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The Aggregate Effects of Fiscal Stimulus: Evidence from the COVID-19 Unemployment Supplement
Miguel Garza Casado, Britta Glennon, Julia Lane, David McQuown, Daniel Rich, and Bruce A. Weinberg
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ABSTRACT

The current economic crisis has highlighted the need for data that are both timely and local so that the effects of fiscal policy options on local economies can be evaluated more immediately. This paper highlights the potential value of using two new sources of near real-time data to inform decisions about the appropriate stimulus approach to implement. 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 make use of discrete changes in stimulus payments to construct a framework for evaluating real-time effects of fiscal policy on local economic activity. In particular, we leverage cross-county and over-time variation in the relative size of the Federal Pandemic Unemployment Compensation (FPUC) COVID-19 supplement to Unemployment Insurance – from $0 to $600 to $300 between March and September 2020 - to estimate the local economic impact of unemployment, earnings replacement, and the interaction between the two. We find that higher earnings replacement rates lead to significantly more consumer spending, even with increases in the unemployment claimant rate, which is consistent with the goal of the fiscal stimulus.

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1. Introduction

The COVID-19 pandemic led to a series of unprecedented and sharp fiscal interventions designed to attenuate the sharp economic downturn. The most immediate action was a federal supplement to existing Unemployment Insurance (UI) benefits of an additional $600 a week, beginning in the week ending March 21, 2020 (Karpman and Acs 2020). Those benefits ended at the end of July. The second action was the replacement of the $600 a week benefit by a supplement of $300 a week that lasted to the beginning of September. The structure of those benefits resulted in dramatic, high-frequency fluctuations in the amount of economic stimulus to states and counties, depending on the number of local claimants who received the benefits and the amount to which their lost wages were replaced. In this paper we make use of the universe of weekly benefits data in the fifth largest state in the economy – Illinois – to estimate the links between those two stimuli and the aggregate spending in each county. We also argue that the source data used in this paper can be used for similar and extended analyses in other states.

The literature on the effects of fiscal stimuli on consumption spending provide mixed evidence on the effectiveness of such interventions. The early arguments of Friedman and Modigliani were that temporary increases in income would be saved, rather than spent, resulting in little fiscal impact(Friedman 1957; Merton 1987). Later work has argued that many consumers – even the wealthy – operate on a “hand-to-mouth” basis, and spend large fractions of government transfers(Kaplan, Violante, and Weidner 2014). Empirical work consistently shows much greater marginal propensities to consume than predicted by basic models; more recent work in heterogeneous agent macroeconomics has tried to rectify the disparity between theory and evidence(Kaplan and Violante 2014; Carroll et al. 2020).

Given the theoretical ambiguity, the need for rigorous empirical work and local, real-time data to inform policy interventions is especially pressing. 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 the data toolkit for decision-makers can be expanded to evaluate fiscal impact in near-real time. Existing data can be combined to do so: in particularly, state administrative records on unemployment claims can aggregated at the county level and combined with county level credit- and debit- card transaction data. The first dataset, unemployment claims records, provides universal and weekly information on the claims, benefits, and previous earnings of claimants, and makes it possible to calculate individual-level replacement rates and unemployment claimant rates that can be aggregated to any level of geography, demographic group and industry. The second data source, transaction-level data on credit and debit card purchases can proxy economic activity at a daily basis at the county level (Chetty et al. 2020). Unlike much prior work which has focused on estimating the fiscal impact on a micro marginal propensity to consume, these detailed individual- and county-level data allow us to estimate a *macro* spending impact of a change in UI benefits that encompasses multiplier effects.

The analytical contribution is made possible by the differential impact of COVID-19 – and of the subsequent enhanced unemployment benefits – across industries, regions, and time to obtain plausibly exogenous variations in unemployment and replacement rates to estimate their effects on economic activity. Our estimates are relatively unique in that they give aggregate effects that are relevant for policy makers - namely estimates that include local spillovers from all individuals in a local area to local businesses - rather than the effects on individual consumption, or effects across geographic areas which are more typical in the literature (Chodorow-Reich 2019). Importantly, this means that we estimate a macro spending impact of a cash payout that accounts for any multiplier effects, rather than a micro marginal propensity to consume. The data and the approach can scale to all states in the nation, can incorporate spillovers across counties, and can inform decision-making in a timely manner, not just for this downturn, but for future recessions.

The data are drawn from the state of Illinois, which like every other state in the country, saw a massive shock in March 2020. Unemployment claims soared from an average of 140,000 a month in 2019 to almost 800,000 a month for the subsequent six months. The stimulus injected about $475 million a week into the Illinois economy over and above the unemployment benefits that would otherwise have been paid out. For many individuals, the payout of UI benefits plus $600 exceeded their prior earnings – a wage replacement rate greater than one. The analysis outlined below estimates that replacing the Federal Pandemic Unemployment Compensation (FPUC) supplement to unemployment insurance of $600 at the end of July 2020 and replacing it with $300 supplement reduced consumption by 5%. Thus, the effects of large reductions in benefits on consumer spending are quite substantial.

2. Background

As indicated, the effects of fiscal stimulus on consumption have been debated at least since Friedman and Modigliani in the 1950's, and been reinvigorated by recent empirical work suggesting that temporary stimulus is more effective than was previous believed, albeit with heterogeneous effects(Kaplan, Violante, and Weidner 2014). 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 and Surico 2014). Parker 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 (Parker et al. 2013). The analysis of the effects of the stimulus during the 2007-2009 Great Recession also support the notion that temporary measures are effective. Elmendorf and Furman provide a good overview of lessons learned and argue that interventions should be timely, targeted and temporary (Elmendorf and Furman 2008). In other words, they mean that a stimulus should be implemented only if a decline occurs over a specific period, should be targeted at those who spend the most (the most vulnerable families), and 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.

A large stream of empirical work has emerged examining the implications of unemployment insurance benefits for labor markets, household spending, and economic recovery, given the focus on increasing unemployment insurance benefits as a policy response to the 2020 crisis[8]. 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. Their sample, which consisted of 444 unemployed workers, provided

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

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, and Vavra 2020).

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 et al. 2020). A study of the spending patterns of about 5 million Chase Bank customers 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, and 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.

While these papers help understand individual responses to fiscal stimulus, they do not provide effects on aggregate activity, which are particularly useful for policy. Our work suggests that including local multiplier effects can result in sizeable estimates of the economic impact of fiscal policies such as increased unemployment benefits. It is worth noting that the UI claims data studied here are very similar in structure in every state across the country. State Departments of Labor have been learning how to convert claims data to data on claimants, and then to longitudinal data on claimant cohorts so the approach can be scaled up and used to evaluate fiscal policy impact on local economies in near real-time for future crises.[9] In addition, since the data described in this paper have detailed information on education, prior earnings, race and ethnicity for well over a million individuals, they could be used in future research to provide more precise estimates about the distributional consequences of different policies; state Departments of Labor have also been learning how to do so.

3. Data

We combine two primary data sources in order to generate a unique dataset that permits the analysis of the combined effect of increased unemployment claimant rates and stimuli-enhanced earnings replacement rates on economic activity[10]. The first dataset provides information at the individual level about weekly unemployment claims, benefits received, and previous earnings, which are then used to construct unemployment claimant and earnings replacement rates at the county and industry level. The second dataset provides information on daily changes in debit and credit spending at the county level.

3.1 Unemployment Claimant and Earning Replacement Data

[9] Indeed, the Department of Labor's Employment and Training Administration recently sponsored a training program for 30 states to make similar use of the claims data for analysis; 8 states have already done so. https://performancereporting.workforcegps.org/announcements/2020/10/14/18/46/Coleridge-training-course.

[10] 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.

The data that we use to construct measures of unemployment claimant rates and earnings 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. These claims data are transformed into claimant data, and linked longitudinally to create cohort level data[11]. There are many key advantages for policymakers when compared to survey data. The data are extremely timely, since they are reported every week, so that policies can be developed in response to immediate needs. They are highly geographically granular, so that heterogeneity in spatial effects can be taken into consideration. Finally, it is possible to examine demographic heterogeneity since, for each individual claimant, the dataset contains not only benefit details such as total amount paid, but also claimant details such as age, race, gender, educational attainment, and pre-separation occupation and industry.

The second is the Quarterly UI Wage Records[12], which contain quarterly wages for all UI-covered jobs in Illinois. These records are filed by employers and include roughly 96% of private non-farm wage and salary employment(Stevens 2007). 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. 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.

Unemployment claimant rate

The construction of the unemployment claimant rate measure is conceptually different from the BLS unemployment measure, which directly asks individuals whether they are "actively looking for work in the survey week". The unemployment claimant rate measure is directly based on the count of individuals who certified and received unemployment benefits for the weeks between that ending January 25, 2020 and that ending September 5, 2020. The BLS measure has the advantage of familiarity, but has been criticized for being atheoretical (Card 2011) and for not providing a measure that is useful for policymakers(Brandolini 2018; Brandolini and Viviano 2016). The sample size is a major limitation: Ganong's analyses of pandemic unemployment studied responses from fewer than 500 individuals. The claimant measure has the advantage of timeliness, and granularity, but has the disadvantage of not covering specific sectors of the labor market.(Stevens 2007). The sample size is generous: over 13 million datapoints on over a million individuals in the time-period studied. In order to minimize definitional confusion, we refer to this new measure as the "unemployment claimant rate" throughout.

We construct two versions of the unemployment claimant 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 level, or to a county-industry-week level respectively. The denominator for the unemployment claimant rate at the county-week level is derived from the 2019 Local Area Unemployment Statistics (LAUS) workforce data. The denominator for the unemployment claimant rate at the county-industry-week level is derived from the 2018 Illinois American Community

[11] https://ada.coleridgeinitiative.org/eta-class-home (password adrf).

[12] UI wage records and their coverage are extensively described elsewhere. (Stevens 2007)

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 15 of the 47 counties with consumption data. The regression analysis that uses a shift-share instrumental variable approach is therefore limited to those 15 counties[13]. This constraint does not apply to our OLS specifications.

Earnings Replacement rates

We calculate the earnings replacement rates by creating a ratio of the total amount paid in UI benefits[14] for each certified claimant - for each week from the week ending January 25, 2020 to the week ending September 5, 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. These records are used to construct measures on each claimant's work and earnings history in the year prior to the COVID-19 pandemic. We then divide the aggregate 2019 wages by 52 to get a 2019 average weekly wage for each certified claimant.

Weekly county-level earnings replacement rates 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[15] 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 aggregated and anonymized purchase data from consumer credit and debit card spending. The data are seasonally adjusted and indexed relative to January 2020 and are presented as a 7-day moving average at the county level.

3.3 Final Dataset

The final dataset is at the county-week level, from January 25 to September 5, 2020, Illinois is the sixth largest state in the United States, with a population of about 13 million[16], a workforce of about 6 million[17] and a GDP of about $900 billion[18]. 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.

Appendix Table 1 provides summary descriptive statistics, but three sets of pictures illustrate the variation in each of the three key measures that we leverage in this paper: the variation over time, the variation across counties, and the heterogeneity in the relationship between the earnings replacement rate and spending.

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[13] The unemployment claimant 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 claimant rates across the state.

[14] 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.

[15] https://tracktherecovery.org/

[16] https://www.census.gov/quickfacts/IL

[17] https://www.bls.gov/eag/eag.il.htm

[18] https://www.bea.gov/sites/default/files/2020-07/qgdpstate0720_0_0.pdf

First, the effect of the pandemic was sharp and strong in Illinois. Figure 1 shows the trends in unemployment claimant 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 in March. The immediate effect of the $600 FPUC supplement in 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. The shock of the change in unemployment benefits at the end of July is also apparent, with the average replacement rate dropping from 1.2 to just under 1 and with the flattening of consumer spending.

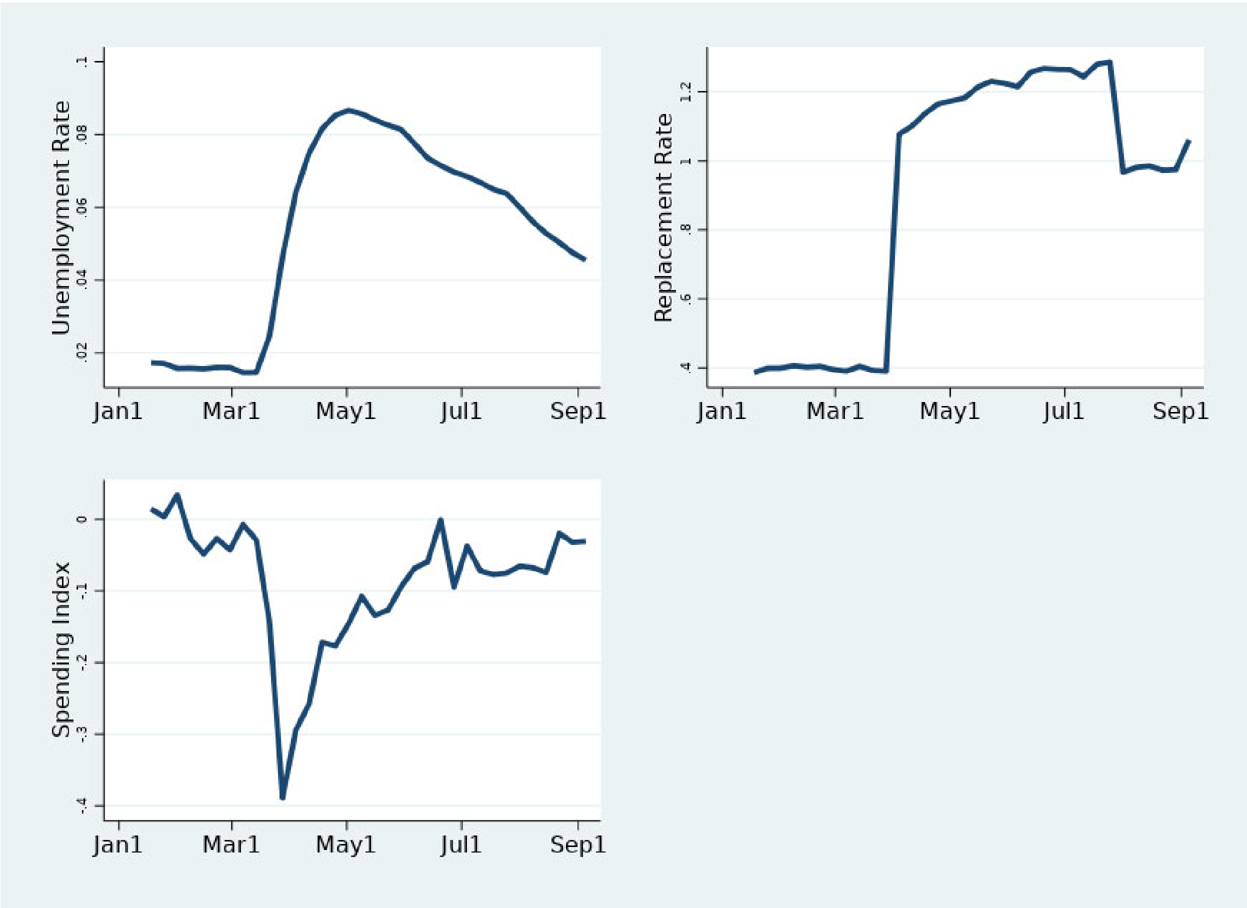
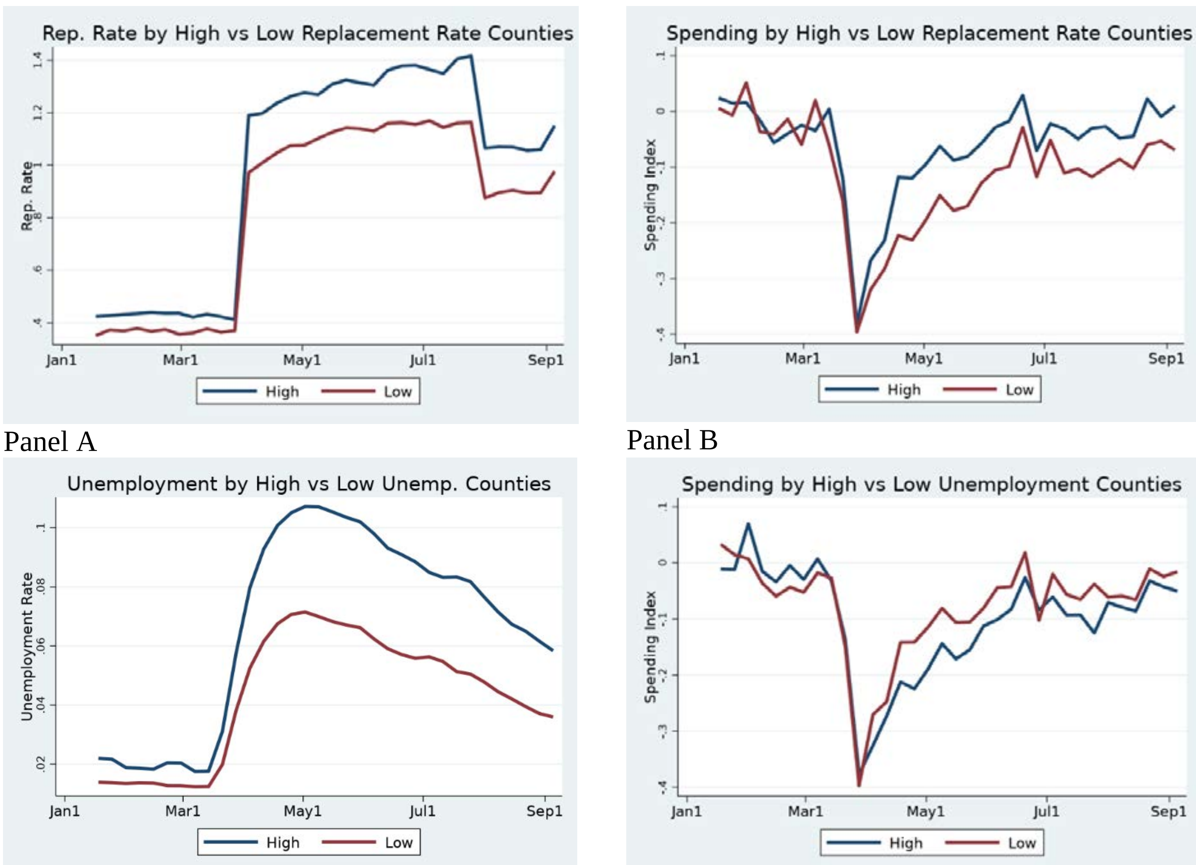


Figure 1: The Pandemic – and CARES Act - Effect

Figure 2 shows spending across different sets of counties. Specifically, we split counties based on values at the beginning of April 2020. Panel A shows the replacement rate in counties with high and low replacement rates. Panel B shows spending in each of these counties. The replacement rates and in spending (relative to the beginning of the year) are remarkably similar through early March, at which point spending declines essentially equally in both sets of counties. After the $600 FPUC supplement, replacement rates jump up more (by construction) by about 20% in the counties with higher replacement rates. Spending also rebounds by a bit under 10% more and much more quickly in the counties with high replacement rates than in those with low replacement rates. Thus, the differences in replacement rates correlate in an intuitive way with differences in spending.

Panel C reports the rates of UI receipt for counties with high and low UI receipt in early April. The counties with high UI rates in early April initially had UI rates of roughly 2% (compared to roughly 1% for the counties with low UI rates in early April). The high UI counties experience a much larger increase in UI rates (to 11%) compared to 7% for those with lower UI rates in early April, before closing the gap as both sets of counties trend downward. Panel D shows spending by unemployment claimant rate in April. Spending drops by roughly the same amount in high and low unemployment counties, but rebounds more and more quickly in low unemployment counties than in high unemployment counties after the introduction of the FPUC[19]



Panel A

Panel B

Panel C

Panel D

Figure 2. Spending by Counties.

4. Conceptual Framework and Empirical Approach

In this framework, we use counties by week 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, as noted above, since similar data are available for each state, a similar approach could be used for every state.

[19] An parallel analysis that stratified counties by 2019 average per capita income shows that spending falls more in high income counties, which have the lowest replacement rates, than in low income counties.

The main outcome measure of interest is the level of economic activity, as described above: an index of credit/debit spending at the county level compared to January 2020. The independent measures include the unemployment claimant rate and the earnings replacement rate.

More formally, the baseline model can be written as:

$$EconActivity_{ct} = \beta_0 + \beta_1 Unemp_{ct} + \beta_2 ReplacementRate_{ct} + f(t, c, \theta_c) + \epsilon_{ct} \quad (1)$$

where *c* indexes counties and *t* indexes weeks. $Unemp_{ct}$ denotes our measure of the unemployment claimant rate based on UI receipt rates and $ReplacementRate_{ct}$ gives the replacement rate, both of which vary by county and week. Our main specifications include two-way county and time fixed effects, but we also explore a specification with cubics in time fully interacted with county fixed effects, both captured flexibly by $f(t, c, \theta_c)$. One might naturally expect the effects of the replacement rate to vary with the share of people receiving benefits (or, alternatively, the effects of unemployment to vary with the replacement rate). We also estimate a model that includes interactions between $Unemp_{ct}$ and the $ReplacementRate_{ct}$. Formally,

$$EconActivity_{ct} = \beta_0 + \beta_1 Unemp_{ct} + \beta_2 ReplacementRate_{ct}$$
$$(2) + \beta_3 Unemp_{ct} \times ReplacementRate_{ct} + f(t, c, \theta_c) + \epsilon_{ct}$$

Of course, as we show below, such a model with three correlated variables, a moderate sized sample, and two-way fixed effects is challenging to estimate, but yields similar estimates to those from model (1).

Instrumental Variables

There are potential concerns with endogeneity in our analysis. We might worry about reverse causality; local spending may well affect local unemployment. Furthermore, we might worry about omitted variables; for example, the counties with the highest incomes both experienced the largest declines in spending and have the lowest replacement rates. To address these concerns, we develop a series of shift-share instruments for the endogenous independent variables, $Unemp_{ct}$ and $ReplacementRate_{ct}$.

In the case of our instrument for the unemployment claimant 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 claimant 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,

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

5. **Results**

Table 1 reports summary statistics and OLS estimates, introducing the explanatory variables one at a time. Column (1) reports the relationship between the unemployment claimant rate and spending. We find that each 1% increase in unemployment claims leads to a decline in spending of 1.6%. If the only regressor is the replacement rate (as in column (2)), then a 1% increase in the replacement rate increase spending by roughly .2%. When both the unemployment claimant rate and replacement rate are included together (in column (3)), the estimates on each are slightly lower than when they are included separately, but both remain economically and statistically significant.[20] The estimates indicate that a 1% increase in unemployment claimants reduces spending by 1.491% and a 1% increase in the replacement rate increases spending by .167%. Reducing the $600 FPUC unemployment insurance supplement to $300 reduced the replacement rate by roughly .3, which would be associated with a 5% reduction in spending. To provide context, the $300 reduction in unemployment insurance benefits corresponds to a decline in income of roughly 25% for 7% of the population or a reduction in income of 1.75% if the unemployed and employed have similar incomes.

Column (4) adds an interaction between the replacement rate and the unemployment claimant rate. Intuitively, the effect of the replacement rate should depend on the number of people who are receiving benefits and vice versa. Unfortunately, since this specification includes three correlated variables and two-way (county and time) fixed effects, the estimates become noisy.[21] That said, when evaluated at the mean unemployment claimant rate, the implied effect of an increase in the replacement rate is .143, which is quite similar to the coefficient in column (3). Similarly, at the mean replacement rate, the implied effect of an increase in the unemployment claimant rate is -1.77, which is also similar to the coefficient in column (3). Given that the interaction in column (4) introduces noise, we instead focus on the estimates in column (3) and use these as our baseline results.

Table 2 shows that the estimates are remarkably robust to a series of alternative specifications. Column (1) repeats our baseline model for convenience. Column (2) uses a different replacement rate measure based on the gross benefit as opposed to the amount of the payment (net of deductions). Column (3) addresses the considerable uncertainty about benefit levels after the expiration of the $600 FPUC. Ultimately $300 Lost Wage Assistance (LWA) was paid per week retroactively after a delay of several weeks. Our baseline assumption is that people anticipated the $300 LWA supplement, but column (3) calculates benefits assuming that people did not build the $300 LWA supplement into their consumption. The estimates are remarkably similar to the baseline estimates. Our model obviously leverages variation over time as well as variation across counties, but the correct timing assumptions are not clear. Columns (4) and (5) address concerns about timing by lagging unemployment and replacement rates by one and two weeks respectively. While these estimates are broadly similar, the one-week lag models fit the data slightly better. This finding suggests that the effects of unemployment and replacement rates may not be immediate, which seems plausible. Perhaps more importantly, these estimates suggest that most

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[20] While the UI rate and the replacement rate are strongly positively correlated overall (ρ=.68, weighted), indicating that unemployment was higher in lower income counties (i.e. those with lower replacement rates), after eliminating county and week variation, as in our regressions, the two are actually slightly negatively correlated (ρ=-.13, weighted). Thus, including both variables simultaneously weakens both.

[21] The correlation between the Unemployment claimant rate and the interaction is .87 and the correlation between the replacement rate and the interaction is .28.

identification is off the broad rather than the precise timing. Column (6) provides unweighted estimates, in contrast with prior estimates, which weight by population. These are broadly similar, but yield a smaller estimate of the replacement rate. Column (7) excludes Cook County, which accounts for roughly 40% of the population and economic activity in the state of Illinois. In this specification, the unemployment claimant rate becomes much smaller and insignificant, while the replacement rate becomes slightly larger. Column (8) explores an alternative specification of our time and county effects, including a cubic in the week interacted with county. The coefficient on the unemployment claimant rate in this model is considerably higher than that in our baseline model while the coefficient on the replacement rate is slightly higher. At the same time, the fit of this model is considerably worse than the previous models.

As indicated, we are concerned that the OLS estimates may be biased because changes in consumption would affect local employment and because the counties with the highest incomes experienced the largest declines in consumption while having the lowest replacement rates. Table 3 reports instrumental variables estimates, with the second stage estimates in the top panel and the first stage estimates in the bottom panel. (As indicated, one disadvantage of the IV estimates is that they can only be computed for 15 counties instead of the 47 used elsewhere because of the further need to use county-level data on industry composition from the American Community Survey.) Column (1) reports estimates with the unemployment claimant rate alone. The first stage estimates are significant and the first stage F-statistic on the excluded instrument is just above 10. The second stage estimate is quite similar to the corresponding estimate in column (1) of Table 1. Column (2) reports estimates for the replacement rate alone. Here the instrument is a strong predictor and first stage F-statistic on the excluded instrument is 40. The second stage estimate is larger than the corresponding estimates in column (2) of Table 1, but it is imprecise. Columns (3) and (4) report first stage estimates for the model with both the unemployment claimant rate and replacement rate, with instruments for those two variables. Column (3) shows that the instrument for the replacement rate is essentially unrelated to the unemployment claimant rate. In column (4), the instrument for the unemployment claimant 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). In both columns (3) and (4) the first stage F-statistics on the excluded instruments fall (because there are now 2 instruments). The second stage estimates for the unemployment claimant rate and replacement rate are both larger (in magnitude) than the corresponding estimates in Table 1, although neither difference is statistically significant.

Appendix Table 2 reports two stage least squares estimates for the same robustness checks that are reported in Table 2. The estimates are higher than those in Table 2, but the differences are typically smaller than those for our baseline specification and the estimates are not statistically significantly different from those in Table 1. We conclude that whatever bias introduced by endogeneity that is not controlled using the two-way fixed effects is secondary to the large shocks that were experienced because of the pandemic itself.

Conclusion

This paper quantifies the large aggregate effect of the COVID-19 fiscal stimulus on spending and economic activity. In Illinois, proposed cuts to unemployment insurance benefits are expected to have large effects on consumer spending, with a $300 change in benefits resulting in a 5% decrease on spending. The results are robust across a wide range of specifications and the use of instrumental variables.

In addition to quantifying the aggregate effects of fiscal stimulus, this paper contributes in another way. The weekly data used here are timely 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. Baseline Fixed Effects Estimates of the Determinants of County-Level Spending

	Mean (SD)	(1) Spending relative to Jan2020	(2) Spending relative to Jan2020	(3) Spending relative to Jan2020	(4) Spending relative to Jan2020
Unemployment	0.0704	-1.595***		-1.491***	-2.809*
	(0.0406)	(0.418)		(0.382)	(1.053)
Replacement Rate	0.815		0.204*	0.167*	0.0538
	(0.352)		(0.0782)	(0.0812)	(0.105)
Unemployment*RR	0.0690				1.270
	(0.0495)				(0.949)
N		1598	1598	1598	1598
F		14.55	6.813	12.12	8.253
R-squared		0.872	0.864	0.875	0.876
County FEs		YES	YES	YES	YES
Week 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 claimant rate is measured using the share of people claiming unemployment insurance.
The mean of the dependent variable is -0.150 (SD=0.134).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

	(1) Baseline	(2) Alternate RR	(3) No LWA	(4) 1 Week Lag	(5) 2 Week Lag	(6) Unweighted	(7) Without Cook County	(8) Time Specification
Unemployment	-1.491***	-1.377**	-1.554***	-1.505***	-1.420***	-1.395*	-0.258	-4.647***
	(0.382)	(0.395)	(0.387)	(0.346)	(0.336)	(0.571)	(0.738)	(0.505)
Replacement Rate	0.167*	0.160*	0.143*	0.184*	0.185*	0.0594	0.201*	0.243***
	(0.0812)	(0.0596)	(0.0572)	(0.0721)	(0.0746)	(0.0715)	(0.0849)	(0.0527)
N	1598	1316	1598	1598	1598	1598	1564	1598
F	12.12	16.35	14.48	18.34	16.43	4.502	4.441	141.5
R-squared	0.875	0.886	0.875	0.877	0.876	0.685	0.807	0.752
County FEs	YES	YES	YES	YES	YES	YES	YES	
Week FEs	YES	YES	YES	YES	YES	YES	YES	
County * Cubic in Week								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 claimant 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 3. Baseline Instrumental Variables Estimates of the Determinants of County-Level Spending.

	(1)	(2)	(3)	(4)
Second Stage:	Spending relative to Jan2020	Spending relative to Jan2020	Spending relative to Jan2020	
Unemployment	-1.778**			-2.249***
	(0.760)			(0.732)
Replacement Rate		0.311		0.313**
		(0.189)		(0.143)
First Stage:	Unemp.	Rep. Rate	Unemp.	Rep. Rate
Unemployment IV	6.439**		6.439**	9.401*
	(1.942)		(1.941)	(3.706)
Replacement Rate IV		5.160***	0.00182	5.153***
		(0.815)	(0.261)	(0.812)
N	510	510	510	510
F-Statistic (Excluded IVs)	10.99	40.08	5.753	23.52
County FEs	YES	YES	YES	YES
Week 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 claimant rate is measured using the share of people claiming unemployment insurance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Table 1: Summary Descriptive Statistics

	Mean	SD
Credit/Debit Spending relative to January 2020	-0.150	0.134
Share of Labor Force claiming Unemployment	0.0704	0.0406
Replacement Rate	0.815	0.352
Share of Labor Force claiming Unemployment interacted with the Replacement Rate	0.0690	0.0495

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

	(1) Baseline	(2) Alternate RR	(3) No LWA	(4) 1 Week Lag	(5) 2 Week Lag	(6) Unweighted	(7) Without Cook County	(8) Time Specification
Unemployment	-2.249**	-2.189*	-2.313**	-1.916*	-1.741*	-3.239	-74.95	-6.014***
	(0.732)	(0.940)	(0.749)	(0.755)	(0.773)	(3.983)	(2886.3)	(0.299)
Replacement Rate	0.313*	0.238*	0.237*	0.264	0.245	0.182	-0.660	0.347***
	(0.143)	(0.105)	(0.100)	(0.134)	(0.130)	(0.168)	(38.01)	(0.0231)
N	510	510	420	510	510	510	510	510
First Stage F-	5.753	4.094	5.776	5.468	5.093	1.602	0.250	719.99
Statistics	23.53	18.39	22.02	23.34	23.09	9.854	19.48	874.16
Week FEs	YES	YES	YES	YES	YES	YES	YES	
County * Cubic in Week								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 claimant rate is measured using the share of people claiming unemployment insurance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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