Putting the Paycheck Protection Program into Perspective: An Analysis Using Administrative and Survey Data

Michael Dalton

Bureau of Labor Statistics

10/25/22
First Draft November 2021
New Draft Very Soon!

Views expressed do not reflect those of the Bureau of Labor Statistics

Paycheck Protection Program

- Created in March 2020 with $669 billion in funding and administered by the Small Business Admin (SBA)
  - This amount is 85% of the estimated size of the *entire* American Recovery and Reinvestment Act of 2009
  - There was a second round in 2021 - Not using that for this analysis

Paycheck Protection Program

- Created in March 2020 with $669 billion in funding and administered by the Small Business Admin (SBA)
  - This amount is 85% of the estimated size of the *entire* American Recovery and Reinvestment Act of 2009
  - There was a second round in 2021 - Not using that for this analysis
- Vast majority of employers in U.S. were eligible
  - Loan can be converted to grant if specific payroll criteria met
  - Otherwise, loan had 1% interest rate with 2 (or 5) year maturity

Paycheck Protection Program

- Created in March 2020 with $669 billion in funding and administered by the Small Business Admin (SBA)
  - This amount is 85% of the estimated size of the *entire* American Recovery and Reinvestment Act of 2009
  - There was a second round in 2021 - Not using that for this analysis
- Vast majority of employers in U.S. were eligible
  - Loan can be converted to grant if specific payroll criteria met
  - Otherwise, loan had 1% interest rate with 2 (or 5) year maturity
- Purpose of program was for small business employers to maintain payroll by supplying direct payments of up to 10 weeks of payroll costs (max $10 million)

Given the size and scope, **what impacts can we actually attribute to the program?**

Assessing PPP Impact

- Regression discontinuity around eligibility - rather small effects on employment
  - Autor et al (2020), Chetty et al (2020), Hubbard and Strain (2020)
  - Focuses on largest loans and largest eligible employers (and smallest ineligible employers)

Assessing PPP Impact

- Regression discontinuity around eligibility - rather small effects on employment
  - Autor et al (2020), Chetty et al (2020), Hubbard and Strain (2020)
  - Focuses on largest loans and largest eligible employers (and smallest ineligible employers)
- Geographic differences in loan access as instrument
  - Small-ish employment effects - Granja et al (2022)
  - Larger employment effects - Bartik et al (2021), Doniger and Kaye (2021), Bartlett and Morse (2020), Faulkender et al (2020)
  - Kurmann et al (2021) and Bartik et al (2021) find evidence of reduced closures

Assessing PPP Impact

- Regression discontinuity around eligibility - rather small effects on employment
  - Autor et al (2020), Chetty et al (2020), Hubbard and Strain (2020)
  - Focuses on largest loans and largest eligible employers (and smallest ineligible employers)
- Geographic differences in loan access as instrument
  - Small-ish employment effects - Granja et al (2022)
  - Larger employment effects - Bartik et al (2021), Doniger and Kaye (2021), Bartlett and Morse (2020), Faulkender et al (2020)
  - Kurmann et al (2021) and Bartik et al (2021) find evidence of reduced closures
- Difference-in-Difference
  - Positive employment effects - Autor et al (2022)
  - Most similar to what you'll see here today

Where does this paper fit in?

- Using the full wage record database of employers
  - Full employment and wage history and rich information about establishments
  - Not subject to sample churn
  - Can easily match it to other survey data at the BLS
- Longer-term effects, in particular on closures
- Use wage data to assess pass-through of PPP to wages paid
- Dynamic diff-in-diff strategy using microdata
- More detailed heterogeneity analysis

Key Results

- One month after PPP approval, PPP has the effect of...
  - 8.1% increase in employment
  - 5.6% decline in probability of closure
  - 12.2% increase in wages

Key Results

- One month after PPP approval, PPP has the effect of...
  - 8.1% increase in employment
  - 5.6% decline in probability of closure
  - 12.2% increase in wages
- Effects fall after first month but are persistently positive up to 12 months after PPP approval

Key Results

- One month after PPP approval, PPP has the effect of...
    - 8.1% increase in employment
    - 5.6% decline in probability of closure
    - 12.2% increase in wages
- Effects fall after first month but are persistently positive up to 12 months after PPP approval
- Estimate of $27,690 of PPP loans per employee-month retained after 6 months
    - Estimate goes to $16,199 after 12 months - long term results because of reduced closures
- $3.12 of PPP spent per dollar of wages retained after 12 months

Paycheck Protection Program

- Using published PPP microdata with employer name, address, date of approval, and amount of loan
- Focusing only on first round of PPP from April 2020 through August 2020
- Remove some loans that are out of scope for the wage records
  - Self-employed
  - Independent Contractors
  - Sole proprietorship
  - Non-profit Religious Organizations
- **Remaining:** 3.8 million loans worth $483 billion

Quarterly Census of Employment and Wages

- Covers all establishments that pay into the Unemployment Insurance (UI) system nationwide
  - **Covers more than 95% of all jobs**
- Gives monthly employment and quarterly wages
- Employer names and addresses
- Can track establishment over time
  - Before pandemic and after receipt of PPP loan
  - Using data through September 2021
- Can also partially map establishments by firm
  - Relies on **Employment Identification Number (EIN)**
  - Though, this is an imperfect measure of firms
  - Important for thinking about who the PPP loan recipient actually is

Record Linking

- Fuzzy text match on employer name and address between PPP and QCEW
- Finds closest name and geography match
- This linkage allows analysis of those that did - and did not - get approved for PPP loan and when that approval happened

Record Linking

- Fuzzy text match on employer name and address between PPP and QCEW
- Finds closest name and geography match
- This linkage allows analysis of those that did - and did not - get approved for PPP loan and when that approval happened
- Employment, wages, and closure status before and after PPP approval

Match Rate of PPP to QCEW

Descriptor	Total Number of Loans (millions)	Total Dollar Amount ($billions)	% of Loans Matched	% of Loan $ Amount Matched
All Loans	3.84	483.5	76.3	87.9
Removing Loans Reporting Only 1 Job	3.3	476.7	80.5	88.5
Removing Loans Reporting 0 or 1 Job	2.7	412.2	82.5	88.8

Match Rate Verification

The True Effect of PPP

- We want to estimate the **true treatment effect** of receiving PPP
- A particularly thorny econometric question
  - PPP approval is **not random** - based on choice on behalf of establishment - **”selection effects”**

The True Effect of PPP

- We want to estimate the **true treatment effect** of receiving PPP
- A particularly thorny econometric question
  - PPP approval is **not random** - based on choice on behalf of establishment - **"selection effects"**
  - Beyond selection effects, standard difference-in-difference has problems in this context

The True Effect of PPP

- We want to estimate the **true treatment effect** of receiving PPP
- A particularly thorny econometric question
  - PPP approval is **not random** - based on choice on behalf of establishment - **"selection effects"**
  - Beyond selection effects, standard difference-in-difference has problems in this context
    - PPP approved over the course of 4 months - multi-period treatment means two-way fixed effects do not give true causal parameters without additional strong assumptions
    - Those who got PPP earlier look different than those who got it later - **treatment heterogeneity**

The True Effect of PPP

- We want to estimate the **true treatment effect** of receiving PPP
- A particularly thorny econometric question
  - PPP approval is **not random** - based on choice on behalf of establishment - **"selection effects"**
  - Beyond selection effects, standard difference-in-difference has problems in this context
    - PPP approved over the course of 4 months - multi-period treatment means two-way fixed effects do not give true causal parameters without additional strong assumptions
    - Those who got PPP earlier look different than those who got it later - **treatment heterogeneity**
  - Want to look at effect for full sample - not just establishments in a particular size range

Callaway and Sant'anna (2021)

- Related to Goodman-Bacon (2021) and Sun and Abraham (2020)
- Dynamic diff-in-diff
- Allows for estimating **average treatment on the treated (ATT)** effect of policy change
- Handles treatment heterogeneity
- Handles differential treatment timing
- Controls for time invariant characteristics to better deal with selection effects - makes use of rich QCEW data!
- Allows for event study parameters
- **Estimation strategy relying on *full* sample, not restricted to subpopulation**

Bottom line: This gives a credible estimation strategy for assessing PPP

Detailed Equations

Defining the Dependent Variable

$$\boldsymbol{E^*_{imyjc}} = \overbrace{\frac{e_{imyjc}}{\frac{\sum_{t=2017}^{2019} e_{imtjc}}{3}}}^{\text{Employment of Establishment i}} - \frac{\sum_{k \neq i \in j,c} e_{kmyjc}}{\sum_{k \neq i \in j,z} e_{km2019jc}}$$

- $\boldsymbol{E^*_{imyjz}}$ is the dependent variable of interest
- e_{imyjz} is employment
    - for establishment i
    - Month m and year y [post-pandemic]
    - establishment i's 4-digit industry j
    - establishment i's physical location county c

Defining the Dependent Variable

$$\boldsymbol{E^*_{imyjc}} = \underbrace{\frac{e_{imyjc}}{\frac{\sum_{t=2017}^{2019} e_{imtjc}}{3}}}_{\text{Avg. Employment Prior to Pandemic}} - \frac{\sum_{k \neq i \in j,c} e_{kmyjc}}{\sum_{k \neq i \in j,c} e_{km2019jc}}$$

- Employment relative to average employment in 3 years prior to pandemic
  - Same calendar month for the baseline deals with seasonality
  - Uses information prior to any pandemic effects

Defining the Dependent Variable

$$E^*_{imyjc} = \frac{e_{imyjc}}{\frac{\sum_{t=2017}^{2019} e_{imtjc}}{3}} - \overbrace{\frac{\sum_{k \neq i \in j,c} e_{kmyjc}}{\sum_{k \neq i \in j,c} e_{km2019jc}}}^{\text{Employment Change in County - Industry}}$$

- Subtract employment change in establishment i's county - industry
  - Geography specific effects
    - Bank access
    - Local COVID policies
    - Local COVID incidence
  - Industry specific effects
    - COVID-specific impacts

Defining the Dependent Variable

$$\boldsymbol{E}^*_{\boldsymbol{imyjc}} = \frac{e_{imyjc}}{\frac{\sum_{t=2017}^{2019} e_{imtjc}}{3}} - \frac{\sum_{k \neq i \in j,c} e_{kmyjc}}{\sum_{k \neq i \in j,c} e_{km2019jc}}$$

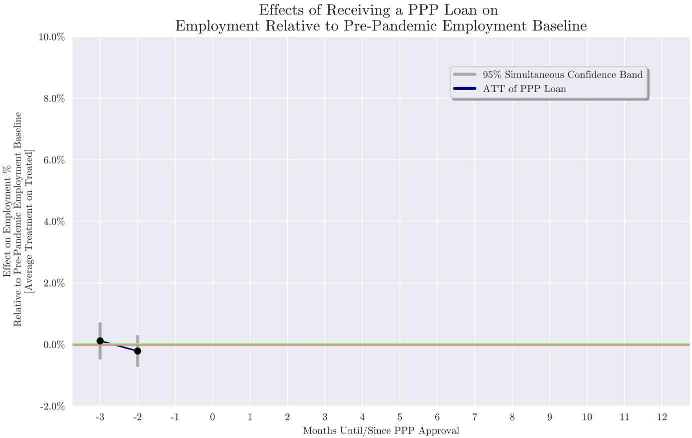
Example:

- Establishment reports employment of 11 in June 2020
- Average June employment for establishment from 2017-2019: 10
- County-4-digit industry of establishment has lost 5% of 2019 employment as of June 2020
- $\boldsymbol{E}^*_{\boldsymbol{imyjc}} = 100 * [\frac{11}{10} - .95] = 15$

Control Variables

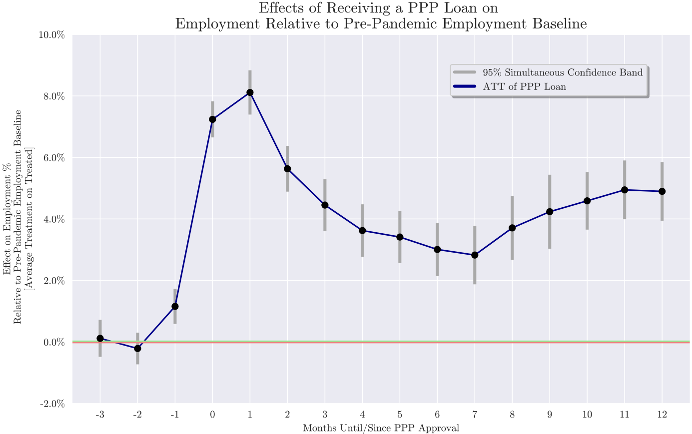
ATT on Employment

- Pre-treatment months
- Statistically null or economically close to zero
- **Evidence of satisfying key assumption: parallel trends**



ATT on Employment

- **8.1% increase in employment due to approval in month 1**
- **Effect falls but still significant 12 months after PPP approval**
- 4.9% higher employment 12 months after approval
- Effect increases after second COVID wave
  - Extended effects due to avoiding closure?

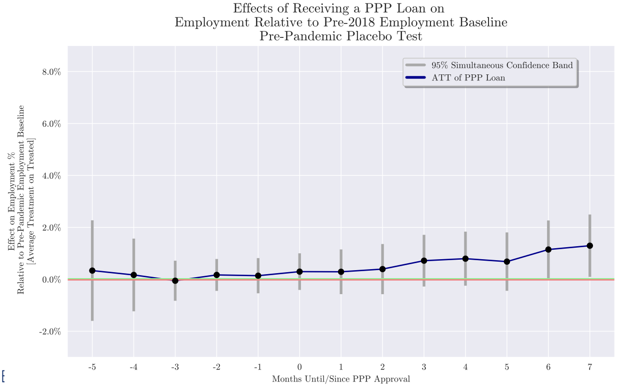


Placebo Test

- Think back to happier times, when the word "pandemic" instead elicited thoughts of the "Antonine Plague" and "The Black Death"
  - 2018-2019 employment change relative to pre-2018 employment
- Do the same establishments that receive PPP in 2020 have any different trajectory pre-pandemic compared to non-receiving establishments?

Placebo Test

- Think back to happier times, when the word "pandemic" instead elicited thoughts of the "Antonine Plague" and "The Black Death"
  - 2018-2019 employment change relative to pre-2018 employment
- Do the same establishments that receive PPP in 2020 have any different trajectory pre-pandemic compared to non-receiving establishments?



Imputing Audience Comments

Imputing Audience Comments

"Mike, you rube! Establishments struggling the most because of COVID are going to apply for PPP, and that will dampen the effects you find compared to the true ATT!"

- Bartik et al (2021) find those with less cash-on-hand and more impacted by COVID were more likely to apply, but...
- Also report that less cash on hand was less likely to get approval

Imputing Audience Comments

"Mike, you rube! Establishments struggling the most because of COVID are going to apply for PPP, and that will dampen the effects you find compared to the true ATT!"

- Bartik et al (2021) find those with less cash-on-hand and more impacted by COVID were more likely to apply, but...
- Also report that less cash on hand was less likely to get approval

Another point - treatment misclassification

$$ATT^* = \frac{\hat{AT}T}{P(PPP{*}{=}0|PPP{=}0)+P(PPP{*}{=}1|PPP{=}1)-1}$$

This gives an $\hat{AT}T$ **that undershoots the true** ATT^* **by about 22%**

Almost entirely driven by false negatives - **can I improve the match?**

Imputing Audience Comments, pt. 2

Imputing Audience Comments, pt. 2

"Mike, you knucklehead! Businesses that were going to fail weren't going to apply for PPP, so you are *overestimating* the true ATT!"

- Loans were forgivable if the establishment met certain payroll criteria, but...
- Even if the criteria couldn't be met, loans had a 1% interest rate with a maturity of 2 years (changed to 5 years for later-stage loans)
- Most loans are under $25k with no collateral requirement - these would be forgivable in the event of business closure

Imputing Audience Comments, pt. 2

"Mike, you knucklehead! Businesses that were going to fail weren't going to apply for PPP, so you are *overestimating* the true ATT!"

- Loans were forgivable if the establishment met certain payroll criteria, but...
- Even if the criteria couldn't be met, loans had a 1% interest rate with a maturity of 2 years (changed to 5 years for later-stage loans)
- Most loans are under $25k with no collateral requirement - these would be forgivable in the event of business closure

Can try to bound potential violations of parallel trends

Interpreting Medium-Term Effects

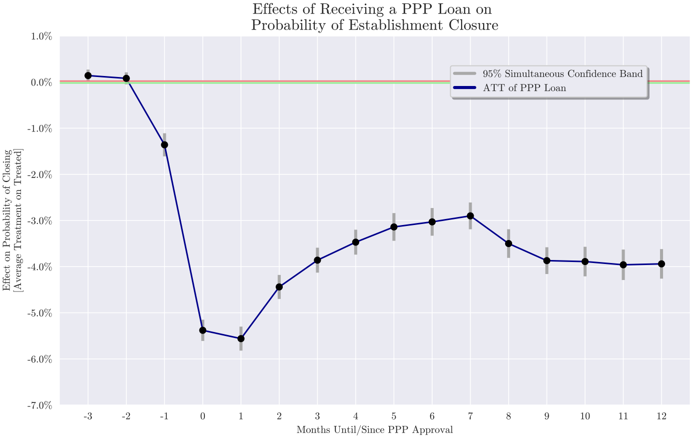
- The immediate effect of PPP (t=0, t=1, t=2) make sense, but...
- **What to make of $t > 2$ effects?**

Interpreting Medium-Term Effects

- The immediate effect of PPP (t=0, t=1, t=2) make sense, but...
- **What to make of $t > 2$ effects?**
- Are establishments who get PPP more likely to participate in other programs?
- If so, some of the medium-term effects may be due to participating in more programs
  - I am controlling for EIDL participation or PPP 2021, plus this was a smaller set of programs
- Is this picking up longer-term avoidance of closures?

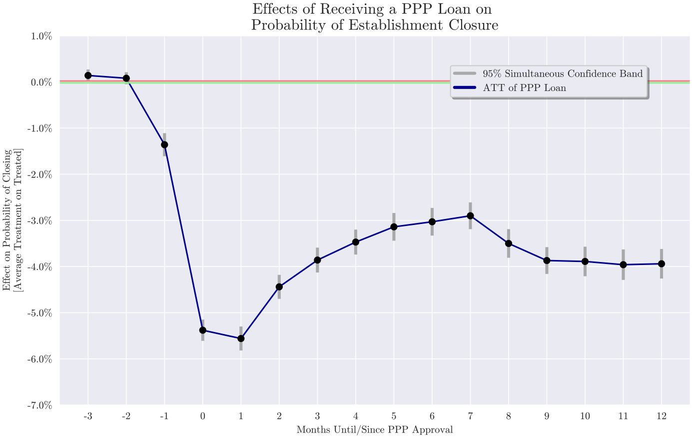
ATT on Probability of Closures

- **5.6% decrease in probability of closure in first month**
- **Effect falls initially but still statistically significant 12 months after PPP approval**
- 3.9% decline in closure probability 12 months out



Effect on Closures

- For those businesses open in 2019, about 15% reported being closed in September 2021.
- Estimates suggest without PPP **16.7% of businesses would have closed**
  - **11% increase in permanent business closures without PPP**



Comparison to Previous Results

- Full sample estimates in line with Autor et al (2022)
- Why were previous results relying on size cutoffs so much smaller?
  - Chetty et al (2020); Autor et al (2020); Hubbard and Strain (2020)

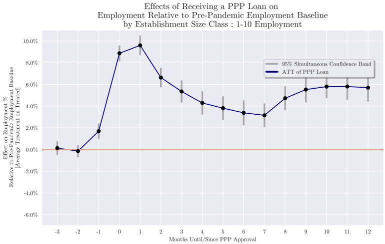
CES Hours

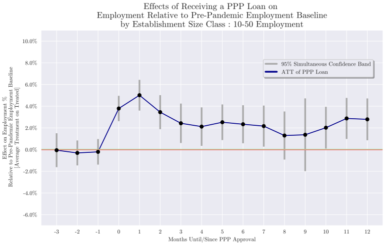
Alternative Results - By Size

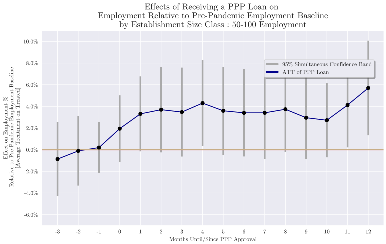
- Biggest employment effects are for smallest size class
- Establishments of size 100+ have an imprecisely estimated null effect

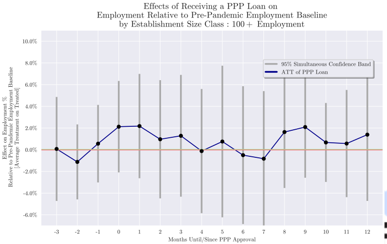
Alternative Results - By Size

- Biggest employment effects are for smallest size class
- Establishments of size 100+ have an imprecisely estimated null effect
-



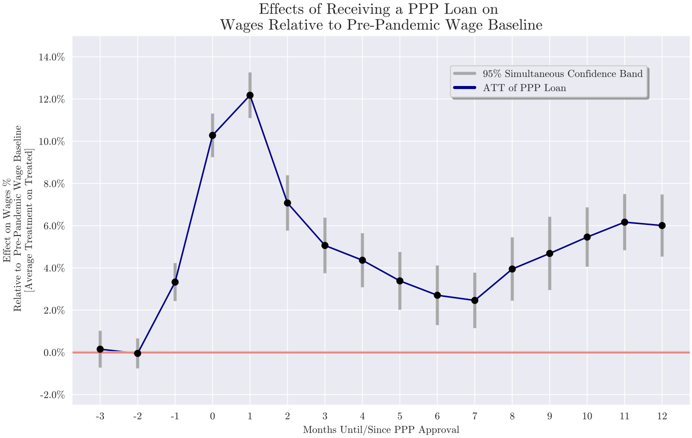






ATT on Wages

- **9.9% increase in wages in first month**
- **Effect falls but still statistically significant 12 months after PPP approval**
- 6% increase in wages 12 months out



Interpreting Money Spent Relative to Outcomes

Month t	ATT_t Employment % (1)	ATT_t Wages % (2)	Retained due to PPP Employee Months (3)	Retained due to PPP Monthly Wages ($) (4)
ATT_0	7.24	10.28	3,234,634	19,641,710,192
ATT_1	8.11	12.18	3,626,237	23,276,331,554
ATT_2	5.63	7.08	2,517,038	13,522,847,969
ATT_3	4.45	5.06	1,989,255	9,673,784,520
ATT_4	3.62	4.36	1,618,702	8,337,439,536
ATT_5	3.41	3.38	1,524,265	6,466,518,334
ATT_6	3.01	2.7	1,343,794	5,165,913,697
ATT_7	2.82	2.46	1,262,541	4,700,333,551
ATT_8	3.71	3.95	1,657,407	7,540,448,892
ATT_9	4.23	4.68	1,892,717	8,953,817,193
ATT_{10}	4.59	5.46	2,050,797	10,435,225,941
ATT_{11}	4.94	6.17	2,210,040	11,783,229,541
ATT_{12}	4.9	6.01	2,188,050	11,478,576,523

Columns (1) and (2) are estimates previously shown in figures

Interpreting Money Spent Relative to Outcomes

Month t	ATT_t Employment % (1)	Wages % (2)	Retained due to PPP Employee Months (3)	Monthly Wages ($) (4)
ATT_0	7.24	10.28	3,234,634	19,641,710,192
ATT_1	8.11	12.18	3,626,237	23,276,331,554
ATT_2	5.63	7.08	2,517,038	13,522,847,969
ATT_3	4.45	5.06	1,989,255	9,673,784,520
ATT_4	3.62	4.36	1,618,702	8,337,439,536
ATT_5	3.41	3.38	1,524,265	6,466,518,334
ATT_6	3.01	2.7	1,343,794	5,165,913,697
ATT_7	2.82	2.46	1,262,541	4,700,333,551
ATT_8	3.71	3.95	1,657,407	7,540,448,892
ATT_9	4.23	4.68	1,892,717	8,953,817,193
ATT_{10}	4.59	5.46	2,050,797	10,435,225,941
ATT_{11}	4.94	6.17	2,210,040	11,783,229,541
ATT_{12}	4.9	6.01	2,188,050	11,478,576,523

Columns (1) and (2) are estimates previously shown in figures
Columns (3) and (4) are solved from
(3) = (1) x 45million / 100
(4) = (2) x 191billion / 100
where 45 million is the 2019 monthly employment at establishments receiving PPP

and $191 billion is the 2019 monthly wages at establishments receiving PPP

$ of PPP Relative to Jobs Saved After 12 Months

Total Retained due to PPP		$ of PPP Loans per...	
Employee Months	Monthly Wages ($)	Employee-Month Retained	Dollar-Wage Retained
(3)	(4)	(5)	(6)
27,115,477	140,976,177,444	$16,199	$3.12

Columns (5) and (6) are
(5) = **439billion** / (3)
(6) = **439billion** / (4)
where **$439 billion** is the total matched $ of approved PPP loans

$ of PPP Relative to Jobs Saved After 12 Months

Total Retained due to PPP		$ of PPP Loans per...	
Employee Months (3)	Monthly Wages ($) (4)	Employee-Month Retained (5)	Dollar-Wage Retained (6)
27,115,477	140,976,177,444	$16,199	$3.12

Columns (5) and (6) are
(5) = **439billion** / (3)
(6) = **439billion** / (4)
where **$439 billion** is the total matched $ of approved PPP loans

- Can invert (6) to get percent of PPP dollars going to wage retention: **32.1%**

$ of PPP Relative to Jobs Saved After 12 Months

Total Retained due to PPP		$ of PPP Loans per...	
Employee Months	Monthly Wages ($)	Employee-Month Retained	Dollar-Wage Retained
(3)	(4)	(5)	(6)
27,115,477	140,976,177,444	$16,199	$3.12

Columns (5) and (6) are
(5) = **439billion** / (3)
(6) = **439billion** / (4)
where **$439 billion** is the total matched $ of approved PPP loans

- Can invert (6) to get percent of PPP dollars going to wage retention: **32.1%**
- Boushey and Glenn (2012) estimate that the cost to an employer of turnover is about 20% of lost employee salary
- Difficult to put $ value on keeping businesses from closing
- Long-term costs to an employee of becoming unemployed
- Employee would move to unemployment insurance if they had lost their job - that cost is saved by being retained
- Ignores general equilibrium effects - what happens to new businesses?

Conclusion

- Presented credible estimation strategy that reconciles prior research results
- PPP loans lead to improvement in employment, ability to stay open, and wages for up to 12 months post-PPP approval
- 12 months post-PPP, establishments are 3.9% less likely to have closed
- PPP loans measure to $16,199 per employee-month retained after 12 months
- PPP loans measure to $3.12 per dollar of wage retained after 12 months
- Lowest wage establishments, high poverty areas, smallest establishments, and youngest establishments show the lowest cost of retaining employment and wages per PPP $
    - These are average effects, not marginal effects, so some caution should be given to interpreting the estimates
- Noise in matching - dampens effects
- What has happened to new businesses?

Michael Dalton
Research Economist
ERPDS
www.bls.gov
202-691-7403
dalton.michael@bls.gov

Controls Included

- Employment Growth from 2018 to 2019
- Sector
- Size x multiunit status
- Monthly closure status for each calendar month in 2019 Bins for age
- Bins for wage class
- Franchise dummy
- Urban classification
- Receipt of EIDL Grant or Loan
- PPP eligibility status

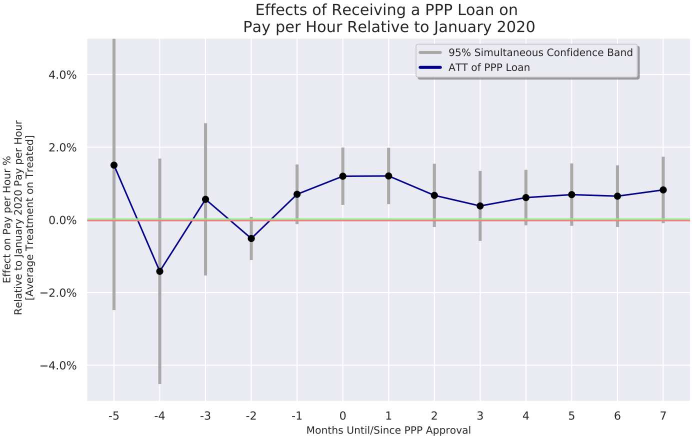
Return

Pay per Hour in CES

- Make estimate of "pay per hour"

Pay per Hour in CES

- Make estimate of "pay per hour"
- **1.2% increase in pay per hour in first month**
- **Overall ATT of .73%**



Return

Estimation Methodology

Semi-parametric estimation of an ATT for each

- month t and
- for each group, defined by month of PPP receipt, p
- $PPP_p = 1$ for every month t for establishments receiving PPP in month p, zero otherwise
- $D_t = 1$ for every month where $t \geq p$ and $PPP_p = 1$
- Y_t is the outcome variable at month t
- δ is the 1 month anticipation term
- X are the time invariant control variables

Estimation Methodology

$$ATT_{p,t} =$$

$$\mathbb{E}\left[\overbrace{\left(\frac{PPP_p}{\mathbb{E}(PPP_p)} - \frac{\frac{Prob_{p,t+\delta}(X)(1-D_{t+\delta})}{1-Prob_{p,t+\delta}(X)}}{\mathbb{E}\left[\frac{Prob_{p,t+\delta}(X)(1-D_{t+\delta})}{1-Prob_{p,t+\delta}(X)}\right]} \right)}^{\text{Inverse Probability Weight}} \overbrace{(Y_t - Y_{p-\delta-1} - c_{p,t,\delta}(X))}^{\text{Outcome Regression}} \right],$$

Estimation Methodology

$$ATT_{p,t} = \mathbb{E}\left[\overbrace{\left(\frac{PPP_p}{\mathbb{E}(PPP_p)} - \frac{\frac{Prob_{p,t+\delta}(X)(1-D_{t+\delta})}{1-Prob_{p,t+\delta}(X)}}{\mathbb{E}[\frac{Prob_{p,t+\delta}(X)(1-D_{t+\delta})}{1-Prob_{p,t+\delta}(X)}]}\right)}^{\text{Inverse Probability Weight}} \overbrace{(Y_t - Y_{p-\delta-1} - c_{p,t,\delta}(X))}^{\text{Outcome Regression}}\right],$$

$$\text{where} \quad \text{Prob}_{p,t+\delta}(X) = \mathbb{E}(PPP_p | X, PPP_p + (1 - D_{t+\delta}) = 1)$$

Inverse Probability Weight is basically a matching score estimator (Abadie (2005))

Higher weight goes to control group observations that have X similar to employers receiving PPP in month p

Estimation Methodology

$$ATT_{p,t} =$$

$$\mathbb{E}\left[\overbrace{\left(\frac{PPP_p}{\mathbb{E}(PPP_p)} - \frac{\frac{Prob_{p,t+\delta}(X)(1-D_{t+\delta})}{1-Prob_{p,t+\delta}(X)}}{\mathbb{E}[\frac{Prob_{p,t+\delta}(X)(1-D_{t+\delta})}{1-Prob_{p,t+\delta}(X)}]}\right)}^{\text{Inverse Probability Weight}} \overbrace{(Y_t - Y_{p-\delta-1} - c_{p,t,\delta}(X))}^{\text{Outcome Regression}}\right],$$

$$\text{where} \quad c_{p,t,\delta}(X) = \mathbb{E}[Y_t - Y_{p-\delta-1} | X, D_{t+\delta} + PPP_p = 0]$$

Outcome Regressions predict are similar to diff-in-diff (Heckman et al (1998))

Return

Verifying Record Linking Using BRS

- BRS is online survey of 160,000 employers conducted July 2020 - September 2020
- Asked about receiving *any* loan/grant from government

Verifying Record Linking Using BRS

- BRS is online survey of 160,000 employers conducted July 2020 - September 2020
- Asked about receiving *any* loan/grant from government
- **Takeaway: High correlation between PPP match and reporting received loan or grant. Good news.**

Match Type	Geography	Fuzzy Match Score	Number of BRS Respondents	**Percent Reporting in BRS Received Loan/Grant of Any Type**
Exact Address Match	City	Exact	45714	**97.7%**
Address Match	City	-	11024	**94.6%**
Exact Match	City	Exact	6485	**97.0%**
Fuzzy Match	City	High	341	**92.8%**
Fuzzy Match	City	Medium	471	**91.4%**
Fuzzy Match	City	Low	531	**86.4%**
Fuzzy Match	City	Lowest	235	**80.0%**
Exact Match	County	Exact	1126	**96.4%**
Fuzzy Match	County	High	64	**95.3%**
Fuzzy Match	County	Medium	58	**91.4%**
Exact Match	State	Exact	997	**92.3%**
BRS Respondents with no PPP Match			95338	39.0%

Ratio of Loan Amount to 2019 Wages

Less noisy measure: Take ratio of PPP Loan Amount to Total Wages in 2019 in QCEW

Ratio of Loan Amount to 2019 Wages

Less noisy measure: Take ratio of PPP Loan Amount to Total Wages in 2019 in QCEW

- Ratio of .19 = 10 weeks of salary
- Some variation, but interquartile range stays close to .19

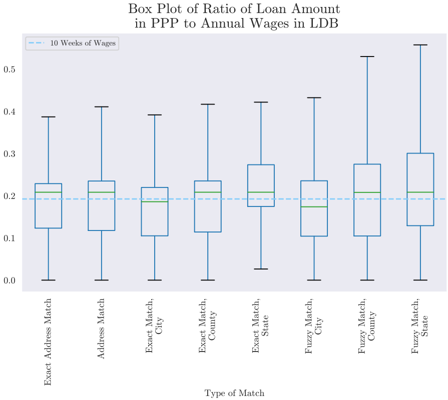
Plot for Employment

Ratio of Loan Amount to 2019 Wages

Less noisy measure: Take ratio of PPP Loan Amount to Total Wages in 2019 in QCEW

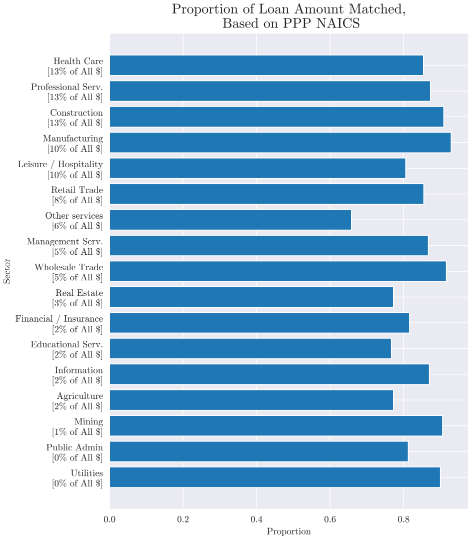
- Ratio of .19 = 10 weeks of salary
- Some variation, but interquartile range stays close to .19

Plot for Employment



Match Rate by Reported Sector on PPP Application

Worst match rate for Educational Services - but not that much variation



Box plot of Reported Retained Jobs to Employment

Take ratio of Retained Jobs to Average Employment in 2019 in QCEW

Box plot of Reported Retained Jobs to Employment

Take ratio of Retained Jobs to Average Employment in 2019 in QCEW

- Ratio of 1 = Expected
- Some variation, but interquartile range stays close to 1

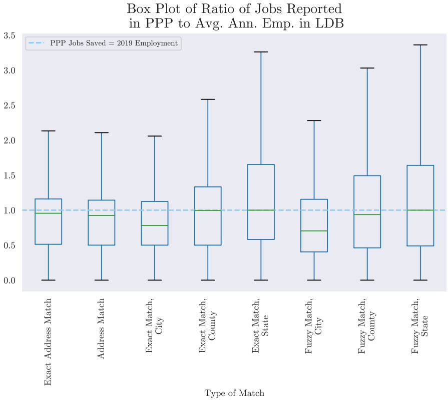
Return

Box plot of Reported Retained Jobs to Employment

Take ratio of Retained Jobs to Average Employment in 2019 in QCEW

- Ratio of 1 = Expected
- Some variation, but interquartile range stays close to 1

Return



Record Linking

Match looks good!
Let's carry on with the real results.

Return