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The Effect of Fiscal Stimulus: Evidence from COVID-19
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ABSTRACT

Policymakers, faced with different options for replacing lost earnings, have had limited evidence to inform their decisions. The current economic crisis has highlighted the need for data that are local and timely so that different fiscal policy options on local economies can be more immediately evaluated. This paper provides a framework for evaluating real-time effects of fiscal policy on local economic activity using two new sources of near real-time data. The first data source is administrative records that provide universal, weekly, information on unemployment claimants. The second data source is transaction level data on economic activity that are available on a daily basis. We use shift-share approaches, combined with these two data sources and the novel cross-county variation in the incidence of the COVID-19 supplement to Unemployment Insurance to estimate the local impact of unemployment, earnings replacement, and their interaction on economic activity. We find that higher replacement rates lead to significantly more consumer spending – even with increases in the unemployment rate – consistent with the goal of the fiscal stimulus. Our estimates suggest that, based on the latest data, eliminating the Federal Pandemic Unemployment Compensation (FPUC) supplement would lead to a 44% decline in local spending. If the FPUC supplement is reduced to $200, resulting in a reduction of the replacement rate by 44%, spending would fall by 28%. Even if the FPUC supplement is reduced to $400, the replacement rate would fall by 29% and spending would fall by 12%. Because these data are available in every state, the approach can be used to inform decision making not just in this current crisis, but also in future recessions.

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1. Introduction

The current economic downturn has highlighted the lack of local, real-time data being used to inform policy-makers about the effects of fiscal policy decisions on local economies. Key decisions are being made with considerable uncertainty about how state and local individuals and businesses "will respond to recent fiscal and monetary policy actions taken by the federal government"(Congressional Budget Office [CBO], July 2020; Swagel, 2020). This paper shows how existing state administrative records on unemployment can be combined with transaction data on economic activity to expand the data toolkit for decision-makers and allow for near-real-time evaluation of the effectiveness of various fiscal policies. Our approach can scale to all states in the nation, and can inform decision-making not just for this downturn, but for future recessions.

The Covid-19 pandemic led to unprecedented levels of job losses in 2020. The immediate fiscal response was to supplement the existing Unemployment Insurance benefits with an additional $600 a week with the passage of the CARES Act, beginning in the week ending March 21, 2020 (Karpman & Acs, 2020). That stimulus, however, ended the week of July 25th; the subsequent policy debate centered on the nature of the response to the continued fragile state of the economy. One set of proposals centered on the size of the earnings supplement - whether it should continue or drop to lower levels such as $0, $200 or $400 a week (Courtney Weaver, July 20, 2020). Another set of proposals suggested that the supplement, rather than being lump sum, should simply change the wage replacement formula – to 70% or 90% of benefit determination[2], rather than the current 47%. The effects of these different proposals is unknown, so that by the time policymakers and academics understand the impact of a policy, the crisis is long over (Farrell et al., 2020). Ideally, data would be current, aggregated to geographical units that could be used to inform local policy, and would combine current information on unemployment, income replacement rates and economic activity.

Our analysis is made possible by two new sources of near real-time data that have all of these features. The first data source is administrative records on 1.26 million individuals that provide universal and weekly information on their claims, benefits, and previous earnings. This data source makes it possible to calculate individual-level replacement rates and unemployment rates that can be aggregated to any level of geography and industry. The second data source is transaction-level data on credit and debit card purchases – our measure of economic activity - that are available on a daily basis at the county level(Chetty, Friedman, Hendren, & Stepner, 2020).

The literature documents substantial variation in the impact of economic shocks on different industries and different geographies. The COVID-19 crisis is similar to prior shocks in that it has affected different industries, and hence different geographic areas (because of differences in industry composition across geographic areas) to different degrees. The differential impact of the COVID-19 shock on unemployment, combined with pre-existing variation in industry composition across geography, means that replacement rates also vary by geographic region. In this paper, we exploit such variation across industries and regions using a shift-share instrumental variable approach to estimate the local impact of unemployment, earnings replacement, and their interaction on economic activity.

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[2] The current system uses the highest two earnings quarters of the previous five quarters to determine the replacement rate.

We find that higher replacement rates lead to significantly more consumer spending – even with increases in the unemployment rate – consistent with the goal of the fiscal stimulus. The Federal Pandemic Unemployment Compensation (FPUC) supplement to unemployment insurance of $600 ended at the end of July 2020. Prior to its expiration, the average UI payment received each week was $812, which would fall to approximately $257, implying a decline in the replacement rate of 68%. Our estimates suggest that, based on the latest data, a reduction to zero benefits would lead to a 44% decline in local spending. If the FPUC supplement is reduced to $200, resulting in a reduction of the replacement rate by 44%, spending would fall by 28%. Even if the FPUC supplement is reduced to $400, the replacement rate would fall by 19% and spending would fall by 12%. Thus, the effects of large reductions in benefits on consumer spending are quite substantial.

2. Background

The literature on the effects of fiscal stimulus on consumption spending goes back to the 1950's. Friedman and Modigliani hypothesized that temporary increases in income would be saved, rather than spent, resulting in little fiscal impact. More recently, however, the literature has argued that many consumers, even though wealthy, operate on a "hand-to-mouth" basis, and spend large fractions of government transfers (Kaplan, Violante, & Weidner, 2014). While young, low income individuals are very likely to have a high marginal propensity to consume, so are middle-aged high-income individuals who are likely to have much wealth tied up in illiquid assets. In this model, the impact of fiscal policy depends on both income and demographic characteristics. In an empirical analysis of the effects of the 2001 and 2008 tax cuts, Misra and Surico use consumer expenditure survey data to document substantial heterogeneity in the spending impact depending on the income level of individual families (Misra & Surico, 2014). Palmer et al. also use survey data, with targeted questions, to show that spending increased by 12-30% as a result of the stimulus tax payments of about 100 billion dollars sent to 130 million families.

Certainly the analysis of the effects of the stimulus during the 2007-2009 Great Recession support the notion that temporary measures are effective. Elmendorf and Furman provide a good overview of lessons learned (Elmendorf & Furman, 2008). They argue that interventions should be timely, targeted and temporary. By that they mean that a stimulus should be implemented only if a decline occurs over a specific period, it should be targeted at those who spend the most (the most vulnerable families), and it should be temporary in nature. While both fiscal and monetary policy should be implemented, fiscal policy has the advantage of being able to be implemented quickly, particularly if, as now, the federal funds rate is close to zero. They argue that increasing spending on unemployment insurance benefits (or food stamps) or targeted tax cuts, is to be preferred to infrastructure investments, temporary tax incentives or more general tax cuts.

The effects of the 2020 crisis, with its particular focus on increasing unemployment insurance benefits has produced a large stream of empirical work examining the implications for labor markets, household spending, economic recovery, and more [3]. Of particular relevance to this paper, and to the hand-to-mouth literature is Ganong et al. (2020), which combined public use data from the Current Population Survey with information about each state's UI system under the CARES Act to calculate wage replacement rates.

[3] See, for example, the compendium produced by the National Bureau of Economic Research https://nber.org/wp_covid19_07202020.html

Their sample, which consisted of 444 workers, provided the basis for examining the effect of different policies on the distribution of benefits and labor supply incentives – and emphasizes the heterogeneity of those effects even in such a small sample. (Ganong, Noel, & Vavra, 2020) The data described in this paper, which has detailed information on education, prior earnings, race and ethnicity for well over a million individuals, could provide more precise estimates about the distributional consequences of different policies.

The third strand of work has focused on estimating the impact of epidemics on spending patterns. Baker et al. use bank account data transaction-level data from a non-profit to study changes in the spending patterns of 4.735 customers (Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020). A study of the spending patterns of about 5 million customers of Chase Bank customer suggests that spending declines were directly related to the pandemic rather than labor market effects(Cox et al., 2020). They find that there are substantial differences between customers with different income levels. On the theoretical side, Carroll et al. have built a sophisticated consumer spending model with micro economic foundations that shows the link between layoffs, benefits and consumption spending(Carroll, Slacalek, & White, 2020). It distinguishes between those individuals who are "deeply" unemployed versus those who are "normally" unemployed and allows policy-makers to explore the effects of different assumptions about who gets unemployed, and how long it takes them to return to employment. The data in this paper, which can track unemployment and benefit patterns of cohorts of individuals for each week after their initial claim for unemployment, can be used to differentiate these two types of individuals

3. Data

We combine two primary data sources at the county and week level in order to generate a unique dataset that permits the analysis of how unemployment and replacement rates affect economic activity[4]. The first dataset provides information at the individual level of weekly unemployment claims, benefits received, and previous earnings, which are then used to construct unemployment and replacement rates at the county and industry level. The second dataset provides information of daily changes in debit and credit spending at the county level.

3.1 Unemployment and Earning Replacement Data

The data that we use to construct measures of unemployment rates and replacement rates come from the administrative records of the Illinois Unemployment Insurance system, which are themselves broken into two main data sets.

The first of these is the Unemployment Insurance (UI) certified claims data generated weekly for the Program for Measuring Insured Unemployed Statistics (PROMIS) system. The dataset contains records of UI claimants' weekly certifications for past weeks of benefits and provides a complete universe of certified claims with a two-week lag. It has a number of advantages for policy-makers when compared to survey data. They are extremely timely, since they are reported every week. The dataset can be used to generate overall counts of claimants as of a benefit week and also contains benefit details such as total

[4] The source data are deidentified and hosted in a secure facility – the Administrative Data Research Facility at the Coleridge Initiative – which is FedRAMP moderate certified and has Authorization to Operate from both the Census Bureau and USDA. Only authorized individuals can access the data, only for approved and statistical purposes, and only summary analytical statistics are released.

amount paid and claimant details including age, race, gender, educational attainment, and their pre-separation occupation and industry.

The second is the Quarterly UI Wage Records[5], which contain quarterly wages for all UI-covered jobs in Illinois and are used to obtain information on each individual's work and earnings history in the year prior to the COVID-19 pandemic.

Unemployment rate

The construction of the unemployment rate measure is conceptually different from the BLS measure, which directly asks individuals whether they are "actively looking for work in the survey week". We construct a measure directly based on the count of individuals who certified and received unemployment benefits for week ending January 25, 2020 to June 27, 2020. We construct two versions of the unemployment rate: one at the county-industry-week level, and one at the county-week level. The former is necessary for constructing the shift-share instrumental variables, the latter is used for the core specification. The numerator comes from aggregating the weekly number of certified UI claims to a county-industry-week level, and to a county-week level respectively. When calculating the unemployment rate at the county-industry-week, the denominator comes from the 2018 Illinois American Community Survey (5 year) data on the workforce. While the ACS data have the advantage of industry-specific workforce estimates, one shortcoming is that they only include county-industry level data for 18 counties in Illinois. Our regression analysis is therefore limited to an analysis of those 18 counties[6].

Replacement rates

We calculate the replacement rates by creating a ratio of the total amount paid in UI benefits[7] for each certified claimant - for each week from the week ending January 25, 2020 to the week ending June 27, 2020 - to their 2019 average weekly wage.

The 2019 average weekly wage is calculated for each individual from their earnings as reported in the quarterly Illinois UI Wage Record file. Total wages (sometimes called wages or gross wages) for a quarter are the total amount of wages paid or payable (depending on the wording of the State law) to covered workers for services performed during the quarter, on all the payrolls of whatever type during the quarter. Bonuses paid are included in the payroll figures. Also included, when furnished with the job, is the cash value of such items as meals, lodging, tips and other gratuities, to the extent that State laws and regulations provide. Total wages include both taxable and nontaxable wages. We then divide the aggregate 2019 wages by 52 to get a 2019 average weekly wage for each certified claimant.

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[5] UI wage records and their coverage are extensively described elsewhere (Burgess, Lane, & Stevens, 2000; Stevens, 2007)**,** but briefly the State's compensation law covers most employers with one or major employees. The only major excluded employers are the federal government, self-employed individuals, some small agricultural enterprises, and philanthropic and religious organizations. Employment of individuals who receive no salary at all, who are totally dependent upon commissions, and who work on an itinerant basis with no fixed location or home base is not reported by covered employers. The Quarterly UI Wage Records can also be linked to firm-level data from the Quarterly Census of Employers and Wage to obtain additional information about each employer.

[6] The unemployment rates in the maps, in contrast, use the 2019 Local Area Unemployment Statistics program data as a workforce measure, which encompasses all 102 counties in Illinois, to provide a broader depiction of unemployment rates across the state.

[7] The total UI payment received field includes both regular benefits, dependent allowances, and the Federal Pandemic Unemployment Compensation addition and subtracts tax withholding and benefit discounts due to wages earned.

Weekly county-level wage replacement ratios are calculated by taking the mean of the county residents' weekly UI benefit paid amount and dividing it by the mean of their weekly 2019 wages. Only individuals with nonzero wages and paid benefit amounts are included in this calculation.

3.2 Economic Activity Measures

Our second primary source of data comes from a public database[8] that tracks a variety of timely measures of local economic activity(Chetty et al., 2020). For the purposes of this paper, we utilize their spending data from Affinity Solutions. These are seasonally adjusted credit and debit card spending, relative to January 25, 2020, presented as a 7-day moving average and at the county level.

3.3 Final Dataset

The final dataset is at the county-week level, from January 25 to June 27, 2020, and covers 18 counties in Illinois. Illinois is the sixth largest state in the United States, with a population of about 13 million[9], a workforce of about 6 million[10] and a GDP of about $900 billion[11]. In the week ending July 4, nearly 650,000 workers claimed unemployment insurance. Total UI payments received in that week, including the $600 FPUC supplement, were $445 million.

While Table 1 provides summary descriptive statistics, three sets of pictures are useful to summarize the features we exploit in this paper – the variation in each of the three key measures over time; the variation across counties, and the heterogeneity in the relationship between the earnings replacement rate and spending.

First, the effect of the pandemic was sharp and strong in Illinois. Figure 1 shows the trends in unemployment rates, replacement rates and spending over time for Illinois. The shock of the pandemic is apparent: we see a massive drop in consumer spending and a large spike in unemployment. The immediate effect of the CARES Act fiscal stimulus is also apparent in both the sharp increase in earnings replacement (in excess of 100%), as well as in the sharp – and immediate - increase in consumer spending, despite continued high levels of unemployment.

[8] https://tracktherecovery.org/
[9] https://www.census.gov/quickfacts/IL
[10] https://www.bls.gov/eag/eag.il.htm
[11] https://www.bea.gov/sites/default/files/2020-07/qgdpstate0720_0_0.pdf

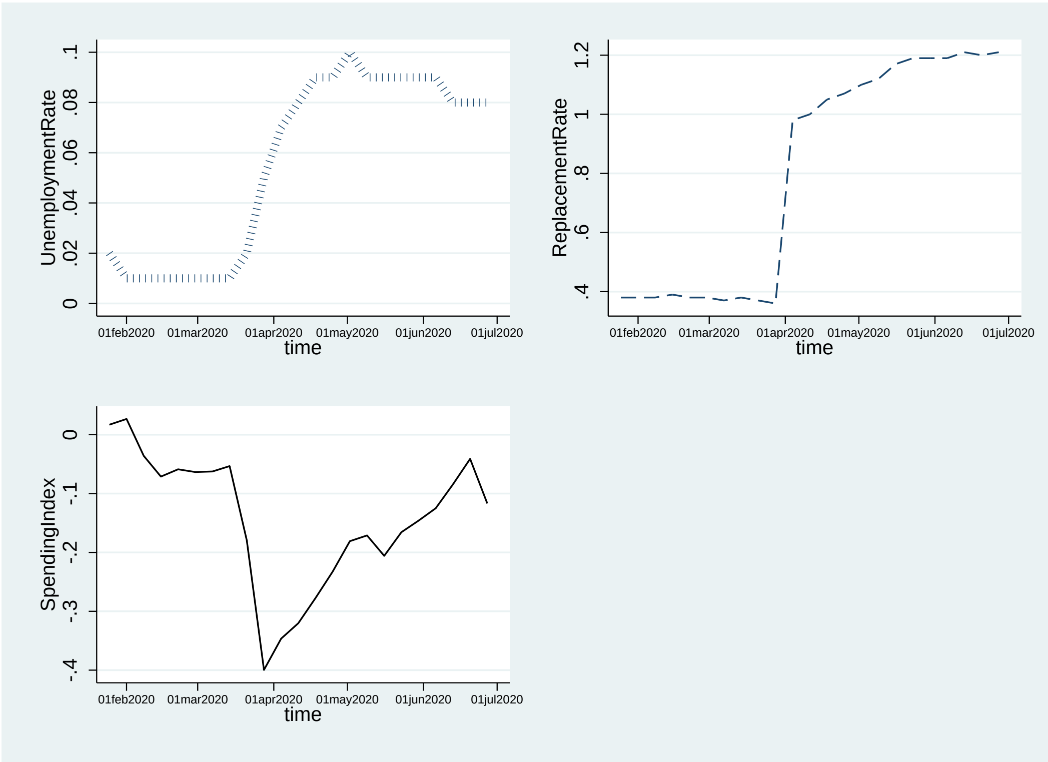

Figure 1: The Pandemic – and CARES Act - Effect

Second, the heterogeneity in unemployment rates and replacement rates across counties is evident in Figure 2. At the end of June 2020, average unemployment rates range from a low of 2% in the west and south of the state to 11% in the northeast. Wage replacement rates range from just over 100% in the northeast to almost 200% in the northwest and southwest of the state.

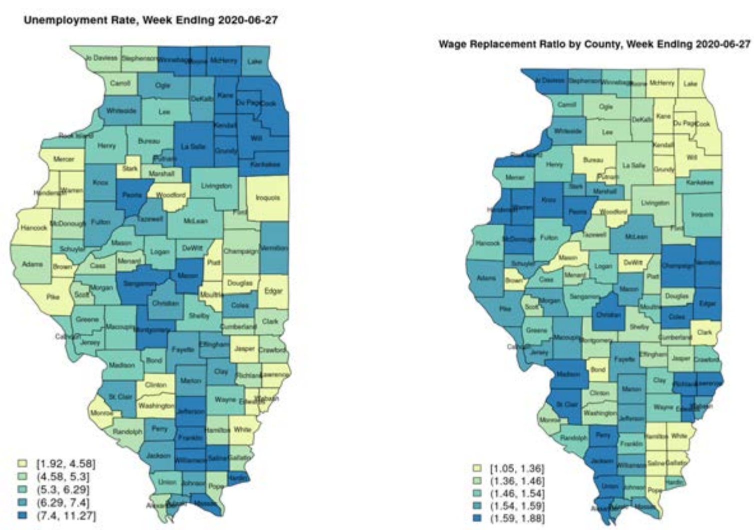

Figure 2 County heterogeneity in Unemployment and replacement rates

The third feature is the positive relationship between replacement rates and spending, as well as the heterogeneity across counties, which is clearly visible in Figure 3.

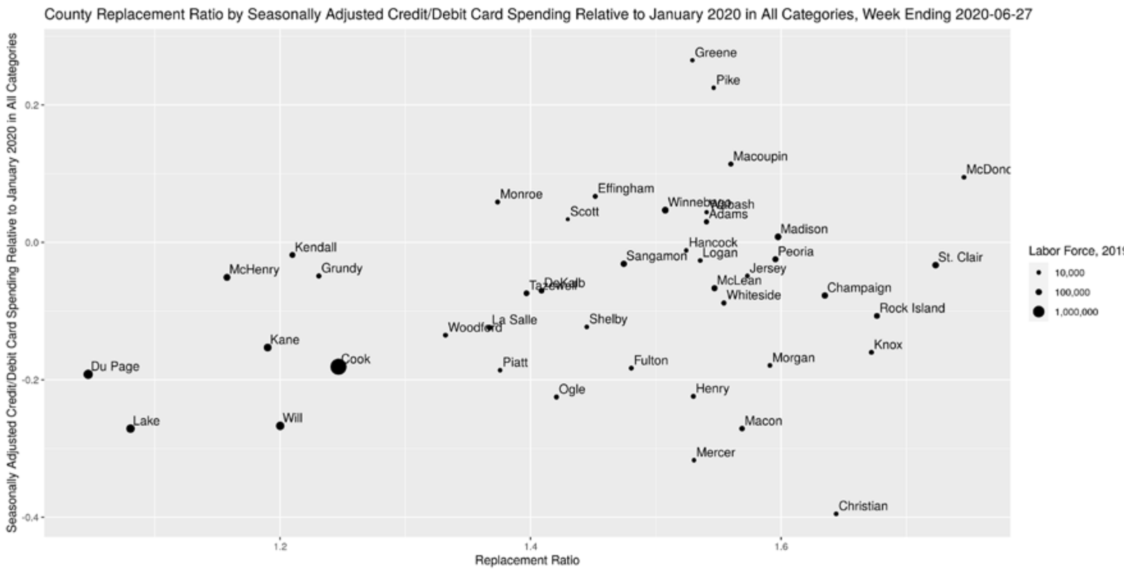

Figure 3: Relationship between Replacement Rates and Spending

4. Conceptual Framework and Empirical Approach

In this framework, we use counties as the unit of analysis to estimate the impact of changes in unemployment levels and earnings replacement rates on local economic activity. Our approach has the advantage of both describing local level heterogeneity in economic pain and enabling local policy makers to target additional specific interventions. Of course, although the data used here are for the state of Illinois, since similar data are available for each state, a similar approach could be used for every state.

The main outcome measure of interest is the level of economic activity, as described above: an index of credit/debit spending compared to January 2020. The independent measures include the unemployment rate and the earnings replacement rate. Of course, since unemployment rates and replacement rates interact with each other in affecting the outcome, the baseline regression interacts the two measures.

More formally, the baseline model can be written as:

$$EconActivity_{ct} = \beta_0 + \beta_1 Unemp_{ct} + \beta_2 ReplacementRate_{ct} + \beta_3 Unemp_{ct} \times ReplacementRate_{ct} + f(t, c, \theta_c) + \epsilon_{ct}$$

where c indexes counties and t indexes weeks. Our main specifications include cubics in time fully interacted with county fixed effects, captured by $f(t, c, \theta_c)$.

Given that local demand may affect unemployment overall and by industry, we develop a series of shift-share instruments for each endogenous independent variable: $Unemp_{ct}, ReplacementRate_{ct}$ and $Unemp_{ct} \times ReplacementRate_{ct}$. Specifically, we rely on differences in the initial industrial composition in each county interacted with state-level unemployment rates and/or state-level replacement rates by industry to develop instruments.

In the case of our instrument for the unemployment rate, we take the share of workers in each industry *i* who are unemployed in week *t*, $Unemp_{it}$, and weight them by the share of employment in each county that is in that industry, $Share_{ci,0}$, in a base period, which is 2018. We calculate the industry unemployment rate by taking the number of certified UI claims for each industry in each week and dividing that by the workforce in that industry in 2018. We then sum the weighted product across industries to construct a shift-share instrument for unemployment, as follows:

$$IV_{ct}^{Unemp} = \sum_{i=1}^{I} Share_{ci,0} * Unemp_{it}$$

Our instrument for replacement rates is developed analogously, using the baseline industry employment shares to weight industry-specific UI replacement rates. We estimate the industry-specific UI replacement rate using the mean total benefits received in each week for the workers previously employed in each industry divided by the mean weekly UI earnings in 2019 in that industry. Our UI benefit level is the actual amount of money that people receive including the $600 FPUC supplement (as relevant) after deductions like childcare. Formally, we estimate,

$$IV_{ct}^{RR} = \sum_{i=1}^{I} Share_{ci,0} * RR_{it}$$

Lastly, we construct our instrument for interactions between the unemployment rate and the replacement rate by taking a weighted average of the product of the industry unemployment rates and replacement rates where the weights are the county industry employment shares. Formally, we construct,

$$IV_{ct}^{UnempXRR} = \sum_{i=1}^{I} Share_{ci,0} * Unemp_{it} \ * RR_{it}$$

5. **Results**

Table 2 reports OLS estimates, introducing the explanatory variables one at a time. Column (1) reports the relationship between the unemployment rate and spending. We find that each 1% increase in unemployment claims leads to a decline in spending of 1.5%. If the replacement rate is the only regressor, it is only weakly positively related to spending (column (2)). However, when both the unemployment rate and replacement rate are included together (column (3)), both become strong predictors of spending. A 1% increase in the unemployment rate is associated with a decrease in spending of more than 6%, while a 1% increase in the replacement rate is associated with an increase in spending of over 0.5%.

Clearly, however, the effect of the replacement rate should depend on the number of people who are receiving benefits and the effect of the unemployment rate should depend on the replacement rate, so it is logical to capture the interrelationships by incorporating an interaction term. We do this in column (4). The results show that the coefficient on unemployment becomes substantially more negative, the coefficient on the replacement rate becomes negative, and the interaction between the unemployment rate and replacement rate is large and positive. While all coefficients are highly statistically significant, the main effects cannot be interpreted easily without considering the interaction term. Prior to April, the replacement rate was typically around 0.4, so that a 1% increase in unemployment was associated with a reduction in spending of roughly 6%. Starting in April, replacement rates regularly exceed 1, and are often closer to 1.2. At a replacement rate of 1.2, increases in unemployment are associated with an increase in spending of over 5%. While the coefficient on the replacement rate (without an interaction) has a negative sign, this turns out to be a consequence of including the interaction term. Our proxy for unemployment averages just over .05 over the entire sample. At this unemployment rate, a 1% increase in the replacement rate increase spending by roughly 0.2. At the peak unemployment rate, near 0.1, a 1% increase in the replacement rate is associated with a spending increase of slightly under 1%.

Table 3 reports estimates for a range of robustness checks. The estimates are remarkably robust across specifications. The first set of estimates (Column 2) are not weighted by the size of the labor force. The second set (column 3) include controls for time (month) fixed effects and a separate set of county fixed effects. The third set (Column 4) uses a different replacement rate measure based on the gross benefit as opposed to the amount of the payment (net of deductions). The last column (column 5) excludes Cook County, which accounts for roughly 40% of Illinois population and economic activity. The size and precision of the estimates is extremely stable across each specification.

As indicated, we are concerned that the OLS estimates may be biased because changes in demand would affect local employment. Table 4 reports first stage equations. Column (1) reports estimates for the first stage equation with just the unemployment rate. Here the instrument has a plausible coefficient of slightly above 1 and is a very strong predictor of the unemployment rate. Column (2) reports estimates for the replacement rate alone. Here the instrument has a plausible coefficient of slightly beneath 1 and is highly significant. Columns (3) and (4) report first stage estimates for the models with the unemployment rate and replacement rate with instruments for just those two variables. The instrument for the replacement rate is essentially unrelated to the unemployment rate, so the estimates in column (3) are quite similar to those in column (1). In column (4), the instrument for the unemployment rate is a strong predictor of the replacement rate, but the instrument for the replacement rate itself remains quite similar to that in column (2). Columns (5), (6), and (7) report first stage equations for our full model. Column (5) reports estimates for the unemployment rate. It shows that that the instrument for the unemployment rate is strong and has a plausible magnitude of essentially 1. The other two instruments are considerably smaller in magnitude and insignificant. Column (6) reports estimates for the replacement rate. Here the instrument for the replacement rate is strong and statistically significant and has a plausible coefficient of essentially 1. The instrument for the unemployment rate is negative while that for the unemployment rate interacted with the replacement rate is positive. Column (7) reports first stage estimates for the unemployment rate interacted with the replacement rate. Our instrument for that variable is a strong predictor with a magnitude of just under 1. The other two instruments are weak predictors. The first stage F-statistics on the excluded instruments range from roughly 300 to over 800.

Table 5 reports our second stage estimates. The estimates are also strong and precise. They are generally similar to the fixed effects estimates in Table 2, although sometimes slightly larger in magnitude. Turning to column (4), the coefficients on the unemployment rate and is opposite in sign and slightly smaller than its interaction with the replacement rate. Before April 2020, when the replacement rate averaged roughly 0.4, increases in unemployment are associated with a decline in spending of roughly 7%. But since April when the replacement rate has frequently been closer to 1.2, increases in unemployment were associated with an increase in spending of roughly 6%. In the case of the replacement rate, the estimates imply that at unemployment rates beneath 4.6, increases in the replacement rate are associated with greater spending. Since April, with the unemployment rate frequently close to 0.1, a 1% increase in the replacement rate is associated with an increase in spending of .88 points.

The FPUC supplement to unemployment insurance of $600 ended at the end of July 2020. Prior to its expiration, the average weekly benefit paid was $812, which would fall to $257, implying a decline in the replacement rate of 68%. The replacement rate was roughly 1.25 in the latest data, so the new replacement rate would be roughly .4, all else equal. At the unemployment rate of .077 in the latest data, spending this reduction in benefits would lead to a decline in spending of 44%. If the FPUC supplement is reduced to $200, the replacement rate would fall by 44%. The implied reduction in spending from these benefits would be 28%. Even if the FPUC supplement is reduced to $400, the replacement rate would fall by 19% and spending would fall by 12%. Thus, substantial declines in the generosity of UI benefits are predicted to have dramatic adverse effects on local spending.

Table 6 reports estimates for the same set of robustness checks as reported in Table 3. The estimates are remarkably robust across the various specifications.

Conclusion

This paper provides evidence that the fiscal stimulus deployed in response to the economic shock engendered by COVID-19 had important and substantial effects on spending and economic activity. In Illinois, proposed cuts to unemployment insurance benefits are expected to have large effects on consumer spending, with the largest cuts leading to cuts in local spending of 44% from current levels. The results are robust to multiple specifications.

The paper contributes in another way. The data that are used here, which are timely, weekly and universal, can be used to estimate the impact of stimulus effects for all states in the country, and inform decision-making at all levels of government – federal, state and local. More precise analysis is also possible, because the dataset is large enough to permit estimates to be generated by different demographic, geographic, and income groups. As a result, further research could examine the size of the consumption effect on both the “hand-to-mouth” segment and the low income segment of the population. The individual data can be structured as cohorts, so that the impact of the composition of unemployment by whether claimants are “deeply unemployed” or “normally unemployed” can be examined. Policy makers can be informed about the regional differences in fiscal stimulus, to better inform the allocation of resources to training providers and economic development agencies.

Table 1: Summary Descriptive Statistics

	Mean	SD
Credit/Debit Spending relative to January 2020	-0.1432	0.1325
Share of Labor Force claiming Unemployment	0.0574	0.0367
Replacement Rate	0.8032	0.3967
Share of Labor Force claiming Unemployment interacted with the Replacement Rate	0.0581	0.0474

Table 2. Baseline Fixed Effects Estimates of the Determinants of County-Level Spending

	(1)	(2)	(3)	(4)
	Spending relative to Jan2020	Spending relative to Jan2020	Spending relative to Jan2020	Spending relative to Jan2020
Unemployment	-1.490***		-6.149***	-12.04***
	(0.117)		(0.266)	(0.315)
Replacement Rate		0.0404***	0.538***	-0.525***
		(0.00744)	(0.0489)	(0.104)
Unemployment*RR				14.55***
				(0.770)
N	391	391	391	391
F	162.7	29.50	274.0	1093.6
R-squared	0.885	0.879	0.914	0.956
Cubic in Time *County FEs	YES	YES	YES	YES

Standard errors in parentheses
Standard errors clustered at the county level
The units of observation are county-week pairs.
All are weighted by workforce.
The unemployment rate is measured using the share of people claiming unemployment insurance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Alternative Fixed Effects Estimates of the Determinants County-Level Spending.

	(1) Baseline	(2) Unweighted	(3) Month FE	(4) Alternate RR	(5) Without Cook County
Unemployment	-12.04***	-11.50***	-10.90***	-11.76***	-12.30***
	(0.315)	(0.721)	(0.550)	(0.311)	(0.732)
Replacement Rate	-0.525***	-0.313***	-0.469***	-0.626***	-0.389***
	(0.104)	(0.0622)	(0.0605)	(0.0948)	(0.0742)
Unemployment*$$	14.55***	11.63***	9.017***	14.01***	13.63***
	(0.770)	(1.186)	(0.830)	(0.674)	(1.495)
N	391	391	391	391	368
F	1093.6	128.3	832.6	875.4	149.6
R-squared	0.956	0.907	0.876	0.952	0.930
Cubic in Time *County FEs	YES	YES		YES	YES
Month FE & County FEs			YES		

Standard errors in parentheses
Standard errors clustered at the county level
The units of observation are county-week pairs.
All are weighted by workforce unless otherwise specified
The unemployment rate is measured using the share of people claiming unemployment insurance.
The alternative measure of the replacement rate is the gross benefit level as opposed to the net payment received.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Baseline 1st Stage Equations for the Determinants of County-Level Spending.

	(1) Unemp.	(2) Replacement Rate	(3) Unemp.	(4) Replacement Rate	(5) Unemp.	(6) Replacement Rate	(7) Unemp.*RR
Unemployment IV	1.166***		1.139***	-0.700***	1.120***	-0.874***	-0.0278
	(0.0605)		(0.0416)	(0.108)	(0.0283)	(0.131)	(0.0484)
Replacement Rate IV		0.914***	0.00230	0.960***	-0.00192	0.922***	-0.00348
		(0.0259)	(0.00207)	(0.0300)	(0.00321)	(0.0385)	(0.00535)
Unemployment*RR IV					0.0559	0.507*	1.056***
					(0.0656)	(0.223)	(0.120)
N	391	391	391	391	391	391	391
F-Statistic (Excluded IVs)	493.1	855.9	680.5	444.3	620.4	329.9	530.5
Cubic in Time *County FEs	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
Standard errors clustered at the county level
The units of observation are county-week pairs.
All are weighted by workforce.
The unemployment rate is measured using the share of people claiming unemployment insurance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Baseline 2SLS Estimates of the Determinants of County-Level Spending.

	(1) Spending relative to Jan2020	(2) Spending relative to Jan2020	(3) Spending relative to Jan2020	(4) Spending relative to Jan2020
Unemployment	-4.028***		-7.937***	-13.38***
	(0.257)		(0.407)	(0.832)
Replacement Rate		-0.137***	0.530***	-0.733***
		(0.0132)	(0.0294)	(0.0524)
Unemployment*RR				16.10***
				(0.637)
N	391	391	391	391
Cubic in Time * County FEs	YES	YES	YES	YES

Standard errors in parentheses
Standard errors clustered at the county level
The units of observation are county-week pairs.
All are weighted by workforce.
The unemployment rate is measured using the share of people claiming unemployment insurance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Alternative 2SLS Estimates of the Determinants County-Level Spending.

	(1) Baseline	(2) Unweighted	(3) Month FEs	(4) Alternate RR	(5) Without Cook County
Unemployment	-13.38***	-14.23***	-13.51***	-13.24***	-14.98***
	(0.832)	(0.578)	(0.639)	(0.806)	(0.926)
Replacement Rate	-0.733***	-0.592***	-0.631***	-0.750***	-0.682***
	(0.0524)	(0.0875)	(0.141)	(0.0498)	(0.070)
Unemployment*RR	16.10***	14.44***	13.40***	14.92***	16.65***
	(0.637)	(1.209)	(0.921)	(0.588)	(1.500)
N	391	391	391	391	368
Cubic in Time *County FEs	YES	YES		YES	YES
Month FE & County FEs			YES		

Standard errors in parentheses
Standard errors clustered at the county level
The units of observation are county-week pairs.
All are weighted by workforce unless otherwise specified
The alternative measure of the replacement rate is the gross benefit level as opposed to the net payment received.
The unemployment rate is measured using the share of people claiming unemployment insurance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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