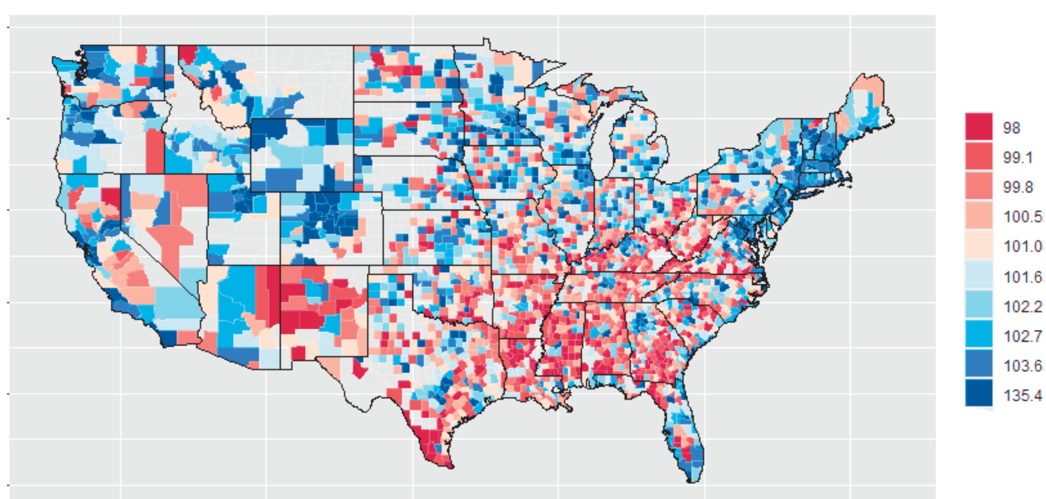


Source: GoDaddy and UCLA Anderson Forecast

These components are related, but not perfectly so. Figure 9 shows how the sub-indices of receptivity (which includes broadband access) and reception by state correlate and rank, where higher values of the receptivity sub-index indicate higher digital infrastructure and human capital, and higher values of the reception sub-index indicate more online businesses. Consistent with the positive correlation between broadband and online microbusiness density in Figure 8, we find a positive correlation (the red line) between receptivity and reception. The figure shows that D.C., a dense urban city and the national capital, has the highest index values while Mississippi and West Virginia have the lowest. States that are above the red line (average regression line), such as Florida, California, New York, Nevada, and Arizona, have better reception than the national average given their receptivity. On the other hand, those below the red line, such as Alaska, Minnesota, and Wisconsin, have relatively weaker reception given their receptivity.

The question we want to ask here is whether the index captures variation in labor market outcomes, such as the unemployment rate, that is not explained by microbusiness density alone. We can get a sense that microbusiness density

Figure 10 Microbusiness Index (Even-Weight), U.S. Counties, March 2021



Note: Blue colors indicate higher values.
Sources: GoDaddy and UCLA Anderson Forecast

and our index capture different information by comparing Figure 10, which shows the variation in the composite index across counties in March 2021, and Figure 7, which shows microbusiness density. This comparison indicates that our index captures information about online microbusinesses that is not fully reflected in the number of microbusinesses per capita. In both measures, the coasts tend to both have higher values of the index and higher microbusiness density, but the Midwest and mountain states have higher index values despite having relatively lower reception (number of microbusinesses per capita).

We repeat the analysis in the prior section (Equations 11, 12, and 13), but add our composite index as an explanatory variable (evenWgtIndex) and limit the sample period to April 2020 – March 2021, the time period for which we can calculate the index. If our index is useful for explaining the variation in local labor markets above and beyond what we can learn from microbusiness density, we would expect to see that the coefficient on the index is statistically significant. We find that this is the case for the analogs of Equations 11 and 12, but is not the case for the analog of Equation 13 (see the table below and the full results in Appendix 8 showing Equations 11B – 13B). In the cases of Equations 11B and 12B, the coefficient on our index is statistically significant and of the predicted sign: counties with a higher index value tend to have lower unemployment rates and higher employment to population ratios even after controlling for microbusiness density. The coefficients on our index variable are also larger in magnitude than are those on the density variable, and the microbusiness density coefficients change sign relative to Equations 11 and 12. In the case of Equation 13B, we do not find that changes in the index (evenWgtIndex_D1) help explain changes in employment above and beyond the microbusiness density variable. One possible explanation is that our index better explains cross-sectional patterns than time series patterns. Still, these results generally support the idea that the microbusiness density variable (part of the reception component of the composite index) misses information about online microbusinesses and highlights the importance of including other facets of online microbusinesses in our index, such as the activity component.

Conclusions

Broadband is necessary and important infrastructure in the digital era of the 21st century. It allows people to connect, learn, teach, sell products to a larger market, and do business. The report provides three findings: (1) Counties with higher broadband access have a lower unemployment rate, (2) Counties with more broadband access have more online microbusinesses and that the presence of these businesses correlates with better labor market outcomes, and (3) the number or density of microbusinesses alone is not sufficient to describe all aspects of online microbusinesses, so we develop an index with three components, receptivity, reception, and activity, that illuminates real-time dynamics for this understudied type of small business.

Eq.	Dependent Variable	Main Explanatory Variable	Other Explanatory Variables	Adj. R-Squared	Appendix Number
11B	Unemployment rate	Even-weight index ***	Microbusiness density, COVID case rate, COVID death rate, State fixed effects, Time fixed effects	0.605	8
12B	Employment to population	Even-weight index ***	Microbusiness density, COVID case rate, COVID death rate, State fixed effects, Time fixed effects	0.482	8
13B	Change in employment	Change in even-weight index	Lag(change in employment), Change in the number of microbusinesses, COVID cases, COVID deaths, State fixed effects, Time fixed effects	0.242	8

Appendix 1

Equation 1. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	8.743646	0.306	28.606	0.000
broadband	-0.049470	0.004	-12.327	0.000
Observations: 2865			**Adj. R2: 0.05**	

Equation 2. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	9.703197	0.561	17.302	0.000
broadband	-0.023430	0.007	-3.604	0.000
chci	-0.017688	0.005	-3.394	0.001
mincome	-0.000009	0.000	-2.299	0.022
Observations: 2865			**Adj. R2: 0.058**	

Equation 3. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	1.408073	0.469	3.005	0.003
broadband	-0.011642	0.005	-2.331	0.020
urate2002	0.931157	0.021	44.740	0.000
chci	-0.000286	0.004	-0.071	0.943
mincome	0.000018	0.000	5.768	0.000
Observations: 2865			**Adj. R2: 0.446**	

Equation 4. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	1.847906	0.458	4.038	0.000
broadband	-0.023975	0.005	-4.831	0.000
urate2002	0.822170	0.022	37.277	0.000
urate2004	0.065973	0.005	12.529	0.000
chci	-0.001013	0.004	-0.259	0.796
mincome	0.000020	0.000	6.664	0.000
Observations: 2865			**Adj. R2: 0.474**	

Appendix 2

Equation 5. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	3.332215	0.446	7.470	0.000
broadband	-0.023447	0.005	-4.934	0.000
urate2002	0.808074	0.021	38.334	0.000
urate2004	0.056603	0.005	11.181	0.000
chci	-0.009655	0.004	-2.558	0.011
mincome	0.000015	0.000	5.073	0.000
population19	0.000001	0.000	10.450	0.000
pdensity	0.000147	0.000	9.259	0.000
Observations: 2864			**Adj. R2: 0.521**	

Equation 6. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	2.672877	0.499	5.358	0.000
broadband	-0.016156	0.005	-3.387	0.001
urate2002	0.803698	0.021	38.433	0.000
urate2004	0.057250	0.005	11.393	0.000
chci	-0.008786	0.004	-2.301	0.021
mincome	0.000015	0.000	5.250	0.000
population19	0.000001	0.000	10.447	0.000
pdensity	0.000134	0.000	8.490	0.000
casep	-0.051870	0.010	-5.218	0.000
deathp	0.000256	0.000	8.499	0.000
Observations: 2864			**Adj. R2: 0.533**	

Appendix 3

Equation 7. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	0.09753	0.349	0.279	0.780
broadband	-0.00710	0.003	-2.252	0.024
urate2002	0.76188	0.017	45.673	0.000
urate2004	0.10155	0.004	23.148	0.000
chci	0.00197	0.003	0.767	0.443
mincome	-0.00001	0.000	-3.944	0.000
population19	0.00000	0.000	9.911	0.000
pdensity	0.00013	0.000	13.117	0.000
casep	0.02122	0.008	2.808	0.005
deathp	0.00005	0.000	2.401	0.016
Alaska	2.19636	0.382	5.749	0.000
Arizona	0.98964	0.255	3.879	0.000
Arkansas	0.75079	0.142	5.297	0.000
California	1.59376	0.164	9.734	0.000
Colorado	2.86784	0.159	18.013	0.000
Connecticut	3.81548	0.310	12.320	0.000
Delaware	1.79436	0.479	3.747	0.000
D.C.	1.00250	0.825	1.216	0.224
Florida	1.10667	0.144	7.691	0.000
Georgia	0.35522	0.123	2.892	0.004
Hawaii	7.20520	0.426	16.932	0.000
Idaho	0.75048	0.170	4.424	0.000
Illinois	1.10627	0.132	8.356	0.000
Indiana	-0.11596	0.132	-0.876	0.381
Iowa	0.64730	0.135	4.802	0.000
Kansas	0.11785	0.137	0.863	0.388
Kentucky	-0.39453	0.131	-3.018	0.003
Louisiana	1.59685	0.150	10.649	0.000
Maine	2.12976	0.246	8.663	0.000
Maryland	2.12600	0.203	10.467	0.000

coefficient	estimate	std error	t statistic	p value
Massachusetts	2.14804	0.251	8.564	0.000
Michigan	0.00984	0.146	0.068	0.946
Minnesota	0.57267	0.144	3.968	0.000
Mississippi	0.98759	0.144	6.878	0.000
Missouri	0.11290	0.130	0.869	0.385
Montana	0.12567	0.183	0.687	0.492
Nebraska	-0.12551	0.146	-0.861	0.389
Nevada	0.63794	0.249	2.560	0.011
New Hampshire	-0.30036	0.278	-1.079	0.281
New Jersey	2.46667	0.213	11.575	0.000
New Mexico	3.31856	0.188	17.688	0.000
New York	1.27651	0.152	8.391	0.000
North Carolina	0.99258	0.132	7.538	0.000
North Dakota	1.57158	0.162	9.680	0.000
Ohio	-0.71774	0.139	-5.180	0.000
Oklahoma	0.54943	0.142	3.864	0.000
Oregon	2.21537	0.185	11.972	0.000
Pennsylvania	1.35770	0.148	9.145	0.000
Rhode Island	1.95468	0.378	5.174	0.000
South Carolina	1.74005	0.158	11.012	0.000
South Dakota	0.09070	0.157	0.579	0.563
Tennessee	0.07759	0.133	0.582	0.560
Texas	3.40207	0.118	28.840	0.000
Utah	0.15435	0.226	0.682	0.495
Vermont	0.05628	0.252	0.223	0.823
Virginia	2.01111	0.128	15.704	0.000
Washington	0.63985	0.178	3.593	0.000
West Virginia	0.43055	0.161	2.677	0.007
Wisconsin	0.42610	0.144	2.950	0.003
Wyoming	1.72834	0.226	7.640	0.000

Observations: 2864 **Adj. R2: 0.826**

Appendix 4

Equation 8. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	10.8314	0.486	22.273	0.000
computer	-0.068119	0.006	-12.021	0.000
Observations: 2865			**Adj. R2: 0.05**	

Equation 9. Dependent Var: Unemployment Rate in March 2021

coefficient	estimate	std error	t statistic	p value
(Intercept)	1.699771	0.588	2.889	0.004
computer	0.011295	0.006	1.757	0.079
urate2002	0.818868	0.021	38.793	0.000
urate2004	0.053065	0.005	10.650	0.000
chci	-0.015167	0.004	-3.983	0.000
mincome	0.000009	0.000	3.098	0.002
population19	0.000001	0.000	10.112	0.000
pdensity	0.000138	0.000	8.726	0.000
casep	-0.055867	0.010	-5.616	0.000
deathp	0.000283	0.000	9.408	0.000
Observations: 2864			**Adj. R2: 0.532**	

Equation 10. Dependent Var: Density of GoDaddy's Online Microbusiness

coefficient	estimate	std error	t statistic	p value
(Intercept)	-16.3513	2.700	-6.056	0.000
broadband	0.308193	0.035	8.694	0.000
Observations: 2866			**Adj. R2: 0.025**	

Appendix 5

Equation 11. Dependent Var: Unemployment Rate

coefficient	estimate	std error	t statistic	p value
(Intercept)	3.644	0.063	58.00	0.000
density_of_microbiz	-0.038	0.002	-20.30	0.000
pd_cases	-13.135	2.068	-6.35	0.000
pd_deaths	832.475	61.832	13.46	0.000
6/1/2018	0.007	0.054	0.13	0.899
10/1/2018	-0.155	0.054	-2.87	0.004
11/1/2018	-0.209	0.054	-3.86	0.000
2/1/2019	-0.114	0.054	-2.12	0.034
7/1/2019	-0.184	0.054	-3.40	0.001
9/1/2019	-0.331	0.054	-6.12	0.000
10/1/2019	-0.234	0.054	-4.33	0.000
11/1/2019	-0.247	0.054	-4.58	0.000
12/1/2019	-0.313	0.054	-5.79	0.000
1/1/2020	-0.245	0.054	-4.53	0.000
2/1/2020	-0.343	0.054	-6.35	0.000
3/1/2020	0.346	0.054	6.39	0.000
4/1/2020	9.330	0.054	172.38	0.000
5/1/2020	7.057	0.054	130.07	0.000
6/1/2020	4.164	0.054	76.81	0.000
7/1/2020	3.593	0.054	66.02	0.000
8/1/2020	2.479	0.055	45.09	0.000
9/1/2020	2.498	0.055	45.50	0.000
10/1/2020	1.766	0.055	31.83	0.000
11/1/2020	1.682	0.060	28.27	0.000
12/1/2020	1.621	0.065	24.75	0.000
1/1/2021	1.036	0.065	15.93	0.000
2/1/2021	0.958	0.059	16.24	0.000
3/1/2021	0.783	0.055	14.14	0.000
Alaska	1.737	0.185	9.38	0.000
Arizona	3.452	0.121	28.46	0.000
Arkansas	0.303	0.069	4.38	0.000
California	3.133	0.074	42.26	0.000
Colorado	0.424	0.082	5.16	0.000
Connecticut	1.381	0.150	9.21	0.000
Delaware	1.713	0.239	7.15	0.000
Florida	0.614	0.071	8.61	0.000
Georgia	0.172	0.059	2.89	0.004
Hawaii	4.589	0.206	22.25	0.000
Idaho	-0.526	0.085	-6.18	0.000
Illinois	1.506	0.065	23.19	0.000
Indiana	0.211	0.065	3.23	0.001
Iowa	-0.974	0.067	-14.55	0.000
Kansas	-1.048	0.067	-15.70	0.000
Kentucky	0.937	0.065	14.51	0.000
Louisiana	1.747	0.072	24.23	0.000
Maine	-0.301	0.121	-2.48	0.013
Maryland	0.775	0.096	8.09	0.000
Massachusetts	2.009	0.126	15.92	0.000
Michigan	2.324	0.068	34.01	0.000
Minnesota	0.149	0.068	2.20	0.028
Mississippi	2.613	0.067	39.13	0.000
Missouri	-0.131	0.063	-2.09	0.037
Montana	0.301	0.091	3.30	0.001
Nebraska	-1.817	0.070	-26.02	0.000
Nevada	0.880	0.125	7.02	0.000
New Hampshire	-0.004	0.136	-0.03	0.979
New Jersey	2.736	0.101	27.04	0.000
New Mexico	2.266	0.089	25.39	0.000
New York	1.861	0.073	25.55	0.000
North Carolina	1.088	0.064	16.91	0.000
North Dakota	-1.014	0.079	-12.86	0.000
Ohio	1.508	0.066	22.95	0.000
Oklahoma	-0.120	0.069	-1.72	0.085
Oregon	1.413	0.090	15.61	0.000
Pennsylvania	2.312	0.070	33.13	0.000
Rhode Island	1.759	0.185	9.49	0.000
South Carolina	0.278	0.078	3.56	0.000
South Dakota	-1.285	0.077	-16.71	0.000
Tennessee	1.020	0.065	15.64	0.000
Texas	0.749	0.057	13.15	0.000
Utah	-0.674	0.115	-5.87	0.000
Vermont	-0.366	0.126	-2.91	0.004
Virginia	0.276	0.062	4.41	0.000
Washington	2.404	0.083	29.05	0.000
West Virginia	2.638	0.075	35.20	0.000
Wisconsin	0.272	0.070	3.91	0.000
Wyoming	0.018	0.118	0.15	0.880

Observations: 67,622 **Adj. R2: 0.639**

Appendix 6

Equation 12. Dependent Var: Employment to Population Ratio

coefficient	estimate	std error	t statistic	p value	coefficient	estimate	std error	t statistic	p value
(Intercept)	39.841	0.192	207.45	0.000	Illinois	3.514	0.199	17.70	0.000
density_of_microbiz	0.459	0.006	80.87	0.000	Indiana	5.408	0.199	27.16	0.000
pd_cases	-1.589	6.320	-0.25	0.802	Iowa	9.867	0.205	48.22	0.000
pd_deaths	-1256	189	-6.64	0.000	Kansas	8.288	0.204	40.63	0.000
6/1/2018	0.110	0.165	0.67	0.505	Kentucky	-1.465	0.197	-7.43	0.000
10/1/2018	0.006	0.165	0.04	0.970	Louisiana	-1.320	0.220	-5.99	0.000
11/1/2018	0.102	0.165	0.62	0.535	Maine	6.378	0.371	17.20	0.000
2/1/2019	0.049	0.165	0.30	0.766	Maryland	5.477	0.293	18.70	0.000
7/1/2019	0.261	0.165	1.58	0.115	Massachusetts	5.477	0.386	14.20	0.000
9/1/2019	0.328	0.165	1.98	0.047	Michigan	1.516	0.209	7.26	0.000
10/1/2019	0.316	0.165	1.92	0.055	Minnesota	10.327	0.206	50.05	0.000
11/1/2019	0.243	0.165	1.47	0.141	Mississippi	-3.016	0.204	-14.78	0.000
12/1/2019	0.294	0.165	1.78	0.075	Missouri	3.304	0.192	17.18	0.000
1/1/2020	0.276	0.165	1.67	0.095	Montana	4.929	0.279	17.66	0.000
2/1/2020	0.300	0.165	1.82	0.069	Nebraska	12.700	0.213	59.50	0.000
3/1/2020	-0.374	0.165	-2.27	0.023	Nevada	1.984	0.383	5.18	0.000
4/1/2020	-5.293	0.165	-32.00	0.000	New Hampshire	7.437	0.416	17.90	0.000
5/1/2020	-4.078	0.166	-24.59	0.000	New Jersey	2.462	0.309	7.96	0.000
6/1/2020	-3.026	0.166	-18.26	0.000	New Mexico	-1.562	0.273	-5.73	0.000
7/1/2020	-2.777	0.166	-16.69	0.000	New York	0.328	0.223	1.47	0.141
8/1/2020	-1.754	0.168	-10.44	0.000	North Carolina	0.491	0.197	2.50	0.012
9/1/2020	-1.789	0.168	-10.66	0.000	North Dakota	9.644	0.241	40.01	0.000
10/1/2020	-1.199	0.170	-7.07	0.000	Ohio	3.237	0.201	16.12	0.000
11/1/2020	-1.229	0.182	-6.75	0.000	Oklahoma	2.773	0.212	13.06	0.000
12/1/2020	-1.045	0.200	-5.22	0.000	Oregon	1.665	0.276	6.02	0.000
1/1/2021	-0.896	0.199	-4.51	0.000	Pennsylvania	3.262	0.213	15.30	0.000
2/1/2021	-0.992	0.180	-5.50	0.000	Rhode Island	5.795	0.566	10.23	0.000
3/1/2021	-1.036	0.169	-6.12	0.000	South Carolina	0.377	0.237	1.59	0.112
Alaska	3.176	0.566	5.61	0.000	South Dakota	9.058	0.235	38.53	0.000
Arizona	-2.909	0.371	-7.85	0.000	Tennessee	0.120	0.200	0.60	0.547
Arkansas	-0.778	0.212	-3.68	0.000	Texas	1.631	0.174	9.37	0.000
California	-1.710	0.227	-7.55	0.000	Utah	1.367	0.351	3.90	0.000
Colorado	6.748	0.251	26.88	0.000	Vermont	7.533	0.384	19.61	0.000
Connecticut	6.630	0.458	14.47	0.000	Virginia	3.559	0.191	18.64	0.000
Delaware	-1.641	0.732	-2.24	0.025	Washington	1.022	0.253	4.04	0.000
Florida	-3.233	0.219	-14.79	0.000	West Virginia	-1.188	0.229	-5.19	0.000
Georgia	0.103	0.182	0.57	0.570	Wisconsin	8.254	0.213	38.79	0.000
Hawaii	-2.064	0.630	-3.27	0.001	Wyoming	8.348	0.359	23.23	0.000
Idaho	5.967	0.260	22.95	0.000					

Observations: 67,597 **Adj. R2: 0.37**

Appendix 7

Equation 13. Dependent Var: Employment Difference Over Two Periods

coefficient	estimate	std error	t statistic	p value	coefficient	estimate	std error	t statistic	p value
(Intercept)	0.272	0.195	1.40	0.162	Hawaii	-0.120	0.641	-0.19	0.852
lag(emp_hhold_S_D1)	0.109	0.004	28.03	0.000	Idaho	-0.025	0.265	-0.09	0.925
number_of_microbiz_D1	0.000	0.000	20.09	0.000	Illinois	-0.210	0.203	-1.03	0.301
population	0.000	0.000	-22.66	0.000	Indiana	-0.063	0.203	-0.31	0.757
d_cases	0.000	0.000	20.85	0.000	Iowa	-0.099	0.209	-0.47	0.635
d_deaths	-0.004	0.001	-6.14	0.000	Kansas	-0.060	0.208	-0.29	0.774
6/1/2018	0.058	0.169	0.35	0.729	Kentucky	-0.089	0.201	-0.44	0.658
10/1/2018	0.037	0.169	0.22	0.827	Louisiana	-0.079	0.225	-0.35	0.724
11/1/2018	0.035	0.169	0.21	0.835	Maine	-0.053	0.378	-0.14	0.889
2/1/2019	0.121	0.169	0.72	0.473	Maryland	-0.083	0.298	-0.28	0.780
7/1/2019	0.173	0.169	1.03	0.304	Massachusetts	0.180	0.393	0.46	0.647
9/1/2019	0.156	0.169	0.92	0.356	Michigan	-0.031	0.213	-0.14	0.886
10/1/2019	0.018	0.169	0.11	0.914	Minnesota	-0.056	0.211	-0.27	0.791
11/1/2019	-0.009	0.169	-0.05	0.956	Mississippi	-0.069	0.208	-0.33	0.739
12/1/2019	0.087	0.169	0.52	0.606	Missouri	-0.034	0.196	-0.17	0.862
1/1/2020	0.041	0.169	0.24	0.808	Montana	-0.079	0.285	-0.28	0.782
2/1/2020	-0.002	0.169	-0.01	0.990	Nebraska	-0.087	0.218	-0.40	0.691
3/1/2020	-1.101	0.169	-6.53	0.000	Nevada	-0.036	0.390	-0.09	0.926
4/1/2020	-7.704	0.169	-45.60	0.000	New Hampshire	0.031	0.423	0.07	0.941
5/1/2020	2.159	0.172	12.58	0.000	New Jersey	0.117	0.314	0.37	0.709
6/1/2020	1.492	0.169	8.83	0.000	New Mexico	-0.055	0.278	-0.20	0.843
7/1/2020	0.111	0.169	0.65	0.513	New York	-0.003	0.227	-0.01	0.990
8/1/2020	1.004	0.169	5.95	0.000	North Carolina	-0.001	0.201	0.00	0.997
9/1/2020	-0.209	0.169	-1.24	0.216	North Dakota	-0.102	0.246	-0.41	0.679
10/1/2020	0.614	0.169	3.63	0.000	Ohio	0.023	0.205	0.11	0.910
11/1/2020	-0.389	0.169	-2.30	0.021	Oklahoma	-0.064	0.216	-0.30	0.766
12/1/2020	-0.402	0.170	-2.36	0.018	Oregon	0.137	0.281	0.49	0.627
1/1/2021	-0.433	0.170	-2.54	0.011	Pennsylvania	0.009	0.218	0.04	0.965
2/1/2021	-0.202	0.170	-1.19	0.233	Rhode Island	-0.102	0.577	-0.18	0.860
3/1/2021	0.134	0.169	0.79	0.427	South Carolina	0.043	0.242	0.18	0.860
Alaska	-0.046	0.577	-0.08	0.937	South Dakota	-0.092	0.240	-0.38	0.701
Arizona	0.639	0.380	1.68	0.092	Tennessee	-0.038	0.204	-0.19	0.852
Arkansas	-0.061	0.216	-0.28	0.778	Texas	0.002	0.178	0.01	0.991
California	-0.044	0.235	-0.19	0.851	Utah	0.178	0.357	0.50	0.618
Colorado	0.022	0.255	0.09	0.931	Vermont	-0.116	0.391	-0.30	0.766
Connecticut	-0.564	0.467	-1.21	0.227	Virginia	-0.082	0.195	-0.42	0.673
Delaware	-0.264	0.744	-0.35	0.723	Washington	0.059	0.258	0.23	0.818
Florida	0.165	0.222	0.74	0.459	West Virginia	-0.060	0.234	-0.26	0.797
Georgia	-0.024	0.185	-0.13	0.896	Wisconsin	-0.069	0.217	-0.32	0.751
Observations: 67,592			**Adj. R2: 0.092**		Wyoming	-0.077	0.367	-0.21	0.834

Appendix 8

Equation 11B. Dependent Var: Unemployment Rate

coefficient	estimate	std error	t statistic	p value
(Intercept)	24.451	0.712	34.333	0.000
evenWgtIndex	-0.119	0.007	-16.534	0.000
density_of_microbiz	0.007	0.001	7.000	0.000
pd_cases	-3.139	2.676	-1.173	0.241
pd_deaths	833.575	81.073	10.282	0.000
(date and state controls omitted from the table)				
Observations:	31760	Adj. R2:	0.605	

Equation 12B. Dependent Var: Employment to Population Ratio

coefficient	estimate	std error	t statistic	p value
(Intercept)	-52.359	1.395	-37.535	0.000
evenWgtIndex	0.914	0.014	64.955	0.000
density_of_microbiz	-0.029	0.002	-14.362	0.000
pd_cases	2.403	5.242	0.458	0.647
pd_deaths	-1292.175	158.798	-8.137	0.000
(date and state controls omitted from the table)				
Observations:	31748	Adj. R2:	0.482	

Equation 13B. Dependent Var: Employment Difference Over Two Periods

coefficient	estimate	std error	t statistic	p value
(Intercept)	583.041	166.219	3.508	0.000
lag(emp_hhold_S_D1)	-0.005	0.002	-1.854	0.064
number_of_microbiz_D1	0.240	0.032	7.581	0.000
evenWgtIndex_D1	-6.116	21.515	-0.284	0.776
population	0.006	0.000	54.958	0.000
d_cases	-0.228	0.009	-26.733	0.000
d_deaths	7.151	0.454	15.754	0.000
(date and state controls omitted from the table)				
Observations:	28993	Adj. R2:	0.242	

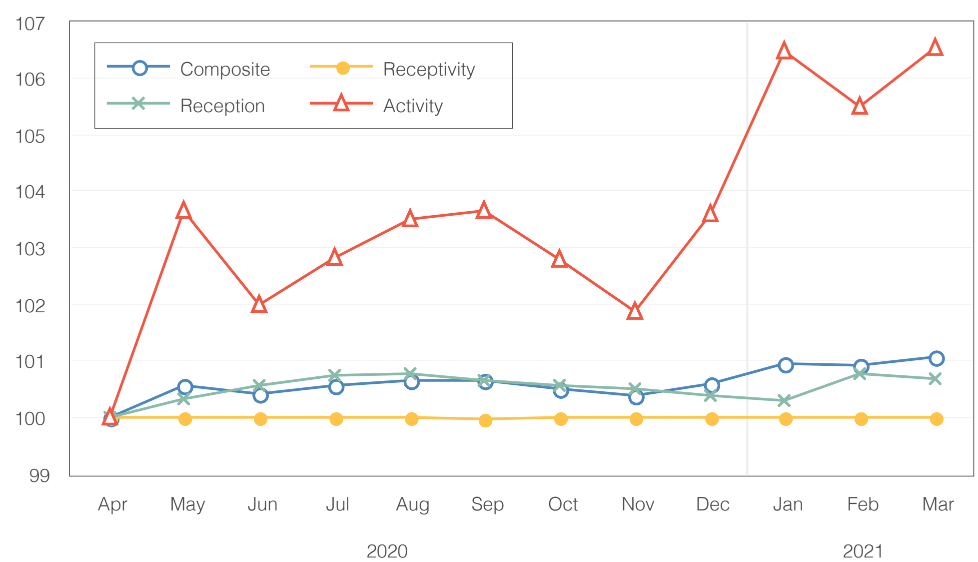
Appendix A

To calculate the main or composite index, we first normalize the GoDaddy variables, to create a common scale, and then take the average over these (normalized) variables.[9] In addition to the composite index, we create sub-indices for three facets of online microbusinesses (reception, receptivity, and activity) using the variables that pertain to each category. We then re-scale all indices (the composite and the three sub-indices separately) and center them to average 100 in April 2020.

The activity dimension plays a major role in the variation of the index over time. This can be seen in Figure 11, which shows the composite index for the U.S. as a whole along with the three sub-indices for receptivity, reception, and activity. The composite index rises in May 2020, followed by a slight dip in June, then a steady rise through September. The index falls in October and November, but since then has generally risen. This pattern largely fits with the economic stopping and starting since April 2020 due to the pandemic, recession, and recovery. Initially, businesses may have invested in their online presence, leading to a spike in May. Businesses started to open up in the summer, but some areas reinstated restrictions as coronavirus cases rose in the fall, which could explain the index's decline from September through November. The holiday and shopping season, with more consumers looking to make their holiday purchases online, likely contributed to the rise in the index since November. When we collect multi-year data, we will be able to detect whether there is a seasonal pattern in the activity index.

The figure also shows that reception (which captures the extensive margin – the growth rate and number of how many online microbusinesses are operating) smoothly rose in the summer, fell in the fall/early winter and then rose, giving an indication of when businesses decided to take their operations online. Receptivity is flat through the sample period, which is by construction since receptivity is based on variables that are only updated at an annual frequency. The variation in the activity index (which captures the intensive margin – how intensively and frequently business owners and their customers use the business's website) is what seems to be driving the main patterns we see in the composite index, suggesting that much of the variation in our composite index, at least over this historically unusual time period, is driven by the intensive margin of online microbusiness owners' and their customers' use of the business's websites.

Figure 11. Microbusiness Index Time Series (U.S.) – Even-Weight Index



Sources: GoDaddy and UCLA Anderson Forecast

9. We also employ more complex methods to create an index that is a weighted average, rather than a simple average, of the GoDaddy variables. This index and methodology is explained in a forthcoming special report about online microbusinesses.