The Cost of COVID-19: Pandemic Incomes and The Causal Effects of Non-Pharmaceutical Interventions Pre-Analysis Plan

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Abstract

The COVID-19 pandemic marked a significant shock to incomes yet few studies have used administrative tax data to analyze the heterogeneous effects of the pandemic on incomes. This paper uses administrative tax data from the California Franchise Tax Board (FTB) in addition to newly released BEA county GDP data to analyze the effect of the pandemic on incomes. In addition, using detailed data on non-pharmaceutical interventions (NPIs), we attempt to quantify the causal impact of NPIs on incomes.

Keywords: Coronavirus, COVID-19, Real GDP, Economic Growth

JEL Codes: E3, E6, H3

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1 Introduction

One important economic question about the COVID-19 pandemic is whether lower income people took bigger income hits than higher income individuals, even after accounting for various pandemic-era transfers such as Pandemic Unemployment Assistance and Economic Impact Payments (EIPs)—stimulus checks.

While many studies (see for example Spiegel and Tookes (2021)) have attempted to assess the effects of COVID-19 NPIs on mortality, relatively few studies have attempted to examine the effects of COVID-19 NPIs on economic activity. Early in the COVID-19 pandemic, a debate took place over whether it was the pandemic itself or NPIs that depressed economic growth during the Spanish Flu in the early 20th century (Barro (2020) and Barro, Ursua and Weng (2020)). Lilley, Lilley and Rinaldi (2021) argue that NPIs are responsible for depressed economic growth during the Spanish Flu whereas Verner, Correia and Luck (2022) argued it was the pandemic rather than NPIs.

While a limited amount of economic data was being tracked in the early 20th century, the widespread availability of various type of data including administrative microdata during the COVID-19 pandemic allows researchers to attempt to explore the effects of pandemics on incomes as well as the effects of NPIs.

This paper uses newly released BEA county GDP data in addition to administrative tax data from the California Franchise Tax Board (FTB) to analyze the effect that the pandemic has on incomes.

BEA county GDP data allows us to examine NPI effects across the entire US at the county level while California Franchise Tax Board (FTB) data allows us to examine NPI effects on individual incomes with greater degrees of heterogeneity albeit over a smaller region exclusively in California.

First, we document several facts about how incomes evolved over the pandemic by family size and industry.

Next, using detailed data on non-pharmaceutical interventions (NPIs), we attempt to quantify the causal impact of NPIs on incomes.

Specifically, we use the data on county level COVID-19 NPIs collected by Spiegel and Tookes (2021) who only explore the effects of NPIs on mortality, leaving the direct economic effects of NPIs unexplored. While some studies like Arias et al (2022) have attempted to estimate the casual effects of lockdowns on health and macroeconomic outcomes, their approach is structural in that they use structural vector autoregression (SVARs) and Local Projections (LPs) to quantify the effects of non-pharmaceutical policy interventions while modeling the pandemic from a SIR approach. In contrast, we take a reduced form approach.

We show using detailed county level NPI data from Spiegel and Tookes (2021) that many NPIs are plausibly exogenous and relatively uncorrelated with the number of COVID-19 cases and deaths within a county. We then use difference-in-differences exploiting the variation in the rollout of NPIs and their duration in a given country to measure the causal effects of NPIs on incomes and GDP.

This paper proceeds as follows. In Section 2, we review related literature. In Section 3, we discuss describe we describe the data. In Section 4, we discuss descriptive statistics for individual incomes from individual tax returns during COVID-19. In Section 5, we describe the empirical methodology. Sections 6 presents the results respectively. Section 7 concludes.

2 Literature Review

Barro (2020) finds the impact of NPIs on overall deaths in the 1918 was statistically insignificant and that the average duration of each type of NPI (school closings, prohibitions on public gatherings, and quarantine/isolation) was only around one month. This suggests that the 1918 might not be the best comparison for 2020.

Many other papers have analyzed the effects of COVID-19 on economic activity although few to our knowledge have taken a systematic accounting of the impact on individual incomes. Chetty et al (2022) analyze the effects on consumption, small business revenues as well as small business openings, job openings and employment on a real-time basis, regularly updating their results on tracktherecovery.org.

Many other papers have analyzed the effects of various COVID-19 economic relief policies. Since, the onset of the COVID-19 recession, policymakers at both the Federal Reserve and in Congress were quick to act. The Federal Reserve on March 16, 2020 announced $700 billion of Treasury and Mortgage Backed Security (MBS) long-term asset purchases (often referred to as quantitative easing or "QE"), and followed up with establishing new facilities on March 23, 2020 that would also buy corporate bonds (the Primary Market Corporate Credit Facility and Secondary Market Corporate Credit Facility). On the same day that the Federal Reserve made this latter announcement, corporate bond market spreads peaked and quickly began to fall as corporate bond markets had stabilized. In this time, non-financial corporations raised records amounts of cash as they embarked on navigating an uncertain COVID-19 economy. Rebucci, Hartley, and Jimenez (2022) find using an event study of various central bank quantitative easing announcements that in developed nations, sovereign bond QE announcements had an average effect of -0.13% on the 10-year government bond yields in advanced economies and an average effect -0.23% on the 10-year government bond yields in emerging markets.

Meanwhile, Congress passed the Coronavirus Aid, Relief, and Economic Security Act (CARES) Act, a \$2.2 trillion economic stimulus bill passed by the 116th U.S. Congress and signed into law by President Donald Trump on March 27, 2020 which included authorizations for \$2,400 Economic Impact Payment (EIP) rebates (stimulus checks) to each married couple filing jointly making less that \$150,000 in Adjusted Gross Income (AGI) or \$1,200 to individuals making less than \$75,000 in AGI (these amounts phase out above these income thresholds and phase out completely at \$198,000 and \$99,000 respectively for couples and single individuals), and Federal Pandemic Unemployment Compensation (FPUC), which provides an additional \$600 per week for those receiving unemployment benefits, and \$349 billion for the Paycheck Protection Program (PPP) which was later increased in the amount of another \$320 billion by Paycheck Protection Program and Health Care Enhancement Act signed into law on April 24, 2020. Later in December 2020, President Trump on December 28, 2020 signed a second major stimulus bill into law (roughly on the magnitude of \$900 billion in static cost) which paid out another round of stimulus checks in the amount of \$600 per individual and \$1,200 for couples with the same income thresholds as the CARES Act and extended the Federal Pandemic Unemployment Compensation (FPUC) at \$300 per week. In March 2021, the American Rescue Plan (ARP), a third major stimulus bill (costing in the static amount of \$1.9 trillion), championed by newly elected President Biden, was signed into law after being passed in Congress through reconciliation. Some measures include additional stimulus checks in the amount of \$1,400 per individual (and \$2,000 per couple), relief for states and municipalities, child allowances.

Autor et al (2022), and Granja, Makridis, Yannelis and Zwick (2022) explore the effects of the Coronavirus Aid, Relief, and Economic Security Act (CARES) Act Paycheck Protection Protection program (PPP) of grants to small businesses, both finding it was poorly targeted, skewed toward higher income individuals.

Coombs et al (2022) analyze the effects of early withdrawal of CARES Act pandemic unemployment assistance (PUA) finding that early unemployment benefits cutoffs were associated with slightly improved employment gains.

Chetty et al (2022) analyze the consumption response to Economic Impact Payment (EIP) checks using administrative credit card spending data from Affinity Solutions finding relatively large marginal propensities to consume (MPCs) particularly for lower income households who received checks.

Similarly Karger and Rajan (2020) use transaction-level bank account data showing that Covid-19 stimulus payments increased consumer spending by 46% of the stimulus amount, low-income individuals spend 60% of their stimulus check within two weeks, high-income individuals spend 24% of their stimulus check within two weeks.

With respect to NPIs ("lockdown" policies), there has been intense debate about their economic effects. There is a heavy debate over what degree government lockdowns and NPIs (non-pharmaceutical interventions) represent a negative externality. One helpful framework to think about pandemics is in terms of externalities. Individuals with the disease have the ability to infect others nearby without their consent. On the one hand, government shutdowns may be partially responsible for continued unemployment in an effort to save lives. On the other, it's possible that by preventing the spread of the disease it has an effect that prevents further spread of the disease and allows people to return to work faster. Correia, Luck and Verner (2020) find that cities with longer NPIs during the 1918 influenza pandemic had better employment outcomes. Berkes et al (2020) find that longer NPIs had no effect on patenting activity in 1918. Lilley, Lilley and Rinaldi (2021) argue that NPIs are responsible for depressed economic growth during the 1918 Spanish Flu.

While some studies like Arias et al (2022) have attempted to estimate the casual effects of lockdowns on health and macroeconomic outcomes, their approach is structural in that they use structural vector autoregression (SVARs) and Local Projections (LPs) to quantify the effects of non-pharmaceutical policy interventions while modeling the pandemic from a SIR approach.

In contrast, we take a reduced form approach. We show using detailed county level NPI data from Spiegel and Tookes (2021) that many NPIs are plausibly exogenous and relatively uncorrelated with the number of COVID-19 cases and deaths within a county. We then use difference-in-differences exploiting the variation in the rollout of NPIs and their duration in a given country to measure the causal effects of NPIs on incomes and GDP.

3 Data

3.1 California Franchise Tax Board (FTB) Individual Administrative Tax Filings

This paper uses the universe of individual administrative tax record data for the calendar years 2000 to 2020 obtained from the California Franchise Tax Board.

From these returns, we have population-level coverage of certain variables measured from the California Form 540. Variables for which we have full coverage include Taxable Income and California AGI, Federal AGI, Capital Gains (we observe the sum of long term and short term capital gains), Interest, and Dividends. Three filing statuses account for the near-universe of filings: single, married joint-filers, and head of household.

"Total Income," which is then adjusted to AGI through subtractions. AGI then becomes taxable income by removing deductions. State and federal quantities differ due to state and federal specific adjustments. For example, state and local taxes could at the time still be itemized in deductions from federal AGI.

The FTB designates one spouse the "primary taxpayer" and the other a "redundant spouse," and the data include identical records for each party reflecting household quantities. All of our analysis is conducted at the level of a primary taxpayer which is our unit of observation.

All dollar amounts are inflation-adjusted to 2020 dollars using inflation factors from the FTB.

Table 1 will contain summary statistics for the full sample, 2000-2020.

This data is a rich dataset that can be used analyze incomes across the income distribution and how they were impacted by COVID-19. Other studies have used such California data including Rauh and Shyu (2022) which studies the response to California top marginal income tax rate changes and Rauh (2022) which studies net migration in response to various types of tax changes.

3.2 Bureau of Economic Analysis (BEA) GDP County Level Data

Since 2019, the Bureau of Economic Analysis (BEA) has published Gross Domestic Product (GDP) by County for all years going back to 2000. With county GDP data from 2000-2021, we analyze both how county GDP changed throughout the pandemic (what counties experienced larger shocks to economic activity) as well as the effects of different types of NPIs on county GDP.

3.3 Non-Pharmaceutical Intervention (NPI) Data of Spiegel and Tookes (2021)

Spiegel and Tookes (2021) construct a time-series database of business and related restrictions for every county in the United States from March through December 2020. Spiegel and Tookes (2021) catalogues various types of non-pharmaceutical interventions (NPIs) including high risk business closures, restaurant and bar closures, employee mask policies, mask mandates for the general population. In addition, they catalogue the prices number of days each type of NPI lasted for in a given county. We construct a NPI duration/intensity variable by calculating the number of days each type of NPI lasted in each county in 2020. This variable for each type of NPI will be the chief treatment variable we will use in exploring the effects of NPIs on both individual incomes from the California Franchise Tax Board (FTB) individual administrative tax filing data as well as the county GDP data.

4 COVID-19 Pandemic Incomes

The effects of the COVID-19 pandemic on incomes across the income distribution can be estimated in a simple event study of incomes before and after the pandemic.

In the first stage, we run an AR(1) regression to estimate incomes based on prior data up until and including 2019:

$$Income_{i,t} = \alpha + \beta_1 Income_{i,t-1} + \gamma X_i + \epsilon_i$$

We can analyze the evolution (or surprises) in taxable income across the income distribution during the COVID-19 pandemic by taking residuals (below) and averaging them by 2019 income decile buckets:

$$COVIDIncomeImpact_i = Income_{2020,t} - \hat{\alpha} - \hat{\beta}_1 Income_{i,2019} - \hat{\gamma} X_i$$

These estimates/surprises give us a sense of the overall effects of the COVID-19 pandemic. These may very well subsume both the effects of lower economic activity due to a spreading pandemic as well as any potential effects of NPIs on economic activity.

To separate the effects of NPIs on economic activity from the pandemic effects on NPIs, we use detailed institutional data on NPIs as a source of plausibly exogenous variation.

5 The Effects of Non-Pharmaceutical Interventions NPIs

The county level lockdowns lend themselves to a difference-in-difference estimation strategy akin to Spiegel and Tookes (2021) who study the effects of NPIs on mortality. The main outcome variables of interest include individual level annual incomes using 2020 as the post year (when the lockdowns went into place). We also extend our NPI effects analysis nationally using BEA county level GDP data from 2000 to 2020.

The lockdown data used in Spiegel and Tookes (2021) varies according to type of non-pharmaceutical intervention (NPI). We use several different types of NPIs to understand the effects of different types of NPIs on economic growth. In some specifications, we control for covariates such as the number of COVID-19 cases or deaths in a given county. The reason for including such controls is that it is possible that pandemic itself (and related voluntary social distancing) rather than mandated lockdowns and NPIs are causing economic activity to decline. This is the argument put forward by Verner et al (2022).

Other papers such as Arias et al (2022) have attempted to better understand the effects of COVID-19 lockdowns using more structural models like SIR models that account for the possible endogeneity of COVID-19 NPIs with county level variation in the pandemic. We argue however that in the cross section, pandemic intensity at the county level is relatively uncorrelated with NPI intensity which makes the case that NPI policy may be to some degree heterogeneous, capricious and plausibly exogenous.

5.1 Difference-In-Differences Approach

One approach to measuring the effects of plausibly exogenous county-level lockdowns on individual incomes and county GDPs uses difference-in-differences specifications comparing individuals (California FTB tax return incomes) and counties (BEA county GDP data) with and without various types of lockdowns. We estimate a difference-in-difference regression as follows:

$$Income_{i,t} = \alpha + \beta_1 Post_t + \beta_2 NPITreated_i + \beta_3 Post_t NPITreated_i + \gamma X_i + \epsilon_i$$

where $Post_i$=1 after 2020, the year COVID-19 lockdowns were introduced and $NPITreated_i$ is the number of days in 2020 a given county is under a specific type of lockdown. β_3 is the difference-in-difference estimator which measures the effects of an additional day of lockdown.

Other controls we use include the digital-labor intensity of each industry in a given county to quantify the possibility that some counties are easily able to work from home given a higher concentration of digital jobs. Digital job concentration can be measured by the share of digital workers within each industry derived from information on tasks at an occupational level from the Department of Labor's O*NET which can be applied to county level GDP data as in Hartley and Makridis (2020).

5.2 Synthetic Control Methods

For the sake of robustness, we next implement the synthetic difference-in-differences (SDID) approach of Arkhangelsky et al. (2021). Synthetic differences-in-differences ("SDID") is a synthesis of ideas underlying the synthetic controls and difference-in-differences methods for causal program evaluation. The main advantage of the method over standard difference-in-differences is that it reweights control observations to weaken the parallel trends assumption. While we find that broadly parallel trends are observed between the treatment group and various sub-samples of the control group that can be selected through propensity score matching techniques, SDID is preferable to these ad hoc techniques in that it retains the logic of ad hoc techniques that aim to make the parallel trends assumption plausible but does not require the use of arbitrary sample restrictions.

Instead, SDID generates unit weights that align pre-exposure trends in the outcome of unexposed units with those for the exposed units, and it generates time weights so that the average posttreatment outcome for each of the control units differs by a constant from the weighted average of the pretreatment outcomes for the same control units.

In an elastic nets model, these kinds of estimators minimize the distance between the treated outcome and an affine combination of the untreated outcome for the pre-treatment period, regularized the intercept μ is not regularized by the elastic-net (en) penalty:

$$(\hat{\mu}^{en}, \hat{\omega}^{en}) = _{\mu,\omega} Y_{i,pre} - \mu - Y_{C,pre} \cdot \omega_2^2 + \lambda \cdot (\alpha\omega_1 + (1-\alpha)\omega_2)$$

The parameter $\lambda \geq 0$ determines the amount of regularization, and $\alpha \in [0, 1]$ determines the type. The case $\alpha = 1$ corresponds to a LASSO

The case $\alpha = 0$ corresponds to a Ridge penalty function, which captures a preference for smaller weights.

Estimated weights from the above are then used in a weighted two-way fixed effects difference-in-differences regression intended to recover the Average Treatment Effect on the Treated ("ATT"). The ATT for individual i is the gap (i.e., difference) between the observed and counterfactual outcome:

$$\hat{\eta}_{i,t} = Y_{i,t} - \hat{Y}_{i,t}(0).$$

Our primary dependent variables of interest is an individual's likelihood of filing a tax return and log taxable income. Thus, we use this variable to generate SDID weights. In this procedure, 2000-2019 is the pre-period and 2020-2021 is the post-period, since the treatment begins in 2020 (we only have access to 2020 California tax return data for the post-period). As in the recent synthetic controls literature, SDID uses L2 regularization (also known as "ridge regression") to estimate its entity weights. This procedure introduces dispersion into the weights by shrinking the OLS coefficients (when well-defined) uniformly toward zero in a ratio sense. Regularization stabilizes estimated weights by controlling their variance; to see this note that least-squares with L2 regularization is equivalent to adding a constant positive term to the diagonal of the variance-covariance matrix used to calculate the OLS estimator.

To conduct inference with SDIDs, we use Jackknife standard errors.

We also recognize the potential for there to be confounding factors influencing the number of children a household has which may be related to the labor supply decision. To examine these possibilities we conduct extensive placebo tests, by estimating a synthetic control group for all of the untreated individuals as well as treated individuals. The goal is to see whether we consistently find average out-of-sample placebo effects to be close to zero.

6 Results

First, we will test for evidence of substantially different pre-trends between our treatment and control populations.

Figure 1 will plot the annual distributions of incomes for California households in the years directly before and during the COVID-19 pandemic (2019, 2020)

Figure 2 will plot the median income for California households over time (2000-2020)

Figure 3 will plot the change incomes for California households from 2019 to 2020 versus county NPI duration.

Table 2 will present the results of difference-in-difference estimates for the effects of NPI interventions on individual California incomes.

Table 3 will present the results of difference-in-difference estimates for the effects of NPI interventions on county level GDPs.

Figure 4 will present results from our placebo tests.

7 Conclusion

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Table 1: Summary Statistics

	Mean	SD	p1	p10	p50	p90	p99
Wage							
Federal AGI							
California AGI							
Taxable Income							
Dependents							
Married							
Cal AGI/Fed AGI Ratio							

Notes: The table shows summary statistics for all observations pooled over the time period 2000-2020. The level of observation is the household, as reflected in the primary taxpayer observation which aggregates spousal income. California AGI differs from Federal AGI in two ways: (a) it includes only California source income; and (b) California and Federal law differ slightly in their definitions of AGI.

Figure 1: Annual Distributions of Annual Incomes for California Households Over Time Before and During The COVID-19 Pandemic (2019, 2020)

Figure 2: Median Income for California households Over Time (2000-2020)

Figure 3: Change Individual California Household Incomes from 2019 to 2020 Versus County NPI Duration

Figure 4: Placebo Tests for ATTs

Table 2: Difference-In-Difference Estimates For The Effects of NPI Interventions On Individual California Incomes

	Treated Group		
	Business Closures	Restaurant and Bar Closures	Mask Mandates
$NPITreated$			
$Post$			
$NPITreated * Post$			
$Covariate1$			
$Covariate2$			
$Covariate3$			
$Constant$			
F-test			
N			

Notes: $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

Table 3: Difference-in-Difference Estimates For The Effects of NPI Interventions on County Level GDPs

	Treated Group		
	Business Closures	Restaurant and Bar Closures	Mask Mandates
$NPITreated$			
$Post$			
$NPITreated * Post$			
$Covariate1$			
$Covariate2$			
$Covariate3$			
$Constant$			
F-test			
N			

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$