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The Paycheck Protection Program and Unemployment During the COVID-19 Recession

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Abstract

The Paycheck Protection Program (PPP) in the United States was created to help small businesses maintain payrolls in the wake of the COVID-19 recession. Using PPP loan microdata and local area labor force statistics, I find that PPP loans are positively correlated with the year-over-year change in the unemployment rate, suggesting that PPP effectively follows contractions in the economy and is targeted well.

1. INTRODUCTION

The ongoing worldwide pandemic of coronavirus disease 2019 (COVID-19) has caused immense harm and suffering for billions of people around the globe. In the United States of America, this pandemic and governments' efforts to slow the spread of the virus has caused both demand and supply shocks resulting in the most severe recession that the U.S. has faced since the Great Depression of the 1930s (Dilger et al., 2020).

It's under this grim picture that the federal government of the United States has engaged in extraordinary measures to deliver fiscal relief to Americans and pull the U.S. economy back from the brink. One of the programs initiated by the federal government in response to this recession has been the approximately $650 billion Paycheck Protection Program (PPP). This program allowed small and medium sized firms to receive low-interest loans from banks to cover up to 250% of monthly pre-recession payrolls if the firm could attest that it was substantially affected by the pandemic. These loans also had the potential to be forgiven altogether if firms met a set of criteria laid out by the federal government (Cowley & Flitter, 2020).

In this paper, I investigate the effectiveness of the Paycheck Protection Program at the metropolitan area-level by examining whether the loans issued in this program were effectively targeted to address the losses in payrolls due to the pandemic and resulting recession. This was done by using PPP loan-level data from the U.S. Small Business Administration (SBA) and the U.S. Department of the Treasury (hereafter referred to as Treasury) as well as local area unemployment statistics from the U.S. Bureau of Labor Statistics (BLS).

This research contributes to a growing literature studying the United States' response to the COVID-19 recession. Prior research on the PPP primarily uses administrative payroll microdata from private payroll software companies as a high-frequency measure of unemployment (Autor et al., 2020; Chetty et al., 2020; Granja et al., 2020). Other literature such as Bartik et al. (2020b) uses proprietary survey data of employers to estimate the effects of the PPP. All these studies largely seek to establish causal relationships between the PPP and firms' payrolls. This paper instead seeks to investigate how effectively the program targeted small businesses in need. The question of targeting is the primary novel contribution that this paper makes.

The paper proceeds as follows. The next section describes the history of the COVID-19 pandemic, the authorizing legislation/design of the Paycheck Protection Program, as well as previous research on the PPP. I then describe the dataset that I used for this research. In Section 4, I explain the methodology behind this research and why I aimed to examine correlations in these data rather than prove causation. In Section 5, I present results on the degree to which metropolitan areas received PPP loans as well as associations from ordinary least squares regression analyses. Section 6 concludes and discusses the implications of my results for future research and economic policymaking.

2. LITERATURE REVIEW

The Coronavirus Aid, Relief, and Economic Security Act, or CARES Act, is the United States federal government's primary legislation to-date for combatting the economic fallout from the ongoing COVID-19 pandemic. The bill was signed into law on March 27, 2020 and is the largest economic stimulus bill in American history amounting to over 10% of the country's gross domestic product (GDP) at passage (Digler et al., 2020).

As the pandemic reached a high degree of severity in the U.S. in March 2020, many states rushed to implement stay-at-home orders in order to curb the spread of SARS-CoV-2, the virus that causes COVID-19. While previously the federal government had implemented travel restrictions on foreign countries with significant outbreaks, these stay-at-home orders constituted a domestic shutdown of all non-essential activities with the goal of reducing SARS-CoV-2 transmission. The first statewide stay-at-home order was issued in California on March 19, followed swiftly in 20 other states within the span of a week. By April 7, 43 states and the District of Columbia had issued state-at-home orders, essentially putting their entire economies on pause (Moreland et al., 2020).

Foreseeing a sharp drop in economic activity and a subsequent tidal wave of job losses, the U.S. Congress acted to create a new program that would allow financial intermediaries such as banks and credit unions to offer forgivable loans to businesses with fewer than 500 employees[1] on the condition that the funds would be used to retain employees on firm's payrolls. This scheme, the Paycheck Protection Program, began on April 3 and was quickly exhausted of funds within 2 weeks (on April 16), demonstrating the enormity of demand caused by the COVID-19 economic contraction. A second round of PPP funding was authorized shortly after the program was exhausted. This second round began April 27 and continued until its exhaustion on August 8 (Cowley & Flitter, 2020). A third round of PPP funding was authorized months later through the Consolidated Appropriations Act of 2021 (Probasco, 2021). For the purposes of this paper, the third round of PPP funding was not analyzed.

There remains rather limited research on the PPP and its effects due to its relative novelty and the length of time since passage of the program. For instance, since BLS does not publish high-frequency unemployment statistics, it is difficult to ascertain a causal link between the program's disbursement of funds to affected firms and unemployment rates. Nevertheless,

[1] The food services sector was exempt from the 500-employee cap for receiving PPP loans due to the sector's prevalence of franchises and other distributed business entities.

existing research primarily draws on data from Treasury and SBA about the PPP loans that were issued as well as with other non-governmental data to examine the program's effects.

A new paper by Autor et al. (2020) uses administrative payroll microdata to examine the effects of the PPP on eligible versus ineligible firms. The paper estimates that the, "PPP boosted employment at eligible firms by 2 to 4.5 percent" and that the program, "increased aggregate U.S. employment by 1.4 million to 3.2 million jobs through the first week of June 2020". Nevertheless, while these data seem to indicate a causal relationship between the PPP and aggregate employment, the authors are sure to highlight the limitations of this approach. One primary limitation is that data on the effectiveness of the PPP involves examining firms that elected to apply for the loans in the first place. The result is a high degree of endogeneity that could cause the effects of the PPP to be overstated.

This research by Autor et al. aligns with earlier research conducted by the Harvard economist Raj Chetty and Opportunity Insights. These authors compared firms below and above the 500-employee eligibility cap on the PPP to detect the effect of the program on employment. This methodology was also used by Autor et al. in their research. However, unlike the more recent research by Autor et al., Chetty et al. found very little difference on small business employment as a result of the PPP (Chetty et al., 2020).

These findings by Chetty et al. were compounded by additionally similar research by Granja et al. (2020) who investigated the effects of the PPP using administrative payroll microdata paired with banking institutions' call reports in order to determine how financial intermediaries influenced the program's implementation and effect on unemployment. These authors found in the first round of the PPP, "limited evidence that PPP funding has significant effects on employment or local economic activity during the first month of the program" and that in later months, more evidence was found but that large effects could still be ruled out.

Another study by Bartik et al. (2020a) also sought to examine aggregated PPP loan-level data directly and its effects on employment by using state-level variations in receiving PPP loans. These authors found that states with higher PPP loans granted were associated with less unemployment. However, these authors don't attempt to assert causality as their regression models are relatively simple and don't factor in various confounding variables.

Each of these major previous studies seems to find a causal relationship between the PPP and employment, largely at the firm-level. However, there remains gaps in these literature about the effectiveness at which the PPP targeted firms in need. Bartik et al. (2020b) sought to investigate this question with their paper that uses proprietary survey data of small businesses. These authors found advantages and disadvantages with the setup of the PPP as a fiscal relief measure for small businesses since it relies on existing banking relationships.

Using the survey data that they collected, these authors found that the efficacy of the PPP was mixed. "Firms that were impacted by COVID-19 more were not significantly more likely to receive a loan" and that, "firms with connections to the banks were more likely to receive loans, even though the loans do not seem more effective for that group" (Bartik et al., 2020b). These results from Bartik et al. (2020b) are a fascinating result, however, their results are limited to the firm-level. There remains a gap in the literature for an analysis of the effectiveness of the PPP at the aggregated metropolitan area-level.

3. DATA

The data that I rely on for this study comes from two main sources. The first is PPP loan-level data published by Treasury and SBA. These data were bifurcated and published state-by-state for loans under $150,000 and all together for loans over $150,000. Treasury and SBA have stated that these data were split in the manner that they were so as to allow greater disclosure of which firms received the loans over $150,000. Since the loans over $150,000 are named to individual firms, they do not have exact loan amounts published and instead each list a range of dollars that the loan falls into (U.S. Small Business Administration, 2020).

Due to these limitations, for the purposes of this study, the volume of loans to medium-sized businesses (loans over $150,000) were set aside in favor of the volume of loans to small-sized businesses (loans under $150,000), the volume of loans regardless of amount, and the amount of money loaned to small-sized businesses in loans of $150,000 or less.

These loan-level data are published alongside various information about the firms receiving these loans as well as certain demographic characteristics of the firms' principals. For the purposes of this study, I matched the ZIP code of each loan recipient with its corresponding metropolitan statistical area (MSA) using HUD-USPS ZIP Code Crosswalk files[2] (U.S. Department of Housing and Urban Development Office of Policy Development and Research, 2020). Then, I aggregated the volume of loans issued to each MSA and compiled statistics of the volume of loans issued to small-sized businesses per MSA, the total volume of loans issued per MSA, and the amount of money loaned to small-sized businesses per MSA.

[2] Metropolitan statistical areas do not comprise the entirety of the area of the United States. Some loans issued in the PPP were issued to firms in ZIP codes outside of MSAs and therefore were excluded from my analysis.

After aggregating the three PPP loan statistics for each MSA, my final step was to transform each variable to per capita terms. I did this by dividing all three of the PPP loan statistics for MSAs by the 2019 population estimate for each MSA as determined by the U.S. Census Bureau's 2019 American Community Survey (ACS). These PPP loan statistics were transformed to per capita terms in order to control for the effects of population on PPP loans received and unemployment rates for particular MSAs.

The second dataset that I assembled for this research came from the Local Area Unemployment Statistics program of the Bureau of Labor Statistics (BLS). This program utilizes the Current Population Survey (CPS), a monthly survey administered by the Census Bureau, as well as other survey estimates and models to calculate localized labor force statistics for the United States (U.S. Bureau of Labor Statistics, 2020). CPS asks households about various activities, including the employment status of each member of a particular household (U.S. Census Bureau, 2019). Using BLS data, I collected unemployment rates for each MSA for the months of April, May, June, and July of 2020 as well as of those same months in 2019.[3] From there, I calculated the year-over-year change in the unemployment rate for each MSA.

The unemployment rate statistics that I collected for this study were non-seasonally adjusted. These statistics were used intentionally as the pandemic has caused seasonally adjusted labor force statistics to be skewed. This is because the traditional seasonal patterns that the labor force experiences did not occur in the same way this year (Stats NZ, 2020; U.S. Census Bureau, 2020).

[3] I chose to exclude unemployment statistics beyond the month of July since many of the other programs/funds in the CARES Act expired in July 2020 and therefore began to affect macroeconomic indicators in a significant enough way to warrant their exclusion (Hansen, 2020).

I chose these two data sets for my research as they're well suited to addressing my research question posed in the introductory paragraphs of this paper. Aggregated PPP loan-level data offer direct insights into the geographic targeting of the PPP. As for non-seasonally adjusted statistics of the year-over-year change in the unemployment rate for MSAs, these data are useful as they provide evidence as to the extent of the economic shock in particular MSAs and how well PPP loans target these areas.

The unit of analysis in this project is the metropolitan statistical area. Therefore, there are 383 observations in this data set, one for each MSA, except for the Poughkeepsie–Newburgh–Middletown, NY MSA.[4] The data set I assembled is cross-sectional data and features 4 dependent variables of interest: change in the unemployment rate for April, May, June, and July; and 3 independent variables of interest: volume of loans issued to small-sized businesses, volume of loans issued to all business, and total amount of money loaned to small-sized businesses.

Summary statistics for these data are available in Table 1. Notably, the unemployment summary statistics reflect that there has been a dramatic increase in unemployment year-over-year. Additionally, the amount of money loaned to small-sized businesses per capita has a large range (1001.520) that suggests that even when controlling for population, certain MSAs received dramatically more PPP monies than others. Also, of note is that for the amount of money loaned to small-sized businesses per capita, the mean (396.594) and median (392.976) are quite close but that they suggest that the distribution of monies loaned skews slightly to the right.

[4] Metropolitan statistical areas are defined and delineated by the U.S. Office of Management and Budget (OMB). In 2013, the Poughkeepsie–Newburgh–Middletown, NY MSA was removed by OMB and merged into the New York-Newark-Jersey City, NY-NJ-PA MSA. This decision was later reversed by OMB in 2018. Seemingly due to this decision, the Local Area Unemployment Statistics program does not publish data for the Poughkeepsie MSA, even since the MSA was reinstated by OMB (U.S. Office of Management and Budget, 2018). Due to this lack of data, I removed this MSA from my dataset.

It is important to note that these data have limitations in that PPP loan data is entirely self-reported and various errors were made by lenders and recipients in these public disclosures. Additionally, newspaper and watchdog reports suggest that firms that received PPP loans may not have contributed monies towards payrolls as the program was intended (Whoriskey, 2020). This is likely to cause some issues in the use of these data for this analysis.

4. METHODOLOGY

In this section I present the regression equation that I use to answer my research question about the targeting of the PPP. The method used here is an ordinary least squares (OLS) method for a linear regression model. The equation I am estimating is $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon$ where Y is the year-over-year change in a non-seasonally adjusted unemployment rate variable, X_1 is a PPP loan variable, and X_2, X_3 and X_4 are regional dummy variables.

These statistical estimates that my regression models make will not be used to interpret causality. Since this paper seeks to investigate the targeting of PPP loans, there is no need to prove a causal relationship between PPP loans and unemployment rates. Rather, we are interested in the correlations this research suggests and the signs on the estimators. Furthermore, even if I wished to prove causal inference in this paper, the regression models presented here are not sophisticated enough to capture the wide array of complex macroeconomic indicators that influence the unemployment rate and would likely be subject to omitted variable bias. Additionally, if I was attempting to prove causality in this analysis, my research would likely be subject to selection bias as the group of firms that receive PPP loans are not randomized and because my methodology does not include the use of a control group.

5. RESULTS

Since this research utilizes 4 dependent variables, 3 independent variables of interest, and a set of dummy variables, there will be 24 regression models presented in tables at the end of this paper. Table 2 contains 6 regressions (two for each independent variable of interest with the dummy variables on-and-off) for the year-over-year change in the non-seasonally adjusted unemployment rate for April 2020. Table 3 contains the same for May 2020, Table 4 for June 2020, and Table 5 for July 2020.

Evaluating the various regressions included in Tables 2 – 5 requires us to not simply examine each table in a vacuum and instead compare the months to one another. For instance, Table 2 shows the only instances in which the sign on the coefficient for the independent variable isn't positive (the coefficients for volume of PPP loans to small-sized businesses per capita and for volume of PPP loans per capita).

For April 2020, when examining the sign on the coefficient for volume of PPP loans to small-sized businesses per capita, we can determine that every additional loan per capita was associated with a decrease in the year-over-year change in the unemployment rate for that month. If I were seeking to examine and prove a causal relationship between the PPP and change in the unemployment rate, this result would suggest that the program is effective at reducing unemployment. However, since I am unable to truly prove a causal relationship between these parameters using this methodology, this paper does not assert a causal relationship between these variables and instead focuses on the correlations between PPP loans and the change in the unemployment rate.

When examining these correlations for April 2020, it appears that the PPP drove additional loans to local areas that were experiencing a decrease in the year-over-year unemployment rate. This suggests that the program was not well targeted as we would expect additional PPP loans to be flowing to areas experiencing the largest economic shock. However, this is not necessarily a good way of analyzing the program as whole. When examining the PPP timeline, we know that the program was only just off the ground when the April 2020 CPS was conducted.

A more effective result would perhaps be found by examining the regressions in Table 3 for May 2020. Here, we see evidence that suggests that PPP loans were well targeted as the volume of loans issued and the amount of monies issued are all positively correlated with the year-over-year change in the unemployment rate, suggesting that loans were flowing to areas that needed them. This correlation is also witnessed in Tables 4 and 5. I consider these results to have greater explanatory power than the results from April 2020 as by the time that these surveys were being conducted, the PPP had been operational for long enough for us to begin seeing the fuller picture of the program's implementation.

Despite all the signs appearing positive for the coefficients on the independent variables in Tables 3 – 5, there does seem to be a difference between the models that include dummy variables to control for regional effects. For instance, May and June 2020 each show fairly large differences in the coefficient estimates between models that do and do not account for regional effects. But then, when we examine Table 5, we see that the disparities largely disappear. We may be able to conclude that these differences are the result of the pandemic itself and that as the first wave of the COVID-19 pandemic began to subside in the summer months, regional effects began to play less of a factor as those MSAs that were hardest hit in the beginning of the pandemic began to equalize with the rest of the country.

Of course, it is worth reiterating that these results do not come close to proving a causal relationship between the PPP and unemployment rates. But this was never the intention of this paper. Rather, these results suggest that PPP loans tended to follow areas that were experiencing spikes in unemployment, even when accounting for population differences between MSAs and regional effects.

6. CONCLUSIONS

As the pandemic rages on and Congress mulls President Joe Biden's American Rescue Plan, it seems incumbent on the economics profession and economic policymakers to examine whether the Paycheck Protection Program accomplished what it set out to do. As the program's authors believed, the point of PPP was to support payrolls and prevent small businesses from going bankrupt (Whoriskey, 2020).

In this paper, I examined the existing research on the PPP and discovered that while most previous research has found causal links between firm-level employment and the PPP, few papers have sought to address the question of the program's targeting and effectiveness. Using PPP microdata from SBA and Treasury along with labor force statistics from BLS, I was able to find that PPP loans are associated with increases in the year-over-year change in the unemployment rate at the MSA level. These results suggest that the PPP did hit the mark in following unemployment and helping those areas that were most impacted by the labor market shock caused by COVID-19.

However, this is not to suggest that this research is definitive. Various limitations exist with the approach that I undertook, most notably my inability to prove a causal link. But even beyond that, PPP loan microdata is notoriously error-filled and the lack of a higher-frequency unemployment statistic in this analysis limits my ability to confidently assert that PPP loans were following where the pandemic was worst.

The implications however of what I did find seem to be significant. If the PPP does in fact follow contractions in the economy, then it seems worthwhile for Congress to refill the coffers for this program. However, there are still limitations associated with the program as it structured. As Granja et al. (2020) found, existing relationships with financial institutions are a significant predictor of which firms will seek out and receive PPP loans. Economic policymakers might well be served by instituting more expansive and higher frequency data collection for this program as well as perhaps transitioning it to a grant provided directly by SBA. Of course, the pandemic has continued to prove that it is difficult to switch gears quickly while the country is in an economic crisis. Therefore, restructuring the program now may be ill-advised for policymakers.

As the pandemic continues and we get more and more removed from the first two rounds of PPP, I hope that economists will continue to examine this program and its effectiveness. Perhaps if Congress wanted to examine this question in depth, it could authorize SBA to run a randomized control trial of the PPP alongside a group of economists. More realistically though, I think additional research in this area should seek to gather and examine high-frequency local economic indicators alongside survey data of PPP loan recipients as well as of those firms who have been denied PPP loans to determine whether PPP loans are actually going to those firms that are hardest hit.

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TABLE 1: DESCRIPTIVE STATISTICS

	Number of observations	Mean	Standard deviation	Minimum	Maximum
Year-over-year change in the unemployment rate, April 2020	383	10.81	4.019	4.000	32.100
Year-over-year change in the unemployment rate, May 2020	383	8.697	3.536	1.000	31.500
Year-over-year change in the unemployment rate, June 2020	383	5.994	3.025	-0.200	30.000
Year-over-year change in the unemployment rate, July 2020	383	5.238	2.439	0.100	19.500
Volume of PPP loans to small-sized businesses per capita	383	0.012	0.004	0.002	0.028
Volume of PPP loans per capita	383	0.014	0.004	0.002	0.032
Amount of money loaned to small-sized businesses per capita	383	396.594	129.879	8.560	1010.080
Northeast region:[5] 1=in, 0=not in	383	0.131	0.337	0.000	1.000
Midwest region: 1=in, 0=not in	383	0.251	0.434	0.000	1.000
South region: 1=in, 0=not in	383	0.415	0.493	0.000	1.000

SOURCE: Local Area Unemployment Statistics, April – July 2019 and April – July 2020; Paycheck Protection Program Loan Level Data, August 2020; American Community Survey, 2019

[5] These regional dummy variables correspond with the regions defined by the Census Bureau (U.S. Census Bureau, 2018). For MSAs that are in states that are in different census regions, both regional dummy variables are activated.

TABLE 2: ESTIMATES OF THE EFFECT OF PPP LOANS ON THE YEAR-OVER-YEAR CHANGE IN THE UNEMPLOYMENT RATE, APRIL 2020

	(1)	(2)	(3)	(4)	(5)	(6)
Volume of PPP loans to small sized businesses per capita	-71.477 (52.039)			-78.201 (50.861)		
Volume of PPP loans per capita		-48.617 (46.519)			-61.304 (45.560)	
Amount of money loaned to small-sized businesses per capita			0.002 (0.002)			0.002 (0.002)
Northeast region: 1=in, 0=not in				1.386* (0.678)	1.397* (0.678)	1.470* (0.682)
Midwest region: 1=in, 0=not in				1.615** (0.550)	1.622** (0.551)	1.674** (0.552)
South region: 1=in, 0=not in				-0.576 (0.499)	-0.585 (0.500)	-0.457 (0.506)
Adjusted R-square	0.002	0.0005	0.009	0.051	0.049	0.048
Number of observations	383	383	383	383	383	383

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

TABLE 3: ESTIMATES OF THE EFFECT OF PPP LOANS ON THE YEAR-OVER-YEAR CHANGE IN THE UNEMPLOYMENT RATE, MAY 2020

	(1)	(2)	(3)	(4)	(5)	(6)
Volume of PPP loans to small sized businesses per capita	14.354 (45.896)			7.285 (45.238)		
Volume of PPP loans per capita		29.211 (40.963)			17.643 (40.484)	
Amount of money loaned to small-sized businesses per capita			0.003* (0.001)			0.003* (0.001)
Northeast region: 1=in, 0=not in				0.912 (0.603)	0.912 (0.603)	1.022 (0.602)
Midwest region: 1=in, 0=not in				0.815 (0.489)	0.817 (0.489)	0.879 (0.488)
South region: 1=in, 0=not in				-0.767 (0.444)	-0.755 (0.444)	-0.651 (0.445)
Adjusted R-square	-0.002	-0.001	0.009	0.030	0.031	0.040
Number of observations	383	383	383	383	383	383

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

TABLE 4: ESTIMATES OF THE EFFECT OF PPP LOANS ON THE YEAR-OVER-YEAR CHANGE IN THE UNEMPLOYMENT RATE, JUNE 2020

	(1)	(2)	(3)	(4)	(5)	(6)
Volume of PPP loans to small sized businesses per capita	26.102 (39.243)			10.713 (34.648)		
Volume of PPP loans per capita		41.796 (35.000)			17.546 (31.005)	
Amount of money loaned to small-sized businesses per capita			0.002 (0.001)			0.002 (0.001)
Northeast region: 1=in, 0=not in				2.685*** (0.462)	2.684*** (0.461)	2.760*** (0.462)
Midwest region: 1=in, 0=not in				0.238 (0.375)	0.239 (0.375)	0.281 (0.374)
South region: 1=in, 0=not in				-1.756*** (0.340)	-1.746*** (0.340)	-1.679*** (0.341)
Adjusted R-square	-0.002	0.001	0.007	0.223	0.223	0.229
Number of observations	383	383	383	383	383	383

* p ≤ 0.05, ** p ≤ 0.01, *** p ≤ 0.001

TABLE 5: ESTIMATES OF THE EFFECT OF PPP LOANS ON THE YEAR-OVER-YEAR CHANGE IN THE UNEMPLOYMENT RATE, JULY 2020

	(1)	(2)	(3)	(4)	(5)	(6)
Volume of PPP loans to small sized businesses per capita	59.053 (31.517)			50.403 (26.947)		
Volume of PPP loans per capita		62.111* (28.094)			49.543* (24.098)	
Amount of money loaned to small-sized businesses per capita			0.002* (0.001)			0.002** (0.001)
Northeast region: 1=in, 0=not in				2.507*** (0.359)	2.501*** (0.359)	2.586*** (0.359)
Midwest region: 1=in, 0=not in				-1.520*** (0.291)	-1.523*** (0.291)	-1.481*** (0.291)
South region: 1=in, 0=not in				-1.050*** (0.264)	-1.035*** (0.265)	-0.983*** (0.265)
Adjusted R-square	0.007	0.010	0.012	0.277	0.278	0.284
Number of observations	383	383	383	383	383	383

* p ≤ 0.05, ** p ≤ 0.01, *** p ≤ 0.001