Title
Essays in Macroeconomics

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Publication Date
2021

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
SANTA CRUZ

ESSAYS IN MACROECONOMICS

A dissertation submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

David A. Zink

June 2021

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Contents

List of Figures

List of Tables

Abstract

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This dissertation studies topics related to monetary policy, macro finance, and international finance. The first two chapters study (1) the impact of shadow banks on the transmission of monetary policy, and (2) the effects of securitized versus balance sheet credit booms on the severity of the Great Recession. These studies utilize micro data, which allows me to carefully construct econometric specifications that take seriously issues of endogeneity that are ubiquitous in macroeconomics. The third chapter is co-authored work with Michael Hutchison and Fernando Chertman. In this paper, we study the behavior of Taylor rules and foreign exchange intervention functions in large emerging market economies.

In Chapter 1 I present empirical evidence that shadow banks weaken the pass through of monetary policy to the real economy by weakening the bank lending channel. I construct a dataset of home mortgage loan originations from the Home Mortgage Disclosure Act (HMDA) matched with county level home prices and labor market outcomes for years 2000 through 2019. I find that shadow banks expand mortgage originations relative to traditional banks as the monetary policy rate increases. This effect is economically large even when controlling for loan demand by comparing shadow and traditional bank lenders within the same

county. In addition, I estimate the impact of shadow bank presence on the transmission of monetary policy to the real economy by exploiting county level heterogeneity in shadow bank exposure. My results indicate that as the monetary policy rate increases counties with more exposure to shadow banking experience smaller contractions in home prices, employment, and wages relative to those with less exposure to shadow banking. These results indicate that the recent expansion in shadow mortgage banking has weakened an important channel through which monetary policy affects the real economy.

In Chapter 2 I separately estimate the effect of local credit booms driven by balance sheet lending and those driven by securitization during the 2002-2006 period on the severity of the 2007-2009 Great Recession in the United States. I link data on bank mortgage originations from HMDA with bank financial statements and county level economic outcomes. I exploit geographic variation in bank origination activity across counties to construct county level measures of exposure to securitization and balance sheet lending activity during the 2002-2006 credit boom that are orthogonal to local economic conditions. Results show that 2002-2006 securitization exposure is predictive of declines in home prices, employment, and a rise in mortgage delinquencies during the 2007-2009 crisis period. The same is not true for balance sheet lending, which has a small positive effect on crisis period home prices and minimal employment effects. Results suggest that this difference is driven by risk taking that is specific to securitized lending. Balance sheet booms generate an expansion in lending to higher quality

borrowers, while securitization booms increase credit availability at the lower end of the credit distribution.

The final chapter investigates extended Taylor rules and foreign exchange intervention functions in large Emerging Markets (EM), measuring the extent to which policies are designed to stabilize output, inflation, exchange rates and accumulate international reserves. We focus on two large emerging markets - India and Brazil. We also consider the impact of greater capital account openness and which rules dominate when policy conflicts arise. We find that output stabilization is a dominant characteristic of interest rate policy in India, as is inflation targeting in Brazil. Both countries actively use intervention policy to achieve exchange rate stabilization and, at times, stabilizing reserves around a target level tied to observable economic fundamentals. Large unpredicted intervention purchases (sales) accommodate low (high) interest rates, suggesting that external operations are subordinate to domestic policy objectives. We extend the work to Chile and China for purposes of comparison. Chile's policy functions are similar to Brazil, while China pursues policies that substantially diverge from other EMs.

to my parents and my sister

Acknowledgments

I received tremendous support from the economics department throughout my career at UCSC. Without this I would not have been able to finish my dissertation. First, I would like to thank my adviser Carl Walsh. His first and second year courses are what initially made me excited to study topics related to monetary policy and financial intermediation. I would also like to thank Michael Hutchison. Co-authoring a paper with Professor Hutchison was one of the highlights of my career at UCSC and it taught me numerous lessons about the research process. I would also like to thank Alonso Villacorta, who was always willing to carefully dissect my research ideas for hours at a time and provided invaluable feedback. I am also thankful to Galina Hale for providing me tremendous feedback and advice on my research papers and on presentation and interview skills during my job search.

I am thankful for several other members of the economics department at UCSC: Brenda Samaniego de la Parra, Grace Weishi Gu, Natalia Lazzati, Carlos Dobkin, Alan Spearot, Kai Pommerenke, and all participants in the macro workshop. I am also grateful for the advising and teaching I received during my undergraduate studies at UW La Crosse: I am thankful to John Nunley, Sheida Teimouri, and Tushar Das for challenging me during my undergraduate studies and encouraging me to apply for graduate school.

I am indebted to my classmates in the economics department and friends in Santa Cruz for the support and encouragement throughout the past six years.

A special thank you to Luka Kocic, Fernando Chertman, Jiayi Xu, Zijing Zhu, Mai Hakamada, and Sophie Morley.

Finally, thank you to my family for their love and support throughout my life. To my parents Valerie and Douglas - thank you for the hard work and sacrifices you've made to put me and Jessica in positions to be successful. To my sister Jessica - thank you for the friendship and support you've provided me throughout the highs and lows of my graduate career.

Chapter 1

The Effects of Shadow Banking on the Transmission of Monetary Policy

1.1 Introduction

Decades of research has documented that monetary policy operates through a bank lending channel: increases in the Federal Funds rate prompt a contraction in the supply of bank loans[1]. This causes a reduction in real economic activity if borrowers cannot frictionlessly substitute between bank and nonbank credit. The growth of shadow banking in the aftermath of the 2007-2009 crisis has expanded access to nonbank lending, potentially undermining the

[1]See Bernanke and Blinder (1988), Bernanke and Blinder (1992), Kashyap and Stein (1995).

real economic effects of monetary policy by allowing borrowers to more easily substitute nonbank loans for reductions in the supply of bank loans[2]. The rise in shadow banking has been especially pronounced in the residential mortgage market. Shadow mortgage lenders, which are defined as non-depository lending institutions, have increased their market share from 25% of annual originations in 2007 to nearly 60% in 2019 (Figure 1.1). In this paper, I explore the impact of shadow mortgage lenders (henceforth referred to as shadow banks) on the bank lending channel of monetary policy and estimate the effect of their presence on the transmission mechanism to the real economy.

Utilizing loan and county level data from 2000 through 2019, my results indicate that shadow bank presence weakens the bank lending channel of monetary policy. I first show that increases in the Federal Funds rate prompt shadow banks to expand mortgage originations relative to traditional banks. This effect is economically large, and is operable for both home purchase loans and refinancings. Next, I explore the effects of shadow bank presence on the transmission of monetary policy to the real economy by exploiting heterogeneity in shadow bank exposure across counties. I find that shadow bank presence weakens the pass through of monetary policy to home prices, employment, and wages. As the monetary policy rate increases, counties with more exposure to shadow banking experience smaller contractions in home prices, employment, and wages compared to counties with less exposure to shadow banking.

[2]See 2014 Goldman Sachs report "The Coming of the New Shadow Bank" for an overview of the post crisis rise in shadow banking.

The existing literature has documented two mechanisms through which monetary policy affects the supply of bank loans. A rise in the monetary policy rate causes (1) a reduction in asset prices, and (2) deposit outflows. Lower asset prices tighten bank balance sheet constraints, prompting a reduction in bank loans[3]. Deposit outflows similarly cause banks to reduce credit supply[4]. Neither of these mechanisms are likely to apply to shadow banks. Shadow banks do not rely on deposits to fund originations. Instead, they operate an originate to distribute model and sell nearly 100 % of originations to secondary market investors shortly after origination. Additionally, reliance on the secondary market to finance originations means that shadow banks do not hold loans on their balance sheet. Therefore, a monetary policy induced reduction in asset prices that tightens lender balance sheet constraints is not likely to alter the lending capacity of shadow mortgage lenders. Monetary policy may still affect the credit supply of shadow banks through the risk premium and liquidity channels [5]. That said, my results provide evidence that the contractionary effects of monetary policy tightenings on mortgage originations are weaker for shadow banks than for traditional banks.

Estimating credit supply effects of monetary policy is challenging because monetary policy simultaneously affects the supply and demand for credit. Therefore, any observed differential effect of monetary policy on shadow bank relative to traditional bank lending may be due to credit demand factors instead

[3]See Gertler and Karadi (2011), Van Den Heuvel (2006), Kishan and Opiela (2000).
[4]See Bernanke and Blinder (1988), Drechsler et al. (2017).
[5]See Drechsler et al. (2018a), Drechsler et al. (2018b).

of credit supply. I overcome this identification challenge by utilizing loan level data from the Home Mortgage Disclosure Act (HMDA) from years 2000 through 2019. For each lender and year, this dataset allows me to compute the number of mortgage originations in each county in the United States. I exploit the geographical dimension of my data to control for confounding demand side factors with county by year fixed effects. Consequently, my credit supply estimates rely on within county-year variation between banks and shadow banks. The assumption underlying this approach is that monetary policy does not differentially affect bank and shadow bank credit demand within the same county.

My estimates indicate that shadow banks expand home purchase originations by 456 basis points and refinancings by 476 basis points relative to traditional banks for every 100 basis point increase in the monetary policy rate[6]. This result is not driven by macroeconomic conditions during the 2007-2009 financial crisis, or contemporaneous and expected future GDP and inflation. The magnitude of the estimate is unchanged when re-estimating the specification on a sample of the 500 largest lenders, suggesting that my cross-sectional results are not driven by small community lenders and that shadow banking affects the aggregate response of credit supply to monetary policy.

After establishing that shadow bank credit supply is less sensitive to monetary policy, I evaluate the real effects of shadow banking on the pass through of monetary policy. Shadow mortgage lenders may dampen the transmission

[6]Keep in mind that this is a relative effect. I do not find that monetary policy causes shadow banks to expand originations, but that it causes them to expand originations *relative* to traditional banks.

mechanism to the real economy through two channels. First, this may occur through the supply of credit to households. Shadow banks are active in markets for both home purchase and home equity loans, and so the weaker credit supply response of shadow banks to monetary policy may prompt an expansion in home equity-based borrowing by making these loans more widely available. Home equity loans may subsequently be used for real outlays by households. Second, this may arise through the impact of credit supply on home prices. The weaker credit supply response of shadow banks to monetary policy may affect home prices through the demand for housing. Home prices subsequently affect consumption and investment through the networth of households[7].

I analyze the real economic effects of shadow banking on the transmission of monetary policy by exploiting heterogeneous exposure to shadow banking across counties. For each county and year, I define exposure to shadow banking as the twice lagged share of total county home purchase mortgage originations by shadow banks. These counties are more reliant on shadow banks, and therefore mortgage lending in these counties is less sensitive to monetary policy. I combine this exposure data with county level data on home prices, as well as county level employment and wage data at the sector level. I estimate the heterogeneous response of home prices to monetary policy across counties with different exposure to shadow banking. I include a set of county fixed effects, time fixed effects, and a range of time-varying county level controls. Next, I estimate the heterogeneous response of employment and wages at the county-sector across counties with dif-

[7]See Mian and Sufi (2014).

ferent exposure to shadow banking. Importantly, I control for differences in the labor market response to monetary policy across sectors by including a set of sector by time fixed effects. Therefore, my estimates come from comparing the employment and wage response to monetary policy within the same sector across counties with different exposure to shadow banking. This controls for differences in the sensitivity of employment and wages to monetary policy across industries.

Results at the county level indicate that exposure to shadow banking is associated with a muted effect of monetary policy on home purchase loans, mortgage refinancings, home prices, employment growth, and wage growth. I find that a one standard deviation increase in shadow bank exposure generates a 310 basis point expansion in refinancings and a 110 expansion in home purchase loans for every 100 basis point increase in the monetary policy rate[8]. This effect is economically large and alters the transmission of monetary policy to home prices. Specifically, I find that a one standard deviation increase in shadow bank exposure leads to a 19 basis point expansion in home price appreciation for every 100 basis point increase in the monetary policy rate. My estimates for employment at the county-sector level indicate that a one standard deviation increase in shadow bank exposure increases employment growth by 12 basis points for every 100 basis point increase in the monetary policy rate. For wages, I estimate that a one standard deviation increase in shadow bank exposure generates a 19 basis point

[8]Keep in mind that these are *relative* effects. That is, as the monetary policy rate increases, counties with more exposure to shadow banking experience an expansion in mortgage lending *relative* to counties with less exposure to shadow banking. I do not estimate the aggregate effect of monetary policy on the supply of originations because it cannot be disentangled from the demand channel.

increase in total wage growth and a 8 basis point increase in average wage growth for every 100 basis point increase in the monetary policy rate. I additionally find that these labor market results are primarily driven by employment and wage growth in the construction and services industries. Given that these industries are more likely to be driven by local economic conditions, this finding is consistent with the idea that my results are driven by the effect of shadow bank exposure on the transmission of monetary policy to the local mortgage market.

I consider a wide range of econometric specifications to explore the possibility that my estimates are driven by unobserved macroeconomic or county level characteristics. For the lender level results, I include controls for contemporaneous and expected future macroeconomic conditions that are interacted with a shadow bank indicator variable. Across specifications, these additional controls lead to no meaningful change in the magnitude of my estimates, therefore mitigating concern that results are confounded by macroeconomic conditions other than monetary policy. At the county level, macroeconomic controls are interacted with the constructed measure of shadow bank exposure, in addition to a vector of county level variables that control for labor market characteristics, demographics, household credit constraints, and local bank concentration in deposit and lending markets. These control variables do not materially change the coefficient of interest across any of the county-level results.

This paper relates to the large literature on the bank lending channel of monetary policy, which posits that monetary policy affects the real economy through the supply of bank loans. Traditionally, monetary policy is thought to affect the supply of bank loans through its effect on required reserves (Bernanke and Blinder (1988), Bernanke and Blinder (1992), Kashyap and Stein (1995), Kashyap and Stein (2000)). Changes in the conduct of monetary policy over the past decade have generated excess reserves in the banking system, making the traditional mechanism implausible. The research has since emphasized mechanisms that operate through (1) deposit flows and (2) balance sheet constraints (Drechsler et al. (2017), Van Den Heuvel (2006), Kishan and Opiela (2000), Gambacorta and Mistrulli (2004)). These papers all focus on the impact of monetary policy on traditional bank loans. My paper contributes to this literature by demonstrating that shadow banks weaken the real economic effects of the bank lending channel by offsetting monetary policy induced contractions in bank loans.

A contemporaneous working paper analyzing the bank lending channel of monetary policy in the presence of shadow banking is Elliott et al. (2019). Elliott et al. (2019) estimate the effect of monetary policy on shadow bank credit supply in the market for auto loans, syndicated corporate loans, and residential mortgages. My paper diverges from Elliott et al. (2019) in two ways. First, my analysis emphasizes the effect of shadow bank presence on the pass through of monetary policy to the real economy. Second, the results for mortgage lending in Elliott et al. (2019) indicate that shadow banks originate loans for larger amounts relative to traditional banks in response to a monetary tightening. My results for credit supply differ by showing that shadow banks originate more loans than traditional banks in response to a monetary tightening. Although these findings are consistent with one another, the distinction between them is meaningful because the literature has documented that fluctuations in aggregate mortgage lending are primarily driven by the extensive margin (number of loans) rather than the intensive margin (loan size) (Gilchrist et al. (2018)). Moreover, changes in mortgage lending along the extensive margin may have a larger impact on housing demand by making credit available to non-homeowners. This in turn affects the real economy through the impact of home prices on household wealth (Mian and Sufi (2009)). Lastly, my paper includes data through 2019, while Elliott et al. (2019) include data through the third quarter of 2012. This seemingly small difference is actually significant because the shadow mortgage market has grown substantially since 2009. The new era of shadow mortgage lenders rely heavily on government sponsored enterprise (GSE) financing and are primarily active in the conforming mortgage market. Therefore, they may respond differently to monetary policy shocks than the shadow banks from the pre financial crisis era.

An additional related paper is Xiao (2020), which studies the effect of shadow banking on the transmission of monetary policy to deposit markets. Results indicate that monetary tightenings cause deposits to flow from commercial banks and into the shadow banking sector. My results on lending complement those from Xiao (2020) by demonstrating that, consistent with an influx of funding, monetary policy tightenings cause shadow banks to expand originations relative to traditional banks.

This research also has ties to the literature on the risk taking channel of monetary policy. Adrian and Shin (2010) formally model a risk taking channel, demonstrating that lower monetary policy rates incentivize banks to originate loans to riskier borrowers. Empirical research in this area has utilized cross sectional data to estimate the effects of monetary policy on bank risk taking. Results have shown that loose monetary policy causes expansions in risky lending by under capitalized lenders. Jiménez et al. (2014) offers support for the risk taking channel in Spain, while Delis et al. (2017) shows that U.S. banks increase holdings of risky syndicated loans when rates fall. My paper complements this research by considering the effects of monetary policy on shadow bank lending, which may partially offset the risk taking channel of monetary policy by transferring credit intermediation to a less regulated part of the financial system.

The paper proceeds as follows. Section 2 details the construction of the dataset and key variables. Section 3 presents aggregate trends in mortgage lending by traditional and shadow banks from 2000 through 2019. The lender level empirical methodology and results are presented in section 4, while section 5 describes the county level empirical methodology and results. Section 6 concludes.

1.2 Data

I construct a novel dataset from several sources. Loan level data from the Home Mortgage Disclosure Act are combined with county level data to estimate the credit supply and real economic effects of shadow banking on the pass through of monetary policy. The following section contains a detailed discussion of each dataset utilized.

1.2.1 Lender Level Data

Home Mortgage Disclosure Act Data: The primary data source is the Home Mortgage Disclosure Act (HMDA). HMDA data are collected at the loan application level from 2000 through 2019. All mortgage lenders with over 30 million in assets must submit HMDA data to the Federal Financial Institutions Examination Council (FFIEC) each year. In the majority of my analysis, the sample is restricted to originations of owner-occupied home purchase loans for one-to-four-family dwellings. I additionally consider refinancings as the dependent variable in a subset of specifications. Refinancings constitute a type of home equity-based borrowing by households, which may be used to finance real outlays. However, HMDA does not allow refinancings to be differentiated between ”straight” refinancings (that are used exclusively to pay off the balance on an existing mortgage) versus ”cash-out” refinancings (which are used to remove equity from the home). This limitation is notable because cash-out refinancings are more likely to affect real outlays by households. For the lender level analysis, originations are aggregated to the lender level within each county and year. Originations are summed to the county-year level for the county level analysis.

Classifying lenders: All lenders that accept deposits or are a subsidiary of a deposit taking institution are classified as banks. I follow the following procedure to identify lenders that are banks or are subsidiaries of banks. First, call report data are merged with HMDA data following the method outlined in Loutskina and Strahan (2009). All HMDA lenders that are matched with call report data and are part of a bank holding company that accepts deposits are classified as banks. The origination activity of these lenders is aggregated to the bank holding company level. I classify the remaining HMDA lenders based on their regulatory agency and name. All lenders that are regulated by the Office of the Comptroller of the Currency (OCC), National Credit Union Association (NCUA), Federal Deposit Insurance Company (FDIC), Office of Thrift Supervision (OTS), or Consumer Finance Protection Bureau (CFPB) are classified as banks. Similarly, all lenders that are regulated by the Department of Housing and Urban Development (HUD) are classified as shadow banks. The remaining lenders are regulated by the Federal Reserve System. I classify these lenders based on their name[9]. Specifically, any lender with a name or parent name that contains "BANK", "BK", "BANCO", "BANC", "B&T", "BNK", "CU", "FS", "CREDIT", or "BC" are classified as banks. The majority (>99%) of shadow banks are regulated by HUD, while the majority of lenders regulated by the OCC, FRS, FDIC, and OTS are classified as traditional banks.

The percentage of lenders classified as traditional banks within each regulatory agency is presented in Table 1.1. The percentage of HMDA filers classified as traditional banks within each regulatory agency is largely similar to Buchak et al. (2018), who also uses HMDA data to study shadow banking. The

[9]Of the 2462 lenders regulated by the FRS, 469 are not matched with call reports and are classified based on their name.

Table 1.1: Lender Classification by Regulatory Agency. This table presents the percentage of traditional banks within each regulatory agency.

Agency	Percent Traditional Banks
OCC	100%
FRS	90.5%
FDIC	100%
OTS	100%
NCUA	100%
HUD	0.35%
CFPB	99.9%

exception is FRS regulated lenders. I classify a larger percentage of FRS regulated lenders as banks than Buchak et al. (2018). This is because I merge HMDA data with call reports, which allows me to identify a large group of seemingly independent mortgage lenders that are actually mortgage lending arms of bank holding companies. My classification scheme classifies these lenders as banks. This decision is based on two reasons. First, these lenders are part of bank holding companies, which are subject to capital requirements and are generally exposed to more regulatory scrutiny than independent mortgage lenders. Given that regulatory differences between shadow and traditional banks are an important mechanism through which monetary policy may differentially affect credit supply decisions of banks and shadow banks, classifying these lenders as shadow banks may understate this differential effect. Second, bank holding companies raise deposits which can be allocated among their bank and nonbank subsidiaries. Therefore, mortgage lenders that are subsidiaries of bank holding companies may be reliant on deposits to finance mortgage originations. Given that deposit flows are an important channel through which monetary policy affects bank lending, I choose to classify these lenders as banks.

Table 1.2 presents summary statistics at the county-lender level. In the average year, the typical lender originates 11 home purchase mortgages. The last four columns of Table 1.2 present summary statistics separately for banks and shadow banks. There are differences in borrower traits between the two types of lenders. Shadow banks originate loans to borrowers that have lower incomes and borrow smaller amounts. These means have large standard deviations and so the differences between banks and shadow banks are not statistically significant.

Table 1.3 shows summary statistics at the lender level. The average lender originates 537 home purchase loans in a given year across all counties. The average shadow bank originates roughly six times as many loans as the average traditional bank in the typical year. This difference in origination volumes between shadow and traditional banks is driven primarily by the fact that shadow banks actively lend in a larger number of counties. Within each county, shadow banks and traditional banks do not differ in the number of loans originated (Table 1.2). However, the average shadow bank is active in 158 counties while the average traditional bank actively lends in just 29 counties during a given year. The average lender sells 38% of originated loans to the secondary market. This statistic differs dramatically between shadow and traditional banks. Shadow banks sell an average of 88% of originations to the secondary market, while traditional banks sell just 30% of loans to the secondary market on average. This demonstrates that traditional banks rely much more heavily on balance sheet financing, potentially leaving them more exposed to changes in monetary policy.

Table 1.2: County-Lender Summary Statistics. This table presents summary statistics at the lender-county level. Summary statistics are presented seperately for traditional and shadow banks. The sample period is 2000 through 2019. The underlying data are from the HMDA.

	All		Traditional Banks		Shadow Banks	
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
log(Originations)	1.29	1.46	1.28	1.46	1.29	1.46
Originations	11.29	73.84	11.66	76.98	10.88	70.10
Mean loan size	179.55	141.84	184.52	162.77	173.55	111.17
Mean borrower income	88.45	118.22	96.75	135.35	78.69	93.24
Shadow bank	0.47	0.50	0.00	0.00	1.00	0.00
N	3,852,869		2,162,302		1,690,567	

Table 1.3: Lender Summary Statistics. This table presents summary statistics at the lender level. Summary statistics are presented separately for traditional and shadow banks. The sample period is 2000 through 2019. The underlying data are from the HMDA.

	All		Traditional Banks		Shadow Banks	
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Active counties	47.54	190.09	29.45	144.22	158.44	340.39
Originations	536.91	5,541.03	343.4	4,881.62	1,723.47	8,438.6
Percent sold	38.35	41.68	29.86	37.48	88.18	27.98
Percent sold to GSE	10.28	23.35	9.57	21.94	14.47	30.01
Shadow bank	0.14	0.35	0.0	0.0	1.0	0.0
N	133,881		115,762		18,119	

1.2.2 County Level Data

Home price data: Home price data for roughly 2400 counties are obtained from Zillow. Published at a monthly level, the Zillow Home Value Index (ZHVI) is equal to the median estimated home value within each county. The monthly Zillow data are converted to an annual series by averaging the fourth quarter home value within each county. The Zillow data are used as an alternative to the more well known Core Logic Case-Schiller home price index. An advantage of the Zillow data over the Case-Schiller index is that it is based on the entire housing stock within a county, whereas the Case-Schiller index is calculated from homes that have sold at least twice in recent history. This biases the Case-Schiller index towards the value of homes that are older and tend to sell more often.

Employment data: Employment data by industry are retrieved from the U.S. Census County Business Patterns (CBP) survey at the 4-digit NAIC level. Industries are divided into four categories (tradable, nontradable, construction, or other) using the classification scheme of Mian and Sufi (2014). Some counties do not specify employment within each 4-digit industry code, but report a range in which the value falls (for example, between 100 and 500 employees). Following Mian and Sufi (2014), I replace these missing values with the midpoint of the given range. Total employment and wages within NAICs supersector are obtained at the county level from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW)[10]. The QCEW data are converted to annual series by taking the average fourth quarter values within each county.

Demographic data: County level population data by race is obtained from the National Cancer Institute (NCI). The NCI population estimates are

[10]There are 11 NAICs supersectors. They consist of (1) natural resources and mining, (2) construction, (3) manufacturing, (4) trade, (5) information, (6) finance, (7) professional, (8) education and health, (9) leisure, (10) other services, and (11) government. To reduce the effect of outliers, I limit the sample to observations for which the absolute value of year-over-year changes in wage and employment growth are less than 100%.

based on U.S. Census data. They have been modified to take into account changes in the set of race categories used by the census over the sample period, so that race categories remain consistent over the entire period.

I complement the county data with a measure of bank deposit market power. Specifically, I use the Summary of Deposits from the FFIEC to compute the deposit market Herfindahl-Hirschman Index (HHI) within each county. I similarly construct the county level lending market HHI using the HMDA data. Finally, I obtain data on the share of subprime borrowers (those with a credit score below 660) within each county from the Federal Reserve bank of St. Louis. Table 1.4 presents county level summary statistics for all counties, and separately for counties with high and low exposure to shadow banking. In a given year, 109 lenders originate mortgages in the average county. Counties with high exposure to shadow banks on average have more active lenders and a larger population. Additionally, high exposure counties tend to have higher median home values than low exposure counties. The racial demographics and industry composition do not differ substantially between counties with high and low shadow bank exposure. Average employment growth and home value appreciation also do not differ significantly between high and low exposure counties. The time series of average county home value appreciation and average employment growth are plotted in appendix Figure 1.4. Both graphs follow the expected pattern, with employment and home value growth increasing from 2000 through 2006, before falling rapidly from 2006 through 2008 and recovering from 2009 through 2019.

Table 1.4: County Summary Statistics. This table presents summary statistics at the county level. Summary statistics are presented separately for counties with high and low exposure to shadow banks. Counties in which shadow banks have higher (lower) than the within year median shadow bank market share are defined as high (low) shadow bank counties. The sample period is 2000 through 2019. The underlying data are from the HMDA, BLS, Census, Zillow, and NIC. *Zillow median home value data is not available for all counties. These variables have sample sizes of 39,491 (all counties), 17,706 (low counties), and 21,785 (high shadow counties). The remaining sample sizes are as shown in the table.

	All		Low Shadow Bank		High Shadow Bank	
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Active lenders	109.21	99.43	77.45	62.85	140.65	117.29
log(Originations)	5.35	1.82	4.88	1.57	5.82	1.93
Originations	1,222.34	4,285.37	487.03	1,392.82	1,949.08	5,790.01
Δ log(Home value)*	0.02	0.06	0.02	0.05	0.03	0.06
Home value (000s)*	146.18	98.66	125.46	94.09	162.73	99.1
Δ log(Employment)	0.0	0.05	0.0	0.05	0.0	0.05
Δ log(Total wage bill)	0.03	0.08	0.03	0.07	0.03	0.09
Δ log(Average wage)	0.03	0.05	0.03	0.05	0.03	0.05
Percent white	86.95	15.77	88.39	15.76	85.56	15.59
Percent black	9.59	14.57	8.43	14.49	10.74	14.57
Percent retired	15.94	4.33	16.67	4.07	15.22	4.46
Percent nontradable	29.76	10.07	30.05	10.04	29.47	10.08
Percent construction	14.2	8.88	14.09	9.1	14.3	8.64
Percent other industry	49.04	12.24	48.95	12.42	49.12	12.04
Subprime share	0.33	0.09	0.31	0.09	0.34	0.09
Deposit HHI	0.22	0.04	0.22	0.05	0.21	0.04
Lending HHI	0.11	0.09	0.13	0.1	0.08	0.07
Population (000s)	102.19	319.9	50.3	128.31	153.49	426.46
Shadow bank share	0.33	0.17	0.21	0.1	0.46	0.13
N	56,322		27,980		28,342	

1.2.3 Macroeconomic Data

Measure of monetary policy: The effective Federal Funds rate and shadow Federal Funds rate are used as the measure of monetary policy. The shadow rate is taken from Wu and Xia (2016) and is commonly used in the literature to measure the stance of monetary policy at the zero lower bound (Delis et al. (2017)). Intuitively, the shadow rate is calculated by fixing the pre-zero lower bound term structure and computing what the current Federal Funds rate would have to be given current long term rates. A continuous measure of monetary policy is obtained by using the Federal Funds rate during non-ZLB periods and the shadow rate during ZLB periods. This monthly series is converted to an annual one by taking the average within each year. The resulting series is plotted in appendix Figure 1.5.

GDP and inflation: Quarterly data on real GDP is obtained from the Federal Reserve Economic Database (FRED). The quarterly series is converted to an annual series by taking the average within each year. Real GDP growth is calculated as the log change in annual real GDP. Monthly data on core CPI (all items excluding food and energy) is obtained from FRED. The monthly series is converted to an annual one by taking within year averages. Inflation is calculated as the log change in annual CPI. Data on expected inflation and GDP growth at the two year horizon are obtained from the Survey of Professional Forecasters.

1.3 Aggregate Trends in Shadow Banking

Before proceeding to the main empirical analysis, I present descriptive statistics to highlight the dramatic change that shadow banks have brought to the US mortgage market over the past two decades, as well as the differences between shadow and traditional banks. Figure 1.1 shows total annual home purchase mortgage originations by traditional and shadow banks from 2000 through 2019. Both shadow and traditional banks saw sharp contractions in originations following 2006 (Panel A). Shadow bank originations contracted more sharply than those of traditional banks, and shadow bank market share fell from almost 50% in 2006 to about 30% in 2007. This was driven by the failure of several large shadow banks from 2007 through 2009. Eight of the ten largest shadow banks in 2006 failed from 2007 to 2009. Shadow bank market share has rebounded sharply since the 2007-2009 crisis. Shadow banks originated roughly 57% of mortgages in 2019, which is higher than at any point during the 2002-2006 housing boom. The dominant market share of shadow mortgage lenders suggests that fluctuations in their credit supply may have large effects on residential investment by households.

The expansion in shadow banking that has occurred since the financial crisis has been widespread throughout the United States. Figure 1.3 depicts shadow bank market share by county in 2000, 2006, 2009, and 2019. Comparing the graphs for years 2000 and 2006, the expansion in shadow banking that occurred during the housing boom was primarily confined to the southwestern

United States. This is not the case for the post crisis expansion in shadow banking. Comparing panels C and D of Figure 1.3, shadow banks have expanded throughout the United States during the post crisis time period.

Figure 1.2 displays the disposition of loan sales by lender type from 2000 through 2019. Traditional banks hold a significantly larger share of originated loans on their balance sheet throughout the sample period. This share reached a minimum of 25% in 2009, before increasing to about 40% of total traditional bank originations in 2019. Given that monetary policy affects bank balance sheets, this potentially leaves traditional bank mortgage lending more sensitive to changes in monetary policy. The role of GSEs in financing traditional bank mortgage originations has expanded in the aftermath of the financial crisis, fluctuating around 40% since 2009.

Shadow banks sell roughly 90% of originations to secondary market purchasers. Panel B of Figure 1.2 shows that the type of purchasers to which shadow banks sell originated loans has shifted dramatically from the 2000 through 2019. During the housing boom, shadow banks relied heavily on non-GSE purchasers. In 2006, 13% of shadow originations were sold to a GSE (the equivalent number for traditional banks is 23%). The new wave of shadow banks that have since come to dominate the mortgage market rely heavily on GSE funding. From 2010 to 2019 the percentage of shadow bank originations sold to a GSE increased from 11% to 46%.

Figure 1.1: Shadow Bank Market Share. Panel A shows the number of mortgages originated by shadow banks and traditional banks in each year from 2000 through 2019. Panel B shows the percentage of mortgages originated by shadow banks in each year from 2000 through 2019. Data are from HMDA.

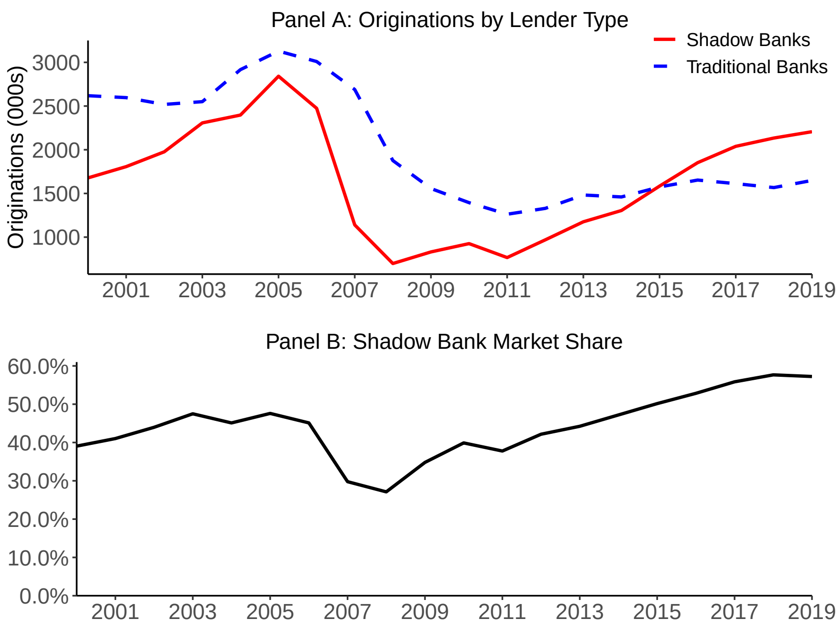


Figure 1.2: Disposition of Loan Sales: Traditional Banks versus Shadow Banks. This figure shows the percentage of originations by lender type sold to various types of loan purchasers from 2000 through 2019. Calculations are based on HMDA data. Sales to private securitization were not identified in HMDA before 2004. GSE includes sales to Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac.

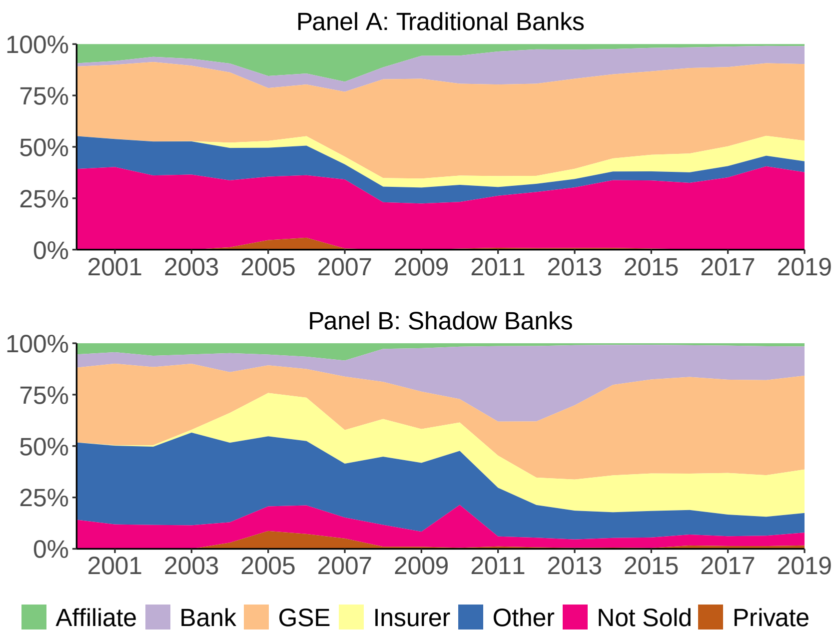
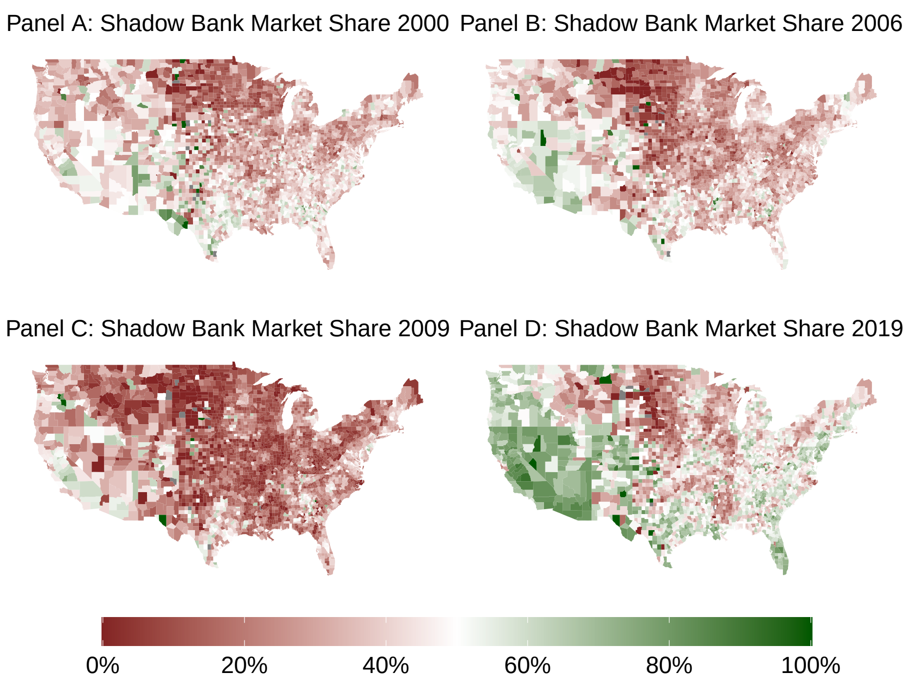


Figure 1.3: County-level Shadow Bank Market Share. This figure displays the percentage of county level home purchase mortgage originations by shadow banks in 2000, 2006, 2009, and 2019. Shadow banks originate less than 50% of loans in counties that are shaded red, exactly 50% of mortgages in counties that are shaded white, and over 50% of loans in counties that are shaded green. Data are from HMDA.



1.4 Lender Level Analysis

The first stage of this research estimates the heterogeneous loan supply response to monetary policy between banks and shadow banks. This is complicated by the fact that monetary policy simultaneously affects loan demand and loan supply. Traditionally, the bank lending channel literature has attempted to mitigate this problem by including time fixed effects and estimating the heterogeneous response to monetary policy across lenders[11]. This approach assumes that the demand for credit from all lenders is similarly affected by monetary policy, and so differences in lending across lenders are supply driven. In my paper, this approach would generate biased estimates if the loan demand response to monetary policy differs between shadow and traditional bank borrowers. Following Drechsler et al. (2017), I improve on the traditional methodology by exploiting the geographical dimension of my data and comparing the lending response to monetary policy between banks and shadow banks within the same county. I do this by including a set of county by time fixed effects in my baseline specification. Therefore, my approach allows for differences in the credit demand response to monetary policy between banks and shadow banks, but assumes these differences are negligible when comparing lenders within the same county and time period. The intuition underlying this identification strategy is that borrowers located within the same county do not differ systematically between banks and shadow banks and are similarly affected by monetary policy. Therefore, any differences in

[11] This approach is used in Kashyap and Stein (1995), Kashyap and Stein (2000), Gambacorta and Mistrulli (2004), Kishan and Opiela (2000) among others.

the lending response to monetary policy between banks and shadow banks within the same county must be driven by credit supply factors.

Identification is additionally complicated by the possibility that monetary policy is correlated with other aggregate shocks that have a differential effect on the credit supply decision of traditional and shadow banks within the same county. I mitigate these concerns by including macroeconomic variables that control for contemporaneous and expected future output and inflation. I allow the lending response to these aggregate shocks to differ between traditional banks and shadow banks.

1.4.1 Originations

I estimate the following fixed effects panel regression:

$$\begin{aligned} log\left(Originations_{ijt}\right) = \alpha_{jt} + \lambda_i + \gamma \times ShadowBank_i + \beta \Delta i_t \\ \times ShadowBank_i + \boldsymbol{X_t} \times ShadowBank_i + \epsilon_{ijt} \end{aligned} \tag{1.1}$$

where the dependent variable is the log of total mortgage originations by lender i in county j during year t. The parameters α_{jt} are county-year fixed effects, λ_i are lender fixed effects, and Δi_t is the contemporaneous change in the measure of monetary policy. $ShadowBank_i$ is an indicator variable equal to one if lender i is a shadow bank and zero otherwise. Monetary policy endogenously responds to contemporaneous and expected future output and inflation (Walsh (2017)). The vector $\boldsymbol{X_t}$ consists of these variables interacted with the shadow bank indicator variable to allow for differential effects of current and expected future output and inflation on traditional versus shadow bank lending within the same county. The parameter of interest is β, which tests for differential effects of monetary policy on shadow bank relative to traditional bank lending. Specifically, β can be interpreted as the effect of a one percentage point increase in the monetary policy rate on the percent change in shadow bank originations relative to those by traditional banks within the same county and year. It is important to note that the aggregate effect of monetary policy (Δi_t) on originations is absorbed by the county-year fixed effects in Equation 1.1. Therefore, I estimate the heterogeneous effect of monetary policy on shadow bank lending relative to traditional bank lending. This is a limitation in all studies that utilize cross sectional data to estimate credit supply effects of monetary policy. Standard errors are clustered at the commuter zone and lender level [12].

Results for Equation 1.1 are presented in Table 1.5. Columns 1-3 consider home purchase loans, while Columns 4-6 consider refinancings. Column 1 contains results for the baseline model, omitting macroeconomic controls. The estimated coefficient of interest is positive and statistically significant at the 1% level. The macroeconomic controls are added as control variables in Column 2, and are interacted with the shadow bank indicator variable[13]. This leads a a negligible increase in magnitude of the estimated effect. This suggests that unobserved macroeconomic conditions are not biasing the coefficient of interest. The point estimate in Column 2 indicates that a 100 basis point increase

[12] I group counties into commuter zones using data from the US Department of Agriculture. Commuter zones are integrated economic regions that are larger than counties. There are roughly 700 commuter zones in the US compared to 3000 counties.

[13] The macro controls include GDP growth, inflation, expected GDP growth, and expected inflation.

in the monetary policy rate causes a 456 basis point expansion in shadow bank originations relative to those of traditional banks. Column 3 tests for differential effects of monetary policy on shadow bank versus traditional bank lending during the financial crisis, which lasted from 2007 through 2009. The triple interaction term $crisis_t \times \Delta i_t \times ShadowBank_i$ is indistinguishable from zero[14]. Columns 4-6 present the analogous results for refinancings. Across all three columns, the results suggest that shadow banks expand refinancings relative to traditional banks when the monetary policy rate increases. The coefficient in Column 5 implies that shadow banks expand originations by 476 basis points relative to traditional banks for every 100 basis point increase in the monetary policy rate. As is the case with home purchase loans, Column 6 shows that the strength of this channel does not differ during the financial crisis. This finding suggests that shadow banks may weaken the transmission of monetary policy to the real economy through the supply of home-equity based loans.

[14]An additional concern is that results are driven by the heightened regulatory burden placed on banks in the aftermath of the 2007-2009 crisis. The appendix presents results omitting banks that were most exposed to these heightened regulatory requirements. Results show that omitting these banks leads to no meaningful change in the estimated effect.

Table 1.5: Lender-County Originations. This table presents regressions of the form: $log\,(Originations_{ijt}) = \alpha_{jt} + \lambda_i + \gamma \times ShadowBank_i + \beta\Delta i_t \times ShadowBank_i + \boldsymbol{X_t} \times ShadowBank_i + \epsilon_{ijt}$ where the dependent variable is either the log of new home purchase originations or refinancings in county j during year t by lender i. Estimates indicate that shadow banks expand lending relative to traditional banks in response to monetary policy tightenings. Columns 1 through 3 consider home purchase loans while columns 4 through 6 consider refinancings. The underlying data on county originations are from HMDA. $ShadowBank_i$ is an indicator variable that is equal to 1 if lender i is a shadow bank and 0 otherwise. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. $Crisis_t$ is equal to 1 for years 2007 through 2009. Δi_t is the change in the monetary policy rate from year $t-1$ to year t. The sample period is 2002 through 2019. Standard errors are clustered at the commuter zone and lender level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	Home Purchase Loans			Refinancings		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta i_t \times ShadowBank_i$	4.40***	4.56***	5.23***	5.17***	4.76***	5.55***
	(1.08)	(1.50)	(1.54)	(1.08)	(1.50)	(1.55)
$crisis_t \times \Delta i_t \times ShadowBank_i$			0.46			3.38
			(2.79)			(2.83)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
ShadowBank × Macro	No	Yes	Yes	No	Yes	Yes
R^2	0.31	0.31	0.31	0.38	0.38	0.38
N	3560360	3560360	3560360	4686571	4686571	4686571

1.4.2 Results for Large Lenders

In order to affect the transmission of monetary policy to the real economy through the supply of credit, it must be the case that large shadow banks are less sensitive to monetary policy relative to large traditional banks. The mortgage market is concentrated. Although the average year in my sample contains 6,251 lenders, the largest 500 mortgage lenders originate 86% of all loans from 2000 through 2019. If the results in Table 1.5 do not generalize to the largest mortgage lenders, then it is unlikely for shadow banking to have any real effects on monetary policy transmission. Moreover, large banks have greater access to market based (non-deposit) funding and therefore are potentially more capable of shielding their loan portfolio from monetary policy rate hikes. I address these concerns by re-estimating Equation 1.1 on a subsample of the data that includes only the 500 largest lenders in each year.

Results for large lenders are presented in Table 1.6. Overall the point estimates are similar in magnitude to those from Table 1.5, revealing that the estimated effect of interest does not meaningfully differ between large and small lenders. Column 2, which includes macroeconomic controls, shows that shadow banks expand originations by 526 basis points relative to traditional banks for every 100 basis point increase in the monetary policy rate. This estimate is nearly identical to that from the results including all lenders in Table 1.5. The triple interaction term in Column 3 suggests that the estimated effect does not differ during the financial crisis. Finally, the point estimate in Column 5 demonstrates that large shadow banks expand originations for refinancings by 574 basis points relative to large traditional banks for every 100 basis point increase in the monetary policy rate. Column 6 suggests that this effect does not differ during the financial crisis.

Table 1.6: Large Lender-County Originations. This table presents regressions of the form: $log\,(Originations_{ijt}) = \alpha_{jt} + \lambda_i + \gamma \times ShadowBank_i + \beta\Delta i_t \times ShadowBank_i + \boldsymbol{X_t} \times ShadowBank_i + \epsilon_{ijt}$ where the dependent variable is either the log of new home purchase originations or refinancings in county j during year t by lender i. The sample in period t is restricted to include only lenders who are in the top 500 of total originations in time $t-1$. Estimates indicate that shadow banks expand lending relative to traditional banks in response to monetary policy tightenings.Columns 1 through 3 considers home purchase loans while columns 4 through 6 consider refinancings. The underlying data on county originations are from HMDA. $ShadowBank_i$ is an indicator variable that is equal to 1 if lender i is a shadow bank and 0 otherwise. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. $crisis_t$ is equal to 1 for years 2007 through 2009. Δi_t is the change in the monetary policy rate from year $t-1$ to year t. The sample period is 2002 through 2019. Standard errors are clustered at the commuter zone and lender level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	Home Purchase Loans			Refinancings		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta i_t \times ShadowBank_i$	4.93***	5.26***	6.35***	5.78***	5.74**	6.63***
	(1.44)	(2.00)	(2.03)	(1.57)	(2.34)	(2.41)
$crisis_t \times \Delta i_t \times$ $ShadowBank_i$			3.11			−0.16
			(4.29)			(4.71)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
ShadowBank × Macro	No	Yes	Yes	No	Yes	Yes
R^2	0.37	0.37	0.37	0.47	0.47	0.47
N	2389460	2389460	2389460	2692826	2692826	2692826

1.5 County Level Analysis

The results from the previous section indicate that shadow bank credit supply is less sensitive to monetary policy. In this section I exploit heterogeneity in shadow bank exposure across counties to explore the effect of shadow bank presence on the transmission of monetary policy to the real economy. Given the results on credit supply, the presence of shadow banks may dampen the transmission mechanism to the real economy through the effect of credit supply on aggregate demand. This may operate through two channels. First, the smaller shadow bank response of mortgage refinancings to monetary policy may affect real outlays by households through the supply of home equity-based credit. Second, the smaller response of shadow bank home purchase originations to monetary policy potentially mutes the effect of monetary policy on home prices through the demand for housing. Home prices are an important determinant of household net worth, and so this may affect the real economy through household demand[15].

I define a county level measure of exposure to shadow banking by aggregating the origination data to the county level and computing the twice lagged share of home purchase loans that are originated by shadow banks within each county[16]. Specifically, shadow bank exposure in county j at time t is measured as:

[15] Fluctuations in the supply of mortgage credit have previously been shown to be an important determinant of real economic activity by Mian et al. (2020), Mian and Sufi (2014), among others.

[16] I choose the second lag over the first lag because shadow bank market share in year $t-1$ may be correlated with home prices or employment in year $t-1$, which by construction is correlated with employment growth and home price appreciation from year $t-1$ to year t.

$$Exposure_{jt} = \frac{\sum_i Loans_{i,j,t-2} \times I(i)}{\sum_i Loans_{i,j,t-2}}$$

where $I(i)$ is an indicator function that is equal to 1 if lender i is a shadow bank and zero otherwise. I utilize this measure of exposure to estimate the heterogeneous effect of monetary policy across counties with different exposure to shadow banking. Specifically, I estimate variations of the following county level equation:

$$Y_{jt} = \alpha_j + \lambda_t + \gamma \times Exposure_{jt} + \beta \Delta i_t \times Exposure_{jt} + \boldsymbol{X_t} \times Exposure_{jt} + \epsilon_{jt} \quad (1.2)$$

where Y_{jt} refers to either the log of total mortgage originations, log change in the median home value, log change in total employment, or log change in wages. The parameter of interest is β, which tests for heterogeneous effects of monetary policy across counties with different shadow banking exposure. Identification of β relies on the assumption that the credit demand response to monetary policy is not correlated with shadow bank exposure[17]. This identifying assumption is stronger than what was required for the lender-county results in the previous section because local demand shocks cannot be parsed with county by time fixed effects (this would absorb all variation in the outcome variable). Instead, county and time fixed effects are included separately, which are denoted by α_j and λ_t in Equation 1.2. Results for employment and wages additionally include sector by time fixed effects. As with the lender-level analysis, the aggregate effect of monetary policy on the dependent variable (the coefficient on Δi_t) is absorbed

[17]The appendix contains estimates using an alternative measure of exposure that is equal to shadow bank market share in surrounding counties. Results are unchanged.

by the time fixed effects in Equation 1.2. Given that monetary policy rate hikes cause aggregate reductions in all of the dependent variables considered, a positive β in Equation 1.2 indicates that counties with more exposure to shadow banking experience an increase in the dependent variable *relative* to counties with less exposure to shadow banking in response to monetary policy rate hikes[18].

The vector $\boldsymbol{X_t}$ includes contemporaneous and expected future real GDP growth and inflation as additional macroeconomic controls. These macroeconomic controls, along with the measure of monetary policy, are interacted with $Exposure_{jt}$ and a set of time varying county specific control variables. The county level control variables are lagged by two years, and consist of demographics (percent white, percent black, percent retired), industry composition (percent in construction industry, percent in nontradable industry, percent in other industry). I additionally include the subprime population share (the share of the population with a credit score below 660) and the local bank deposit and loan market Herfindahl-Hirschman Index (HHI)[19]. The subprime population share accounts for differences in borrower credit constraints across counties. This is interacted with the monetary policy rate to control for the balance sheet channel of monetary policy, which posits that borrowers with tighter balance sheet constraints are more affected by monetary policy. The deposit HHI index is the key dependent variable in Drechsler et al. (2017) and is interacted with the monetary policy rate

[18]Given that monetary policy causes an aggregate reduction in all dependent variables considered, an equivalent way to say this is that a positive β suggests counties with more exposure to shadow banking experience a smaller contraction in the dependent variable *relative* to counties with less exposure to shadow banking.

[19]HHI is a measure of market concentration. Drechsler et al. (2017) show that deposit market concentration can fully explain the deposits channel of monetary policy.

to account for differences in exposure to the deposits channel of monetary policy across counties.

1.5.1 Results on County Level Originations

I begin by demonstrating that the lender-county results on originations aggregate up to the county level. In order for shadow banking exposure to dampen the transmission of monetary policy to county level home prices, employment, and wages through the supply of credit, it must be the case that mortgage originations are less sensitive to monetary policy in high exposure counties.

Results are presented in Table 1.7. Columns 1 and 2 show results for home purchase loans. The coefficient of interest (on the interaction of the monetary policy rate with shadow bank exposure) is positive and statistically significant across all specifications. This indicates that, in response to monetary policy rate hikes, counties with greater exposure to shadow banking experience smaller contractions in mortgage lending compared to counties with less exposure to shadow banking. Column 2 includes time varying county level controls that are interacted with the monetary policy rate and the macroeconomic controls. Importantly, including these interaction terms increases the magnitude of the estimated effect. This mitigates concern that the heterogeneous effect of monetary policy across counties with different exposure to shadow banking are in fact being driven by shadow bank exposure and not differential exposure to the deposit channel of monetary policy or differences in borrower characteristics across counties. The coefficient of interest in Column 2 implies that a one standard deviation increase in shadow bank exposure generates a 110 basis point expansion in home purchase originations for every 100 basis point increase in the monetary policy rate[20]. The coefficient on the interactions of monetary policy with the deposit market HHI has the expected negative sign is significant[21]. Comparing the coefficients in Column 2 can be informative of the aggregate strength of the shadow exposure channel of monetary policy. Drechsler et al. (2017) argue that deposit market power can explain the entirety of the transmission of monetary policy to the supply of credit through bank balance sheets. Taking the standard deviation of deposit market HHI from Table 1.4 (0.04), the point estimate in Column 2 suggests that a 100 basis point increase in the monetary policy rate leads to a 48 basis point reduction in originations for every one standard deviation increase in deposit market HHI. The analogous number for a one standard deviation increase in shadow bank exposure is 110 basis points. This suggests that shadow bank exposure has a quantitatively large effect on the transmission of monetary policy to credit supply when compared to the deposit channel of monetary policy from Drechsler et al. (2017).

[20]The standard deviation of shadow bank exposure is 0.17 (Table 1.4). Column 2 of Table 1.7 implies a one standard deviation increase in shadow bank exposure generates a $100 \times 6.47 \times 0.17 = 109.9$ basis point expansion in originations for every 100 basis point increase in the monetary policy rate

[21]Counties with higher deposit market HHIs are more affected by monetary policy through the deposit channel (see Drechsler et al. (2017)).

Table 1.7: County Originations. This table presents regressions of the form: $Y_{jt} = \alpha_j + \lambda_t + \gamma \times Exposure_{jt} + \beta \Delta i_t \times Exposure_{jt} + \boldsymbol{X_t} \times Exposure_{jt} + \epsilon_{jt}$ where the dependent variable is either the log of new home purchase originations or refinancings. Estimates indicate that monetary policy has a smaller effet on mortgage lending in counties with more exposure to shadow banking. The dependent variable is the log of new mortgage originations in county j during year t. Columns 1-2 consider home purchase loans while columns 3-4 consider refinancings. The underlying data on county originations are from HMDA. $ShadowExposure_{j,t}$ is the shadow bank market share in county j during year $t-2$. $DepositHHI_{j,t-2}$ is the county deposit HHI index in county j during year $t-2$ (as calculated in Drechsler et al. (2017)). Δi_t is the change in the monetary policy rate from year $t-1$ to year t. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. The sample period in all other specifications is 2002 through 2019. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	Home Purchase Loans		Refinancings	
	(1)	(2)	(3)	(4)
$\Delta i_t \times ShadowExposure_{j,t}$	3.90***	6.47***	15.82***	18.28***
	(1.33)	(1.43)	(1.35)	(1.43)
$\Delta i_t \times DepositHHI_{j,t-2}$		−12.03**		3.31
		(6.01)		(5.75)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
County Controls × Macro	No	Yes	No	Yes
R^2	0.98	0.98	0.98	0.98
N	53245	53245	53245	53245

Columns 3 and 4 present results for mortgage refinancings. The point estimate is once again positive and statistically significant in all specifications. The similar magnitude of the estimate in Columns 3 and 4 mitigates concern that results are driven by unobserved county level characteristics. The coefficient of interest in Column 4 implies that a one standard deviation increase in shadow bank exposure leads to a 310 expansion in mortgage refinancings for every 100 basis point increase in the monetary policy rate.

These county level results establish that shadow banking weakens the response of aggregate county home purchase and refinancing originations to monetary policy. These are important conditions for shadow mortgage lenders to weaken the pass through of monetary policy to the real economy. The weakened response of home purchase loans indicates that housing demand may be less sensitive to monetary policy in high exposure counties, potentially affecting employment through the effect of home prices on aggregate demand. Likewise, the muted response of refinancings to monetary policy indicates that shadow bank exposure diminishes the effect of monetary policy on the quantity of home equity-based loans, which may be used for real outlays by households.

1.5.2 Results on Home Prices

In this section I estimate the effect of shadow bank exposure on the transmission of monetary policy to home prices. The previous section demonstrated that shadow bank presence weakens the pass through of monetary policy to home purchase loans. This section establishes that this dampening effect is

Table 1.8: County Home Appreciation. This table presents regressions of the form: $Y_{jt} = \alpha_j + \lambda_t + \gamma \times Exposure_{jt} + \beta \Delta i_t \times Exposure_{jt} + \boldsymbol{X_t} \times Exposure_{jt} + \epsilon_{jt}$ where the dependent variable is the log change in the median home value in county j from year $t-1$ to year t. Estimates indicate that monetary policy has a smaller effect on home price appreciation in counties with more exposure to shadow banking. The underlying data on median home values are from Zillow. $ShadowExposure_{j,t}$ is the shadow bank market share in county j during year $t-2$. $DepositHHI_{j,t-2}$ is the county deposit HHI index in county j during year $t-2$ (as calculated in Drechsler et al. (2017)). Δi_t is the change in the monetary policy rate from year $t-1$ to year t. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. The sample period in all other specifications is 2002 through 2019. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	(1)	(2)
$\Delta i_t \times ShadowExposure_{j,t}$	1.52^{***}	1.12^{***}
	(0.21)	(0.23)
$\Delta i_t \times DepositHHI_{j,t-2}$		-2.42^{**}
		(0.97)
County FE	Yes	Yes
Year FE	Yes	Yes
County Controls	No	Yes
County Controls × Macro	No	Yes
R^2	0.53	0.55
N	39917	39917

strong enough to further weaken the downstream effect of monetary policy on home prices. Given that home prices affect local demand through household net worth, these results provide evidence that shadow banks may weaken the effect of monetary policy on employment and wages through household demand.

Equation 1.2 is estimated with the log change in the median county home price as the dependent variable. Column 1 of Table 1.8 presents results for the baseline model. The estimated coefficient of interest is positive and statistically significant at the 1% level. Given that monetary policy rate hikes lower home appreciation, this positive point estimate indicates that counties with more exposure to shadow banks experience smaller contractions in home appreciation in response to interest rate hikes. Column 2 includes county level controls that are interacted with the macroeconomic controls. The estimate remains positive, stable, and statistically significant at the 1% level. Using the standard deviation of county level exposure to shadow banking from Table 1.4 (0.17), the point estimate in Column 2 indicates that a one standard deviation increase in shadow bank exposure causes a 19 basis point increase in home price appreciation for every 100 basis point increase in the monetary policy rate.

1.5.3 Results on Employment

The previous two sections establish two important results that must be true in order for shadow mortgage lenders to weaken the effect of monetary policy on the real economy through a credit supply channel. First, the supply of mortgage credit is less sensitive to monetary policy in counties with greater exposure to shadow banking. This may affect the real economy through the impact of refinancings on real outlays by households. Second, home prices are less sensitive to monetary policy in counties with more exposure to shadow banking. This may also affect the real economy through the impact of household net worth on aggregate demand. In both cases, local demand is less affected by monetary policy in counties with greater exposure to shadow banking. Given that local demand affects employment growth, this should result in a weaker employment response to monetary policy in counties with greater shadow banking exposure. My methodology does not allow me to differentiate between these two channels. However, I can explore the extent to which shadow bank presence weakens the transmission mechanism to employment by once again exploiting heterogeneity in shadow bank exposure across counties.

I modify Equation 1.2 by using the log change in sector level county employment from year $t-1$ to year t as the dependent variable. This allows me to exploit variation in employment across counties within the same sector. I do this by including a set of sector by time fixed effects, which control for time varying differences in employment growth within the same sector. These fixed effects eliminate concern that shadow banks have higher exposure in counties in which employment is concentrated in industries that are less affected by monetary policy.

Table 1.9 presents results. The baseline specification in Column 1 is positive and statistically significant at the 1% level, suggesting that shadow bank exposure weakens the pass through of monetary policy to employment growth. Again, recall that monetary policy rate hikes lower employment, thus the positive coefficient indicates that counties with more exposure to shadow banking experience smaller reductions in employment compared to those with less exposure to shadow banking in response to monetary policy rate hikes. County controls are included in Column 2, which leads to no meaningful change in the point estimate. The coefficient of interest in Column 2 indicates that a one standard deviation increase in shadow bank exposure leads to a 12 basis point increase in employment growth for every 100 basis point increase in the monetary policy rate[22]. Put differently, this estimate implies that in response to a 100 basis point increase in the monetary policy rate, a county in which 75% of mortgages are originated by shadow banks (of which there were 175 in 2019) will on average experience a 35 basis point increase in employment relative to a county in which 25% of mortgages are originated by shadow banks (of which there were 405 in 2019).

Results are presented separately for each sector in Table 1.10. Disaggregating results by sector is a natural choice for this setting. County shadow bank exposure affects the transmission of monetary policy through the supply of credit to households, which in turn affects real economic activity locally. Therefore, one would expect the employment results to be strongest within industries that are more exposed to local economic conditions[23]. The results in Table 1.10 largely confirm this hypothesis. The effect of shadow exposure on the transmission of monetary policy to employment is positive and significant in the construction, trade, information, finance, and professional services industry. With the exception of trade and construction, these are all service providing industries that are likely to be more exposed to local economic conditions. Construction employment may be affected by both local and national economic conditions. Finally, employment in the tradable goods sector consists of both retail and wholesale

[22] The standard deviation of shadow bank exposure is 0.17 (Table 1.4.), so this is calculated as $100 \times 0.70 \times 0.17 = 11.9$.

[23] A similar argument is made in Mian and Sufi (2014) and Mian et al. (2017), among others.

trade. Retail trade is likely to be driven by local economic conditions, whereas employment in wholesale trade is determined by national and global economic conditions. Therefore, the positive and significant effect for employment within this industry may be attributed to either a local demand or general equilibrium channel.

Table 1.9: County Employment and Wages. This table presents regressions of the form: $Y_{ijt} = \alpha_j + \lambda_{it} + \gamma \times Exposure_{jt} + \beta \Delta i_t \times Exposure_{jt} + \boldsymbol{X_t} \times Exposure_{jt} + \epsilon_{jt}$ Estimates indicate that monetary policy has a smaller effet on employment and wages in counties with more exposure to shadow banking. The dependent variable is the log change in either empoyment or wages for sector i in county j from year $t-1$ to year t. Columns 1-2 consider employment, columns 3-4 consider the total wage bill, and columns 5-6 consider average wages. The underlying data on county originations are from HMDA. $ShadowExposure_{j,t}$ is the shadow bank market share in county j during year $t-2$. $DepositHHI_{j,t-2}$ is the county deposit HHI index in county j during year $t-2$ (as calculated in Drechsler et al. (2017)). Δi_t is the change in the monetary policy rate from year $t-1$ to year t. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. The sample period in all other specifications is 2002 through 2019. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	Employment		Total Wage Bill		Average Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta i_t \times ShadowExposure_{j,t}$	0.59***	0.70***	0.99***	1.11***	0.40**	0.42**
	(0.19)	(0.21)	(0.24)	(0.25)	(0.17)	(0.18)
$\Delta i_t \times DepositHHI_{j,t-2}$		0.82		0.07		−0.76
		(0.76)		(0.89)		(0.61)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes	No	Yes
County Controls × Macro	No	Yes	No	Yes	No	Yes
R^2	0.04	0.04	0.05	0.05	0.03	0.03
N	549238	549238	549238	549238	549238	549238

1.5.4 Results on Wages

I conclude the county level analysis by estimating the effect of shadow banks on the transmission of monetary policy to wages at the sector-county level. I consider the total wage bill and average wage as dependent variables. The total wage bill is indicative of local demand to the extent that wages are correlated with income, which determines consumption. I additionally consider the average wage bill as a dependent variable because it allows me to verify that the results on total wages and employment growth are being driven by an increase in labor demand and not supply. This is because a supply driven increase in employment and total wages should be accompanied by a decrease in average wages, while a demand driven increase should be accompanied by an increase in average wages.

Equation 1.2 is estimated using total wage growth or average wage growth at the sector-county level (measured in log changes) as dependent variables. Results for total wage growth are presented in Columns 3 and 4 of Table 1.9. The estimated parameter of interest is positive and statistically significant at the 1% level across both specifications. This demonstrates that counties with more exposure to shadow banking experience smaller contractions in wage growth compared to counties with less exposure to shadow banking in response to monetary policy rate hikes. Comparing Columns 3 and 4, including time varying county level controls does not change the magnitude of the estimate. The point estimate in Column 4 implies that a one standard deviation increase in shadow bank exposure generates a 19 basis point increase in total wage growth for every

Table 1.10: County Employment by Sector. This table presents regressions of the form: $Y_{jt} = \alpha_j + \lambda_t + \gamma \times Exposure_{jt} + \beta \Delta i_t \times Exposure_{jt} + \boldsymbol{X_t} \times Exposure_{jt} + \epsilon_{jt}$ The dependent variable is the log change in employment for a given sector in county j from year $t-1$ to year t. The underlying data on county originations are from HMDA. $ShadowExposure_{j,t}$ is the shadow bank market share in county j during year $t-2$. $DepositHHI_{j,t-2}$ is the county deposit HHI index in county j during year $t-2$ (as calculated in Drechsler et al. (2017)). Δi_t is the change in the monetary policy rate from year $t-1$ to year t. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. The sample period in all other specifications is 2002 through 2019. All specifications include county fixed effects, year fixed effects, time varying county controls, and a vector of macro controls that are interacted with the time varying county controls. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

Panel A:	Natural Resources	Construction	Manufacturing	Trade	Information	Finance
$\Delta i_t \times ShadowExposure_{j,t}$	−0.05	2.64***	0.32	0.70**	2.04***	0.84**
	(0.80)	(0.72)	(0.67)	(0.27)	(0.77)	(0.41)
R^2	0.08	0.13	0.16	0.11	0.07	0.08
N	46875	46991	47979	53235	41314	51033

Panel B:	Professional Services	Education	Hospitality	Other Services	Public admin.
$\Delta i_t \times ShadowExposure_{j,t}$	2.46***	−0.02	−0.35	−0.02	0.84
	(0.74)	(0.50)	(0.46)	(0.60)	(0.61)
R^2	0.06	0.05	0.07	0.07	0.05
N	49654	52165	52143	47257	51142

Table 1.11: County Wages by Sector. This table presents regressions of the form: $Y_{jt} = \alpha_j + \lambda_t + \gamma \times Exposure_{jt} + \beta \Delta i_t \times Exposure_{jt} + \boldsymbol{X_t} \times Exposure_{jt} + \epsilon_{jt}$ The dependent variable is the log change in the total wage bill for a given sector in county j from year $t-1$ to year t. The underlying data on county originations are from HMDA. $ShadowExposure_{j,t}$ is the shadow bank market share in county j during year $t-2$. $DepositHHI_{j,t-2}$ is the county deposit HHI index in county j during year $t-2$ (as calculated in Drechsler et al. (2017)). Δi_t is the change in the monetary policy rate from year $t-1$ to year t. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. The sample period in all other specifications is 2002 through 2019. All specifications include county fixed effects, year fixed effects, time varying county controls, and a vector of macro controls that are interacted with the time varying county controls. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

Panel A:	Natural Resources	Construction	Manufacturing	Trade	Information	Finance
$\Delta i_t \times ShadowExposure_{j,t}$	0.35	3.93***	1.01	1.46***	0.96	1.03*
	(0.96)	(0.98)	(0.74)	(0.38)	(0.79)	(0.54)
R^2	0.09	0.12	0.12	0.12	0.07	0.08
N	46875	46991	47979	53235	41314	51033

Panel B:	Professional Services	Education	Hospitality	Other Services	Public admin.
$\Delta i_t \times ShadowExposure_{j,t}$	2.33***	0.66	0.54	0.25	0.86
	(0.89)	(0.57)	(0.51)	(0.78)	(0.61)
R^2	0.07	0.08	0.08	0.07	0.08
N	49654	52165	52143	47257	51142

100 basis point increase in the monetary policy rate.

Results for average wage growth are displayed in Columns 5 and 6 of Table 1.9. The coefficient is positive and significant in both specifications. Taken together with the results on employment and total wages, this indicates that shadow bank presence dampens the transmission of monetary policy to total wages and employment through a labor demand channel. Again, this is because a labor supply driven increase in employment growth and total wages should be accompanied by a decrease in the average wage. This result is also consistent with the idea that shadow bank presence weakens the effect of monetary policy on employment through the impact of credit supply on local demand.

Results by sector are presented in Table 1.11. The results are largely consistent with those found for employment by sector. Shadow exposure has a positive and statistically significant affect on the transmission of monetary policy to wages in the construction, trade, finance, and professional services sectors. The only sector for which results are inconsistent with those for employment by sector in Table 1.10 is information, which has a positive but insignificant coefficient.

1.6 Conclusion

This research presents evidence that shadow banks dampen the transmission of monetary policy to the real economy by weakening the bank lending channel. Increases in the monetary policy rate cause shadow banks to expand mortgage originations relative to traditional banks. This weakens the real effects of monetary policy. When monetary policy rates increase, counties with more exposure to shadow banking experience a relative increase in mortgage originations, home prices, employment, and wages relative to counties with less exposure to shadow banking.

I establish these results by employing a methodology that takes seriously confounding demand side factors. I do this by creating a novel dataset that combines lender mortgage origination activity across counties together with county level data on home prices, labor market characteristics, demographics, borrower credit constraints, and local bank market power. I control for confounding loan demand factors in my benchmark results for credit supply by including a full set of county by year fixed effects, therefore relying on within county and year variation in origination activity between banks and shadow banks. I assess the real effects of shadow banking on monetary policy transmission by exploiting variation in exposure to shadow banks across counties. I include a vector of time varying county characteristics and time varying sector fixed effects that control for differences in demographics and exposure to the bank lending and balance sheet channels of monetary policy across counties and employment sectors. I demonstrate that including these additional controls has no meaningful effect on the magnitude of the estimated effect of interest, mitigating concerns that results are driven by unobserved county characteristics.

These findings have important implications for the conduct of monetary policy. Shadow banks have rapidly accumulated market share over the past decade. The reliance on secondary market financing means that the traditional bank lending channel of monetary policy does not apply to shadow banks. Therefore, it is critical for central banks to understand how these shadow banks respond to monetary policy. The results in this paper suggest that shadow mortgage lenders weaken the bank lending channel, and consequently dampen the sensitivity of home prices, employment, and wages to monetary policy.

1.7 Appendix-Figures

Figure 1.4: Average County Employment and Home Value Appreciation. This figure displays the average county level home value appreciation (Panel A) and employment growth (Panel B). Home value data are from Zillow. Employment data are from BLS QCEW survey.

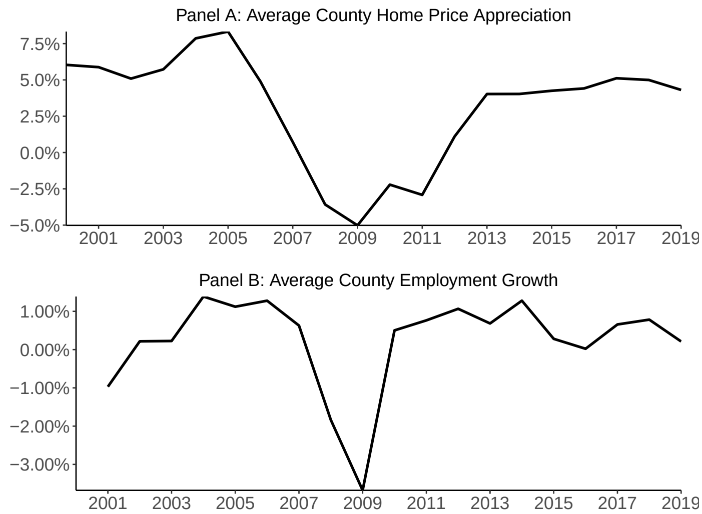
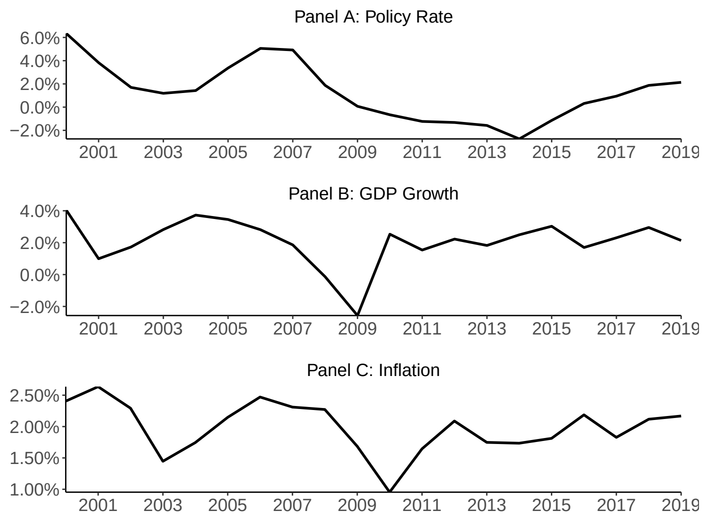


Figure 1.5: Macro Time Series. This figure plots the evolution in the monetary policy rate (Panel A), real GDP growth (Panel B), and inflation (Panel C). Underlying data are from Wu and Xia (2016) and FRED.



1.8 Appendix-Alternative Measure of Exposure

A potential concern with the measure of shadow banking exposure utilized thus far is that shadow banks may systematically sort into counties that are less effected by monetary policy. In this case, the weaker effects of monetary policy in counties with high exposure to shadow banking may be due to unobservable county characteristics and not shadow bank presence. I address this potential source of bias by adopting an alternative measure of shadow bank exposure that is equal to the share of mortgages originated by shadow banks in adjacent counties. Specifically, I define adjacent shadow bank exposure in county j in year t as follows:

$$AdjacentExposure_{jt} = \frac{\sum_i Loans_{i,k,t-2} \times I(i)}{\sum_i Loans_{i,k,t-2}}$$

where k denotes originations by lender i in counties that are adjacent to j. This measure of exposure is conceptually similar to that used in Autor et al. (2014) to instrument for import supply from China. The baseline county level results using adjacent exposure are presented in Table 1.12. Results remain unchanged.

Table 1.12: Robustness to Alternative Measure of Exposure. This table presents regressions of the form: $Y_{jt} = \alpha_j + \lambda_t + \gamma \times AdjacentExposure_{jt} + \beta \Delta i_t \times AdjacentExposure_{jt} + \boldsymbol{X_t} \times Exposure_{jt} + \epsilon_{jt}$ where $AdjacentExposure_{jt}$ is equal to the shadow bank market share in counties adjacent to county j in time $t-2$. Δi_t is the change in the monetary policy rate from year $t-1$ to year t. $\boldsymbol{X_t}$ is a vector of macroeconomic controls. The dependent variables are listed in the column headers. The sample period in all other specifications is 2002 through 2019. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	Home Purchase Originations	Refinancings	Home Price Appreciation	Employment Growth	Wage Growth
$\Delta i_t \times AdjacentExposure_{j,t}$	3.95**	18.09***	0.97***	0.61***	1.19***
	(1.64)	(1.69)	(0.32)	(0.24)	(0.27)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No
County Controls	Yes	Yes	Yes	Yes	Yes
County Controls × Macro Controls	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	No	No	No	Yes	Yes
R^2	0.98	0.98	0.55	0.04	0.05
N	53159	53159	39824	548317	548317

1.9 Appendix-Omitting Large Lenders

The lender-county level results on originations may be biased by regulatory changes that occurred in the aftermath of the 2007-2009 Great Recession and coincide with monetary policy changes. These regulatory changes only affected banks, and therefore may have caused shadow banks to expand originations relative to traditional banks. I mitigate this concern by re-estimating Equation 1.1 excluding banks that were affected by the Dodd Frank Act. The Dodd Frank Act consisted of several regulatory changes that affected banks with over $10 billion in assets. An additional set of reforms applied to banks with over $50 billion in assets. Following Bouwman et al. (2018), I assume that banks with assets below $7 billion were not affected by the $10 billion threshold and banks with less than $35 were not affected by the $50 billion threshold. I re-estimate Equation 1.1 including only shadow banks and these non-affected banks. Results are presented in Table 1.13. Point estimates are virtually unchanged from the benchmark results.

Table 1.13: Lender-County Originations: Omitting Large Lenders. This table presents results for the effect of monetary policy on shadow bank relative to traditional bank mortgage lending, omitting large banks that are affected by the Dodd Frank Act regulatory size requirements. The first two columns omit banks with over 35 billion in assets and the last two columns omit banks with over 35 billion in assets. These thresholds come from Bouwman et al. (2018). The dependent variable is the log of new mortgage originations by lender i in county j during year t. The underlying data on county originations are from HMDA. $ShadowBank_i$ is an indicator variable that is equal to 1 if lender i is a shadow bank and 0 otherwise. Δi_t is the change in the monetary policy rate from year $t-1$ to year t. The sample period is 2002 through 2019. Standard errors are clustered at the commuter zone and lender level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	Omitting Assets $\geq$ 35B		Omitting Assets$\geq$7B	
	Home Purchase Loans	Refinancings	Home Purchase Loans	Refinancings
$\Delta i_t \times ShadowBank_i$	5.76***	7.95***	5.59***	7.68***
	(1.46)	(1.66)	(1.47)	(1.68)
Lender FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
ShadowBank × Macro	Yes	Yes	Yes	Yes
R^2	0.30	0.30	0.41	0.41
N	3316465	3110647	2164602	2014177

1.10 Appendix-List of Large Lenders

Table 1.14: Largest Traditional and Shadow Banks as of 2006. This table lists the ten largest traditional and shadow banks by 2006 market share. Underlying data is from HMDA.

Panel A: Traditional Banks

Name	Market Share
Wells Fargo Bank	5%
National City Bank	5%
JPMorgan Chase Bank	3%
Suntrust Bank	3%
Bank of America	2%
First Horizon Home Loan Corp	2%
Fremont Inv & Loan	1%
Wachovia Bank	1%
Indymac Bank	1%
Abnamro Mortgage	1%

Panel B: Shadow Banks

Name	Market Share
Countrywide Bank	8%
American Home Mortgage	2%
New Century Mortgage Corp	2%
WMC Mortgage Corp	2%
Option One Mortgage Corp	1%
First Magnus Financial Corp	1%
Taylor, Bean, & Whitaker	1%
PPH Mortgage Co	1%
Homecomings Financial Network	1%
Decision One Mortgage Co LLC	1%

Table 1.15: Largest Traditional and Shadow Banks as of 2019. This table lists the ten largest traditional and shadow banks by 2019 market share. Underlying data is from HMDA.

Panel A: Traditional Banks

Name	Market Share
Wells Fargo Bank, National Association	3%
JPMorgan Chase Bank, National Association	2%
Bank of America, National Association	2%
Navy Federal Credit Union	1%
Primelending	1%
USAA Federal Savings Bank	1%
U.S. Bank National Association	1%
Flagstar Bank, FSB	1%
Citizens Bank, National Association	1%
The Huntington National Bank	1%

Panel B: Shadow Banks

Name	Market Share
United Shore Financial, LLC	4%
Quicken Loans, LLC	3%
Fairway Independent Mortgage Company	3%
Caliber Home Loans, INC.	2%
NVR Mortgage Finance, Inc.	2%
Guild Mortgage Company	1%
LoanDepot.com, LLC	1%
Mortgage Research Center, LLC	1%
Movement Mortgage, LLC	1%
Guaranteed Rate, INC.	1%

Chapter 2

The Impact of Securitized versus Balance Sheet Mortgage Lending Booms on the Severity of the Great Recession

2.1 Introduction

A large body of research has documented that credit booms are predictive of future recessions, and cause recessions to be deeper when they do occur[1]. This literature has not differentiated between credit booms that are driven by expansions in balance sheet lending versus those that are driven by expansions

[1]See López-Salido et al. (2017), Krishnamurthy and Muir (2017), etc.

in securitized lending. This distinction is important because securitized loans are sold to the secondary market after origination, and therefore are more affected by moral hazard issues than balance sheet loans, which are held by the originating institution until maturity. In this paper I contribute to the literature by separately estimating the effect of balance sheet and securitization driven expansions in mortgage lending during the 2002-2006 housing boom on the severity of the 2007-2009 recession in the United States. Utilizing geographical variation in bank mortgage lending activity across counties, my results indicate that county level exposure to securitized lending during the 2002-2006 period leads to an expansion in originations to risky borrowers that generates sharp declines in home prices, a rise in mortgage delinquencies, and a fall in nontradable and construction employment during the 2007-2009 crisis. The same is not true for exposure to balance sheet lending, which generates boom period expansions in originations to safer borrowers and has a small positive effect on crisis period home prices and employment.

These results are important for several reasons. First, they contribute to the understanding of the 2007-2009 crisis by emphasizing that the negative effects of the 2002-2006 credit boom were largely caused by expansions in securitized lending. While the role of mortgage securitization in the US housing crisis has been widely studied in the literature (for example Mian and Sufi (2009)), this paper is the first to explicitly compare the effects of balance sheet and securitized lending expansions on the real economy during the crisis. Additionally, the market share of lenders that rely heavily on securitization to finance mortgage originations has grown rapidly since 2009[2]. To that end, it continues to be important for policy makers to understand the differential effects of balance sheet versus securitization driven credit booms.

Estimating the causal effect of exposure to securitization and balance sheet lending on real economic outcomes is loaded with identification issues. For example, credit demand simultaneously affects home prices and the number of securitized mortgage originations. To overcome this challenge to identification, I construct county level measures of exposure to securitization and balance sheet lending that are uncorrelated with local economic conditions such as credit demand. I do this by obtaining loan level data from the Home Mortgage Disclosure Act (HMDA). For each loan, HMDA data discloses the county in which the underlying property is located and whether the loan was sold to the secondary market (securitized) or retained on the originator's balance sheet. I obtain HMDA data for years 2001 through 2006 and aggregate the number of securitized and balance sheet originations within each county for each lender in my sample. Adapting the identification strategy from Amiti and Weinstein (2018), I exploit bank origination activity across counties to estimate bank specific shocks to the supply of balance sheet and securitized mortgage lending that are uncorrelated with local economic conditions.

I first analyze the relationship between the estimated shocks and bank balance sheet characteristics. I find that bank balance sheet characteristics ex-

[2]This is driven by an increase in shadow banking. See Buchak et al. (2018).

plain more variation in the estimated balance sheet shock than in the securitized lending shock. This result is intuitive, suggesting a tight connection between bank balance sheet capacity and the supply of mortgages that are retained by the originating bank. Specifically, I find that liquidity, income, and bank size are statistically significant drivers of the estimated balance sheet shock. Securitization activity is likely to be driven by secondary mortgage market conditions, and therefore has a weaker connection with bank balance sheet characteristics. Bank funding cost is the only balance sheet characteristic that has a statistically significant effect on the estimated securitization shock.

I obtain a county level measure of exposure to securitized and balance sheet lending during the 2002-2006 credit boom that is uncorrelated with local economic conditions by taking a weighted average of the bank specific shocks within each county over the 2002-2006 time period. I show that the resulting county level measures of exposure to securitized and balance sheet lending are predictive of actual county level securitized and balance sheet lending activity during the 2002-2006 credit boom. I further combine these variables with county level data on home prices, employment, and mortgage delinquencies during the 2000 through 2012 period.

I implement a difference in differences methodology to separately estimate the effect of boom period exposure to securitization and balance sheet lending on the severity of the post 2006 crisis. I begin by estimating the effect of exposure on the local housing market. My results indicate that a one standard deviation increase in boom period exposure to securitized mortgage lending generates a 7% decrease in home price appreciation during the 2007-2009 downturn. The corresponding estimate for exposure to balance sheet mortgage lending indicates that a one standard deviation increase in boom period exposure to balance sheet lending generates a 3% increase in home price appreciation during the 2007-2009 period. This finding is statistically significant at the 5% level. These results indicate that the effect of the credit boom on the fall in crisis period home prices can be explained entirely by securitized and not balance sheet lending. Consistent with the results for home prices, I find that a one standard deviation increase in exposure to securitized lending generates a 1.6 percentage point increase in mortgage delinquencies, while a one standard deviation increase in balance sheet exposure leads to a 1.2 percentage point decrease in mortgage delinquencies during the crisis period. These results are robust to the inclusion of baseline county level demographic and labor market controls interacted with time fixed effects.

I next evaluate the effect of balance sheet and securitization exposure on the local labor market during the crisis period. Again utilizing a difference in differences specification, I separately estimate the effect of each exposure variable on employment in the nontradable, tradable, construction, and all other sectors. Considering employment in each sector separately is a natural choice for my setting because employment in the nontradable and construction sectors are more responsive to local economic conditions than employment in the tradable sector.

My results indicate that a one standard deviation increase in boom period exposure to securitized lending generates a 1.9 percent decrease in nontradable and 8.2 percent decrease in construction employment growth during the crisis period. I find no statistically significant effect of securitization exposure on employment in the tradable sector, and a noisy ($p \leq 0.1$) but negative effect on employment in the "other" sector. For balance sheet exposure, I find no evidence of employment effects in the nontradable, tradable, or construction sectors. I find some evidence of a positive employment effect in the "other" employment sector. Specifically, I find that a one standard deviation increase in boom period exposure to balance sheet lending generates a 1.8 percentage point increase in "other" employment growth (statistically significant at the 10% level).

I conclude by comparing the effects of balance sheet and securitization exposure on the types of mortgages that are originated during the 2002-2006 credit boom. Securitization exposure generates a large increase in high risk lending during the credit boom while balance sheet exposure leads to a decrease in high risk originations during this time period. This finding is consistent with the idea of moral hazard in securitization markets. This result suggests that securitization exposure worsened the effect of the 2007-2009 crisis by allocating credit to riskier borrowers.

2.2 Related Literature

A large literature has linked credit booms to subsequent economic downturns. Papers using aggregate data have shown that narrow credit spreads are predictive of a subsequent rise in spreads that coincide with a contraction in real economic activity. López-Salido et al. (2017) are the first to document this for the United States, while Krishnamurthy and Muir (2017) present similar findings for an international panel of countries. Jordà et al. (2016) focus on mortgage credit specifically, using an international panel to show that recessions preceded by a large expansion in mortgage lending are deeper and longer lasting. This literature does not differentiate between balance sheet and securitized lending, which is the primary contribution of my paper.

My paper is most closely related to research that utilizes variation in bank lending activity across counties and firms to understand the mechanisms through which credit supply expansions affect the real economy. The literature has found that bank exposure to the 2007-2009 financial crisis generated a contraction in credit supply that led to a reduction in real economic activity (Chodorow-Reich (2014), Mondragon (2015), Greenstone et al. (2020)). Gilchrist et al. (2018) separately estimate the real economic effects of expansions in credit during the 2003-2007 period and 2007-2010 period, finding that reductions in credit supply to households generate a drop in construction activity during both periods and a fall in broad based employment measures during the 2007-2010 bust period. The literature has also found that expansions in credit supply affect the severity of the bust through the credit driven household demand channel. Expansions in the supply of credit to households generate increases in household leverage, causing a sharp reduction in household wealth and aggregate demand when home prices fall. This leads to a reduction in employment through a fall in household demand. This mechanism is documented for the 2007-2009 crisis in the United States by Mian and Sufi (2014) and Di Maggiol and Kermani (2017). Mian et al. (2017) and Mian et al. (2020) find similar support for the credit-driven household demand channel using an international panel of countries and state level data in the early 1980s. My paper differs from the above mentioned literature by separately estimating the real economic effects of securitization driven credit supply expansions and balance sheet driven credit supply expansions.

A central component of my findings is that securitization driven credit booms are different than balance sheet driven booms because of risk taking in securitization markets. To that end, my paper has ties to the literature on securitization and lender risk taking. Several papers have been published on this topic since the onset of the 2007-2009 crisis, and the evidence points to the presence of moral hazard in securitization markets. Mian and Sufi (2009) show that subprime zip codes experienced larger expansions in credit from 2002 through 2005, and that loans to these regions were more likely to be sold to the secondary market. Using loan level data, Keys et al. (2010) and Demyanyk and Van Hemert (2011) find that securitization reduced credit screening incentives for mortgage originators in the US during the credit boom that preceded the 2007 crisis. Piskorski et al. (2015) and Griffin and Maturana (2016) focus on misrepresentation of borrower characteristics by mortgage originators, showing that this was more likely to happen for loans that were securitized and that these loans had higher default probabilities. Theoretical research has shown that securitization may increase risk in the economy by allowing idiosyncratic risks on individual loans to be diversified. This leads investors to accept a higher default risk on individual loans at the cost of increasing aggregate risk in the economy by making credit available to a riskier pool of borrowers (Segura and Villacorta (2020), Gennaioli et al. (2013)). My paper contributes to the literature on securitization and risk taking by empirically estimating the real economic effects of expansions in securitized lending.

2.3 Data

This paper constructs a novel dataset from several sources. Loan level data from the Home Mortgage Disclosure Act (HMDA) are used to construct county level measures of exposure to securitized and balance sheet lending that are uncorrelated with local economic conditions. Bank balance sheet data are obtained to understand the drivers of securitized and balance sheet lending at the bank level. Finally, county level data are included to estimate the effects of exposure to securitization and balance sheet lending on county level outcomes. The following section contains a detailed discussion of each of these datasets.

2.3.1 Home Mortgage Disclosure Act Data

The primary data source comes from the Home Mortgage Disclosure Act (HMDA). HMDA data are collected at the loan application level from 2001 through 2006. All mortgage lenders with over 30 million in assets must submit HMDA data to the Federal Financial Institutions Examination Council (FFIEC) each year, and so this data source covers the vast majority of the US mortgage market. The sample is restricted to home purchase loans originated by banks, bank holding companies, and mortgage lenders that are subsidiaries of banks or bank holding companies. For each year, I aggregate the HMDA data to the lender-county level.

The HMDA data contain several important loan characteristics, including borrower demographic information (income, race, gender), as well as the county in which the property is located. Crucial for this analysis, the dataset contains a flag indicating whether a loan is sold by the lender during the year of origination[3]. Throughout this paper, the term "securitized lending" is used to refer to all loans that are sold by the originating institution. If the loan is sold, the HMDA data further indicate whether the loan was sold to a GSE, commercial or savings bank, life insurance company, private securitizer (for years after 2003), or an affiliate institution. I classify all loans that are not retained on the balance sheet of the originator as securitized, including loans that are sold to affiliate institutions within the same bank holding company. Affiliate sales are

[3]The data doesn't indicate whether loans originated in previous years are sold. This is a limitation, however HMDA has previously been used to study securitization (see Buchak et al. (2018), who use HMDA data to study the rise of shadow banking in the post crisis era)

dominated by large bank holding companies, which were more active in private securitization markets during the housing boom. That said, it is likely that the majority of affiliate sales are securitized by the purchasing institution. This is supported by Appendix Figure 2.4, which shows that affiliate sales rapidly increased along with private securitization from 2004 through 2006, before falling dramatically after 2006. If affiliate sales consisted primarily of loans that are kept on the balance sheet of the purchasing institution, then one would expect them to follow a similar trend as balance sheet lending during the 2000-2016 period. Figure 2.4 clearly shows that this is not the case.

Table 2.1: Lender-County summary statistics. This table presents summary statistics at the lender-county level. Securitized loans are those sold by the lender during the year of originations, while balance sheet loans are those that are not. Aggregate loans are the total of securitized and balance sheet loans. The sample period is 2002 through 2006.

	Mean	St. Dev.	N
$SecuritizedLoans_{i,j,t}$	19.09	136.99	428344
$\Delta log(SecuritizedLoans_{i,j,t})$	0.09	0.81	160034
$BalanceSheetLoans_{i,j,t}$	7.19	51.06	428344
$\Delta log(BalanceSheetLoans_{i,j,t})$	-0.04	0.83	128207

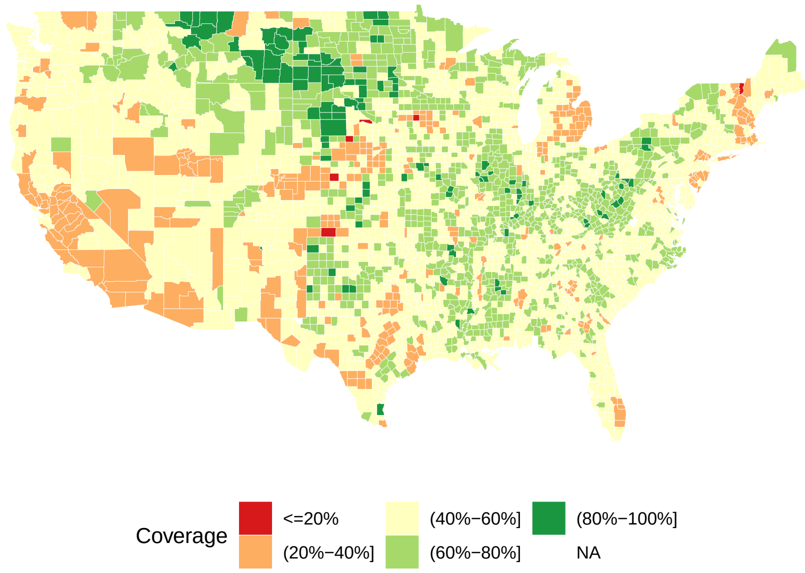
HMDA data does not allow for loan sales to be reliably differentiated between sales to the GSEs and private purchasers. This is because many loans that are purchased by private institutions on the secondary market are subsequently sold to the GSEs, and hence do not represent private securitization. I therefore do no separately consider the effects of GSE and private securitization. This is a potential limitation because government regulations prevent GSEs from purchasing subprime loans. That said, the GSEs were heavily involved in the purchasing of Alt-A and high risk loans during the housing boom. These are loans that, while not technically subprime, have characteristics of higher risk loans such as low documentation, low FICO scores, adjustable interest rates, or high loan to value ratios. According to Jaffee (2010), 31% of loans guaranteed by Fannie Mae and 30% of loans guaranteed by Freddie Mac as of 2009 fell into the higher risk category.

I restrict the sample to include banks who either actively originate securitized or balance sheet loans in at least three commuter zones in a given year. This strengthens the plausibility of the assumptions underlying my empirical methodology, which relies on geographic variation in bank origination activity across counties. Summary statistics at the lender-county level are presented in Table 2.1. The sample size varies because not every lender originates loans that are both held on balance sheet and securitized in every county in which they are active. The average county coverage for years 2002 through 2006 is shown in Figure 2.1. The average county includes 51% of HMDA loan originations for this time period.

2.3.2 Lender Balance Sheet Data

Lender balance sheet data are obtained from FFIEC Call reports. Since HMDA data are only available on an annual basis, the balance sheet data are restricted to those from the fourth quarter of each year. All call report data are aggregated to the bank holding company level. HMDA data are merged with call report data following Loutskina and Strahan (2009). Summary statistics for the

Figure 2.1: Geographic Distribution of Sample Coverage. This figure depicts the percentage of HMDA originations in each county that are included in the sample. The average coverage is 51 %.



final panel of lenders are presented in Table 2.2 for years 2002 through 2006.

2.3.3 Local Economic Outcomes

This paper makes use of county level data from several sources. Home price data are obtained from Zillow. Published at a monthly level, the Zillow Home Value Index (ZHVI) is equal to the median estimated home value within each county. This is used as an alternative to the more well known Core Logic Case-Schiller home price index, which is not publicly available at the county level. The Zillow data is advantageous because it is based on the estimated market value

Table 2.2: Lender Summary Statistics. This table presents summary statistics at the lender level. $SecuritizationShock_{i,t}$ and $BalanceSheetShock_{i,t}$ are the estimated credit supply shocks for securitized loans and balance sheet loans. See text for details. Bank funding cost is equal to total interest expense divided by total liabilities. Size is equal to the log of total assets. Liquidity ratio is equal to the sum of securities (available for sale and held to maturity), currency and coin, federal funds sold, repurchase agreements, and interest bearing balances divided by total assets. Income is equal to bank income divided by total assets. Tier 1 capital is the ratio of tier 1 capital to risk weighted assets. The sample period is 2002 through 2006.

	Mean	St. Dev.	N
$SecuritizationShock_{i,t}$	-0.06	0.56	3246
$BalanceSheetShock_{i,t}$	-0.08	0.78	5433
$FundingCost_{i,t}$	0.02	0.01	6545
$Tier1Ratio_{i,t}$	0.10	0.02	6545
$Income_{i,t}$	0.01	0.01	6545
$LiquidityRatio_{i,t}$	0.29	0.13	6545
$log(Assets_{i,t})$	12.97	1.38	6545

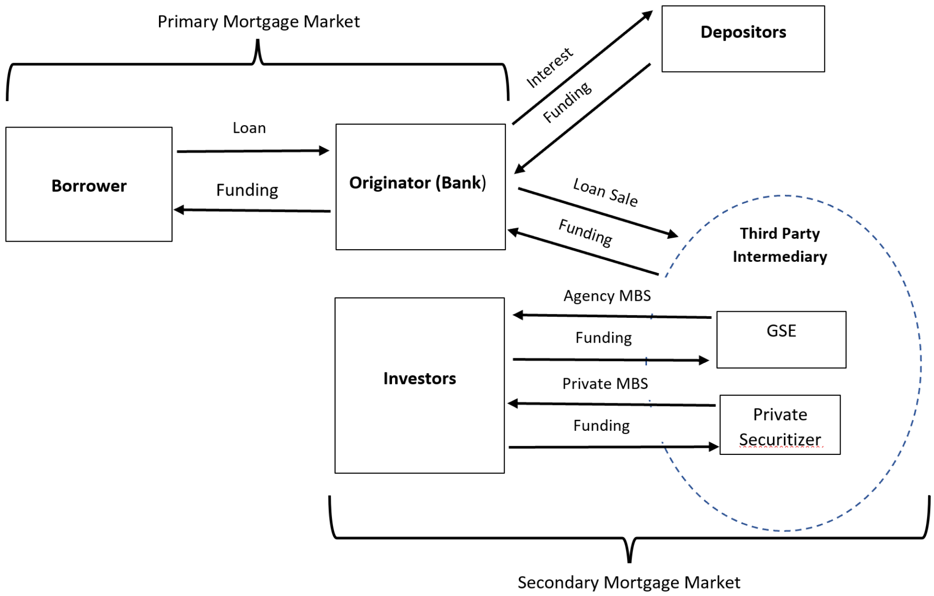
of all homes within a county, whereas the Case-Schiller index is based only on the value of homes that have sold more than once. This biases the Case-Schiller index towards the value of older homes that are older and sell more frequently. The monthly data are converted to an annual series by averaging the fourth quarter home value within each county. Employment data by industry are retrieved from the U.S. Census County Business Patterns survey at the 4-digit NAIC level. Industries are divided into four categories (tradable, nontradable, construction, or other) using the classification scheme of Mian and Sufi (2014). Some counties do not specify employment within each 4-digit industry code, but report a range in which the value falls (for example, between 100 and 500 employees). Following Mian and Sufi (2014), I replace these missing values with the midpoint of the given range. County level population data by race is obtained from the National Cancer Institute (NCI). The NCI population estimates are based on U.S. Census data. They have been modified to take into account changes in the set of race categories used by the census over the sample period, so that race categories remain consistent over the entire period. County level data on mortgage delinquencies is collected from the Consumer Financial Protection Bureau (CFPB). This data are available for years 2008 and later, and reports the percentage of outstanding mortgage loans in each county that are at least 90 days delinquent. County level data on employment and the retired population are taken from the BLS QCEW survey. Finally, data on the subprime credit population within each county are obtained from Equifax.

Summary statistics for the county level data are reported in Appendix Table 2.12 for years 2000 through 2012. The sample size varies considerably across data sources. CFPB reports delinquency data for 500 counties in years 2008 and later. Zillow home price data are available for all years, but not all counties. Both of these datasets include data for all major population centers in the United States.

2.4 Methodology

Banks have traditionally financed their asset portfolio by issuing debt and holding loans on their balance sheet until maturity, using periodic loan payments to repay creditors. While this funding structure still exists, banks fre-

Figure 2.2: Bank Mortgage Funding. This figure depicts the mortgage funding structure of a typical bank. Depositors fund balance sheet loans, while secondary market investors fund originations that are sold on the secondary market.



quently tap into capital markets to fund their loan portfolios. In this case, banks originate loans and then sell them to a third party intermediary. For mortgage loans, this third party may be another bank, a special purpose vehicle, or Government Sponsored Enterprises (GSE). The purchaser of these loans may hold them as whole loans on their balance sheet, or repackage them into MBS and sell them on the secondary market[4]. This process is illustrated for the case of mortgages in Figure 2.2.

The goal of this paper is to estimate the causal effect of balance sheet and securitization driven credit supply expansions on real economic outcomes. Credit quantities observed in the data are simultaneously determined by supply and demand, and thus cannot be used directly to pin down the causal effect of credit

[4]See Gorton and Metrick (2012) for a detailed review of the securitization process.

supply expansions. Following Greenstone et al. (2020), Amiti and Weinstein (2018) Gilchrist et al. (2018), and Ivashina et al. (2020), I model bank lending activity as a linear function of time varying bank and county specific shocks. Specifically, I estimate the following fixed effects model separately for securitized and balance sheet originations:

$$\Delta log\left(Y_{ijt}\right) = \alpha_{jt} + \lambda_{it} + \epsilon_{ijt} \tag{2.1}$$

for bank i in county j at time t. The dependent variable is the log change in either securitized or balance sheet originations. The α_{jt} are county by time fixed effects and represent county specific shocks to the dependent variable. These absorb variation in lending activity that are common to all banks within a county. Consequently, the α_{jt} represent changes in lending that are determined by local economic conditions, including credit demand and borrower riskiness. Crucial to my analysis are the λ_{it}, which are bank by time fixed effects and represent bank-time specific shocks to the dependent variable. These absorb variation in lending activity that are common to a bank within a given year across counties. Therefore, the λ_{it} represent bank specific shocks to the supply of credit. The assumptions underlying this specification are that (1) credit demand is county specific (not bank specific) and (2) credit supply is bank specific (not county specific). For example, it assumes that a local demand shock does not prompt borrowers within the same county to systematically demand more credit from some banks relative to others. Similarly, it assumes that credit supply shocks do not cause banks to systematically lend more in certain counties relative to others.

Following the literature, I estimate Equation 2.1 using weighted least squares (WLS). Weights are given by base period lender market shares (within each loan type) in each county. Specifically, the weights for lender i in county j and time t are given by

$$W_{ijt} = \frac{Loans_{ij,t-1}}{\sum_{i \in j} Loans_{ij,t-1}}$$

where $Loans_{ij,t-1}$ refers to either the number of securitized or balance sheet originations. These weights help pin down the λ_{it} by ensuring that banks which are particularly important in a certain county are weighted more heavily. I restrict my sample to banks that are active in at least three commuter zones. This reduces noise in the estimated λ_{it} and lessens the likelihood that the estimates are driven by changes in economic conditions that are common across all counties in which a bank is actively lending.

After estimating Equation 2.1 separately for securitized and balance sheet loans, the resulting λ_{it} terms are aggregated within each county to obtain county level measures of balance sheet and securitization exposure. In particular, the county level measures of exposure are computed as

$$SecuritizationExposure_{jt} = \frac{Loans_{ij,t-1}}{\sum_{i \in j} Loans_{ij,t-1}} \lambda_{it}$$

$$BalanceSheetExposure_{jt} = \frac{Loans_{ij,t-1}}{\sum_{i \in j} Loans_{ij,t-1}} \lambda_{it}$$

which is equal to the weighted sum of all λ_{it} within each county. $Loans_{ij,t-1}$ refer to either the number of securitized or balance sheet mortgage originations.

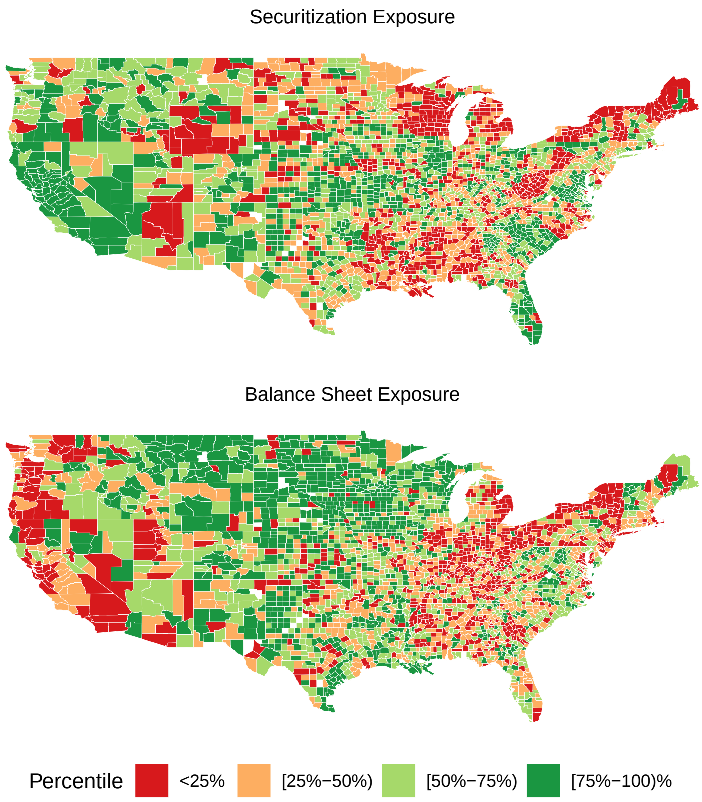
Lags are used to compute market shares to ensure that weights are not determined endogenously. Finally, each of the county level shocks are summed over the years 2002 through 2006 in order to have an estimate of total boom period exposure for each type of credit expansion:

$$SecuritizationExposure_{j,2002:2006} = \sum_{t=2002}^{2006} SecuritizationExposure_{jt}$$

$$BalanceSheetExposure_{j,2002:2006} = \sum_{t=2002}^{2006} BalanceSheetExposure_{jt}$$

The exposure measures are normalized to have a standard deviation of one and mean zero. The geographic distribution of the resulting county level measures of aggregate 2002-2006 exposure to securitized and balance sheet lending are shown in Figure 2.3. The correlation between the estimated shocks is low (correlation coefficient is 0.01).

Figure 2.3: Geographic Distribution of Exposure. This map displays the geographic distribution of securitization and balance sheet exposure percentiles from 2002 through 2006. See text for details on the construction of the exposure variables. Counties in white are missing values.



2.5 Lender Level Analysis

I begin by analyzing characteristics of the lender level credit supply shocks (the λ_{it} from Equation 2.1 for securitized and balance sheet loans. I estimate the relationship between these estimated shocks and bank balance sheet variables to help understand which balance sheet characteristics drive the shocks to the supply of securitized and balance sheet originations. I estimate the following equation for bank i in year t:

$$\lambda_{it} = \alpha_i + \gamma_t + \boldsymbol{X_{i,t-1}\beta} + \epsilon_{it} \tag{2.2}$$

The vector $X_{i,t-1}$ includes the tier 1 capital ratio, liquidity ratio, income, funding cost, and bank size[5]. All bank balance sheet variables are measured in the fourth quarter of year $t-1$. The dependent variable λ_{it} is either the securitized or balance sheet lending shock from Equation 2.1.

Results are presented in Table 2.3. Comparing Columns 1 and 2, balance sheet characteristics play a larger role in explaining the balance sheet shock than they do in explaining the securitization shock. This is indicated by the difference in R^2 values (0.68 versus 0.50). This finding is intuitive, given that balance sheet lending should be constrained by the balance sheet capacity of the bank. The same is not true for securitized originations because they are sold to the secondary market shortly after origination. Expansions in securitized lending may be driven by secondary market factors such as investor demand for mortgage backed securities rather than balance sheet capacity. Examining the coefficients, Column 1 indicates that funding cost is a significant and negative driver of the securitization shock. This is potentially driven by the cost of short term borrowing that banks must undertake in order to fund originations before they are sold to the secondary market. For balance sheet lending, liquidity ratio, income, and bank size are all significant drivers. The positive coefficient on the liquidity ratio

[5]Bank funding cost is equal to total interest expense divided by total liabilities. Size is equal to the log of total assets. Liquidity ratio is equal to the sum of securities (available for sale and held to maturity), currency and coin, federal funds sold, repurchase agreements, and interest bearing balances divided by total assets. Income is equal to bank income divided by total assets. Tier 1 capital is the ratio of tier 1 capital to risk weighted assets.

Table 2.3: Estimated Shocks and Bank Balance Sheet Characteristics. This table presents results for the effect of bank balance sheet characteristics on the estimated balance sheet and securitization shocks (Equation 2.2). The sample period is 2002 through 2006. See text for details. Standard errors are clustered at the lender level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	$SecuritizationShock_{i,t}$	$BalanceSheetShock_{i,t}$
$Tier1Ratio_{i,t-1}$	-1.05	-0.87
	(1.68)	(1.43)
$LiquidityRatio_{i,t-1}$	-0.09	1.41^{***}
	(0.24)	(0.27)
$Income_{i,t-1}$	1.38	-7.12^{*}
	(4.37)	(3.91)
$FundingCost_{i,t-1}$	-10.34^{**}	-4.42
	(5.01)	(5.14)
$Size_{i,t-1}$	-0.06	-0.29^{***}
	(0.11)	(0.11)
Bank FE	Y	Y
Year FE	Y	Y
R^2	0.50	0.68
N	3246	5433

suggests that banks with more liquidity have a greater capacity to hold new loans on their balance sheet. Similarly, the negative coefficient on bank size suggests that larger banks expand balance sheet lending at a slower pace.

2.6 County Level Analysis

I begin the county level analysis by first demonstrating that the county level securitization and balance sheet lending exposure variables are in fact predictive of actual securitized and balance sheet lending at the county level. This confirms that these exposure variables are valid proxies for actual securitization and balance sheet lending activity at the county level. I then present the main results of the paper, estimating the effect of total boom period exposure to securitization and balance sheet lending shocks on home price appreciation, employment, and mortgage delinquencies during the crisis period.

2.6.1 Validity of Estimated Shocks

I adopt an econometric specification that allows for total exposure to securitized and balance sheet lending from 2002 through 2006 to have a different effect on the dependent variable in each year. This follows the specification used in Greenstone et al. (2020). I estimate the following equation separately for securitization and balance sheet exposure:

$$\begin{aligned} Y_{jt} = \alpha_j + \lambda_t + \sum_{t=2001}^{2006} \beta_t Exposure_{j,2002:2006} \times I\left[year_t = t\right] \\ + \boldsymbol{X_{i,2001}} \times I\left[year_t = t\right] + \epsilon_{jt} \end{aligned} \tag{2.3}$$

where j refers to counties and t to years. $Exposure_{j,2002:2006}$ refers either to total securitization exposure or balance sheet exposure from years 2002 through 2006. Y_{jt} is either the log of securitized or balance sheet originations. $I\left[year_t = t\right]$ is an indicator function equal to one in year t and zero otherwise. Following the literature, Equation 2.3 is estimated using county level population shares in $t-2$ as weights. This specification allows for the estimated exposure variables to have a different effect on the path of the outcome variable from 2002 through 2006 while also controlling for unobserved baseline differences between counties through the inclusion of county fixed effects. The base year is 2001 and each exposure variable is normalized to have mean zero and unit standard deviation. Therefore, β_t is the effect of a one standard deviation increase in exposure on the dependent variable in year t relative to 2001. The cumulative effect of each exposure variable on the outcome can be computed by summing coefficients. For example, the cumulative effect of a one standard deviation increase in securitization exposure on securitized originations from 2002 through 2006 is given by:

$$\beta = \beta_{2002} + \beta_{2003} + \beta_{2004} + \beta_{2005} + \beta_{2006}$$

The vector $\boldsymbol{X_{i,2001}}$ consists of baseline (2001) county level control variables. This includes racial composition (percent white, percent black, percent other race), industry composition (share of employment in construction, tradable, and nontradable goods), labor market characteristics (retired share and unemployment rate), and the percent of subprime borrowers. These baseline control variables are interacted with a full set of time indicator variables to control for the possibility that results are driven by baseline differences between counties. Standard errors are clustered at the commuter zone level.

Results are presented in Table 2.4. Each exposure variable has a positive and economically large effect on the dependent variable during the 2002-2006 credit boom. Summing the coefficients in Column 1, a one standard deviation increase in securitization exposure results in a 19.2% increase in securitized originations from 2002 through 2006. The effect for balance sheet lending is even larger. A one standard deviation increase in balance sheet exposure results in a 34.5% increase in balance sheet originations during the 2002-2006 time period. Both of these estimates are statistically significant at the 1% level. These results confirm that the constructed exposure variables are predictive of actual balance sheet and securitized lending at the county level.

Table 2.4: Effect of Securitization and Balance Sheet Exposure on 2002-2006 Securitization and Balance Sheet Lending. This table presents results for the effect of 2002-2006 securitization and balance sheet exposure on boom period securitization and balance sheet lending. The dependent variable is either the log of new securitized (column 1) or balance sheet (column 2) mortgage originations in county j during year t. The sample period is 2001 through 2006. Both specifications include county fixed effects, year fixed effects, and baseline controls interacted with year indicator variables. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	Securitized Lending	Balance Sheet Lending
$Sec.Exposure_{j,2002:2006} \times 2002$	0.030***	
	(0.010)	
$Sec.Exposure_{j,2002:2006} \times 2003$	0.065***	
	(0.016)	
$Sec.Exposure_{j,2002:2006} \times 2004$	0.041***	
	(0.012)	
$Sec.Exposure_{j,2002:2006} \times 2005$	0.050***	
	(0.014)	
$Sec.Exposure_{j,2002:2006} \times 2006$	0.005	
	(0.017)	
$B.S.Exposure_{j,2002:2006} \times 2002$		0.015
		(0.012)
$B.S.Exposure_{j,2002:2006} \times 2003$		0.061***
		(0.021)
$B.S.Exposure_{j,2002:2006} \times 2004$		0.048**
		(0.019)
$B.S.Exposure_{j,2002:2006} \times 2005$		0.101***
		(0.028)
$B.S.Exposure_{j,2002:2006} \times 2006$		0.121***
		(0.039)
Total effect on 2002-2006 lending	0.192***	0.345***
	(0.056)	(0.104)
R^2	0.994	0.987
N	12710	12710

2.6.2 Boom Period Exposure and Post 2006 Outcomes

The previous section confirmed that the constructed county level measures of exposure to securitized and balance sheet lending during the 2002-2006 credit boom are predictive of actual securitized and balance sheet lending during this period. Given that these exposure variables are plausibly uncorrelated with local economic characteristics (including credit demand), these variables allow me to estimate the causal effect of boom period exposure to expansions in the supply of securitized and balance sheet mortgage lending on post 2006 economic conditions. Specifically, I estimate the effect of 2002-2006 exposure to balance sheet and securitized lending on crisis period home prices, mortgage delinquencies, and employment. In the following sections I present results from regressions that take the following form:

$$\begin{aligned} Y_{jt} = \alpha_j + \lambda_t + \sum_{t=2000}^{2012} \beta_t Exposure_{j,2002:2006} \times I\left[year_t = t\right] \\ + \boldsymbol{X_{i,2001}} \times I\left[year_t = t\right] + \epsilon_{jt} \end{aligned} \tag{2.4}$$

where $Exposure_j$ is equal to either securitization or balance sheet exposure from 2002 through 2006. The dependent variable is either home price appreciation, employment growth, or the delinquency rate on outstanding mortgages. α_j are county fixed effects and λ_t are year fixed effects. Following the literature, Equation 2.4 is estimated with weighted least squares, with weights given by county level population shares in time $t-2$. The vector $\boldsymbol{X_{i,2001}}$ contain baseline county controls. These are interacted with the year indicator variables to control for the possibility that exposure is correlated with county level characteristics that affect the path of the dependent variable during the post 2006 period. Equation 2.4 is a difference in differences specification with continuous treatment. Each parameter β_t captures the effect of a one standard deviation increase in $Exposure_j$ on the outcome in year t relative to the base year, which is taken to be 2006 unless otherwise noted. The total effect of a one standard deviation increase in exposure on the outcome from 2007 through 2009 can be computed as follows:

$$\beta_{2007:2009} = \beta_{2007} + \beta_{2008} + \beta_{2009}$$

2.6.3 Home Prices

Results for the effect of boom period securitization exposure on home prices are presented in Table 2.5. Column 1 presents results for the most parsimonious model, without baseline control variables. Summing coefficients on the interaction terms from 2007 through 2009, results indicate that a one standard deviation increase in securitization exposure generates a 7.6% decrease in home price appreciation from 2007 through 2009. Estimates in Column 1 may be driven by baseline differences in demographics and labor market characteristics between counties. This issue is addressed by including baseline (2001) demographic and labor market controls that are interacted with the year indicator variables. Column 2 presents results for the model that includes demographic controls. These include racial composition (percent white, percent black, percent other) and the share of the population that is retired. Comparing the point estimates in Column

1 and Column 2, this leads to essentially no change in the estimates. Column 3 includes baseline controls for industry composition (percent employed in tradable, nontradable, construction, and all other industries), the unemployment rate as of 2001, and the percent of households with a subprime credit score. Again, the estimates in Column 3 are essentially identical to those from Column 1. This indicates that results are being driven by securitization exposure and not baseline differences between counties. The positive and significant coefficient on the interaction of the exposure variable with the 2012 indicator variable is also reassuring. This indicates that home prices in high exposure counties began to recover after the conclusion of the 2007-2009 downturn. This confirms that the effect of exposure on home prices during the 2007-2009 period is being driven by the 2007-2009 recession and is not picking up differential long term trends in home price appreciation between counties with high and low exposure to securitization.

Results for balance sheet lending exposure are displayed in Table 2.6. Column 3 contains results for the most robust specification. The point estimates indicate that a one standard deviation increase in balance sheet exposure generated a 3% increase in home price appreciation from 2007 through 2009. This estimate statistically significant at the 5% level. This suggests that boom period expansions in balance sheet lending may have lessened the severeness of the 2007-2009 bust. This finding is in opposition to the existing literature on credit booms and busts, which posits that the collapse in housing prices during the 2007-2009 period was caused by the rapid expansion in mortgage credit from

2002 though 2006. According to this literature, counties with greater exposure to mortgage originations (regardless of whether they are driven by securitized or balance sheet lending) during the 2002-2006 period should experience a larger reduction in home prices during the crisis period. The results in Tables 2.5 and 2.6 indicate that this depends crucially on whether the expansion in mortgage originations is driven by securitized or balance sheet lending. Securitization exposure during the boom period leads to a large reduction in home prices during the ensuing crisis, while balance sheet exposure leads to a slight increase in home prices during the crisis period.

Table 2.5: Effect of Securitization Exposure on Post Crisis Home Prices. This table presents results for the effect of 2002-2006 securitization exposure on home price appreciation (Equation 2.4). The dependent variable is the log change in the median home value in county j from year $t-1$ to year t. The sample period is 2000 through 2012. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	(1)	(2)	(3)
$SecuritizationExposure_{j,2002:2006} \times 2000$	0.020***	0.014***	0.019***
	(0.006)	(0.005)	(0.004)
$SecuritizationExposure_{j,2002:2006} \times 2001$	0.016***	0.016***	0.019***
	(0.005)	(0.005)	(0.005)
$SecuritizationExposure_{j,2002:2006} \times 2002$	0.019***	0.017***	0.020***
	(0.007)	(0.005)	(0.005)
$SecuritizationExposure_{j,2002:2006} \times 2003$	0.029***	0.030***	0.029***
	(0.008)	(0.007)	(0.006)
$SecuritizationExposure_{j,2002:2006} \times 2004$	0.040***	0.041***	0.038***
	(0.009)	(0.007)	(0.006)
$SecuritizationExposure_{j,2002:2006} \times 2005$	0.024***	0.028***	0.025***
	(0.006)	(0.005)	(0.005)
$SecuritizationExposure_{j,2002:2006} \times 2007$	−0.025***	−0.027***	−0.026***
	(0.005)	(0.005)	(0.006)
$SecuritizationExposure_{j,2002:2006} \times 2008$	−0.038***	−0.038***	−0.033***
	(0.008)	(0.007)	(0.006)
$SecuritizationExposure_{j,2002:2006} \times 2009$	−0.014***	−0.013***	−0.011**
	(0.005)	(0.005)	(0.004)
$SecuritizationExposure_{j,2002:2006} \times 2010$	0.003	0.004	0.006*
	(0.004)	(0.003)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2011$	−0.005	−0.004	−0.002
	(0.003)	(0.003)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2012$	0.021***	0.021***	0.022***
	(0.005)	(0.005)	(0.005)
Total effect on 2007-2009 home prices	−0.076***	−0.078***	−0.070***
	(0.016)	(0.016)	(0.015)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Baseline demographic controls	N	Y	Y
Baseline labor market controls	N	N	Y
R^2	0.594	0.631	0.657
N	19725	19725	19725

Table 2.6: Effect of Balance Sheet Exposure on Post Crisis Home Prices. This table presents results for the effect of 2002-2006 balance sheet exposure on home price appreciation (Equation 2.4). The dependent variable is the log change in the median home value in county j from year $t-1$ to year t. The sample period is 2000 through 2012. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	(1)	(2)	(3)
$BalanceSheetExposure_{j,2002:2006} \times 2000$	-0.019^{***}	-0.012^{**}	-0.009^{*}
	(0.005)	(0.005)	(0.005)
$BalanceSheetExposure_{j,2002:2006} \times 2001$	-0.021^{***}	-0.018^{***}	-0.016^{***}
	(0.005)	(0.005)	(0.004)
$BalanceSheetExposure_{j,2002:2006} \times 2002$	-0.022^{***}	-0.018^{***}	-0.016^{***}
	(0.006)	(0.005)	(0.005)
$BalanceSheetExposure_{j,2002:2006} \times 2003$	-0.036^{***}	-0.031^{***}	-0.028^{***}
	(0.007)	(0.006)	(0.006)
$BalanceSheetExposure_{j,2002:2006} \times 2004$	-0.032^{***}	-0.025^{***}	-0.022^{***}
	(0.008)	(0.007)	(0.007)
$BalanceSheetExposure_{j,2002:2006} \times 2005$	-0.021^{***}	-0.017^{***}	-0.015^{***}
	(0.005)	(0.005)	(0.005)
$BalanceSheetExposure_{j,2002:2006} \times 2007$	0.009^{**}	0.008^{*}	0.008^{**}
	(0.004)	(0.004)	(0.004)
$BalanceSheetExposure_{j,2002:2006} \times 2008$	0.022^{***}	0.017^{**}	0.015^{**}
	(0.008)	(0.007)	(0.007)
$BalanceSheetExposure_{j,2002:2006} \times 2009$	0.011	0.007	0.006
	(0.008)	(0.007)	(0.007)
$BalanceSheetExposure_{j,2002:2006} \times 2010$	-0.006	-0.007^{*}	-0.007^{*}
	(0.004)	(0.004)	(0.004)
$BalanceSheetExposure_{j,2002:2006} \times 2011$	-0.006	-0.008^{**}	-0.009^{**}
	(0.004)	(0.004)	(0.004)
$BalanceSheetExposure_{j,2002:2006} \times 2012$	-0.018^{***}	-0.017^{***}	-0.015^{***}
	(0.005)	(0.005)	(0.005)
Total effect on 2007-2009 home prices	0.041^{**}	0.032^{*}	0.030^{**}
	(0.017)	(0.017)	(0.015)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Baseline demographic controls	N	Y	Y
Baseline labor market controls	N	N	Y
R^2	0.581	0.610	0.639
N	19725	19725	19725

2.6.4 Mortgage Delinquencies

The previous section established that boom period securitization exposure caused significant home price depreciation from 2007 through 2009 while balance sheet exposure did not. In this section I explore the possibility that securitization exposure generated home price depreciation through an increase in mortgage delinquencies. Mortgage foreclosures were a defining feature of the 2007-2009 crisis and lead to a drop in home prices by increasing the supply of available housing. I consider the percentage of outstanding mortgage that are at least 90 days delinquent as a proxy for the county level mortgage foreclosure rate. The 90 day delinquency rate has previously been used in the literature by Nadauld and Sherlund (2013). Data for mortgage delinquencies are not available for years prior to 2008. Consequently, I take 2008 as the base year for the estimation of the difference in differences specification in Equation 2.4. If exposure drives delinquencies before 2008 then this will attenuate my estimate towards zero. Although aggregate delinquencies began to increase prior to 2008, the bulk of crisis period foreclosures occurred from 2008 through 2010 and so this possible attenuation isn't a major concern.

Results for the impact of securitization exposure on mortgage delinquencies are presented in Table 2.7. Baseline controls are interacted with year indicator variables and are added successively across columns. Column 3 contains the most robust specification, and indicates that a one standard deviation increase in securitization exposure leads to a 1.6 percentage point increase in the county delinquency rate from 2009 through 2011. This is a large effect. The average county had a delinquency rate of 3.4% in 2009 and 3.7% in 2011. Point estimates from Columns 1 and 2 are similar in magnitude, suggesting that time varying unobserved county level characteristics are not biasing the estimates.

Table 2.8 presents results for balance sheet exposure. Across all specifications, boom period exposure to balance sheet lending has a negative and significant effect on delinquencies. Taken together with the results on home prices, these findings are consistent with the idea that boom period exposure to securitization generated a large expansion in credit to risky borrowers, resulting in a surge in mortgage delinquencies that drove down home prices. The same is not true for balance sheet lending exposure, which has a positive effect on 2007-2009 home price appreciation and generated a decline in 2009-2011 delinquencies.

Table 2.7: Effect of Securitization Exposure on Post Crisis Mortgage Delinquincies. This table presents results for the effect of 2002-2006 securitization exposure on mortgage delinquincies (Equation 2.4). The dependent variable is the percentage of outstanding mortgages that are 90+ days delinquent at the end of year t in county j. The sample period is 2008 through 2012. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	(1)	(2)	(3)
$SecuritizationExposure_{j,2002:2006} \times 2009$	0.688^{***}	0.720^{***}	0.607^{***}
	(0.134)	(0.129)	(0.121)
$SecuritizationExposure_{j,2002:2006} \times 2010$	0.776^{***}	0.813^{***}	0.674^{***}
	(0.142)	(0.142)	(0.133)
$SecuritizationExposure_{j,2002:2006} \times 2011$	0.315^{***}	0.398^{***}	0.323^{***}
	(0.083)	(0.090)	(0.087)
$SecuritizationExposure_{j,2002:2006} \times 2012$	-0.098	0.002	-0.027
	(0.125)	(0.099)	(0.096)
Total effect on 2009-2011 delinquincies	1.779^{***}	1.931^{***}	1.604^{***}
	(0.324)	(0.338)	(0.319)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Baseline demographic controls	N	Y	Y
Baseline labor market controls	N	N	Y
R^2	0.884	0.904	0.912
N	2320	2320	2320

Table 2.8: Effect of Balance Sheet Exposure on Post Crisis Mortgage Delinquincies. This table presents results for the effect of 2002-2006 balance sheet exposure on mortgage delinquincies (Equation 2.4). The dependent variable is the ratio of outstanding mortgages that are 90+ days delinquent at the end of year t in county j. The sample period is 2008 through 2012. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	(1)	(2)	(3)
$BalanceSheetExposure_{j,2002:2006} \times 2009$	-0.501^{***}	-0.422^{***}	-0.385^{***}
	(0.131)	(0.136)	(0.115)
$BalanceSheetExposure_{j,2002:2006} \times 2010$	-0.669^{***}	-0.554^{***}	-0.505^{***}
	(0.159)	(0.161)	(0.137)
$BalanceSheetExposure_{j,2002:2006} \times 2011$	-0.470^{***}	-0.369^{***}	-0.352^{***}
	(0.133)	(0.125)	(0.115)
$BalanceSheetExposure_{j,2002:2006} \times 2012$	-0.260^{*}	-0.184	-0.190
	(0.150)	(0.123)	(0.122)
Total effect on 2009-2011 delinquincies	-1.640^{***}	-1.346^{***}	-1.242^{***}
	(0.386)	(0.397)	(0.342)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Baseline demographic controls	N	Y	Y
Baseline labor market controls	N	N	Y
R^2	0.876	0.894	0.906
N	2320	2320	2320

2.6.5 Employment

In this section I estimate the effect of balance sheet and securitization exposure on employment. I consider employment in the nontradable and tradable sectors separately. Intuitively, nontradable employment is more sensitive to local economic conditions than employment in the tradable sector. Therefore, a reduction in employment that is driven by county specific exposure to securitized or balance sheet lending should have a stronger effect on nontradable than tradable employment. I additionally consider employment in the construction sector (which also is sensitive to local economic conditions) and all other sectors.

Results are presented in Tables 2.9 - 2.10. Columns one through four of Table 2.9 present the effect of a one standard deviation increase in securitization exposure on employment growth in each sector relative to 2006. All specifications include baseline demographic and labor market controls that are interacted with year indicator variables. Results for nontradable employment indicate that a one standard deviation increase in precrisis securitization exposure leads to a 1.9 % decrease in nontradable employment growth, which is statistically significant at the 5% level. The corresponding estimate for tradable employment growth is noisy and indistinguishable from zero. The results for construction employment are large, and indicate that a one standard deviation increase in boom period securitization exposure leads to a 8.2% reduction in employment growth. Given that construction is also likely to be driven by local demand, this result is consistent with the findings for nontradable employment. Finally, employment growth in the other category, which comprises the largest share of total employment, is indistinguishable from zero.

Table 2.10 shows results for boom period exposure to balance sheet lending. Estimates indicate that 2007-2009 employment growth in the nontradable, tradable, and construction sectors are unaffected by boom period balance sheet exposure. The corresponding estimates for the "other" employment category is small but positive and significant at the 5% level. These estimates are consistent with the findings for home prices and delinqueincies, and again suggest that securitization exposure had a large negative effect on the severity of the 2007-2009 crisis while balance sheet exposure did not.

Table 2.9: Effect of Securitization Exposure on Crisis Employment. This table presents results for the effect of 2002-2006 securitization exposure on employment growth by sector (Equation 2.4). The dependent variable is the log change in employment in county j from year $t-1$ to year t for each sector. The sample period is 2000 through 2012. All estimates are relative to 2007. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	nontradables	tradables	construction	other
$SecuritizationExposure_{j,2002:2006} \times 2000$	-0.000	-0.007	-0.009^{***}	0.001
	(0.003)	(0.011)	(0.003)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2001$	0.002	0.024^{**}	-0.007^{**}	-0.005
	(0.003)	(0.010)	(0.004)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2002$	-0.002	-0.006	-0.003	-0.001
	(0.004)	(0.012)	(0.005)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2003$	-0.001	-0.010	0.001	-0.005
	(0.004)	(0.011)	(0.004)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2004$	0.001	-0.008	-0.013^{***}	-0.003
	(0.003)	(0.010)	(0.005)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2005$	-0.001	-0.001	-0.003	-0.002
	(0.003)	(0.010)	(0.004)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2007$	-0.002	-0.008	-0.020^{***}	-0.005
	(0.004)	(0.011)	(0.005)	(0.004)
$SecuritizationExposure_{j,2002:2006} \times 2008$	-0.007^{**}	-0.006	-0.030^{***}	-0.005
	(0.003)	(0.009)	(0.005)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2009$	-0.010^{***}	-0.005	-0.032^{***}	-0.006^{*}
	(0.003)	(0.009)	(0.005)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2010$	-0.006^{*}	-0.017^{*}	-0.026^{***}	-0.005^{*}
	(0.003)	(0.009)	(0.004)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2011$	-0.003	-0.009	-0.014^{***}	-0.003
	(0.003)	(0.010)	(0.004)	(0.003)
$SecuritizationExposure_{j,2002:2006} \times 2012$	0.000	0.000	-0.009^{**}	-0.006^{**}
	(0.003)	(0.010)	(0.004)	(0.003)
Total effect on 2007-2009 employment	-0.019^{**}	-0.020	-0.082^{***}	-0.016^{*}
	(0.01)	(0.024)	(0.013)	(0.01)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Baseline demographic controls	Y	Y	Y	Y
Baseline labor market controls	Y	Y	Y	Y
R^2	0.196	0.063	0.268	0.145
N	25562	25562	25562	25562

Table 2.10: Effect of Balance Sheet Exposure on Crisis Employment. This table presents results for the effect of 2002-2006 balance sheet exposure on employment growth by sector (Equation 2.4). The dependent variable is the log change in employment in county j from year $t-1$ to year t for each sector. The sample period is 2000 through 2012. All estimates are relative to 2007. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	nontradables	tradables	construction	other
$BalanceSheetExposure_{j,2002:2006} \times 2000$	-0.001	-0.012	-0.014^{***}	0.000
	(0.003)	(0.011)	(0.004)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2001$	0.002	-0.000	-0.009^{***}	0.005^{*}
	(0.003)	(0.010)	(0.003)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2002$	-0.003	-0.011	-0.006	-0.006^{*}
	(0.004)	(0.012)	(0.005)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2003$	0.003	-0.016	-0.006	-0.003
	(0.003)	(0.012)	(0.004)	(0.005)
$BalanceSheetExposure_{j,2002:2006} \times 2004$	0.005^{*}	-0.009	-0.010^{***}	0.000
	(0.003)	(0.013)	(0.004)	(0.004)
$BalanceSheetExposure_{j,2002:2006} \times 2005$	0.007^{**}	-0.001	-0.001	0.002
	(0.003)	(0.011)	(0.004)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2007$	0.008^{**}	-0.008	-0.009	0.006
	(0.004)	(0.014)	(0.006)	(0.004)
$BalanceSheetExposure_{j,2002:2006} \times 2008$	0.006^{*}	0.005	-0.005	0.007^{**}
	(0.004)	(0.011)	(0.006)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2009$	0.001	-0.004	-0.003	0.005
	(0.004)	(0.009)	(0.007)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2010$	-0.000	-0.019^{*}	-0.005	0.001
	(0.004)	(0.011)	(0.005)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2011$	-0.002	-0.015	-0.006	-0.000
	(0.003)	(0.010)	(0.004)	(0.003)
$BalanceSheetExposure_{j,2002:2006} \times 2012$	0.002	-0.009	-0.011^{**}	0.000
	(0.003)	(0.014)	(0.005)	(0.003)
Total effect on 2007-2009 employment	0.015	-0.007	-0.017	0.018^{**}
	(0.01)	(0.029)	(0.017)	(0.01)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Baseline demographic controls	Y	Y	Y	Y
Baseline labor market controls	Y	Y	Y	Y
R^2	0.196	0.063	0.263	0.146
N	25562	25562	25562	25562

2.6.6 High Risk lending

The main finding of this paper is that precrisis exposure to securitized lending deepened the ensuing recession, while balance sheet exposure did not. What is driving the differential effect of securitization versus balance sheet exposure on the severity of the crisis? One possibility is that securitization exposure worsens the effects of the crisis by allocating credit to riskier borrowers. This could be due to moral hazard problems in securitization markets, which incentivize lenders to originate bad loans.

In this section, I present evidence that precrisis exposure to securitization is associated with large increases in high risk loans. This effect is not operable for precrisis balance sheet lending exposure, which is associated with a drop in high risk originations during this time period. I identify high risk loans using the HMDA flag for higher priced loans. From 2004 through 2006, these are loans that have an interest rate of more than 3 percentage points above a Treasury security with the same maturity. This definition has previously been used to identify high risk loans by Nadauld and Sherlund (2013). HMDA data does not contain a flag for high priced loans for years prior to 2004. Because 2004 lies in the middle of the "boom" period, this means I am not able to control for baseline differences in high risk lending activity across counties. To that end, I estimate the following equation for county j in year t:

$$\begin{aligned} Y_{jt} &= \alpha + \lambda_t + \beta_{2004} Exposure_{j,2004:2006} \\ &+ \sum_{t=2005}^{2006} \beta_t Exposure_{j,2004:2006} \times I\left[year_t = t\right] + \boldsymbol{X_{j,2001}} \times I\left[year_t = t\right] + \epsilon_{jt} \end{aligned} \tag{2.5}$$

where Y_{jt} is the log of high risk mortgage originations in county j during year t. Standard errors are clustered at the commuter zone level. Observations are once again weighted by population shares in time $t-2$. Like Equation 2.4, this specification allows me to compute the cumulative effect of exposure on high risk lending from 2004 through 2006. The difference is that county fixed effects are not included. This means that identification comes from variation across counties. The total effect of exposure on 2004-2006 high risk originations can be computer by taking the sum $\sum_{t=2004}^{2006} \beta_t$.

Results are presented in Table 2.11 . Column 1 indicates that a one standard deviation increase in securitization exposure generates a 31% increase in high risk lending from 2004 through 2006, which is statistically significant at the 1% level. The corresponding estimate for balance sheet lending is -27% and is also statistically significant at the 1% level. These estimates are large in magnitude. However, keep in mind that aggregate subprime originations increased by roughly 250 % from 2002 through 2006 (Simkovic (2013)).

Table 2.11: Effect of Securitization and Balance Sheet Exposure on 2002-2006 High Risk Lending. This table presents results for the effect of 2002-2006 securitization and balance sheet exposure on boom period high risk lending (Equation 2.5). The dependent variable is the log of new higher priced mortgage originations in county j during year t. The sample period is 2004 through 2006. Standard errors are clustered at the commuter zone level. *, **, and *** denotes significance at the 0.1, 0.05, and 0.01 level.

	(1)	(2)
$SecuritizationExposure_{j,2002:2006}$	0.273^{***}	
	(0.105)	
$SecuritizationExposure_{j,2002:2006} \times 2005$	0.048^{***}	
	(0.011)	
$SecuritizationExposure_{j,2002:2006} \times 2006$	-0.007	
	(0.017)	
$BalanceSheetExposure_{j,2002:2006}$		-0.248^{**}
		(0.098)
$BalanceSheetExposure_{j,2002:2006} \times 2005$		-0.015
		(0.013)
$BalanceSheetExposure_{j,2002:2006} \times 2006$		-0.007
		(0.014)
Total effect on 2002-2006 high risk lending	0.314^{***}	-0.270^{***}
	(0.1)	(0.1)
County FE	N	N
Year FE	Y	Y
Baseline demographic controls	Y	Y
Baseline labor market controls	Y	Y
R^2	0.595	0.592
N	6093	6080

2.7 Conclusion

In this paper I present evidence that securitization driven credit booms have different effects on the real economy than credit booms that are driven by expansions in balance sheet lending. I adopt a methodology that exploits the geographic dimension of my data to construct county level measures of exposure to securitized and balance sheet lending during the 2002-2006 boom period that are plausibly orthogonal to local economic conditions such as credit demand. I additionally control for unobservable time-invariant differences between counties with different exposure to balance sheet and securitized lending by utilizing a difference in differences model. Finally, I include a wide range of county specific demographic and labor market controls to mitigate concern that my results are driven by county level characteristics other than exposure to securitized or balance sheet lending.

Focusing on the 2002-2012 period in the United States, I show that county level exposure to securitized lending during the 2002-2006 boom period is associated with a steep drop in home prices, a rise in delinquencies, and a fall in employment in the nontradable and construction sectors during the subsequent crisis period. The real economic effects of boom period exposure to balance sheet lending on crisis period outcomes are less dire. I find a small positive effect of boom period balance sheet exposure on crisis period home prices, and find that balance sheet exposure leads to a drop in crisis period mortgage delinquencies. I additionally find that the crisis period employment effects of balance sheet exposure are indistinguishable from zero. I present suggestive evidence that the differential effect of securitization versus balance sheet exposure on the severity of the crisis is driven by risk taking incentives that are unique to securitized lending. Specifically, I find that securitization exposure leads to a large expansion in higher risk lending, while balance sheet exposure leads to a large drop in high risk lending. Both measures of exposure (balance sheet and securitized) have similar effects on the total quantity of mortgages originated during the 2002-2006 housing boom.

2.8 Appendix

Figure 2.4: Affiliate Sales and Private Securitization. This figure depicts aggregate data on total annual loan sales to private securitizers and affiliate institutions. Balance sheet loans are those that are not sold by the originating institution during the year in which they are originated. Data on private securitization is not available prior to 2004. Underlying data are from HMDA.

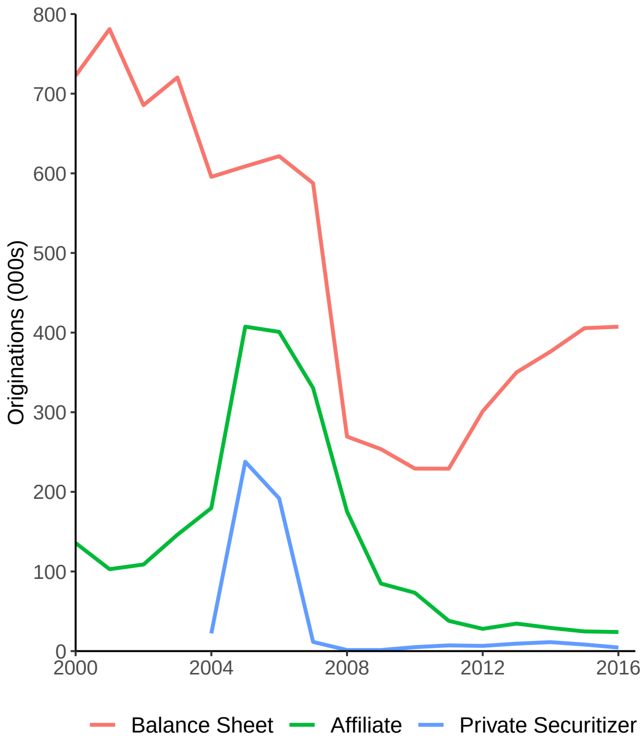


Table 2.12: County Summary Statistics. This table presents summary statistics at the county level. $SecuritizationExposure_{j,2002:2006}$ and $BalanceSheetExposure_{j,2002:2006}$ are the cumulative estimated credit supply shocks for securitized and balance sheet lending from years 2002 through 2006 in county j. See text for details. $log(Originations_{jt})$ is the log of total originations in county j during year t. $log(Securitized_{jt})$ and $log(BalanceSheet_{jt})$ refer to the log of loans in county j during year t that are either sold to the secondary market (securitized) or held on the balance sheet of the originating lender. $log(HighRisk_{jt})$ is the log of higher priced loans originated in county j during year t. $ActiveLenders_{jt}$ is the number of lenders in the sample that originate a loan in county j during year t. The sample period is 2002 through 2012.

	Mean	St. Dev.	N
$ActiveLenders_{jt}$	35.80	35.80	27626
$BlackShare_{j,2001}$	0.09	0.09	27626
$ConstructionShare_{j,2001}$	0.15	0.15	27626
$\Delta log(ConsturctionEmployment_{jt})$	-0.01	-0.01	27545
$\Delta log(NonTradableEmployment_{jt})$	0.01	0.01	27615
$\Delta log(OtherEmployment_{jt})$	0.01	0.01	27626
$\Delta log(TradableEmployment_{jt})$	-0.02	-0.02	25631
$HomeAppreciation_{jt}$	0.02	0.02	19725
$Delinquent_{jt}$	3.28	3.28	2320
$log(Securitized_{jt})$	4.97	4.97	27591
$log(BalanceSheet_{jt})$	4.13	4.13	27495
$log(Originations_{jt})$	5.38	5.38	27613
$log(HighRisk_{jt})$	2.95	2.95	18257
$NonTradableShare_{j,2001}$	0.27	0.27	27626
$SecuritizationExposure_{j,2002:2006}$	0.03	0.03	27626
$BalanceSheetExposure_{j,2002:2006}$	-0.10	-0.10	27626
$RetiredShare_{j,2001}$	0.14	0.14	27626
$SubprimeShare_{j,2001}$	0.35	0.35	27626
$TradableShare_{j,2001}$	0.11	0.11	27626
$UnemploymentRate_{j,2001}$	5.00	5.00	27626
$WhiteShare_{j,2001}$	0.89	0.89	27626

Chapter 3

Facing the quadrilemma: Taylor Rules, Intervention Policy and Capital Controls in Large Emerging Markets[1]

3.1 Introduction

The traditional "trilemma" set of policy constraints, where a country needs to balance tradeoffs between degrees of monetary independence, exchange rate stability and controlled capital account openness, has in the recent literature

[1]This chapter is co-authored work with Michael Hutchison and Fernando Chertman published in the Journal of International Money and Finance (Chertman, Fernando, Hutchison, Michael and Zink, David, (2020), Facing the Quadrilemma: Taylor rules, intervention policy and capital controls in large emerging markets, Journal of International Money and Finance, 102, article 102122)

been extended to a "quadrilemma" with a fourth policy goal of financial stability (Aizenman and Aizenman (2019)). The later consideration for emerging markets is frequently focused on stability from international financial shocks in the form of sharp movements in capital flows, exchange rate instability and U.S. interest rate fluctuations. Emerging markets have always looked beyond the domestic objectives of inflation and output gaps, emphasized in large advanced economies and embodied in interest rate Taylor Rules, toward external objectives.

In attempting to achieve these external objectives, emerging markets frequently complement policy interest rates with foreign exchange market intervention and capital controls as additional policy instruments. Given that four policy objectives are combined with only three policy instruments (policy interest rate, intervention and capital controls), the "Tinbergen Principle" doesn't hold (i.e. equal instruments and objectives) and policy makers may at times face tradeoffs in achieving all their goals. In this context, the IMF (2012) finds that the number of countries actively managing their exchange rates has increased substantially since the Global Financial Crisis and that Brazil, Chile, Colombia, Turkey, and other emerging markets with announced inflation targeting regimes have increased both the frequency and the size of their interventions. Changes in capital controls are also a powerful macroeconomic management tool in some emerging markets (Fernández et al. (2016)), but are generally used infrequently.

Theoretical work has investigated the tradeoffs associated with domestic and external policy objectives, and where intervention and capital controls may contribute to macroeconomic and financial stability (e.g. Gonçalves (2008), Cavallino (2019), Farhi and Werning (2012), Jeanne (2012)). For example, the theoretical framework of Gonçalves (2008) argues that official accumulation of foreign reserves may be perceived as interventions to influence the exchange rate, undermining the credibility of floating exchange rates and inflation targets. He develops a theoretical framework to study the interaction between reserve accumulation and monetary policy, and highlights the trade-off between the speed of reserve accumulation and anti-inflationary credibility.

In related work, Cavallino (2019) develops a New Keynesian small open economy model that characterizes the optimal use of foreign exchange intervention in response to exchange rate fluctuations driven by capital flows. In his model, an increase in foreign demand for domestic assets appreciates the domestic currency and generates a boom-bust cycle in the economy. In response to such a shock, the optimal foreign exchange intervention in his model is to lean against the wind and stabilize the path of the exchange rate. By leaning against the wind, the central bank reduces the real appreciation (and the consumption boom triggered by the inflow of capital) and reduces the output gap. It is not optimal for the central bank to fully stabilize the exchange rate in this framework since it reduces some of the benefits of portfolio capital flows.

Most empirical work on macroeconomic policy functions, especially for advanced economies, emphasize policy interest rates as reflected in Taylor rules. Taylor rules for emerging markets often recognize external considerations by including an exchange rate stabilization objective, e.g. Aizenman et al. (2011). We extend previous work investigating modified Taylor rules by considering a second policy rule linking foreign exchange market intervention to exchange rate stability and an objective to accumulate reserves to a target level. Specifically, we explore how large emerging-market economies have in practice managed to accumulate substantial reserve levels over time (for precautionary purposes, reducing the likelihood of financial instability), despite substantial cyclical variation, while at the same time following monetary policy rules designed to stabilize inflation, output and the exchange rate.

We focus on two policy instruments, interest rates and foreign exchange market intervention, and four policy objectives—inflation, output, exchange rates and foreign reserve target. Against this background, we also investigate (1) the impact of changes in the intensity of capital controls, though this instrument is only infrequently cyclically applied in most EMs, and the impact of the transmission of U.S. interest rates; and (2) cases of very large discretionary (unpredicted) intervention operations and interest rate changes, evaluating whether the interest rate instrument (internal balance) or intervention operations (external balance) dominate when policy conflicts arise. Although not able to capture all aspects of the quadrilemma with our analysis, we are able to shed light on practical policy considerations for internal and external balance in the use of the two major tools - monetary policy and intervention policy.

Our primary interest is in two large emerging market economies, Brazil and India, with a comparative analysis of the largest EM, China, and one small open economy, Chile. Most theoretical and empirical work in this area focuses on small open economies (SOEs) and attempts to measure where each country lies on a spectrum of policy tradeoffs. However, large emerging markets should display somewhat different characteristics than SOEs in the reserves-exchange rate-monetary policy nexus. In particular, large EM interest rates should not in principle be completely determined by the "center country" (some inherent monetary independence compared with the SOEs) and potential foreign capital inflows are not infinite (as in the SOE model).

Brazil and India use capital controls extensively as a macroeconomic management tool. Although India has been gradually reducing capital controls over the past two decades, it continues to have quite strict international capital controls. Brazil is much more open financially but continues with fairly extensive controls. According to the Fernández et al. (2016) data set on capital control restrictiveness using the IMF Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) as the underlying data source, India and Brazil placed 0.93 and 0.65, respectively in 2017. (The range is from 0 with no restrictions to 1 as completely closed). The authors characterize India with "walls" to external financial flows and Brazil with a "gate." Net liberalization has occurred over the past two decades as corresponding values for India and Brazil in 2000 were 1.0 and 0.85, respectively[1]. (The U.S. had a restrictiveness index of 0.16 in

[1]China is also characterized by Fernandez et al. (2016) as having "walls" with a capital account restrictiveness measure of 0.85 in 2017 and 1.0 in 2000. Chile is more much more open, with a restrictiveness measure of 0.45 in 2017 (and 0.88 in 2000).

2017 and 0.13 in 2000 using this methodology). This allows us to explore whether variations in this instrument has impacted the effectiveness of other instrument of macroeconomic management.

These emerging markets have also experienced very large reserve accumulations, motivated at least in part by the desire to reduce the likelihood or severity of financial crises. This fact, in combination with active foreign exchange policies, is an important element of macroeconomic and macro-prudential management. However, their stated macroeconomic policies and monetary regimes are very different. In particular, the Central Bank of Brazil has had an explicit inflation targeting regime since 2001 while the Reserve Bank of India is characterized by substantial discretion in policy actions[2].

We empirically evaluate the significance of these regime differences on Taylor rules as well as intervention policy functions, and whether capital controls influence policy actions and the transmission of U.S. interest rate changes to policy rates. We also consider whether interest rate policy (internal balance) dominates or is subordinate to intervention policy (external balance) when policy conflicts arise. We use time-series methods for our methodology and employ quarterly data. Additional features of our analysis are the incorporation of a measure of "adequate" reserves, calculated by the IMF, into our intervention equation, and a measure of capital account openness, based on the work of Pasricha et al. (2015) and Pasricha (2017), into the interest rate rule (Taylor rule)

[2]Chile also has an inflation targeting regime, while the People's Bank of China monetary policy demonstrates substantial discretion.

and intervention rule equations.

We include China in our study as a counterpoint to the other large EMs. As China's institutions are quite different, it is an interesting comparison case. And, as a counterpart to our analysis of large emerging markets, we also consider a small commodity-based emerging market - Chile. Chile is a small open economy, largely commodity-based and with very open capital markets. We investigate whether the revealed policy choices for large emerging markets carry over to small emerging markets like Chile. The remainder of the paper is organized as follows. Section 2 presents some background on macroeconomic management and external considerations in Brazil and India. Section 3 presents the basic model. Section 4 presents data and methodology. Section 5 presents the empirical results for Brazil and India. Section 6 extends the analysis to China and Chile. Section 7 concludes.

3.2 Macroeconomic Management in Large Emerging Market Economies

Our focus emerging markets - India and Brazil- have experienced challenges to macroeconomic and financial stability similar to other emerging markets and advanced economies. Managing domestic output and inflation objectives in tandem with exchange rate and balance of payments stability has frequently been a balancing act between multiple targets and limited policy instruments. Neither of these countries explicitly state that they follow a Taylor rule in setting interest rates, but in monetary policy statements note that inflation is a priority and usually point to the state of the economy as a consideration in setting policy. Our objective is to quantify the relative importance of these factors. Similarly, authorities rarely provide an explicit intervention policy guide but ex post policy statements often refer to "disorderly" exchange market conditions, reserve and current account developments, and so forth in explaining their actions. Again, our objective is to quantity, if possible, the relative weight that these various considerations play in systematically influencing intervention operations. Previous research and policy statements help guide us in our empirical specifications.

In particular, the Reserve Bank of India formally states that its primary objective is to maintain price stability, while "...keeping in mind the objective of growth" and announced recently a "flexible inflation targeting" regime[3]. Empirical work has found that India alternates between an emphasis on output and inflation in pursuing domestic macroeconomic stability (Hutchison et al. (2013); Gupta and Sengupta (2014); Kaur (2018)), and maintaining orderly conditions in the foreign exchange markets as an official objective of the Reserve Bank of India (RBI) (Hutchison and Pasricha (2016)). RBI is the manager of the foreign exchange regulation act (FEMA, 2004), which also gives it the power to impose capital controls. In practice, this objective has meant very active management of controls on international capital movements and frequent foreign exchange mar-

[3]The Reserve Bank of India (July 2019) states that the goals of monetary policy are: "The primary objective of monetary policy is to maintain price stability while keeping in mind the objective of growth. Price stability is a necessary precondition to sustainable growth." Moreover, in May 2016, the Reserve Bank of India (RBI) Act, 1934 was amended to provide a statutory basis for the implementation of the flexible inflation targeting framework.

ket intervention operations, as well as at least one episode (in 2013) of interest rate defense of the exchange rate. These considerations make understanding the linkages between monetary policy, capital controls and foreign exchange market intervention operations central to a study of macroeconomic management in India.

Hutchison and Pasricha (2016) find that India has followed active foreign exchange market intervention and capital control policies. They argue that intervention policy is mainly directed toward limiting exchange rate appreciation, during which times dollar purchases were generally large, and not directed toward limiting depreciation. This policy may have allowed relative stability in the real exchange rate, hence maintaining India export competitiveness, as the exchange rate depreciated over longer-periods to offset relative high inflation in India. Intervention policy and exchange rate depreciation also allowed greater monetary autonomy, especially during a period associated with increased financial liberalization of the international capital account. Moreover, reserve accumulation—through USD purchases on the foreign exchange market—is a desirable objective to the extent that it provides a stock of precautionary reserves in the event of a balance of payments/currency crisis or sudden stop in private capital inflows that generally finance persistent current account deficits in India. On the other hand, the exchange rate has not been a “nominal anchor” for monetary policy in India, and as a consequence high inflation is a recurring problem.

Control of international financial capital movements is another policy instrument that has been frequently employed to influence financial flows in and out of India and the exchange rate (Hutchison et al. (2012); Patnaik and Shah (2012); Hutchison and Pasricha (2016)). Although the overall trend was towards financial liberalization of the capital account, capital control actions (i.e. tightening and easing of restrictions on capital flows) have been actively used as an instrument to "lean against the wind" of exchange rate pressures in both directions. Whether or not capital controls policies have been effective is evaluated by Patnaik and Shah (2012).

Similar, tradeoffs between domestic and external objectives have also confronted the Central Bank of Brazil. The country is the largest emerging market to adopt an inflation targeting regime (IT), starting in July 1999 and formally continuing to date. Paiva (2017) argue that the Central Bank of Brazil (BCB) succeeded in anchoring inflation expectations and gaining credibility until 2011, when a new discretionary-based policy was adopted despite a formal IT rule. However, it is evident from numerous policy statements that output stabilization is also an important element in setting interest rate policy in Brazil. Minutes from a recent monetary policy report from the Central Bank of Brazil (2019), for example, note that: "The Copom members assessed that economic conditions with anchored inflation expectations, underlying inflation measures at appropriate levels, 2020 inflation projected around or slightly below target, and high *level of slack in the economy prescribe stimulative monetary policy*, i.e., interest rates below the structural interest rate level. The structural interest rate is a reference for the conduct of monetary policy"[4]. Hence, in this case it is also of interest to measure the weights the central bank places on the inflation target as opposed to output stabilization and other factors in setting interest rates. Other factors may include the exchange rate. For example, Aizenman et al. (2011) find that commodity-based emerging markets with an IT regime such as Brazil are still very likely to smooth exchange rates as part of their Taylor Rule interest rate setting policy.

The Central Bank of Brazil also intervenes in the foreign exchange market to smooth excessive exchange rate volatility and to manage the level of international reserves (Gnabo et al. (2010)). Although intervention activity varies over time, waning in recent years, spot-market interventions and the sale of exchange swaps are predominantly against the wind in terms of USD. In terms of the effectiveness of intervention, several studies find that FX intervention, including through swaps, can affect the exchange rate, e.g. Kohlscheen and Andrade (2014), Barata and Barroso (2014), Chamon et al. (2017), and De Oliveira and Novaes (2007), for example, find that in periods of relative tranquility the level of the exchange rate is affected more strongly by interventions (in both the spot and the derivatives markets) than the stance of monetary policy, while interventions appear ineffective during episodes of high exchange rate volatility.

[4]Minutes of the 223rd Meeting of the Monetary Policy Committee (Copom) Banco Central do Brasil, June 18-19, 2019. Italics in the quote are our own.

3.3 Model

The basic analytical framework consists of two policy rules: a modified Taylor rule and a foreign exchange intervention policy function. Policy is directed toward achieving two domestic objectives, output and inflation stabilization, and two international macroeconomic objectives, exchange rate stabilization and a target level of international reserves to reduce the risk of capital stops and financial instability. Two instruments are associated with policy functions, and one instrument, fluctuations in capital controls, is taken as a pre-determined variable. In addition to the two policy reaction functions, foreign exchange market is directly linked to changes in international reserves through an accounting identity.

The Taylor rule is modified to capture the central bank's objective of reducing output variations around trend, inflation variations from target, and stabilize the nominal exchange rate. Given hysteresis found in policy actions we include a lagged interest rate as is standard in most studies. The modification of the Taylor rule to include an exchange rate target is standard in the emerging markets literature (e.g. Aizenman et al. (2011)). This formulation takes the form:

$$i_t = \alpha_1 + \alpha_2(y_t - y^*) + \alpha_3(\pi_t - \pi^*) + \alpha_4(e_t - e_{t-1}) + \alpha_5 i_{t-1} + \varepsilon_t \qquad (3.1)$$

where i_t is the central bank interest rate operating instrument, $(y_t - y^*)$ is (log) output less (log) output trend (i.e. percentage deviation from trend output), $(\pi_t - \pi^*)$ is inflation deviation from target, $(e_t - e_{t-1})$ is the (log) nominal exchange rate change, and ε_t is the error term. Stabilizing objectives ("leaning against the wind") of output, inflation and the exchange rate suggests that $\alpha_2 > 0$, $\alpha_3 > 0$, and $\alpha_4 > 0$.

The foreign exchange management fund is postulated to intervene in the foreign exchange market (foreign exchange purchases are positive values) to stabilize the exchange rate and to manage foreign reserves around the target level. Hence, there are potentially two instruments focused on exchange rate management. In addition, the target level may itself vary over time as suggested by the very rapid buildup of international reserves by emerging market economies during the period prior to the Global Financial Crisis (GFC). The intervention equation takes the form:

$$I_t = \beta_1 + \beta_2(e_t - e_{t-1}) + \beta_3(R_t - R_t^*) + \mu_t \tag{3.2}$$

where I_t is foreign exchange market intervention (USD purchases (purchases of foreign exchange are positive values and sales are negative values, as a percent of last quarter's stock of international reserves), $(R - R^*)$ is the (log) stock of international reserves less the (log) of the target reserve level (i.e. percentage deviation from target reserves) and μ_t is the error term. Foreign exchange sales intervention to slow exchange rate depreciation $(e_t - e_{t-1} > 0)$ suggests $\beta_2 < 0$. A rise in the stock of reserves above the target value also suggests foreign exchange sales intervention, $\beta_3 < 0$.

Intervention is linked to international reserves through an accounting identify, i.e. the rise (fall) in international reserves equals foreign exchange intervention purchases (sales) plus interest earnings on foreign reserves and valuation changes:

$$R_t - R_{t-1} = I_{t-1} + i^*_{t-1} R_{t-1} + VAL_{t-1} \tag{3.3}$$

where i^*_{t-1} is the interest rate on foreign exchange reserves and VAL_{t-1} is valuation changes on international reserve holdings. Hence, intervention is directly linked to the target for international reserves. Our assumption is that i^*_{t-1} and VAL_{t-1} are exogenous variables.

As extensions of the basic models represented by Equations 3.1 and 3.2, we also include the terms-of-trade and the current account in both equations. A rise in either the terms-of-trade or the current account have wealth and liquidity effects on the economy and could elicit a monetary response. Similarly, a terms-of-trade change could impact the foreign exchange market (increasing foreign exchange receipts), as could a rise in the current account by increasing liquidity in the market. Both of these variables also have proved important in other studies of macroeconomic policy in EMs (e.g. Aizenman et al. (2011)).

We also investigate the extent to which U.S. interest rates (i^*_t) and capital account openness ($openness_t$) constrain domestic interest rate policy (Taylor rule) and, for ($openness_t$), enters into decisions to intervene in the foreign exchange market. We would expect U.S. interest rates to enter directly into interest rate policy decisions, in addition to the indirect channel via the exchange rate, especially in the post-GFC period when greater movement of international capital was generally allowed in both Brazil and India. The effect of greater capital market openness (liberalization) on both interest rate and intervention policies would depend on the directional response of net private capital flows, which in turn on market conditions and whether institutional measures liberalized controls on inflows or outflows.

3.4 Data and Methodology

3.4.1 Data

We employ quarterly data over the period 1999q1-2018q4 in our analysis. The exact sample period varies slightly between regression specifications due to data availability. Descriptions of each variable and the date range over which they are available are explained in the appendix[5].

Macroeconomic developments for both countries are detailed in the summary statistics of Table 3.1 and Figures 3.1-3.7. Panel A of Table 3.1 shows the full sample period, Panel B shows the pre-GFC crisis sample period and Panel C shows the post-GFC crisis period. India generally has a much more stable macroeconomy than Brazil, with lower interest rates, lower inflation and more stable (lower standard deviation) exchange rates, intervention and reserves (relative to "adequate" reserves)[6]. Figure 3.1 shows the output gap; Figure 3.2 inflation (and, for Brazil, evolution of the inflation target); Figure 3.3 money market interest

[5]Two appendices - sources of data and detailed variable definitions - are omitted from the text for brevity but are available from the authors upon request.

[6]It is an intriguing question as to why Brazil has had a much more volatile economy than India, with prime candidates more restrictive capital controls in India and, hence, less volatile capital movements; more volatile external shocks in Brazil associated with dependence on commodities and terms-of-trade fluctuations; and so on. Our focus is not in addressing this issue but to compare monetary and intervention policies in the two countries. Differences in policies, however, may play an important role in explaining relative volatility of these economies.

rates; Figure 3.4 exchange rates (left panel, level of the domestic currency per USD; right panel, percent change); Figure 3.5, left column, is the level of international reserves and the "adequate reserves" level (estimated by the IMF) and the right column is the net spot foreign exchange market intervention; Figure 3.6 is the reserve gap (difference between actual reserves and adequate reserves as a percent of adequate reserves; Figure 3.7 is the measure of cumulative step of external capital account openness (cumulative net changes).

We use a standard measure of the output gap given by the cyclical deviation of industrial production from its trend. We seasonally adjusted both series using the U.S. Census Bureau X-13 procedure. HP filter estimates of the logged series are employed to obtain trend and cyclical output measures. The cyclical portion is multiplied by 100, yielding an output gap measure that can be interpreted as the percent deviation of industrial production from its trend level. The output gap measures are shown in Figure 3.1. This series has been employed in other studies investigating monetary policy in both Brazil and India. (Kaur (2018); Gupta and Sengupta (2014); De Almeida et al. (2003))). It is evident from the figure that output gap volatility has been much larger in Brazil than India.

As noted, Brazil has had an inflation target since 1999. This target has changed several times over the sample period, shown in Figure 3.2, but for most of the sample the midpoint target was 4.5%. India does not have an announced inflation target. For purposes of econometric estimation, we assume the target is constant and therefore subsumed in the constant term of the estimated Taylor rule for India. We follow other studies (e.g. Gupta and Sengupta (2014); De Melo Modenesi et al. (2013))) and use the WPI index to construct the inflation rate in India and the IPCA index for Brazil. Inflation averaged 4.7% in India and 5.2% in Brazil over the sample period, with similar volatility, shown in Table 3.1. Brazil has been slightly above its inflation target over the sample period (0.4% above).

Money market interest rates are employed in both studies, shown in Figure 3.3. Despite similar inflation rates, Brazil has almost double the nominal (and real) interest rates than India. This may reflect both real growth equilibrium factors (determining equilibrium real interest rates), risk premium differences, institutional features of the two economies, and that Brazil is more financially open. The stance of monetary policy is measured with the money market interest rate. For India, this is the 3-month interbank lending rate. For Brazil, we use the SELIC rate, which is the overnight interbank lending rate. The nominal exchange rate employed in the study, shown in Figure 3.4, is the value of local currency against the USD. Brazil has experienced higher average depreciation (1.0% quarterly average) over the sample than India (0.7% quarterly average), shown in Table 3.1, and much higher exchange rate volatility.

Foreign exchange market intervention is defined as foreign currency purchases (domestic currency sales) in the foreign exchange market, valued in millions USD, shown in the right panels of Figure 3.5. This data is obtained from the Central Banks of Brazil and India, respectively. Negative values represent foreign currency sales (domestic currency purchases) in the foreign exchange market. The advantage of this measure is that it only reports active intervention in the foreign exchange market and excludes interest earnings and valuation effects on reserves. (Many studies proxy intervention by changes in reserves). Both countries actively intervened in the foreign exchange market during most of the sample period, though Brazil ceased its intervention activity in recent years.

Reserves are defined as international reserves less gold but including SDRs, shown in the left panels of Figure 3.5. Reserve data for Brazil and India are obtained from the central bank of each country. No reserve targets are announced in either country. As a proxy, we use the IMF series on reserve adequacy for both Brazil and India. The IMF defines international reserve adequacy (RA) for emerging market economies with floating exchange rates as $RA = (5\% \times \mathit{Exports}) + (5\% \times \mathit{Broad\ Money}) + (30\% \times \mathit{Short\ Term\ Debt}) + (15\% \times \mathit{Other\ Liabilities})$. The IMF measure of reserve adequacy is only available at the annual level. An approximate quarterly series is estimated using a cubic spline interpolation. The resulting quarterly series are also plotted in the left panels of Figure 3.5. It is apparent that both countries grew reserves very substantially since the early 2000s, pausing at the time of the GFC. After that period, reserve growth in reserves continued in India and flattened out in Brazil.

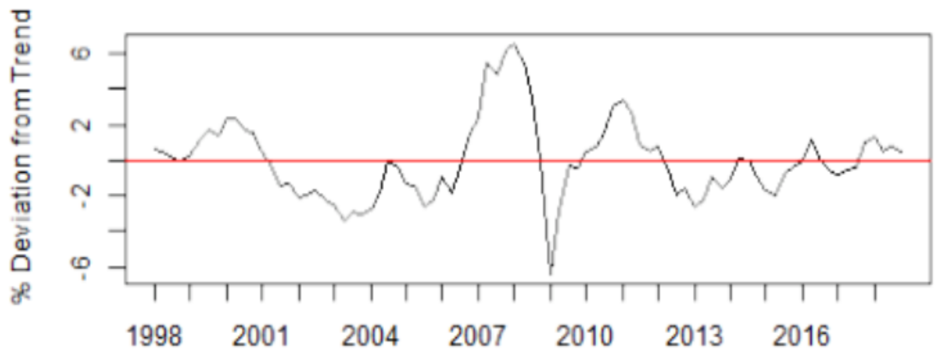
The reserve "gap," measured by the difference between actual reserves and reserve adequacy (as a percentage of reserve adequacy), is shown in Figure

3.6. This figure shows that India exceeded its "reserve adequacy" metric from around 2002, peaking at almost 100% just before the GFC. Since that time, the reserve gap declined before stabilizing at about 30%. Brazil's reserve gap was negative until 2007 but has been consistently positive since 2010, fluctuating around 50% from 2014 until 2018.

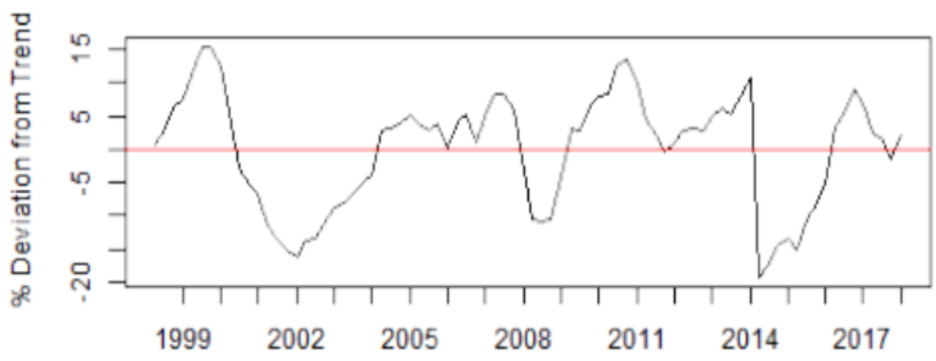
Capital Openness Index, shown in Figure 3.7, is taken by accumulating net capital account liberalization or restrictiveness changes based on the Pasricha et al. (2015) dataset, updated in Pasricha (2017). This is a dataset of capital control actions for 16 emerging market economies, where country-level measures of capital control changes are based on a weighted sum of the capital account changes for a given year, where the weights are given by the share of the country's international investment position that are affected by the policy change. We take the cumulative sum of these changes so that they can be interpreted as the level of capital openness for a given country, albeit not comparable across countries in level form. The resulting time series for Brazil and India is shown in Figure 3.7. This index has been used in Pasricha et al. (2015), Pasricha (2017), and Aizenman and Binici (2016). Some of the advantages of this series are that it results in a measure of capital openness that varies more regularly than several measures such as the Chinn-Ito index (Chinn and Ito (2006) or Fernández et al. (2016)). This is because it presumably takes into account all regulatory changes for a given country and weights them according to their estimated impact on capital flows.

Table 3.1: Descriptive Statistics

Panel A: 1999Q1 - 2018Q4		India			Brazil	
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.
i	84	6.98	1.62	76	13.447	4.579
$\hat{Y}$	84	0.00	2.24	76	-0.207	9.554
π	80	4.56	3.19	76	5.242	3.385
$\pi - \pi^*$	80	4.56	3.19	76	0.419	1.023
Δe	83	0.73	3.04	76	1.019	8.498
$R - R^*$	84	33.12	27.68	76	1.244	49.978
I_{spot}	84	1.56	3.89	76	2.63	6.769
I_{total}	84	0.01	11.64	76	2.581	7.12
openness	60	20.76	15.84	60	1.802	1.193
t.o.t.	76	107.27	11.33	80	95.15	14.37
curr. acc.	83	-1.37	2.01	88	-1.89	2.19
Panel B: 1999Q1 - 2008Q4		India			Brazil	
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.
i	44	6.93	1.63	36	16.931	3.775
$\hat{Y}$	44	0.25	2.61	36	-0.624	10.049
π	40	4.56	3.19	36	6.268	3.870
$\pi - \pi^*$	40	4.56	3.19	36	0.546	1.254
Δe	43	0.50	2.87	36	-0.148	8.109
$R - R^*$	44	29.68	36.78	36	-42.709	33.72
I_{spot}	44	2.32	4.79	36	4.263	9.358
I_{total}	44	0.14	11.37	36	3.988	9.801
openness	32	8.07	5.67	32	1.409	1.346
t.o.t.	36	106.15	15.36	40	95.58	17.78
curr. acc.	43	-0.78	1.92	47	-1.43	2.61
Panel C: 2009Q1 - 2018Q4		India			Brazil	
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.
i	40	7.04	1.63	40	10.312	2.5
$\hat{Y}$	40	-0.27	1.74	40	0.168	9.198
π	40	3.97	4.05	40	5.057	2.908
$\pi - \pi^*$	40	3.97	4.05	40	0.305	0.755
Δe	40	0.98	3.24	40	2.069	8.801
$R - R^*$	40	36.91	10.51	40	40.802	19.869
I_{spot}	40	0.72	2.34	40	1.161	2.199
I_{total}	40	-0.16	12.08	40	1.315	2.794
openness	28	35.27	10.11	28	2.252	0.798
t.o.t.	40	103.77	2.97	40	97.82	9.34
curr. acc.	40	-2.31	1.61	41	-2.42	1.43



Panel A: India

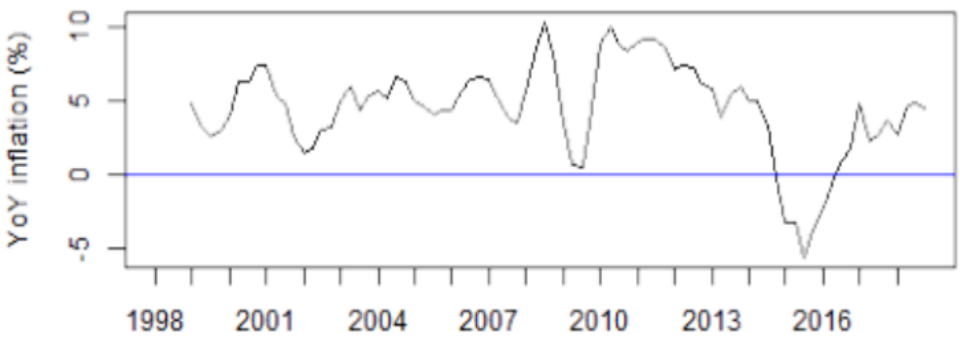


Panel B: Brazil

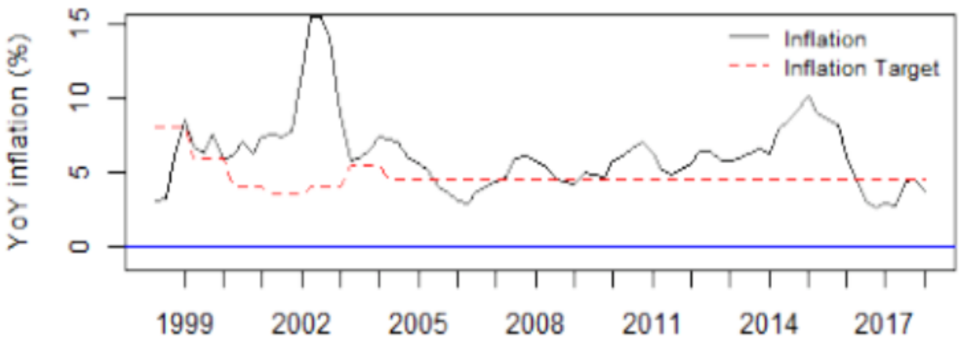
Figure 3.1: Output Gap

3.4.2 Methodology

Turning to methodology, our baseline time series models for Brazil and India are estimated over the 1999q1-2018q4 period. We allow for sample shifts before (1999q1-2008q4) and after the Global Financial Crisis (2009q1-2018q4), as the external environment changed markedly at this time, likely impacting policy behavior. We employ a methodology that considers the endogeneity of



Panel A: India



Panel B: Brazil

Figure 3.2: Inflation

the reserve gap. The contemporaneous reserve gap is influenced by the scope of intervention operations. Consequently, we treat the reserve gap variable as endogenous and instrument for it with its lagged value. Exchange rate fluctuations are likely to suffer from a two-way causality issue as well. However, we do not employ instrumental variables for the exchange rate. There are two reasons for this decision. First, exchange rates are notoriously difficult to predict and thus

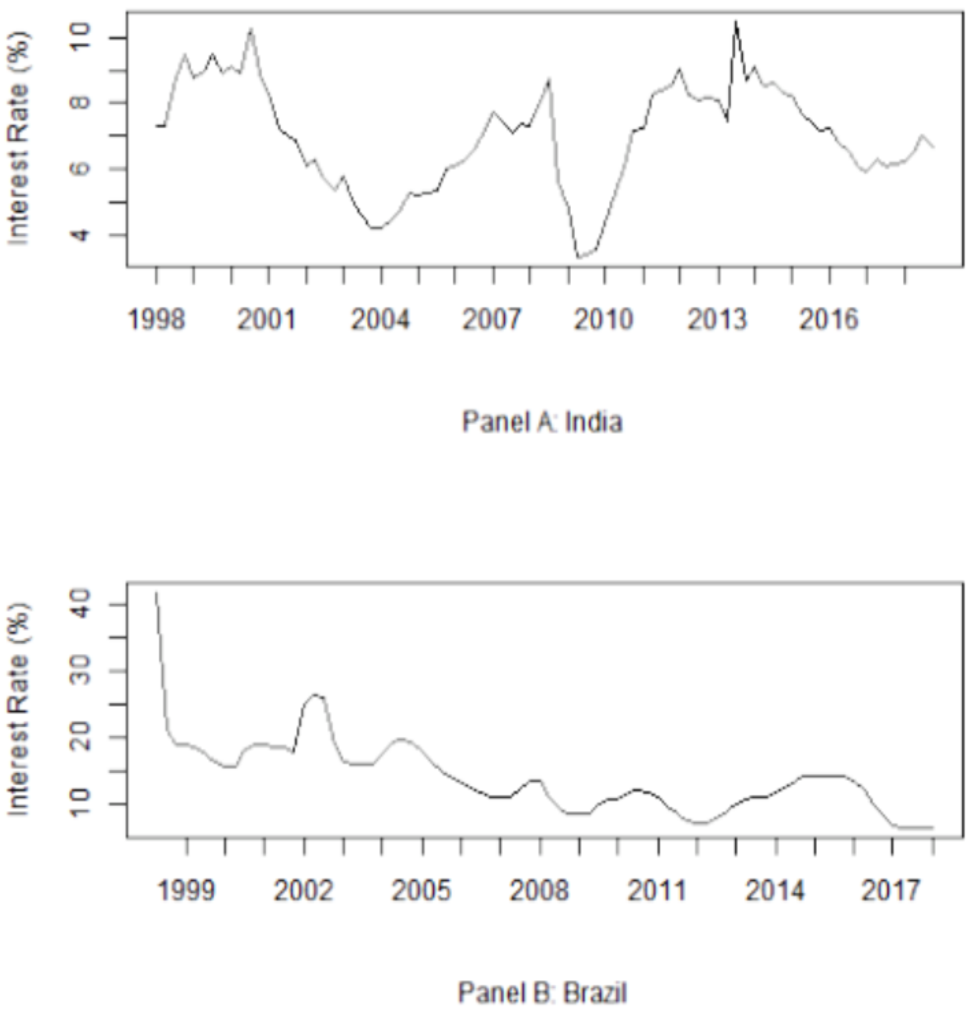


Figure 3.3: Money Market Interest Rates

finding a strong instrument is a daunting task. Weak instruments lead to results that perform poorer than OLS estimates (Stock, Wright, and Yogo 2002), and it isn't clear that instrumenting for the exchange rate leads to improved estimates. The second reason is that the bias of the exchange rate coefficient works against our hypothesis. This is because lower interest rates and foreign currency purchases lead to exchange rate depreciation, whereas we expect depreciation to

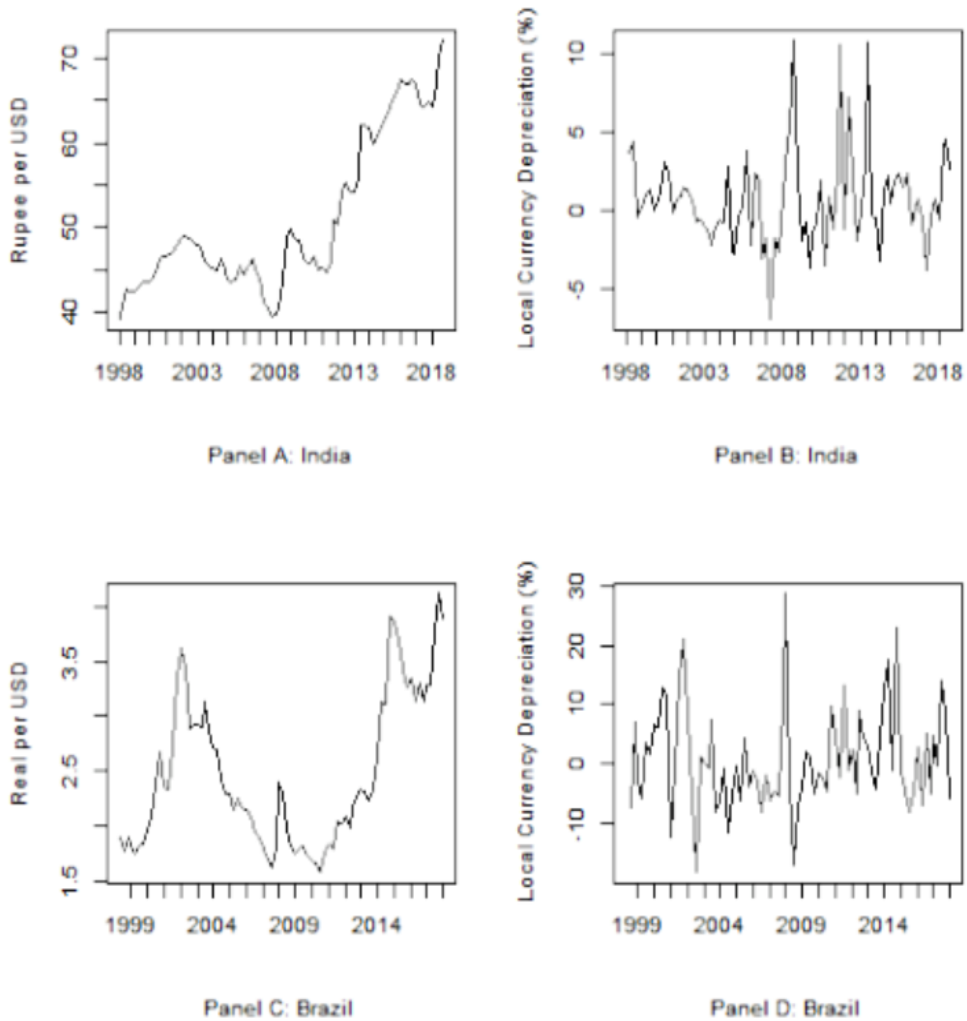


Figure 3.4: Exchange Rates

cause higher interest rates and purchases of domestic currency. Our results for the exchange rate can therefore be interpreted as a lower bound on the true effect of exchange rates on interest rate and intervention policy. Both inflation and the output gap are assumed to respond to interest rate changes only with a lag and are treated as pre-determined variables. We estimate HAC Newey-West standard errors to account for potential autocorrelation and heteroscedasticity in the error term.

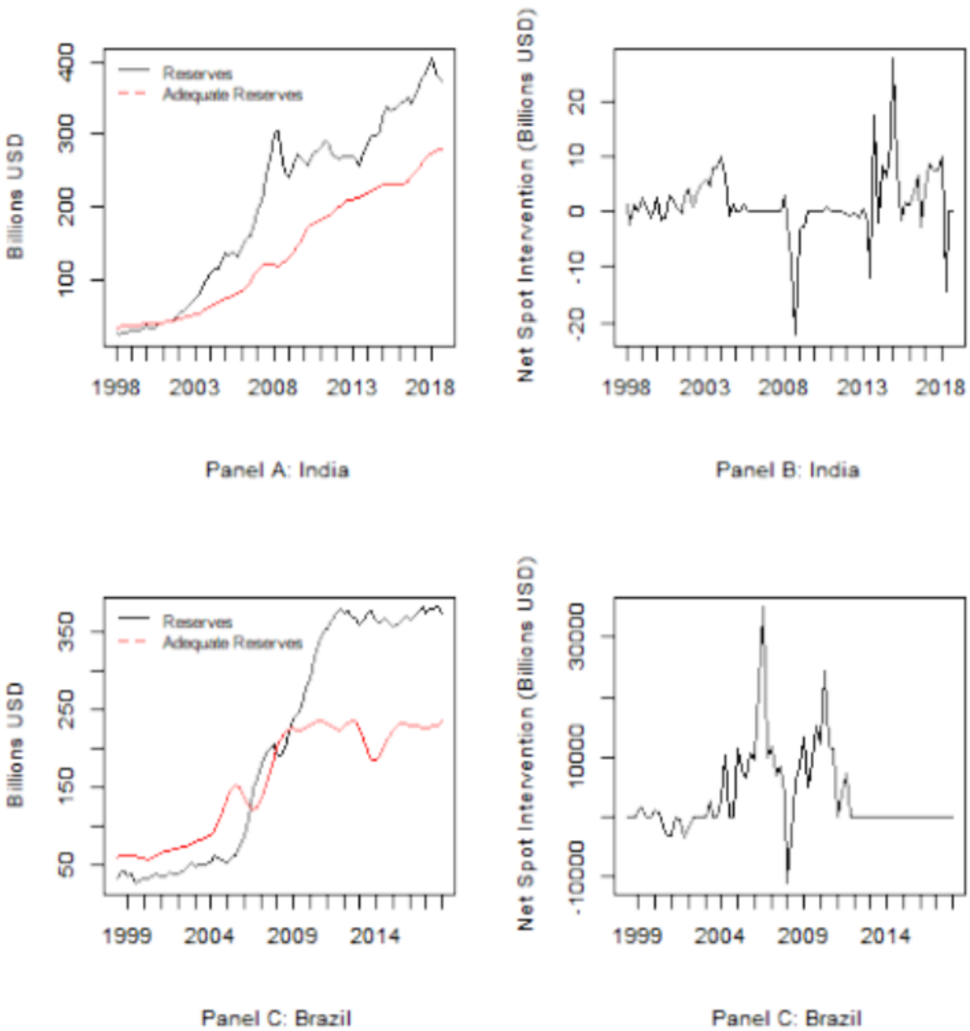


Figure 3.5: Reserves, Reserve Adequacy and Foreign Exchange Market Intervention

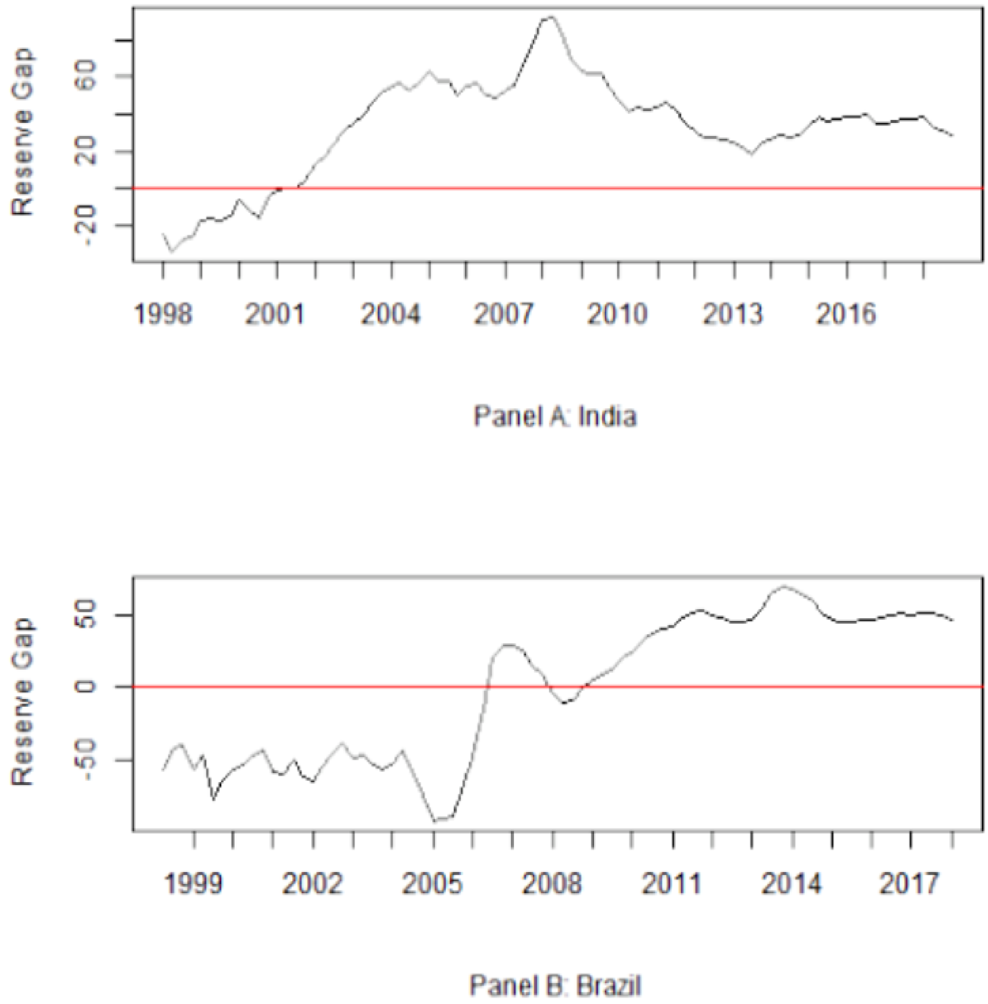


Figure 3.6: Reserve Gap

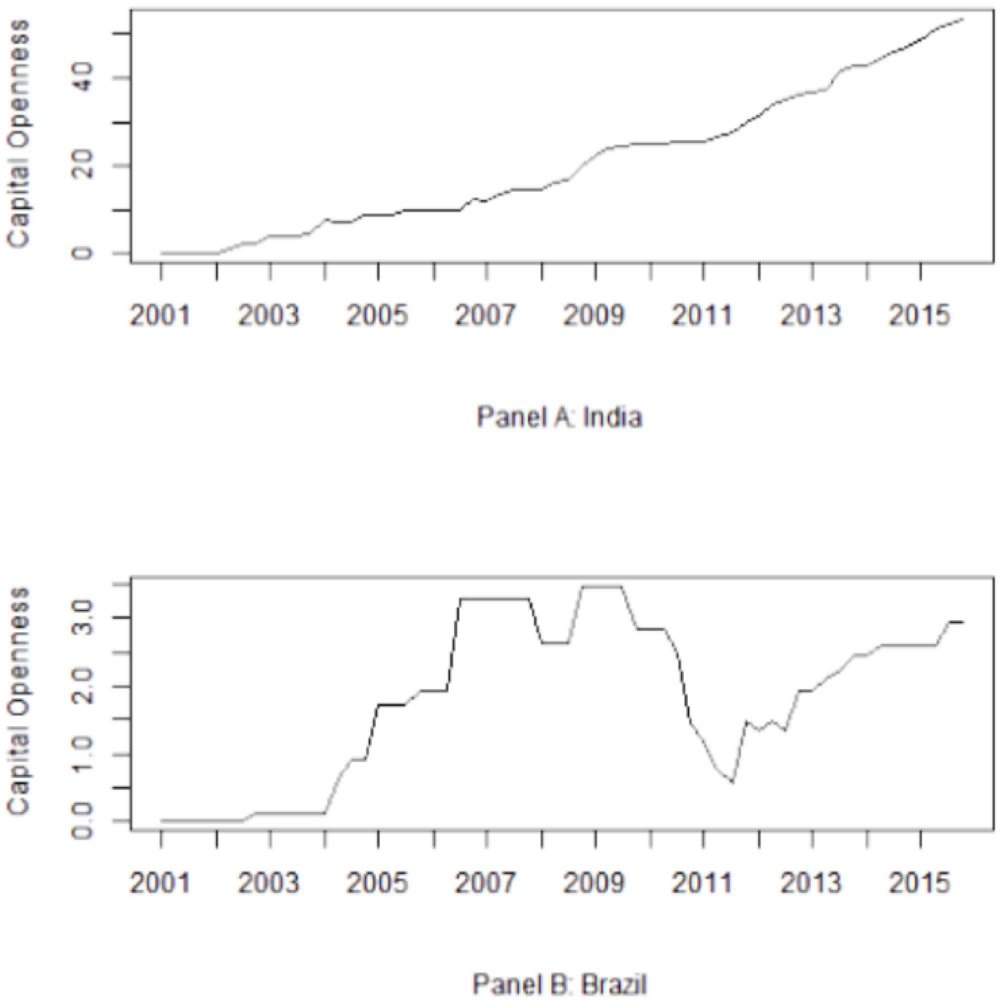


Figure 3.7: Capital Openness

3.5 Results

3.5.1 Baseline and Extended Full Sample Results

Table 3.2 shows the full-sample baseline results for Brazil and India (Column 1), together with the extended model including the terms-of-trade and the current account (Column 2). Panel A reports the extended Taylor rule model estimations and Panel B the intervention functions. Spot intervention operations are employed in the intervention function estimates reported in Panel B[7].

The results shown in Panel A indicate very different monetary policies pursued by India and Brazil over the full sample period. India has systemically pursued output stabilization, raising domestic interest rates on average by 11 basis points in response to a one percentage point rise in the output gap. We find no evidence that the Reserve Bank of India systematically responds to inflation or exchange rates in setting money market rates over the full sample period. Brazil, on the other hand, responds strongly to deviations from its inflation target, confirming the central bank's commitment to an IT regime, increasing the interest rate by 60 basis points for every 1 percentage point above the inflation target. The extended results also suggest that the Central Bank of Brazil responds to exchange rate depreciation by raising interest rates. In sharp contrast with India, no output stabilization by Brazil's central bank is indicated over the full sample.

The additional variables (terms-of-trade and current account) of the

[7]We also considered a measure of intervention aggregating spot and forward transactions. The results were unchanged, omitted for brevity, and are available from the authors upon request.

extended model do not appear significant for India, but the terms-of-trade does enter significantly for Brazil. An improvement in the terms-of-trade in Brazil is associated with a (statistically significant) decline in interest rates. Interest rate policy is highly persistent in both countries, especially in India (lagged dependent variable coefficient equals 0.81-0.82 in India and 0.65-0.66 in Brazil).

Although following quite different Taylor rules, India and Brazil are similar in foreign exchange market intervention policy responses to exchange rate changes, shown in Panel B of Table 3.2. Both countries respond strongly to exchange rate movements in "leaning against the wind" intervention operations, selling (buying) about 0.17-0.22% in Brazil and 0.30-0.48% in India, of the stock of international reserves in response to a one percent depreciation (appreciation) of the domestic currency against the USD.

Only India appears to systematically target reserves around a level associated with observable economic fundamentals. A rise (fall) in actual reserves above (below) the target induces a significant sale (purchase) in foreign exchange (as a percent of last period's total reserves)[8]. Differences also emerge between the two countries in terms of responses to terms-of-trade fluctuations and the current account. A terms-of-trade improvement in Brazil reduces U.S. dollar intervention purchases - most likely attributable to higher foreign exchange earnings for Brazilian exports. No intervention response is noted to changes in the current account in Brazil. By contrast, the current account is estimated to be highly sig-

[8]This result is statistically significant in the baseline model at the 1% level, but not statistically significant in the extended model.

nificant for intervention policy in India, with a rise in the surplus (as a percent of GDP) leading to a significant increase in U.S. Dollar purchases, perhaps absorbing excess liquidity generated by the surplus in the foreign exchange market in the face of fairly restrictive capital controls. Although the exchange rate response remains significant in Indian intervention policy, albeit weaker than in the basic equation, targeting of reserves is no longer statistically significant (although the coefficient estimate is very similar, it is measured with less precision).

It is noteworthy that both India and Brazil built very substantial foreign exchange reserve positions during the sample period. This is reflected in the empirical model by the significant positive constant terms in the intervention regressions, indicating substantial average foreign exchange purchases (as a percentage of existing reserves).

3.5.2 Policy Shifts and the Global Financial Crisis

We address whether policy shifts occurred at the time of the GFC in Table 3.3, comparing the pre-GFC 1999Q1-2008Q4 period with the post-GFC 2009Q1-2018Q4 period. We present both the baseline model and the extended model in Table 3.3, but focus our discussion on the extended model results.

The full sample results on output and inflation carry over to the sub-sample results—during both sub-samples India focused on output stabilization and Brazil focused on inflation targeting. Nonetheless, we find some evidence that India began responding to inflation deviations in the post-crisis period[9] and

[9] The coefficient is 0.04 (not statistically significant) for the early period and 0.03 (statistically

Table 3.2: Baseline Results

Panel A: Interest Rate Policy	Dependent Variable: i_t			
	India		Brazil	
	(1)	(2)	(1)	(2)
c	1.13^{***}	1.16^{**}	3.51^{***}	5.87^{***}
	(0.39)	(0.56)	(1.31)	(1.38)
$\hat{Y}$	0.11^{***}	0.11^{***}	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.04)
$\pi - \pi^*$	0.02	0.02	0.60^{***}	0.60^{***}
	(0.02)	(0.02)	(0.22)	(0.16)
Δe	0.03	0.03	0.02	0.03^{*}
	(0.06)	(0.06)	(0.02)	(0.015)
i_{t-1}	0.82^{***}	0.81^{***}	0.65^{***}	0.66^{***}
	(0.05)	(0.05)	(0.11)	(0.04)
t.o.t.		-0.00		-0.013^{**}
		(0.00)		(0.012)
current account		-0.04		0.11
		(0.03)		(0.17)
R^2	0.83	0.82	0.85	0.86
Num. obs.	80	76	79	79

Panel B: Intervention Policy	Dependent Variable: I_t			
	India		Brazil	
	(1)	(2)	(1)	(2)
c	3.23^{***}	3.12	3.12^{*}	25.17^{***}
	(0.71)	(6.21)	(1.70)	(9.36)
Δe	-0.48^{***}	-0.30^{**}	-0.22^{**}	-0.17^{**}
	(0.15)	(0.11)	(0.09)	(0.074)
$R - R^*$	-0.04^{***}	-0.04	-0.04	-0.03
	(0.01)	(0.03)	(0.04)	(0.02)
t.o.t.		0.01		-0.23^{**}
		(0.05)		(0.09)
current account		0.91^{***}		0.18
		(0.24)		(0.39)
R^2	0.13	0.45	0.11	0.32
Num. obs.	83	76	75	75

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

also to terms-of-trade changes in both pre- and post-crisis samples. The current account is only statistically significant for India in the pre-crisis sample.

As stated, inflation targeting dominated the Central Bank of Brazil's interest rate policy in both sub-periods, as it did in the full sample period, but the estimated response is weaker in the post-GFC period[10]. This finding sheds some light on the concern that Brazil is adhering less to inflation targeting in recent years (Paiva (2017)). However, no output response is estimated in Brazil in either sub-period, nor is there evidence of systematic responses to exchange rates, terms-of-trade or current account movements.

Exchange rate stabilization is a dominant feature of intervention policy for India in the pre and post-GFC, with quite similar responses, as for the full sample period. All the coefficient estimates are significant at the 5% level or better. By contrast, the estimates for the two sub-samples in Brazil are not statistically significant (unlike the full sample).

Stronger responses are suggested in the management of foreign exchange reserves in India from the pre to the post-GFC[11], and the response in the latter period - selling foreign exchange when reserves are above target - is consistent with a stabilizing role. The response for the reserve gap is significantly negative in Brazil both periods, with policy targeting a desired reserve level, and the coefficient estimates are similar. The terms-of-trade played a role in intervention

significant) for the later period. The difference in coefficient values is not statistically significant.

[10]However, this difference in coefficient estimates is not statistically significant at conventional levels (z-statistic 0.96).

[11]The z-statistic measuring differences in coefficient estimates is 2.53 (significant at the 5% level).

policy for both countries in the pre-GFC period, but not in post-GFC period. A rise in the current account surplus induced USD purchases in both periods for India, probably to absorb surplus liquidity in the foreign exchange market and limit pressure on the Rupee to appreciate in the face of capital controls. Surprisingly, the opposite result is obtained (negative and statistically significant) for Brazil in the post-GFC period.

3.5.3 Transmission of U.S. Interest Rates and Capital Controls

In this section we explore the extent to which policy interest rates in India and Brazil are directly tied to U.S. interest rates in addition to the indirect link via the exchange rate. We also consider the impact of external financial account openness on policy interest rates and foreign exchange market intervention policy.

The results are reported in Table 3.4. U.S. interest rates did not move enough during the post-GFC, encompassing the zero-lower-bound period, to warrant inclusion in the sample so only the pre-GFC period is presented in our Taylor rule equation estimates. Column (1) in Panel A for India and Brazil include the U.S. interest rate in the baseline Taylor rule regression, while Column (2) reports estimates with the U.S. interest rate and openness. The estimates indicate that domestic money market rates move about 18-27 (Brazil) to 24-25 (India) basis points for a 1 percentage point move in U.S. interest rates, though only the estimates for India are statistically significant.

The results in Table 3.4 suggest quite different policy responses to cap-

Table 3.3: Pre and Post Global Financial Crisis

Panel A: Interest Rate Policy				Dependent Variable: i_t				
	India				Brazil			
	Pre-Crisis		Post-Crisis		Pre-Crisis		Post-Crisis	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
c	1.48^{***}	0.39	0.86	-6.32^{**}	8.66^{***}	5.13	1.90^{**}	-0.15
	(0.50)	(0.85)	(0.53)	(2.68)	(1.55)	(3, 30)	(0.76)	(1.27)
$\hat{Y}$	0.12^{*}	0.18^{***}	0.16^{***}	0.15^{***}	0.01	0.03	0.02	0.01
	(0.07)	(0.06)	(0.03)	(0.04)	(0.03)	(0.05)	(0.02)	(0.01)
$\pi - \pi^*$	-0.02	0.04	0.04^{**}	0.03^{**}	0.60^{***}	0.61^{***}	0.50^{***}	0.43^{***}
	(0.05)	(0.07)	(0.01)	(0.02)	(0.16)	(0.17)	(0.09)	(0.08)
Δe	-0.02	-0.03	0.08	0.10	0.01	-0.02	0.01	0.01
	(0.03)	(0.02)	(0.08)	(0.09)	(0.03)	(0.03)	(0.01)	(0.01)
i_{t-1}	0.79^{***}	0.57^{***}	0.86^{***}	0.85^{***}	0.41^{***}	0.30^{***}	0.74^{***}	0.72^{***}
	(0.05)	(0.13)	(0.08)	(0.09)	(0.08)	(0.07)	(0.07)	(0.10)
$t.o.t.$		0.02^{*}		0.07^{**}		0.06		0.02
		(0.01)		(0.03)		(0.04)		(0.02)
$cur.\ acc.$		-0.07^{**}		-0.07		0.13		-0.15
		(0.03)		(0.06)		(0.22)		(0.10)
R^2	0.85	0.84	0.86	0.87	0.78	0.80	0.93	0.94
Num. obs.	40	36	40	40	39	39	40	40

Panel B: Intervention Policy				Dependent Variable: I_t				
	India				Brazil			
	Pre-Crisis		Post-Crisis		Pre-Crisis		Post-Crisis	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
c	3.57^{***}	-23.78^{*}	4.63^{**}	7.92	3.64^{*}	46.71^{***}	5.06^{***}	3.65^{**}
	(1.15)	(13.46)	(1.82)	(8.26)	(2.05)	(8.65)	(1.08)	(1.42)
Δe	-0.66^{**}	-0.37^{**}	-0.35^{**}	-0.35^{**}	-0.37^{***}	-0.11	0.04^{**}	0.02
	(0.30)	(0.14)	(0.15)	(0.15)	(0.10)	(0.14)	(0.02)	(0.02)
$R - R^*$	-0.03^{*}	0.07	-0.10^{**}	-0.10^{***}	-0.03	-0.13^{***}	-0.09^{***}	-0.09^{***}
	(0.02)	(0.06)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.01)
$t.o.t.$		0.21^{**}		-0.02		-0.53^{***}		0.00
		(0.10)		(0.08)		(0.10)		(0.01)
$cur.\ acc.$		1.13^{***}		0.51^{**}		-0.25		-0.38^{**}
		(0.30)		(0.24)		(0.39)		(0.18)
R^2	0.15	0.63	0.14	0.26	0.11	0.37	0.29	0.36
Num. obs.	43	36	40	40	35	35	40	40

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Pre-Crisis corresponds to periods before 2009Q1

ital account liberalization in India and Brazil. For India, in the pre-GFC period, an increase in openness led to lower money market interest rates (8 basis points, Panel A) and sales of foreign exchange (0.97 percent of reserves) by the central bank (Panel B). No significant impact on intervention policy from greater openness is seen in the post-GFC. In Brazil, steps toward greater openness (restrictiveness) also is associated with lower (higher) domestic interest rates (61 basis points), but prompted the purchase of foreign currency by the central bank in the pre-GFC (6.17 percent of reserves) and sales of foreign currency in the post-GFC (1.5 percent of reserves).

These differences may be explained in part by how the pattern of financial market liberalization/openness and market conditions affected net capital flows in the two periods and across the two countries, leading to varying policy responses. Shown in Figure 3.7, India—though much more financially closed generally than Brazil—set out on a gradual process of external financial liberalization over the sample period. The number of liberalization measures (positive steps in the figure) far exceeded the number of restrictive measures (negative steps in the figure), so that over 50 net liberalization steps were taken between 2001 and the end of 2015. Brazil, on the other hand, used capital control more as a cyclical policy instrument, at times loosening and at times tightening controls. The number of net liberalization steps (positive) only slightly outnumbered the number of restrictive (negative) steps over course of the full sample.

For India, it appears that a rise in openness led to net capital outflows in the pre-GFC, perhaps because of a tendency to liberalize outflows more than inflows, indirectly creating incipient pressure for currency depreciation, and in turn prompting the central bank to "absorb" the impact on the foreign exchange market by selling foreign exchange (an official capital inflow). Less private capital inflow may also have adversely impacted domestic investment, leading the Reserve Bank of India to respond by lowering the policy rate. The effect of liberalization of inflows and outflows may have been more balanced post-GFC as no impact on intervention operations is found.

The results for Brazil, on the other hand, suggest that an increase in openness led to a surge in net private capital inflows during the pre-GFC period, leading the central bank to offset the impact on the foreign exchange market by making large USD purchases. The capital inflow associated with greater openness during pre-GFC was also associated with lower money market rates, suggesting that the central bank allowed private capital inflows to loosen domestic financial market conditions. The contrasts with post-GFC, where a net increase in openness was associated with net capital outflows and official sales of foreign exchange reserves. Liberalization in this period may have been more directed to relaxation of controls on outflows than inflows or attributable to adverse market conditions.

3.5.4 Linkage across policies

Tradeoffs between interest rate and intervention policies are not explicitly addressed using our basic methodology. It is possible that "errors" in one policy function, i.e. deviations from predicted values, are discretionary policy

Table 3.4: Capital Account Liberalization (Openness)

Panel A: Interest Rate Policy - Pre GFC

	Dependent Variable: i_t			
	India		Brazil	
	(1)	(2)	(1)	(2)
c	1.987***	3.2289***	6.4176*	8.8692**
	(0.3249)	(0.8176)	(3.4913)	(4.1772)
$\hat{Y}$	0.1277**	0.2475***	−0.0176	0.0041
	(0.0691)	(0.0578)	(0.0390)	(0.0416)
$\pi - \pi^*$	−0.0276	.0909	0.5248	0.5183
	(0.0489)	(.0849)	(0.3105)	(0.3798)
Δe	0.0323	0.0590	0.0089	0.0006
	(0.0336)	(0.0373)	(0.0294)	(0.0279)
i_{t-1}	0.5994***	0.4054***	0.5103*	0.4080
	(0.0455)	(0.1175)	(0.2598)	(0.3249)
i_{US}	0.2474***	0.236***	0.1872	0.2717
	(0.0511)	(0.0473)	(0.2306)	(0.3268)
openness		−0.0809***		−0.6089*
		(0.0284)		(0.3550)
R^2	0.8908	0.8766	0.8198	0.8369
Num. obs.	40	32	32	32

Panel B: Spot Intervention

	Dependent Variable: I_t			
	India		Brazil	
	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis
c	4.78***	−2.09	−9.39***	8.06***
	(1.35)	(4.51)	(2.14)	(1.77)
Δe	−0.26**	−0.27*	−0.27	−0.00
	(0.11)	(0.16)	(0.20)	(0.02)
$R - R^*$	0.12	−0.02	−0.14***	−0.08***
	(0.10)	(0.05)	(0.03)	(0.02)
openness	−0.97**	0.11	6.17***	−1.50***
	(0.42)	(0.09)	(0.81)	(0.51)
R^2	0.66	0.30	0.49	0.41
Num. obs.	32	28	32	28

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Pre-Crisis corresponds to periods before 2009Q1

actions connected to the second policy function. For example, unexpectedly low interest rates (intervention) may be linked to unexpectedly low intervention (interest rates) as authorities are attempting to manage the exchange rate via the Taylor rule rather than direct intervention operations. In other words, there may be tradeoffs and substitutions between the internal and external policy functions that are manifested in the error terms.

We address this issue in two ways. Our first approach is to estimate the two equations using a Three Stage Least Squares (3SLS) systems estimator[12]. This method takes into account systemic linkages among the errors of the two policy equations while also accounting for the endogeneity of the reserve gap in the intervention equation. The estimates, not reported for brevity are virtually identical to the extended model results reported in Table 3.2, Column 2 for both India and Brazil's interest rate (Panel A) and intervention (Panel B) policy equations[13]. This indicates that the error terms in the two equations are not significantly correlated in a simple way. This is confirmed by the simple error correlations across the two equations– statistically insignificant correlation coefficients of -0.16 (standard error 0.11) for India and 0.02 (standard error 0.11) for Brazil.

We also explore possible linkages between large policy errors in the two equations since policy tradeoffs or conflicts may only be manifested during partic-

[12]Greene (2012) shows that the seemingly unrelated regressions model, estimated equation by equation, is inefficient compared with an estimator that makes use of the cross-equation correlations of the disturbances. Following Greene (2012), we estimate both equations jointly with a three-stage least squares estimator (the IV estimator is simply equation-by-equation 2SLS). This procedure is asymptotically efficient.

[13]These results are available from the authors upon request.

ular episodes. For example, a country may not respond to substantial pressure on the exchange rate in the Taylor rule if domestic conditions are clearly not warranting an interest rate change, placing greater emphasis on intervention policy. We identify the intervention policy errors (interest rate policy errors) that are equal to or larger than the 90th percentile in absolute value and regress these on the associated interest rate policy (intervention policy) function errors in Table 3.5. These results indicate that the equations are related in a highly non-linear way. In particular, large intervention policy errors in both India and Brazil are negatively and significantly correlated with corresponding interest rate policy errors. That is, unexpectedly large USD purchases (sales) by the foreign exchange fund are associated with lower (higher) than predicted interest rates. This suggests that episodes of especially large unexpected intervention purchases/sales may be designed to limit the need for interest rate changes in macro policy management. Interestingly, we do not find that large interest rate errors are correlated with associated intervention errors[14]. Discretionary intervention policy actions appear to serve as a "pressure valve" when policy conflicts arise, subordinate to interest rate policy.

[14]Not reported for brevity but available from the authors upon request.

Table 3.5: Residual Analysis

Dependent Variable ϵ_{taylor}	India	Brazil
c	0.14	0.87***
	(0.12)	(0.10)
$\epsilon_{intervention}\lvert(\lvert\epsilon_{intervention}\rvert) > p90$	−0.21*	−0.09*
	(0.11)	(0.04)
R^2	0.17	0.05
Num. obs.	16	16

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

3.6 Robustness: Extensions to China and Chile

In this section we contrast our results for Brazil and India with two other emerging markets, Chile and China. The contrasts between Chile and China are stark. Chile is a small open economy with inflation targeting, high dependence on commodity exports, flexible exchange rates and a very open capital account. China, on the other hand, is the largest emerging market—the second largest economy in the world after the United States—with discretionary monetary policy, dominance of manufacturing exports, rigid exchange rate and largely closed to (non-FDI) external capital flows. China is also characterized by heavy government involvement in the financial sector, government majority ownership in large banks, and regulated interest rates.

Chile is included to check the robustness of the results to a small open market-oriented EM with high dependence on commodity exports and a policy commitment to inflation targeting. China, of course, is the obvious choice to include in our study due simply to its importance to the world economy, rapid growth and buildup of international reserves. It is not a country of emphasis in this study, but rather an extension of our work, because China's macroeconomic institutions differ so markedly from other large EMs.

3.6.1 Chile

Chile was the second country in the world to adopt inflation targeting (IT), setting its first annual target in September 1990, and IT was used as a device to bring inflation gradually down to a stationary 3% level (Schmidt-Hebbel and Tapia (2002)). As noted in its 2019 monetary policy report:[15] "The main objective of the Central Bank of Chile's monetary policy is to keep inflation low, stable, and sustainable over time. Its explicit commitment is to keep annual CPI inflation at around 3% most of the time, within a range of plus or minus one percentage point."[16] Although the main objective of policy is focused on inflation, it does not preclude secondary objectives and several articles suggest that both internal and external factors may play a role in determining domestic interest rates (e.g. Edwards (2015)). Navdon and Vial (2016), for example, emphasize the impact of commodity prices and the exchange rate on inflation in Chile. Nonetheless, monetary policy statements from the central bank generally do not refer to output stabilization as a reason for policy changes.

Table 3.6 shows the empirical estimates results for Chile. Panel A indi-

[15] Monetary Policy Report, June 2019, Central Bank of Chile.

[16] This quote continues to state that output stabilization is a derivative of achieving stable inflation, but not an explicit objective of policy: "Low, stable inflation promotes economic activity and growth while preventing the erosion of personal income. Moreover, focusing monetary policy on achieving the inflation target helps to moderate fluctuations in national employment and output."

cates that over the full sample period interest rate policy responded significantly in the expected ways to both inflation and the output gap. But the estimates suggest that greater focus in Chile was on inflation targeting in the pre-GFC period and on output targeting during the post-GFC period[17]. In the pre-GFC period, improvements in the terms-of-trade (and associated wealth gains and improving economy) were associated with interest rate hikes. Rising current account surpluses, in tandem with increased financial market liquidity, led to nominal interest rate declines. No statistically significant responses to either the terms-of-trade nor the current account were found in the post-GFC period, reflecting in part a low and largely unchanged policy interest rate during this period[18].

Panel B of Table 3.6 indicates that Chile's intervention policy targeted the reserve gap and was also impacted by the current account (with official purchases of USD declining with a rise in the surplus) during the post-GFC[19,20]. There is no systemic evidence of intervention policy directed towards exchange rate management in the full sample period or either sub-sample.

[17] These differences are statistically significant. The z-statistic measuring the significance of the difference in the output gap (inflation target) is -2.60 (1.74), significant at the 1% (5%) level.

[18] These differences are statistically significant. The z-statistic for the difference in coefficients on the terms-of-trade (current account) between the two periods is 2.83 (-2.40), significant at the 1% (5%) level.

[19] We do not have central bank data on intervention for Chile and China (as we do for India and Brazil). We proxy for intervention by the change in international reserves, adjusted for interest earnings and valuation effects (as in Equation 3.3). We estimate interest earnings as the U.S. interest rate multiplied by lagged level of reserves. This adjusted series is divided by the lag level of reserves and regressed on the U.S. interest rate, as a proxy for valuation effects. The estimated coefficient on the U.S. interest rate is multiplied by the observed U.S. interest rate in each quarter to extract valuation effects from our intervention measure. As a robustness test of this approach, we made the same calculation of adjusted reserves for Brazil and India, and correlated our estimated intervention with actual intervention data. The correlations are 0.71 and 0.62, respectively, for Brazil and India. This suggests that our "adjusted reserve change" proxy for intervention is a reasonable estimate of actual intervention.

[20] However, only the shift in the reserve gap coefficient between the two periods is statistically significant (z-statistic of 3.90, significant at the 1% level).

Table 3.6: Chile Policy Rules

Panel A: Interest Rate Policy	Dependent Variable: i_t					
	Full Sample		Pre-Crisis		Post-Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
c	0.76^{***}	1.60^{***}	0.40	-2.98^{***}	1.79^{***}	2.11
	(0.25)	(0.54)	(0.35)	(0.95)	(0.52)	(1.43)
$\hat{Y}$	0.07^{***}	0.10^{***}	0.02	-0.03	0.21^{***}	0.18^{**}
	(0.03)	(0.02)	(0.03)	(0.04)	(0.06)	(0.07)
$\pi - \pi^*$	0.20^{***}	0.18^{***}	0.22^{***}	0.28^{***}	0.05	0.07
	(0.06)	(0.05)	(0.04)	(0.05)	(0.12)	(0.11)
Δe	0.02	0.01	0.01	0.01	0.00	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
i_{t-1}	0.64^{***}	0.58^{***}	0.74^{***}	0.65^{***}	0.44^{***}	0.40^{***}
	(0.08)	(0.09)	(0.08)	(0.09)	(0.05)	(0.04)
$t.o.t.$		-0.01		0.04^{***}		-0.00
		(0.00)		(0.01)		(0.01)
current account		-0.07		-0.11^{**}		-0.06
		(0.04)		(0.05)		(0.05)
R^2	0.81	0.82	0.84	0.88	0.84	0.85
Num. obs.	80	76	40	36	40	40

Panel B: Intervention Policy	Dependent Variable: I_t					
	Full Sample		Pre-Crisis		Post-Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
c	1.63^{**}	2.80	1.41^{**}	3.67	13.62^{***}	19.08^{***}
	(0.64)	(3.83)	(0.60)	(8.25)	(4.94)	(5.62)
Δe	0.08	0.07	0.08	0.04	0.26	0.24
	(0.08)	(0.08)	(0.11)	(0.06)	(0.19)	(0.18)
$R - R^*$	-0.00	-0.00	0.01	0.02	-0.14^{***}	-0.23^{***}
	(0.01)	(0.01)	(0.03)	(0.03)	(0.05)	(0.05)
$t.o.t.$		-0.01		-0.02		0.01
		(0.04)		(0.08)		(0.03)
current account		-0.04		-0.14		-0.80^{**}
		(0.17)		(0.25)		(0.37)
R^2	0.00	0.01	0.03	0.05	0.05	0.05
Num. obs.	75	75	35	35	40	40

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Pre-Crisis corresponds to periods before 2009Q1

3.6.2 China

Analyzing monetary policy in China is not straightforward as the People's Bank of China (PBoC) uses more than one instrument for monetary policy and these instruments have evolved over time (Chen et al. (2017)). The PBoC currently uses seven instruments of implementation of monetary policy, including the rediscount rate on loans to banks and other benchmark interest rates.[21] Moreover, stronger emphasis has been placed on targeting interest rates as the major monetary policy instrument in recent years (Zengping and Genliang (2019)). Given China's extensive use of capital controls and direct involvement in the banking sector and foreign exchange market, we modify the intervention equation in two ways beyond the models estimated for the other three countries investigated. First, we extend the intervention equation by including the broad money supply as an explanatory variable (M2, measured in USD as 100*log(M2) divided by the log lag of nominal GDP)[22]. In addition we treat the current account as an endogenous variable[23]. This methodological adjustment is taken because tight capital controls on the financial account in China could lead to either current account surpluses or FDI inflows automatically increasing international reserves.[24]

[21]Other instruments noted on the PBoC website in 2018 were open market operations, reserve requirement ratios, standing lending facility, medium-term lending facility, and pledged supplementary lending facility.

[22]This follows Schröder (2017) who finds both M2 and portfolio equity liabilities as significant determinants of reserve demand. The latter variable is not available past 2011 and not employed in our study. (It from the Lane and Milesi-Ferretti database, updated online through 2011 only).

[23]We instrument the contemporaneous current account in China with three lags of itself.

[24]This is related to the discussion of what constitutes intervention, "passive" increases in reserves that may be caused by interest earnings or valuation effects or "active" purchases and sales in the foreign exchange market. This is further complicated in the Chinese case by extensive

Table 3.7 shows the empirical estimates for China. Panel A shows the Taylor rule estimates and panel B the intervention rule estimates. It is apparent that the central bank in China raises the policy rate in respond to an uptick in inflation, a very robust link that holds across sample periods and model specifications. Policy rates are also linked to the output gap, but with unexpected and significant negative sign, indicating that interest rates are reduced the larger is the output gap. Since GDP is only available for China on an annual basis, this result could be associated with the interpolation methodology. However, when employing industrial production rather than GDP as the output measure[25], the significant positive coefficient is also obtained, and stands in contrast to estimates from the other EMs in the sample. There is also evidence that large current account surpluses in the pre-GFC period were associated with substantial liquidity in the Chinese financial system, leading the central bank to reduce interest rates. No estimated linkage with the terms-of-trade is statistically significant.

On the external side, we find no evidence that intervention policy systemically responds to (albeit small) variations in the nominal exchange rate or

capital controls.

[25]GDP data in China is only available at an annual level. Quarterly estimates of GDP are obtained by implementing a cubic spline interpolation. As a result, it is not possible to decompose the approximate quarterly series into the trend and cyclical components that would be needed to calculate the output gap. A simple quarter over quarter growth rate is calculated from the interpolated series and used as an alternative measure of the output gap in China. A potential concern with this methodology is that the variation in the interpolated series is being driven by statistical noise rather than actual output fluctuations in China. To alleviate this concern, the baseline Taylor rule in China is re-estimated using both the official annual measure of industrial production, interpolated to a quarterly series, and a quarterly measure of industrial production growth from the OECD. These two alternative measure of the output gap leaves the results qualitatively unchanged. Most noteworthy is that negative and statistically significant coefficients on the output gap are robust to using industrial production. Results omitted for brevity but are available from the authors upon request.

to the broad money supply (M2). However, we find a strong and robust intervention response to deviations in the reserve gap—the central bank systemically reduces its USD purchases when the reserve gap increases. This result holds across sub-samples and model specifications. This robust result is obtained despite the massive buildup of reserves by China, far exceeding "adequate" levels. Moreover, there is evidence that higher current account surpluses also led to more USD purchases prior to the GFC period, as the foreign exchange fund moved to absorb liquidity in the foreign exchange market, but not afterwards[26].

In summary, applying our methodology to Chile, our small EM extension, is in line with our previous results. On the other hand, the results for China are at odds with the estimates for the other EMs. Estimation of the output gap in the Taylor rule is particularly problematic due to the lack of reliable quarterly output data in China. Nonetheless, we find a strong and robust inflation response in the Taylor rule and an intervention function consistent with targeting international reserve levels.

[26] This difference is statistically significant at the 1% level (z-statistic equals 2.65)

Table 3.7: China Policy Rules

Panel A: Interest Rate Policy	Dependent Variable: i_t					
	Full Sample		Pre-Crisis		Post-Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
c	2.17^{***}	1.77^{*}	1.57^{***}	2.13^{***}	2.86^{***}	4.81
	(0.66)	(0.90)	(0.33)	(0.41)	(0.92)	(3.20)
Y	-0.39^{**}	-0.41^{*}	-0.28^{*}	-0.39^{***}	-0.76^{**}	-0.86^{**}
	(0.18)	(0.24)	(0.15)	(0.07)	(0.35)	(0.40)
$\pi - \pi^*$	0.10^{***}	0.16^{***}	0.04^{*}	0.12^{***}	0.22^{***}	0.17^{**}
	(0.04)	(0.04)	(0.02)	(0.03)	(0.06)	(0.07)
Δe	0.00	-0.02	0.01	0.01	-0.07	-0.05
	(0.02)	(0.03)	(0.03)	(0.02)	(0.05)	(0.05)
i_{t-1}	0.28^{**}	0.17	0.52^{***}	0.36^{***}	0.08	0.05
	(0.13)	(0.12)	(0.13)	(0.08)	(0.12)	(0.15)
$t.o.t.$		0.01		0.00		-0.01
		(0.01)		(0.00)		(0.02)
current account		-0.07^{***}		-0.07^{***}		-0.04
		(0.02)		(0.01)		(0.12)
R^2	0.31	0.37	0.33	0.47	0.35	0.36
Num. obs.	65	64	37	36	28	28

Panel B: Intervention Policy	Dependent Variable: I_t					
	Full Sample		Pre-Crisis		Post-Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
c	26.25^{***}	37.79^{***}	29.23^{***}	-33.44	33.07^{***}	66.64^{**}
	(2.65)	(12.85)	(5.87)	(39.84)	(5.99)	(24.54)
Δe	-0.17	-0.19	-0.15	-0.08	-0.21	-0.24
	(0.10)	(0.17)	(0.14)	(0.24)	(0.14)	(0.26)
$R - R^*$	-0.06^{***}	-0.06^{***}	-0.07^{***}	-0.08	-0.07^{***}	-0.11^{*}
	(0.01)	(0.01)	(0.02)	(0.05)	(0.01)	(0.06)
$t.o.t.$		-0.03		0.25		0.03
		(0.04)		(0.15)		(0.05)
current account		-0.28		1.32^{*}		-1.69
		(0.34)		(0.69)		(1.39)
$M2$		-0.02		0.15		-0.08
		(0.08)		(0.10)		(0.07)
R^2	0.63	0.62	0.27	0.51	0.40	0.33
Num. obs.	59	59	19	19	40	40

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Pre-Crisis corresponds to periods before 2009Q1

3.7 Conclusion

Large emerging markets follow quite different policy configurations in attempting to achieve internal and external balance. India has quite stringent capital controls, and follows a Taylor rule dominated by an output stabilization objective. Inflation has played a much smaller part in influencing interest rates in India, mostly evident in recent years, and the terms-of-trade occasionally plays a role. Brazil, by contrast, has a much more financially open economy and follows an inflation target regime that generally dominates other considerations. Though exchange rate and terms-of-trade fluctuations occasionally influence interest rates in Brazil, we find no evidence that the central bank attempts to stabilize output fluctuations directly.

External policies are more similar in Brazil and India despite differences in capital control regimes. Intervention policies in both countries focus on exchange rate stabilization, i.e. stabilizing the exchange rate with "leaning against the wind" foreign change purchases and sales. In terms of an external financial stability objective, India uses intervention operations to target reserves at a level justified by economic factors. Brazil, on the other hand, started targeting a specific level of reserves only after the Global Financial Crisis (GFC). Controlling for the exchange rate and the international reserves gap, both countries still made large net quarterly purchases of foreign exchange on average over the sample period.

The impact of the liberalization of international capital controls on policy is complex, depending on market conditions and the specific actions taken to lift restrictions on capital inflows or outflows. We find that greater financial openness affected India and Brazil differently, depending on the particular sequence of administrative measures. This led to varying private capital movements and intervention policy responses. We also find that conflicts in internal and external policy occur occasionally and, for both countries, very large discretionary intervention operations appear negatively linked to discretionary interest rate changes. That is, large unpredicted intervention purchases (sales) accommodate low (high) interest rates, suggesting that external operations are subordinate to domestic policy objectives.

The results for Chile, the extension of our study to a small open economy, suggests the central bank follows a true Taylor rule in balancing output and inflation targets but with more emphasis on inflation prior to the GFC and on output after the GFC. The exchange rate does not appear as a factor either in setting interest rates or intervention operations, and targeting a particular level of reserves only appears after the GFC. China has a more complicated institutional framework for macroeconomic policy than the other three EMs, and quality of output data is also a concern. Nonetheless, we find that Chinese interest rate policy responds strongly to inflation and intervention responds to an international reserves target.

In conclusion, each country has its own idiosyncratic policies, varying over time, but commonalities emerge. Policy interest rates always respond to either inflation or output gaps, frequently both, with varying intensities, and intervention is directed toward managing targeted international reserve levels and usually to exchange rate stabilization. Terms-of-trade and current account fluctuations also occasionally influence intervention operations. In conflicts between interest rate and intervention policies, the former — focused on internal balance — appear to dominate policy.

3.8 Appendix - Variable descriptions

- Δe: Percent change in nominal exchange rate, closing price reported by the Central Bank of Brazil and Reserve Bank of India. Quotations denominated in local currency per unit of US dollar. For quarterly data, exchange rate is for March 31st, June 30th, September 30th, and December 31st (or the closest date available). We applied the log changes and presented as percentage, $\Delta e = 100 \times (\ln(e_t) - \ln(e_t - 1)$.

- $\hat{Y}$: India output measured by Industrial Production. Brazil output is quarterly GDP series reported by the Central Bank of Brazil. Log of output series filtered by Hodrick-Prescott (HP) tecnhique. Output gap is the cyclical component of the HP-filtered log(GDP) series.

- π: Inflation calculated as the anualized log change over local price index. India is the wholesale price index, Brazil is the IPCA (National Index of

Consumer Prices, elaborated by the Brazilian Institute of Geography and Statistics). Percent Annualized change, $\pi = 100 \times (\ln(CPI_t) - \ln(CPI_{t-4}))$.

- π^*: India does not publish inflation target. We assume the implicit target constant through the whole period. For Brazil, IT is officially defined by the National Monetary Council and the Central Bank is required by law to pursue it, with some allowed deviations (tolerance bands). The IT changes through time. For 2019, it is defined as 4.25% with a tolerance band of 2% (meaning an accepted interval of [2.25%, 6.25%]).

- $(\pi - \pi^*)$: The inflation gap is measured as the deviation from the target, i.e. $[100 \times (\ln(CPI_t) - \ln(CPI_{t-4})) - \text{inflation target}] = [100 \times (\ln(CPI_t) - \ln(CPI_{t-4})) - \pi^*]$.

- i: Money market rate defined and controlled by the Central Bank of Brazil and Reserve Bank of India, respectively. For Brazil we have used the "SELIC" rate, and for India we've used 3 months money market defined by RBI & India: 1999Q1-2018Q4; Brazil: 2000Q1-2018Q4;

- i^*: The US interest rate is the 3-Month Treasury Bill Rate, published by the Federal Reserve Economic Data (FRED).

- openness: This variable is from Pasricha et al.(2015). The author provided a detailed dataset for the period 2001-2015 with quarterly frequency. Each data series counts the number of capital flow measures (for example, number of easings of inflow controls or tightenings of outflow controls) undertaken by each country. The variables used from the dataset weighted each policy action by the share of the country's international assets or liabilities that the measure was designed to influence. The policy actions in the dataset were counted by effective dates and included changes for which the announcement and effective dates are different. From the dataset we explored two specific series: "wgt_nettighteningin", and "wgt_neteasingout", that correspond to number of net inflow tightenings, weighted, and number of net outflow easenings, weighted, respectively. As we are insterested to understand the degree of openness of the countries studied, we have transformed the first series "net inflow tightenings" to "net inflow easing" by inverting its sign (a positive tightening means a negative easing and a negative tightening means a positive easing). With the quarterly values of easing inflow and easing outflow we chose to work with the cumulative measures of both easing inflow and outflow combined. As this variable was intended to measure openness, we need to measure the easing policies, regardless of inflow or outflow.

- R: Level of Foreign Reserves in USD reported by the Central Bank, includes SDRs and excludes Gold holdings.

- R^*: The Reserve Target values are from IMF "Assessing Reserve Adequacy". The institution's work compares the reserve holdings and alternative metrics of reserve adequacy. This reserves adequacy measure was initially developed in the IMF Board Paper "Assessing Reserve Adequacy" - RAM1 (February 15, 2011), and adjusted in the latest IMF Board Paper "Assessing Reserve Adequacy- Specific Proposals" (December 19, 2014), in order to reflect the outflows during the Global Financial Crisis which were not addressed in RAM1. The IMF Reserve Adequacy estimates adequate volume of reserves for a specific country taking into account exports, imports, broad money, and other liabilities.

- $(R - R^*)$:The Reserve Gap is calculated by the difference of the level of reserves and the adequate level proposed by the IMF (R^*). Log-transformation and percentage presentation is also applied: $100 \times (ln(R) - lnR^*)$

- Appreciation: Dummy variable that assumes value equals to 1 if the local currency appreciates versus US dollar, i.e., $\Delta e < 0$ and value equals 0 otherwise ($\Delta e \geq 0$).

- Spot Intervention: Amount of USD bought and sold in the spot market relative to the level of Reserves.

- Forward Intervention: Amount of USD bought and sold in the forward market relative to the level of Reserves.

- Terms of Trade: Ratio of exports over imports. We have used the following monthly series elaborated by the IMF: Commodity Export Price Index, Individual Commodites Weighted by Ratio of Exports to Total Commodity Exports, Commodity Import Price Index, and Individual Commodites Weighted by Ratio of Imports to Total Commodity Imports. All for the 1999-2018 period.

- Current account: Quarterly data on the net current account balance is obtained from the IMF. The series is normalized by dividing the current account balance by the first lag of nominal GDP and multiplying by 100.

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