Essays on International Finance and Banking

A Dissertation
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Doctor of Philosophy
in Economics

By

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Washington, DC
March 27, 2012

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Abstract

Chapter 1 explores the impact of banks' exposure to market liquidity risk through wholesale funding on their supply of credit during the global financial crisis of 2007-2008. The methodology minimizes the impact of confounding demand factors, by focusing on supply of mortgage lending. By using disaggregated data on mortgage applications, the time variations in banks' decisions to grant mortgage loans is examined, while controlling for bank, borrower, and regional characteristics. The empirical results strongly support the hypothesis that banks which were more reliant on wholesale funding decreased their lending significantly more than retail-funded banks during the crisis. This result holds at the national level as well at the sub-national level in most of the largest Metropolitan Statistical Areas. To further control for applicant characteristics across banks, four million data points are reduced to thousands of pairs of virtually indistinguishable applications and the initial results are still conserved. While the willingness to supply loans was affected by banks' liability structure during the crisis, we find that the demand for mortgages decreased evenly along funding strategy dimension.

Chapter 2 compares the accuracy of the two existing methods for solving stochastic general equilibrium models with dynamic portfolio choice and incomplete markets. The accuracy of these solution methods for the real as well as portfolio variables is analyzed by studying the distribution of Euler equation errors and using a series of accuracy tests. The results indicate that while both methods generate sufficiently accurate solutions for the real variables, there are significant gains from using one method over another when solving for the portfolio allocations.

Chapter 3 employs a novel data set on non-resource GDP to examine the performance of commodity exporting countries in terms of macroeconomic stability and economic growth in a panel of up to 129 countries during the period 1970-2007. Empirical results suggest that the overall government spending in commodity-exporting countries has been procyclical. Moreover, resource windfalls initially crowd out non-resource GDP which then increases as a result of the fiscal expansion. Finally, in the long-run resource windfalls have negative effects on non-resource sector GDP growth.

Index words: Bank liquidity creation, Wholesale funding, Core deposits, Financial crisis, Incomplete markets, Euler equation errors, Commodity prices, Resource windfall, Fiscal policy

Dedicated

To Masha

Acknowledgments

I would never have been able to finish my dissertation without the guidance of my committee members, help from friends, and support from my family.

I am greatly indebted to my thesis advisors who have always provided support, understanding, and guidance throughout the various stages of my studies. Martin D.D. Evans, Dale W. Henderson, and Behzad Diba were always eager to discuss the big picture of my thesis, and guided me through the thesis writing stage and supported me on each step. They were always available to speak with me and offered me an invaluable insight, in both methods and applications in research.

I am thankful to my colleagues and co-authors Rabah Arezki, Jihad Dagher, and Kirk Hamilton for sharing their research experience and insights, which helped me to expand my own work.

I would like to also thank my mother, Saida, and father, Huseyn, who were always there for me in good times and bad. They supported me with words of wisdom and encouraged me to pursue my dreams.

Finally, I must acknowledge the many friends, the economics department, and my fellow graduate students who contributed to making my academic and personal experience at Georgetown an invaluable one.

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Chapter 1

Banks' Liability Structure and Mortgage Lending During the Crisis with Jihad Dagher

1.1 Introduction

The years leading to the global financial crisis have witnessed a rapidly changing financial landscape. Continuously emerging novel financial practices and instruments have posed new challenges to regulators and market participants who have been trying to assess their riskiness and understand their aggregate implications. In that regard, the financial crisis offers an unfortunate opportunity to identify the effects of some of these financial innovations. In particular, this episode could shed light on whether some of these new practices resulted in added vulnerability to the financial system.

One important trend that has been emerging in the banking sector is the increased reliance by banks on non-core deposits, such as short- and long-term borrowing, as their main source of funding (See, e.g. Feldman and Schmidt, 2001; Gatev and Strahan, 2006). Banks with heavy reliance on these deposits, often referred to as wholesale funding, are vulnerable to *bank runs* during episodes of liquidity crises. This simply is a result of wholesale financiers being uninsured creditors, and thus, more at risk of realizing losses.[1] In contrast, retail banks are more likely to see an

[1] Anecdotal evidence supports this view. For example, preceding its failure in 1984, Continental Illinois National Bank and Trust Company experienced a run from wholesale financiers but not from retail depositors.

inflow of insured deposits during episodes of low market liquidity, as shown in Gatev and Strahan (2006).

The goal of this paper is to understand whether the liability structure of banks, specifically the extent of their reliance on wholesale funding, had an impact on their willingness to lend during the latest global financial crisis. To this end, we use comprehensive data on mortgage lending. We examine whether banks that rely to a larger extent on wholesale funding reduced their lending by a greater amount relative to retail funded banks during the crisis. Specifically, we test whether the mortgage loan application rejection rate of wholesale funded banks increased by more during the crisis.

We use two sources of variation to answer the main question in the paper: time variation and variation in the ratio of core deposits to total assets, a measure of the extent to which a bank can be considered retail funded as opposed to wholesale funded. We use a panel on bank mortgage lending between 2005 and 2008 which allows us to control for bank fixed effects. To control for the characteristics of the borrowers and their loans, we use information available from the mortgage data. We also merge the mortgage data with data on bank financials, such as size, measures of liquidity, income, losses, as well as other factors, to control for bank characteristics over time. The availability of geographical data on the location of the property allows us to control for local conditions, both using control variables as well as by estimating our benchmark model at the Metropolitan Statistical Area (MSA) level for the largest MSAs in the Unites States.

The use of loan-level data on mortgage lending is a distinct advantage of this paper and allows us to improve on previous literature in several ways. First, in comparison with using the data on aggregate lending, our approach avoids a potential bias that could arise from systematic difference in portfolios of banks with different liability structure.[2] Second, using the mortgage data, we can carefully control for geographical factors and other characteristics of the borrowers. Finally, the mortgage data allows us to compare the rejection decisions on loan applications instead of comparing credit volume across banks. The change in the rejection rate over time is, in principle, a better indicator of supply and is not polluted by demand confounding factors.

We find a strong and robust relation between a bank's funding strategy and the increase in rejection rate on mortgage applications during the crisis. Specifically, banks that rely to a larger extent on retail funding increase their rejection rate by a lesser amount during the crisis. This finding is robust to a large set of controls and also holds in most of the largest MSAs.

Our benchmark results show that the increase in probability of a rejection was 10.5% higher during the crisis if a borrower applied to a bank with a core deposit to asset ratio (henceforth CD/A) of 56% (lower quartile) compared to an applicant of a bank with a 70% CD/A (upper quartile). Our aggregate results imply a similar pattern. An MSA with an average of 57% CD/A ratio for banks (lower quartile) experienced a 9.75% steeper decrease in the volume of mortgage originations compared to an MSA with an average CD/A of 62% (upper quartile) during the crisis.

The question in this paper is motivated by a long-standing finance literature on the impact of liquidity on credit supply. However, empirical evidence on this direct causal relation is often hard to establish due to the common existence of confounding factors, particularly factors related to the demand for credit; Credit crunch episodes are also typically accompanied by a slowdown in economic activity and thus a decreased demand for loans.

[2]For example, Song and Thakor (2007) suggest that retail banks are more likely to specialize in relationship lending.

An important feature of the recent crisis was the drying up of liquidity which is best illustrated by the widening of the TED spread, which is the difference between the 3-month LIBOR rate and the 3-month Treasury rate. The TED spread rose in the summer of 2007 and remained significantly above its historical average throughout 2008 reaching unprecedented levels in the fourth quarter of that year. A shortage of market funding has a disproportional impact on the liquidity of banks that rely on wholesale funding, an effect widely discussed and well understood in the literature.[3].

Our paper adds to a growing literature on the implications of liquidity on credit. It is well documented that shortages in liquidity are correlated with decreases in demand, both in the time series and in the cross-section. However, few studies have successfully controlled for demand factors to present clear evidence of a direct causality from liquidity to credit supply. These include Gertler and Gilchrist (1994), Peek and Rosengren (2000), Ashcraft (2005), and Khwaja and Mian (2008).

We also complement the recent empirical analysis of Ivashina and Scharfstein (2010) and Cornett *et al.* (2011) in several ways. Ivashina and Scharfstein (2010) use data from Dealscan and show that new bank lending growth fell less drastically at banks that were funded with deposits to a larger extent. However, their data does not enable them to control for demand factors or for some financial ratios, which we obtain from the Call Report data (See section 1.2.1). Cornett *et al.* (2011) also rely on the Call Reports which allow them to extend the analysis in Ivashina and Scharfstein (2010) in several ways.[4] Cornett *et al.* (2011) try to address the demand factors in a robustness exercise that includes state level indicators, interacted with the crisis, and

[3]See, e.g. Allen *et al.* (2010); Allen and Gale (2000); Bologna (2011); Brunnermeier (2009); Brunnermeier and Pedersen (2009); Gatev and Strahan (2006); Huang and Ratnovski (2011); IMF (2010); Ivashina and Scharfstein (2010); Raddatz (2010); Rochet and Vives (2004); Yorulmazer and Goldsmith-Pinkham (2010).

[4]For example, Cornett *et al.* (2011) study the impact of funding on the growth of liquid assets in addition to their impact on loan growth.

also controlling for the share of real estate and business loans. A salient feature of our approach is that it is designed to control for the demand factors using observable borrower characteristics.

The rest of the paper is organized as follows. Section 1.2 describes the data and presents some descriptive statistics and figures. Section 1.3.4 explains the empirical strategy as well as the proposed methodology, and provides the empirical results together with robustness checks. Section 1.4 investigates aggregate supply effects. Section 1.5 concludes.

1.2 Data and Summary Statistics

1.2.1 Data

We construct our dataset by merging data on mortgage applications with data on bank financials. The data appendix provides a detailed description of the steps involved in the construction of the dataset.

Our mortgage related data come from a comprehensive sample of mortgage applications and originations between 2005 and 2008 that were collected by the Federal Reserve under the provision of the Home Mortgage Disclosure Act (HMDA). Under this provision, the vast majority of mortgage lenders are required to report. The HMDA data include information on the year of the application (the data is available on an annual basis), the amount of the loan, the lender's decision, characteristics of the applicant (income, race, gender), and the median income in the census tract of the property. The data also provides useful information on the lender such as the name of the institution, its type, and its regulating agency. We thus can distinguish between banks and their affiliates and other depository (thrifts, credit unions) and non-depository (independent mortgage lenders) institutions. We restrict our attention to mortgage applications made at banks and their affiliates that are related to owner-occupied home purchases of conventional one-to-four-family properties.

We also limit our study to mortgage originations in counties situated in a Metropolitan Statistical Area (MSA) leaving us with 295 MSAs, which account for around 80% of total HMDA mortgage originations in 2005.[5] To minimize noise in the data we focus on banks that were significantly involved in mortgage lending and restrict our attention to banks that originated at least 50 mortgage loans in a given year. A large share of banks account for a small share of originations as they provide mortgage loans occasionally and in small numbers. Lending by these banks is more likely to be affected by idiosyncratic factors that are unrelated to the liquidity crisis. Since our aim is to understand the impact of the crisis on banks' mortgage lending decisions, we are restricted to banks that survived the whole sample period. We therefore balance the sample given the short time component of our data. After imposing these restrictions and excluding loans below $25,000 and above a million, our 2005-2008 sample consists of around 4 million applications at 555 banks.[6]

All regulated depository institutions in the United States are required to file their financial information periodically with their respective regulators. Reports of Condition and Income data are a widely used source of timely and accurate financial data on banks' balance sheets and the results of their operations. Specifically, every

[5]Restricting our sample to MSAs allows us to *control for variables that are otherwise not available, such as measures of house price growth and the housing supply elasticity*, and helps us to minimize any noise in the data that could be brought by the inclusion of areas with a small population.

[6]The original sample includes 4746 banks from which only 555 banks consistently originated more than 50 loans. This restriction on banks reduces the sample from around 5.2 to 4.3 million applications from which around 0.3 million are excluded for being very small or very large loans, to minimize noise from outliers (see e.g. Del'arricia et al. (2008) for similar treatment). Finally, when the data is balanced, the number of observations drops to 4 millions. Note that these restrictions do not affect our main results in what follows.

national bank, state member bank, and insured non-member bank is required by the Federal Financial Institutions Examination Council (FFIEC) to file a Call Report as of the close of business on the last day of each calendar quarter. The specific reporting requirements depend upon the size of the bank and whether or not it has any foreign offices. The availability of agency specific bank IDs in HMDA (Federal Reserve RSSD-ID, FDIC Certificate Number, and OCC Charter Number) allows us to match HMDA lenders that are depository institutions with their financials from the Call Report. We use the available balance sheet data to capture relevant financial information on banks, including our main variable of interest - the ratio of core deposits to assets. We follow the literature and define core deposits to be the sum of a bank's deposits excluding time deposits over $100,000 (See, e.g. Berlin and Mester, 1999).[7]

1.2.2 Summary statistics

Table 1.1 provides summary statistics on loans in our sample. The first column shows the number of originations in millions of dollars before balancing the data. Over the four years, banks in our sample originated a total of around $881 billion dollars, or more than 18% percent of the 4.7 trillion of 1-4 family purchase originations reported over the same period by the Mortgage Banker Association (MBA).[8] As expected, and consistent with the MBA numbers, 2005 saw the highest number of originations related to purchases during this period in the unbalanced data. In the unbalanced data, the volume of originations declined substantially in 2007 with the start of the mortgage crisis and declined by around 46% percent by 2008 compared to 2005. The second column shows the volume of originations in the balanced data.

[7] Although the limit for insured deposits has been increased to $250,000 in 2008, this does not affect our analysis since we use the core deposits at the end of 2007 to classify banks in 2008.

[8] By focusing on banks we have already excluded from our analysis more than 40% of originations by independent mortgage lenders, saving institutions and credit unions.

We next motivate our empirical analysis by comparing the volume and the rejection rate of banks with different liability structure. We measure the extent of a bank's reliance on insured deposits by the ratio of deposits under 100,000 to total assets (CD/A). Figure 1.1 shows the log of the volume of mortgage credit over the 2005-08 period, comparing banks with low, medium, and high CD/A in 2005.

The category of low CD/A comprises banks with a CD/A below the 33th percentile in 2005, the medium CD/A category comprises banks with a CD/A above this limit but below the 67th percentile, and the higher CD/A comprises the rest of the banks. We find that, both in mean and in median low CD/A banks experienced a larger contraction in the volume of credit in 2008 compared to banks that relied more on core deposits.[9] Since the bars represent changes in the log of volume we see that the percentage drop in volume of lending in 2008 compared to 2007 is three times larger for the low CD/A group compared to the high CD/A group in means, and more than twice larger in medians.

Figure 1.2 compares the evolution of the average and median rejection rates of banks in these categories. We also find that relative to the non-crisis years 2005 and 2006, the rejection rate has increased substantially more for the low CD/A category than it did for the high CD/A both in mean and in median. Note that rejection rates are on average higher for the low CD/A group. This might have to do with the way mortgage operations could be carried differently between banks with different liability structure. One would expect for example that banks that aggressively target a large population of potential borrowers would have a higher rejection rates than banks that are less aggressive in their marketing strategy and are more transparent with their

[9]The CD/A ratio is relatively stable over that period, with a slight overall decrease between 2005 and 2007. Thus the choice of the year in which we define the CDA categories has no effect on these patterns. We keep the three sub-samples balanced over the period to enhance comparability and avoid fluctuations due to entry and exit from the sub-samples.

qualification requirements. However, investigating this difference is beyond the scope of this paper. Our main interest is whether the patterns shown in Figure 1.1 and Figure 1.2 are indeed driven by the difference in CD/A ratio across banks and not by confounding factors. We are also particularly interested in understanding whether this difference could be attributed to a heterogeneous response in the *supply* of credit as opposed to merely capturing heterogeneous demand factors that are correlated with CD/A. In the next section we lay out our empirical strategy to estimate the impact of CD/A on the supply of mortgage credit by banks.

1.3 Bank Lending During the Crisis

In this section we study the impact of the crisis on lending by banks with a focus on the interaction of the crisis with their funding strategy. We first explain our estimation strategy. Then, we proceed by presenting the empirical results. Finally, we strengthen our conclusion by conducting a series of robustness tests.

1.3.1 Empirical strategy

Over recent decades, banks have been increasingly relying on wholesale liabilities to fund and facilitate their operations (See, e.g. Feldman and Schmidt, 2001). This funding scheme, which consists mainly of uninsured deposits, notes and debentures, has received more attention recently with the several bouts of severe liquidity shortages experienced shortly prior and during the Great Recession. Unlike retail deposits, wholesale funding are uninsured liabilities for the banks. It is well acknowledged that wholesale funding makes banks more vulnerable to liquidity runs (See, e.g. Ivashina and Scharfstein, 2010). This is particularly the case in countries with credible deposit insurance. In fact, absent the risk of devaluation, banks are likely to experience a net inflow of retail deposits during periods of stress in such countries, as suggested for example by evidence in Gatev and Strahan (2006).

With this heterogeneity in mind, this paper asks the following question: did the vulnerability of wholesale banking to liquidity shocks led to a sharper decline in their credit supply relative to other banks during the crisis? The overarching objective is to better understand the impact of liquidity on credit supply.

To answer this question we focus on mortgage lending by U.S. banks during the 2005-2008 period. By focusing on lending in a specific market we are able to control for market-specific shocks which could affect overall credit by banks through a demand channel, something that would be challenging to control for when using aggregate credit data. Specifically, comparing aggregate credit between banks during the crisis raises the concern that banking activities are heterogeneous across banks and thus the overall credit by banks are affected by their exposure to time varying and heterogeneous demand shocks. Moreover, such variation could take place over factors that are very challenging to control for when using aggregate data. This motivates our focus on mortgage credit where we can compare lending by banks on a similar product, controlling for time-varying factors of regional markets, as well as for applicant characteristics. In addition, the data we use offers us the possibility to focus on the decision of a bank to accept or reject an application which is a better measure of the willingness of a bank to extend mortgage loans, and is less susceptible to idiosyncratic demand shocks facing banks.[10] At the same time, the disaggregated mortgage

[10] One might argue that demand shocks could also affect the willingness of a bank to extend a loan to a particular applicant, for example demand for loans and the rejection rate could be positively correlated due to capacity constraints. While this is likely to be of a second order effect, we later also examine the overall demand for loans across banks to see whether it is correlated with our main explanatory variable.

data we use provides good coverage of the overall mortgage lending, allowing us to draw implications on the aggregate level.

In addition to addressing the potential heterogeneity in demand facing banks we also need to control for potential confounding factors that could be correlated with our main variable of interest, the ratio of core deposits to assets. We do so by controlling for a large set of financial variables taken from the Call Report that are likely to affect overall bank credit such as measures of leverage, profitability, provisions for losses, as well as variables that could be of special importance during the recent crisis such as measures of liquidity and bank involvement in mortgage lending as well as their holding of asset backed securities.

To simplify the discussion we first present the specification for the benchmark estimation before proceeding with various robustness tests.

1.3.2 Model specification

Our dependent variable is a binary variable that reflects the bank's decision of approving or rejecting a mortgage loan application. The objective of our exercise is to test the impact of the funding strategy of a bank, specifically the extent of its reliance on core deposits, on its lending decision during the crisis. We use two sources of identifying variations: the time before and after the financial crisis and the variation in the ratio of core deposits to total assets across banks, as a measure of extent to which a bank can be qualified as a retail lender. Our benchmark model is the following:

$$\begin{aligned} R_{i,k,m,t} = {} & \alpha_t + \lambda_k + \delta_m + \beta X_{i,t} + \phi Z_{k,t-1} + \gamma(Crisis_t \times CDA_{k,t-1}) \\ & + \eta\delta_m \times Crisis_t + \theta(Crisis_t \times Z_{k,t-1}) + \varepsilon_{i,k,t,m} \end{aligned} \tag{1.1}$$

Where $R_{i,k,m,t}$ takes the value of one if a loan application i at bank k in year t that of an individual who resides in the MSA m has been rejected. α_t, λ_k, and δ_m

are time, bank, and MSA fixed effects. $X_{i,t}$ is a vector of variables that captures relevant characteristics that are reported in HMDA for each applicant. These include information on the applicant's income, loan value (which we use to compute loan-to-income ratio), gender, race, and median income of the census tract of the property. We also control for bank characteristics $Z_{k,t-1}$ from the end of the previous period. Specifically, the benchmark controls are: (i) bank's size, captured by the log of total assets, (ii) ratio of liquid assets to total assets, (iii) ratio of unused commitments to total assets, (iv) the ratio of capital to assets (leverage), (vii) the return on equity, and (vii) the ratio of income to total assets. In addition, we introduce several other ratios that could be of relevance to the crisis episode such as shares of real estate, consumer and C&I loans to total assets, and other bank holding and securitization activity. We interact these financial variables with the crisis dummy ($Crisis_t$), defined in the next section, as their impact on lending could vary with the macroeconomic environment and particularly with overall liquidity in the market. Similarly, to control for the heterogeneous impact of the crisis across regions as well as of the varying severity of the housing market collapse, we also interact the MSA fixed effects with the crisis dummy. While this increases the set of exogenous variable by another 295 variables, we believe that this level of disaggregation is important as even MSAs within a same state could be very differently affected by the crisis and particularly with respect to housing prices. Controlling for regional variation is a critical part of our empirical strategy. Therefore we also run our benchmark regression at the MSA level for the major MSAs to investigate the robustness of our main results.

The coefficient of interest is γ. It captures the impact of lagged CD/A ratio on bank rejection decision during the crisis. Our stated hypothesis is that the coefficient is negative in that on average credit by banks that rely more on retail deposits, banks that we know are less vulnerable to the liquidity freeze on the market, is more resilient to the crisis. That is, in comparison with wholesale banks, we expect retail banks to increase their rejection rate by less during the crisis.

We estimate these equations with a linear probability model (LPM) to fit a binary dependent variable. In a panel data setting, the LPM has an important advantage over Probit and Logit models when $N \longrightarrow \infty$ and T is fixed, since the estimates are generally inconsistent in Probit or Logit, but are $\sqrt{N}$ consistent using LPM (Wooldridge, 2002).

1.3.3 Definition of crisis period

HMDA data is available on a yearly basis, without further breakdown at the quarterly or monthly level. Thus, we have several options in defining the crisis period. First we can define the crisis year as 2008 assuming 2007 is a non-crisis year. The second possibility is to include both 2007 and 2008 as crisis years. In both of these cases, however, we would be underestimating or overestimating the effect of the crisis by including a year in the first half of which the funding markets were close to their normal level (in accordance to the TED spread, for example) as either a non-crisis or a crisis year. To avoid this bias, we chose instead to exclude 2007 and thus compare 2008 with 2005 and 2006. Most of our results are, however, robust to including 2007 as crisis year as well as including it as a non-crisis year.

Table 1.2 helps to illustrate this issue and motivate our selection. It shows results from estimating a simplified version of our benchmark model including only crisis year-dummy and the CD/A variable in Panel A and the interaction of these two in Panel B. Our focus is on the coefficient of crisis. We find that, as one would expect, the coefficient is positive (i.e., higher rejection rate) and that it is larger in magnitude when we drop 2007 and focus on 2008 instead. It is the smallest when we take 2007 to be the crisis year while dropping 2008, and it is somewhere in between when we keep

2007 and assume that it is either a crisis or a non-crisis year. Therefore, it is clear that for a more nuanced comparison between crisis and non-crisis year, we should focus on 2008 excluding 2007 from our sample. We also show in Table 1.2 Panel B how the interaction between CD/A and the crisis is negative and significant in all specifications, but that is also larger in magnitude when we avoid the bias induced by improperly assuming 2007 to be either a crisis or a non-crisis year. Note that the coefficient on CD/A also implies that an increase in reliance on retail deposits is associated with an increase in the rejection of applications, everything else constant. This result echoes the difference in rejection rates reported in Figure 1.2 and is not necessarily puzzling. One would expect that the funding by banks also affect their mortgage operations in various ways that could lead to either differences in the volume of applications or, for example, differences in lending standards that could be ultimately reflected in their rejection rates.

1.3.4 Benchmark results

Table 1.3 reports results from fitting equation (1.1) with a Linear Probability Model. In all columns we control for (i) bank fixed effects, (ii) MSA fixed effects, (iii) year fixed effects, (iv) MSA X Crisis dummies. We use two way clustering for standard errors and cluster residuals by Bank and MSA (See Cameron *et al.*, 2006, for details on multi-way clustering). In the first column we only regress the rejection decisions on the X variables, which are characteristics of the applications, and on the main variable of interest together with its interaction with crisis.[11] The coefficients on

[11] Given the large set of regressors we do not report the coefficients for the Z variables but control for them as stated. Since we control for bank fixed effects and due to the small variation in most of the Z variables over the short period of our study the coefficient on these variables are not of primary importance to us. Instead we show their interaction with the crisis.

the X variables are in line with those commonly cited in the literature that studies bank rejection decision in the context of HMDA data. We find that applications by minorities are associated with a higher rejection probability on average, that a higher applicant's income and a higher median income in the census tract of the property are associated with a lower rejection probability, and higher loan to income ratios lead to more rejections on average. The coefficient of interest, γ, on the interaction of CD/A and crisis is negative and significant at the 1% level. As usual with LPM models with micro data, the R^2 of the regression is small, at around 9%. In the second column we introduce the Z variable and in the third column we also interact these variables with the crisis dummy. We find that by interacting Z variables with the crisis the magnitude of the coefficient γ slightly decrease but remains very significant. The result suggest that a one standard deviation increase in core deposits (which is an increase by around 11% in CD/A) is associated with a 28% lower probability of rejection of the mortgage application during the crisis, everything else held constant. The coefficient on the interaction between the Z variables and the crisis are broadly in line with expectations. A higher leverage ratio (computed as common equity to total assets) and a higher liquidity ratio as of end 2007 predict smaller increases in rejection during 2008, while higher provision for losses are associated with a higher rejection rate. We find that banks that had a higher ratio of loans secured by properties continued to lend compared to those banks whose activities were less concentrated in this market, probably to try to sustain an income that they rely on more than the other banks. In the fourth column, we replace the continuous CD/A variable with a discreet variable that takes the value 1 if the bank is in the upper 75% distribution based on CD/A in 2005. We find that these banks on average were 6% less likely to reject during the crisis, everything else constant.

We next examine whether the documented relation also holds for smaller banks in our sample. The motivation of focusing on smaller banks is twofold. First, the larger banks originate disproportionally more loans compared to their size and while we do cluster the standard errors by bank and MSA our results could still be affected by the sheer volume originated by these banks. Second, large banks are complex financial institutions, and controlling for their financial ratios might not fully capture their financial condition at the time of the crisis while smaller banks are more likely to be affected by the local conditions which we do control for with the MSA dummies and their interaction with the crisis dummy. Therefore we reduce our sample to the lower 90% of banks based on their total assets (small banks are commonly defined as such in the literature). The results are shown in column (5). First, we find that the coefficient of interest, γ, is negative and significant, although smaller in magnitude. This comforts us, as it implies that the relation we document is robust, and that the larger banks are unlikely to be outliers but rather strengthen a relation that is already present in the rest of the sample. The result on the X variables are broadly similar to the earlier results, while the interaction between size and crisis now interestingly yields a positive relationship with rejection rates. This suggests that there is possibly an inverted U curve relation between size and rejection during the crisis. Understanding the drivers of this relation is something that deserves further attention but is beyond the focus of this paper.

Another robustness check we perform is to estimate the results for high income individuals who live in districts with high housing supply elasticity, since these are the least likely candidates to be affected by the crisis. To this end we drop individuals who are in lower 75th percentile of the distribution with respect to income and elasticity. The results given in column (6) show that even the credit extended to these borrowers were affected by the liquidity crisis, and more so with wholesale banks.

We also test whether our results are robust for loans that are considered as *Jumbo.* Jumbo loans are the loans above the "conforming loan limit" and are not required by law to be purchased automatically by Fannie Mae and Freddie Mac. The national conforming loan limit for mortgages that finance single-family one-unit houses changed for some locales within our sample period. Since 2007, the limits also vary across the country. To define jumbo loans we use the upper conforming loan limits of $359,650, $417,000, and $729,750 for the years 2005, 2006, and 2008 respectively. This exercise serves as a robustness test for the difference between the banks that originate mortgages to keep versus originate to distribute. Since jumbo loans are difficult to repackage and sell, we can assume that most of these mortgages were originated to be kept by the banks. The results from this estimation are given in the column (7) of Table 1.3, and conform our previous findings.

Although we classify banks by their CD/A within a given year, it is possible that some banks had to reconsider their funding strategy during the financial crisis. As an extra robustness check, we include the year-on-year change in CD/A in our regression and present the results in column (8) of Table 1.3. Note that this decreases our sample, since the the change in 2005 is not available in our data. The results show that even after controlling for this factor, CD/A had a negative significant effect on rejection rates during the crisis, as in previous estimations. The coefficient for the change variable (not presented in the table) is negative, but insignificant.

We next look at results at the MSA level by estimating equation (1.1) for the largest MSAs in the United States. This allows us both to check the robustness of our results as well as to assuage concerns that an imbalance in the data could lead our MSA dummies to imperfectly sweep-out regional factors. We select our sample of MSAs the following way: we choose the largest 15 MSAs in our data based on the number of applications and since only 12 of these MSAs figure in the top 15

MSAs based on population (from census) we also include the three remaining MSAs (Boston, Detroit, and Miami). The results are shown in Table 1.4. All regressions in that table control for the Z variables together with their interaction with the crisis, they also include bank and year fixed effects. We cluster standard errors at the bank level. We find that the documented negative relation between retail lending and the rejection rate during the crisis hold in all MSAs, and that it is significant in 14 out of the top 18 MSAs. Furthermore, we notice that the coefficient lacks significance in smaller MSAs, particularly in the case of Boston and Detroit.

1.3.5 Matching

In the earlier estimations we controlled for applicants characteristics which are available in the HMDA data. However, their inclusion in the right hand sand side of a linear regression does not address for a potentially serious imbalance resulting from a poor distributional overlap of applicant characteristics across banks.[12] One might argue that characteristics such as income, loan to income, or the median income of the census tract could be correlated with bank characteristics such as their liability structure. In panels A and C of Table 1.5 we show that there are statistically significant differences in the applications across banks, although on a relatively mild scale. For example, we find that applicant income and the income of their census tract are significantly higher in the sample of retail banks (upper 75% of banks based on CD/A) while the proportion of minority applicants is significantly lower.

To ensure that this imbalance is not affecting our main results we proceed by matching applicants from the two categories of banks to obtain a more balanced distribution. Ho *et al.* (2007) discuss the advantages of non-parametrically pre-processing the data via matching in order to eliminate imbalance. They show that not only does

[12]See, e.g. Heckman *et al.* (1998) and Dehejia and Wahba (2002).

matching eliminate potential bias that could be hard to address with linear regressions but it also makes the subsequent parametric analysis far less dependent on modelling choices and specifications.

As in Section 1.3.4 we first divide our sample into wholesale and retail bank applications, where we use the banks' CD/A ratio as of 2005 to classify banks as wholesale or retail. We call banks within the highest 75% percentile distribution of CD/A retail banks. Note that this division results in a roughly similar volume of applications between wholesale and retail banks. We then use the Abadie and Imbens (2002) exact matching procedure to match applications on: (i) MSA, (ii) census tract income, (iii) applicant income, (iv) loan to income ratio, (v) race, and (vi) gender.

The procedure allows for exact matching for discreet variables while the program allows for approximate matching for continuous variables (Abadie and Imbens, 2002). Nevertheless, the abundance of applicant data in our case allows us to restrict our matching sample to applications where even the continuous variables are matched almost exactly.[13] We perform this matching within each year to reduce the sub-samples into characteristically similar applicants between wholesale and retail banks. We call this the within-year, or one-way matching sample.

In addition to the within-year matching, we also match applicants across years, and thus ensuring that the characteristics of the borrowers are not only similar across banks, but also across bank-years. This two-way matching serves as a stringent robustness test that helps minimize concerns of changes in applicant characteristics over time and the potential implications this would have on our estimation. Note that we deflate income variable by the county's nominal income growth in the case of the two-way

[13]After matching the individuals between the treatment and the control groups (without replacement) we drop matches which are too far apart, using a variant of *caliper matching* (Cochran and Rubin, 1973). We drop matched pairs with distance in the upper 25^{th} percentile in each matching group.

matching. We therefore reduce our sample around 2.7 million to 0.68 million applications with the within year matching, and 0.13 million applications with the two-way matching.

Matching itself is not an estimation method, and is typically followed by a difference in difference matching estimation or by a regression analysis. Given the various banking and geographical variables that we need to control for we chose to follow the matching by the same regressions as in Table 1.3.

Balancing tests

Upon completion of the matching estimation we conduct balancing tests. The objective of these tests is to ensure that the distribution of the applicant's characteristics does not significantly differ across the treatment (retail or crisis) and the control (wholesale or non-crisis) groups in the matched sample. In other words, the balancing test allows us to check the effectiveness of the matching. We use the Kolmogorov-Smirnov (KS) test of *distributional* differences as well as t-test to compare the means (See, e.g. Almeida *et al.*, 2009). The comparison of the samples post matching are shown in panels B and D of Table 1.5. We can see that neither the t-test nor the KS test can reject the equality of the mean or the distribution of the variables, respectively. For example a quick comparison of the mean and median income between Wholesale and Retail banks we find that they are almost exactly the same with a difference at the third decimal point. This contrasts with the difference in the original sample shown in the panels A and C of the same table. Overall the results of the balancing tests give us comfort that the matching achieved its goal.

Regressions on the matched sub-sample

We next proceed by fitting equation (1.1) to our matched sample. We show the results in the columns (7) - (10) of Table 1.3 for the purpose of comparison with our earlier results. The main coefficient of interest is still negative, and significant at 1%. With one-way matching the magnitude of the coefficient is slightly larger than in non-matched sample, while with two-way matching it is smaller. These estimates confirm and serve as a stringent robustness test for our benchmark results. They imply that even in a sample of almost identical applicants the rejection rates decreased by lesser amount from retail banks compared to wholesale banks.

Logistic regressions

As a robustness, we also estimate the benchmark model using the matched sample by Logistic regression. Columns (13) and (14) present the results for these estimations. The coefficient of -1.18 from the full model can be interpreted as 6.9% extra increase in rejection rate during the crisis when CD/A of a bank increases by 10%. When comparing a bank in the lower quartile of CD/A distribution with that of on the higher quartile the increase in rejection rate is about 10.5%.

1.3.6 Demand for credit

The main objective of this paper is to test whether wholesale lenders decreased their *supply* of credit more during the crisis. Our analysis has thus focused on minimizing the impact of confounding factors in our estimation, specifically from demand factors. We have addressed these concerns by controlling for geographical characteristics, including estimating MSA-level regression and matching households within the same MSA. We have also focused on fitting the rejection decision of a bank which is a variable that captures better the supply of credit in comparison, for example, with mortgage volume originated by banks. To address potential differences in borrower types between banks and across time, we controlled for applicants characteristics. As a next step, we have matched applicants across banks to ensure that our results are not affected by any imbalances in these characteristics.

While it is unlikely that, within the same MSA, demand during the crisis could be unevenly affected between retail and wholesale banks, here we also address this issue. It is reasonable to think that an applicant is interested in obtaining the best mortgage rate and is in fact indifferent (if not also unaware) of the liability structure of the bank (the same does not necessarily apply for firms for example that might be looking for a long term relation with the bank). Nevertheless, since the rejection rate could be affected by overall demand, although we argue it is a second order effect, we examine whether the crisis had affected demand for credit differently between banks.

We therefore estimate variations on the following two equations which are similar to our earlier models:

$$\begin{aligned} A_{k,m,t} = \alpha_t + \lambda_k + \delta_m + \gamma(Crisis_t \times CDA_{t-1}) \\ + \eta\delta_m \times Crisis_t + \varepsilon_{k,t,m} \end{aligned} \tag{1.2}$$

$$\begin{aligned} V_{k,m,t} = \alpha_t + \lambda_k + \delta_m + \gamma(Crisis_t \times CDA_{t-1}) \\ + \eta\delta_m \times Crisis_t + \varepsilon_{k,t,m} \end{aligned} \tag{1.3}$$

where $A_{k,m,t}$ is the log of the number of loan applications at bank k, in MSA m, in year t. Similarly, $V_{k,m,t}$ is the ratio of the volume of loan demanded to the total assets of the bank. We control as usual for time, bank and MSA effects and interact the crisis dummy with the lagged ratio of core deposits to total assets. The coefficient γ capture the relative impact of the crisis on high CD/A banks compared to lower

CD/A banks. We do not control for other time varying bank characteristics, since arguably these are of little relevance to demand.[14]

The results are shown in Table 1.6. We first estimate equations (1.2) and (1.3) in columns (1) and (3) ignoring the interaction between MSA and the Crisis dummy to show the impact of the crisis on overall number and dollar volume of applications. The regressions otherwise include bank, MSA and year fixed effects. We cluster the residuals at MSA and Bank level. As one would expect, we find that the crisis has led to a significant decline in demand for mortgages. The coefficient on the interaction between CD/A is, however, not statistically significant. The results are also similar in columns (2) and (4) where we control for the interaction of MSA dummies with the crisis. We are further comforted that the sign on the coefficient is actually positive assuaging concerns that the increased rejection rate of wholesale banks during the crisis could be a result of an increased demand for mortgage loans from these banks.

A more likely interpretation of these results is instead that the increased rejection rate by these banks has led applicants to seek loans from retail banks but not to a significant extent as the coefficient are not statistically significant. If anything the results suggest that retail banks saw a smaller decline in demand, although this result is again not significant. One can argue that the decline in credit supply from wholesale banks could have led to a small shift in demand for retail lenders. This result however does not affect the interpretation of our earlier results since we find that retail banks have increased their rejection less despite facing a relatively higher demand.

[14] We nevertheless do include but not show these controls and find that they do not affect our main results.

1.4 Aggregate Supply Effects

In the previous sections we showed strong evidence that the crisis had a smaller negative impact on the supply of mortgage credit by retail banks. We also showed that these results were unlikely to be driven by demand factors, also because demand has declined evenly during the crisis across retail and wholesale banks. In this section we look at whether regions with a higher reliance on mortgage lending by retail funded banks experienced a smaller decline in credit, everything else equal.

1.4.1 Motivation and empirical strategy

Our previous findings from loan level data show that lending by wholesale funded banks was more affected by the crisis to liquidity, findings that we showed are both robust and economically significant. Based on these findings alone, however, one cannot conclude that the reliance on wholesale funding by some banks has led to a lower overall mortgage credit in the economy. This is because it is possible, albeit unlikely, that the relative increase in credit supply by retail funded banks went to compensate the relative decline in credit supply by wholesale banks. Even if retail banks compensated to some extent the decline from wholesale banks, the aggregate impact would be smaller than what would be suggested by the earlier results. One way to investigate whether the shortage of credit supply from wholesale funded banks was consequential to the ability of households in obtaining credit is to exploit the geographical heterogeneity of the liability structure of the regional banks. Figure 1.3 shows a histogram of the distribution of the weighted average ratio of core deposits to assets across Metropolitan Statistical Areas (MSAs). It suggests a significant heterogeneity. Our objective in this section is to test whether a higher reliance on core deposit funding for mortgages has helped shield from the impact of the crisis at the

MSA level. Our previous results would suggest that this could be the case, and the housing market in areas where banks relied more on market funding was affected by a double whammy: the housing bust as well as a shortage of credit due to banks' exposure to severe liquidity shocks.

Given the short time component of our panel we estimate the following two regressions:

$$Vol_{m,t} = \delta_m + \beta Vol_{m,t-1} + \beta_2 DVol_{m,t-1} + \phi Z_{m,07} + \gamma \overline{CDA}_{m,07} + \rho M_{m,t-1} + \varepsilon_{m,t} \quad (1.4)$$

$$DVol_{m,08} = \delta_m + \beta_1 DVol_{m,07} + \phi Z_{m,07} + \gamma \overline{CDA}_{m,07} + \rho M_{m,t-1} + \varepsilon_{m,t} \quad (1.5)$$

where $Vol_{i,t}$ stands for the dollar amount of accepted applications in MSA i at time t, $DVol_{m,t}$ represents the change in this volume, and $M_{m,t-1}$ is a set of MSA characteristics such asm change in house prices or GDP per capita.

The results are shown in Table 1.7. We observe that not only the regions with a higher reliance on mortgage lending by retail funded banks had a smaller volume of funding, but they also experienced a smaller decrease in credit, everything else equal. The coefficient of 1.95 in column (1) implies about 2% increase in volume of mortgage originations when the average CD/A in an MSA increases by 1%. If we compare two MSA in the lower and upper quartiles of CD/A distribution (57% and 62%, respectively), then the fall in the volume of originations was by about 10% steeper in the MSA with more wholesale funded banks.

1.5 Conclusion

We examined the impact of banks' exposure to market liquidity risk through wholesale funding on their supply of credit during the financial crisis using comprehensive loan-level data on mortgage lending. We found that wholesale funded banks increased their rejection rate significantly more than retail banks during the crisis, controlling for a large set of potential confounding factors. Our methodology addressed potential demand-driven confounding factors by controlling for regional factors, including by running regressions within Metropolitan Statistical Areas. To address the heterogeneity in applicant characteristics between banks and their potential impact our results, we also match sub-samples of statistically indistinguishable applicants between retail and wholesale banks thus reducing our sample by more than 95 percent and find that our main results remain strong. We also confirm that while *supply* of credit has been more severely affected in the wholesale sample during the crisis, both categories of banks faced a similar decline in *demand*. The aggregate consequences of our results are illustrated in an empirical exercise showing that regions where mortgage credit was to a larger extent funded through wholesale operations suffered a larger contraction in credit, everything else constant.

Figure 1.1: Volume of mortgage originations

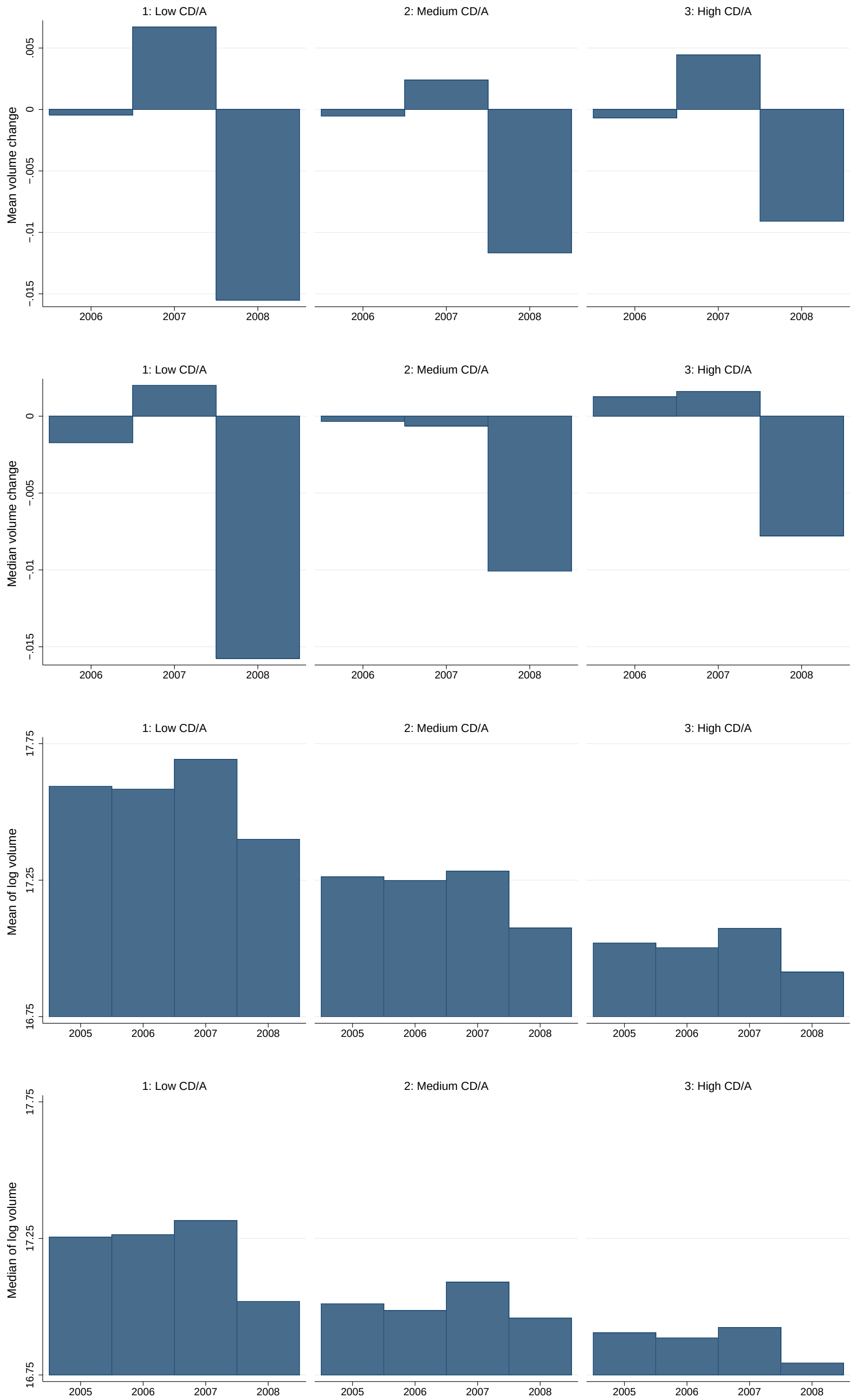

Figure 1.2: Rejection rates

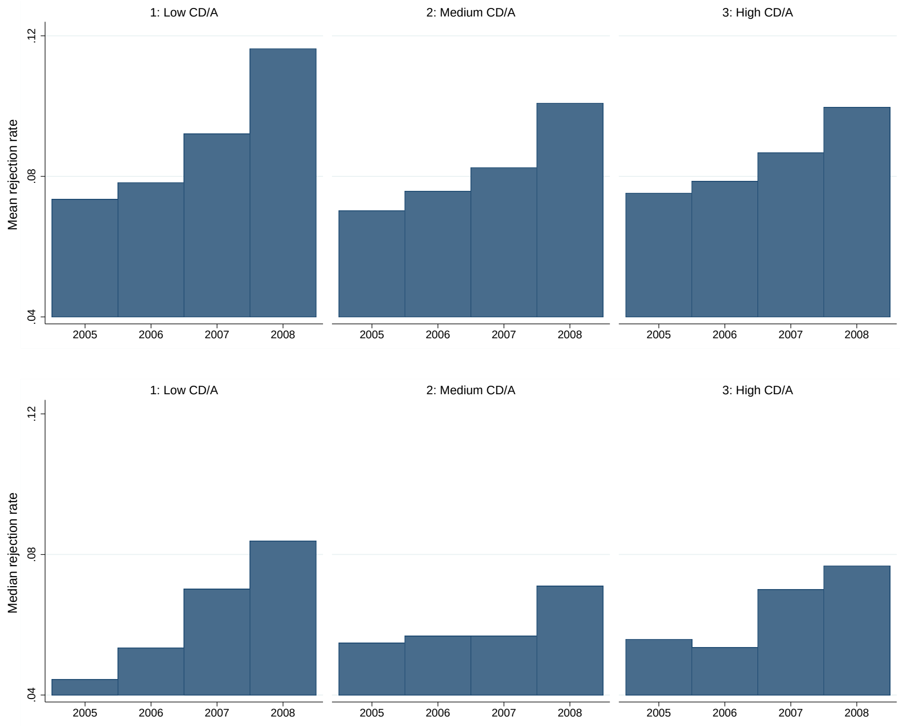

Figure 1.3: Distribution of CD/A

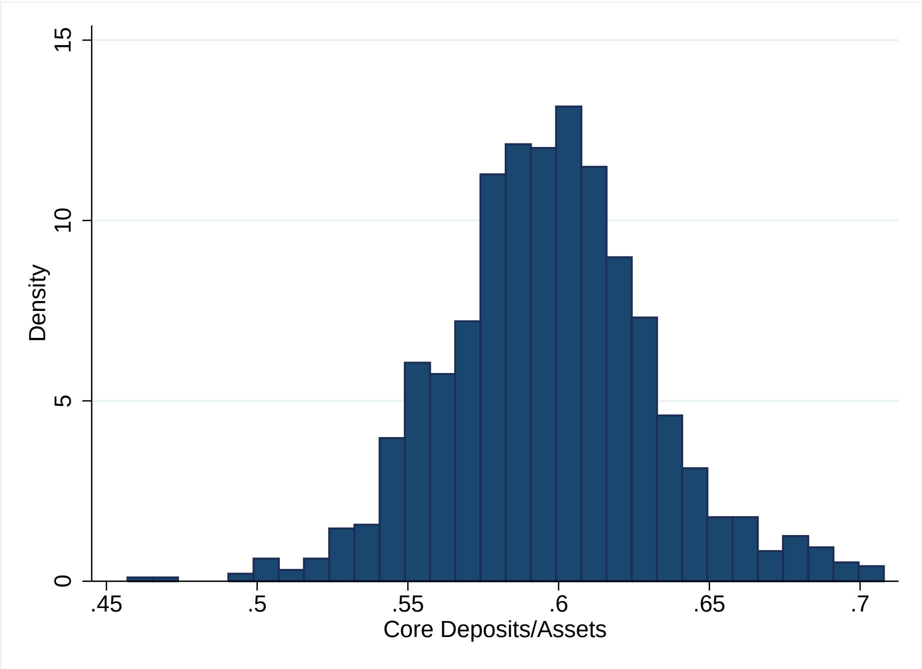

Table 1.1: Summary statistics

	Unbalanced	Balanced				
	Total	Total	Average			
	originations (in Mils $)	originations (in Mils $)	rejection rate	loan amount (in Thous $)	income (in Thous $)	tract income (in Thous $)
2005	255011	177326	0.11	208.65	99.96	74.64
2006	254113	212691	0.12	197.24	104.34	74.23
2007	234781	221052	0.14	210.66	107.01	73.65
2008	137434	128230	0.16	234.75	112.89	79.94
				Median		
2005				165.00	78.00	70.47
2006				150.00	80.00	70.10
2007				166.00	81.00	69.53
2008				198.00	84.00	75.22

Notes: This table shows summary statistics of the applications for each year in our sample. The results presented in the regression tables are from the balanced sample.

Table 1.2: Sellecting the crisis year, 2007 vs. 2008

	Panel A: Without CD/A × crisis interaction			
	Crisis is 08	Crisis is 07 and 08	Crisis is 08 dropping 07	Crisis is 07 dropping 08
Crisis	0.0405***	0.0357***	0.0504***	0.0278***
	(0.0004)	(0.0003)	(0.0005)	(0.0004)
Core Deposit/Asset	-0.4197***	-0.4177***	-0.4019***	-0.3867***
	(0.0013)	(0.0013)	(0.0016)	(0.0014)
Constant	0.3647***	0.3535***	0.3444***	0.3356***
	(0.0008)	(0.0008)	(0.0010)	(0.0008)
R-squared	0.0269	0.0278	0.0255	0.0252
	Panel B: With CD/A × crisis interaction			
	Crisis is 08	Crisis is 07 and 08	Crisis is 08 dropping 07	Crisis is 07 dropping 08
Crisis	0.1998***	0.1256***	0.2357***	0.0894***
	(0.0024)	(0.0015)	(0.0024)	(0.0016)
Core Deposit/Asset	-0.3873***	-0.3424***	-0.3424***	-0.3424***
	(0.0014)	(0.0018)	(0.0018)	(0.0018)
Core Deposit X Crisis	-0.2725***	-0.1555***	-0.3173***	-0.1071***
	(0.0040)	(0.0026)	(0.0041)	(0.0028)
Constant	0.3460***	0.3101***	0.3101***	0.3101***
	(0.0008)	(0.0011)	(0.0010)	(0.0010)
R-squared	0.0280	0.0286	0.0276	0.0257
Observations	4,011,233	4,011,233	2,799,288	3,360,756

Standard errors are in parentheses. Stars imply significance, such that: *** p<0.01, ** p<0.05, * p<0.1. The table is used to justify our choice for the definition of the crisis year.

Table 1.3: LPM baselines and robustness

VARIABLES	(1) Benchmark Estimates	(2) With Z variables	(3) Full Model	(4) Discreate CD/A	(5) Small Banks	(6) Hich income Borrowers	(7) Jumbo Loans	(8) CD/A Change	(9) One Way Matched	(10)	(11) Two Way Matched	(12)	(13) Logit No Z	(14) With Z
X: Male	-0.0020	-0.0023	-0.0024	-0.0024	-0.0044	-0.0180***	-0.0092	-0.0024	-0.0048*	-0.0049*	-0.0072*	-0.0073*	-0.0489***	-0.0501***
	(0.0036)	(0.0033)	(0.0033)	(0.0038)	(0.0028)	(0.0042)	(0.0058)	(0.0037)	(0.0027)	(0.0027)	(0.0041)	(0.0041)	(0.0099)	(0.0098)
X: Hispanic	0.0566***	0.0563***	0.0564***	0.0566***	0.0458***	0.0325***	0.0207	0.0460***	0.0570***	0.0570***	0.0708***	0.0709***	0.4196***	0.4128***
	(0.0073)	(0.0071)	(0.0074)	(0.0079)	(0.0094)	(0.0107)	(0.0162)	(0.0114)	(0.0074)	(0.0071)	(0.0111)	(0.0111)	(0.0260)	(0.0262)
X: Balck	0.0855***	0.0851***	0.0845***	0.0842***	0.0886***	0.0843***	0.0571***	0.0805***	0.0897***	0.0898***	0.1034***	0.1036***	0.6648***	0.6537***
	(0.0060)	(0.0061)	(0.0063)	(0.0068)	(0.0107)	(0.0139)	(0.0157)	(0.0091)	(0.0083)	(0.0083)	(0.0131)	(0.0130)	(0.0343)	(0.0338)
X: Census tract income	-0.0452***	-0.0452***	-0.0451***	-0.0452***	-0.0475***	-0.0401***	-0.0423***	-0.0502***	-0.0481***	-0.0481***	-0.0438***	-0.0437***	-0.4153***	-0.4128***
	(0.0032)	(0.0031)	(0.0031)	(0.0032)	(0.0088)	(0.0044)	(0.0072)	(0.0041)	(0.0040)	(0.0040)	(0.0054)	(0.0053)	(0.0354)	(0.0357)
X: Applicant income	-0.0320***	-0.0320***	-0.0319***	-0.0313***	-0.0338***	0.0120**	-0.0264**	-0.0231***	-0.0158*	-0.0156*	-0.0169*	-0.0168*	-0.1855***	-0.1823***
	(0.0063)	(0.0060)	(0.0064)	(0.0074)	(0.0042)	(0.0050)	(0.0109)	(0.0084)	(0.0093)	(0.0092)	(0.0087)	(0.0087)	(0.0314)	(0.0310)
X: Loan-to-income	0.0057***	0.0057***	0.0057***	0.0057***	0.0052***	0.0045*	0.0030***	0.0083***	0.0065*	0.0065*	0.0030	0.0030	0.0530***	0.0565***
	(0.0015)	(0.0014)	(0.0015)	(0.0017)	(0.0016)	(0.0024)	(0.0011)	(0.0025)	(0.0037)	(0.0037)	(0.0033)	(0.0033)	(0.0091)	(0.0090)
Core deposits X crisis	-0.3119***	-0.3181***	-0.2814***		-0.1559***		-0.2710***	-0.2297***	-0.2975***		-0.2638***		-1.8984***	-1.1829***
	(0.0884)	(0.0527)	(0.0465)		(0.0368)		(0.1004)	(0.0667)	(0.0435)		(0.0441)		(0.1277)	(0.1893)
Retail 25th pct X crisis				-0.0637***		-0.2912***				-0.0634***		-0.0605***		
				(0.0148)		(0.0737)				(0.0136)		(0.0139)		
Size X crisis			-0.0072*	-0.0041	0.0118***	-0.0049*	-0.0152	-0.0053	-0.0063	-0.0048	-0.0051	-0.0038		-0.0938***
			(0.0041)	(0.0040)	(0.0040)	(0.0029)	(0.0110)	(0.0047)	(0.0045)	(0.0044)	(0.0052)	(0.0053)		(0.0220)
Profitability X crisis			0.5742	2.8650	0.1819	-0.6766	14.5097***	2.4101	2.7610	3.6313	1.6219	2.4018		-3.3764
			(2.1092)	(2.4329)	(1.3445)	(2.9134)	(5.1551)	(3.6028)	(2.5612)	(2.5565)	(2.5122)	(2.6307)		(16.7210)
Leverage X crisis			-0.6118**	-0.5509*	-0.0760	-0.2249	-1.5837***	-0.5951	-0.8041***	-0.5533*	-0.4898	-0.2767		-4.7521***
			(0.2552)	(0.2942)	(0.1849)	(0.2822)	(0.5144)	(0.4646)	(0.3104)	(0.2999)	(0.3084)	(0.3119)		(1.5332)
Liquidity X crisis			-0.1239*	-0.0969	0.0371	-0.1751**	-0.6878***	-0.0917	-0.2026**	-0.1363	-0.2900**	-0.2185*		-1.9064***
			(0.0695)	(0.0879)	(0.0491)	(0.0714)	(0.1613)	(0.0978)	(0.0992)	(0.1041)	(0.1151)	(0.1226)		(0.5446)
Losses X crisis			5.2255***	5.8102***	1.3795	-0.1685	-2.9605	5.9383***	1.5825	3.9203*	-0.3688	2.2330		-6.2433
			(1.5922)	(1.8212)	(1.3215)	(0.1109)	(5.0788)	(2.2183)	(2.1481)	(2.2312)	(2.0932)	(1.9570)		(11.1012)
Construction loans X crisis			-0.2930***	-0.3845***	-0.0373	3.0921*	-0.5472*	-0.3638***	-0.3861***	-0.4182***	-0.4118***	-0.4322***		-3.1118***
			(0.0790)	(0.1123)	(0.0562)	(1.7035)	(0.2869)	(0.1217)	(0.0975)	(0.1230)	(0.1057)	(0.1176)		(0.6656)
Unused commitments X crisis			-0.0013	-0.0210	-0.1059***	0.0199	0.0371	-0.0434	-0.0625	-0.0408	-0.0683	-0.0447		-0.5018**
			(0.0550)	(0.0564)	(0.0328)	(0.0412)	(0.0822)	(0.0730)	(0.0611)	(0.0615)	(0.0631)	(0.0649)		(0.2298)
Loans secured by properties X crisis			-0.3281***	-0.3333***	0.0438	-0.1324**	-0.6098***	-0.3241***	-0.4442***	-0.3794***	-0.4861***	-0.4198***		-4.0202***
			(0.0571)	(0.0683)	(0.0376)	(0.0624)	(0.1582)	(0.0804)	(0.0762)	(0.0785)	(0.0783)	(0.0818)		(0.4668)
Consumer and industrial loans X crisis			-0.2788***	-0.1460	0.0852	-0.1658*	-0.9030***	-0.2307*	-0.2786***	-0.0998	-0.3255***	-0.1556		-2.9826***
			(0.1017)	(0.1398)	(0.0762)	(0.0990)	(0.2012)	(0.1216)	(0.1018)	(0.1421)	(0.1079)	(0.1297)		(0.5636)
Return on equity to assets X crisis			-0.0924	-0.2527	0.1583	0.0732	-1.3328**	-0.1264	-0.3681	-0.3209	-0.2229	-0.1716		1.7821
			(0.2709)	(0.2927)	(0.1806)	(0.2774)	(0.5687)	(0.4292)	(0.3601)	(0.3492)	(0.3318)	(0.3313)		(1.7886)
Constant	0.8835***	1.4642***	1.3876***	2.6277***	1.0363***	0.6175**	2.4956***	1.9435*	1.8500***	2.6278***	2.0013***	2.6373***	3.5055***	14.3512***
	(0.0840)	(0.4455)	(0.3165)	(0.4955)	(0.1849)	(0.2687)	(0.3715)	(0.9930)	(0.4935)	(0.5201)	(0.4702)	(0.5218)	(0.7845)	(2.4554)
Observations	2,694,272	2,694,272	2,694,272	2,566,429	312,855	173,257	362,009	2,000,498	688,570	688,570	138,249	138,249	687,209	687,209
R-squared	0.0898	0.0909	0.0917	0.0914	0.2720	0.0766	0.2046	0.1072	0.0968	0.0966	0.1145	0.1144	0.1025	0.1052
Z variables	CD/A only	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	CD/A only	YES
Bank fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
MSA fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
MSA X Crisis	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster Bank	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster MSA	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Pseudo-R^2s are provided for the Logistic regressions. The two-way clustering for the Logit is achieved by defining a unique cluster for each Bank-MSA group.

Table 1.4: MSA level estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	New York	Los Angeles	Chicago	Dallas	Philadelphia	Houston	Washington	Miami	Atlanta
	Wayne	Long Beach	Naperville	Fort Worth	Camden	Baytown	Arlington	Miami Beach	Sandy Springs
	White Plains	Glendale	Joliet	Arlington	Wilmington	Sugar Land	Alexandria	Kendall	Marietta
Variable/MSA ID Number	35644	31084	16974	19124	37964	26420	47894	33124	12060
X: Male	0.0034*	-0.0026	-0.0017	-0.0096**	0.0035	-0.0101	-0.0002	0.0010	0.0045
	(0.0018)	(0.0048)	(0.0024)	(0.0046)	(0.0028)	(0.0082)	(0.0054)	(0.0025)	(0.0030)
X: Hispanic	0.0505***	0.0501***	0.0665***	0.0763***	0.0454***	0.0479***	0.0671***	0.0091	0.0724***
	(0.0065)	(0.0132)	(0.0060)	(0.0076)	(0.0138)	(0.0101)	(0.0047)	(0.0068)	(0.0215)
X: Black	0.0701***	0.0785***	0.1192***	0.1026***	0.074***	0.0933***	0.086***	0.0753***	0.0942***
	(0.0059)	(0.0130)	(0.0084)	(0.0124)	(0.0136)	(0.0125)	(0.0084)	(0.0155)	(0.0154)
X: Census tract income	-0.0399***	-0.042***	-0.0456***	-0.0502***	-0.0622***	-0.039***	-0.0158**	-0.0328***	-0.0434***
	(0.0036)	(0.0062)	(0.0068)	(0.0054)	(0.0069)	(0.0084)	(0.0067)	(0.0042)	(0.0036)
X: Applicant income	-0.0009	-0.0174**	-0.021***	-0.0264***	-0.0184***	-0.0459***	-0.0256***	-0.0269	-0.0376***
	(0.0155)	(0.0080)	(0.0043)	(0.0096)	(0.0060)	(0.0095)	(0.0062)	(0.0178)	(0.0088)
X: Loan-to-income	0.0103***	0.0062*	0.0022*	0.012***	0.0139***	0.0142***	0.0076**	0.015***	0.0051***
	(0.0024)	(0.0036)	(0.0013)	(0.0018)	(0.0019)	(0.0012)	(0.0032)	(0.0023)	(0.0016)
Core deposits X crisis	-0.3361***	-0.1933**	-0.2711***	-0.0880	-0.0946	-0.3371***	-0.4972***	-0.6622***	-0.5138***
	(0.1216)	(0.0933)	(0.0837)	(0.0946)	(0.1184)	(0.1198)	(0.1149)	(0.1660)	(0.0579)
Observations	98,900	70,699	101,623	57,104	42,923	79,138	70,686	36,869	72,306
R-squared	0.0811	0.1008	0.0975	0.0856	0.0957	0.1113	0.0729	0.0928	0.0966

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Boston	Oakland	Detroit	Riverside	Phoenix	Seattle	Minneapolis	Tampa	Baltimore
	Quincy	Fremont	Livonia	San Bernar.	Mesa	Bellevue	St. Paul	St. Petersburg	Townson
		Hayward	Dearborn	Ontario	Scottsdale	Everett	Bloomington	Clearwater	
Variable/MSA ID Number	14484	36084	19804	40140	38060	42644	33460	45300	12580
X: Male	0.0100**	-0.0021	-0.0029	-0.0176*	0.0030	-0.0017	-0.0034	-0.0016	0.0017
	(0.0039)	(0.0037)	(0.0061)	(0.0096)	(0.0044)	(0.0035)	(0.0025)	(0.0037)	(0.0031)
X: Hispanic	0.0564***	0.0583***	-0.0031	0.0526***	0.0687***	0.0566***	0.0751***	0.0675***	0.0485***
	(0.0103)	(0.0107)	(0.0280)	(0.0098)	(0.0125)	(0.0130)	(0.0172)	(0.0069)	(0.0067)
X: Black	0.0899***	0.0844***	0.1083***	0.0629***	0.065***	0.0449***	0.1007***	0.0729***	0.0788***
	(0.0105)	(0.0088)	(0.0135)	(0.0131)	(0.0115)	(0.0102)	(0.0181)	(0.0095)	(0.0061)
X: Census tract income	-0.0211***	-0.0361***	-0.1656***	-0.0417***	-0.0316***	-0.0342***	-0.0305***	-0.0397***	-0.0528***
	(0.0040)	(0.0049)	(0.0090)	(0.0140)	(0.0060)	(0.0079)	(0.0052)	(0.0056)	(0.0072)
X: Applicant income	-0.0261***	-0.0066*	0.0086	-0.0172	-0.0349***	-0.0326***	-0.0204***	-0.0441***	-0.0189**
	(0.0044)	(0.0039)	(0.0131)	(0.0156)	(0.0068)	(0.0122)	(0.0041)	(0.0096)	(0.0086)
X: Loan-to-income	0.012***	0.0154***	0.0231***	0.0087***	0.0014	0.0016	0.003***	0.0074***	0.0055***
	(0.0030)	(0.0051)	(0.0048)	(0.0002)	(0.0011)	(0.0011)	(0.0008)	(0.0013)	(0.0015)
Core deposits X crisis	-0.0615	-0.3326*	-0.1609	-0.1606**	-0.5822***	-0.1601***	-0.4402***	-0.6343***	-0.2642**
	(0.0634)	(0.1963)	(0.2709)	(0.0799)	(0.0755)	(0.0569)	(0.0606)	(0.1548)	(0.1238)
Observations	23,042	39,768	10,571	49,391	54,659	50,050	55,675	41,291	36,996
R-squared	0.0863	0.0884	0.1698	0.0899	0.0966	0.0779	0.1271	0.0815	0.0618
Z variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Z variables X crisis	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster Bank	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 1.5: Balancing tests for two way matching

	Retail matched with wholesale									
	Wholesale			Retail			T-Test		KS-test	
	Mean	Median	St.Dev	Mean	Median	St.Dev	Stat	P-Val	Stat	P-Val
				A: Pre Matching						
Log Income	11.23	11.20	0.66	11.27	11.26	0.66	-51.08	0.00	0.04	0.00
Log Tract Income	11.07	11.08	0.38	11.12	11.14	0.38	-105.05	0.00	0.06	0.00
Loan to income	2.25	2.21	2.64	2.47	2.36	2.50	-61.90	0.00	0.08	0.00
Male	0.64			0.66			-26.49	0.00	0.02	0.00
Black	0.15			0.10			101.19	0.00	0.05	0.00
Hispanic	0.09			0.06			66.79	0.00	0.02	0.00
				B: Post Matching						
Log Income	11.24	11.24	0.48	11.24	11.24	0.48	-0.00	1.00	0.00	1.00
Log Tract Income	11.14	11.15	0.28	11.14	11.15	0.28	-0.03	0.98	0.00	1.00
Loan to income	2.42	2.45	0.96	2.42	2.45	0.96	-0.22	0.82	0.00	1.00
Male	0.66			0.66			0.00	1.00	0.00	1.00
Black	0.09			0.09			0.00	1.00	0.00	1.00
Hispanic	0.05			0.05			0.00	1.00	0.00	1.00
	Pre crisis matched with post crisis (wholesale)									
	Pre Crisis			Post Crisis			T-Test		KS-test	
	Mean	Median	St.Dev	Mean	Median	St.Dev	Stat	P-Val	Stat	P-Val
				C: Pre Matching						
Log Income	11.24	11.21	0.64	11.20	11.17	0.70	22.58	0.00	0.05	0.00
Log Tract Income	11.07	11.08	0.38	11.06	11.08	0.40	9.84	0.00	0.02	0.00
Loan to income	2.13	2.11	2.52	2.70	2.56	2.98	-73.00	0.00	0.18	0.00
Male	0.64			0.66			-15.09	0.00	0.02	0.00
Black	0.16			0.10			64.44	0.00	0.06	0.00
Hispanic	0.10			0.06			46.54	0.00	0.03	0.00
				D: Post Matching						
Log Income	11.24	11.24	0.48	11.24	11.24	0.48	0.16	0.88	0.01	0.82
Log Tract Income	11.14	11.15	0.28	11.14	11.15	0.28	1.15	0.25	0.01	0.43
Loan to income	2.42	2.45	0.96	2.42	2.45	0.96	0.13	0.89	0.01	0.86
Male	0.66			0.66			0.00	1.00	0.00	1.00
Black	0.09			0.09			0.00	1.00	0.00	1.00
Hispanic	0.05			0.05			0.00	1.00	0.00	1.00

Note: The msa, gender, and race variables are matched exactly. KS-test stands for Kolmogorov-Smirnov equality of distribution test, where rejection implies unequal distributions. T-test is the usual equality of means test.

Table 1.6: Demand for mortgages, 2005-2008

VARIABLES	(1)	(2)	(3)	(4)
	Number (log)		Volume / Assets (log)	
Crisis (2008 dropping 2007)	-1.0877**		-0.9215***	
	(0.4652)		(0.3466)	
Core deposits / Assets	-3.2485**	-3.3234**	-2.5746*	-2.7102**
	(1.4031)	(1.4235)	(1.4519)	(1.5054)
CDA x Crisis	1.1646	1.2022	0.5423	0.5746
	(0.7801)	(0.7720)	(0.5806)	(0.5643)
Constant	2.4691***	2.416***	-3.4854***	-3.5594***
	(0.6206)	(0.5953)	(0.6309)	(0.6148)
Observations	11,412	11,412	11,412	11,412
R-squared	0.4489	0.4540	0.6795	0.6827
Bank fixed effects	YES	YES	YES	YES
MSA fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
MSA X Crisis	NO	YES	NO	YES
Cluster Bank	YES	YES	YES	YES
Cluster MSA	YES	YES	YES	YES

Notes: the coefficient of CDA x Crisis is insignificant in all four specifications. This implies that although the supply of mortgage loans was different between banks with wholesale and retail funding strategies, the demand was not affected by the funding behaviour during the crisis.

Table 1.7: Aggregate supply of loans

	(1)	(2)	(3)	(4)
	Log Volume in MSA		Change in log volume in MSA	
VARIABLES	Without Z	With Z	Without Z	With Z
Log volume in MSA (t-1)	0.0379	0.1182		
	(0.1238)	(0.1310)		
Change in log volume in MSA (t-1)	-0.0001	-0.0416	-0.4408***	-0.4496***
	(0.0831)	(0.0819)	(0.0336)	(0.0326)
Change in house price in MSA (t-1)	1.4053***	1.2200***	0.8532***	0.6895***
	(0.2925)	(0.3105)	(0.2437)	(0.2570)
Change in GDP per capita in MSA (t-1)	-0.3375	-0.5315	-0.6179*	-0.8119**
	(0.3648)	(0.4034)	(0.3673)	(0.3533)
Average CD/A	-2.5108***	-2.1479***	-2.9072***	-1.4347**
	(0.7240)	(0.7872)	(0.5981)	(0.6886)
Average CD/A X Crisis	1.9547***	1.2057**	3.1950***	1.5827***
	(0.5337)	(0.6104)	(0.4278)	(0.5688)
Crisis	-1.6354***	-0.3984	-2.5080***	-0.0776
	(0.3312)	(0.6377)	(0.2606)	(0.6689)
Z: Lender size		0.0889*		0.1268***
		(0.0476)		(0.0370)
Z: Profitability		-25.3585		-83.0528**
		(29.8830)		(39.3939)
Z: Leverage		-0.8833		3.9781
		(4.1016)		(3.9889)
Z: Liquidity		1.3264		2.5921**
		(1.0993)		(1.0161)
Z: Losses		24.0175		44.0971**
		(23.1593)		(21.3024)
Z: Return on equity to assets		2.3924		10.5463***
		(3.3008)		(3.8129)
Lender size X Crisis		-0.0645***		-0.0899***
		(0.0178)		(0.0181)
Profitability X Crisis		2.5218		-4.8364
		(13.3148)		(41.2434)
Leverage X Crisis		-0.5203		-1.3488
		(2.2251)		(3.6582)
Liquidity X Crisis		0.6806		0.5401
		(0.7518)		(0.6510)
Losses X Crisis		0.7037*		0.9703***
		(0.3661)		(0.3482)
Return on equity to assets X Crisis				-0.6023
				(4.2619)
Constant	18.6379***	15.1555***	2.2524***	-2.4949**
	(2.1439)	(2.9330)	(0.3892)	(1.1606)
Observations	556	556	556	556
R-squared	0.9967	0.9970	0.9236	0.9369
Z variables	CD/A only	YES	CD/A only	YES
Z variables X Crisis	CD/A only	YEs	CD/A only	YEs
MSA fixed effects	YES	YES	YES	YES
Cluster MSA	YES	YES	YES	YES

Notes: The results presented in this table are from the data aggregated at MSA level. All the bank statistics are averages weighted by the number of originations by a bank within an MSA.

Chapter 2

Comparing Methods for Solving General Equilibrium Models with Incomplete Markets and Portfolio Choice

2.1 Introduction

The vast amount of international portfolio holdings, as documented by Lane and Ferretti (2007); Lane and Milesi-Ferretti (2001), underscore the importance of financial markets in the global economy. If we believe that financial markets can have important effects on the real economy, as shown for instance during the global financial crisis, then the complete markets assumption must be abandoned in favor of the incomplete markets framework. A growing literature has proposed solution methods for dynamic stochastic general equilibrium (DSGE) models which embed both dynamic portfolio choice and incomplete markets. Nevertheless, the statistical properties of these methods remain understudied. In this paper, I assess the relative accuracy of two solution methods for DSGE models, namely, that proposed by Hnatkovska (2010) and later applied by Evans and Hnatkovska (2005, 2011) (*EH*), and that attributed to Devereux and Sutherland (2007, 2009a,b) (*DS*)[1]. While *DS* solves the portfolio and sides of the economy sequentially, *EH* provides a simultaneous solution to both sides of the model.

[1]Although a method based on similar techniques was also proposed by Tille and van Wincoop (2007), I will call it the *DS* method, since I am mainly following the Devereux and Sutherland (2007) in this paper.

The complete markets framework is unfit for drawing solid conclusions about such issues as the effect of financial markets on the real economy, the determinants of the size and composition of international portfolios, their effect on business cycles and on the economy in general, the responses by the monetary and fiscal authorities necessitated by these cross-border portfolios, the role of revaluation effects in external adjustments, and the consequences of financial integration between countries. It is increasingly argued that the new generation of DSGE models should include dynamic portfolio choice and incomplete markets. Gourinchas (2006) underlines how extreme global imbalances will require large and abrupt adjustments, which may have undesired political and economic consequences given the incompleteness of domestic and international asset markets. Obstfeld (2004) highlights on the historical role of financial markets in these adjustments and asserts that building DSGE models of international portfolio allocation with incomplete markets is the next major task in the field of international economics and finance.

Both methods considered here are increasingly popular and aim at solving incomplete market portfolio-choice models. However, they are relatively new and their analytical properties are not well studied. My paper contributes to the literature by presenting a numerical analysis of the accuracy of these methods. I also suggest a novel method of checking the accuracy of a solution for the portfolio side of the economy, and compare the two methods in terms of their ease of applicability and speed. I find that both *DS* and *EH* methods provide us with a sufficiently accurate solution for the real variables, but unlike the *EH* method, there are significant inaccuracies in the solution for the portfolio variables when using the *DS* method.

Other solution methods for DSGE models with incomplete markets have been proposed in the literature. Tille and van Wincoop (2007) use an iterative procedure to find zero and higher order components of an agent's portfolio decision. They apply the solution method to a two-country, two-good, and two-asset model to understand how expected returns and risk characteristics of assets affect international capital flows. There are also solution methods that work in continuous time models: Devereux and Saito (2007) use the continuous time framework to derive some analytical solutions to the portfolio choice. The main drawback of this framework is its inability to handle models with diminishing marginal productivity or sticky nominal goods prices (Devereux and Sutherland, 2007). Judd et al. (2002) provide an alternative solution method for solving DSGE models with incomplete markets and heterogeneous agents, which is based on ad-hoc portfolio penalty functions; the latter can be difficult to justify using microeconomic foundations. The focus in this paper is on the EH and DS methods mainly due to their increased popularity and wide use in academic research.

The rest of this paper is organized as follows. Section 2.2 briefly describes the two methods analyzed. Section 2.3 provides the models used for simulations and describes the accuracy tests. I describe the application of the DS method in Section 2.4. Section 2.5 presents the results of the accuracy tests. Conclusions are deferred to Section 2.6.

2.2 The two methods

In this section, I briefly describe the two solution methods. The first method proposed by Hnatkovska (2010) and later applied by Evans and Hnatkovska (2011) is a combination of perturbation techniques - commonly used in solving macro models, and continuous-time approximations - generally used for solving financial models of portfolio choice. Another widely used solution method is Devereux and Sutherland (2007, 2009a,b), which combines second order approximation of the portfolio optimality conditions with the first order approximation for all of the other model equations to get an analytical, closed-form solution for the zero order portfolio holdings. *DS* can also be used to solve for the first order portfolios by combining third order approximation of the portfolio optimality conditions with the second order approximation of the rest of the model.

The first part of the methodology by Evans and Hnatkovska (2011) consists of approximating the real part of the model to the first or second order by usual perturbation techniques and using the discrete-time analogue of the continuous-time approximation to the portfolio choice equations à la Campbell *et al.* (2003). The next step is to solve the model parameters for the real and portfolio part simultaneously using conventional optimization algorithms. These algorithms need to calculate the gradients and optimal step at each iteration, which slows the convergence process significantly as the number of unknown parameters increases. Although this dimensionality curse is native to any solution method, its consequences are especially severe with the *EH* method because of the use of such optimization algorithms.

The Devereux and Sutherland (2009a) solution for the first order non-portfolio variables and zero order portfolio variables consists of three steps. First, assuming that the first order excess returns are i.i.d. mean zero exogenous variables, the first order solution for the non-portfolio variables are derived. Second, using the solution from the first part, excess returns and consumption differential is approximated as a function of the i.i.d. excess returns and exogenous shocks. Finally, the near-stochastic, or zero order, portfolio holdings are derived using the closed form equation provided by the authors.

The second order solution for the non-portfolio variables and first order solution for the portfolios are derived using a similar procedure. The derived zero-order solution for portfolio together with i.i.d. assumption for the first order portfolios is used to find the second-order solution for the non-portfolio equations. These solutions, in return, are used to get the first order solution for the portfolio variables using another closed-form solution given in Devereux and Sutherland (2007, 2009a).

The *DS* method is widely used due to a number of advantages. It is based on well-known perturbation techniques, which provides researcher with an abundance of tools already developed in the literature. The method is relatively easy to program, especially with software that can use symbolic toolbox. There is no need for iterations as in Tille and van Wincoop (2007) or for non-linear optimization as in Evans and Hnatkovska (2011). The solutions for the real and portfolio parts are derived sequentially; this decreases the computing time significantly, compared to other methods, which is an important concern, due to the dimensionality curse, especially when it comes to solving larger models.

2.3 Model

I estimate six variations of a standard two-country, two-sector, international asset pricing model with many assets, portfolio choice, and incomplete markets. The economy, in its most general form, consists of two countries, called home (H) and foreign (F). Each country is inhabited by a continuum of identical households and firms. Households in this economy can consume and invest in a variety of assets. There are two types of competitive and infinitely lived representative firms which specialize in production of traded and nontraded goods. Financial markets consist of a single internationally traded bond, equities for domestic and foreign traded goods producers, and equities for domestic and foreign nontraded goods producers. Equities are issued by firms as claims to their dividend payments.[2]

[2]The full set of equations and first order conditions for the models considered in this paper are available in Evans and Hnatkovska (2008).

2.3.1 Firms

There are two types of firms in each country: traded (T) and nontraded (N) firms. A representative traded firm in the home country produces domestic traded good, Y_t, using firm-specific capital, K_t via the production function $Y_t = Z_t^T K_t^\theta$, where Z_t^T is the productivity of a domestic traded firm. Foreign traded firms operate in a similar manner producing $\hat{Y}_t$ using foreign capital and productivity.[3] Goods produced by domestic and foreign traded firms can be traded at no cost, eliminating any arbitrage opportunities.

When the total number of shares is normalized to unity, the objective of a domestic firm can be summarized as to maximize the stream of dividends discounted by the domestic shareholders' intertemporal marginal rate of substitution (IMRS). The problem can be written as

$$\max_{I_t} \mathbb{E}_t \sum_{i=0}^{\infty} M_{t+i,t} D_{t+i}^T \tag{2.1}$$

subject to

$$K_{t+1} = (1-\delta)K_t + I_t \tag{2.2}$$

$$D_t^T = Z_t^T K_t^\theta - I_t \tag{2.3}$$

where the dividends paid by a domestic traded firm are represented by D_t^T, I_t is investment, δ is the rate at which physical capital depreciates, $M_{t,t+i}$ is the IMRS between periods t and $t+i$ given in equation (2.15), and $\mathbb{E}_t$ is the expectation operator given the information at the beginning of period t. The problem for the foreign firm is analogous.

Nontraded firms at home and abroad have no investment decision to make and they produce using $Y_t^N = \eta Z_t^N$, where Z_t^N is the productivity and η is a constant.

[3]Throughout this paper "ˆ" marks F country variables.

All the revenues earned by nontraded firms are distributed back to the domestic shareholders in the form of dividends, denoted by D_t^N.

The state of productivity in period t can be represented by a vector of productivity shocks $z_t = [\ln Z_t^T, \ln \hat{Z}_t^T, \ln Z_t^N, \ln \hat{Z}_t^N]'$ which is assumed to follow an AR(1) process given by

$$z_t = az_{t-1} + \Sigma^{1/2} e_t \tag{2.4}$$

where a is a 4×4 matrix, e_t is a 4×1 vector of i.i.d. mean zero unit variance shocks, and $\Sigma^{1/2}$ is a scaling parameter. In this paper shocks are assumed to be uncorrelated, a is a diagonal matrix, and the autocorrelation coefficients for traded and nontraded sector productivity are denoted by ρ^T and ρ^N, respectively.

2.3.2 Consumers

Each country is populated by a continuum of households with identical preferences over traded and nontraded goods. Each period consumers start with a portfolio of assets purchased in the previous period that consists of shares of domestic traded equity A_{t-1}^H that can be traded at price P_t^T, foreign traded equity A_{t-1}^F with price $\hat{P}_t^T$, domestic nontraded equity with price P_t^N, and one period bonds B_{t-1} that yield 1 unit of traded consumption good in period t and were purchased at a price of P_{t-1}^B in period $t-1$. The overall financial wealth of a representative consumer is given by

$$W_t^F = A_{t-1}^H(P_t^T + D_t^T) + A_{t-1}^F(\hat{P}_t^T + \hat{D}_t^T) + Q_t^N A_{t-1}^N(P_t^N + \hat{D}_t^N) + B_{t-1} \tag{2.5}$$

This financial wealth can be used to consume traded goods C_t^T or nontraded goods C_t^N for a price of Q_t^N, and invested back into assets $[A_t^T, A_t^H, A_t^N, B_t]$.

The objective of a representative domestic consumer can be summarized as

$$\max_{\mathbb{C}} \mathbb{E}_t \sum_{i=0}^{\infty} \theta_{t+i} \mathcal{U}(\mathbb{C}_{t+i}) \tag{2.6}$$

subject to

$$C_t^T + Q_t^N C_t^N + A_t^H P_t^T + A_t^F \hat{P}_t^T + Q_t^N A_t^N P_t^N + B_t P_t^B \leq \tag{2.7}$$
$$A_{t-1}^H (P_t^T + D_t^T) + A_{t-1}^F (\hat{P}_t^T + \hat{D}_t^T) + Q_t^N A_{t-1}^N (P_t^N + \hat{D}_t^N) + B_{t-1}$$

where $\theta_{t+i} = \theta_t \beta(\mathbb{C}_t)$ is the endogenous discount factor (EDF) with a discount function β, $\mathbb{C} = \left[C^T, C^N\right]$ is the consumption basket that consists of traded and domestic nontraded goods, and $\mathcal{U}()$ is the convex utility function defined over the basket. I consider two different forms of the utility function: the power-utility, provided in (2.8) and the log-utility form.

$$\mathcal{U}(C^T, C^N) = \frac{\left(\left[\mu_T^{1-\phi}(C^T)^\phi + \mu_N^{1-\phi}(C^N)^\phi\right]^{\frac{1}{\phi}}\right)^{1-\sigma} - 1}{1-\sigma} \tag{2.8}$$

The discount function given by (2.9) ensures the stationarity of the wealth process by making the households more impatient when the consumption increases. This assumption is especially important when markets are incomplete. Following Boileau and Normandin (2008), Schmitt-Grohe and Uribe (2003), and Devereux and Sutherland (2009a), I choose the following functional form for the discount function with $\zeta > 0$ and $\theta_0 = 1$.

$$\beta(C_t^T, C_t^N) = \left(1 + \left[\mu_t^{1-\phi}\left(C^T\right)^\phi + \mu_N^{1-\phi}\left(C^N\right)^\phi\right]^{\frac{1}{\phi}}\right)^{-\zeta} \tag{2.9}$$

The relative weights assigned to traded and nontraded goods by consumers are denoted in the above equations by μ_T and μ_N, respectively.

2.3.3 The equilibrium and market clearing

The equilibrium in this model can be summarized by a set of first-order and market clearing conditions. The first order conditions faced by a representative domestic consumer are

$$
\begin{aligned}
Q_t^N &= \frac{\partial \mathcal{U}/\partial C_t^N}{\partial \mathcal{U}/\partial C_t^T} && (2.10)\\
1 &= \mathbb{E}_t[M_{t+1} R_{t+1}^B] && (2.11)\\
1 &= \mathbb{E}_t[M_{t+1} R_{t+1}^H] && (2.12)\\
1 &= \mathbb{E}_t[M_{t+1} R_{t+1}^F] && (2.13)\\
1 &= \mathbb{E}_t[M_{t+1} R_{t+1}^N] && (2.14)
\end{aligned}
$$

Where the returns for assets are defined as

$$R_{t+1}^H = \frac{P_{t+1}^T + D_{t+1}^T}{P_t^T}, \quad R_{t+1}^F = \frac{\hat{P}_{t+1}^T + \hat{D}_{t+1}^T}{\hat{P}_t^T} \quad R_{t+1}^N = \frac{(P_{t+1}^N + D_{t+1}^N)}{P_t^N} \frac{Q_{t+1}^N}{Q_t^N}, \quad R_{t+1}^B = \frac{1}{P_t^B}$$

The IMRS is given by

$$M_{t+1,t} = \beta\left(C_t^T, C_t^N\right) \frac{\partial \mathcal{U}/\partial C_{t+1}^T}{\partial \mathcal{U}/\partial C_t^T} \tag{2.15}$$

and can be simplified to

$$
\begin{aligned}
M_{t+1} =& \beta\left(C_t^T, C_t^N\right)\left(C_{t+1}^T/C_t^T\right)^{(1-\sigma)(\phi-1)/\phi}\\
&\times \left(\left(C_{t+1}^T + Q_{t+1}^N C_{t+1}^N\right) / \left(C_t^T + Q_t^N C_t^N\right)\right)^{(1-\sigma-\phi)/\phi}
\end{aligned}
$$

with power utility, and

$$M_{t+1} = \beta\left(C_t^T, C_t^N\right)\left(\left(C_t^T + Q_t^N C_t^N\right) / \left(C_{t+1}^T + Q_{t+1}^N C_{t+1}^N\right)\right)$$

for the log-utility case.

The first-order optimality condition for a representative domestic traded firm is given by

$$1 = \mathbb{E}_t[M_{t+1} R_{t+1}^K] \tag{2.16}$$

where $R_{t+1}^K = \theta Z_{t+1}^T K_{t+1}^{\theta-1} + (1-\delta)$ is the one period net return on capital.

There are four sets of market clearing conditions: the bond market $B_t + \hat{B}_t = 0$; traded goods market $C_t^T + \hat{C}_t^T = D_t^T + \hat{D}_t^T$; nontraded goods market $C_t^N = D_t^N$ and

$\hat{C}_t^N = \hat{D}_t^N$; traded equity market $A_t^H + \hat{A}_t^H = 1$ and $A_t^F + \hat{A}_t^F = 1$; and the nontraded equity market clearing condition, $A_t^N = \hat{A}_t^N = 1$.

The model described in this section, which is in its most general form, will be called "Incomplete markets with power utility and EDF" model, and is my benchmark model (i). I will also analyze five of its variations. These variations are: (ii) "Incomplete markets with power utility and no EDF", where I use the exogenous discount factor of 0.99, instead of an endogenous one, (iii) "Incomplete markets with log-utility and EDF", where I replace the power utility with log-utility, (iv) "Incomplete markets with log-utility and no EDF", (v) "Complete markets with power utility", where I achieve completeness by eliminating nontraded goods and equities, and finally, (vi) "Complete markets with log-utility", where the discount rate is exogenous, markets are complete, and the log-utility is used.

2.4 Solution

First, I solve these models using the *EH* method, which is described in detail in Evans and Hnatkovska (2011), and the *DS* method, developed and presented in a series of papers by Devereux and Sutherland (2007, 2009a,b). Since *DS* uses a different notation than in this paper, I first briefly introduce the *DS* notation.

I begin by rewriting the home country budget constraint in terms of real values of asset holdings instead of their shares. If we denote the holdings of domestic and foreign traded equity of an H country household by α_t^H and α_t^F, the bond holdings by α_t^B, and impose the market clearing conditions for the nontraded equities, then the budget constraint for a representative domestic consumer can be written as[4]

$$\sum_i \alpha_t^i = \sum_i R_t^i \alpha_{t-1}^i + Y_t - C_t \tag{2.17}$$

[4]See Appendix B.1 for details.

where $i \in [H, F, B]$, Y_t is the total domestic disposable income given by $D_t^T + Q_t^N D_t^N$, and $C_t = C_t^T + Q_t^N C_t^N$ is the total domestic consumption. Denoting the net foreign assets by $NFA_t = \sum_i \alpha_t^i$ the budget constraint is rewritten as

$$NFA_t = NFA_{t-1} R_t^B + D_t^T + Q_t^N D_t^N - C_t^T - Q_t^N C_t^N + \alpha_{t-1}' r_{x,t} \tag{2.18}$$

where $\alpha_{t-1}' = [\alpha_t^H, \alpha_t^F]$ is the vector of asset holdings except for the bonds, and $r_{x,t}' = [(R_t^H - R_t^B), (R_t^F - R_t^B)]$ is the vector of excess returns over the risk-free bond rate, R_t^B. This budget constraint together with the equations given in the text and their foreign counterparts constitute a full set of equations that I use to find a solution by the DS method.

Note that in this representation the market clearing conditions for asset holdings are $\alpha_t^i + \hat{\alpha}_t^i = 0$. Using this, together with the definition of the net foreign assets, the relation between the real holdings of assets and asset shares is given by

$$A_t^H = (\alpha_t^H + P_t^T)/P_t^T \tag{2.19}$$

$$A_t^F = \alpha^F/\hat{P}_t^T \tag{2.20}$$

$$A_t^N = 1 \tag{2.21}$$

$$B_t = NFA_t - (\alpha_t^H + \alpha_t^F) \tag{2.22}$$

To solve the real part of the model I use the method and the MATLAB algorithms provided by Schmitt-Grohe and Uribe (2004). Their method is easy to implement and utilizes the MATLAB's powerful symbolic toolbox which minimizes derivation errors. After obtaining the values of assets I transcribe them to shares using equations (2.19)-(2.22).

2.5 Testing for Accuracy

I distinguish between the solutions to the real part and the portfolio part, and check the accuracy of each separately. To conduct the accuracy tests, I first simulate each model 1200 times for 300 periods.[5] Simulations start in period zero, where the real variables are set to their steady-state values, there are no bond holdings, the holding of nontraded equity shares are one, and the remainder of the wealth is split equally between domestic and foreign traded equities (*i.e.*, $A_0^H = \hat{A}_0^H = A_0^F = \hat{A}_0^F = 1/2$, $A_0^N = \hat{A}_0^N = 1$, and $B_0 = \hat{B}_0 = 0$). These values for asset holdings at time zero are the same as the approximation point in Evans and Hnatkovska (2011) and they also correspond to the solution for the zero-order portfolio holdings obtained by Devereux and Sutherland (2009a) method. The parameters of the model are chosen to match the properties of quarterly data. The list of parameters and their values are given in Table 2.1.

2.5.1 Accuracy of the real-side

To test the accuracy of the solution for the real-side variables, I use the second order solutions for the return and consumption. I obtain the simulated values for these variables, and use them to compute the Euler equation errors which can be used to measure the accuracy of an approximated solution, according to Judd (1992). Following Heer and Maussner (2009), I then scale these errors by the total consumption in the economy to acquire a scale-invariant measure of approximation error. The exact functional form of the scaled Euler equation errors is

[5] As a robustness check, I also simulated the model for 50, 100, 200, 300, and 500 periods, and obtained similar results

Table 2.1: Parameter values

Parameter	Value	
β		0.99
δ		0.02
θ		0.36
$\Sigma^{1/2}$		0.01
	Complete markets	Incomplete markets
ρ^T	0.95	0.78
ρ^N	N/A	0.99
μ_T	1	0.5
μ_N	N/A	0.5
ϕ	N/A	$1 - 1/0.74$
σ	N/A	2
η	N/A	3.072
ζ- power-utility	N/A	7.157x10^{-3}
ζ- log-utility	N/A	5.111x10^{-3}

Notes: The parameter ζ is calibrated to equate the steady-state value of the endogenous discount factor to 0.99. The rest of the parameter values are taken from Evans and Hnatkovska (2011).

$$\varepsilon^i_{t+1} = 1 - \frac{\left[\beta(C^T_t, C^N_t)\mathbb{E}_t C_{t+1}^{(1-\sigma-\phi)/\phi}\left(\frac{C^T_{t+1}}{C^T_t}\right)^{(1-\sigma)(\phi-1)/\phi} R^i_{t+1}\right]^{\phi/(1-\sigma-\phi)}}{C_t} \tag{2.23}$$

where R^i_t is one of the five different returns. For the complete markets I calculate the ε^i_t for $i \in \{H, F, K, B\}$, where the $\{H, F, K, B\}$ represent the returns on domestic equity, foreign equity, capital, and bond holdings, which I obtain from equations (2.12), (2.13), (2.16), and (2.11), respectively. For the incomplete markets I also calculate ε^N_t, which stands for the Euler equation errors for the domestic equity market, obtained from (2.14).

If the solution method is accurate, the Euler equation errors have portray two main properties: they should be sufficiently close to zero, and orthogonal to any function of the state variables that are known at time t. To asses the size of errors, I analyze their descriptive statistics, given in Table 2.2. The table displays the mean, maximum, 90^{th}, 95^{th}, and 99^{th} percentiles for the absolute value of simulated errors. Each column in the table provides statistics for the simulated errors from the respective Euler equation. For example, column ε^H, presents the results for the equation (2.12). The results for the *DS* method appear to be of the same order of magnitude as those from the *EH* method. They are all close to zero and in most of the cases 99% of errors lie below 0.01. The errors are relatively larger for models with power-utility and there is a similar pattern, when comparing complete models with incomplete ones, across methods. Although the size of the errors is a useful benchmark for assessing the accuracy of any solution method, they are ad-hoc and no conclusive results can be derived.

Next, I check the orthogonality condition by conducting a more formal test for accuracy proposed by den Haan and Marcet (1994) (*DHM*). The *DHM* test is based on the idea that the Euler equation errors should be orthogonal to any arbitrary function of the variables, X_t, which completely characterize the state of the economy at time t. X_t can be any subset of the state variables and their lags. This orthogonality implies that for any stochastic model with a stationary and ergodic solution the following must be satisfied

$$\mathbb{E}_t\left[\varepsilon_{t+1} \otimes h(X_t)\right] = 0 \tag{2.24}$$

where $h(\cdot)$ is any function that transfers a set of state variables X_t into a q-dimensional vector of instruments. The actual test is conducted by testing how close the simulated Euler equation errors, $\hat{\varepsilon}_{t+1}$, and simulated state variables, $\hat{X}_t$, obey (2.24). To this end, I calculate the sample analog of (2.24) by

$$B_T \equiv \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{t+1} \otimes h(\hat{X}_t)}{T} \tag{2.25}$$

Note that this test statistics can be made arbitrarily small by choosing a suitable h function. This is why the test statistic is calculated by normalizing (2.25) by a consistent estimate of the variance of (2.24), A_T.

$$A_T \equiv \frac{\sum_{t=1}^{T} (\hat{\varepsilon}_{t+1} \otimes h(\hat{X}_t))(\hat{\varepsilon}_{t+1} \otimes h(\hat{X}_t))'}{T} \tag{2.26}$$

The DHM test statistics, J_T is then calculated as

$$J_T = T B_T' A_T^{-1} B_T \rightarrow \chi^2_{qm} \tag{2.27}$$

where m is the number of Euler equations used in the test. To decrease the size of type I error, den Haan and Marcet (1994) proposes to obtain the test statistics for different realizations of the exogenous shocks and compare upper and lower 5^{th} percentiles of the simulated test statistics with that of a χ^2_{qm} distribution. If the percentage of *DHM* statistics lying in the critical region is close to the $\alpha = 0.05$, then we fail to reject the orthogonality, and the model is considered accurate.

I calculate the *DHM* test statistics from each simulation and report the upper and lower 5^{th} percentiles in Table 2.3 for both *DS* and *EH* . The set of instruments used to generate Table 2.3 for the complete markets consists of levels of foreign and domestic capital, traded sector productivity shocks, change in wealth, and the two lags of capital and change in wealth variable.[6] For incomplete markets, I also add shocks to nontraded sector productivity.[7] I also obtain results from some other specifications for the instruments, not presented in this paper, and conclude that the results are robust to the choice of instruments.

[6] The instruments are $[Z^T,\ \hat{Z}^T, K_t,\ \hat{K}_t,\ \Delta W_t,\ K_{t-1},\ \hat{K}_{t-1},\ \Delta W_{t-1},\ K_{t-2},\ \hat{K}_{t-2},\ \Delta W_{t-2}]$.

[7] The instruments are $[Z^T,\ \hat{Z}^T, Z^N,\ \hat{Z}^N,\ K_t,\ \hat{K}_t,\ \Delta W_t,\ K_{t-1},\ \hat{K}_{t-1},\ \Delta W_{t-1},\ K_{t-2},\ \hat{K}_{t-2},\ \Delta W_{t-2}]$.

DHM test statistics are again similar for the *EH* and *DS* indicating that the orthogonality condition is satisfied when using either of the two solution methods. In all of the cases around 5% of the simulated test statistics are concentrated in the lower and upper tails of the distribution. The two set of results presented in this section indicate that the real side of the economy is solved with a reasonable degree of accuracy using both methods.

2.5.2 Accuracy of the portfolio-side

The tests for the accuracy of the solution to the portfolio holdings, which I call the accuracy of the portfolio-side, are not as straightforward as the ones for the real-side. There are no Euler equations that embed the portfolio variables; thus, indirect methods are needed to check the accuracy of the portfolio solution. To this end, I employ various known properties of different models in my basket to get the alternative Euler equation errors, which I call *pseudo-errors*. Pseudo-errors, unlike the usual Euler equation errors, employ the simulated portfolios and pass the accuracy tests only if the solutions for portfolios are precise.

I rely on three known properties of the models solved in this paper to conduct accuracy tests for the portfolio solutions. First of all, the analytical solution for the portfolio allocation in complete markets is known; thus, the simulated asset holdings can be compared with theoretical ones. Second, the share of consumption in wealth should be constant in models with log-utility. We can impose this property and calculate implied consumption values, which can be used to calculate the pseudo-Euler equation errors. If the asset holdings are accurate, so will be the wealth and consumption, giving us similar results with *real* errors in the previous section. Note that the constant consumption-wealth ratio is not used while deriving the solution with *DS* , which increases the power of these tests. Finally, the Euler equations utilized to derive the solution impose a separate restriction on each asset return. It is straightforward to show that the return on an optimally invested portfolio should also obey similar conditions. Specifically, return on portfolio, R^W_{t+1}, should obey

$$E_t[M_{t+1}R^W_{t+1}] = 1 \tag{2.28}$$

where

$$R^W_{t+1} = \frac{1}{W^F_t - C_t}\left[A^H_t P^T_t R^H_{t+1} + A^F_t \hat{P}^T_t R^F_{t+1} + A^N_t Q^N_t P^N_t R^N_{t+1} + B_t R^B_{t+1}\right] \tag{2.29}$$

Using the simulated portfolio shares, returns on portfolio can be calculated together with the implied portfolio Euler equation errors. These errors then can be used to perform such tests as *DHM*. This method is more versatile than the previous ones, since it can be applied to all six models in this paper and to any portfolio choice model in general.

Analyzing the distribution of the equilibrium portfolio holdings is a good starting point for this analysis. Table 2.4 presents descriptive statistics for the asset holdings by a domestic consumer. The portfolio holdings in a complete market framework are of a particular interest since their analytical solution is known. Theoretically, in a complete market setup, the risk sharing should be complete and agents should split all of their wealth equally between domestic and foreign traded equities in all periods (*i.e.,* $A^H_t = A^F_t = \frac{1}{2}$ and $B_t = 0$). From the first panel of Table 2.4 we can observe that this theoretical result is confirmed by the *EH* solution. The holdings of domestic and foreign equities are fixed at half, and there is a very small deviation from zero in bond holdings. By contrast, from the second panel we can see that *DS* solutions deviate from their analytical benchmark. To assess the importance of these deviations, I conduct a set of tests, utilizing the results described above as well as simulated portfolio holdings and returns.

As a next step, for the models with log-utility, I use the constant $C_t/W_t = \beta$ ratio to generate the consumption and IMRS series. To this end, I calculate wealth from the simulated portfolios and use their fraction as the pseudo-simulated consumption. Consumption series simulated as such, together with asset returns, are utilized to calculate the pseudo-Euler equation errors. Then I apply the *DHM* test to the pseudo-Euler equation errors obtained and present the results in Table 2.5. The results show that almost all of the *DHM* test statistics lay on the upper 5^{th} percentile of the distribution, which suggests a significant lack of accuracy in the estimated portfolio holdings.[8]

Finally, I use the return on wealth condition in (2.28) as an alternative way for testing the accuracy of portfolio holdings. Next, I calculate the pseudo Euler equation errors from the portfolio optimality condition in (2.29), using portfolios and returns, and conduct the *DHM* tests. Note that the *DHM* test will fail to reject the null only if the solution for the portfolio is accurate. The results for these new tests are presented in Table 2.6. Again, we see a strong rejection of the accuracy of the portfolio solution when the *DS* method is used. In all of the cases the *DHM* test statistics are concentrated at the right-hand-side of the distribution. The results for the *EH* method, on the other hand, show the appropriate distribution for the *DHM* statistics. We can conclude that the approximated portfolio solutions from the *EH* method are more accurate than those from the *DS* method.

The results presented in this section show that although the *DS* method approximates the real side of the economy with sufficient accuracy, the estimated solutions for portfolios do not agree with the implications of the models. This makes the *DS* method a very convenient tool if a researcher's main goal is to analyze the behavior

[8]Note that I do not present results for this test for the *EH* method, because in *EH* wealth to consumption ratio is fixed by construction for the log-utility case.

of real variables. However, if the portfolio solution is of interest, further analysis is necessary. By contrast, the *EH* method passes the tests both for the real side as well as the portfolio side accuracy.

2.6 Conclusion

In this paper, I compared two recently proposed solution methods for the incomplete market DSGE models with portfolio choice by Devereux and Sutherland (2007, 2009a,b), Tille and van Wincoop (2007), and Evans and Hnatkovska (2011); Hnatkovska (2010). Solution methods of this kind are relatively new and their properties and accuracy are not well studied. Unlike the alternative solution method by Evans and Hnatkovska (2011), where authors provide some accuracy tests for the real side of the economy, *DS* method is not tested.

Given the increasing importance of linkages between financial markets and the real economy, incomplete market models are gaining popularity at an increasing speed. Understanding the properties of the solution methods for these models is of a paramount importance. I test the *DS* method with regards to its ability for approximating the real variables, using a basket of models, and compare it with the *EH* method. The analysis here contributes to the literature by proposing a series of tests for the accuracy of the solution for the portfolio variables. Using these tests, I assess the relative accuracy of the solution for portfolio variables from both the *DS* and the *EH* methods.

To check the performance of these methods, I solve six different variations of a standard two-country two-goods international macro model. I then simulate the solution 1200 times for 300 periods, and use the simulated data to calculate the Euler equation errors. I analyze these errors statistically and test their orthogonality with the den Haan and Marcet (1994) accuracy test. I also generate pseudo-errors using some analytical properties of the portfolio variables in these models. These pseudo-errors should exhibit similar properties as the usual Euler equation errors if the solution for the portfolio choice is accurate.

My results indicate that methods considered here provide us with a sufficiently accurate solution for the real variables, but, unlike the *EH* method, there are significant inaccuracies in the solution for the portfolio when using *DS*. This implies that the *DS* method can still be used to analyze the impulse responses of any variable other than portfolio variables or to investigate the business cycle properties of any model. However, if the researcher is interested in analyzing the dynamics of the portfolio variables, attention should be paid to assessing the accuracy of the portfolio solution and the importance thereof.

Table 2.2: Euler equation errors, real side x10^{-3}

	ε^H	ε^F	ε^N	ε^K	ε^B	ε^H	ε^F	ε^N	ε^K	ε^B
	Evans and Hnatkovska					Devereux and Sutherland				
	Complete Marktes, log-utility									
Mean	1.248	1.246		1.425	1.582	1.248	1.248		1.426	1.585
Max	7.954	7.601		8.547	9.244	7.889	7.780		8.592	9.370
90^{th} percentile	2.566	2.565		2.940	3.262	2.570	2.572		2.936	3.266
95^{th} percentile	3.062	3.052		3.495	3.881	3.065	3.068		3.498	3.891
99^{th} percentile	4.040	4.035		4.588	5.089	4.025	4.018		4.611	5.116
	Incomplete Markets, log-utility, no EDF									
Mean	0.906	0.906	0.569	1.289	1.369	0.780	0.777	0.706	1.126	1.213
Max	5.404	5.173	3.604	7.223	7.600	4.455	4.603	4.172	6.041	6.471
90^{th} percentile	1.866	1.867	1.172	2.662	2.834	1.605	1.606	1.456	2.321	2.502
95^{th} percentile	2.219	2.224	1.401	3.168	3.370	1.916	1.914	1.740	2.767	2.983
99^{th} percentile	2.930	2.920	1.837	4.174	4.448	2.524	2.529	2.292	3.641	3.923
	Incomplete Markets, log-utility, with EDF									
Mean	0.780	0.778	0.707	1.127	1.215	1.143	1.141	0.372	1.379	1.463
Max	4.281	4.280	4.069	6.394	6.695	6.344	6.335	2.823	7.300	7.870
90^{th} percentile	1.604	1.605	1.454	2.324	2.512	2.353	2.354	0.770	2.843	3.017
95^{th} percentile	1.912	1.911	1.741	2.765	2.989	2.808	2.805	0.924	3.385	3.596
99^{th} percentile	2.509	2.515	2.287	3.656	3.922	3.695	3.699	1.243	4.463	4.729
	Complete Markets, power-utility									
Mean	1.248	1.251		1.425	1.583	0.882	0.879		1.740	1.822
Max	6.884	6.862		8.014	9.158	5.510	5.054		9.467	9.966
90^{th} percentile	2.571	2.580		2.944	3.273	1.819	1.815		3.591	3.757
95^{th} percentile	3.062	3.072		3.494	3.889	2.172	2.161		4.271	4.473
99^{th} percentile	4.048	4.064		4.619	5.136	2.856	2.845		5.591	5.850
	Incomplete Markets, power-utility, no EDF									
Mean	0.866	0.865	1.602	1.194	1.230	0.736	0.737	1.469	1.043	1.086
Max	4.619	4.692	8.700	6.321	6.285	4.665	4.764	9.092	6.074	6.347
90^{th} percentile	1.782	1.783	3.297	2.457	2.534	1.519	1.519	3.029	2.152	2.244
95^{th} percentile	2.124	2.126	3.939	2.917	3.004	1.813	1.815	3.614	2.574	2.678
99^{th} percentile	2.803	2.792	5.180	3.847	3.967	2.393	2.394	4.735	3.384	3.522
	Incomplete Markets, power-utility, with EDF									
Mean	0.735	0.736	1.466	1.045	1.089	0.585	0.585	1.283	0.963	1.016
Max	4.219	4.653	9.089	6.355	6.632	3.727	3.827	8.161	5.618	5.843
90^{th} percentile	1.516	1.518	3.023	2.155	2.244	1.207	1.210	2.644	1.986	2.094
95^{th} percentile	1.805	1.802	3.598	2.562	2.666	1.443	1.442	3.157	2.376	2.500
99^{th} percentile	2.359	2.374	4.718	3.334	3.486	1.911	1.910	4.139	3.120	3.282

Notes: Columns ε^H, ε^F, ε^N, ε^K, and ε^B provide statistics for the absolute errors from the domestic households Euler equations for the H traded equity, F traded equity, domestic nontraded equity, capital, and bonds, respectively. All errors are of order 10^{-3}.

Table 2.3: den Haan and Marcet tests, real-side

	ε^H	ε^F	ε^N	ε^K	ε^B	Joint	ε^H	ε^F	ε^N	ε^K	ε^B	Joint
	Evans and Hnatkovska						Devereux and Sutherland					
	Complete Marktes, log-utility											
Lower 5%	0.07	0.08		0.07	0.06	0.04	0.03	0.03		0.03	0.03	0.02
Upper 5%	0.08	0.08		0.02	0.02	0.04	0.05	0.05		0.05	0.04	0.04
	Incomplete Markets, log-utility, no EDF											
Lower 5%	0.05	0.03	0.06	0.08	0.08	0.02	0.02	0.02	0.01	0.02	0.02	0.01
Upper 5%	0.06	0.04	0.06	0.07	0.08	0.06	0.06	0.06	0.07	0.06	0.06	0.03
	Incomplete Markets, log-utility, with EDF											
Lower 5%	0.04	0.02	0.04	0.05	0.06	0.02	0.03	0.03	0.06	0.04	0.02	0.04
Upper 5%	0.08	0.07	0.03	0.06	0.08	0.09	0.07	0.07	0.05	0.04	0.05	0.05
	Complete Markets, power-utility											
Lower 5%	0.02	0.05		0.06	0.08	0.04	0.03	0.03		0.03	0.03	0.01
Upper 5%	0.06	0.06		0.03	0.05	0.04	0.04	0.04		0.04	0.04	0.02
	Incomplete Markets, power-utility, no EDF											
Lower 5%	0.03	0.06	0.03	0.02	0.02	0.06	0.02	0.02	0.02	0.01	0.01	0.01
Upper 5%	0.05	0.06	0.05	0.05	0.07	0.04	0.07	0.07	0.08	0.07	0.07	0.03
	Incomplete Markets, power-utility, with EDF											
Lower 5%	0.04	0.04	0.06	0.04	0.03	0.05	0.05	0.01	0.04	0.40	0.03	0.01
Upper 5%	0.04	0.02	0.07	0.06	0.05	0.02	0.06	0.05	0.03	0.02	0.05	0.04

Note: Columns ε^H, ε^F, ε^N, ε^K, and ε^B provide the percentages of the *DHM* test statistics calculated based on the errors from H country households' Euler equation for H traded equity, F traded equity, domestic nontraded equity, capital, and bonds, respectively. The column *Joint* presents the percentiles for the *DHM* statistics for the joint hypothesis using the equities and the capital equations. Equities include both traded and nontraded ones for the incomplete markets, and only traded equities for the complete market models. The percentages close to 0.5 imply the accuracy of a solution.

Table 2.4: The equilibrium portfolio holdings

	A_t^H	A_t^F	B_t	A_t^H	A_t^F	B_t
	Evans-Hnatkovska			Devereux-Sutherland		
	A: Complete Marktes, log-utility					
Mean	0.5000	0.5000	0.0000	0.5000	0.5000	0.0000
St.Dev	0.0000	0.0000	0.0002	0.0000	0.0000	0.0008
Max	0.5000	0.5000	-0.0006	0.5000	0.5000	-0.0040
Min	0.5000	0.5000	0.0014	0.5000	0.5000	0.0111
	B: Complete Markets, power-utility					
Mean	0.5001	0.4998	0.0000	0.5001	0.4998	0.0000
St.Dev	0.0029	0.0034	0.0033	0.0035	0.0034	0.0033
Max	0.4870	0.4835	-0.0156	0.4839	0.4833	-0.0156
Min	0.5135	0.5159	0.0150	0.5162	0.5158	0.0150

Note: A^H and A^F represent the H households' holdings of equity issued by H and F traded firms, respectively. B refers to H households' bond holdings as a share of H wealth. The analytical solution for the complete markets imply the equal holding of A^H and A^F and zero holdings of international bonds.

Table 2.5: Accuracy tests for the DS using constant W/C

	A_t^H	A_t^F	K_t	B_t	A_t^H	A_t^F	A_t^N	K_t	B_t
	Euler Equation Errors x10^{-3}								
	Complete Markets, Log Utility				Incomplete Markets, Log Utility				
Mean	0.906	0.906	0.569	1.289	0.866	0.865	1.602	1.194	1.230
Max	10.747	10.723	8.230	9.312	6.128	8.134	9.272	10.226	8.159
90^{th} percentile	5.000	5.000	3.800	3.800	2.600	3.500	3.500	4.500	3.300
95^{th} percentile	6.500	6.500	4.900	4.900	3.400	4.600	4.600	5.800	4.300
99^{th} percentile	9.300	9.300	7.300	7.300	4.800	6.800	6.800	8.400	6.300
	den Haan Marcet Test								
Lower 5%	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Upper 5%	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	1.000

Note: These tests use the analytical results stemming from the log-utility assumption that share of consumption in the wealth of a households should be a constant (β). They are suitable only for the *DS* method, since in the *EH* method they are true by construction. If the wealth and portfolio is solved accurately, then these errors should be well-behaved in a sense that they should be close to zero and orthogonal to the model's variables, i.e. the upper and lower 5% of the den Haan Marcet statistics should be close to 0.5.

Table 2.6: den Haan and Marcet tests, return on wealth

Model	Euler Equation Errors x10^{-3}					DHM test	
			Percentile				
	Mean	Max	90^{th}	95^{th}	99^{th}	Lower	Upper
	Evans Hnatkovska						
Complete Marktes, log-utility	0.001	0.001	0.001	0.001	0.001	0.06	0.05
Incomplete Markets, log-utility, no EDF	0.624	3.375	1.286	1.531	2.005	0.05	0.04
Incomplete Markets, log-utility, with EDF	0.410	2.361	0.849	1.018	1.359	0.02	0.09
Complete Markets, power-utility	0.912	5.957	1.881	2.249	2.956	0.05	0.02
Incomplete Markets, power-utility, no EDF	0.035	0.601	0.088	0.122	0.207	0.02	0.09
Incomplete Markets, power-utility, with EDF	1.090	6.890	2.244	2.682	3.517	0.07	0.05
	Devereux Sutherland						
Complete Marktes, log-utility	2.126	13.681	4.393	5.222	6.874	0.00	1.00
Incomplete Markets, log-utility, no EDF	2.131	11.802	4.392	5.245	6.902	0.00	1.00
Incomplete Markets, log-utility, with EDF	1.663	9.510	3.432	4.082	5.365	0.00	1.00
Complete Markets, power-utility	1.204	6.797	2.476	2.948	3.861	0.00	1.00
Incomplete Markets, power-utility, no EDF	1.638	9.305	3.370	4.014	5.335	0.00	1.00
Incomplete Markets, power-utility, with EDF	1.318	7.180	2.718	3.221	4.253	0.00	1.00

Note: These statistics are calculated using the pseudo- Euler equation errors obtained from the solution to the portfolios.

Chapter 3

Resource Windfalls, Macroeconomic Stability and Growth: The Role of Political Institutions

with Rabah Arezki and Kirk Hamilton

3.1 Introduction

Fluctuations in commodity prices pose serious challenges to developing countries. In the present paper, we focus on the effects that these price fluctuations may have on commodity-exporting countries. Indeed, the episodes of sharp increases in commodity prices since the early 2000s have renewed the debate among academics and policy makers on the risks faced by commodity exporters. Figure 3.1 shows that the evolution of government spending tracks that of the index of commodity export price in Venezuela and the extent of the synchronization has been increasing during the 2000's commodity price boom. In contrast, Figure 3.2 shows that government spending appears to move exactly opposite compared to the index of commodity export price in Norway. This cursory look at the data seems to suggest that there may be some fundamental factors which may shape the commodity exporters' reaction to commodity price fluctuations. In this paper, we rigorously examine the impact of resource windfalls on macroeconomic stability and long run economic growth using panel data for a world sample of up to 134 countries during the period 1970-2007.

This paper makes two main contributions to the existing literature. First, the paper specifically focuses on the effect of resource windfalls on the non-resource sector. To do so, we use a new dataset on non-resource GDP allowing us to avoid the "noise" introduced by the resource sector's contribution to overall GDP.[1] Indeed, Hartwick (1977) provides a canonical rule for sustainability in resource dependent economies which can help consumption to be maintained indefinitely, even in the face of finite resources and fixed technology. The rule consists in setting genuine saving to zero at each point in time; this sets traditional net savings just equal to resource depletion. From that perspective, non-resource sector GDP should thus be the relevant measure to be used when assessing both macroeconomic stability and long run economic performance in commodity-exporting countries. From a policy perspective, preserving the macroeconomic stability of the non-resource sector specifically will contribute to fostering investments in that sector and thus will contribute to sustained economic growth after natural resources are depleted. Second, unlike in previous studies, the econometric investigation explicitly takes into account the role of fiscal policy (government spending more specifically) in the analysis of the so called "resource curse".[2] Indeed, the resource sector often lacks direct structural linkages with the rest of the economy but exercises a significant externality mostly through the fact that a large chunk of government spending is financed from revenues originating from the resource sector (through state ownership, taxation, export tariffs, etc.). Identifying the nature of that externality can help foster our understanding of both the short run dynamics of the non-resource sector and its long run economic viability after natural resources are depleted.

Our main findings are threefold. First, we find that overall government spending in commodity exporting countries has been procyclical.[3] We also find that resource

[1]Section 3.2 describes the estimation of the non-resource GDP, which takes into account the depletion of the stock of natural resources.

[2]Gylfason (2001) and Sachs and Warner (1995) have provided early evidence of a significant negative correlation between natural resource abundance and economic growth.

[3]Government spending is here defined as procyclical when it comoves with commodity prices

windfalls initially crowd out the non-resource GDP, which then increases as a result of the fiscal expansion. Second, we find that in the long-run resource windfalls have negative effects on the non-resource sector GDP growth, but not over and beyond the government spending. Finally, the effects of resource windfalls on both macroeconomic stability and long-run growth are moderated by the quality of political institutions.

This paper links to the literature on the role of fiscal policy in shaping the economic performance of developing countries. There is ample evidence that fiscal policy in developing countries has achieved mixed results both in the short- and the long-run. In the short-run, Kaminsky *et al.* (2004), among others, provide evidence that fiscal policy tends to be procyclical in developing countries especially when compared to industrialized countries. Three important characteristics of commodity exporting countries complicate the conduct of fiscal policy and are likely to make government spending more procyclical than in non commodity exporting countries. First, government revenues derived from the exploitation of natural resources are more volatile than other sources of government revenue. Second, the size of the revenues derived from natural resources is disproportionately large in commodity exporting countries, notwithstanding the distinction between resource dependence vs. resource abundance. Third, those revenues are prone to rent-seeking behavior as they more directly transit to government coffers.

Cuddington (1989) provides some evidence supporting the claim that fiscal policy is more procyclical in commodity exporting countries. In the long run, there is also mixed evidence that government spending has helped boost developing countries' economic performance (See, e.g. Blejer and Khan, 1984; Gelb, A. and associates, 1988; Khan, 1996) . Gelb, A. and associates (1988) provides anecdotal evidence that governments in commodity exporting countries often embark in large investment projects following commodity price booms. Gelb, A. and associates (1988) argues that those investment projects were plagued by inefficiencies and also contributed to resource misallocation. Those disproportionately large investment projects also get depreciated quickly or even become obsolete as governments are unable to cover the associated high maintenance costs due to lack of financing. Robinson and Torvik (2005) provide a political economy model where "white elephants" may be preferred to socially efficient projects when the political benefits are large compared to the surplus generated by efficient projects. This evidence could suggest that poor long-run economic performance in commodity exporting countries may stem from inefficiencies in government spending rather than underinvestment.

Further, this paper relates to the literature on the so-called "resource curse" focusing specifically on the consequences of resource endowment on the economic performance of commodity exporting countries. This literature has emphasized several channels through which resource windfalls may affect economic performance including the so called "Dutch disease" and a deterioration of institutions to name a few (see Frankel (2011), for a survey).[4] Overall, there is some evidence, albeit controversial, that commodity exporting countries' growth performance compares less favorably with the growth performance of non commodity-exporting countries. Among others, Alexeev and Conrad (2009) provide evidence supporting a more skeptical view of the resource curse. Using traditional cross-sectional growth regressions, they find, for instance, that the empirical association between resource dependence and economic performance is not robust to using samples with different starting years or to the inclusion of additional controls. In a recent attempt to reconcile these conflicting evidences regarding the existence of a resource curse, Collier and Goderis (2007) use panel cointegration techniques allowing them to disentangle the short and long run

[4] This paper departs from the traditional Dutch disease literature distinguishing between tradable and non-tradable sectors. Instead, we focus here on the distinction between the resource and non-resource sector.

effects of resource windfalls on overall GDP growth. They find that commodity price shocks have a positive effect in the short run but a negative effect in the long run. This paper also relates to the literature which has stressed the importance of political institutions in achieving better policy outcomes (See, e.g. Persson, 2002). In their seminal contribution to the growth and institutions literature, Acemoglu *et al.* (2001, 2002) have shown that political institutions are key determinants for long-run economic development.

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The remainder of this paper is organized as follows. Section 3.2 describes the data. Section 3.3 presents the estimation strategy and main results. Section 3.4 discusses a number of robustness checks. Section 3.5 concludes.

3.2 Data

Non Resource GDP (NRGDP)

Non-resource GDP is approximated by subtracting the real values of natural resources rents from total GDP in 2005 PPP adjusted USD (see Hamilton and Ruta (2008), for more details on resource rents computation).[5] Natural resources give rise to rents because they are not produced; in contrast, for produced goods and services competitive forces will expand supply until economic profits are driven to zero. An economic rent represents an excess return to a given factor of production. For each type of

[5]The resource rents data are from World Bank (2011). The GDP data are from Heston *et al.* (2009).

resource and each country, unit resource rents are thereby derived by taking the difference between world prices (to reflect the social opportunity cost of resource extraction) and the average unit extraction or harvest costs (including a "normal" return on capital). Unit rents are then multiplied by the physical quantity extracted or harvested to arrive at total rent.[6]

Resource Windfalls

To capture revenue windfalls from international commodity price booms, we construct a country-specific and plausibly exogenous index. The index consists of a geometric average of international prices of various commodities using (time-invariant) weights based on the average value of exports of each commodity in the GDP for a given country. Annual international commodity price data are for the 1970-2007 period from UNCTAD Commodity Statistics, Energy Information Administration, and World Economic Outlook assumptions. The data on the value of commodity exports is obtained from the NBER-United Nations Trade Database. Because the time-series behavior of many international commodity prices is highly persistent, resource windfall shocks are identified by the (log) change in the international commodity price.[7]

Political Institutions: Democracy

Democracy is measured by the revised combined Polity score (Polity 2) of the Polity IV database (Marshall and Jaggers, 2011). The classification uses a 10-point scale that categorizes four attributes of political systems: the competitiveness of

[6]The energy resources include oil, natural gas and coal, while metals and minerals include bauxite, copper, gold, iron ore, lead, nickel, phosphate, silver, tin, and zinc.

[7]The commodities included in the commodity export price index are aluminum, beef, coffee, cocoa, copper, cotton, gold, iron, maize, oil, rice, rubber, sugar, tea, tobacco, wheat, and wood. In case there were multiple prices listed for the same commodity a simple arithmetic price average was used.

political participation, the competitiveness of executive recruitment, the openness of executive recruitment, and the constraints on the chief executive. At one end of the scale, +10, are the most politically competitive and open democracies. At the other, âĂŞ10, are the least open and competitive autocracies. Following Persson and Tabellini (2003, 2006) and the Polity IV project, we classify countries as deep democracies, if their Polity 2 score is larger than or equal to 6, and as deep autocracies, if their Polity 2 score is smaller than or equal to -6.

3.3 Estimation Strategy and Main Results

3.3.1 Preliminary analysis

Table 3.1 provides basic summary statistics for the variables used in the empirical analysis; namely, the resource windfall index, NRGDP growth (in level and per capita), government spending, government's share in NRGDP (government size), real effective exchange rate (REER), and Polity 2.[8]

In the following, we further explore whether the series used in the empirical analysis are stationary in level or in first difference. Table 3.2 presents the results of three different panel unit root tests. The tests proposed by Levin, Lin and Chu (2002) (LLC) and Im, Pesaran and Shin (2003) (IPS) use as null hypothesis that all the cross-units contain a unit root. We also use the Hadri (2000) Lagrange Multiplier test which uses as null hypothesis that all the cross-units are stationary. The tests provide conflicting results which suggest that we cannot rule out that some of the key variables indeed contain a unit root. When considering the logarithm of NRGDP in level, LLC indicates that we should reject the null of all cross-units containing a unit

[8] Government spending is measured by the ratio of government expenditures to non-resource GDP. Government expenditure data is from Heston *et al.* (2009). The real exchange rate data is obtained from IMF (2010), while the current account data is obtained from IMF (2010).

root while IPS test indicate that we fail to reject the same null hypothesis. The Hadri test rejects the null hypothesis of stationarity of all cross-units. When taking the first difference in the logarithm of NRGDP, LLC and IPS now both reject that the null of all cross-units contain unit roots, while Hadri still indicates that we should reject the null of all cross-units contain stationary series.[9] Similar results are obtained when considering the logarithm of NRGDP per capita. The various panel unit root tests performed on our resource windfall index, government spending, and REER deliver conflicting messages in level suggesting some evidence that those variables contain non stationary series. When taking the first difference of those variables, we now have evidence of stationarity. We further test for the presence of cointegration between these variables using the four tests developed by Westerlund (2007) and Persyn and Westerlund (2008). The results of the various panel cointegration tests are presented in Table 3.3. They clearly fail to reject the null of no cointegration for various combinations of the variables used in the following empirical analysis. Both the evidence of non difference-stationarity and the absence of cointegration between the variables used in our empirical analysis suggest that we should use the variables in differences in our empirical analysis.[10]

3.3.2 Macroeconomic stability

We now turn to the empirical investigation of the experience of commodity exporting countries with macroeconomic stability. To do so, we use panel Vector Auto-Regression (VAR) techniques. The use of panel VAR techniques makes it possible to

[9] According to Hlouskova and Wagner (2006), the Hadri test tends to over-reject the null hypothesis and thus may yield results that directly contradict those obtained using alternative test statistics.

[10] Indeed, using those variables in level would lead to spurious results because of the lack of cointegration relationship between those variables. In contrast, using the series in differences allows us to appropriately explore the relationship between stationary processes.

isolate the dynamics of a statistical relationship and the interdependencies between multiple economic variables; namely, resource windfalls, which assumed to be exogenous, and two endogenous variables: non-resource GDP and government spending. Another advantage of panel VAR techniques is that they allow the simultaneous estimation of all relationships while taking into account specific country characteristics through the use of fixed effects. The method consists of a simultaneous IV-GMM estimation of series of equations. Denoting the vector of endogenous variables by zit and the resource windfall index by pit, our system of equations can be specified as follows:

$$z_{it} = \Gamma_0 + \Gamma_1 z_{i,t-1} + p_{it} + f_i + e_{it} \tag{3.1}$$

$$p_t = \gamma_0 + \gamma_1 p_{t-1} + \varepsilon_t \tag{3.2}$$

where f_i is a set of time-invariant country fixed effects. Mean-differencing, which is usually used in estimating panel data models, will create a bias in the estimates since the fixed effects will be correlated with the independent variables due to presence of a lagged dependent variable. As in Arellano and Bover (1995) we apply forward mean-differencing and use the lagged regressors as instruments in the estimation of the system.[11]

The results of the estimations are presented in Table 3.4. The dynamic effects of the various shocks are illustrated by the impulse responses presented in Figure 3.3. Those results suggest that the average effect of an increase in resource windfalls is followed by a statistically and economically significant increase in government spending. Indeed, we find that an increase of resource windfall by one standard deviation leads at

[11]We are using STATA procedures developed by Love and Ziccino (2006), modified to include an exogenous variable.

its peak to an increase in government spending by slightly less than a tenth of a standard deviation. This result provides supportive evidence that on average commodity-exporting countries have pursued procyclical government spending policy. Figure 3.3 also shows that resource windfall shocks initially crowd out non-resource GDP which in turn increases as a result of the fiscal expansion. An increase by one standard deviation in resource windfall leads on impact to a reduction by about one standard deviation in non-resource GDP and to an increase by half a standard deviation in the following period. The intuition behind this result is that an increase in resource windfalls increases the return of investing in the resource sector leading in turn to a reallocation of factors away from the non-resource sector in favor of the resource sector.[12] As government spending increases in response to an increase in government revenues following a resource windfall, the non-resource sector expands. The latter results provide empirical evidence of a resource sector externality onto the non-resource sector stemming from resource windfalls spurring government spending.

When expanding the empirical analysis to the real exchange rate and the non-resource current account, we find that resource windfalls lead to an increase in the growth of real effective exchange rate and to a deterioration of the non-resource current account (results not reported in tables).[13] Those results are consistent with the so called "Dutch disease". Indeed, government spending directed toward the non'tradable sector with and inelastic supply, leads to an increase in the relative price of non-tradable compared to tradable goods. This increase leads to an appreciation of the real exchange rate with potentially harmful effects on external competitiveness consistent with a deterioration of the non-resource current account following a resource windfall shock.

[12]This result holds when controlling for the changes in REER, as shown in Figure 3.4.

[13]The non-resource current account is constructed by subtracting commodity exports from overall current account.

We now explore whether the quality of political institutions influences the way resource windfall shocks impact macroeconomic stability in commodity-exporting countries. To do so, we split the sample between deep autocracies and deep democracies and run our panel VAR regressions for each sub-sample separately. We find stronger evidence that government spending in autocracies increases following a resource windfall shock. Quantitatively, a one standard deviation shock to resource windfall leads, at its peak, to an about one standard deviation increase in government spending in deep autocracies (Figure 3.6). Those effects are much larger than those from the overall sample. In deep democracies, we find evidence that government spending has been counter-cyclical. Indeed, we find that on impact an increase in one standard deviation in resource windfall index lead to a decrease by slightly less than a standard deviation in government spending (Figure 3.5). During the period following the shock, the effect of a resource windfall on government spending in deep democracies becomes positive but is no longer statistically significant. When comparing the effect on non-resource GDP following a resource windfall shock, we find that in both groups resource windfall shocks initially crowd out non-resource GDP which then increases following the fiscal expansion. However, we find that the evidence of a crowding out effect is quantitatively smaller in deep democracies compared to deep autocracies. Indeed, in autocracies a one standard deviation increase in the resource windfall index leads on impact to a decrease of about a third of a standard deviation in non-resource GDP in autocracies and to a decrease by tenth of a standard deviation in democracies. A large share of commodity windfalls accrues to government sector (through state ownership, taxation, export tariffs, etc.). These results suggest that democracy, through promoting accountability and consensus, reduces the perverse effect that resource windfalls may have on the non-resource sector. Indeed, more accountable government may exercise less discretion in the conduct of fiscal policy in turn leading to less macroeconomic instability. That evidence is consistent with, for instance, Persson (2002) who has stressed the importance of political institutions in achieving better policy outcomes.

3.3.3 Economic Growth

The above-mentioned results suggest that commodity-exporting countries are, on average, subject to macroeconomic instability which in turn can lead to potential adverse effects on their long run economic performance. In addition, one of the key challenges that commodity-exporting countries face is the need to reduce their dependence on commodities by re-balancing their wealth from natural capital in favor of reproducible capital and social capital, including human capital. Figure 3.7 illustrates, for instance, that commodity-exporting countries in Sub-Saharan Africa and the Middle East have a disproportionately higher share (over 30 percent) of their total wealth as natural capital. However, a large increase in government spending risks yielding both poor technical and allocative efficiencies. To take stock of the historical experiences of commodity-exporting countries, we now systematically investigate the impact of government spending on long run non-resource sector growth in the face of resource windfall shocks.

To do so, we use the Pooled-Mean-Group (PMG) techniques developed by Pesaran and Smith (1995), Pesaran (1997), and Pesaran, H. and Smith (1999) to estimate the effects of resource windfalls and government spending on non-resource GDP growth per capita. The use of panel cointegration techniques allows us to separate out the short run from the long run effects of government spending on non-resource GDP growth. The long-run growth regression equation is specified as an ARDL (p,q) process with an error-correction term as follows:

$$\triangle Y_{it} = \sum_{j=1}^{p-1} \gamma_j^i \triangle Y_{i,t-j} + \sum_{j=0}^{p-1} \delta_j^i \triangle X_{i,t-j} + \varphi^i \left[Y_{i,t-1} - \left(\beta_0^i + \beta_1^i X_{i,t-1} \right) \right] + \varepsilon_{i,t} \qquad (3.3)$$

where, Y is the growth rate of real per capita non-resource GDP, and X is a set of variables, namely, our resource windfall index, the share of government spending in non resource GDP, the initial level of income proxied by the lagged value of non-resource GDP per capita, the change in the logarithm of real exchange rate, the quality of political institutions. Disturbance term is denoted by ε.[14] The estimations provide us with a set of short run coefficients γ and δ, a set of long run coefficients β, and a speed of adjustment coefficient φ.

Table 3.5 presents the results of the PMG estimations focusing on the long run coefficients. On average, we find that resource windfall shocks have statistically and economically significant negative effect on the long run non-resource sector GDP growth as shown in column (1). Indeed, we find that increase in our resource windfall by one standard deviation would lead to a reduction of long run economic growth by about a fifth of a standard deviation. We also find that on average, an increase in the share of government spending has a negative effect on long run non-resource GDP growth, as shown in column (2). Those two results are in line with the existing literature providing evidence that resource windfalls and larger governments both lead to weaker long run economic growth. However, what is new is that resource windfalls stop having a significant negative effect on long run non-resource growth when controlling for government spending as shown in columns (3) to (5). This result suggests that government spending is an important vehicle of the resource curse hypothesis. In other words, the externality stemming from the resource sector to the non-resource sector is conveyed through government spending chiefly financed by resource sector

[14]The specification also includes time and fixed effects.

related government revenues. When controlling for the change in the real exchange rate as shown in column (4), resource windfall shocks have a positive effect on non-resource GDP growth. This result confirms that "Dutch disease" is a relevant channel of the resource curse. When controlling for the quality of political institutions as shown in column (5), the above results do not appear to change significantly. Given that the quality of political institutions changes little over time, it is perhaps hard to meaningfully assess the individual effect of democracy on long run economic growth when exploiting within country variation over a few decades.

In Table 3.6 we explore the potential heterogeneity in the effect of resource windfalls and government spending on non-resource GDP growth. We explore whether the quality of political institutions helps alleviate the resource curse by interacting both our resource windfall index and government spending with our measure of the quality of political institutions. We find that the impact of resource windfalls and government spending are moderated by the quality of political institutions. Everything else being equal, an increase in Polity 2 from that of Gabon to that of Norway would lead to a reduction in the effect of resource windfalls on non-resource GDP growth by half. While an improvement in the quality of political institutions could reduce the effect of resource windfall on economic growth, we find that even with the highest quality of political institutions, the effect of resource windfall on non-resource GDP remains negative as shown in columns (1) and (2). In columns (3) and (4), we also provide evidence that the quality of political institutions moderates the effect of government spending on long run non-resource GDP growth suggesting that the benefit of political institutions on economic growth are channeled through better fiscal policy. Indeed, as a large share of commodity windfalls accrues to government sector, more accountable governments can better support non-resource sector's long run economic performance by reducing government spending inefficiencies and resource misallocation. Those results are consistent with the political economy literature which has stressed the importance of political institutions in achieving better policy outcomes (See, e.g. Acemoglu *et al.*, 2001, 2002; Persson, 2002), and has shown that political institutions are key determinants for long-run economic development.

3.4 Robustness Checks

A relevant question is whether countries endowed with mineral and energy resources have fared differently in terms of both macroeconomic stability and economic growth when compared to countries endowed with agricultural resources. To do so, we split our sample distinguishing between countries where agricultural exports dominate from countries where minerals and energy exports dominate. We find that countries which export mostly minerals and energy resources display a statistically significant increase of government spending following an increase in resource windfalls, whereas countries exporting mainly agricultural resources do not display any statistically significant increase (results not reported in tables). We also explore whether countries which export mineral and energy resources are subject to weaker long run economic non-resource sector performance compared to countries which export agricultural resources (results not reported in tables). We find once again that minerals and energy exporters perform less favourably than agriculture exporters in the face of resource windfall shocks. This result confirms that the negative effect of resource windfalls on long run non-resource GDP is a robust feature of minerals and energy exporting countries.

Those results suggest that windfalls originating from "point based" resources (that is geographically more concentrated resources, mostly minerals and energy resources) are more likely to lead to procyclical fiscal policies and poorer growth performance than when windfalls originate from "diffuse" resources (that is more geographically dispersed resources, mostly agricultural commodities). Our results are consistent with those of Isham *et al.* (2005), who provide evidence that mineral and energy exporters are plagued with weaker economic performance and in particular weaker recovery. Point based as opposed to diffuse resources are indeed seen as more subject to rent-seeking behavior weakening the effectiveness of monitoring mechanisms over how much the government receives and how much it spends. Given the potentially higher level of rent seeking by governments in countries endowed with point based resources, it is plausible that those governments would spend more in boom times in order to quell the masses whose grievances in times of plenty may be conducive to unrest and political instability.

Another relevant question is whether our results are driven by the quality of economic institutions rather than political institutions. Indeed, the indicator capturing the quality of political institutions displays a relatively high correlation with the indicator capturing the quality of economic institutions namely the rule of law indicator (0.31). Also, Mehlum *et al.* (2006) provide some evidence that good economic institutions can alleviate the resource curse using standard cross-sectional growth regression. To test whether economic institutions play a moderating role in shaping the effect of resource windfall on economic growth, we try interacting resource windfalls with various (or combination of) indicators capturing the quality of economic institutions including the rule of law or corruption indices from Political Risk Guide (2009). Because the data on economic institution is available from 1985 onwards, we tried both using it as is, and solely using its average value in an interaction term with our resource windfall index. Irrespective of which economic institution indicator we use or of the way in which the indicator is used, we do not find any robust evidence that economic institutions moderate the effect of resource windfalls on non-resource GDP growth. The results are indeed not robust across specifications, and those results are supportive of the "primacy" of political institutions over economic institutions as a tool to moderate the effect of resource windfalls on non-resource GDP growth.

3.5 Summary

This paper examined the performance of commodity-exporting countries in terms of macroeconomic stability and growth in a panel of up to 129 countries during the period 1970-2007. To do so, we used a new dataset on non-resource GDP. Our main findings are threefold. First, we find that on average government spending in commodity-exporting countries has been procyclical. Second, we find that resource windfalls initially crowd out non-resource GDP which then increases as a result of the fiscal expansion. Third, we find that in the long run resource windfalls have negative effects on non-resource sector GDP growth. Yet, the effects turn out to be statistically insignificant when controlling for government spending. Both the effects of resource windfalls on macroeconomic stability and economic growth are moderated by the quality of political institutions.

Figure 3.1: Government Spending and Resource Windfalls in Venezuela

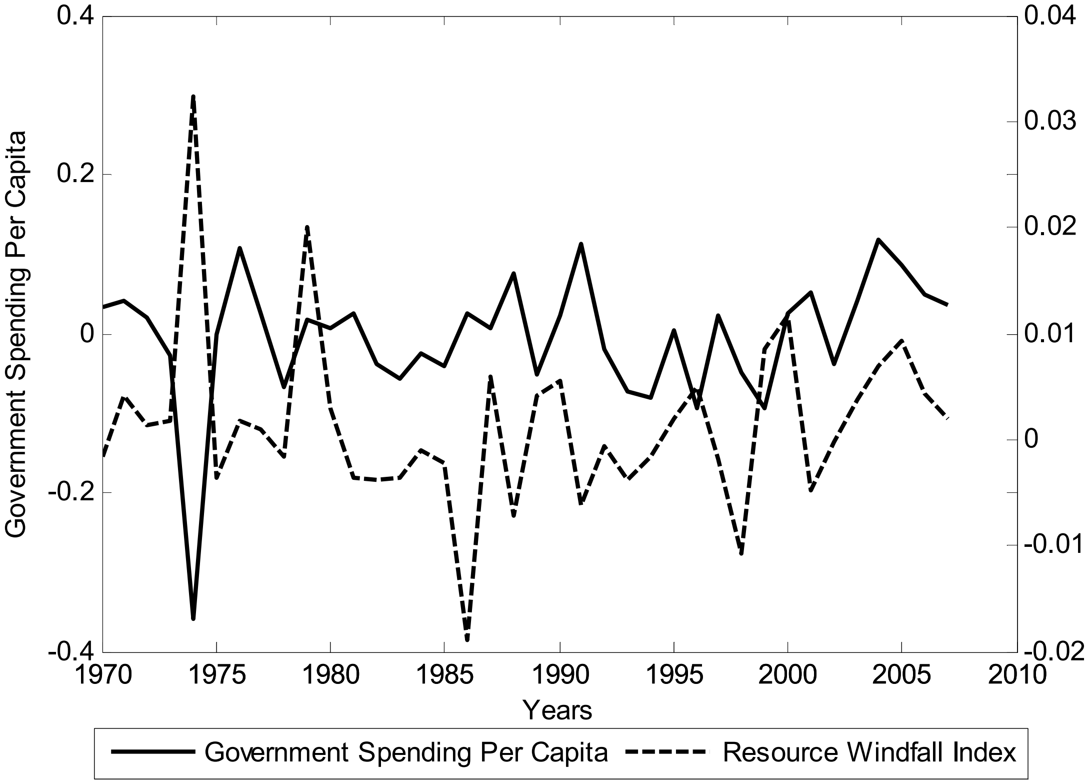

Figure 3.2: Government Spending and Resource Windfalls in Norway

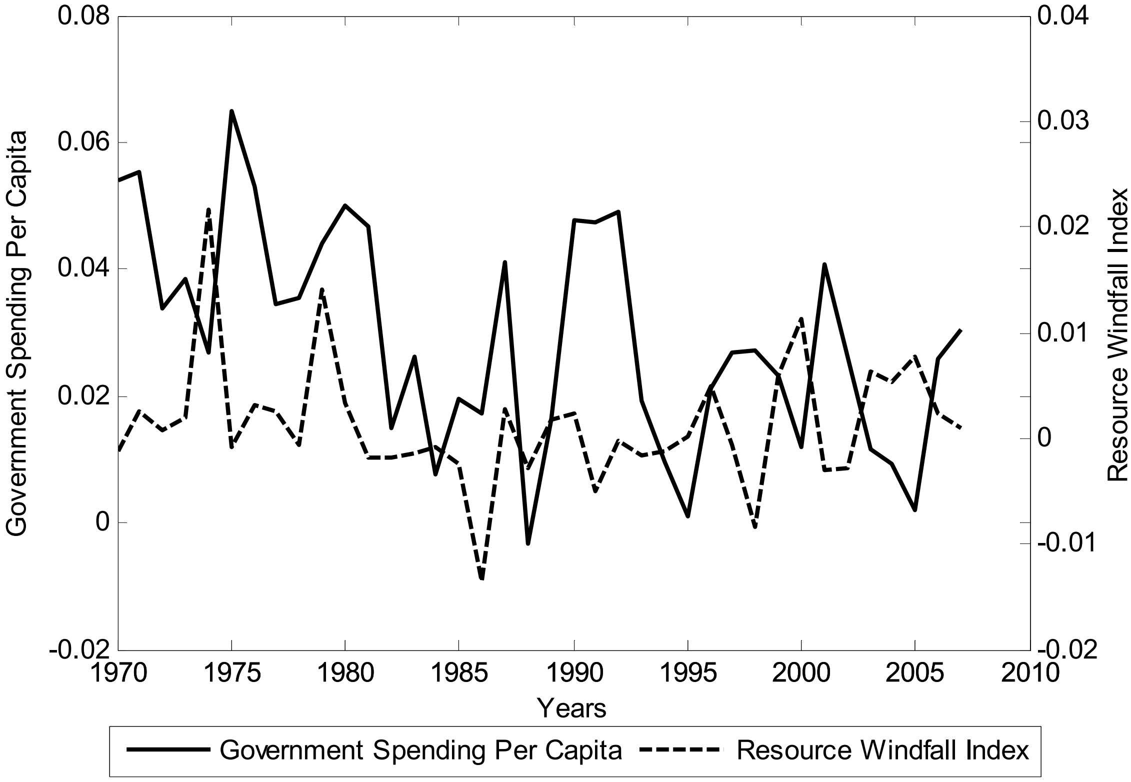

Figure 3.3: Impulse Responses for All Countries

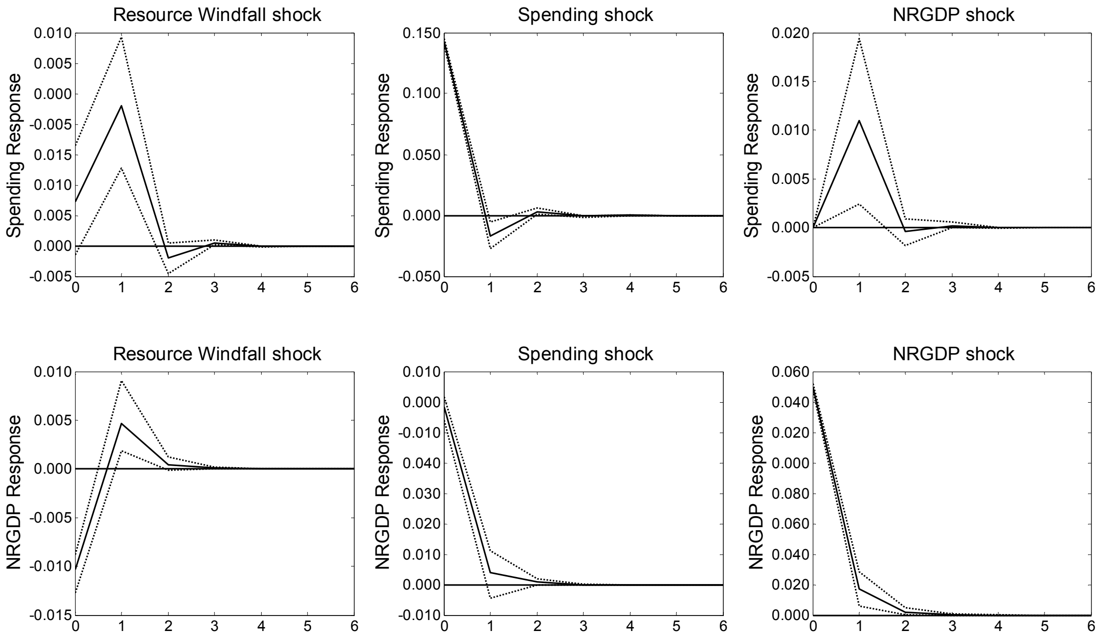

Figure 3.4: Impulse Responses Including REER for All Countries

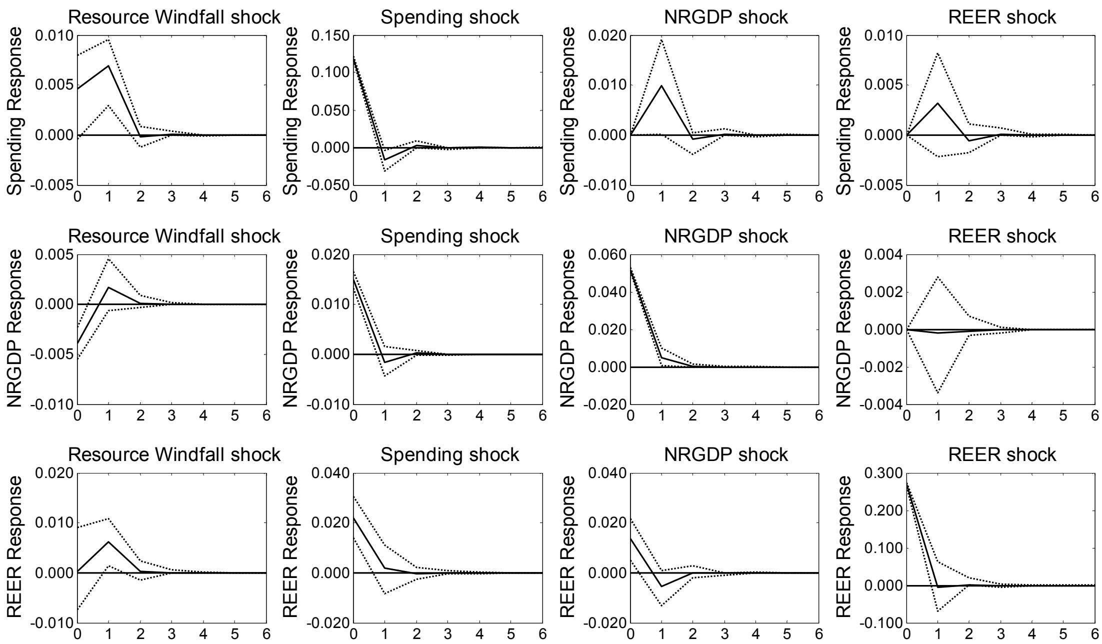

Figure 3.5: Impulse Responses for Democracies

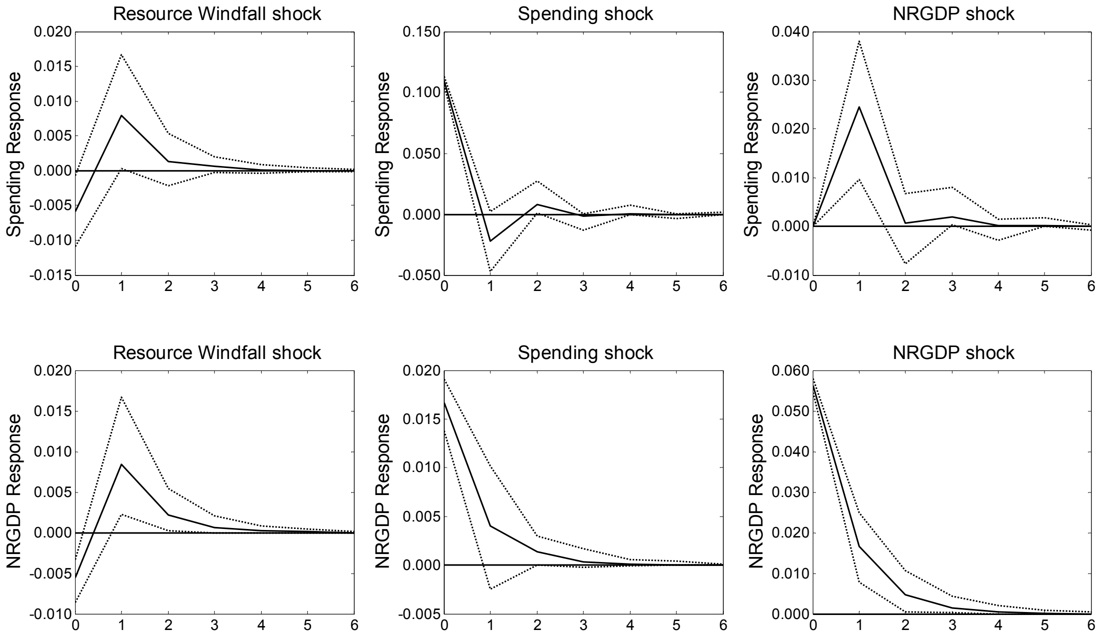

Figure 3.6: Impulse Responses for Autocracies

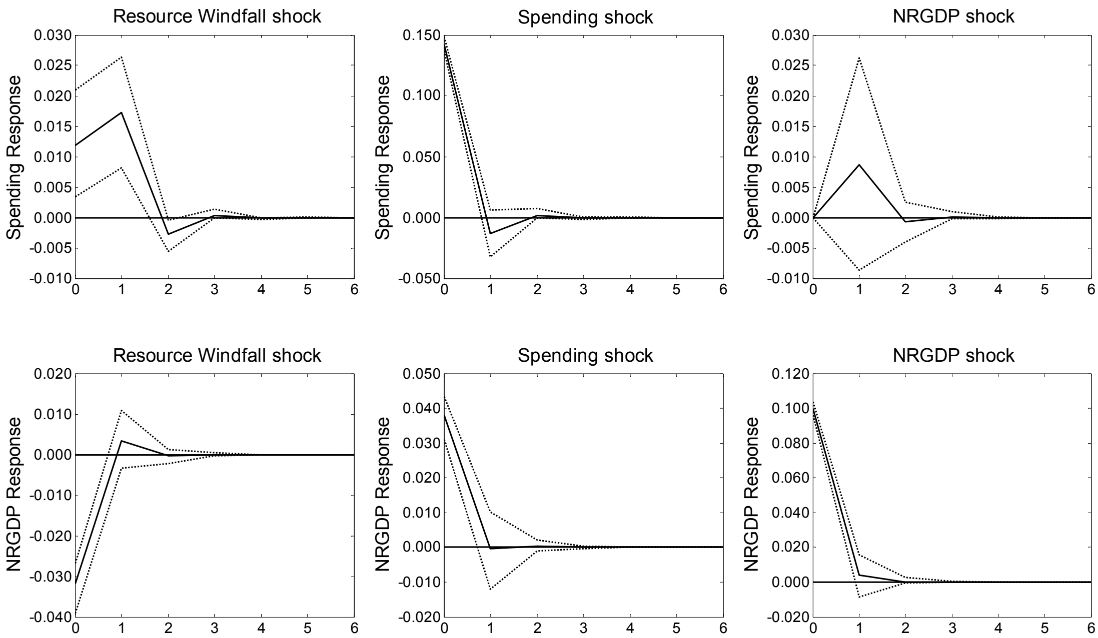

Figure 3.7: Natural Capital Around the World

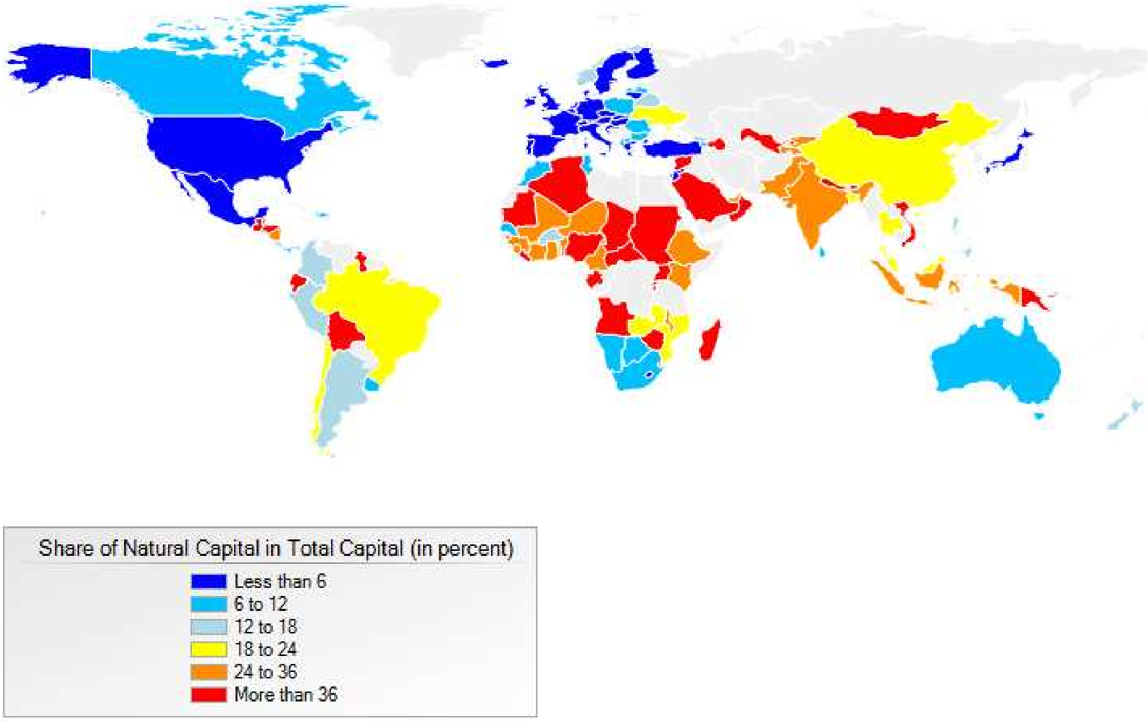

Table 3.1: Descriptive Statistics

Variable	Obs	Mean	St.D.	Min	Max
△ Resource Windfall Index	4823	0.000	0.006	-0.055	0.085
△ log NRGDP	4823	0.032	0.083	-1.108	0.774
△ log Government Expenditure	4823	0.035	0.144	-2.102	1.753
△ log NRGDP Per Capita Growth	3996	0.015	0.067	-0.691	0.553
Initial log NRGDP per capita	3888	8.542	1.134	5.735	11.446
Government share in NRGDP	4104	0.180	0.096	0.014	0.739
△ REER	2944	-0.016	0.263	-11.665	2.189
Polity 2	3560	1.123	7.506	-10.000	10.000
log(Polity 2 +12)	3560	2.344	0.742	0.693	3.091
Average log(Polity2 +12)	3610	2.350	0.578	0.693	3.091

Notes: Pooled-Mean-Group estimations use the logarithm of Polity 2 score plus 12.

Table 3.2: Panel Unit Root Tests

	LLC		IPS		Hadri		# Obs	
Variable	Stat	P-val	Stat	P-val	Stat	P-val	N	T
NRGDP	-6.930	0.000	10.240	1.000	119.260	0.000	129	38
△ NRGDP	-29.650	0.000	-34.260	0.000	4.900	0.000	129	37
Price	-2.720	0.000	-1.890	0.030	36.650	0.000	108	38
△ Price	-32.490	0.000	-33.710	0.000	-2.410	0.990	108	38
Government Size	-2.940	0.000	-2.310	0.010	128.220	0.000	129	38
△ Government Size	-26.620	0.000	-39.480	0.000	-2.460	0.990	129	37
ln(REER)	-5.380	0.000	-4.190	0.230	112.100	0.000	129	28
△ ln(REER)	-22.360	0.000	-26.090	0.000	-6.300	1.000	129	27
Misalignment	-9.540	0.000	-1.640	0.050	105.590	0.000	129	28
△ Misalignment	-20.700	0.000	-26.520	0.000	-6.750	1.000	129	27

Notes: We conduct a series of panel unit root tests to question the stationarity of level and the first difference for each variable. For the first four tests rejection implies stationarity, but for the Hadri test rejection implies unit root. All tests include an intercept, choice of trend is based on auxiliary regression. Trend is included in the tests for NRGDP and Government Size. The sellected statistics for the tests are: adjusted t-statistics for Levin, Lin, and Chu (2002) (LLC) test , z-tilde-bar statistics for Im, Pesaran, and Shin (2003) (IPS) test, and the z-statistics for the Hadri (2000) LM test (Hadri) . N and T stand for number of countries and years, respectively.

Table 3.3: Panel Cointegration Tests

Variables	Ga Stat	Ga p-val	Gt Stat	Gt p-val	Pa Stat	Pa p-val	Pt Stat	Pt p-val
	Intecept							
y, G/NGDP, P	11.77	1.00	7.87	1.00	6.01	1.00	2.75	1.00
y, G/NGDP, P, REER, NCA	15.08	1.00	12.94	1.00	11.48	1.00	9.07	1.00
	Trend and Intercept							
y, G/NGDP, P	2.87	1.00	6.35	1.00	0.21	0.58	1.80	0.96
y, G/NGDP, P, REER, NCA	8.01	1.00	14.44	1.00	7.38	1.00	11.04	1.00

Notes: The underlying idea is to test for the absence of cointegration by determining whether there exists an error correction relation for individual panel members, or for the panel as a whole. Consider the error correction model (3.3), where all variables in levels are assumed to be I(1), and φ^i provides an estimate of the speed of error-correction towards the long run equilibrium for each country i=1,...N. The Ga and Gt test $H_0 : \varphi^i = 0$ for all i versus $H_1 : \varphi^i \leq 0$ for at least one i. These statistics start from a weighted average of the individually estimated φ^i's and their t-ratio's. Rejection of H_0 therefore implies a cointegration in at least one of the cross-sectional units. The Pa and Pt tests use the pooled information over all the cross-sectional units to test $H_0 : \varphi^i = 0$ for all i vs $H_1 : \varphi^i \leq 0$ for all i. Rejection of H_0 should therefore be taken as evidence of cointegration for the panel as a whole. The difference between Ga and Gt as well as between Pa and Pt is in their asymptotic power. Ga and Pa is preferred to Gt and Pt when T is substantially greater than N. We present the results for all four tests for completeness.

Table 3.4: Panel VAR Estimation Results

LHS Variable	RHS Variable	Coefficient	GMM S.Error	GMM t-stat
△ Resource Windfall				
	△ Resource Windfall	-0.012	0.026	-0.456
△ Spending				
	△ Resource Windfall	1.895	0.438	4.328
	△ Spending	-0.148	0.046	-3.217
	△ NRGDP	0.147	0.067	2.188
△ NRGDP				
	△ Resource Windfall	1.005	0.379	2.653
	△ Spending	-0.009	0.015	-0.639
	△ NRGDP	0.114	0.045	2.525
No. of Countries		108		
No. of Observations		4689		

Table 3.5: Pooled-Mean-Group Estimation Results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Long-Run Coefficients					
Initial GDP	-0.089***	-0.051***	-0.074***	-0.107***	-0.061***
	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)
△ Resource Windfall	-1.082***		-0.804	5.399***	-0.160
	(0.454)		(0.501)	(0.657)	(0.497)
Government Size		-0.049***	-0.022	-0.081***	-0.042***
		(0.018)	(0.02)	(0.022)	(0.017)
△ REER				0.018***	
				(0.005)	
Polity 2					0.004***
					(0.002)
Error-CorrectionCoefficient					
ϕ	-0.820***	-0.909***	-0.805***	-0.688***	-0.838***
	(0.034)	(0.03)	(0.04)	(0.048)	(0.042)
Short-Run Coefficients					
△ Growth (t-1)	-0.036	0.021	-0.038	-0.073***	-0.022
	(0.023)	(0.02)	(0.026)	(0.038)	(0.028)
$\triangle^2$ Resource Windfalll	-0.426		-0.79	-5.518***	-0.979**
	(0.535)		(0.673)	(0.681)	(0.582)
△ Government Size		-1.480***	-1.451***	-1.275***	-1.415***
		(0.138)	(0.157)	(0.171)	(0.161)
$\triangle^2$ REER				0.024***	
				(0.014)	
△ Polity 2					-0.058***
					(0.015)
Intercept	-0.010	-0.006	-0.013	-0.019*	-0.010
	(0.01)	(0.005)	(0.008)	(0.011)	(0.007)
No. Of Countries	108	129	94	94	94
No. of Observations	3564	4257	3102	2277	3094

Note: The dependent variable is NRGDP per capita growth. Stars indicate the significance level, as usual. The lag order for the ARDL was chosen using SBIC. Only coefficients associated with the first lags are presented in this table to conserve space.

Table 3.6: Pooled-Mean-Group Estimation Results with Interactive Effects

Variables	Model 1	Model 2	Model 3	Model 4
Long-Run Coefficients				
Initial GDP	-0.080***	-0.062***	-0.075***	-0.041***
	(0.006)	(0.005)	(0.005)	(0.004)
$\triangle$ Resource Windfall	-1.866***	-0.834**		0.388
	(0.597)	(0.497)		(0.429)
Government Size		-0.030**	-0.019	-0.061***
		(0.017)	(0.018)	(0.02)
Polity 2	0.004***	0.003**	0.003	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Polity 2 x Windfall	0.072**	0.160***		
	(0.04)	(0.037)		
Polity 2 x Government Size			0.002***	0.001***
			(0.001)	(0.000)
Error-CorrectionCoefficient				
ϕ	-0.798***	-0.807***	-0.874***	-0.896***
	(0.038)	(0.043)	(0.042)	(0.04)
Short-Run Coefficients				
$\triangle$ Growth (t-1)	-0.056	-0.035	-0.014	0.029
	(0.03)	(0.03)	(0.027)	(0.02)
$\triangle^2$ Resource Windfall	-0.280	-0.511		-2.414***
	(0.755)	(0.623)		(0.551)
$\triangle$ Government Size		-1.342***	-1.568***	-1.520***
		(0.171)	(0.175)	(0.174)
$\triangle$ Polity 2	-0.047***	-0.062***	-0.041***	-0.035***
	(0.017)	(0.017)	(0.014)	(0.013)
$\triangle$ Polity 2 x Windfall	-0.047	-0.059***		
	(0.032)	(0.032)		
$\triangle$ Polity2 x Government size			0.000	0.000
			(0.001)	(0.001)
Intercept	-0.006	-0.007	-0.009	-0.007
	(0.009)	(0.007)	(0.009)	(0.005)
SBIC	4144	4149	4110	4271
No. Of Countries	94	94	94	94
No. of Observations	3290	3290	3290	3290

Note: The dependent variable is NRGDP per capita growth. Stars indicate the significance level, as usual. The lag order for the ARDL was chosen using SBIC. Only coefficients associated with the first lags are presented in this table to conserve space.

Appendix A

Mortgage and Banking Data

A.1 HMDA Data

We use a comprehensive sample of mortgage applications and originations that have been collected by the Federal Reserve under the provision of the Home Mortgage Disclosure Act (HMDA). Under this provision, the vast majority of mortgage lenders are required to report data about their house-related lending activity.[1] HMDA data covered around 95% of all mortgage originations in 2005 (see e.g. Dell'Ariccia et al., 2008), and has a better coverage within MSAs due to stricter reporting requirements in these areas.

The HMDA data provide information on the year of the application (the data is available on an annual basis), the amount of the loan, the lender's decision, and the income of the applicant. The data also provide information on the gender and race of the applicant, as well as other information on the census tract of the property such as the median income and share of minority households.

[1]Lenders are required to report if they meet certain criteria related to size, geographical location, the extent of housing-related lending activity, and regulatory status. Regarding size, a depository institution is subject to HMDA reporting requirements if it has assets of $34 million or more, as of December 31, 2004. In 2010, the Board raised this threshold to $40 million. For a non depository institution, total assets must exceed $10 million, as of December 31 of the preceding year, taking into account the assets of any parent corporation. Regarding the geographical location, lenders must report if they have offices in a Metropolitan Statistical Area (MSA) or if they are non-depository institutions with lending activities on properties located in an MSA. Lenders must also report if they are depository institutions with at least one home purchase loan or if they are non-depository institutions and they originate 100 or more home-purchase and refinancing loans. As for the regulatory status, lenders must report if they are non-depository institutions or if they are depository institutions that are federally insured or regulated.

The raw HMDA data in our sample covering the sample period 2003 to 2008 period contain around 190 million applications. Of these, we keep only loans that are either approved or denied (Action code 1,2, and 3). We further restrict our loans types to be conventional (we exclude Federal Housing Agency, Veterans Administration, Farm Service Agency or Rural Housing Service), the property types to be one to four-family, the loan purpose to be home purchase only (excluding home improvement, refinancing purposes), and the occupancy status to be owner-occupied as principal dwelling. This leaves us with 34 million applications.

We distinguish between the type of lenders based on information available from HMDA on their regulatory agencies. Depository institutions and their affiliates (which we refer to as banks) are listed under the following agencies: Federal Deposit Insurance Corporation, Federal Reserve System, Office of the Comptroller of the Currency, Office of Thrift and Supervision, and National Credit Union Administration. Non-bank mortgage originators (independents) are listed under the Department of Housing and Urban Development.

We restrict our study to mortgage originations in counties situated in an Metropolitan Statistical Area (MSA) for which HMDA has better coverage and data on house prices and on house supply elasticity are available. This leaves us with 773 counties. These counties cover around 80% of total mortgage originations in HMDA in 2005.

We aggregate our data on mortgage originations at the county level which gives us the volume of loans originated in a county during a year. We can also distinguish between the originators. We calculate, in a county, the percentage of loans originated by independent mortgage companies and by banks.

HMDA provides information on the securitization process. Lenders are asked to report whether the originated mortgage was sold to a third party during the same calendar year in which it was originated. HMDA defines 8 types of purchasers. In the benchmark exercise we follow the approach of Mian and Sufi (2009a) and define securitization as being "private securitization", i.e., loans sold to private securitization pools, or sold to life insurance companies, credit unions, mortgage banks, and finance companies. We also supplement this measure with several other measures of securitization such as the share of of GSE securitization, as well as the share of non-securitized loans.

With the originated loan volume information, HMDA data allows us to construct measures on credit growth, bank competition (Herfindahl index) and geographic diversification. More specifically, for Herfindahl index we sum for each county the square of the percentage share of originated loans of the top 15 , 30, and 50 mortgage originators to create three respective competition indicators. The Herfindahl index ranges from near 0 for a county that has much bank competition to 1 for a county that has only bank, i.e. no competition.

For lender geographic diversification, we follow closely the method used in Loutskina and Strahan (2011). The variable measures the extent to which a lender concentrates its lending within a Metropolitan Statistical Area (MSA). The measure equals the sum of squared shares of loans made by a lender in each of the MSAs in which it operates, where the shares are based on originated loans. The geographic diversification measure ranges from near 0 for lenders operating cross most U.S. MSAs to 1 for lenders operating in a single MSA. We construct our county level index by taking weighted average of the indexes of geographical diversification for each lender in the region, weighted by their share of originated loans.

A.2 Inter-University Consortium for Political and Social Research

Inter-University Consortium for Political and Social Research (ICPSR), an affiliated institute of the University of Michigan, maintains a database on demographic and economic characteristics of U.S. counties. The sources of the database include the Bureau of the Census, the Bureau of Economic Analysis, the Bureau of Labor Statistics, as well as other sources (website: http://www.icpsr.umich.edu/icpsrweb/ICPSR/). For our county level analysis, we include the following economic and demographic characteristics: per capita personal income in 2005 ($CA0N0030\_05$), Percent of Black resident population in 2005 (PctBlack05), percent of Hispanic resident population in 2005 (PctH05), and average net international migration from 2001 to 2005 (IntlMig 01,02,03,04,05). We also compute the per capita income growth between 2003 and 2005 using annual growth measures from the U.S. Bureau of Economic Analysis (BEA).

A.3 Federal Housing Finance Agency: House Prices

House Price Index (HPI) is a quarterly data published by the U.S. Federal Housing Finance Agency, an entity created in 2008 from the merging of the U.S. Office of Federal Housing Enterprise Oversight and the U.S. Federal Housing Board. As a weighted, repeated sales index, the HPI measures average price changes in repeat sales or refinancing on single family properties with mortgages that have been purchased or securitized by Fannie Mae or Freddie Mac. The HPI includes indexes for all nine Census Divisions, the 50 states and the District of Columbia, and every Metropolitan Statistical Area (MSA) in the U.S., excluding Puerto Rico. Compared to S&P/Case-Shiller indexes, the HPI offers a more comprehensive coverage of housing price trends in the U.S. metropolitan areas. We use the HPI data at MSA level (most disaggregated level that is available for this variable) and compute the year on year changes as a measure of house price growth in a given MSA.

A.4 Housing Supply Elasticity

Saiz (2010) provides a measure of housing supply elasticity at the MSA level computed based on topological factors. These factors are exogenous to house market conditions and population growth and are computed using both water and land slope constraint information obtained using Geographic Information System (GIS), United State Geographic Service (USGS), and USGS Digital Elevation Model (DEM). The data covers 269 Metropolitan areas using the 1999 county-based MSA or NECMA definitions. The geographic data is calculated using the principal city in the MSA, i.e., the first one on the list of a MSA name.

A.5 Call Report data

All regulated depository institutions in the United States are required to file their financial information periodically with their respective regulators. Reports of Condition and Income data are a widely used source of timely and accurate financial data regarding banks' balance sheets and the results of their operations. Specifically, every national bank, state member bank and insured non-member Bank is required by the Federal Financial Institutions Examination Council (FFIEC) to file a Call Report as of the close of business on the last day of each calendar quarter. The specific reporting requirements depend upon the size of the bank and whether or not it has any foreign offices. The availability of agency specific bank IDs in HMDA (Federal Reserve RSSD-ID, FDIC Certificate Number, and OCC Charter Number) allows us to match HMDA lenders that are depository institutions with their financials from the Call report. For savings institutions, i.e. depository institutions regulated by the OTS, we use the balance sheet information from Statistics on Depository Institutions (SDI), available from the FDIC, and match them with HMDA using OTS docket number.[2] We use the financial information to compute a core deposit ratio as total deposit minus time deposit over \$100,000 divided by total asset (see e.g. Berlin and Mester, 1999). Naturally, for non-depository institutions we assign a zero for this ratio. We then rank lenders based on their core deposit (CD) and pick two thresholds for CD, 0.51 and 0.61, which correspond to the lower quartile and median values. We then compute the percentage share of banks in a county that is above these thresholds.

[2] http://www2.fdic.gov/sdi/

Appendix B

The Full model for Chapter 2

B.1 Transcribing the shares into the real values

The original budget constraint in Chapter 2 is written as:

$$\begin{aligned} & C_t^T + Q_t^N C_t^N + A_t^H P_t^T + A_t^F \hat{P}_t^T + Q_t^N A_t^N P_t^N + B_t P_t^B \\ \leq \; & A_{t-1}^H (P_t^T + D_t^T) + A_{t-1}^F (\hat{P}_t^T + \hat{D}_t^T) + Q_t^N A_{t-1}^N (P_t^N + D_t^N) + B_{t-1} \end{aligned}$$

imposing the market clearing condition for the nontraded equities, $A_t^N = 1, \forall t$ the BC may be written as

$$\begin{aligned} & C_t^T + Q_t^N C_t^N + A_t^H P_t^T + A_t^F \hat{P}_t^T + B_t P_t^B \\ \leq \; & A_{t-1}^H (P_t^T + D_t^T) + A_{t-1}^F (\hat{P}_t^T + \hat{D}_t^T) + Q_t^N D_t^N + B_{t-1} \end{aligned}$$

replacing A_t^H by $(\alpha_t^H + P_t^T)/P_t^T$, A_t^F by $\alpha_t^F / \hat{P}_t^T$, and B_t by α_t^B / P_t^B we can get

$$\alpha_t^H + \alpha_t^F + \alpha_t^B \leq \alpha_{t-1}^H R_t^H + \alpha_{t-1}^F R_t^F + \alpha_{t-1}^B R_t + D_t^T + Q_t^N D_t^N - C_t^T - Q_t^N C_t^N \quad \text{(B.1)}$$

The equation (B.1) presents the budget constraints in a form that is suitable for the DS method.

B.2 Equations for the DS solution method

Budget constraint for the domestic households

$$W_t = W_{t-1} R_t + D_t^T + D_t^N Q_t^N - C_t^T - C_t^N Q_t^N + \xi_{t+1}$$

where ξ_t is the total log excess return.

Exogenous shocks

$$
\begin{aligned}
\ln Z_{t+1}^T &= \rho^T \ln Z_t^T + e_t^T \\
\ln \hat{Z}_{t+1}^T &= \rho^T \ln \hat{Z}_t^T + \hat{e}_t^T \\
\ln Z_{t+1}^N &= \rho^N \ln Z_t^N + e_t^N \\
\ln \hat{Z}_{t+1}^N &= \rho^N \ln \hat{Z}_t^N + \hat{e}_t^N
\end{aligned}
$$

Euler equations

$$
\begin{aligned}
M_{t+1} R_{t+1} &= \hat{M}_{t+1} R_{t+1} \\
P_t^B &= M_{t+1} R_{t+1} \\
P_t^T &= M_{t+1} R_{t+1}^H \\
\hat{P}_t^T &= M_{t+1} R_{t+1}^F \\
P_t^N Q_t^N &= M_{t+1} R_{t+1}^N \\
\hat{P}_t^N \hat{Q}_t^N &= \hat{M}_{t+1} \hat{R}_{t+1}^N
\end{aligned}
$$

Gross payoffs and returns to assets

$$\begin{aligned}
F_t^B &= 1 \\
F_t^T &= (P_t^T + D_t^T) \\
F_t^F &= (\hat{P}_t^T + \hat{D}_t^T) \\
F_t^N &= (P_t^N + D_t^N)Q_t^N \\
\hat{F}_t^N &= (\hat{P}_t^N + \hat{D}_t^N)\hat{Q}_t^N \\
R_t &= F_t^B / P_{Lt}^B \\
R_t^H &= F_t^H / P_{Lt}^H \\
R_t^F &= F_t^F / P_{Lt}^F \\
R_t^N &= F_t^N / (P_{Lt}^N Q_{Lt}^N) \\
\hat{R}_t^N &= \hat{F}_t^N / (\hat{P}_{Lt}^N \hat{Q}_{Lt}^N)
\end{aligned}$$

Relative goods prices

$$\begin{aligned}
Q_t^N &= (\mu_N/\mu_T)^{(1-\phi)}(C_t^N/C_t^T)^{(\phi-1)} \\
\hat{Q}_t^N &= (\mu_N/\mu_T)^{(1-\phi)}(\hat{C}_t^N/\hat{C}_t^T)^{(\phi-1)}
\end{aligned}$$

Firm optimality conditions

$$\begin{aligned}
1 &= M_{t+1}(\theta Z_{t+1}^T K_{t+1}^{\theta-1} + (1-\delta)) \\
1 &= \hat{M}_{t+1}(\theta \hat{Z}_{t+1}^T \hat{K}_{t+1}^{\theta-1} + (1-\delta)) \\
Y_t &= K_{t+1} - (1-\delta)K_t + D_t^T \\
\hat{Y}_t &= \hat{K}_{t+1} - (1-\delta)\hat{K}_t + \hat{D}_t^T
\end{aligned}$$

Production and market clearing

$$
\begin{aligned}
Y_t &= Z_t^T K_t^\theta \\
\hat{Y}_t &= \hat{Z}_t^T \hat{K}_t^\theta \\
D_t^N &= \eta Z_t^N \\
\hat{D}_t^N &= \eta \hat{Z}_t^N \\
C_t^N &= D_t^N \\
\hat{C}_t^N &= D_t^N
\end{aligned}
$$

Dummy variables necessary for the solution

$$
\begin{aligned}
&P_{Lt+1}^T = P_t^T, \qquad \hat{P}_{Lt+1}^T = PT2, \qquad P_{Lt+1}^N = P_t^N, \qquad \hat{P}_{Lt+1}^N = \hat{P}_t^N \\
&P_{Lt+1}^B = P_t^B, \qquad Q_{Lt+1}^N = Q_t^N, \qquad \hat{Q}_{Lt+1}^N = \hat{Q}_t^N \\
&\xi_t^1 = \ln R_t^H - \ln R_t, \qquad \xi_t^2 = \ln R_t^F - \ln R_t \\
&C_t^D = C_t^T - \hat{C}_t^T
\end{aligned}
$$

Appendix C

Data sources and description for Chapter 3

Table C.1: Sources for data in Chapter 3

Variable Description	Source	Release Date
Region	World Bank	2011
Income Group	World Bank	2011
Depletion of Forest resources	Hamilton and Ruta (2008)	2011
Depletion of Mineral resources	Hamilton and Ruta (2008)	2011
Depletion of Energy resources	Hamilton and Ruta (2008)	2011
Depreciation of capital	Hamilton and Ruta (2008)	2011
Population	Penn World Tables 6.3	2009
Purchasing Power Parity Index	Penn World Tables 6.3	2009
Real GDP per Capita	Penn World Tables 6.3	2009
Government Share of Real GDP	Penn World Tables 6.3	2009
Price Level of GDP	Penn World Tables 6.3	2009
Openness in Current Prices	Penn World Tables 6.3	2009
Corruption index (from ICRG)	International Country Risk Guide	2011
Economic Risk index	International Country Risk Guide	2011
External Conflict Risk	International Country Risk Guide	2011

Continued on next page

Table C.1 – continued from previous page

Description	Source	Release
Financial risk Rating	International Country Risk Guide	2011
Internal Conflict Risk	International Country Risk Guide	2011
Law and Order Index	International Country Risk Guide	2011
Political Risk Index	International Country Risk Guide	2011
Democracy Index	Polity IV Project	2009
Autocracy Index	Polity IV Project	2009
Polity Index	Polity IV Project	2009
Polity 2 index	Polity IV Project	2009
Real Effective Exchange Rate	IMF INS databse	2010
Current account Balance	WEO database	2010
Consumer Pirce Index	IMF INS databse	2010
Exchange Rate, Nominal	IMF INS databse	2010
Price of copper	UNCTAD	2011
Price of rice	UNCTAD	2011
Price of natural rubber	UNCTAD	2011
Price of tobacco	UNCTAD	2011
Price of sugar	UNCTAD	2011
Price of gas	EIA	2011
Price of tea	WEO global assumption	2011
Price of maize	WEO global assumption	2011
Price of nickel	UNCTAD	2011
Price of gold	WEO global assumption	2011

Continued on next page

Table C.1 – continued from previous page

Description	Source	Release
Price of wheat	UNCTAD	2011
Price of zinc	UNCTAD	2011
Price of tin	UNCTAD	2011
Price of petroleum	UNCTAD	2011
Price of wool	WEO global assumption	2011
Price of iron ore	UNCTAD	2011
Price of aluminium	UNCTAD	2011
Price of beef	UNCTAD	2011
Price of coffee	UNCTAD	2011
Price of cocoa	UNCTAD	2011
Price of cotton	WEO global assumption	2011
Export Value of copper	NBER-UN Trade Data, 1962-2000	2005
Export Value of rice	NBER-UN Trade Data, 1962-2000	2005
Export Value of natural rubber	NBER-UN Trade Data, 1962-2000	2005
Export Value of tobacco	NBER-UN Trade Data, 1962-2000	2005
Export Value of sugar	NBER-UN Trade Data, 1962-2000	2005
Export Value of gas	NBER-UN Trade Data, 1962-2000	2005
Export Value of tea	NBER-UN Trade Data, 1962-2000	2005
Export Value of maize	NBER-UN Trade Data, 1962-2000	2005
Export Value of nickel	NBER-UN Trade Data, 1962-2000	2005
Export Value of gold	NBER-UN Trade Data, 1962-2000	2005
Export Value of wheat	NBER-UN Trade Data, 1962-2000	2005

Continued on next page

Table C.1 – continued from previous page

Description	Source	Release
Export Value of zinc	NBER-UN Trade Data, 1962-2000	2005
Export Value of tin	NBER-UN Trade Data, 1962-2000	2005
Export Value of petroleum	NBER-UN Trade Data, 1962-2000	2005
Export Value of wool	NBER-UN Trade Data, 1962-2000	2005
Export Value of iron ore	NBER-UN Trade Data, 1962-2000	2005
Export Value of aluminium	NBER-UN Trade Data, 1962-2000	2005
Export Value of beef	NBER-UN Trade Data, 1962-2000	2005
Export Value of coffee	NBER-UN Trade Data, 1962-2000	2005
Export Value of cocoa	NBER-UN Trade Data, 1962-2000	2005
Export Value of cotton	NBER-UN Trade Data, 1962-2000	2005
Import value of cotton	NBER-UN Trade Data, 1962-2000	2005
Import value of iron and steel	NBER-UN Trade Data, 1962-2000	2005
Import value of sugar	NBER-UN Trade Data, 1962-2000	2005
Import value of timber	NBER-UN Trade Data, 1962-2000	2005
Import value of tin	NBER-UN Trade Data, 1962-2000	2005
Import value of wheat	NBER-UN Trade Data, 1962-2000	2005
Import value of zinc	NBER-UN Trade Data, 1962-2000	2005
Import value of cocoa	NBER-UN Trade Data, 1962-2000	2005
Import value of coffee	NBER-UN Trade Data, 1962-2000	2005
Import value of copper	NBER-UN Trade Data, 1962-2000	2005
Import value of petroleum	NBER-UN Trade Data, 1962-2000	2005
Import value of tea	NBER-UN Trade Data, 1962-2000	2005

Continued on next page

Table C.1 – continued from previous page

Description	Source	Release
Import value of wool	NBER-UN Trade Data, 1962-2000	2005
Import value of natural rubber	NBER-UN Trade Data, 1962-2000	2005
Import value of rice	NBER-UN Trade Data, 1962-2000	2005
Import value of aluminium	NBER-UN Trade Data, 1962-2000	2005
Import value of precious stones	NBER-UN Trade Data, 1962-2000	2005
Import value of beef	NBER-UN Trade Data, 1962-2000	2005
Import value of coal	NBER-UN Trade Data, 1962-2000	2005
Import value of gas	NBER-UN Trade Data, 1962-2000	2005
Import value of nickel	NBER-UN Trade Data, 1962-2000	2005
Import value of maize	NBER-UN Trade Data, 1962-2000	2005
Import value of iron ore	NBER-UN Trade Data, 1962-2000	2005
Import value of tobacco	NBER-UN Trade Data, 1962-2000	2005
Import value of gold	NBER-UN Trade Data, 1962-2000	2005

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