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Does Inequality Lead to Credit Growth? Testing the Rajan Hypothesis Using State-Level Data.

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Abstract

This paper uses state-level data to test the Rajan hypothesis, from his book *Fault Lines,* that an increase in inequality can lead to a credit boom. Using dynamic heterogeneous panel estimation methods (i.e. MG, PMG, DFE), we find a significant negative long-run relationship between inequality and real estate lending across U.S. states. In addition, we find evidence indicating that the path of causality runs from inequality to credit.

Keywords: Rajan; inequality; loans; credit; PMG

JEL Classification: E62, H71, R11

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1 Introduction

The recent financial crisis in the U.S. has been attributed to a number of potential factors: failures in financial regulation, inadequate risk management coupled with a lack of an ethical culture in Wall Street, excessive borrowing by households, securitization of mortgages, and easy monetary policy. In his widely-discussed book *Fault Lines*, then IMF Chief Economist Raghuram Rajan (2010) added another potential source: U.S. income inequality. Rajan argued that in the past three decades rising income inequality in the U.S. has led to political pressure for redistribution. U.S. politicians responded by subsidizing housing finance so that low-income households, who otherwise would not have qualified, received improved access to mortgage credit. The resulting lending boom led to a massive run-up in housing prices which eventually led to the banking and financial crisis of 2008-09.

The *Rajan hypothesis* has triggered a lively debate about the role of inequality in the financial crisis. Rajan's critique of government policies explicitly aimed at promoting lending to low-income groups was taken up by the dissenting statement of the Republican members of the U.S. Financial Crisis Inquiry Commission et al. (2011). In response, many Democrats and prominent economists like Paul Krugman (2010) and Daron Acemoglu (2011) are critical of Rajan's argument. To them, rising income inequality in the U.S. had a direct impact on the financial crisis far beyond simply provoking populist meddling.

Although the *Rajan hypothesis* is deeply rooted in the U.S. institutional system, previous attempts to empirically assess his theory – starting with Bordo and Meissner (2012) – have used cross-country OECD data.[1] The *Rajan hypothesis*, however, seeks to the explain the U.S. Financial Crisis, and thus it would be helpful to evaluate its merits with U.S. data. In this paper, we use U.S. state-level income inequality and real estate lending data for 1977 to 2010. Our data covers the buildup of the Crisis and explicitly considers real estate loans, which play an essential role in the narrative of Rajan. In addition, state-level data are

[1] A few authors like Stiglitz (2012), Morelli and Atkinson (2015) and Berisha et al. (2015) have examined the relationship between income inequality and credit using aggregate U.S. data.

uniformly-collected and defined and U.S. states share a common institutional and political background, which reduces potential measurement and omitted variable bias, respectively.

We use mean group, pooled mean group and dynamic fixed effects, all belonging to a class of estimators that separate the long-run equilibria from short-run dynamics. We find a negative long-run relationship between housing credit and inequality across U.S. states. Using Granger causality tests, we show that changes in real estate credit lead to changes in inequality, lending further support to the Rajan hypothesis.

2 Income Inequality, Credit Growth and Crises

While our paper is one of the first to investigate the Rajan hypothesis with U.S. data, there have been a number of cross-country studies, starting with the seminal work by Bordo and Meissner (2012). For organizational purposes, these works can be separated into tests of two hypotheses. First, does credit growth increase the risk of a financial market crisis? Second, does increases in inequality cause higher credit growth?

There is mounting evidence relating growth (or cyclical deviations) of credit and debt to the probability of a crisis (c.f. Kaminsky and Reinhart 1999; Schularick and Taylor 2012; El-Shagi et al. 2013) and its severity (c.f. Claessens et al. 2010; Lane and Milesi-Ferretti 2011; Berkmen et al. 2012) for both advanced and developing economies. Bordo and Meissner (2012) confirm this finding for their sample of 14 OECD countries between 1920 and 2008.

There has been less empirical investigation of the second hypothesis. One of the first tests is Bordo and Meissner (2012). They estimate a dynamic panel model to test the impact of a rise in the top-1 percent income share on real credit growth. Using annual as well as five-year averaged data, they find *no* significant evidence linking rising inequality to credit growth in both the short- and long-run.

Subsequent analysis has examined the robustness of their results to the measurement of the credit variable (Malinen, 2013); first-differences specification (Perugini et al., 2016); cross-sectional dependence (Gu and Huang, 2014); and poolability of the data (Gu and

Huang, 2014).[2] For our purposes, we categorize these criticisms into two main categories: heterogeneity in the slope parameters and distinguishing long- vs. short-run relationships.

Bordo and Meissner (2012) assume that all countries have the same slope parameters for both their short-run (annual) and long-run (5-year) models. Allowing for heterogeneous coefficients, Gu and Huang (2014) find a significant positive relationship between an increase in the top-1 percent and credit growth for Anglo-Saxon countries (i.e. U.S., U.K., Australia), but either no or even a negative relationship for continental Europe (i.e. France, Germany, Denmark). Likewise, Ahlquist and Ansell (2012) find a positive relationship between between income inequality and credit *only* in countries with majority voting systems: U.S., U.K., Australia and Canada. These results indicate that the *Rajan hypothesis* depends critically on the institutional characteristics of a country to the point of getting statistically significant results with different signs.

While Bordo and Meissner (2012) fail to identify a long-run relationship using five-year averages in first differences, subsequent papers instead explicitly model a long-run equilibrium as a levels relationship. For example, Ahlquist and Ansell (2012), Gu and Huang (2012) and Klein (2015) use error-correction methods, which include a long-run levels relationship and first-differenced short-run dynamic terms. They generally find a statistically significant long-run relationship between credit growth and income inequality. Using alternative panel-data approaches, Malinen (2013) and Perugini et al. (2016) also find evidence for a positive long-run relationship in levels..

Our paper uses state-level data to uncover the long-run relationship between income inequality and credit growth. State-level data provides a common institutional and political background whose differences have been found to impact the inequality-credit link. Building on the methodological lessons from the past literature, we use dynamic heterogeneous panel estimation methods (i.e. MG, PMG, DFE) to separate out short-run dynamics from the

[2] An additional critique is the use of a dynamic fixed effects model for the 5-year averages model, which has 17 periods. Judson and Owen (1999) show that the error induced into estimation by instrumenting overcompensates the bias only if T is greater than 30.

long-run relationship. We also apply Granger causality tests to examine the causal direction between inequality and credit.[3]

3 Data and estimation procedure

We use annual data for the 50 U.S. states from 1977 to 2010. Table 1 provides the description, sample statistics, and data sources of each variable. We use the ratios of bank loans (total and real estate) to personal income as our dependent variables. Compiled from the Call Reports, these two measures of credit, especially real estate loans, correspond to the specifics of the Rajan hypothesis.[4] The inequality variables are the share of income earned by the top-1 percent of the population, the Gini coefficient, and the Theil index from Frank et al. (2015). Our economic control variable is the logarithm of real wages and salaries.

Following Pesaran and Smith (1995) and Pesaran et al. (1999), we specify an autoregressive distributed lag (ARDL) of order (p, q) in error-correction form:

$$\begin{aligned}\Delta loan_{i,t} =&\phi_i \left(loan_{i,t-1} - \beta'_{i,1} inequality_{i,t-1} - \beta'_{i,2} lwages_{i,t-1}\right) + \sum_{j=1}^{p-1} \gamma_{i,j} \Delta loan_{i,t-j} \\ &\sum_{k=0}^{q-1} b'_{i,k} \Delta inequality_{i,t-k} + \sum_{k=0}^{q-1} c'_{i,k} \Delta lwages_{i,t-k} + g_i(t) + u_i + \epsilon_{i,t} \qquad (1)\end{aligned}$$

where $i = 1, ..., 49$ and $t = 1977, ..., 2010$. The variables *loan* is the the ratio of loans (total or real estate) to personal income, *inequality* is one of the three measures of income inequality, and *lwages* is the log of real wages and earnings. The $\beta_{i,1}$ and $\beta_{i,2}$ are the long-run coefficients; $\gamma_{i,j}$, $b_{i,k}$ and $c_{i,k}$ are the short-run coefficients; ϕ_i is the error-correction term; u_i are the state effects; and $g_i(t)$ are the state-specific time effects. Following Bassanini and Scarpetta (2002), we use a set of non-overlapping 4-year period dummies to measure $g_i(t)$ although the results are qualitatively similar if we use individual time trends.

[3] We focus on the second part of the Rajan hypothesis since there is virtually no cross-state variation in crisis that would allow us to test the link between credit growth and financial crises

[4] The *Consolidated Report of Condition and Income* (the Call Reports) are quarterly income statement and balance sheet data submitted by all federally-insured banks. We use total loans (rcon1400) and real estate loans (rcon1410) aggregated up to the state level to measure loan volume by state. We exclude bank holding companies since the location of loan origination is unclear. See den Haan et al. (2002) for details.

What makes this dynamic heterogeneous panel setup so attractive for our purpose is that it is unbiased regardless of whether a long-run relationship exists, or if the variables are $I(0)$ or $I(1)$. Essentially, cointegration (or more generally a long-run relationship) presents itself as the joint significance of the levels equation. In our case, this is of particular importance since the results of various stationarity tests are ambiguous.[5]

We start with the most flexible – and least informative – specification, a mean group (MG) estimator where both the long- and short-run coefficients are allowed to differ across states. Due to the presence of a few outliers in the individual coefficient estimates that distort the unweighted means dramatically, we report the robust estimates of the mean, together with its standard error.[6] We then progress by sequentially imposing and testing restrictions that – when valid – can improve the efficiency of the estimation. The next specification is a pooled mean group (PMG) estimator where the long-run coefficients are constant, but the short-run coefficients are allowed to differ. The last specification is a dynamic fixed effects (DFE) model where all coefficients are constrained to be equal across states. The Hausman (1978) tests results of MG vs. PMG and MG vs. DFE fail to reject the null in each case, indicating that both PMG and DFE provide consistent and more efficient estimates of the long-run coefficients. We then test all coefficient restrictions by applying Likelihood Ratio tests. As with most cross-country and regional studies, we reject the coefficients restrictions imposed in PMG and in DFE.[7] Given the contradictory evidence, we report the MG, PMG, and DFE results.

[5] A Fisher aggregated augmented Dickey Fuller (ADF) test as suggested by Maddala and Wu (1999) strongly rejects the null that all individual time series have a unit root, while a Fisher aggregated KPSS test rejects the null that all individual time series are stationary.

[6] Following Bond et al. (2010), the robust estimate of each MG coefficient is obtained by the applying the *rreg* command in Stata to the individual unweighted coefficients. The *rreg* command performs a robust regression, based initially on Huber weights and then on biweights.

[7] The tendency for Likelihood Ratio tests to reject the coefficient restrictions of PMG (and DFE) are discussed in Pesaran et al. (1999) and Pesaran et al. (1998).

4 Results and Conclusions

Table 2 reports the results for total loans. The coefficients for the long-run levels and error-correction term have their expected signs (and values), indicating that the error correction methodology is appropriate. More importantly, the long-run coefficients for each inequality indicator is positive and statistically significant at the 1% level with one exception. The point estimates indicate that a one percent increase in the Top-1 measure is associated with a 0.8 to 2.2 percent increase in total lending, which are in-line with cross-country estimates of (Malinen, 2013) and (Klein, 2015).

Table 3 presents the results for real estate loans. We find a positive long-run relationship between income inequality and real estate lending. As before, the long-run coefficients for each income inequality measure is positive and statistically significant at the 1% level with one exception. This positive relationship between income inequality and housing credit across states provides support for the first part of the Rajan hypothesis.

To examine causality, we estimate a three-variable (inequality, real estate loans, real wages) vector error correction model (VECM) for each state.[8] For each equation in each state, we run three tests: Granger non-causality ($H_0 : b_{i,0} = 0$), weak exogeneity ($H_0 : \phi_i = 0$) and strong exogeneity ($H_0 : b_{i,0} = 0$ and $\phi_i = 0$). We then combine the state-specific probability values into a single Fisher aggregated test statistic and report its probability value along with the number of states that reject at the 5 percent level.

Tables 4a and 4b show the results for inequality causing real estate lending and real estate loans causing inequality, respectively. We find more evidence of inequality causing real estate lending than the reverse.[9] In 4a, the test statistics are much higher with p-values below 0.001, suggesting that the null of non-causality are not true in every state. For the individual states, we reject the null of Granger non-causality and strong exogeneity far more

[8] Our VECM model is a three-equation system where the first-difference of each variable is regressed on a common long-run levels relationship and two lags (and no contemporaneous values) of all three variables.

[9] By applying a similar procedure to a panel of 14 countries, Gu and Huang (2014) find that inequality granger causes total loans but not vice versa

times in 4a than in 4b. Although we reject the null of weak exogeneity for all inequality measures in 4b, the sign of ϕ_i is positive in 32 to 43 states, indicating a significant but unstable long-run relationship running from real estate lending to inequality.

Our state-level results show a positive relationship running from inequality to real estate lending. Although far from providing conclusive proof of the Rajan hypothesis, our results nevertheless provide support to the idea that inequality was indeed one of the drivers of the real estate bubble that burst in 2007.

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Table 1: Data Description, Sample Statistics and Sources

Variable	Description	Mean	Std Dev	Min	Max
Dependent Variables					
Total loans	Total loans / personal income	0.3783	0.1316	0.1468	1.2065
Real Estate loans	Real Estate loans / personal income	0.1766	0.1002	0.0375	1.0949
Inequality Variables					
$Top-1$	Share of personal income earned by top-1 percent	0.1421	0.0460	0.0478	0.3604
Gini	Gini Coefficient	0.5799	0.0718	0.4463	0.8777
Theil	Theil Index	0.7115	0.2110	0.3396	1.6258
Economic Variable					
$log(wages)$	Log of real wages and earnings	10.9165	1.0897	8.6020	13.5303

Data Sources: The loan data was compiled from the Federal Financial Institutions Examination Council (FFIEC) *Consolidated Report of Condition and Income* (the Call Reports). The inequality variables were accessed from Mark Frank at <http://www.shsu.edu/~eco_mwf/inequality.html> and are described by Frank et al. (2015). Wages and earnings were accessed from Bureau of Economic Analysis Regional Accounts at <http://bea.gov/regional/index.htm> and were deflated using Regional Price Parities at the Bureau of Labor Statistics.

Table 2: Results for Total Loans

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Method	MG	MG	MG	PMG	PMG	PMG	DFE	DFE	DFE
Long-Run Coefficients:									
$log(wages)$	0.1668***	0.1785***	0.2141***	0.2077***	0.2046***	0.2178***	0.3827***	0.4407***	0.3408***
	(0.059)	(0.0408)	(0.0568)	(0.0219)	(0.0191)	(0.0208)	(0.1256)	(0.1124)	(0.1237)
$Top-1$	1.1983***			0.8609***			2.2277***		
	(0.2694)			(0.1112)			(0.6772)		
$Gini$		0.3385***			0.2218***			1.2019***	
		(0.0937)			(0.0263)			(0.322)	
$Theil$			0.1020			0.0671***			0.6094***
			(0.0682)			(0.0139)			(0.1483)
Short-Run Coefficients:									
$Errorcorrectionterm$	-0.4228***	-0.4792***	-0.4231***	-0.4128***	-0.4354***	-0.4246***	-0.0625***	-0.0685***	-0.0628***
	(0.0262)	(0.0268)	(0.0268)	(0.0339)	(0.0342)	(0.0375)	(0.0083)	(0.0083)	(0.0082)
Observations	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
Number of states	50	50	50	50	50	50	50	50	50
Time Period	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10
State and Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors in parentheses where ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

Table 3: Results for Real Estate Loans

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Method	MG	MG	MG	PMG	PMG	PMG	DFE	DFE	DFE
Long-Run Coefficients:									
$log(wages)$	0.1782***	0.1541	0.2111	0.1817***	0.1981***	0.1773***	0.1955**	0.2475***	0.1892**
	(0.0778)	(0.1133)	(0.1418)	(0.0222)	(0.0174)	(0.0192)	(0.0884)	(0.0758)	(0.0877)
$Top-1$	0.6121			1.0868***			1.6158***		
	(0.3802)			0.1316			0.4922		
$Gini$		0.338**			0.497***			0.9308***	
		(0.1462)			(0.0297)			(0.2233)	
$Theil$			0.1050***			0.1035***			0.3818***
			(0.0322)			(0.0147)			(0.1041)
Short-Run Coefficients:									
$Errorcorrectionterm$	-0.2976***	-0.3896***	-0.3001***	-0.229***	-0.2564***	-0.2591***	-0.0499***	-0.0569***	-0.0504***
	(0.0251)	(0.0239)	(0.0251)	(0.023)	(0.0211)	(0.0228)	(0.0067)	(0.0067)	(0.0066)
Observations	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
Number of states	50	50	50	50	50	50	50	50	50
Time Period	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10	1979-10
State and Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors in parentheses where ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

Table 4: Causality Tests

(a) Tests of Inequality causing Real Estate Loans

	$Top-1$	$Gini$	$Theil$
Granger non-causality:			
Fisher-aggregated test statistic	367.88	471.74	412.35
p-value	0.000	0.000	0.000
Number of states reject	16	29	23
Weak exogeneity:			
Fisher-aggregated test statistic	318.08	203.24	235.31
p-value	0.000	0.000	0.000
Number of states reject	17	12	12
Strong exogeneity:			
Fisher-aggregated test statistic	374.19	514.02	381.37
p-value	0.000	0.000	0.000
Number of states reject	18	32	20

(b) Tests of Real Estate Loans causing Inequality

	$Top-1$	$Gini$	$Theil$
Granger non-causality:			
Fisher-aggregated test statistic	109.07	110.68	153.05
p-value	0.209	0.180	0.000
Number of states reject	2	4	6
Weak exogeneity:			
Fisher-aggregated test statistic	369.70	206.68	292.70
p-value	0.000	0.000	0.000
Number of states reject	22	15	23
Strong exogeneity:			
Fisher-aggregated test statistic	128.24	174.24	108.89
p-value	0.022	0.000	0.213
Number of states reject	4	9	3

Note: The 'Number of states reject' records the number of state-specific VECM (out of 50) where the null of non-causality is rejected at the 5% level.