

Bounded Rationality in Financial Markets

by

Edder Fernando Martínez Lazo

A dissertation accepted and approved in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
in Economics

Dissertation Committee:

David Evans, Chair

Shankha Chakraborty, Core Member

George Evans, Core Member

Keaton Miller, Core Member

Brandon Julio, Institutional Representative

University of Oregon

June 2025

© 2025 Edder Fernando Martínez Lazo
This work is openly licensed via

CC BY 4.0



DISSERTATION ABSTRACT

Edder Fernando Martínez Lazo

Doctor of Philosophy in Economics

Title: Bounded Rationality in Financial Markets

Agents' beliefs and expectations about financial markets affect resource allocation, regulatory effectiveness, and monetary policy. This dissertation contributes to the literature by introducing a novel perspective on the behavioral aspects of learning and expectation formation in financial markets. While prior studies have largely focused on alternatives to the Rational Expectations paradigm and household finance, my work extends that body of research by presenting new empirical evidence and theoretical insights, particularly regarding adaptive learning in banking and saving motives, that reveal novel mechanisms through which beliefs shape macroeconomic outcomes.

The second chapter examines expectation formation in financial intermediation with biased models due to regularization methods and its relationship with monetary policy. I provide empirical evidence on bounded rationality in bank forecasting by analyzing the timing of Dodd-Frank Act stress test scenarios, which reveals systematic revisions in the pricing of bank securities around the announcement date. Since these scenarios, constructed from professional forecaster surveys, are not designed to predict future shocks, I argue that market participants do not fully price available information beforehand and tend to be overoptimistic about the economic outlook of banks and their market value. To explore macroeconomic implications, I integrate adaptive learning into a New Keynesian model where agents estimate linear models and nowcast bankers' returns while facing multicollinearity issues and the bias-variance

trade-off inherent in regression regularization methods. The findings indicate that post-crisis regulatory reforms increased moral hazard and the equity premium in banking, while the biased forecast model helps explain how bank stock prices reflect future returns. In this framework, the bias-variance trade-off, as a form of bounded rationality in a data-rich environment, dampens banking sector responses, leading to an overestimation of franchise value when facing negative shocks. This behavioral mechanism, in turn, weakens expansionary monetary policy by reducing the standard intertemporal substitution effect. This chapter contributes to the literature by offering empirical evidence on bounded rationality in banking and introducing the concept of biased perception equilibrium as a form of bounded rationality in a data-rich environment with estimation challenges.

The third chapter investigates how capital requirements affect financial inclusion, using Mexico's implementation of Basel III standards in 2013 as a case study. These international regulations were announced in 2010, and following extensive internal debate, Mexican regulators opted for a fully phased-in approach. I argue that anticipation and uncertainty surrounding these regulatory reforms prompted banks to adjust their capital holdings, influencing credit volume and local lending markets. To localize the bank-level changes due to the regulatory policy, I estimate a bank-level credit shock driven by changes in capital ratios, finding that qualitatively, large and small banks changed their lending supply in opposite directions. Utilizing a shift-share design, I compute a municipality-level credit shock, and find that positive credit shocks reduce the number of originated loans and loan sizes, while increasing participation in both retail funding markets and informal credit products. Since the average shock may also capture the predominant type of bank in the locality, these

findings highlight the roles of bank competition and regulatory certainty in enhancing financial inclusion while highlighting directions for policy reform.

The final chapter examines the impact of subjective expectations of stock returns on wealth distribution. I provide empirical evidence linking shifts in investor beliefs to changes in wealth distribution, particularly during the early 2000s. By leveraging externally identified shocks and investor surveys, I document the responsiveness of expectations to new information and establish their medium-run effects on the wealth distribution. Moreover, I introduce a novel perspective on the bequest motive, supported by empirical evidence showing a strong correlation between bequest intentions and stock return expectations. To analyze the distributional impact of belief shifts, I propose and calibrate a simple two-period Overlapping Generations model. This framework can be extended to a multiperiod setting to examine belief formation throughout the life cycle and its role in reinforcing intergenerational links that shape wealth distribution.

CURRICULUM VITAE

NAME OF AUTHOR: Edder Fernando Martínez Lazo

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene, OR, USA
Universidad Nacional Autónoma de Honduras, Honduras
Universidad Tecnológica Centroamericana, Honduras

DEGREES AWARDED:

Doctor of Philosophy, Economics, 2025, University of Oregon
Master, Economics and Development, 2012, Universidad Nacional Autónoma de Honduras
Bachelor, Industrial Engineering, 2008, Universidad Tecnológica Centroamericana
Master of Science, Economics, 2020, Purdue University (Online)
Bachelor in Arts, Mathematical Sciences, 2020, University of Illinois at Springfield (Online)

AREAS OF SPECIAL INTEREST:

Macroeconomics
Finance
Development Economics

PROFESSIONAL EXPERIENCE:

Asset and Liabilities Management (ALM) Analyst, Central American Bank, 2018-2019
Head of the Technical and Actuarial Risks Department, Comisión Nacional de Bancos y Seguros, 2016-2018
Actuarial Coordinator, Comisión Nacional de Bancos y Seguros, 2015-2016
Actuarial Analyst / Actuarial Coordinator, Comisión Nacional de Bancos y Seguros, 2012-2015

GRANTS, AWARDS AND HONORS:

Kleinsorge Fellowship Award, University of Oregon, 2024
Consumer Protection Grant, University of Oregon, 2023
Graduate School Promising Scholar, University of Oregon, 2020
Excellence in Economics Scholarship , Purdue University, 2017
Research Scholarship, Universidad Nacional Autónoma de Honduras, 2010-2011

PUBLICATIONS:

K. Nassar, E. Martínez, A. Pineda. (2017). Determinants of Banks' Net Interest Margins in Honduras *Journal of Banking and Financial Economics*, 100, 1/2017.

ACKNOWLEDGEMENTS

I am deeply grateful to the members of my committee. To my chair, David Evans, whose exceptional mentorship blended with brilliant expertise, patient guidance, and encouragement has been crucial in shaping my best features as an economist. To Shankha Chakraborty, whose timely and thoughtful advice broadened my perspectives and helped me navigate challenges, especially in my second year. To George Evans, whose pioneering work, invaluable insights, and openness to listen and guide students have consistently pointed me in the right direction. To Keaton Miller, whose strong commitment to student development and versatility as an economist and advisor have strengthened my growth as a macroeconomist. To Brandon Julio, for his kind support, engagement, and genuine interest in my work. I also extend my sincerest gratitude to Alfredo Burlando for his continued support and guidance during my third year. I will always carry with me the inspiring scholarship and example of everyone listed here.

Finally, I want to thank my wife, Heidy, whose love, support, and companionship made this journey especially meaningful. To my parents, siblings, and family, for their unwavering love, encouragement, and belief in me.

Any remaining errors are entirely my own.

To my beloved parents, Enma and Arturo, my love Heidi, and to all my family and friends. . . .

TABLE OF CONTENTS

Chapter		Page
I.	INTRODUCTION	19
II.	BOUNDED RATIONALITY IN FINANCIAL INTERMEDIATION AND MONETARY POLICY	23
2.1.	Introduction	23
2.2.	Background Information and Data	29
2.3.	Empirical Analysis	34
2.3.1.	Forecast and Actual Earnings of Banks	34
2.3.2.	Price of Bank Securities and the Dodd-Frank Act Stress Scenarios	35
2.4.	Model	45
2.4.1.	Description of the benchmark model	45
2.4.2.	Financial Intermediaries	46
2.5.	Bounded optimality: Environment	48
2.5.1.	Nowcasts and bank lending	49
2.5.2.	Retrieving the ex-post returns	49
2.5.3.	Biased Perceptions Equilibrium (BPE)	50
2.5.3.1.	Setup and model solution	51
2.5.3.2.	Mapping from beliefs to implied forecasts	52
2.5.3.3.	Biased Perceptions Equilibrium (BPE)	52
2.5.4.	Recursive formulation and Expectational Stability	53
2.6.	Quantitative experiments	56
2.6.1.	Structural change: Agency problems	56
2.6.2.	BPE and Monetary Policy	60

Chapter	Page
2.7. Discussion and Future Research	62
2.8. Conclusion	66
III. CAPITAL REQUIREMENTS AND FINANCIAL INCLUSION: THE IMPLEMENTATION OF BASEL III IN MEXICO	68
3.1. Introduction	68
3.2. Background information	73
3.2.1. The Basel III Accords	73
3.2.2. Mexican adoption of Basel III	74
3.3. The Mexican Banking Industry	76
3.3.1. Key facts	76
3.3.2. Evolution of Regulatory Capital Ratios	79
3.3.3. Integrating the descriptive evidence and research design	84
3.4. Methodology and Data	84
3.4.1. Data	84
3.4.2. Methodology	85
3.4.3. Changes in capital ratios as Credit shocks	87
3.4.4. Credit Shocks and Financial Access	90
3.4.4.1. Validity of the Research Design	93
3.5. Results	96
3.5.1. Municipality-level outcomes	96
3.5.1.1. Lending at the municipality level by poverty rate	100
3.5.2. Financial inclusion at the individual level	103
3.6. Discussion of results	104
3.7. Conclusion	108

Chapter	Page
IV. DISTRIBUTIONAL EFFECTS OF BELIEF CHANGES ABOUT STOCK RETURNS	109
4.1. Introduction	109
4.2. Data	114
4.2.1. Data mapping to the empirical analysis and model	116
4.3. Empirical Facts and Analysis	116
4.3.1. Descriptive analysis	116
4.3.2. Professional forecasters and Investors' beliefs	118
4.3.3. Stock holdings, bequest motive, and beliefs	121
4.4. Empirical analysis	122
4.4.1. Investor optimism and new information	124
4.4.2. Wealth distribution and information shocks	124
4.4.3. Subjective expectations on stock returns and the bequest motive	125
4.5. Two-period OLG model	127
4.6. Discussion and Future Research	131
APPENDICES	
A. CHAPTER II APPENDIX	133
A.1. GK (2011) model	133
A.1.1. Households	133
A.1.2. Banks maximization problem	134
A.1.3. Firms	135
A.1.3.1. Intermediate good firms	135
A.1.3.2. Capital producing firms	136
A.1.3.3. Retail firms	136

Chapter	Page
A.1.4. Resource constraint and government policy	136
A.1.4.1. Credit policy	137
A.2. Model: Rational Expectations	138
A.3. Steady state of the model	140
A.3.1. Steady-state	140
A.4. Medium-run calibration	142
A.4.1. Expected Premium	142
A.4.2. Leverage Ratio	142
A.5. Calibration results	144
A.6. Structural Change: Impulse Response Functions	145
A.7. Data Appendix	148
A.7.1. Compustat Bank	148
A.7.2. Monetary shocks	148
B. CHAPTER III APPENDIX	149
B.1. Data Appendix	149
B.1.1. Bank data	149
B.1.2. Financial survey data	150
B.2. Descriptive evidence	151
B.2.1. Markups, returns, and regulatory capital	151
B.2.2. Reallocation of credit at the bank level	154
B.2.3. Number of serviced municipalities and states	156
B.2.4. Consumer loans market	157
B.2.5. Average loan size and bank size	159
B.3. Components of the Regulatory Capital Ratio	163
B.4. Tables	165

Chapter	Page
C. CHAPTER IV APPENDIX	171
C.1. Ordered Logistic Regressions: Expected equity premium	171
C.2. Local projections	173
C.3. Logistic Regressions	175
C.4. Regressions of the Self-reported probability of leaving bequests . . .	177
C.5. Linear approximation of the bequest motive	178
REFERENCES CITED	180

LIST OF FIGURES

Figure		Page
1.	Median Price-to-Book ratio and 1-yr ahead ROE of US banks	34
2.	Binned Scatterplot: Forecasts and Actual Price-to-Earnings Ratio of Banks	35
3.	Event Study: Bank Bonds Market	41
4.	Event Study: Credit Default Swaps market for bank securities	44
5.	Response to monetary easing of 25bps	61
6.	Financial vulnerabilities and risk taking	61
7.	Monetary Policy and Ridge Adjustments	62
8.	Capital Ratios by Bank Size	80
9.	Event Study: Regulatory Capital Ratio	82
10.	Predicted shock and municipality characteristics	96
11.	Total originated loans, by poverty rate	102
12.	Lending rates on personal loans.	102
13.	Index of Sentiment Levels, Baker and Wurgler (2006)	117
14.	Wealth and Stock holdings (Share of aggregate volume). Fed's Distributional Finance Accounts.	119
15.	Evolution of long-run mean expectations, SPF Philadelphia Fed.	120
16.	Mean beliefs by type, UBS/Gallup Survey	121
17.	Percent of gross assets, all decedents	122
18.	Binned scatterplots: Bequest Expectations and Stock return expectations	126
A.19.	Financial measures: Leverage Ratio	142
A.20.	Responses to structural change	145

Figure	Page
A.21.Responses to structural change	146
A.22.Responses to structural change	147
B.2.1Markups, Returns, and Regulatory Capital by Bank type	152
B.2.2Participation of Commercial loans and Consumer loans, % of Total loans	155
B.2.3Consumer loans, by type. Average share	156
B.2.4Number of municipalities and state served by each bank	157
B.2.5Event Studies: Personal loans and Payroll loans	158
B.2.6Event Studies: Lending rates Personal loans and Payroll loans	159
B.2.7Reduced-form estimates: Coefficient on $\mathbb{1}_{year} \times GAPB_{b2010} \times Top5$	161
B.3.1Components of the Regulatory Capital Ratio	164
C.2.1Central Bank Information shock	173
C.2.2Monetary policy shock	174

LIST OF TABLES

Table	Page
1. Release dates of the DFAST supervisory scenarios	32
2. Descriptive Statistics	33
3. Bank Stock Returns: 15 Days Before & After DFAST Stress Scenarios Release	39
4. Bond shocks: 15-day window	41
5. CDS residuals regressions	44
6. Timing of the model:	48
7. Model Calibration: Standard deviation of exogenous processes	56
8. Target Medium-Run moments	57
9. Structural change: summary of results	59
10. Number of branches, municipality level	78
11. Regulatory Capital Ratio, 2007-2015	83
12. Biennial credit shock as a function of the initial change in capital ratio	93
13. Municipality characteristics	95
14. (log) Number of originated personal loans at the municipality level (2011-2019)	97
15. Lending rate, personal loans	98
16. (log) Number of originated payroll loans at the municipality level	99
17. Lending rate, payroll loans	99
18. Change in saving accounts. log. differences.	100
19. Change in debit cards. log. differences.	100
20. Municipality characteristics, 2010	101

Table	Page
21. Ordered logistic regressions: Expected Performance of Stock Market . . .	125
22. Aggregate Moments of the Model	129
23. Model moments by agent type: Base and alternative	130
24. Capital (stock) holdings: Base and alternative	131
A.25 Mean risk premium, relative to 10-yr US Treas. Bond.	142
A.26 Bank-level estimated changes (relative to pre-2008)	143
A.27 Structural change: Results	144
B.4.1 Respondent has credit, State level Level	165
B.4.2 Respondent has personal loan	166
B.4.3 Respondent has payroll loan	167
B.4.4 Respondent has saving account	168
B.4.5 Respondent had loan application rejected	169
B.4.6 Respondent has used informal credit products	170
C.1.1 Implied expected equity premium: Pessimistic agents	171
C.1.2 Implied expected equity premium: Neither	172
C.1.3 Implied expected equity premium: Optimistic	172
C.3.4 Investment Target - Next 12 months	175
C.3.5 Investment Target - Next 5 years	176
C.4.6 Bequest Expectations and Stock Return Expectations	177

CHAPTER I

INTRODUCTION

Expectations are fundamental to studying and understanding economic theory and policy. Economic agents face multiple forward-looking trade-offs and value their available choices based on their expectations. Herbert Simon, in his seminal work "Models of Man, Social and Rational" (Simon, 1957), laid the foundation for alternatives to the rational utility-maximizing person. Simon introduced the principle of bounded rationality to characterize decision-making processes in which individuals, constrained by "*...knowledge, foresight, and time...*" (Simon, 1957, p. 199), construct simplified models of reality and behave optimally within these constraints. Interestingly, four years later, John Muth (1961) introduced the Rational Expectations (RE) hypothesis which asserts that decision makers make optimal use of available information when forecasting, and the hypothesis remains the benchmark characterization of belief formation in economics. The RE hypothesis assumes that decision makers have access to all relevant information and produce unbiased forecasts. This dissertation aims to contribute to this field by examining the role of bounded rationality in financial markets by introducing a novel focus of bounded rationality in banking and wealth distribution.

While extensive research has demonstrated that the RE hypothesis does not hold in financial markets (see, e.g., Adam, Marcet, and Beutel 2017; M. Brunnermeier et al. 2021; d'Haultfoeuille, Gaillac, and Maurel 2021; Gomes, Haliassos, and Ramadorai 2021; Kézdi and Willis 2011), Chapter II provides an introduction to bounded rationality in financial intermediation, specifically banking. Agents' beliefs about financial intermediaries shape resource allocation, regulatory effectiveness, and monetary policy. Bounded rationality, in particular, can introduce

significant macroeconomic consequences. I investigate whether market participants in financial intermediation exhibit bounded rationality, finding systematic overpricing of banks—likely driven by uncertainty surrounding worst-case scenarios. To explore further macroeconomic implications, I integrate adaptive learning into a New Keynesian model where agents estimate linear models and nowcast bankers’ returns while facing a bias-variance trade-off. My findings suggest that post-crisis regulatory reforms increased both moral hazard and the equity premium in banking while adaptive learning explains the informativeness of franchise value regarding future returns. The bias-variance trade-off, as a form of bounded rationality, leads to attenuated banking responses, resulting in the overestimation of franchise value after adverse shocks to the banks’ value. This behavioral tendency reduces the effectiveness of expansionary monetary policy, as higher perceived returns on net worth mitigate standard intertemporal substitution.

In Chapter III, I examine the empirical implications of regulatory changes and financial access. I analyze the link between capital requirements and financial inclusion by studying Mexico’s 2013 implementation of Basel III standards. Announced in 2010, the regulations underwent a staggered rollout debate before Mexican regulators opted for full and immediate adoption. Key findings include: (i) Mexican banks exceeded fully phased-in capital requirements, yet their capital ratios declined between 2010 and 2012, and (ii) markups decreased in the post-reform period. Exploiting exogenous variation in local lending markets, I examine credit volume shocks as a transmission mechanism of bank equity adjustments, allowing for the construction of a localized exposure measure. Using a shift-share design similar to Greenstone, Mas, and Nguyen (2020), I decompose credit volume changes at the bank-municipality level and estimate the anticipatory component of bank

equity adjustments, interpreted as a bank-level credit shock. The results suggest that positive credit shocks negatively impact loan origination and that greater access to formal credit is tied to smaller loan sizes at larger banks. Additionally, the policy led to greater participation in retail funding markets, increased reliance on informal credit products, and higher loan rejection rates. Collectively, these findings indicate that once regulatory uncertainty dissipated, banks reduced precautionary equity holdings, heightening competition and expanding financial inclusion. Future research building on these findings could explore bank competition via credit rationing and formal finance system reforms to improve financial accessibility.

In Chapter IV, I examine how changes in subjective expectations of stock returns can influence wealth inequality through various saving motives. I document several empirical findings that suggest a significant link between beliefs about equity returns and wealth distribution. Additionally, I propose that these beliefs interact with the bequest motive and influence saving decisions during retirement, and support this view with empirical evidence that suggests a strong correlation between subjective beliefs on stock returns and the likelihood of leaving bequests. Using externally identified shocks and investor surveys, I find significant responsiveness of investors' perception to new information and then estimate the IRFs of the wealth shares, finding non-negligible shifts that may persist beyond one year. To understand this link, I introduce a portfolio problem with a risk-free bond and equity, and the warm-glow bequest motive is derived from the expected value of bequeathable assets. These features help me explain the extensive and intensive margin and differential responses and quantify the strength of the belief channel, supporting the view that exogenous changes in beliefs have a relevant distributional effect via the rebalancing of portfolios.

Finally, the contributions in this dissertation establish a foundation for broader inquiries into bounded rationality, belief heterogeneity, and financial intermediation. Natural extensions of this research include interactions between financial institution liquidity and solvency, asset pricing under belief disagreement, and the industrial organization of banking. Further avenues could explore the intersection of financial institutions, macro-development, and consumer finance in emerging economies.

CHAPTER II

BOUNDED RATIONALITY IN FINANCIAL INTERMEDIATION AND MONETARY POLICY

2.1 Introduction

Economic agents make decisions based on their expectations about future outcomes. Under the Rational Expectations (RE) hypothesis, they are assumed to have complete knowledge of the true structure of the economy and the distribution of outcomes, allowing them to compute expected returns and asset prices. Although RE remains the standard benchmark in Economics, extensive empirical evidence suggests that actual market behavior deviates from this assumption, particularly in financial markets (see, e.g. Adam et al. 2017; M. Brunnermeier et al. 2021; Choi and Robertson 2020; Gomes et al. 2021; Kézdi and Willis 2011).

Expectations are fundamental in financial intermediation and the resource allocation process, as optimal behavior of market participants relies on their expectations about the intertemporal trade-offs inherent to the conventional functions of financial intermediaries, namely asset transformation, risk management, and information processing. (Freixas & Rochet, 2008a). Empirical evidence suggests that bank lending is driven by expectations (Anolli, Beccalli, & Molyneux, 2014; Falato & Xiao, 2023; Suss & Hughes, 2023), while deposit outflows and bank runs are the result of agents' perceptions of the value of banks and anticipated liquidity needs¹ Additionally, bank ownership incurs an opportunity cost, estimated using the Capital Asset Pricing Model (CAPM) or analyst forecasts, influencing loan pricing and funding structures (Dick-Nielsen, Gyntelberg, & Thimsen, 2022; Kovner & Van Tassel, 2022).

¹For an overview, see Freixas and Rochet (2008a).

In this line of thought, I study the macroeconomic implications of bounded rationality in financial intermediation, specifically in banking, and how it affects the effectiveness of regulatory changes and monetary policy. Herbert Simon, in his seminal work "Models of Man, Social and Rational" introduced the principle of bounded rationality to characterize decision-making processes in which individuals, constrained by "*...knowledge, foresight, and time...*" (Simon, 1957, p. 199), construct simplified models of reality and behave optimally within these constraints. Thus, at its core, bounded rationality can be conceptualized as optimal decision making with limited information and limited capacities, and any theory of bounded rationality can be generated "*by relaxing one or more of the assumptions*" of the rational benchmark (de Clippel & Rozen, 2024).

I set out to explore three key questions about boundedly rational expectations in banking. First, is there evidence of the existence of bounded rationality in bank forecasting? Second, how can biased perceptions of returns to financial intermediation affect the ability of post-2008 crisis reforms to mitigate moral hazard? Lastly, how does this form of bounded rationality interact with monetary policy?

The empirical analysis of this paper addresses the first question by identifying systematic forecast errors in banking. My first analysis studies the association between the residualized series of actual forecast earnings and the actual earnings of banks, finding a less than one-for-one correspondence. The second component of my empirical work, exploits the timing of the DFA stress test scenarios and the responses of the stock, bond, and credit default swap markets; I find that market participants tend to overestimate bank market values, requiring higher returns in reaction to the worst-case scenarios presented by the Fed, the latter being arguably, redundant information given their design and intended purpose.

To understand the macroeconomic implications of bounded rationality in banking, I consider the usage of regularization methods in forecast models in light of multicollinearity issues. I revisit Adaptive Learning as an alternative to RE. This strand of literature conceives agents as time-series econometricians who form their expectations and make decisions using linear models (G. W. Evans & Honkapohja, 2001; G. W. Evans & McGough, 2020, 2021), which in practice, is reinforced by the wide usage of the CAPM in financial markets (Agarwal, Green, & Ren, 2018; Berk & Van Binsbergen, 2016).² While the RE solution can be adaptively learned under certain circumstances, individuals may run into estimation issues, even in a data-rich environment. Economic predictive models are most likely characterized by high-dimensional models (Giannone, Lenza, & Primiceri, 2021) and data-driven choices of regularization methods are almost optimal for large-dimensional problems (Abadie & Kasy, 2019). Given these considerations, I posit that multicollinearity issues in forecast models can effectively constitute a form of bounded rationality. I consider the Ridge adjustment as a regularization method considering its practical and theoretical dominance when true effects are smoothly distributed and non-zero (Abadie & Kasy, 2019).

I embed agent-level learning in the New Keynesian model with financial intermediaries of Gertler and Karadi (2011) and consider boundedly rational agents that estimate the marginal returns of net worth and assets, which allows them to estimate the franchise value of banks and to choose the quantity of deposits they make with financial intermediaries. Agents are said to be boundedly rational in this model since the fundamental value of the bank is not observable and they must retrieve *ex post* estimates of non-observable returns. In lieu of restricting their information

²Using regression methods, practitioners estimate a measure of excess return due to non-diversifiable risk, namely the *market beta* of an asset.

set, I consider a setting where agents observe all the relevant variables and face a bias-variance trade-off so as to emulate a data-rich environment.

To address the question of the role of bounded rationality in financial intermediation in the unfolding of regulatory reforms and monetary policy, two quantitative experiments are conducted using the proposed model. In the structural change experiment, I find that the considered form of bounded rationality influenced the development of post-crisis economic activity. The post-crisis regulatory changes resulted in a higher moral hazard risk. Beyond the additional capital requirements, the observed bank deleveraging can be attributed to costlier enforcement that resulted in a structural decline in bank market value. With the contraction of bank lending, physical capital becomes scarce and the ex-post rate of return increases, which explains the increase in corporate spreads between 2010 and 2014. Following the structural change and under Biased Perceptions, returns are overestimated, resulting in higher perceived market value, which mitigates the effects of bank deleveraging due to moral hazard issues.

The second experiment shows that an expansionary monetary shock with bounded rationality in financial intermediation leads to optimistic perceived returns to intermediation - relative to the RE response - that result in a smaller reduction of the franchise (market) value of intermediaries and their balance sheet. On impact, initial real activity is driven by standard intertemporal substitution that is attenuated by increased savings in the form of deposits deposit holdings (and heightened risk taking by banks) as households perceive a higher bank market value since the response of the expected risk premium and return estimates.

These results indicate that bounded rationality in financial intermediation influences the design and effectiveness of both monetary and macroprudential

policy. My findings shed light on the implications of linear models with regularized estimators, which may arise in a data-rich environment with increasing information productivity. Agents' beliefs based on such models lead to sluggish expected returns and overestimated market values. This results in increased deposit inflows to banks whose fundamental value is below the agents' estimate, which, as previously stated, dampens the efficacy of monetary policy. Moreover, this form of bounded rationality can amplify financial vulnerabilities by increasing bank leveraging and risk-taking behavior. It can also hinder market discipline, as deposit holders may fail to interpret market signals about the banks' insolvency or structural issues. Furthermore, with optimistic net worth returns, banks may endogenously choose lower equity buffers against adverse losses, thus straining the conduct of macroprudential policy.

Related literature. *Information content of Stress Tests announcements:* The empirical work of this paper is related to the literature that has examined the **results** of the stress tests. Morgan, Peristiani, and Savino (2014) compute abnormal returns around four stress test events and use one of them to proxy for the latent GAP, and conclude that markets already identify underperforming banks, and the stress test results only inform about the size of the gap. Flannery, Hirtle, and Kovner (2017) find that the results of the DFA stress tests provide information both on the stress-tested Bank Holding Companies and on the general state of the banking industry. Cornett, Minnick, Schorno, and Tehranian (2020) find that stress-tested banks manage their balance to increase their probability of performing well and passing the test. Moreover, Glasserman and Tangirala (2016) finds that, at the time of the article, the results of the stress test became predictable and less informative. Relative to these works, my contribution is to examine the effects of information shocks arising from the release of stress test *scenarios*.

Bounded Rationality and Adaptive Learning: Branch and Evans (2010) develop a theory of underparameterization and learning with a simple asset pricing model where agents choose optimally misspecified models and multiple equilibria arise. Branch and Evans (2011) propose a simple simple linear asset pricing model with adaptive learning in which learning dynamics can generate deviations from fundamental equilibrium. Monetary policy has also been extensively studied from the perspective of adaptive learning and bounded rationality (Airaudò, Nisticò, & Zanna, 2015; Carvalho, Eusepi, Moench, & Preston, 2023; Milani, 2008). My work is closely related to Rychalovska (2016) where the author considers reduced-form expectation formations in an environment with the financial accelerator mechanism and finds that the amplifying effects depend on the learning specification form. Relative to these papers, my contribution is to explicitly account for bounded rationality in financial intermediation by embedding agent-level learning in a general equilibrium setting.

Financial Markets and Monetary Policy: The link between financial markets and monetary policy has been vastly studied. As noted in Bauer, Bernanke, and Milstein (2023), empirical work has shown the operation of the risk-taking channel of monetary policy through financial institutions. Bernanke and Kuttner (2005) find a sizeable effect of monetary policy on stocks and provide an early interpretation of the channel acting through changes in "precautionary savings". Other work has found that monetary policy influences the bonds market via term premia and corporate spreads (Jarociński & Karadi, 2020; Nakamura & Steinsson, 2018) and pricing of default risk (Gilchrist & Zakrajšek, 2012). Many of these papers are based on the premise of asymmetries of information between the central bank and private agents. Drechsler, Savov, and Schnabl (2018) develop a dynamic asset pricing framework that captures the effect of monetary policy on risk premia through the liquidity

premium and volatility of risky assets. Kekre and Lenel (2022) study a New Keynesian environment with heterogeneous preferences, where monetary policy acts through heterogeneous marginal propensities to save in capital. Coimbra and Rey (2024) study financial stability by imposing heterogeneous net worth constraints and its implications on the risk-taking channel of monetary policy.

Relative to all these papers, my paper embeds agent-level learning and expectation formation in a general equilibrium framework with financial intermediaries without relying on externally imposed constraints or a heterogeneous distribution of preferences.

Overview. The rest of the paper is structured as follows. Section 2.2 presents background information for the empirical analysis. Section 2.3 motivates the discussion by providing empirical evidence that agents systematically overestimate bank market value due to risk mispricing. Section 2.4, succinctly describes the base model, and in Section 2.5, I introduce an agent-level learning model based on the New Keynesian model with financial intermediaries of Gertler and Karadi (2011) and define the Restricted Perception Equilibrium (RPE) with a bias-variance trade-off to discipline the model. Section 2.6 presents the quantitative experiments. I analyze the post-GFC reforms as a structural change by adopting an indirect inference approach. Finally, I conduct an experiment with a monetary shock under Restricted Perceptions in the post-GFC period. Sections 2.7 and 2.8 discuss the results and conclude.

2.2 Background Information and Data

The United States has implemented numerous reforms to improve the resilience of its financial system: implementation of Basel II rules in 2008, the signing and enactment of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) in July 2010, and the ruling of Basel III in July 2013, which,

among many other measures, extended its predecessor and required banks to hold enough capital to withstand a series of stress tests.³ Beginning in 2013, the Federal Reserve’s capital assessment of large banks consisted of two primary components: the Dodd-Frank Act Stress Test (DFAST) and the Comprehensive Capital Analysis and Review. The initial definition of bank size for required financial institutions with total consolidated assets of more than \$50 billion was later increased to \$250 billion after amendments by the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA). Starting in 2020, large Bank Holding Companies (those with more than \$100 billion in total assets) are subject to a stress capital buffer determined from their DFAST results.

As part of its supervisory efforts, the Federal Reserve conducts an annual supervisory stress test⁴, and publishes four documents: i) stress test scenarios approximately 6 months before the actual test, which in essence describe hypothetical recessions, and ii) supervisory stress test methodology: Comprehensive details about the models; iii) Supervisory Stress Test Results: Aggregate and individual results of the supervisory stress tests on eligible banks; and iv) Large Bank Capital Requirements: Individual capital requirement for all large banks.

The announcement of the stress tests results is usually a press release stating whether the BHC has sufficient capital to absorb losses and continue lending to households and businesses under stressful conditions with the corresponding summary of results. Previous work has found that *results* of the stress tests of the largest banks affect the information environment and bank management (Cornett et al., 2020; Flannery et al., 2017).

³Capital requirement is to be understood as the common equity to be held as a percentage of the bank’s risk-weighted assets

⁴<https://www.federalreserve.gov/publications/2022-Stress-Test-Scenarios.htm>

Stress Test Scenarios. The stress test scenarios describe a hypothetical set of conditions designed to assess the strength and resilience of banking organizations in an adverse economic environment⁵. These scenarios are not intended to be interpreted as the Fed’s forecasts and are designed according to publicly available well-defined guidelines. The baseline scenario is constructed based on ”*prevailing views of private-sector forecasters,..., government agencies, and other public-sector organizations... near the beginning of the annual stress-test cycle.*”, whereas for the adverse scenarios, the Board intends to use a *recession approach* where the Board specifies the future paths of variables (typically increasing unemployment, declining asset prices, and decreasing loan demand) so as to recreate a typical or specific recreation of a postwar US recession.⁶

To test for the existence of bounded rationality in financial intermediation in the form of biased beliefs, I study the extent to which stress test scenarios convey new information to agents. I analyze the timing of their release and the subsequent response of the price of bank securities. Since these scenarios are based on available information, I argue that, under the null hypothesis of Rational Expectations, the risk of financial intermediaries has already been priced in, as agents are presumably endowed with enough information and knowledge of the economic structure to scenarios. On the other hand, if the Fed’s view and processing of the data have an informational content (either by revealing the relationship between the

⁵Supervisory scenarios include trajectories for variables that capture economic activity, asset prices, and interest rates in the US economy and financial markets and three variables (real gross domestic product (GDP) growth, inflation, and the US/foreign currency exchange rate) in each of the four countries/country blocks. A global market shock is included in the trading portfolio of six BHCs with large exposure to trading and private equity

⁶Policy Statement on the Scenario Design Framework for Stress Testing” (12 C.F.R. pt. 252, appendix A)

stressed economic variables or by improving consensus among private agents), market participants will effectively update their estimates and price will respond.

Table 1. Release dates of the DFAST supervisory scenarios

Year	Date
2013	November 15, 2012
2014	November, 1, 2013
2015	October, 23, 2014
2016	January, 28, 2016
2017	June, 22, 2017
2018	February, 1, 2018
2019	February, 5, 2019

Source: Own work based on Federal Reserve Board. More information available on <https://www.federalreserve.gov/supervisionreg/stress-tests-capital-planning.htm>

Although the release date is known, the surprise shock may arise from the financial resilience of the bank as perceived and priced by investors after updating their worst-case scenario. For the prices of bank bonds, bank stocks, and credit default swap spreads on bank securities, I conduct event studies centered on the release dates of the DFAST stress scenarios (Table 2.2).

Data. For the empirical analysis and calibration of the model, I use data from the Compustat Bank data set for bank financial ratios available, and bond trading data from the Trade Reporting and Compliance Engine, both available in Wharton Research Data Services Wharton Research Data Services (2020). The Credit Default Swap spread data is retrieved from the S&P Capital IQ service.

Table 2 shows the descriptive statistics of the variables of interest. The simple leverage ratio is the ratio of assets to net worth and is an indicative metric of the composition of the balance sheet and a coarse measure of risk. The Price-to-Book (PtB) ratio is a valuation metric that is used to determine the relative capitalization of a stock. It is given by dividing the market value of the stocks of a firm by its book

Table 2. Descriptive Statistics

<i>All</i>	Leverage ratio	Price-to- Book ratio	β	
			Banks	Non-banks
Mean	2.35	0.28	0.52	1.07
25th perc	2.17	0.00	0.21	0.50
Median	2.37	0.30	0.40	0.97
75th perc	2.55	0.61	0.70	1.49
<i>Pre-2008</i>				
Mean	2.41	0.43	0.40	1.03
25th perc	2.25	0.14	0.14	0.35
Median	2.43	0.43	0.33	0.81
75th perc	2.61	0.73	0.55	1.47
<i>Post-2009</i>				
Mean	2.24	0.11	0.63	1.07
25th perc	2.07	-0.11	0.28	0.63
Median	2.24	0.15	0.48	1.03
75th perc	2.40	0.39	0.85	1.47

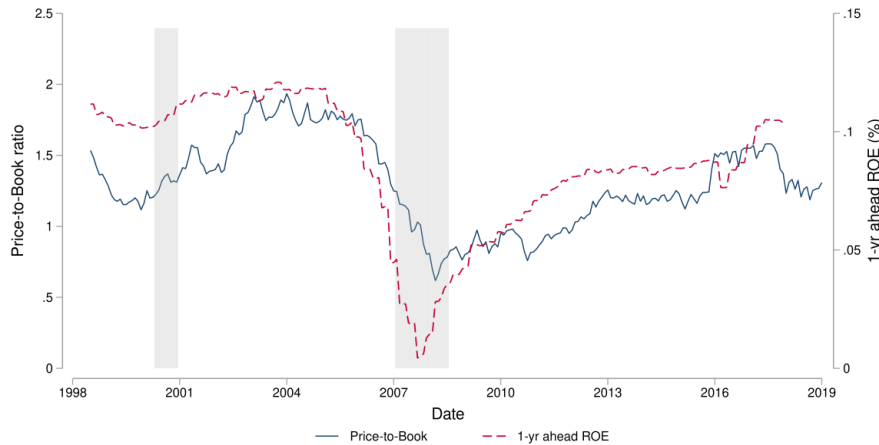
Notes: Lev. ratio: Leverage ratio, PtB: Price-to-Book ratio, in logs. The sample period for these series is 1990-2019. β : CAPM estimate of cost of equity, estimated using a window of 60 days. Sample period, 2000-2019.
Source: Compustat and Beta suite, Wharton Research Data Services

value. We also present the CAPM β estimate for banks and nonbanks. Recall that this regression-based estimate is a factor loading on the market equity premium used to quantify the non-diversifiable risk of a given stock.

The importance of the PtB ratio lies in its informational content. Corporations are required to disclose their financial statements, and with the enhanced financial reporting and auditing standards introduced by the Sarbanes-Oxley Act of 2002, firms also disclose material off-balance sheet liabilities, obligations, and transactions. A perfectly informative balance sheet will coincide with the market value and the PtB ratio will be equal to one. Previous work has shown that financial markets have become more informative (Bai, Philippon, & Savov, 2016; Farboodi & Veldkamp, 2020) and that stock prices provide additional information to managers and affect their investment decisions (Chen, Goldstein, & Jiang, 2007). In banking, Begenau, Bigio, Majerovitz, and Vieyra (2020) document the informational content of market equity relative to future cashflows and loan charge-offs and document the

informativeness of the price-to-book ratio (namely, Tobin’s Q), finding that it predicts profitability over the next two years, which can be seen in Figure 1

Figure 1. Median Price-to-Book ratio and 1-yr ahead ROE of US banks



Source: Compustat Quarterly Ratios of Banks, based on SIC codes. Shaded areas represent the NBER based recession dates.

This metric is also related to market discipline, that is, external governance based on market signals⁷, one of the fundamental pillars of financial regulation. To conclude, I highlight three notable aspects regarding the distribution of these series: there was a reduction in both bank leverage and PtB ratios, while the cost of capital, as proxied by the estimated betas, significantly rose for banks.

2.3 Empirical Analysis

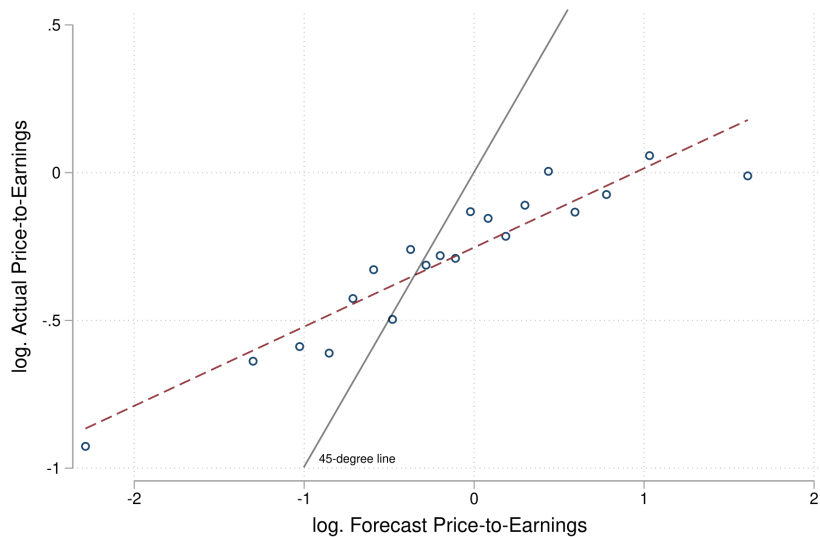
2.3.1 Forecast and Actual Earnings of Banks. Extensive research has shown that the Rational Expectations (RE) hypothesis does not hold in financial markets (see, for example, Adam et al. 2017; M. Brunnermeier et al. 2021; d’Haultfoeuille et al. 2021; Gomes et al. 2021; Kézdi and Willis 2011). To motivate

⁷Market discipline may also be defined as the the ability of banks’ creditors to effectively assess the risk behavior of banks and making the bank pay the cost of market value losses. For a review, see Freixas and Rochet (2008a)

our discussion, Figure 2 presents a binned scatterplot of the residualized forecast and the actual price-to-earnings ratio of financial institutions.

Figure 2 presents a binned scatterplot of residualized forecast and realized earning, after purging the effects of macroeconomic variables, bank characteristics, time, and bank-fixed effects. The strong association between these series remains, suggesting that the conditional expectations of the forecast and realized values differ systematically, providing evidence against RE. This analysis assumes that the data-generating processes of forecasted and realized earnings are equivalently specified and differ only in systematic error. A formal test based on d'Haultfoeuille et al. (2021) is left for future work.

Figure 2. Binned Scatterplot: Forecasts and Actual Price-to-Earnings Ratio of Banks



Source: Own elaboration based on available forecasts in the WRDS Compustat Bank database.

The Price-to-Earnings ratio is the share price of a company relative to its earnings per share. The regression controls for macroeconomic variables, time and bank-fixed effects. Number of observations (companies): 4,647 (359)

2.3.2 Price of Bank Securities and the Dodd-Frank Act Stress

Scenarios. To understand the effects of bounded rationality in bank forecasting,

I exploit the timing and design of the Dodd-Frank Stress Test (DFAST) scenarios and analyze the market response of three types of bank securities. These stress tests, introduced under Section 165 of the Dodd-Frank Act, are among the enhanced prudential standards implemented by the Federal Reserve Board to assess the resilience of systemically important financial institutions. While only large bank holding companies⁸ and nonbank companies designated as systemically important are subject to these tests, the Federal Reserve releases the stress scenarios regarding the path of macroeconomic variables which are made available to the public. As stated by the Fed, DFAST scenarios are not intended to be forecasts⁹; and their formulation follows well-defined guidelines with the baseline scenario following the average projections of the economic forecasters.

To test this hypothesis, I use a simple regression time discontinuity design centered on the release date of the stress scenarios and examine the market reaction of stocks, bonds, and Credit Default Swaps (CDS) issued by financial institutions¹⁰. According to the Efficient Market Hypothesis, investors adjust their assessments of financial institutions' solvency and resilience when new worst-case scenario information is released. My working hypothesis is that the release of the DFAST scenarios does not affect the prices of bank securities when perfectly rational market participants have factored the Fed's scenario data into their pricing.

⁸U.S. bank holding companies (BHCs), savings and loan holding companies (SLHCs), and intermediate holding companies of foreign banking organizations (IHCs) with \$100 billion or more in assets are subject to the Board's supervisory stress test rule (12 C.F.R. pt. 238, subpart O; 12 C.F.R. pt. 252, subpart E) and capital planning requirements (12 C.F.R. § 225.8; 12 C.F.R. pt. 238, subpart S)

⁹There are six observations of the stress scenarios for the period 2013–2019. Although this is a small sample, I find that the only meaningful correlation between the stressed deviation of output and unemployment occurs with the actual change in unemployment two periods ahead. This aligns with the autoregressive structure of the unemployment rate time series.

¹⁰As classified under the Standard Industrial Classification (SIC) system

As a way to capture the severity of the scenario, I compute the difference between the adverse scenario and the baseline scenario for real GDP growth and the unemployment rate for the test horizon. For example, the 2018 Supervisory Scenarios were released in February 2018 and provide a baseline scenario, an adverse scenario, and a severely adverse scenario for the quarters Q1:2018 to Q1:2021. Based on the timing and severity of the scenario, I estimate the following model:

$$r_{i,d} = \sum_{j=0}^2 \alpha_{t+j} \mathbb{1}_{(d>a_y)} \hat{y}_{t+j} + \sum_{j=0}^2 \beta_{t+j} \mathbb{1}_{(d>a_y)} \hat{u}_{t+j} + I_y + I_i + \gamma_d Z_d + \varepsilon_{i,d} \quad (2.1)$$

where $r_{i,d}$ is the yield or return of the bank security i on day d of quarter t , $\hat{y}_j$ and $\hat{u}_j$, the deviation of the adverse scenario from the baseline scenario of real GDP growth and the unemployment rate for quarter t , respectively. The indicator variable $\mathbb{1}_{(d>a_y)}$ denotes whether the scenario for year y has been released after date a_y . Year fixed effects I_y and fixed-security effect are also included, which absorbs any year-specific condition that could shape the design of the stress scenario. The vector Z_d is a set of control variables for macroeconomic conditions such as the corporate bond spread, term premium. I also include the Systemic Risk Indicator by the Philadelphia Fed, a measure of systemic risk in the US financial services industry, which captures the risk of widespread stress in the banking system. The coefficients of interest are α_{t+j} and β_{t+j} , as they capture any post-announcement effects of the Fed's view of the severity and path of the scenarios, marginal to the year fixed effects.

A potential confounding factor in event studies is the possibility that markets respond to other concurrent information disclosures. Publicly traded U.S. banks file 10-K and 10-Q financial reports with the Securities and Exchange Commission (SEC), and regulators release Call Reports, which have been shown to influence market reactions (Badertscher, Burks, and Easton 2018). These reports typically cluster around 30 days after the end of the quarter, potentially overlapping with stress test

disclosures in 2015 and 2016. However, since the release dates of the stress tests do not systematically coincide with other disclosures, I posit that the observed market reactions stem primarily from the informational content of the stress scenarios. The regressions also include the Monetary and Central Bank Information Shocks identified by Jarociński and Karadi (2020) that overlap with the post-release date to corroborate that these worst-case scenarios are not confounded with the FOMC announcement (when coinciding).

Bank stock returns. Previous work has documented the informativeness of stock prices about future performance finding a strong correlation between the market value of banks, their future cash flows, and their default risk (Begenau et al., 2020). Bank stock prices will reflect updated views of the banks’ resilience provided that the released stress scenarios convey new information about tail-risk outcomes.

To compute abnormal returns of bank stock returns, I use the U.S. Daily Event Study tool by Wharton Research Data Services with each event being each release date of the stress scenarios (See Data Appendix). Abnormal returns are computed using the Market-Adjusted Model, as the excess of the bank return over the CRSP Value-weighted market return, thus implicitly assuming market beta of 1. We then construct the bank-level data set with cumulative abnormal returns starting 15 days before the announcement. Table 3 shows positive cumulative abnormal returns of stocks issued by financial intermediaries, suggesting that the investors’ required returns increase after the release of stress scenarios.

Our results suggest that agents incorporate the severity of the scenarios and revise their expectations. A subset of the coefficients of interest is statistically significant once we account for current macroeconomic variables, revealing that the information conveyed by the scenarios affects stock pricing. Different coefficients on

Table 3. Bank Stock Returns: 15 Days Before & After DFAST Stress Scenarios Release

	Abnormal return			Cumulative return		
	(1)	(2)	(3)	(4)	(5)	(6)
Post= $1 \times GDP_t$ dev.	0.173*** (4.16)	0.172*** (4.15)	0.0259 (0.36)	0.208 (0.65)	0.207 (0.65)	-1.552*** (-5.52)
Post= $1 \times GDP_{t+1}$ dev.	0.00967 (0.19)	0.0108 (0.21)	0.0494 (0.62)	1.095** (2.69)	1.095** (2.69)	-0.850* (-2.06)
Post= $1 \times GDP_{t+2}$ dev.	-0.0908 (-1.68)	-0.0921 (-1.70)	0.352*** (4.44)	-3.028*** (-6.93)	-3.029*** (-6.94)	-1.014* (-2.11)
Post= $1 \times Unemp_t$ dev.	-1.063*** (-4.57)	-1.065*** (-4.58)	-1.242*** (-4.35)	-6.505** (-3.28)	-6.506** (-3.28)	-7.302*** (-3.61)
Post= $1 \times Unemp_{t+1}$ dev.	1.912*** (6.90)	1.918*** (6.91)	-1.964*** (-4.20)	4.805 (1.86)	4.811 (1.86)	-3.834 (-1.58)
Post= $1 \times Unemp_{t+2}$ dev.	-0.871*** (-4.47)	-0.874*** (-4.48)	2.885*** (9.90)	-4.978** (-2.59)	-4.982** (-2.59)	-3.301 (-1.75)
BAA Corporate Bond Spread			0.0190 (0.09)			-6.337*** (-8.59)
Yield on 5-yr U.S. Treasury Securities			-4.871*** (-12.36)			2.558* (2.09)
5-yr Term Premium			13.34*** (14.70)			-10.25*** (-3.59)
Monetary Policy Shock			1.597 (0.71)			9.668** (3.00)
Central Bank Info. Shock			-38.46*** (-12.81)			18.83*** (4.01)
Systemic Risk Indicator			-0.188*** (-4.38)			-1.393*** (-12.17)
Year x Bank	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Weekday	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>	<i>Yes</i>
Observations	79369	79369	76792	79369	79369	76792

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Returns calculated using the U.S. Daily Event Study tool by Wharton Research Data Services.

the path of stressed variables also indicate that agents also revise their beliefs on the path of the economy. On average, the daily abnormal return is revised downward with more severe real GDP growth and the unemployment rate of the quarters t and $t + 1$. The 2-quarter ahead stressed unemployment rate has the opposite effect on the post-announcement abnormal returns, as higher returns are required when with worst-case scenarios.

Turning to the cumulative abnormal returns, which allow for studying the total impact of the event while accounting for the trajectory of abnormal returns at the

bank level, I find an overall upward revision driven by more severe GDP scenarios, whereas the shortest-term unemployment rate declines.

While previous work has shown that macroeconomic news and rating actions have been found to have an effect on stock prices (Andersen, Bollerslev, & Diebold, 2007; J. Hull, Predescu, & White, 2004; Zhang, Zhou, & Zhu, 2009), my results are qualitatively different in that the stress scenarios purportedly do not contain information about current or future shocks, and unlike rating actions, these are economy-wide scenarios. The results of the regressions on the cumulative abnormal returns show that the stressed output path results in higher cumulative returns, suggesting that prior the announcement, agents were optimistic about bank performance and valuation.

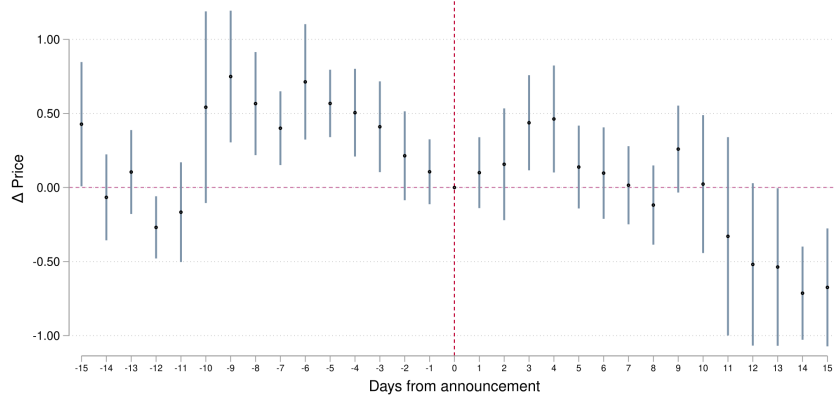
Bonds markets. I turn to the bond market for two reasons. First, the bonds market are less liquid and transparent than stock markets, and the response of bondholder may be substantially different. Second, DFAST scenarios or, more generally, information on tail risks or worst-case scenarios may have a twofold effect if, in the spirit of Gilchrist and Zakrajšek (2012), the bond spreads are comprised of default risk and the variation in risk pricing.¹¹

Figure 3 shows a bond-level event study of transactions of securities issued by financial intermediaries around the date of publication of the DFAST scenario.¹² The evidence suggests that prices decline over time, as investors demand higher returns. Agents revise their risk measures when tail-risk scenarios emerge. Disagreement in worst-case outcomes, that is effectively priced through volatility assumptions.

¹¹I leave for future research the rigorous identification of the effects these scenarios on each component.

¹²All transactions reported through the Transaction Reporting and Compliance Engine (TRACE). Beginning in July 2002, bond dealers were required to report all trades in publicly issued corporate bonds to the National Association of Security Dealers.

Figure 3. Event Study: Bank Bonds Market



Event studies using FINRA reported trades. Regressions include macroeconomic, year-issuer, security and day fixed effects. Number of observations(banks): 131,699 (592)

Table 4. Bond shocks: 15-day window

	Price				Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post= $1 \times GDP_t$ dev.	0.238 (0.86)	-0.322 (-0.71)	1.000*** (4.24)	0.607 (1.06)	-0.0845** (-2.66)	0.00342 (0.13)	-0.259*** (-12.61)	-0.0429 (-1.61)
Post= $1 \times GDP_{t+1}$ dev.	0.587 (1.78)	-0.343 (-0.76)	1.198*** (3.69)	0.519 (1.88)	-0.206*** (-4.88)	-0.141** (-3.09)	-0.386*** (-4.87)	-0.208*** (-3.54)
Post= $1 \times GDP_{t+2}$ dev.	0.00213 (0.01)	1.095 (1.34)	-1.025** (-3.18)	0.374 (0.47)	0.135** (3.11)	0.112** (2.73)	0.218*** (6.82)	0.0663 (0.87)
Post= $1 \times Unemp_t$ dev.	2.016 (0.63)	0.501 (0.12)	2.320 (0.51)	2.957 (0.53)	-0.162 (-0.57)	0.115 (0.45)	0.379 (0.38)	0.950 (0.97)
Post= $1 \times Unemp_{t+1}$ dev.	6.025*** (3.54)	0.0549 (0.02)	17.37*** (7.78)	5.071 (1.87)	-0.718** (-3.12)	-0.747** (-3.00)	-1.890*** (-6.42)	-0.988*** (-5.19)
Post= $1 \times Unemp_{t+2}$ dev.	-2.511** (-3.06)	0.851 (0.34)	-9.775*** (-4.93)	-0.715 (-0.19)	0.0800 (0.79)	0.339** (2.82)	0.0658 (0.16)	-0.123 (-0.21)
Seller =1		0.0847 (1.20)	0.111 (1.53)	0.116 (1.65)		-0.0497*** (-12.88)		-0.0416*** (-10.56)
Moody's BAA Corporate Bond Spread		-7.442* (-2.39)		-5.666* (-2.36)		0.269* (2.53)		0.780*** (4.10)
Yield on 5-yr U.S. Treasury Securities		-7.254** (-2.98)		-9.780*** (-4.35)		1.180*** (4.63)		1.018*** (4.12)
5-yr Term Premium		12.46** (3.15)		23.69** (3.09)		-1.553** (-2.83)		-1.058* (-1.96)
Monetary Policy Shock		0.00142 (0.02)		-0.0570 (-0.79)		-0.0168*** (-4.19)		-0.00453 (-1.17)
Central Bank Info. Shock		-0.0126 (-0.13)		-0.127 (-1.24)		-0.0133* (-2.55)		-0.00133 (-0.24)
Systemic Risk Indicator		-1.017 (-0.84)		0.0325 (0.05)		-0.0431 (-1.50)		-0.0313 (-1.63)
Constant	103.0*** (56.69)	133.4*** (14.15)	103.8*** (70.71)	133.5*** (19.59)	3.557*** (55.59)	1.598** (3.11)	3.661*** (35.36)	0.502 (1.90)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Effects	No	No	No	Yes	No	Yes	No	Yes
Observations	787, 212	786, 869	1, 570, 138	1, 553, 410	442, 678	442, 597	879, 906	868, 345
Number of bonds	9, 714	9, 701	13, 188	12, 935	2, 569	2, 568	2, 951	2, 940
Initial price	98.71	98.73	102.2	102.2	3.831	3.831	3.683	3.683

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

FINRA reported trades. Includes Issuer-year fixed effects. Prices do not include charged commissions. Yield is not available for some securities.

Although noisily estimated, the regressions in Table 4 show that stressed output reduces the price of bonds (Column 4). The negative coefficient estimates

corresponding to the 1-quarter ahead of the stressed output deviation in the yield regressions (Columns 5-8) indicate the lower bond prices are driven by updated beliefs on adverse scenarios. Moreover, I also control for the transaction type (buyer/seller) and estimate the bid-ask spread to assess the significance of the post-release effect. A one-percentage-point negative deviation in output is five times the spread. Analogously to the results Table 3, more severe unemployment scenarios reduce the yield on bonds, and more importantly, the upward revisions of bank bond yields support the view that agents tend to be overoptimistic on their views of banking, and when confronted with the Fed’s hypothetical scenarios, they revise their perceptions.

Credit Default Swaps market. The previous event studies do not distinguish whether the observed behavior is due to an overall increase in risk. The general consensus among the Financial Economics literature is that Credit Default Swap (CDS) spreads are a direct measure of credit risk and the CDS market has a lead on bond markets for financials (Coudert & Gex, 2013). Che and Sethi (2014) provide a microeconomic foundation for CDS markets and investors’ beliefs. In the absence of credit derivatives, perceptions about the pay-off of the worst-case scenario determine the expected pay-off and funding equilibrium. In debt markets with covered credit default swaps, investors’ portfolio is constrained by a collateral constraint which depends on the worst-case expected payoff, which in turn induces a direct relationship between bond price and the worst-case payoff while the CDS spread decreases.

For these reasons, the analysis of the CDS market is left for last, as CDS spreads are a direct market measure derived from specialized markets that price risk. A CDS is a contract in which one party sells protection to another against the failure (by a third party) to pay the contractual debt (Che & Sethi, 2014). In other words, the

buyer of a CDS acquires insurance against the default of a third party and obtains the right to sell the bond in case of this event. Approximately bond spreads and CDS spreads should be approximately equal¹³ (Coudert & Gex, 2013; J. Hull et al., 2004; J. C. Hull & White, 2000)).

I examine abnormal deviations in CDS around the release date of the stress scenarios. Given the design of the stress testing process, we can reasonably assume that the shock (if any) affects the perceived resilience of the banking industry in the stress scenario rather than the perceived likelihood of occurrence of such a scenario. Following Flannery et al. (2017) I estimate:

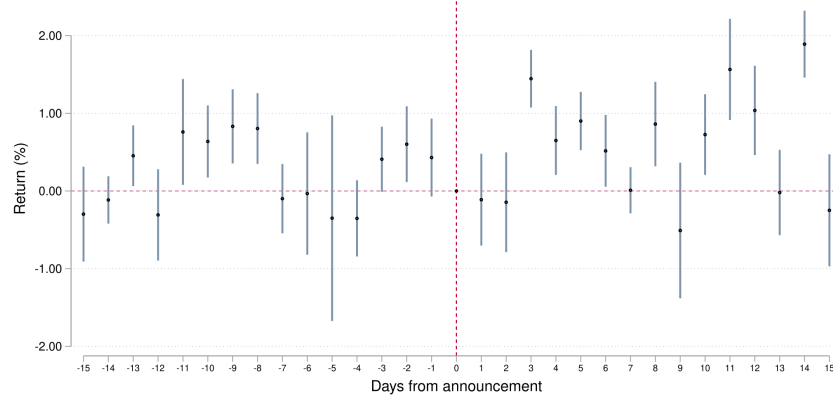
$$(CDS_{i,t} - CDS_{i,t-1}) = \gamma_0 + \gamma_1 (CDX_{i,t} - CDX_{i,t-1}) + \varepsilon_{i,t} \quad (2.2)$$

where $CDS_{i,t}$ denotes the CDS spread on the 5-year CDS contract of the i th bank on day t , and CDX is the spread of the CDX North America Investment Grade CDS index. The residual of estimating Equation 2.2 is used to calculate the abnormal change and is the corresponding dependent variable to be used in regression 2.1. As stress scenarios may convey information relevant to other sectors in the economy, the CDS spread is purged from the overall pricing effect of this new information on the equity market (which is assumed to be reflected by the CDX index) so that the residual captures the marginal effect on financial intermediaries.

Figure 4 shows that after the release of the stress scenarios, the market participants adjust their estimates of the risk of credit of financial intermediaries, with some non-negligible anticipation effects. The estimates in column 4 of Table 5 show the mean effect after 15 days, and we find a similar result as in other markets, severe output deviations result in upward revisions of the spread.

¹³Consider a portfolio with a bond and its corresponding CDS, both issued by the same company for the same maturity: this portfolio is riskless and therefore, it must yield the risk-free rate.

Figure 4. Event Study: Credit Default Swaps market for bank securities



Event studies of the residual spread of Bank CDS and the Investment grade CDS index. Number of observations(banks): 5,817 (33)

Table 5. CDS residuals regressions

	7-day		15 day	
	(1)	(2)	(3)	(4)
Post=1 $\times$ $GDP_t dev.$	0.305 (1.08)	-2.021 (-1.92)	-0.0972 (-0.62)	-2.519** (-3.34)
Post=1 $\times$ $GDP_{t+1} dev.$	-0.0980 (-0.57)	-1.678* (-2.35)	-0.0831 (-0.31)	-1.058 (-1.87)
Post=1 $\times$ $GDP_{t+2} dev.$	0.431* (2.35)	-0.891 (-1.35)	0.595 (2.06)	-0.470 (-0.72)
Post=1 $\times$ $Unemp_t dev.$	5.173** (3.02)	7.050 (1.31)	0.315 (0.23)	-5.723 (-1.34)
Post=1 $\times$ $Unemp_{t+1} dev.$	2.712 (1.49)	20.93*** (8.00)	-6.328* (-2.34)	4.010 (0.99)
Post=1 $\times$ $Unemp_{t+2} dev.$	-1.990 (-1.35)	-28.21*** (-16.90)	5.516 (2.06)	-10.56*** (-3.88)
Baa Corporate Bond Yield (10-yr)		2.021 (0.53)		-3.055 (-1.49)
Yield on 5-Year U.S. Treasury Securities		0.512 (0.09)		1.647 (0.46)
Term Premium on a 5 Year Zero Coupon Bond		-30.94 (-1.50)		-24.90*** (-4.30)
Monetary Policy Shock		0.373*** (4.23)		0.111 (1.29)
Central Bank Info. Shock		0.859*** (11.32)		0.475*** (7.78)
Systemic Risk Indicator		2.363* (2.51)		1.397** (3.77)
Year Fixed Effect	No	Yes	No	Yes
Weekday Effect	No	Yes	No	Yes
Observations	2,205	1,579	4,557	3,174

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Summary. Upon the release of DFAST adverse scenarios, agents demand higher returns on bank stocks and bonds, as well as higher CDS spreads. This suggests that they systematically overestimate banks’ market value, largely due to their perception of output trajectories in adverse scenarios. Our findings indicate that agents’ forecast models may fail to price risk-tail scenarios, stemming from their limited understanding of the true economic distribution. While competing explanations exist as to why market participants may not anticipate the Fed’s view of the worst-case scenario, we interpret these empirical results as further evidence that agents exhibit bounded rationality in estimating returns to financial intermediation.

2.4 Model

To further understand the implications of bounded rationality in financial intermediation, I embed adaptive learning in the model of Gertler and Karadi (2011) (GK), a New Keynesian model with financial intermediaries. In my setting, agents retrieve ex-post returns and estimate marginal returns and the franchise value of banks, which allows them to make their saving choice pinning down the banks’ balance sheet and aggregate lending to intermediate firms.

2.4.1 Description of the benchmark model. Households face habit formation and choose consumption, labor, and short-term debt holdings (bank deposits and government bonds), the latter earning the risk-free interest rate. In GK, banks face an exogenous exit probability and accumulate net worth, and their franchise value is the expected terminal net worth. Under RE, households are assumed to know the franchise value that determines the amount of bank deposits. At the same time, banks lend to intermediate firms to finance their next-period holding of physical capital. As the latter are perfectly competitive and face idiosyncratic risk, loans earn the ex-post rate of return of physical capital making the lending rate a

risky rate. As will be presented, bank assets, namely loans, are in turn a function of the marginal return on assets and on net worth, which in turn depend on the expected risk premium, that is, the expected difference of the risky rate on loans and the risk-free rate. The final output is bundled by differentiated retail firms that use intermediate output as the sole input. An description of the base model of GK is provided in Appendix 1.

2.4.2 Financial Intermediaries. What follows is a recursive formulation of the problem of financial intermediaries in GK. Let N_{jt} be the net worth of intermediary j , B_{jt} the deposits obtained from households, S_{jt} the quantity of financial claims and Q_t their relative price.

$$\text{Balance sheet: } Q_t S_{jt} = N_{jt} + B_{jt+1} \quad (2.3)$$

Banks pay the noncontingent real gross return R_{t+1} at $t + 1$. Assets earn the stochastic return R_{kt+1} over the period: Intermediate firms finance their capital purchases and pay, at the end of period t , the ex-post return R_{kt+1} . Banks accumulate equity by retaining earnings and pay dividends when exiting. The law of motion of equity is given by:

$$N_{jt+1} = R_{kt+1} Q_t S_{jt} - R_{t+1} B_{jt+1} \quad (2.4)$$

$$= (R_{kt+1} - R_{t+1}) Q_t S_{jt} + R_{t+1} N_{jt} \quad (2.5)$$

Let $\beta\Lambda_{t,t+1}$ the banker's stochastic discount factor applied to $t + 1$ earnings at t , it must be the case that for bankers to operate in time t :

$$E_t \beta \Lambda_{t,t+1} (R_{kt+1} - R_{t+1}) \geq 0 \quad (2.6)$$

In the absence of financial frictions banks obtain funds up to the point where the risk-adjusted premium is equal to zero $E_t \beta \Lambda_{t,t+1} (R_{kt+1} - R_{t+1}) = 0$. Banks have a

superior monitoring technology that justifies their existence in the model¹⁴ and face an exogenous exit probability θ (when exiting, bankers become workers) and seek to maximize their expected terminal worth V_{jt} :

$$V_{jt} = \max_{\{S_{jt}\}} E_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \beta^{i+1} \Lambda_{t,t+1+i} N_{jt+1} \quad (2.7)$$

At time t , lenders (namely, households) are willing to supply funds if the following incentive constraint holds:

$$V_{jt} \geq \lambda Q_t S_{jt} \quad (2.8)$$

where λ is the fraction of assets that bankers can divert: so long as the franchise value of the banks exceeds the value of diverting assets, bankers continue operating. Note that the bank's problem can be written as

$$V_{jt} = \max_{S_{jt}, B_{jt+1}} E_t \beta \Lambda_{t,t+1} [(1-\theta)N_{jt+1} + \theta V(N_{jt+1})] \quad (2.9)$$

subject to

$$\textbf{Balance sheet} \quad Q_t S_{jt} = B_{jt+1} + N_t \quad (2.10)$$

$$\textbf{Law of motion for net worth} \quad N_{jt+1} = R_{kt+1} Q_t S_{jt} - R_{t+1} B_{jt+1} \quad (2.11)$$

$$\textbf{Incentive constraint} \quad V(N_t) \geq \lambda Q_t S_{jt} \quad (2.12)$$

As shown by GK, the franchise value can be written as

$$V_{jt} = \nu_t Q_t S_t + \eta_t N_{jt} \quad (2.13)$$

$$= (\nu_t \phi_t^* + \eta_t) N_{jt} \quad (2.14)$$

with the leverage ratio defined as $\phi \equiv QS/N$ and

$$\begin{aligned} \nu_t &= E_t \{ (1-\theta) \beta \Lambda_{t,t+1} (R_{kt+1} - R_{t+1}) + \beta \Lambda_{t,t+1} \theta x g_{t,t+1} \nu_{t+1} \} \\ \eta_t &= E_t \{ (1-\theta) + \beta \Lambda_{t,t+1} \theta z_{t,t+1} \eta_{t+1} \} \end{aligned} \quad (2.15)$$

¹⁴This feature is not explicitly modeled in GK

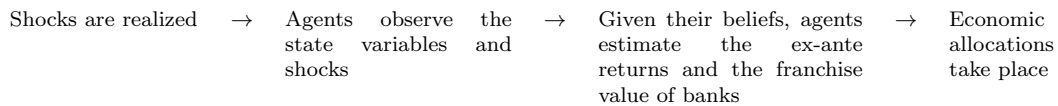
where $xg_{t,t+i} \equiv Q_{t+i}S_{jt+i}/Q_tS_{jt}$ is the gross rate in assets between t and $t+i$, and $z_{t,t+i} \equiv N_{jt+i}/N_{jt}$. ν_t can be interpreted as the expected discounted value of expanding assets while holding net worth constant. Likewise, η_t is the expected discounted value of an additional unit of N_{jt} while holding assets constant.

2.5 Bounded optimality: Environment

This section introduces biased perceptions in the environment of Gertler and Karadi (2011). I assume that there are no asymmetries of information between banks and households, all agents use the same nowcast models, and the banker's problem and the exogenous probability of exit θ are common knowledge. In this setup, agents must estimate the franchise value of banks and which they use to decide the quantity of deposits. Specifically, agents hold beliefs (in the form of a set of coefficients of linear models) on the marginal return on assets and net worth, $\hat{\nu}_t$ and $\hat{\eta}_t$, respectively, which are then used to compute the franchise value in the analogous version of Equation 2.14.

With Rational Expectations, agents have perfect knowledge of the economic structure and estimate the current expected values of the marginal returns and franchise value using the true distributions. Under the form of bounded rationality herein considered, I assume agents behave as econometricians and use the best linear model (in the least-square sense and constrained by a bias-variance trade-off) to estimate the nowcasts of the marginal returns that determine the banker's franchise value, which in turn allows them to make their deposit decision. Table 6 shows the timing of the model.

Table 6. Timing of the model:



For the purpose of this paper and to focus on financial intermediaries, we assume that agents hold rational beliefs for all other forward-looking variables such as consumption, inflation, and net investment.

2.5.1 Nowcasts and bank lending. Let $x_{t-1} \in \mathbb{R}^{n_x}$ be the vector of predetermined variables and $\varepsilon_t \in \mathbb{R}^{n_\varepsilon}$ be exogenous shocks. Letting $\psi^k = [\psi_x^k \ \psi_\varepsilon^k \ \psi_0^k]'$, $k \in \{\eta, \nu\}$ represent the agents' (stacked) beliefs about the log deviation of marginal return on net worth, η , and assets, ν , the nowcast of the log deviation (from steady state) of marginal return k is given by $\log \hat{k} = \psi_0^k + \psi_x^{k'} \hat{x}_{t-1} + \psi_\varepsilon^{k'} \varepsilon_t$, so that the level is given by

$$\text{Net worth:} \quad \tilde{\eta}_t = \eta_{ss} \exp(\psi_0^\eta + \psi_x^{\eta'} \hat{x}_{t-1} + \psi_\varepsilon^{\eta'} \varepsilon_t) \quad (2.16)$$

$$\text{Assets:} \quad \tilde{\nu}_t = \nu_{ss} \exp(\psi_0^\nu + \psi_x^{\nu'} \hat{x}_{t-1} + \psi_\varepsilon^{\nu'} \varepsilon_t) \quad (2.17)$$

where η_{ss} and ν_{ss} are the corresponding steady-state values. As in GK, we stay in the local region of the steady state where the Incentive Constraint (Equation 2.8) always binds, so that the leverage ratio is directly pinned down by the nowcasts of the marginal return of assets and net worth, $\hat{\nu}_t$ and $\hat{\eta}_t$:

$$\phi_t^* = \frac{\hat{\eta}_t}{\lambda - \hat{\nu}_t} \quad (2.18)$$

2.5.2 Retrieving the ex-post returns. In our model with bounded rationality, neither the true returns nor the fundamental value of the bank franchise is available. As agents require data about the realized returns to estimate their models, I assume agents compute ex-post marginal return on net worth and on assets, denoted by $\tilde{\eta}_{t-1,t}$ and $\tilde{\nu}_{t-1,t}$ respectively, based on the deterministic lagged versions of equations 2.15:

$$\tilde{\eta}_{t-1,t}^{ep} = (1 - \theta) + \beta \Lambda_{t-1,t} \theta z_{t-1,t} \hat{\eta}_t \quad (2.19)$$

$$\tilde{\nu}_{t-1,t}^{ep} = (1 - \theta) \beta \Lambda_{t-1,t} (R_{kt} - R_t) + \beta \Lambda_{t-1,t} \theta x g_{t-1,t} \hat{\nu}_t \quad (2.20)$$

Note that the $t - 1$ ex post returns depend on the time t nowcast. This adaptive learning algorithm is a version of saddle-path learning with agents using a perceived law of motion that has the same form as the saddle-path relationship in rational expectations equilibrium (Ellison & Pearlman, 2011; G. W. Evans & Honkapohja, 2001; Greiner & Semmler, 1996).

Given a linearized solution of the model, the log ex post returns can be written as a linear combination of the state variables and shocks. The mapping between beliefs Ψ and ex-post returns is described in the next section.

The equilibrium conditions under BPE are the same as those of the Rational Expectations model (Appendix A.2), except for the definition of the nowcasts and the backward-looking measurement of the returns.

2.5.3 Biased Perceptions Equilibrium (BPE). I introduce the concept of Biased Perceptions Equilibrium (BPE) as a solution concept to discipline the learning model. While previous research has investigated equilibrium biases in various contexts (e.g., Heller and Winter 2020; Hoff and Stiglitz 2010; Jehiel 2018), my implementation of BPE advances the adaptive learning literature by examining its macroeconomic implications through the lens of the banking sector. Under Rational Perceptions Equilibrium (RPE), agents employ a time-invariant, optimal misspecified model, generating the best linear prediction (in the least-squares sense) based on their restricted information set. Expanding on this concept, we introduce BPE, where agents have access to all relevant variables but are subject to estimation biases. To emulate the dynamics of a data-rich environment, a bias-variance trade-off is incorporated, which captures econometric challenges, such as multicollinearity, that practitioners frequently face.

This approach is inspired by empirical evidence supporting dense modeling techniques, as highlighted by Giannone et al. (2021), and by the documented presence of sluggish beliefs in the rational inattention literature (for an overview, see Maćkowiak, Matějka, and Wiederholt 2023).

Hoerl (1962) first proposed an estimate that adds a small positive quantity to the diagonal of the squared predictor matrix when the predictors are not orthogonal.¹⁵ I apply a Tikhanov regularization to the second-moment matrix of the standardized state variables. This regularization is the addition of a constant to the diagonal elements of the matrix and is also known as Ridge regression. Computationally, this approach addresses ill-conditioned variance covariance matrix that may arise with .

2.5.3.1 Setup and model solution. We can now proceed to define the Biased Perceptions Equilibrium. Let $x_{t-1} \in \mathbb{R}^{n_x}$ be the vector of predetermined variables, $y_t \in \mathbb{R}^{n_y}$ be the jump/choice variables, and $\varepsilon_t \in \mathbb{R}^{n_\varepsilon}$ be exogenous shocks. Let the function $F : \mathbb{R}^{n_x} \oplus \mathbb{R}^{n_x} \oplus \mathbb{R}^{n_y} \oplus \mathbb{R}^{n_y} \oplus \mathbb{R}^{n_\varepsilon} \rightarrow \mathbb{R}^{n_f}$, conditional on beliefs $\Psi = [\Psi^\eta \quad \Psi^\nu]$ represent the equilibrium conditions. The equilibrium conditions under the described setup with bounded rationality are the same , and denote it as

$$\mathbb{E}_t [F(x_{t-1}, x_t, y_t, y_{t+1}, \varepsilon_t) | \Psi] = 0 \quad (2.21)$$

Using perturbation methods, a local approximation around the steady state can be constructed. The dynamics in terms of log deviations from the steady state of the system described by Equation 2.21 can be written as

$$\hat{y}_t = h_x \hat{x}_{t-1} + h_\varepsilon \varepsilon_t \quad (2.22)$$

$$\hat{x}_t = g_x \hat{x}_{t-1} + g_\varepsilon \varepsilon_t \quad (2.23)$$

¹⁵A popular formulation of the Ridge problem is the constrained minimization problem

$$\hat{\psi}^i = \underset{\psi^i}{\operatorname{argmin}} (Y - Z\psi^i)'(Y - Z\psi^i) + \gamma^b(\psi^i \psi^{i'} - c)$$

See van Wieringen 2015

where the $n_y \times n_k$ matrix $\bar{h}_k \equiv \bar{h}(\Psi)_k$, $k \in \{x, \varepsilon\}$ denotes the boundedly rational policy function that solves for the temporary equilibrium given beliefs Ψ . Likewise, the law of motion of the states is given by the matrices g_x and g_ε . The vector of control variables includes the ex-post marginal returns as auxiliary variables. Letting the row vector $\bar{h}_i^j$ represent the policy function of the control variable j , the expression for the log deviation of the ex-post measurement is

$$\widetilde{\eta^{ep}}_{t-1,t} = \bar{h}_x^{\tilde{\eta}} \tilde{x}_{t-1} + \bar{h}_\varepsilon^{\tilde{\eta}^{ep}} \varepsilon$$

2.5.3.2 Mapping from beliefs to implied forecasts. Iterating forward and taking expectations using the information set at time t , the implied forecast of the marginal return after all the economic decisions have taken place is given by

$$\begin{aligned} E_t[\widetilde{\eta^{ep}}_{t,t+1}] &= E_t [\bar{h}_x^{\tilde{\eta}} \hat{x}_t + \bar{h}_\varepsilon^{\tilde{\eta}} \varepsilon_{t+1} + \zeta_{t+1}] \\ &= \bar{h}_x^{\tilde{\eta}} (g_x \tilde{x}_{t-1} + g_\varepsilon \varepsilon_t) \\ &= \begin{bmatrix} 0 & \bar{h}_x^{\tilde{\eta}} g_x & \bar{h}_x^{\tilde{\eta}} g_\varepsilon \end{bmatrix} \begin{bmatrix} 1 & x_{t-1} & \varepsilon_t \end{bmatrix}' \\ &\equiv \Xi^{\eta'} z_t \end{aligned} \tag{2.24}$$

where Ξ^η is the implied **forecast** of the marginal return on net worth, z_t is the $n_z \times 1$, set of $n_z = n_x + n_\varepsilon$ regressors used by agents, and ζ_{t+1} is an i.i.d. variable with mean zero representing an unknown shock or measurement error. Similarly, we can write the implied forecast rule for the marginal return on assets as $E_t[\tilde{\nu}_{t,t+1}] = \Xi^{\nu'} z_t$. Thus, ex ante beliefs Ψ are mapped to the (ex post) forecast rules $[\Xi^\eta \quad \Xi^\nu]'$ that produce updated returns $E_t[\widetilde{\eta^{ep}}_{t,t+1}]$.

2.5.3.3 Biased Perceptions Equilibrium (BPE). I consider a situation where bias arises from the Ridge adjustment, which is a regularization of non-zero estimates. The agents assume that returns k_t are given by $k_t = \psi^{i'} z_t + \epsilon_t^i$, using data $t = 1, \dots, T$ on the $n_z \times 1$ vector z_t and the implied return of Equation 2.24, k_t , where

ψ^i solves the Ridge constrained problem,

$$\psi^k = \underset{\psi^i}{\operatorname{argmin}} (K - Z\psi^i)'(K - Z\psi^i) + \gamma^b \psi^i \psi^{i'} \quad (2.25)$$

where $Z = [z'_1 \dots z'_n]$ is the regression matrix, and γ^b denote the regularization factor for a maximum target bias b . Given a tolerable maximum amount of bias b^* , I define the Biased Perception Equilibrium as

- i). The set of optimal time-invariant beliefs $\Psi^* = [\psi^{\eta*} \quad \psi^{\nu*}]$ (in the Ridge least squares sense)
- ii). Given the time-invariant beliefs that satisfy the optimality and market equilibrium conditions.
- iii). Given the mapping from ex ante beliefs Ψ_{Ridge} to the implied forecast rule Ξ_{Ridge} , $T(\Psi_{Ridge}) = \Xi_{Ridge}$, we have

$$\|\Psi_{Ridge} - \Xi_{Ridge}\| = b^*$$

2.5.4 Recursive formulation and Expectational Stability. The Ridge estimate is given by

$$\psi_t^k = \left(\sum_{i=1}^T z_i z_i^T + \gamma I \right)^{-1} \left(\sum_{i=1}^T z_i k_i \right) \quad (2.26)$$

Let $R_j = j^{-1} \left(\sum_{i=1}^j z_i z_i^T \right) + \gamma I$ and $\psi_j^k = R_j^{-1} \left(\sum_{i=1}^j z_i k_i \right)$. It can be shown that the Ridge estimator can be computed using the Recursive Least Squares algorithm.

$$\psi_t^k = \psi_{t-1}^k + t^{-1} R_t^{-1} z_t (z_t' (\Xi^k - \psi_{t-1}^k)) \quad (2.27)$$

$$R_t = R_{t-1} + t^{-1} (z_t z_t' - R_{t-1}) \quad (2.28)$$

Following G. W. Evans and Honkapohja 2001, we can analyze the recursive formulation as a stochastic recursive algorithm and evaluate its convergence.¹⁶ Fixing the values of ψ^i which also means that R is also fixed, we proceed to write the ODE

$$\begin{aligned}
g_{\psi,R} &= \lim_{t \rightarrow \infty} ER^{-1}z_t z'_t (\Xi^k - \psi^k) \\
&= \lim_{t \rightarrow \infty} R^{-1}E(z_t z'_t + \gamma I - \gamma I)(\Xi^k - \psi^k) \\
&= \lim_{t \rightarrow \infty} (I - \gamma R^{-1})(\Xi^k - \psi^k)
\end{aligned} \tag{2.29}$$

$$\begin{aligned}
g_{\psi,S} &= \lim_{t \rightarrow \infty} Ez_t z'_t - R \\
&= Ez_t z'_t - Ez_t z'_t - \gamma I = -\gamma I
\end{aligned} \tag{2.30}$$

where $R = Ez_t z'_t + \gamma I$. We corroborate that, conditional on observing all state variables and shocks and $\gamma = 0$, the Rational Expectations equilibrium is a fixed point of this mapping, which indicates that under the saddle-path learning algorithm we consider, agents can, in principle, learn the RE solution.

Asymptotic properties can be assessed using the expectation stability principle by considering the differential equation as a continuous-time deterministic system (D. Evans, Evans, & McGough, 2022). If E-stable, our mapping of the ex-post returns based on saddle-path learning will push beliefs towards the rest point (i.e., the BPE beliefs) of Equations 2.29 and 2.30. To check for Lyapunov stability of the system, I compute the Jacobian matrix of the differential equation evaluated at the BPE, and find that the real components of all its eigenvalues are less than one, which implies the system's local stability.

¹⁶For a stochastic recursive algorithm of the form $\theta_t = \theta_{t-1} + \delta_t Q(t, \theta_{t-1}, X_{t-1})$, where θ_t is a vector of parameter estimates and X_t is the set of state variables, an ordinary differential equation (ODE) can be associated $\frac{dh(\theta)}{d\tau} = h(\theta(\tau))$ where $h(\theta) = \lim_{t \rightarrow \infty} E(Q(t, \theta, X(\theta)))$

For the quantitative experiments, I use the probability limit of the Ridge estimate, as given by the Slutsky theorem,

$$\tilde{\psi}_{Ridge}^i = plim(\psi_{Ridge}^i) = (\Omega_z + \gamma I)^{-1} \Omega_z \Xi_{Ridge}^i \quad (2.31)$$

where Ω_z is the variance-covariance matrix of the regressors. For a closed form of the estimate, I impose that the set of BPE beliefs based on the Ridge estimate is a fixed point of Equation 2.31. It trivially follows that $\gamma^b = 0$ implies that unbiased beliefs coincide with the implied forecasts from the policy functions and the law of motion.

Real-time learning. In our experiments, we consider structural change while allowing real-time learning. Under Rational Expectations, agents update their policy functions upon a change in the underlying parameter. To study the role of , beliefs are assumed to be updated using recursive least-squares learning with constant gain:

$$R_{zt} = R_{zt-1} + c(z_t z_t' - R_{zt-1}) \quad (2.32)$$

$$\psi_t^i = \psi_{t-1}^i + c R_t^{-1} z_t (\tilde{i}_t^{ep} - \psi_{t-1}^{i'} z_t) \quad (2.33)$$

where R_{zt} is the second moment matrix of z , c is the constant gain used to update beliefs, and $\tilde{i}^{ep} \in \{\tilde{\eta}^{ep}, \tilde{\nu}^{ep}\}$.

Model simulation and calibration. Identifying the maximum bias b^* remains a daunting task. While our empirical work suggests that indeed $b^* > 0$, this value can be time-varying and even endogenous¹⁷. For the quantitative experiments that follow, I use a Ridge Adjustment $\gamma^b = 2e^{-13}$ which yields a maximum bias $b^* = 0.0425$ (approximately 1% of the corresponding coefficient) with the purpose to show the effect of a minimal deviation from RE.

I keep the base calibration of the structural parameters in GK, only needing to calibrate the standard deviation of the innovations. This is particularly important

¹⁷I leave this aspect for future research

because the second-moment matrix of the regressors enters our definition of BPE and real-time learning under structural change. We target several data moments for the pre-2008 period to account for the state of the economy prior to the Great Financial Crisis, corresponding to the analytical standard deviations of the linearized solution using the boundedly rational policy functions. The target moments and calibrated values are shown in Table 7.

Table 7. Model Calibration: Standard deviation of exogenous processes

Parameter	Description	Value	Target
σ_ξ	Capital quality shock	0.14%	Std. dev. output gap of 1.9%
σ_ξ	Monetary shock	0.041%	Std. dev. eff. fed funds rate of 0.4%
σ_n	Net worth shock	1.2%	Std. dev. (log) leverage ratio of 0.15

The standard deviation over 1990Q1:2007Q4 of the Effective Fed funds rate and the pre-2008 within-bank leverage ratio is 0.47% and 0.18 respectively. Given the structure of the model and the responsiveness of output to all the processes, I match the standard deviation of output and minimize the distance to the other targets.

2.6 Quantitative experiments

2.6.1 Structural change: Agency problems. Before examining the connection between monetary policy and bounded rationality in financial intermediation, the question of whether agency problems and overall risk have increased, along with the potential role of bounded rationality in the unfolding of the regulation, is addressed. The base model incorporates moral hazard risk as the parameter λ , the fraction of assets to be diverted, which is inversely related to optimal leverage.

While post-crisis financial regulations sought to improve financial stability, it remains uncertain whether the agents' beliefs on financial intermediaries amplify financial vulnerabilities and risk taking. The Dodd-Frank Act (DFA) introduced stricter systemic risk regulations, improved disclosure requirements, and provided the Federal Reserve with a new mandate to maintain financial stability (Acharya &

Richardson, 2012); while establishing the ground for stringent liquidity and capital requirements for banks. However, the emergence of shadow banking (Acharya & Richardson, 2012; Irani, Iyer, Meisenzahl, & Peydro, 2021) and increased funding using riskier deposits¹⁸ cast doubts on the direction of the reforms. Evidence suggests that banks have become less risky individually and more vulnerable to systemic contagion (Calluzzo & Dong, 2015), and while stringent capital requirements reduce the probability of financial crises in imperfect markets, large capital or size-dependent requirements can dampen stability (Corbae & D’Erasmus, 2021; Egan, Hortaçsu, & Matvos, 2017).

If post-crisis regulation mitigated agency problems in the financial sector, the banker’s incentive to deviate funds should decrease, and holding everything else constant, the model predicts that bankers expand their balance sheet as households are willing to lend more funds. To identify this structural change, I adopt a quasi-indirect inference approach to estimate the post-reform fraction of divertible assets and the steady state value of the risk premium and the leverage ratio.¹⁹

Table 8. Target Medium-Run moments

Value	Description	Target	Description
$R_k - R$	Realized risk premium	30.00%	Increase of BAA bond spread relative to 10Y
ϕ	Leverage Ratio	-2.30%	Avg. within-bank change in lev. ratio

Notes: The target moment is the 40-quarter average of the variable in order to match the observed 5-year mean between January 2010 and December 2014. Regression results presented in Table

Given the persistence of the leverage ratio and the market (franchise) value series, the bank-level changes are estimated dynamic panel data estimators, controlling for bank-level variables. A.26.

¹⁸The share of uninsured deposits in commercial banks and savings institutions increased from 30.04% to 41.14% between 2010 and 2019. Own calculations based on the FDIC Quarterly Banking Report

¹⁹The steady state value of the risk premium and the leverage ratio pin down the financial sector in the base model

Since the post-reform steady states under RE and BPE are likely to differ, I match the model moments with the medium-run averages in the data for the 5-year period 2010-2014, in order to restrict the analysis to the zero lower bound period and account for the fact that we do not have enough data to describe in full the business and financial cycles in the post-2008 period. I solve for the **steady-state** values and the parameter λ that generate the impulse response functions consistent with the medium run targets described in Table 8. Each simulated path includes rescaled monetary shocks (using the calibrated standard deviation of the model) by Jarociński and Karadi (2020) to account for the monetary policy regime of the era.

Table 9 shows the resulting parameters and steady state values from the recalibration exercise based on the data moments. Column 1 contains the base values of the model, while columns 2-5 present the RE and BPE calibrations that match the target change in leverage and the realized risk premium in Table 8 without including externally identified rescaled monetary shocks (columns 2-3) and after considering the sequence of shocks (columns 4-5). In every case, the ratio of divertible assets relative to output exceeds the baseline value. Although the Dodd-Frank Act was designed to impose stricter controls on agency problems, the model indicates the opposite, aligning with mispriced governmental guarantees within the system and the ongoing debate regarding too big-to-fail banks within a concentrated banking sector. (Acharya & Richardson, 2012). A salient feature of the model with bounded rationality is that the observed data moments can only be elicited by larger changes in the structural parameter.

Appendix Table A.27 shows the average values of the selected untargeted moments. After accounting for the monetary policy of the period, bank deleveraging unfolds similarly with both the RE and BPE calibrations. This is followed by a decline

Table 9. Structural change: summary of results

Target avg. change: Realized premium: 30%, Leverage ratio: -2.30%							
Value	Description	Base	No MP shocks		MP shocks		
			RE	BPE	RE	BPE	BPE, lng
		(1)	(2)	(3)	(4)	(5)	(6)
λ	% Divertible Assets	0.3815	0.4110	0.4147	0.3910	0.3935	0.3940
$E_{ss}[R_k - R]$	s.s. Risk premium	1.0000	1.0774	1.0886	1.0044	1.0127	1.0149
ϕ_{ss}	s.s. Leverage Ratio	4.0000	3.7132	3.6854	3.8222	3.8054	3.8048
η_{ss}	Marg. return on equity	1.5110	1.5112	1.5133	1.4806	1.4833	1.4848
ν_{ss}	Marg. return on assets	0.0037	0.0040	0.0041	0.0037	0.0037	0.0037
$\log V/N$	log. FVtN	1.5260	1.5261	1.5284	1.4946	1.4975	1.4989
$\lambda QS/Y$	Div. Assets-to-Output	2.5447	2.7274	2.7500	2.6075	2.6226	2.6252
$\text{Corr}(\log V/N, \eta_{t+4})$	Corr. logFVtN and η_{t+4}		0.9973	0.9966	0.6982	0.7604	0.8128

Notes: The target moment is the 20-quarter average of the variable in order to match the observed 5-year mean between January 2010 and December 2014.

s.s. Variable: Steady state of the listed variable. log. FVtN: log. Franchise Value-to-Net Worth. Corr. logFVtN and η_{t+4} : Correlation between log FVtN and future returns. RPE, lng: Restricted Perceptions Equilibrium, with learning and constant gain of 5%. The constant gain is the weight agents attribute to new observations in order to update their beliefs.

in output, consistent with the credit contraction attributed to the passage of the DFA.(Bordo & Duca, 2018) However, in our considered form of bounded rationality, a crucial difference arises in the early periods: bank franchise value is driven by relatively optimistic perceptions that result in lower bank leverage.

The recalibration exercise results, which incorporate real-time learning, are presented in column 6. Here, agents adjust their expectations in response to the structural change, leading to an increase in franchise value-to-net worth ratios. Consistent with the literature on price informativeness, a visual inspection of Figure 1 reveals a strong correlation between the Price-to-Book (PtB) ratio and the 1-year-ahead Return on Equity²⁰. The adaptive learning model better accounts for the upward trend in the median PtB ratio observed from 2015 to 2019. This model also explains the informativeness of the PtB ratio, the significant shift in the distribution

²⁰Between 2000 and 2019, the correlation between the log PtB and the one-year ahead ROE is 0.4885. We tested this hypothesis by regressing future performance on the PtB ratio and failed to reject the null hypothesis of no change. A regression of the 1 year forward pice-to-earnings ratio on the log PtB suggests a strong association between the current valuation and future expectations on bank performance, which increased in the post-crisis period. Results are not shown.

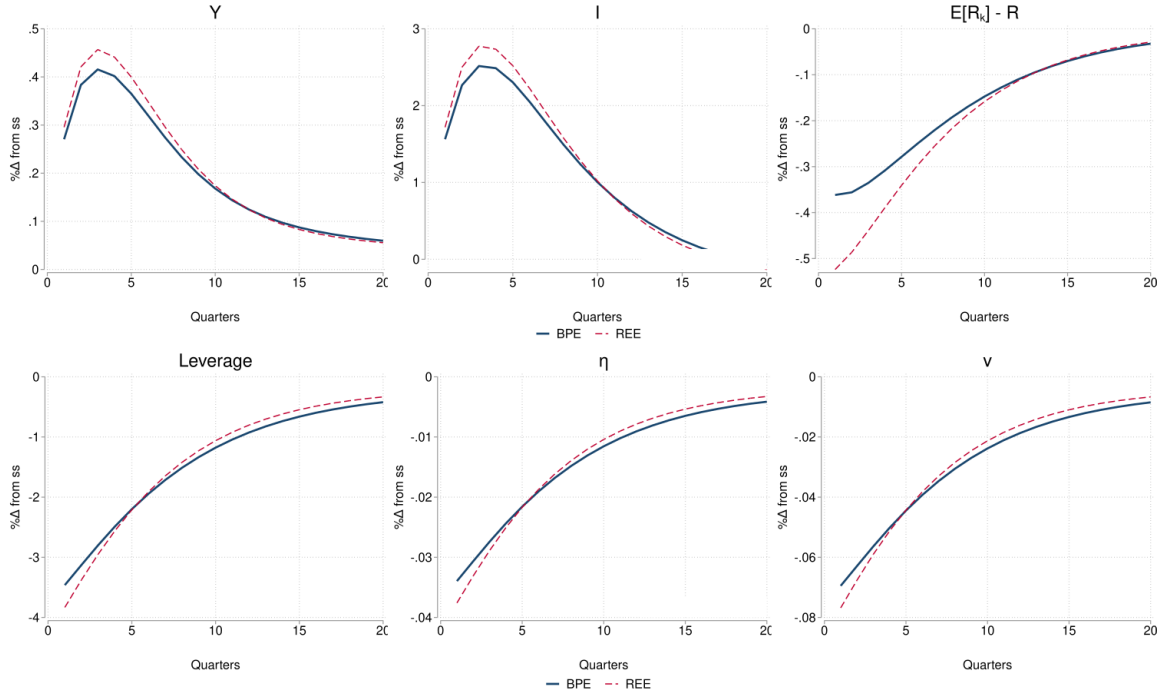
of capital cost estimates (Table 2), and the lower capitalization rate. Accordingly, we support the hypothesis that agents updated their beliefs following the enactment of the Dodd-Frank Act.

Taking stock: The results of the model indicate that the post-crisis reforms in the financial system led to higher moral hazard risk. Bank deleveraging followed as a result, since households had lower incentives to make deposits, and the scarcity of physical capital raised the ex-post rate of return of corporate bonds, as observed in the data. Adaptive learning played a role in the pass-through of these frictions onto the economy. Consistent with the data, adaptive learning implies a larger long-run equity premium which elicits a higher transitional market (franchise) value of banks, as agents learn about the change of the parameter and update their beliefs. Under our considered form of bounded rationality, returns are overestimated, resulting in a higher perceived market value that mitigated bank deleveraging due to increased agency issues.

2.6.2 BPE and Monetary Policy. I turn to the analysis of the link between restricted perceptions and the risk-taking channel of monetary policy. For this purpose, I recalibrate the model according to the previous section is in the steady state described in column 7 of Table A.27. Then we recompute the BPE and RE policy functions. For the following experiment, the central bank implements an expansionary monetary policy via an unexpected decrease of one hundred basis points of the policy instrument.

Compared to REE, the initial BPE response results in higher perceived returns to intermediation in the earlier periods, which later translates into a sluggish leveraging with negligible effects. The core effect of biased perceptions is seen in the early quarters, when the standard intertemporal effects on consumption are attenuated by

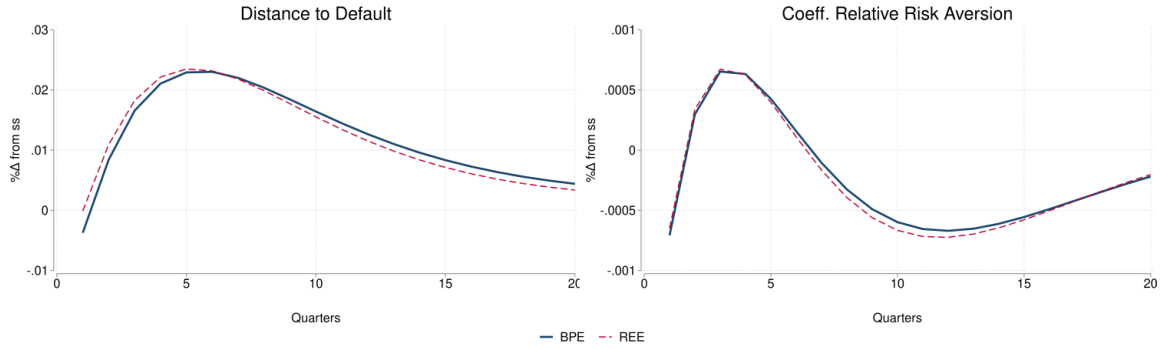
Figure 5. Response to monetary easing of 25bps



Notes: Impulse Response Functions of the log.deviation of the variables from the steady-state value.

relatively optimistic perception of returns that reduce deposit outflows. With biased perceptions, a decrease in the interest rate results in lower consumption growth, as households estimate a higher franchise value of banks and prefer to hold more deposits.

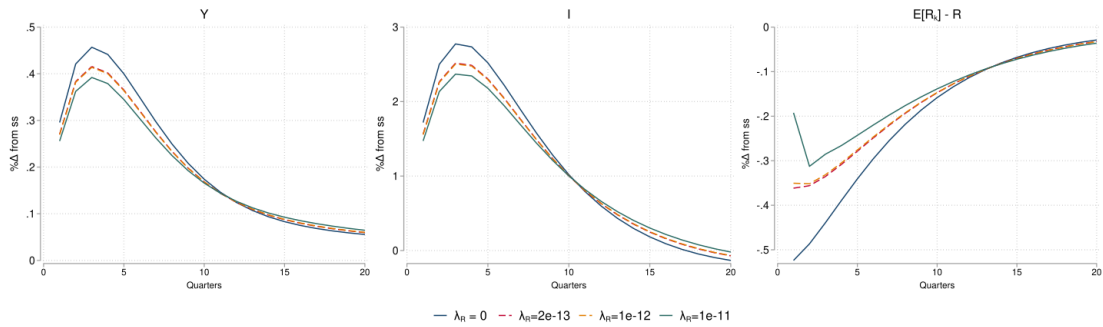
Figure 6. Financial vulnerabilities and risk taking



Notes: Impulse Response Functions of the log.deviation of the variables from the steady-state value. Distance to default is computed as $\frac{\ln(QS/(QS-N)) + (R - \sigma_{R_k}/2)^4}{\sigma_{R_k}^2}$ in accordance with the systemic risk indicators by the Cleveland Fed.

Figure 6 shows the model-implied measures of bank solvency and the risk attitudes of households to assess the trade-off between monetary policy, financial stability and risk taking. While a minor difference, the BPE response of the Distance-to-Default shows a detrimental response driven by the drop in assets relative to the banks' deposit base, which depending on the initial conditions of the bank, could be enough to trigger solvency concerns and bank runs.

Figure 7. Monetary Policy and Ridge Adjustments



We conclude our discussion by examining the effects of increased Ridge adjustments. In an environment where orthogonal shocks drive data variance, regularization methods tend to shrink the corresponding coefficients. As shown in Figure 7, larger adjustments introduce biased responses that further dampen the impact of monetary policy. These findings suggest that the effectiveness of other policy tools, such as forward-guidance shocks, may be influenced by the prevalence of these estimation approaches.

2.7 Discussion and Future Research

One of the main results of the paper centers on the role of agents' perception in determining the medium-run dynamics of the financial sector. Although subtle, the consequences of adaptive learning about returns to financial intermediation have shaped the medium-run transition of the economy. In the absence of the introduced

bias-variance trade-off²¹ the model with saddle-path learning embeds the Rational Expectation solution, implying that agents can eventually learn to forecast as if they were perfectly rational when they retrieve ex post measures based on optimality conditions. If this is the case, why do agents tend to overestimate the market value of banks, as suggested by the findings of the empirical analysis?

This phenomenon may arise from the way agents estimate and specify their forecast models. With the rise of information productivity, agents have more information at their disposal that exacerbates the bias-variance trade-off, a view that is supported by previous work showing that dense predictive models are preferred, and examined the implications of machine learning in Economics (Abadie & Kasy, 2019; Giannone et al., 2021; Goulet Coulombe, Leroux, Stevanovic, & Surprenant, 2022). A key feature of the bounded rationality in financial intermediation we consider is the less pronounced response of perceived returns compared to the Rational Expectations path, leading to sluggish reversion. The reason for this common trait in our structural change and monetary policy experiments is that the largest coefficients of the true implied forecast are attenuated when applying the ridge adjustment to alleviate multicollinearity issues, as the ridge regression is a constrained minimization problem subject to a penalty of the sum of the squared coefficients. Although the introduced bias is relatively small, the effects are non-negligible and indicate the direction of the effects of more restricted beliefs.

Although rational inattention (see the survey in Maćkowiak et al. 2023) is a competing explanation for the formation of expectations on returns to financial intermediation, the usage of models based on a subset of regressors is itself a form of bounded rationality. We could reasonably posit that agents do not observe all the

²¹The adjustment induces a maximum bias of 1.0% of the true coefficient

state variables and shocks, especially those affecting the intermediate goods firm. The equilibrium forecast model in this setup is the linear model that yields the best linear forecast of the implied returns, within the class of regression-based linear models. The model here introduced is a primer on agent-level learning in financial intermediaries and we leave for future research the implications of estimation methods such as Lasso or Principal Components regressions, and misspecified models on the formation of expectations in financial intermediaries, motivated by the emergence of machine learning and the suggestive evidence in Farboodi and Veldkamp (2020) on the shift in incentives from conducting fundamental forecasts to seeking arbitrage opportunities based on demand shocks.

The form of bounded rationality considered in this paper affects the banks' balance sheet and economic outcomes through belief-driven deposits. In our model, optimistic estimates of returns to financial intermediation lead to the perception of higher bank franchise values, and effectively to increased deposit holdings and lending. Bounded rationality in deposit allocation and bank valuation may have further implications. Previous work has established that deposit markets are sensitive to agents' financial sophistication and financial distress banks. Drechsler, Savov, and Schnabl (2017) argue that low financial sophistication (as proxied by income, education, and age) is a source of market power that allows banks to earn higher spreads on deposits. In Egan, Hortaçsu, and Matvos (2017), the indirect utility of the depositors depends on the probability of default of the banks and, for equity holders, the optimal injection of capital is given by a threshold defined by the bank's franchise value, and in their model, "good" and "bad" equilibria arise from depositors' beliefs on survival probabilities. Thus, as evidence suggests, heterogeneous beliefs shape the industrial organization of the banking sector. I leave for further research

bounded rationality with heterogeneous beliefs in settings where agents must learn about the banks' default probability.

It is worth noting that multiple researchers have highlighted the unintended consequences of post-crisis regulation. In this paper, I show that moral hazard risks increased and that bounded rationality in financial intermediaries leads to overpriced market value of banks, which helps explain the existence of wrong incentives to internalize systemic risk and the mispricing of government guarantees (Acharya & Richardson, 2012), or the negligible impact of risk oversight in large banks (Balasubramanyan, Daniel, Haubrich, & Naveen, 2024). In a similar fashion, central bank secrecy may have a positive effect of secrecy in lending facilities on the perceived quality of bank assets (Gorton & Ordoñez, 2020), the boundedly rational optimism on returns during the post-reform period may explain the recovery of the overall market value of banks. In relation to this discussion and our empirical evidence, it is worth considering the degree to which disagreement between the Fed and market participants about future aggregate demand (as in Caballero and Simsek 2022) and its impact on perception on financial intermediaries.

To conclude our discussion, it is worth highlighting the implications of bounded rationality in financial intermediaries (as considered in this paper) in the conduct of monetary policy. Although the results of the conventional monetary policy experiment show a small effect of bounded rationality in financial intermediaries on the effectiveness of monetary policy in raising output and investment, they allow us to assess the general mechanism. Optimistic perceptions of returns to intermediation will raise the banks' franchise/market value, increase deposit holdings, and bank leverage. This effect exacerbates the stages of risk-taking of financial intermediaries (as measured by bank leverage) after a monetary easing. On impact, bank solvency

declines, while in later periods, bank lending slows due to reduced deposit holdings driven by a lower perception of the banks' franchise value.

2.8 Conclusion

In this paper, I study the role of agents' beliefs on financial condition and how restricted perceptions determined the unfolding of the financial regulations that followed the 2008 financial crisis. Empirically, I document that agents tend to overestimate the market value of banks. Under restricted perceptions, returns are overestimated, resulting in a higher perceived market value, which mitigates deleveraging. Expansionary monetary policy is less effective as households perceive higher returns on net worth, which increases the banks' franchise value and savings in the form of deposits, thus attenuating the standard intertemporal substitution of consumption, with modest short-run negative effects on financial stability.

These results indicate that bounded rationality in financial intermediation influences the design and effectiveness of both monetary and macroprudential policy. My findings shed light on the implications of linear models with regularized estimators, which may arise in a data-rich environment with increasing information productivity. Agents' beliefs based on such models lead to sluggish expected returns and overestimated market values. This results in increased deposit inflows to banks whose fundamental value is below the agents' estimate, which, as previously stated, dampens the efficacy of monetary policy.

Additionally, this form of bounded rationality can amplify financial vulnerabilities by increasing bank leveraging and risk-taking behavior. It can also hinder market discipline, as deposit holders may fail to interpret market signals about the banks' insolvency or structural issues. Furthermore, with optimistic net worth returns, banks

may endogenously choose lower equity buffers against adverse losses, thus straining the conduct of macroprudential policy.

CHAPTER III

CAPITAL REQUIREMENTS AND FINANCIAL INCLUSION: THE IMPLEMENTATION OF BASEL III IN MEXICO

3.1 Introduction

According to the Modigliani-Miller Theorem (1958), the capital structure of a firm is irrelevant as funds are channeled in an optimal way (M. K. Brunnermeier, Eisenbach, & Sannikov, 2012). Nonetheless, it is widely acknowledged that the frictionless market paradigm is not applicable to financial markets due to the characteristic information asymmetry of financial systems and financial frictions such as balance-sheet constraints to financial intermediaries, lack of financial access (Galí, 2015), and market power (Clark, Houde, & Kastl, 2021). Understanding the interaction between two financial frictions, namely bank equity and financial access becomes a relevant avenue of research.

This paper explores the general question of balance-sheet constraints, macro-prudential policy, and financial inclusion by examining the implementation of the Basel III standards in Mexico starting in 2013. The reform imposed additional capital requirements, a type of balance-sheet constraint that can be understood as the ratio between the bank's eligible common equity and its risk-weighted assets. The regulatory change was announced in 2010 and implemented beginning in 2013. Besides other measures, the policy introduced a new definition of high-quality capital and additional capital buffers.¹ By the early 2010s and prior to the reform, the Mexican banking industry had large capital buffers as a result of the capitalization programs that followed the 1994 peso crisis and subsequent financial system reforms

¹See [https://www.cnbv.gob.mx/Documents/Basilea%203%20en%20M%C3%A9xico%20\(v16\).pdf](https://www.cnbv.gob.mx/Documents/Basilea%203%20en%20M%C3%A9xico%20(v16).pdf) and <https://www.bis.org/bcbs/publ/d315.pdf>

during the 2000s. Although the Basel III requirements were initially announced to be a six-year staggered implementation, the fully phased-in requirements entered into force in 2013.

A brief overview of access to finance in Mexico is warranted to further motivate my research question. According to the Financial Inclusion Surveys², the percentage of the Mexican adult population with at least one financial product surged between 2012 and 2015, going from 56% to 68%, and remained constant from 2015 to 2018. Likewise, the account ownership gender gap registered a significant decline of seven percentage points in the 2012-2015 period and a one percentage point decrease in the following three-year period.

To what extent did the implementation of the new capital rules affect financial access? It is not clear whether tighter capital requirements have a negative effect on financial inclusion. We could argue that banks could adjust their risk exposures and contract their lending which could either come from a smaller pool of borrowers (thus affecting extensive margin) or smaller loans (intensive margin). Moreover, the effects of increased capital requirements in an overcapitalized banking industry are also unclear, and in the uncertain context prior to the enactment of new capital rules, the eventual resolution of the regulatory process can effectively represent a loosening of bank capital holdings in the presence of strong anticipation effects.

Informed by key facts about the Mexican banking industry, I examine the effect of risk-based capital requirements on financial inclusion at the state and municipality levels by exploiting the exogenous change in banking regulations and geographic heterogeneity in bank presence. Using publicly available consumer loan

²https://www.gob.mx/cms/uploads/attachment/file/421411/Cuadriptico_2018_ENG.pdf

and operational data at the bank-municipality level for the period 2011-2019, I construct a shift-share instrument to study the local effect of the policy as given by the exposure to credit (volume) shocks arising from bank-level capital shocks. Using microdata from Financial Inclusion surveys (2012, 2015, and 2018) I conduct the analysis at the individual-state level and examine the potential relationship between capital requirements and the extensive margin of access to finance.

My findings are in line with the standard prediction that posits the existence of financial stability - competition trade-off (Egan, Hortaçsu, and Matvos 2017, Clark et al. 2021, Corbae and D’Erasmus 2021), which succinctly, refers to the situation where increased competition results in banks having riskier portfolios, eroded valuation, and lower profits. In the case of Mexico, the descriptive suggests the converse: an overall decline in capital ratios and higher competition. I argue that the two information shocks to banks, namely, the 2010 international announcement of the Basel III accords and the 2012 fully phased-in adoption of the capital requirements by the Mexican regulators (in opposition to the expected staggering of requirements at the time), resulted in an overall reduction of capital ratios between 2010 and 2012 that set the stage for the effects of the reform. My descriptive evidence suggests that banks had a differential response based on their size, with larger banks extending smaller personal loans on average. From there, I show the relevance of the credit volume shocks as a transmission mechanism of bank equity adjustments which allows me to construct a measure of local exposure to the plausibly exogenous variation in capital ratios. To do so, I decompose changes in credit volume and estimate the component driven by bank equity adjustments. I find that the number of originated personal loans and lending rates declined in municipalities with higher exposure to credit shock. Moreover, I find that exposure to positive shocks resulted in higher usage of informal credit products

and higher loan application rejection rates. My findings are suggestive that despite the positive effect of the reduction of capital ratios and the credit shock that followed, the loan needs of a subset of the population remained unattended, as banks sought to retain market shares and manage credit risk by endogenously choosing the default rate of the pool of borrowers, which explains the increase in loan application rates.

Literature Review.— My paper contributes to the literature that studies the local effects of financial systems using quasi-experimental settings with plausibly exogenous policy changes. Burgess and Pande (2005) leverage on a state policy that allowed a quasi-experimental setting and show that opening branches in rural unbanked locations in India was associated with a reduction in rural poverty, increased savings mobilization, and credit provision. Fafchamps and Schündeln (2013) study the case of Morocco and using bank branch presence as a local measure of financial development and find that local bank availability is associated with faster growth for small and medium-sized firms in sectors with growth opportunities. Moreover, Beck, De Jonghe, and Schepens (2013) document cross-country variation in the relationship between banking competition and stability and use a Z-score (a measure of the bank’s distance to insolvency) and Lerner’s index to empirically examine this relationship. Chong, Lu, and Ongena (2013) find that more intense banking competition in China is associated less constrained smaller and medium enterprises. Beck, Levine, and Levkov (2010) consider the impact of bank regulation, specifically, the liberalization of intrastate branching on the distribution of income within the US. Using a Difference-in-Differences design, they control for the interaction of branch deregulation with a unit banking indicator, the small bank share, the small firm share, and population dispersion and find that deregulation tightened the income distribution, by boosting incomes in the lower part of the income distribution with little impact on incomes

above the median. Delis, Hasan, and Kazakis (2013) use an index of supervisory power as an instrument and assess the impact of cross-country and timely variations in bank regulatory policies on income inequality and show that i) banking deregulation generally leads to lower inequality, and ii) banks pass on their increased costs and higher capital requirements to the relatively lower-income population that lacks good credit and collateral. My paper contributes to this strand of literature by formulating a shift-share instrument to exploit and localize the variation from a bank-level regulatory reform.

This work builds on the literature on credit markets and the propagation of shocks in these markets propagate to economic outcomes. My work is closely related to Greenstone et al. (2020), where the authors use a shift-share instrument to examine county-level shocks in the US and the effect of credit markets on real activity. In my case, I argue that the regulatory shock arising from the implementation of the Basel III accords in Mexico induced a bank-level credit shock.

My paper contributes to the macroeconomics literature on macroprudential reforms by exploring predictions of the models at the local level such as the expansionary lending response of large banks under imperfectly competitive markets as a result of an increase in capital requirements by increasing lending to gain loan market and deter small bank entry, while fringe banks shift their portfolios to safer securities (Corbae & D’Erasmus, 2021), and the effect of subsidy to equity issuance such that banks hold more capital reduces credit spreads and their volatility (Akinci & Queralto, 2022), and tighter capital requirements reduce competitive pressure on equity returns, as banks are safer now (Begenau & Landvoigt, 2021)

The rest of the paper is organized as follows. Section 2 provides background information, while Section 3 presents several empirical facts that inform the research design of the paper. Section 4 introduces the methodology of the paper. Section 5 presents the estimation results while in Section 6, I posit plausible explanations for my finding, before concluding in Section 7.

3.2 Background information

3.2.1 The Basel III Accords. The Basel Committee on Banking Supervision (BCBS), hosted by the Bank of International Settlements, is the primary global standard setter for the prudential regulation of banks and provides a forum for regular cooperation on banking supervisory matters. Its 45 members comprise central banks and bank supervisors from 28 jurisdictions. Among such standards is a set of risk-based capital requirements that requires minimum bank equity. It is worth noting that Mexico is represented in the BCBS by two institutions.

The Committee was integrated in September 2010 and the Basel III rule text was released by the end of the year³. This rule is an internationally agreed set of measures developed as a response to the financial crisis of 2007-2009 and introduced higher minimum levels of capital (CET1, Tier 1, and total capital ratios) and improves its quality, with CET1 becoming the predominant form of regulatory capital, with internationally harmonized adjustments. CET1 is the highest quality of regulatory capital, as it absorbs losses immediately when they occur. Banks can in principle adjust their balance sheet to meet capital requirements using different channels, such as asset reallocation, raising interest rates, or increasing retained earnings. The Liquidity Coverage Ratio is the main metric of the Basel III liquidity standards,

³<https://www.bis.org/press/p101216.htm>

and the minimum requirement was scheduled to apply in 2019, being gradually implemented starting in 2015.

The Committee conducted as well, a comprehensive quantitative study based on a total of 263 participating banks from 23 Committee member jurisdictions. The static exercise predicted a sizeable decline of the high-quality capital (CET1) ratio of large banks (Group 1 banks in the study) from an 11.1% gross ratio to a net ratio of 5.7%, while for the other banks in the sample the average decline in ratios from 10.7% to 7.8% (BIS, 2010)⁴.

In December 2017, Basel III Committee issued the finalized reforms which *“...enhanced the robustness and risk sensitivity of the standardized for credit risk...”* mainly by improving the granularity of the risk weight treatment and exposure. Furthermore, the rule introduced a leverage ratio buffer for Globally Systemic Important banks. These revisions and the rescheduled minimum capital requirements for market risk were set to be implemented in 2022.

3.2.2 Mexican adoption of Basel III. In September 2010, the Mexican central bank, *Banco de Mexico* and CNBV issued a joint press release⁵ announcing Mexico’s participation in the recently created Basel Committee, arguing that the new measures would have no major impact as the Mexican system had in place strict capital rules as a result of the Mexican 1994 financial crisis. The new rule was announced in 2010 and initially was expected to be phased in over a six-year period. Nonetheless, the enacted regulation did not allow for the gradually increasing capital requirements.

⁴<https://www.bis.org/publ/bcbs186.htm>

⁵<https://www.banxico.org.mx/publicaciones-y-prensa/miscelaneos/%7B1882AF0C-2DD7-E7D7-31A7-709859F2E78B%7D.pdf>

The National Regulatory Improvement Commission (CONAMER), an entity with the authority to review proposed regulatory measures, issued its final opinion in November 2012 which challenged the view of the SHCP, the entity issuing the regulation, and its ex-ante assessment of a negligible 20 basis point decline of capital ratios, and posited credit rationing and the hampering of financial inclusion. CONAMER recommended a gradual rollout of the policy, whereas the SHCP deemed the Mexican system resilient and well-capitalized enough to adopt the fully phased out without hampering financial access and credit operations, under the premise that the standards would allow these institutions to access low-cost funding.⁶ Banks on their side, favored the gradual rollout of the policy.

Finally, the requirements were implemented in their fully phased-in levels starting in 2013 with Mexican regulators allowing for phased-out eligibility of certain equity instruments and deferred taxes.

As the focus of this paper is the initial phase of the Basel III reforms, a note must be made on other aspects of the overarching set of guidelines issued by the Basel Committee that go beyond the early years of the reform. As noted by the Committee's Regulatory Consistency Assessment Programme,⁷ the Mexican regulators issued the liquidity regulation draft for consultation in October 2015 and the final rule entered in force in January 2015, and the domestic regulation was deemed to be already compliant. Regarding the 2017 revision, Mexican regulators released a press note and announced the implementation of the 2017 revisions⁸. These elements is beyond

⁶The regulatory file can be found at <https://cofemersimir.gob.mx/expedientes/10706>

⁷<https://www.bis.org/bcbs/publ/d316.pdf>

⁸<https://www.banxico.org.mx/publicaciones-y-prensa/miscelaneos/%7BBBC0A2D9C-202F-6516-EEE9-61119ADD11C1%7D.pdf>

the period of analysis of this paper, and while the phased-in liquidity requirements overlap with the initial stage of the capital reforms, I restrict my analysis to the latter.

An important note on definitions and terminology: In general a risk-based capital ratio refers to the relationship between eligible bank equity (as defined by the standards) and risk-weighted assets (RWA). For credit risk RWA, the main risk category for financial intermediaries, asset exposures are adjusted using standardized risk weights. These weights are not to be confused with default probabilities, and the lowest risk weight is denoted by 0%. The Mexican regulators use the term "Regulatory Capital Ratio" to denote the Basel III total capital ratio, which is based on three categories of eligible bank equity defined in the Basel framework.⁹

3.3 The Mexican Banking Industry

3.3.1 Key facts. *a) Regulatory Capital Ratios declined between the announcement of the Basel III standards in 2010 and the enactment of the rules in Mexico in 2013.*

As the minimum RCR set by the new capital rule in Mexico starting in 2013 was 10.5%, clearly the new regulation was non-binding and banks adjusted during the period between 2010 and 2012 under the uncertainty of whether the implementation of the requirements was to be staggered. This fact is central to my research design and is examined in detail in the following sub-section.

b) Average markups over borrowing rates declined during the post-reform, and large banks remained consistently above the mean markup

⁹More details can be found on https://www.bis.org/basel_framework/

As of December 2010, there were 41 commercial banks and the top 5 banks managed 74% of total assets, whereas in 2019, the number of commercial banks rose to 51 and the top 5 banks held 69% of total assets. Financial intermediation markups arise either from higher revenue in credit markets or trading activities or lower funding costs. As shown in Appendix Figure B.2.1a, the markup over the borrowing rates has decreased and converged over time which suggests that competition in the Mexican banking sector increased during the 2010s. Nonetheless, it is worth noting that the (asset-weighted) average markup of large banks remains above the overall mean. Altogether, these facts are suggestive of an association between the eventual resolution of the Mexican reform and increased competition during the post-reform period, in line with the converse of the standard prediction that tighter capital requirements dampen competition.

c) Larger banks differ from the overall banking industry in dimensions such as capitalization and lending behavior.

Profitability measures shed light on the drivers of the observed markups. While the Return on Assets (ROA) and the Return over Equity (ROE) indicators follow a similar pattern throughout the period of analysis, bank-size-related differences are noticeable for the latter. Equally well-run banks with the same ROA will have different ROE depending on their funding structure. Moreover, highly leveraged banks have larger ROE at the expense of the safety of equity holders. Figure B.2.1c suggests that differences in markups are driven mainly by heterogeneous funding structures (Panel c Figure B.2.1), as larger banks remained consistently above the mean ROE of the industry. Although this facet is not examined in this paper, larger banks might exert market power in funding markets: In 2010 the top 5 banks

concentrated 76% (74%) of total borrowed funds (assets) and by the end of the decade, this share dropped to 69% (69%).

d) Although banks did not contract either lending or risk exposures, their loan portfolio shifted toward safer instruments.

Banks might shift their portfolios to safer instruments to meet risk-based capital requirements and their target solvency buffer (Cohen and Scatigna 2016 and Corbae and D’Erasmus 2021). In light of capital requirements, standardized risk weights are factors to adjust bank exposures according to their credit risk, with consumer loans having larger risk weights. Appendix B.2.4 explores the loan portfolio of banks

e) Banking presence at the municipality level, as measured by the per capita number of branches experienced a negligible decline.

There are no signs of a significant expansion of bank presence, as measured by the number of branches. The mean number of branches increased from 4.6, in 2010 to 5.2, and 50% of municipalities (1,228) remain underserved with no branches. In terms per (adult) capita terms, the number of branches has effectively declined, as shown in Table 10.

Table 10. Number of branches, municipality level

	Number of Branches			
	Total		per 10,000 adults	
	2010	2019	2010	2019
Mean	4.6	5.2	0.5	0.5
Std. dev.	21.5	22.0	1.3	0.8
Percentile				
50th	0	0	0	0
75th	1	2	0.7	0.8
90th	6	8	1.7	1.7
95th	17	21	2.2	2.1
99th	114	122	3.9	3.3

Total Municipalities: 2,456

This fact allows me to rule out any result arising from a potential trend in financial development. There is, however, spatial heterogeneity in personal loan markets at the municipality and state levels (See Appendix B.2.3)

f) Average personal loan size at the municipality level declined in the post-reform period and it is associated with large banks' initial level of capitalization. Moreover, lending rates for this type of loan experienced a transitory decline.

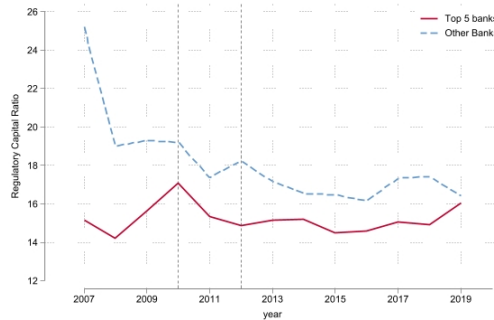
Appendix B.2.4 documents bank lending at the municipality level. The volume of (real) personal loans and count of originated loans have increased over time, with the latter growing at a higher rate which in turn results in lower average real loan size. The reduced-form analysis in Appendix B.2.5 shows that the initial capital ratio of large banks is associated with smaller average loans at the bank-municipality level. Along with the higher participation of consumer loans in the loan portfolio of large banks, this fact suggests that improvements in financial access were driven by higher bank competition by catering to underserved populations by offering smaller loans.

3.3.2 Evolution of Regulatory Capital Ratios. I continue my analysis by examining the evolution of the Regulatory Capital Ratio by bank size. As previously shown, the distinction based on bank size is relevant for bank capital management, and now I explore the potentially heterogeneous response of banks to capital requirements and to the introduction of the Common Equity Tier 1 (CET1) capital, one of the innovations of Basel III.

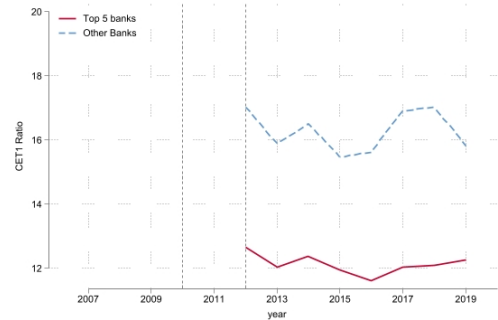
First, smaller banks have larger capital amounts relative to the risk-weighted assets as depicted in 8a. Second, the overall RCR has declined since 2010, with a steeper change for smaller banks. One plausible explanation is that banks remained expectant of the final rule (given the uncertainty surrounding the phased-

in implementation of the minimum requirements) and then adjusted their equity holdings once the new regulation was enacted.

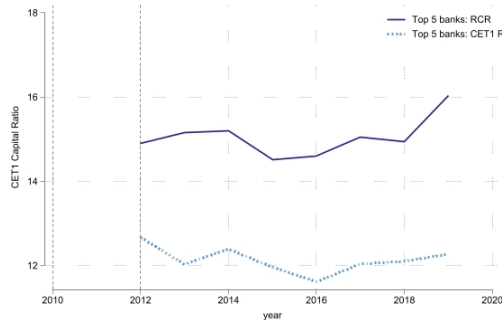
Figure 8. Capital Ratios by Bank Size



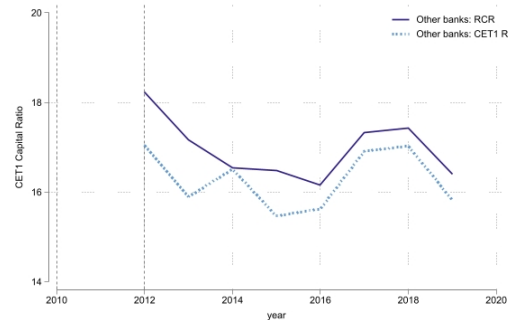
(a) Avg. Regulatory Capital Ratio by Bank size



(b) Avg. Common Equity Tier 1 Capital Ratio by Bank size



(c) Capital Ratios: Top 5 Banks



(d) Capital Ratios: Non-Top 5 Banks

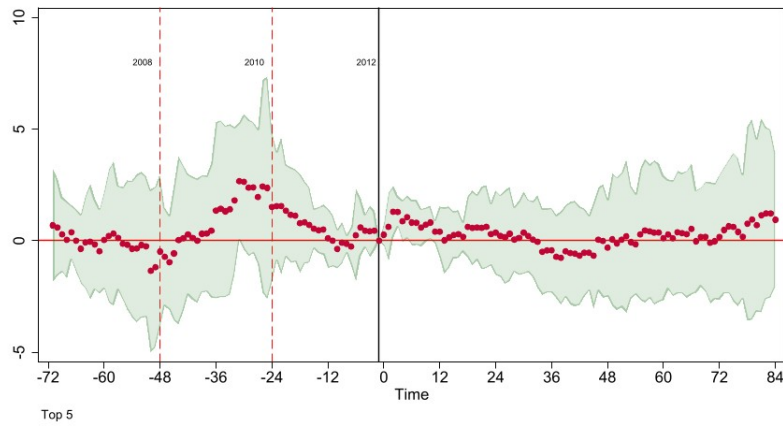
Taking stock of Figure 8, the evolution of the RCR in the post-reform suggests that banks have responded differently depending on their size: the average capital ratio of large banks increased in the post-reform period. Smaller banks have remained overcapitalized and rely on high-quality capital presumably due to costly equity issuance and to insure themselves against insolvency. Figure 8d shows that the capital of smaller banks is mainly comprised of CET1 capital, which is constituted of retained earnings, namely, non-distributed profits. For either type of bank, the series shows

excess capital holdings which are explained by the existence of buffer stock motive (Corbae & D’Erasmus, 2021).

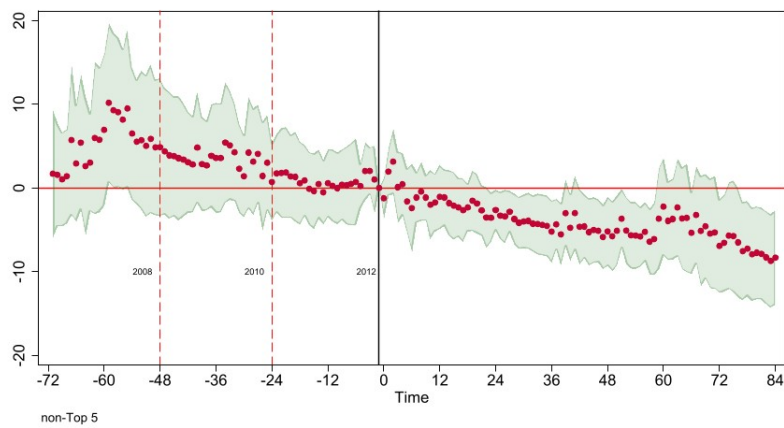
Appendix B.3 provides further descriptive evidence on the adjustments of the main components of the regulatory capital ratio. Recall that the RCR (as labeled by the Mexican regulator) is the ratio between eligible bank equity and total risk-weighted assets¹⁰ Overall, banks continued to expand both their assets and capital. Arguably, the adjustments during the period 2010-2012 set the stage for capitalization in the post-reform period. Consistent with our revision of the profitability measures, the analysis of these adjustment mechanisms is suggestive of increased competition in credit markets, as banks’ RWA expansion did not defer to equity growth.

¹⁰There are three risk categories for Risk-Weighted Assets (RWA). RWA for credit risk are the main component and computed using a set of standardized weights for asset exposures.

Figure 9. Event Study: Regulatory Capital Ratio



(a) Top 5 banks



(b) Non-Top 5 banks

Includes bank fixed effect. Robust standard error.

The event studies shown in Figure 9 are in line with Figure 8a and, despite the noisy estimates, these studies highlight the differential response of banks across time. While the RCR of large banks exhibits a temporary uptick after the Great Financial Crisis, for smaller banks, a clear downward trend is depicted.

To test for changes in the RCR levels by bank type, I consider three clearly defined stages: i) the pre-2011 Basel III announcement, ii) the Pre-reform period

(Jan 2011 - Dic 2012), and iii) the post-reform period (2013 onwards), and run the following regression

$$RCR_{bt} = \alpha_{pre-2011} + \alpha_{pre-ref} \mathbb{1}_{pre-ref,t} + \alpha_{pre-ref,Top5} \mathbb{1}_{Top5,b} \times \mathbb{1}_{pre-ref,t} + \\ + \beta_{post-ref,Top5} \mathbb{1}_{Top5,b} \times \mathbb{1}_{post-ref,t} + \beta_{post-ref} \mathbb{1}_{post-ref,t} + \delta_b + \varepsilon_{bt}$$

where $\mathbb{1}_{pre-ref,t}$ and $\mathbb{1}_{post-ref,t}$ are indicator variables equal to one when the t month is in the pre-reform and post-reform period respectively, δ . The coefficients of interest are $\alpha_{pre-ref}$ and $\alpha_{pre-ref,Top5}$ as they measure the differential response of banks during the pre-reform period (relative to the pre-2011 period). Table 11 reports the results using different estimation samples and allowing a differential effect for 2010. The test results for equality of the coefficients of interest are also reported. These findings suggest that large banks had a different response during the pre-reform period (2011-2012).

Table 11. Regulatory Capital Ratio, 2007-2015

	Dep. Variable: RCR			
	2007-2016	2008-2015	2007-2016	2008-2015
Pre-reform period (Jan 2011-Dic 2012)	-26.0503** [7.669]	-13.7693* [5.916]	-31.9456** [9.390]	-16.6743* [6.827]
Post-reform period (Jan 2013 onwards)	-29.8399*** [8.504]	-17.4645* [7.207]	-35.7129** [10.281]	-20.3657* [8.121]
Top 5 $\times$ Pre-reform period (Jan 2011-Dic 2012)	26.1001** [7.682]	13.6908* [5.940]	26.4032** [7.811]	13.7218* [5.955]
Top 5 $\times$ Post-reform period (Jan 2013 onwards)	29.5583** [8.532]	17.2741* [7.249]	29.8391** [8.649]	17.3012* [7.261]
Base: Pre-2011 period	57.6030*** [4.514]	46.1629*** [3.723]	63.4136*** [6.286]	49.0523*** [4.690]
2010 Dummy	No	No	Yes	Yes
F-stat	3.36	1.52	2.67	1.34
Number of obs.	5,076	4,080	5,076	4,080
F-stat: Test for equal adjustment during pre-reform period	11.55	5.38	11.56	5.70
p-value: Test for equal adjustment	0.00	0.02	0.00	0.02

Base period: Pre-2011. Includes bank fixed effects. Monthly observations. Column names denote the estimation sample

In conclusion, banks' regulatory ratios declined during the pre-reform period, arguably, due to the unfolding of the reform process and the resolution of the

uncertainty arising from the debate between the Mexican banking industry and the Mexican regulator about the fully phased-in requirements. In this dimension, bank size also mattered as smaller banks distinctively hold larger capital ratios presumably as a self-insurance mechanism (as shown by the relative importance of the high-quality CET1 capital).

3.3.3 Integrating the descriptive evidence and research design. The documented bank behavior and overall response to the announcement of reforms in Mexico highlight both i) bank size as an important dimension to be accounted for in the research design and, ii) the consumer loan market as the margin through which the new capital rules might have affected financial access.

3.4 Methodology and Data

3.4.1 Data. *1. Bank data:* Balance sheet and Income Statement data are from the Statistical Bulletins published by the CNBV. This data set contains the standard information for each bank operating in the Mexican banking sector. Using this data, I create a panel data set at an annual frequency over the period 2007-2019. As the CET1 ratio came into place in 2013, I take the reported ratio in January 2013, as the end-of-year ratio of 2012.

2. Loan data at the bank-municipality level: CNBV publishes in their *Portafolio de Información*¹¹ data on personal and payroll loans at the bank-municipality level starting in 2011. These loans are of unrestricted use with the sole distinction that payroll loan payments are deducted directly from the borrower's bank account. The data sets describe the interest rate, total amount, and the number of originated loans for each bank-municipality pair during the reporting bimonthly period. I collapse

¹¹<https://portafolioinfo.cnbv.gob.mx/Paginas/InicioModoExcel.aspx>

these reports at the bank-municipality-year level by aggregating loan amounts and origination and computing the weighted lending rate.

3. Operative data: The number of bank branches, ATMs, saving accounts, and other operative series are collected and published by the CNBV at the bank-municipality level.

4. Financial Access Surveys: Since 2012, the National Institute of Statistics and Geography conducts triennial Financial Inclusion surveys in Mexico (2012, 2015, and 2018). These data sets allow me to examine the usage of financial services. The microdata is publicly available and the surveys are consistent across years and permit for a panel-data analysis at the state level. Representativeness of the surveys is at the regional and national levels.

More details on these data sources can be found in Appendix B.1.

3.4.2 Methodology. Given the endogeneity of credit market participation and bank capitalization, I exploit the exogenous variation coming from the implementation of the Basel Accords after the financial crisis of 2007-2009. As previously argued, banks held precautionary capital prior to the enactment of the reform. My general identifying assumptions are i) the post-crisis reforms are exogenous, ii) changes in capital requirements act through balance-sheet constraints on other financial frictions, and iii) predicted credit shocks arising from the regulatory reform are independent of the municipality market shares.

From the perspective of this work, the implementation of Basel III in Mexico is exogenous and imposed an additional balance sheet constraint on the banking sector. I take 2010 as the base year as it marks both the international announcement of the Basel III accords and a pronounced change in capital ratios in the Mexican banking

industry. The premise is that banks with initial large capital holdings were able to expand their lending once the rules became known and effective in 2013.

The empirical approach is to first establish the non-triviality of bank lending response at the municipality level to the enactment of new non-binding capital rules, and secondly, show that differential exposure to bank shocks arising from regulatory change had an effect on local credit markets and municipality-level financial access measures. Finally, I explore financial access measures at the individual-state level.

For a given financial access measure at the local spatial market (e.g. municipality or county level) f_{mt} , the model of interest is:

$$f_{mt} = \beta K_{mt} + \epsilon_{mt} \quad (3.1)$$

where K_{mt} is a measure of allocated bank capital at the same level, and β is the structural parameter of interest. In addition to the potential correlation between the structural error term ϵ_{mt} and K_{mt} , an additional concern arises as the latter can only be formulated in a hypothetical manner. In theory, banks allocate their capital to satisfy regulatory capital requirements in sufficiently competitive markets (Hellmann, Murdock, & Stiglitz, 2000), to choose their size and leverage (Begenau & Landvoigt, 2021), and hold solvency buffers in the presence of market power (Corbae & D’Erasmus, 2021), among many other bank-level choices.¹² Moreover, empirical evidence suggests that rather than bank-level characteristics, factors such as geographic variation, spatial heterogeneity, and branch density shape retail local

¹²Adapting the framework of Holmstrom and Tirole (1997), Freixas and Rochet (2008b) examine the link between moral hazard, bank capital, and the substitutability between bank capital and regulatory monitoring

funding and lending markets (see Clark et al. 2021, Aguirregabiria, Clark, and Wang 2019, Drechsler et al. 2017, Nguyen 2019 and Ji, Teng, and Townsend 2021).

As banks allocate capital across business units (Bajaj, Binmore, Dasgupta, and Vo 2018, Goel, Lewrick, and Tarashev 2020) rather than geographic locations, and measures of capital allocation at the municipality level, namely any proxy for K_{mt} , are unavailable, I examine the effect of bank-level variation of equity, by studying outcomes of the adjusting mechanisms. Changes in bank lending are among these mechanisms (Cohen & Scatigna, 2016) and can be mapped to the municipality level.¹³ I focus on the exposure of location m to changes in outcomes of such capital decisions.

Letting $\Delta \log Q_{mt}$ denote lending volume growth in municipality m over some period beginning in time t , and $\Delta \log Q_{mbt}$ bank lending growth over the same span, and α_{mb} the market share of bank b at municipality m . we can write the following identity

$$\Delta \log Q_{mt} = \alpha_{mbt} \sum \Delta \log Q_{mbt}$$

I assume that for a given initial change in regulatory capital ratio $\Delta \log RCR_{0b}$ representing the net effect of variation of risk-weighted assets and eligible equity, lending growth in subsequent periods is a function of the base adjustment, $\Delta \log Q_{mbt} = f(\Delta \log RCR_{0b})$, and thus linking bank-level equity changes to outcomes at the local level.

3.4.3 Changes in capital ratios as Credit shocks. How did the regulatory capital reform translate to a municipality-level credit shock? My general

¹³The relation between changes in bank capital, regulatory capital ratios, and lending can be easily shown using accounting identities

argument is that the information shocks that characterized the reform process resulted in exogenous banks' balance-sheet rearrangements that were transmitted to local personal loan markets. The aforementioned shocks are i) the Basel Committee announcement in 2010, ii) the unfolding of the regulatory reform and the decision of the Mexican regulators to implement the fully phased-in requirements by the end of 2012; and the change in regulatory capital ratios between 2010 and 2012 is assumed to be an exogenous adjustment, as bank owners update their target capital ratios and portfolios. Risk-weighted assets and equity are stock variables and the adjustment occurs via net growth of securities and loans, equity issuance, and retained earnings policies. Among these adjustment strategies, changes in loan origination transmit the bank-level equity shock to a municipality-level credit shock.

The main research design and the specification of the credit shock are informed by the descriptive analysis, specifically i) the characteristic adjustment of capital ratios between 2010 and 2012, ii) the documented differences in capital management between large banks and their counterparts, and iii) the observed heterogeneity both in banking presence and lending at the municipality level. The premise is that municipalities were exposed differentially to credit shocks and the goal is to localize the bank-level effect of the new capital rule at the municipality and state level in the spirit of a shift-share instrument. These types of instruments have been widely used and identification is given by either exogenous market shares (Goldsmith-Pinkham, Sorkin, & Swift, 2020) or exogenous industry shocks (Borusyak, Hull, & Jaravel, 2022). As previously stated, the new capital rule can be argued to have induced an exogenous credit shock given the discussion regarding the staggered adoption of the policy.

Following Greenstone et al. (2020) I assume credit shocks at the municipality level are comprised of a local fixed effect, d_m and a general bank fixed effect s_b , in order to account for common changes in bank lending across municipalities and banks.

$$\Delta \log Q_{mby} = d_m + s_b + \mathbb{D}_{Nb} + \varepsilon_{mb} \quad (3.2)$$

where $\Delta \log Q_{mby} \equiv \log(Q_{mb(y+2)} + Q_{mb(y+1)}) - \log(Q_{mby} + Q_{mb(y-1)})$ is the log-difference of bank b total lending (of personal loans) at municipality m for two consecutive bienniums centered around year y . I adopt this approach to attain a stable characterization of bank lending. Thus for the biennium in 2011, $\Delta \log Q_{mb2011}$ denotes the log difference between total lending during the period 2011-2012 and the period 2013-2014. To account for the effect of banks that began extending loans in 2013, I set $Q_{mby} = 0.01$ and define a dummy variable $\mathbb{D}_{Nb}$ which is equal to one when the bank's share is zero in the initial period. Though these banks will not contribute to the shift-share instrument, this specification controls for omitted variables in the estimation of the municipality's fixed effects. Note that Equation 3.2 does not include a time-fixed effect as the equation will be estimated using cross sections for two consecutive bienniums.

Furthermore, I assume that banks' fixed effect can be further decomposed in terms of their initial capital ratio adjustment between 2010 and 2012:

$$s_b = \beta_1 \Delta RCR_{2012b} + \beta_2 \mathbb{1}_{Top5b} \times \Delta RCR_{2012b} + \bar{s}_b \quad (3.3)$$

where $\Delta RCR_{2012b} = RCR_{2012b} - RCR_{2010b}$ denotes the change of the end-of-year regulatory capital ratio. The dummy variable $\mathbb{1}_{Top5b}$ controls for any differential

response of large banks, as documented in Appendices B.1 and B.3.¹⁴ Assuming the introduction of new capital rules induces a new equilibrium, my specification captures the initial effect of the transitional dynamics during the given period.

For the sub-sample indexed by y , I estimate the following equation, with $y = 2012$ being the basis for the credit shock:

$$\Delta \log Q_{mby} = d_m + \beta_1 \Delta RCR_{2012b} + \beta_2 \mathbb{1}_{Top5b} \times \Delta RCR_{2012b} + \bar{s}_b + \mathbb{D}_{Nb} + \varepsilon_{mb} \quad (3.4)$$

and the shift-share instrument for the municipality-level credit shock using the bank-level instrumentalized shocks is given by¹⁵:

$$z_m = \sum_b \alpha_{mb} \left\{ \hat{\beta}_1 \Delta RCR_{2012b} + \hat{\beta}_2 \mathbb{1}_{Top5b} \times \Delta RCR_{2012b} \right\} \quad (3.5)$$

where α_{mb} is the market share for the total volume of loans of bank b at municipality m over the period 2011-2012. Unlike Greenstone et al. (2020), I use the level of the non-standardized shock in order to examine the implications of the positive and negative shocks.

It is worth noting that I restrict my analysis to reduced-form regressions on the instrument. Future work can examine the effect of credit on other outcomes such as poverty and formal markets using this instrument.

3.4.4 Credit Shocks and Financial Access. I assess the effect of the policy change on measures of financial access. Given the available data, I first study banking outcomes at the municipality level associated with financial access. To this

¹⁴This model assumes that loan supply evolves according to the following law of motion:

$$Q_{mbt+1} = Q_{mbt} e^{d_m} e^{\beta_1 \Delta RCR_{2012}} e^{\beta_2 \mathbb{1}_{Top5b} \times \Delta RCR_{tb}} e^{\bar{s}_b} e^{\varepsilon_{tm}}$$

In steady state, we can argue that $\Delta RCR_{tb} = 0$.

¹⁵Formally, the bank-level shock is not observed and is estimated in an initial step. As noted by (Borusyak et al., 2022) this procedure potentially introduces biases. Following their discussion, the underlying assumption in my setting is that changes in capital ratios are viewed as noisy estimates of the latent bank equity demand shocks and that bank equity supply shocks are negligible.

end, I run the regression:

$$f_{mt} = \alpha_0 + \phi \mathbb{1}_{t>2012} z_m + \beta X_{mt} + \varepsilon_{tm} \quad (3.6)$$

where f_{mt} is an aggregate outcome of bank lending and financial access for municipality m during period t . I first examine the number of originated loans and lending rates both for personal loans and payroll loans, aggregating over banks for a given municipality m , in order to test the significance of the predicted municipality-level shock z_m on bank lending. The total number of originated loans at the municipality level is simple the sum of bank-reported originated loans, while lending rates are computed as the loan weighted average of bank-reported lending rates. Analyzing these outcomes, allow me to study the link between credit markets and financial access.

I then examine financial access measures that are consistently reported at the municipality level by CNBV, the Mexican regulator, and have an associated question in the corresponding triennial Financial Inclusion Surveys. I compute the annual log difference of the outstanding number of credit cards, debit cards, and saving accounts. I follow this approach to test for the effect of the municipality-level credit shock arising from capital adjustments on other markets. Moreover, this analysis will support the extensive-margin analysis to be conducted based on the surveys, described below.

Drawing from the microdata of Financial Inclusion surveys, I then analyze the potential implications of exposure to credit shock on an individual's financial access during the period 2012-2018. As the survey microdata only allows for identifying the location of the respondent at the state level, I conduct this analysis based on the

aggregated credit shock

$$Y_{ist} = \alpha_{0s} + \sum_{j \in \{2012, 2015, 2018\}} \mathbb{1}_{j=t} \{ \phi_{1,2013} z_s \} + \gamma' X_{it} + \alpha_{st} + \varepsilon_{ist} \quad (3.7)$$

where Y_{ist} is equal to one when respondent i in state s has access or uses the financial product Y , X_{it} is a set of covariates for individual i , and α_{st} is a state-year fixed effect.

The identifying assumption is given by

$$E \left(\sum \alpha_{mb} \left\{ \hat{\beta}_1 \Delta RCR_{2012} + \hat{\beta}_2 \mathbb{1}_{Top5b} \times \Delta RCR_{2012} \right\} \varepsilon \right) = 0 \quad (3.8)$$

where β_i are the estimated coefficients in equation 3.6, ε represents the unobserved error term in equations 3.6 and 3.7 respectively. Underlying trends at the municipality level (i.e. economic growth or financial deepening) might be correlated to market shares and as argued by Borusyak et al., 2022, identification is achieved by the exogeneity of the shock. Likewise, individual unobservables at the state level (in the case of the state-level analysis) could be moving jointly with market shares. In either case, these factors are highly unlikely to be correlated with past changes in bank capitalization (especially during the time between the issuance of the Basel III international guidelines and their implementation in Mexico) and previous realizations of the unobservables.

As previously indicated, new banks began serving local personal loan markets in the post-reform period and a potential threat to the identification strategy is the existence of underlying competition trends, which can be partially rebutted by the negligible change in the number of bank branches per capita between 2010 and 2019 (see Table 10). Given that my preferred specification relies on the pre-reform local

market structure and new banks entered the personal loan market¹⁶ in the post-reform. I assume these effects are captured by the municipality and state-year fixed effects.

3.4.4.1 Validity of the Research Design.

First-stage analysis: Initial capital ratio and credit shocks. We need to establish that the regulation induced a lending credit shock with a differential response depending on bank size. Table 12 shows the estimation results of Equation 3.4 for the base sub-sample for the shock namely, the change in local credit between the biennial 2011-12 and 2013-2014 ($y = 2012$ as defined in the previous section)

Table 12. Biennial credit shock as a function of the initial change in capital ratio

	(1) $\Delta \log Q_{mb2012}$	(2) $\Delta \log Q_{mb2014}$	(3) $\Delta \log Q_{mb2016}$
ΔRCR_{2012b}	-1.057*** (2.147e-04)	0.968*** (7.288e-05)	4.097*** (4.746e-05)
$\mathbb{I}_{Top5b} \times \Delta RCR_{2012b}$	1.205*** (2.142e-04)	-1.001*** (7.242e-05)	-4.460*** (4.667e-05)
Number of (unweighted) observations	4,556	7,086	8,332
p-value	0.000	0.000	0.000
R-square	0.996	0.997	0.994

Weighted by bank lending at the beginning of the biennium. Includes bank fixed effect and municipality fixed effect

The coefficients of interest are shown in Column 1, which are based on the log. difference of the biennial volume of originated personal loans for the periods 2011-2012 and 2013-2014, the immediate pre and post-years of the reform. To better understand the first coefficient, suppose that a small bank b reduces its RCR by 1 percentage point ($\Delta RCR_{2012b} = -1$); the negative coefficient on the RCR change predicts that this contraction in regulatory capital led to a positive credit shock in the pre-reform period of 1.057. For larger banks, the shock has the opposite effect which means that following a reduction in the RCR, the volume of lending decreased

¹⁶According to my own calculations based on the available statistical bulletins, between 2012 and 2014 there were four new entrants to the personal loan market and their total market share amounted to 3.90 percent.

in the early years of the reform. It is worth noting that, for the banks in the 2011-2012 estimation sample, the loan-weighted average log difference in RCR is -0.1595 for the top 5 banks (4 of them in the personal loan market in 2011) and -0.0836 for the other banks (15 banks) ¹⁷

As seen in columns 2 and 3, the initial change in capital ratios during the period 2010-2012, traced out the post-reform lending behavior of banks: Building on the previous thought exercise, and for a small bank, an initial contraction in regulatory capital of -1 in anticipation of the reform, resulted in an increase of 1.057 between the biennial 2011-2012 and 2013-2014, followed by a deceleration of credit as given by the ancillary columns (2) and (3). These estimated coefficients are consistent as well with additional features of the Basel III accords, namely, the requirement of counter-cyclical buffers and bank-size dependent requirements, both of which provide a plausible explanation for the net effect of the adjustment for larger banks.

Hence, given the generalized decline in capital ratios, the predicted credit shock z_m becomes positive if the local personal loan market is serviced mainly by smaller banks. I also estimate the predicted shock based on payroll loan data and find that the correlation between these shocks is significant and positive (0.0495), which indicates that the shock arising from the payroll loans market is orthogonal to my preferred shock.

Covariates and municipalities characteristics. In a similar fashion as Greenstone et al. (2020), the validity of the design relies on the assumption that banks' lending shocks arising from capital ratio adjustments between 2010 and 2012 are not

¹⁷It must be noted that for the Mexican banking industry, the (asset-weighted) average decline in RCR between 2010 and 2012 was -2.68 percentage points for the top 5 banks and -6.00 for the other banks.

systematically correlated to shocks to outcomes in the post-reform period. A possible threat to identification is the existence of unobserved trends in financial deepening or economic development driving changes in capital ratios, yet, as previously argued, the Basel III accords were issued by an international committee in response to the Great Financial Crisis and the Mexican regulator sought to implement these capital standards at its fullest. Furthermore, even though equilibrium capital ratios and the level of these trends might be correlated, we argue that the adjustment in the capital is responding to an exogenous change and therefore, not correlated with the local characteristics of municipalities that drove the strategic branch allocation.

Table 13. Municipality characteristics

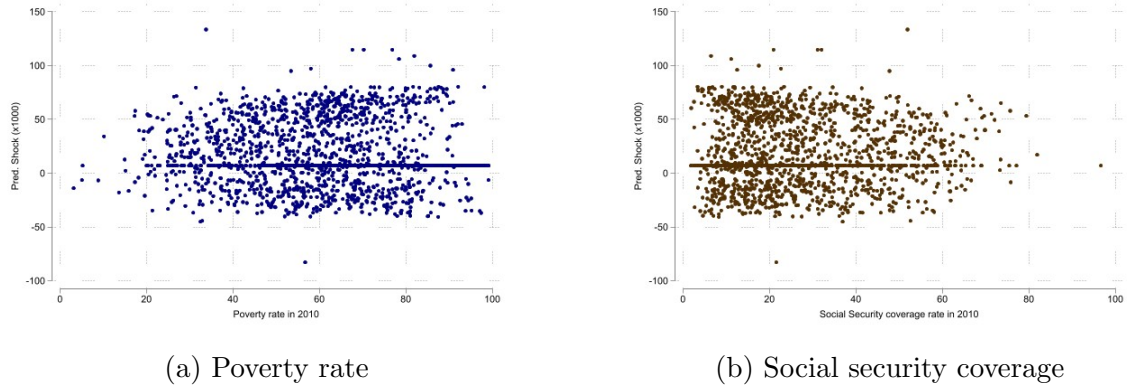
	Avg.	Min.	50th perc.	Max.	N
Below median in predicted shock					
Pred. Shock (x1000)	-1.02	-83	7.1	7.1	1,352
Population in 2020	26,830	274	9,245	1,484,243	1,352
Poverty rate in 2010	69.2	3.2	72	99	1,352
Area, square miles	339	1.4	105	12,777	915
Social Security coverage rate in 2010	22.5	1.9	19	97	1,352
Nbr. Branches in 2010	2.86	0	0	402	1,352
Above median in predicted shock					
Pred. Shock (x1000)	44	7.2	46	133	792
Population in 2020	97,673	1,591	41,965	1,807,581	792
Poverty rate in 2010	57.3	10	59	98	792
Area, square miles	500	2.5	171	20,059	735
Social Security coverage rate in 2010	28.3	1.9	24	82	792
Nbr. Branches in 2010	9.37	0	3	233	792
Total					
Pred. Shock (x1000)	15.6	-83	7.1	133	2,144
Population in 2020	53,000	274	16,147	1,807,581	2,144
Poverty rate in 2010	64.8	3.2	66	99	2,144
Area, square miles	411	1.4	133	20,059	1,650
Social Security coverage rate in 2010	24.6	1.9	20	97	2,144
Nbr. Branches in 2010	5.26	0	0	402	2,144

Unweighted calculations

As seen in Table 13, there is non-negligible variation municipality-level shock z_m between and across municipalities, and the shock is potentially associated with socio-demographic characteristics. Figure 10 shows there is not a systematic relation between the credit shock z_m , poverty rates, and social security coverage rates. The

observed sequence of observations bunched at a given shock, correspond to a subset of municipalities that were served by a single bank.

Figure 10. Predicted shock and municipality characteristics



As an additional check, I confirm that no systematic association between municipality-level credit shock and the municipal characteristic exists (e.g. poorer municipalities have lower shocks) and compute the correlation between municipality m fixed effect (d_m) and the standardized predicted shock (z_m) based on loan type l and find it positive and close to zero for each type of loan (0.0769 for personal loans and 0.0656 payroll loans).

In summary, Table 13 and Figure 10 suggest that poverty rates and social security coverage are weakly associated with the predicted shock z_m . I take these covariates as proxies for income level and formality of the labor market and argue that the quasi-experimental setting of the policy reform is valid conditional on these variables.

3.5 Results

3.5.1 Municipality-level outcomes. Table 14 presents the estimates of equation 3.6 which reports a significant effect of the shock arising from bank capitalization in 2010-2012. Recall that the overall RCR declined over this period and that, from Table 12, the bank shock is increasing only for a reduction of capitalization

of smaller banks. Thus, our predicted credit shock is positive when the municipality is mostly served by smaller banks.

The coefficient on the interaction between the indicator variable and the shock implies that loan origination in the subsequent years declines in highly exposed locations. From Table 14, column (5), a 0.01 increase in the shock implies 14.1% fewer originated loans. In line with our premise from the reduced-form analysis, the number of originated personal loans increases when the municipality is serviced by larger banks, which we found, extended smaller loans. This is suggestive that larger banks expanded their lending toward less banked municipalities.

Table 14. (log) Number of originated personal loans at the municipality level (2011-2019)

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Year $\geq$ 2013 $\times$ Pred. shock	-9.3771*** [2.031]	-12.8616*** [1.430]	-12.9626*** [1.417]	-14.1009*** [1.328]	-14.1015*** [1.326]
Poverty rate, last census		-0.0198*** [0.004]	-0.0201*** [0.004]	-0.0189*** [0.005]	-0.0189*** [0.005]
Year $\geq$ 2013 $\times$ Poverty rate, last census		0.0182*** [0.001]	0.0186*** [0.001]	0.0185*** [0.001]	0.0185*** [0.001]
Adult population (millions)		-4.9345** [1.460]	-4.9839** [1.497]	-5.7474*** [1.419]	-5.7422*** [1.450]
Number of branches (thousands)			6.6004 [6.069]	6.8860 [6.430]	6.9118 [6.320]
Avg. relative spread (Other mun.)				-0.0014 [0.002]	-0.0014 [0.002]
Number of branches (Other mun.)					0.6148 [11.001]
Year Fixed Effect	Yes	No	No	No	No
State-Year Fixed Effect	No	Yes	Yes	Yes	Yes
F-stat (all)	595.15	.	.	.	.
F-stat (excluding State-Year Fixed Effect)		118.95	94.04	81.88	75.39
Number of obs.	19,079	19,018	19,018	18,170	18,170

Weighted by 2010 population. Includes municipality fixed effects. Standard errors clustered on state are in brackets.

Table 15 shows that the credit shock also had a negative effect on lending rates of personal loans, in accordance with our premise of increased competition in the post-reform period.

Table 15. Lending rate, personal loans

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Year $\geq$ 2013 $\times$ Pred. shock	-309.4976*** [31.872]	-344.5810*** [33.910]	-345.0571*** [33.755]	-379.4145*** [21.759]	-379.4975*** [21.566]
Poverty rate, last census		-0.1236* [0.047]	-0.1252* [0.047]	-0.1142* [0.047]	-0.1132* [0.047]
Year $\geq$ 2013 $\times$ Poverty rate, last census		0.1852*** [0.027]	0.1872*** [0.028]	0.1923*** [0.028]	0.1933*** [0.028]
Adult population (millions)		-49.3843*** [11.198]	-49.6177*** [10.799]	-49.7165*** [10.298]	-48.9693*** [10.117]
Number of branches (thousands)			31.1623 [26.651]	22.7187 [24.172]	26.4240 [22.832]
Avg. relative spread (Other mun.)				0.0505 [0.027]	0.0511 [0.027]
Number of branches (Other mun.)					88.3297 [137.860]
Year Fixed Effect	Yes	No	No	No	No
State-Year Fixed Effect	No	Yes	Yes	Yes	Yes
F-stat (all)	251.61	.	.	.	.
F-stat (excluding State-Year Fixed Effect)		47.19	36.18	76.33	73.07
Number of obs.	19,219	19,158	19,158	18,310	18,310

Weighted by 2010 population. Standard errors clustered on state are in brackets.

It is important to note the coefficients on the adult population and poverty rates. Loan origination and lending rates of personal loans are decreasing in the adult population, which is suggestive of a leftward shift of the demand curve for loans, which could be indicative that locations with larger population have lower wages and therefore, demand for consumption-enhancing loans declines.¹⁸

For payroll loans, we find that total originated loans did not respond to the credit shock. As shown in the descriptive section, payroll loans as a share of consumer loans, increased over time which denotes a preexisting trend. These loans are safer relative to personal loans given that payment can be automatically deducted from the borrowers' accounts and are extended mainly to formal workers, is to be expected that the reforms would not have any bearing on originated loans. The effect of the shock is negligible relative to our result for personal loans.

¹⁸For simplicity, I refrain from analyzing the implications of the presence of borrowing-constrained individuals

Table 16. (log) Number of originated payroll loans at the municipality level

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Year $\geq$ 2013 $\times$ Pred. shock	0.6321 [0.637]	0.0896 [0.531]	0.0358 [0.529]	-0.0263 [0.582]	-0.0259 [0.582]
Poverty rate, last census		0.0005 [0.002]	0.0003 [0.002]	0.0007 [0.001]	0.0007 [0.001]
Year $\geq$ 2013 $\times$ Poverty rate, last census		-0.0011 [0.001]	-0.0009 [0.001]	-0.0006 [0.001]	-0.0006 [0.001]
Adult population (millions)		-0.4663 [0.485]	-0.4925 [0.394]	-0.2738 [0.474]	-0.2776 [0.458]
Number of branches (thousands)			3.5038** [1.121]	3.1993** [1.094]	3.1803* [1.223]
Avg. relative spread (Other mun.)				-0.0001 [0.001]	-0.0002 [0.001]
Number of branches (Other mun.)					-0.4519 [4.529]
Year Fixed Effect	Yes	No	No	No	No
State-Year Fixed Effect	No	Yes	Yes	Yes	Yes
F-stat (all)	412.31	.	.	.	.
F-stat (excluding State-Year Fixed Effect)		1.82	2.98	2.00	2.94
Number of obs.	18,954	18,893	18,893	18,052	18,052

Weighted by 2010 population. Standard errors clustered on state are in brackets.

Table 17. Lending rate, payroll loans

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Year $\geq$ 2013 $\times$ Pred. shock	-5.8019* [2.821]	-4.7224** [1.525]	-4.7525** [1.531]	-4.6473** [1.410]	-4.6209** [1.423]
Poverty rate, last census		-0.0040 [0.008]	-0.0041 [0.008]	-0.0035 [0.008]	-0.0038 [0.008]
Year $\geq$ 2013 $\times$ Poverty rate, last census		0.0043 [0.005]	0.0044 [0.005]	0.0021 [0.004]	0.0018 [0.004]
Adult population (millions)		6.2884** [2.211]	6.2736** [2.185]	6.8271** [2.422]	6.5891** [2.075]
Number of branches (thousands)			1.9701 [3.315]	-0.4783 [2.005]	-1.6583 [2.956]
Avg. relative spread (Other mun.)				0.0106** [0.003]	0.0104** [0.003]
Number of branches (Other mun.)					-28.1286 [33.597]
Year Fixed Effect	Yes	No	No	No	No
State-Year Fixed Effect	No	Yes	Yes	Yes	Yes
F-stat (all)	176.03	.	.	.	.
F-stat (excluding State-Year Fixed Effect)		6.32	5.31	3.55	3.52
Number of obs.	19,219	19,158	19,158	18,310	18,310

Weighted by 2010 population. Standard errors clustered on state are in brackets.

I examine changes in the number of saving accounts and debit cards. As presented in Table 18 and 19, a positive effect is found, suggesting that retail deposit markets became an important source of funding, as per the resolution of the new capital rules allowed banks to expand their lending and deposit capacity: an

additional unit of deposits can be allocated one for one and in credit and the growth in RWA funded needs not to be matched by increases in capital.

Table 18. Change in saving accounts. log. differences.

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Year $\geq$ 2013 $\times$ Pred. shock	16.1997*** [3.388]	14.4831* [5.874]	14.5589* [5.902]	19.7151*** [4.930]	20.2259*** [5.161]
Poverty rate, last census		-0.0184 [0.009]	-0.0177 [0.010]	-0.0131 [0.009]	-0.0147 [0.010]
Year $\geq$ 2013 $\times$ Poverty rate, last census		0.0061 [0.007]	0.0057 [0.007]	0.0033 [0.007]	0.0016 [0.007]
Adult population (millions)		0.5486 [1.547]	0.5389 [1.552]	1.2944 [1.493]	0.4707 [1.735]
Number of branches (thousands)			-2.2170 [3.503]	-3.5123 [3.042]	-8.2233 [4.065]
Avg. relative spread (Other mun.)				0.0004 [0.006]	0.0006 [0.006]
Number of branches (Other mun.)					-83.0554* [37.170]
Year Fixed Effect	Yes	No	No	No	No
State-Year Fixed Effect	No	Yes	Yes	Yes	Yes
F-stat (all)	1,549.19	.	.	.	.
F-stat (excluding State-Year Fixed Effect)		4.13	12.44	21.73	15.59
Number of obs.	1,887	1,886	1,886	1,728	1,728

Weighted by 2010 population. Standard errors clustered on state are in brackets.

Table 19. Change in debit cards. log. differences.

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Year $\geq$ 2013 $\times$ Pred. shock	1.3322*** [0.349]	2.0373*** [0.429]	2.0493*** [0.423]	2.2906*** [0.467]	2.2981*** [0.462]
Poverty rate, last census		0.0049*** [0.001]	0.0050*** [0.001]	0.0049*** [0.001]	0.0048*** [0.001]
Year $\geq$ 2013 $\times$ Poverty rate, last census		-0.0045*** [0.001]	-0.0046*** [0.001]	-0.0048*** [0.001]	-0.0049*** [0.001]
Adult population (millions)		-0.4448 [0.541]	-0.4394 [0.520]	-0.3785 [0.608]	-0.4792 [0.629]
Number of branches (thousands)			-0.9541 [0.985]	-1.0157 [0.997]	-1.5102 [0.897]
Avg. relative spread (Other mun.)				0.0009 [0.001]	0.0009 [0.001]
Number of branches (Other mun.)					-11.6268 [10.910]
Year Fixed Effect	Yes	No	No	No	No
State-Year Fixed Effect	No	Yes	Yes	Yes	Yes
F-stat (all)	222.49	.	.	.	.
F-stat (excluding State-Year Fixed Effect)		14.50	11.17	11.74	10.60
Number of obs.	17,064	17,011	17,011	16,239	16,239

Weighted by 2010 population. Standard errors clustered on state are in brackets.

3.5.1.1 Lending at the municipality level by poverty rate.

Before turning to the analysis at the individual-state level, I examine response heterogeneity

based on the municipality poverty rates. I classify municipalities according to their (population-weighted) poverty rate.

Table 20. Municipality characteristics, 2010

Quartile	Avg. Shock	Population (Thousands)	Avg. Population (Thousands)	Poverty rate (%)	Avg. Number of branches
1	0.0138	28,264	624.6	24.71	116.8
2	0.0191	28,228	890.3	35.16	100.3
3	0.0314	28,555	180.7	48.87	15.3
4	0.0287	29,492	68.9	74.42	3.1
Total	0.02329	114,539	436.3	46.11	58.1

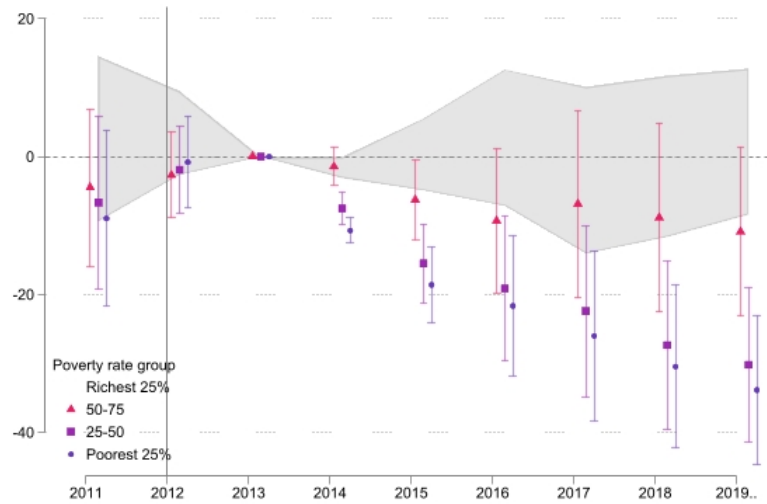
Weighted by total population

Table 20 shows that municipalities below the median (population-weighted) poverty rate experienced on average, the largest shocks, and have fewer residents and bank branches. To test for heterogeneity, I estimate the following model:

$$f_{mt} = \alpha_0 + \sum_{i=1}^4 \phi_{i,t} \times q_{m,i} \times z_{st} + \beta X_{mt} + \varepsilon_{tm} \quad (3.9)$$

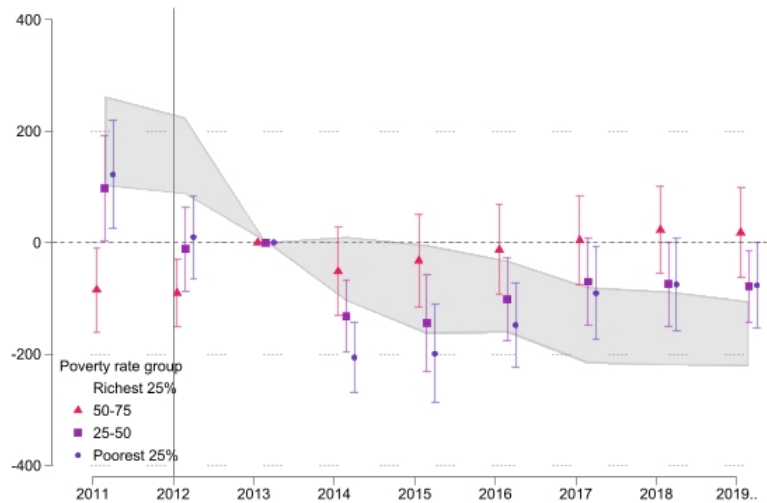
where f_{mt} denotes the financial outcome of interest of municipality m at time t and q_{mi} is an indicator for whether municipality m is in quartile i . I set quartile 1, that is, municipalities with the 25% richest population, and the year 2013 as the base levels. Figure 11 plots the $\phi_{i,t}$ in Equation 3.9 and shows that the poorest quartile had a significantly different response, with larger shocks implying a lower number of extended loans, relative to the other municipalities.

Figure 11. Total originated loans, by poverty rate



The graph does not show the year base level for either group.
 The shaded area represents the confidence interval for the richest 25%

Figure 12. Lending rates on personal loans.



The graph does not show the year base level for either group.
 The shaded area represents the confidence interval for the richest 25%

The evidence suggests a differential response across municipalities. After the initial credit shock, the temporary drop in lending rates documented in Section B.2.4

is driven by the local markets serving the 50% poorest population, as depicted in Figure 12.

3.5.2 Financial inclusion at the individual level. Appendix Tables B.4.1-B.4.6 show the estimation results of Equation 3.7. The dependent variables are all binary responses to having access to or having used a financial product, and therefore evidence of the effect of the reforms on the extensive margin. For our preferred specification (column 6), state-level exposure to the pre-reform shock base level in 2012 is highly correlated with the outcomes. Recall these estimations are conducted using microdata from triennial Financial Inclusion surveys, beginning in 2012. This is to be expected as the periods overlap and the highly significant coefficients based on microdata support favor the relevance at the municipality level of our constructed shock using the change in capital ratio between 2010 and 2012.

The effects of the enactment of the new capital rule are captured by the interaction of the year dummy and the predicted credit shock measure. Individuals in states with higher exposure to the shock are more likely to have access to credit and personal loans, while the likelihood of having had a payroll loan (Table B.4.3) declined in 2018, possibly due to the initial expansion of loan origination and evolution of formal labor markets that lead to a relatively lower number of unserved formal workers.

Though the analysis of general equilibrium outcomes is beyond the purpose of this paper, a suitable question is whether these changes in credit markets had any impact on other financial access outcomes. The new capital rule and subsequent bank behavior contributed to saving account access. Table B.4.4 shows that after an initial

plunge between 2012 and 2013, individuals were more likely to hold saving accounts in states with higher exposure to the constructed credit shock.

The survey data allows me to explore the side effects of post-reform bank lending behavior. As shown in Table B.4.5, loan application rejection rates based on self-reported data increased between 2012 and 2018. A plausible explanation is an increased loan demand due to the public’s perceived expansion of banking while banks continued to enforce their lending standards and screening procedures. A priori, there is no reason that the regulation will have a direct effect on the demand side of credit markets.

Moreover, state-level exposure to the average bank-credit shock originated by banks’ initial capital adjustment resulted in higher usage of informal credit products (e.g. loans from relatives, pawnshops, and moneylenders) only after a transitory decline in the early years, as shown in Table B.4.6. Together with our results on loan-application rejection rates and the documented increased competition, the findings are suggestive that the loan needs of a subset of the population remained unattended, as banks sought to retain market shares and manage credit risk by endogenously choosing the default rate of the pool of borrowers.

Finally, as noted in the introduction of this paper, women’s financial access experienced a surge between 2012 and 2015. As shown by the subset of coefficients on gender and interactions in the appendix tables, none of the results is suggestive of any gender-based heterogeneity arising from the regulatory shock.

3.6 Discussion of results

A standard prediction of general equilibrium models is that tighter capital requirements lead to credit contraction and higher lending rates (Benetton 2021,

Clark et al. 2021, Corbae and D’Erasmus 2021, Akinci and Queralto 2022, Begenau and Landvoigt 2021) and potential inefficiencies as aggregate bank capital can be argued to be directly related to optimal capital requirements (Malherbe, 2020). Nonetheless, the general question of the effect on financial access remains as the expansion or contraction of aggregate lending does not necessarily imply a direct relationship with the number of originated loans.

My results suggest that the resolution and enactment of the new capital rules in Mexico effectively induced a reduction of the precautionary holdings of capital that characterized the period 2010-2012. The resolution of the regulatory process led to lower regulatory capital ratios. As the regulation entered into force in 2013, consumer loan markets became more competitive.

The quasi-experimental setting of the Basel III reforms indicates that the mechanisms through which the competition-stability trade-off (Egan, Hortaçsu, and Matvos 2017, Clark et al. 2021) affects financial access measures depends on the local market structure and banks’ business model. In the Mexican case, the volume of personal loans expanded, and large banks characteristically extended smaller loans. In local markets mostly serviced by smaller banks, the initial credit expansion was followed by a deceleration in loan origination. These results are suggestive that large banks might opt to cater to riskier borrowers by extending smaller loan contracts, while smaller banks tend to manage their credit risk by refining their pool of borrowers and expanding their loan portfolio. The latter is supported by my finding of increased rejection rates in markets that experienced a higher shock, and the general view that smaller banks might have limited access to wholesale funding.

A striking fact is the observed decreasing average personal loans. Although this empirical fact does not necessarily imply credit rationing, I posit the latter as a plausible explanation as it has been argued to arise as a market response to adverse selection (Jaffee and Russell 1976, Stiglitz and Weiss 1981), which might be relevant given the spatial distribution of bank branches. While bank branching is a strategic choice (Degryse, Kim, and Ongena 2009 and Nguyen (2019)), distance matters for loans based on soft information gathered by branch officers, and the effect of distance on lending conditions is a reflection of monitoring costs (Freixas & Rochet, 2008b). As borrowing-constrained consumers are willing to pay higher rates (Karlan & Morduch, 2010), loan size and distance-related costs become a relevant dimension for nonprice competition.

This paper does not explore the cost of equity as a potential consequence of capital regulations. This type of regulation brings about shifts in the funding structure of banks and arguably the cost of equity and lending (Miles, Yang, & Marcheggiano, 2013). The magnitude and direction of increased capital are contested and the core of this subject is whether higher solvency reduces the volatility of equity: For the US, M. Baker and Wurgler (2015) argue posit the low-risk anomaly as to why well-capitalized banks face a higher cost of capital, while Kovner and Van Tassel (2022) find a negative effect since the passage of the Dodd-Frank Act. Using a cross-country-bank sample for Belkhir, Naceur, Chami, and Samet (2021) document a negative association between higher capital, and the survey in Birn et al. (2020) favors the argument of the low-risk anomaly and highlights loan rates being one of the salient costs of increased capital.

What can we say about the cost of capital in Mexico and financial access? As shown in Figure B.3.1, bank capital growth spiked in 2009, stalled during 2013, and

surged afterward, despite the downtrend in capital ratios. Moreover, the new rule imposed further restrictions on equity issuance and dividend payouts. Altogether, it is plausible that the cost of capital rose as a result of the general equilibrium effects of the policy, despite the downtrend in capital ratios.

In the competitive credit-rationing framework of Jaffee and Russell 1976, consumer loan supply is directly related to the cost of equity, meaning that an exogenous change in the cost of capital will shift loan supply in the same direction. Assuming the economy starts out from a credit rationing equilibrium and holding the cost of capital constant, a temporary decrease in lending rates with smaller loan sizes is consistent with the prediction of the model of temporal profit opportunities, as a new entrant can offer smaller loan contract (which yield lower default rates and are preferred by borrowers). The results of this paper fit the model's prediction of multiple-contract equilibria where "dishonest" borrowers are only temporarily self-revealing by choosing larger loan sizes, or alternatively, the transition from a non-rationing equilibrium to credit rationing with higher capital costs.

The analysis based on microdata sheds light on the extensive margin and suggests that individuals in states with higher exposure to credit shocks were i) more likely to access credit and saving accounts and ii) more likely to have their loans rejected. The lending capacity and size of banks are determined by the funding structure, including the deposit capacity¹⁹ and the resolution of the regulation which effectively constraint banks' asset portfolio can also have an effect on retail fund markets. As the banking industry expands its lending under new capital rules, the need for borrowed funds

¹⁹In many settings, banks act as quantity setters in retail funding markets i.e. choose the quantity of deposits. See for example Stiglitz and Weiss 1981, Hellmann et al. 2000, Drechsler et al. 2017, Begenau and Landvoigt 2021, Corbae and D'Erasmus 2021

leads to higher competition in the deposits market and therefore an improvement in financial access via saving account holdings.

3.7 Conclusion

In this paper, I find that balance-sheet constraints have a transitional effect on banks' lending behavior and the loan market at the municipality level, all of which are determined by the underlying loan market structure. The evidence suggests that the most salient effect of new capital rules in Mexico occurred via the anticipation effect it had on banks. Declining bank capital ratios and markups suggest that banks held precautionary equity buffers to face the uncertainty surrounding the final rule and once the new regulation was enacted, credit markets became more competitive. Bank lending continued to expand and for larger banks, the average personal loan size at the municipality level is negatively correlated with the initial 2010 regulatory capital ratio.

Increased access to formal credit via smaller loan sizes and a rise in retail funding market participation are associated with the policy. Related outcomes such as higher usage of informal credit and loan application rejection rates are also suggestive of more general effects. Future research venues are bank competition through credit rationing and policy reforms of formal finance systems to expand financial inclusion.

CHAPTER IV

DISTRIBUTIONAL EFFECTS OF BELIEF CHANGES ABOUT STOCK RETURNS

4.1 Introduction

How do beliefs about asset returns influence wealth distribution? This question has grown increasingly relevant with the expanding availability of information, new propagation mechanisms, and emerging technologies such as Artificial Intelligence, all of which have eased the *limited information processing capacity* proposed by (Sims, 2003). Evidence suggests that the financial sector has become more efficient in processing information, shifting the focus from acquiring fundamental data to analyzing non-fundamental shocks to prices, inducing structural changes in how financial analysis and investment strategies are conducted (Farboodi & Veldkamp, 2020).

Beliefs significantly influence household portfolio allocation decisions. The seminal work of Merton, 1969 establishes that optimal portfolio shares depend on expected asset returns and volatility, while empirical studies have documented how beliefs shape portfolios and trading activity (Choi & Robertson, 2020; Giglio, Maggiori, Stroebel, & Utkus, 2021). Moreover, the general reasons that shape the wealth distribution, namely stochastic earnings, differential saving rates, and idiosyncratic returns to wealth (Benhabib, Bisin, & Luo, 2019; De Nardi & Fella, 2017), all involve intertemporal trade-offs that are evaluated based on individuals' beliefs.

Stocks represent a fundamental class of risky assets that embodies such trade-offs. These financial instruments are characteristically held by wealthier groups. Economists have long recognized the macroeconomic significance of the stock market

(Fischer & Merton, 1984), as well as the relationship between expectations and stock prices (Adam et al., 2017; Harrison & Kreps, 1978). Extensive research has also focused on measuring subjective expectations, as highlighted in surveys by (Manski, 2004, 2018). The observed heterogeneity in survey responses suggests the importance of understanding how beliefs about stock returns influence wealth distribution. In the early 2000s, technological advances, abnormal valuation ratios, and weakened forecasting relationships raised concerns about stock market outlooks (Campbell & Shiller, 2001). Historical evidence suggests that the adoption of information technology significantly impacted aggregate stock valuations in the early 1970s (Hobijn & Jovanovic, 2001), and similar advancements in computing power in the late 1990s likely contributed to shifts in equity valuation through the accumulation of intangible assets or the formation of price bubbles (Jorgenson, 2001).

In this paper, I examine how belief shocks, through asset allocation choices, interact with various saving motives that contribute to the characteristic right-skewed tail of wealth distributions. To motivate my analysis, I present empirical findings that highlight a significant relationship between beliefs about equity returns and wealth distribution. In particular, descriptive data and empirical evidence suggest a relevant connection between the bequest motive and stock return expectations. This novel perspective revisits a discussion from the early 2000s, when Campbell and Shiller (2001) identified the link between the baby boom and stock demand, and Poterba (2001) tested the "asset market meltdown" hypothesis, the idea that baby boomers would sell off their assets en masse, leading to a sharp decline in holdings. However, Abel 2001 argued that an altruistic bequest motive could generate sustained asset demand among retirees, which aligns with the lack of empirical support for the meltdown hypothesis. I propose the existence of a stochastic bequest motive

that depends on subjective beliefs to further study the life-cycle and distributional implications of changes in beliefs.

To establish the link between changes in beliefs on stock returns and the dynamic of the wealth distribution, I use externally identified shocks and investor surveys, and first determine that informational shocks affect stock return expectations, as investors' perception are significantly responsive to the economic outlook inferred from stock markets. To study the medium-run effect of these fluctuations in beliefs, I estimate the Impulse Response Functions of the wealth shares using local projections and finding non-negligible shifts of the wealth distribution that go beyond twelve months. To understand this link, I calibrate and estimate a two-period model with heterogeneous agents with different beliefs about the distribution of outcomes. I introduce a portfolio problem the warm-glow bequest motive is derived from the expected value of bequeathable assets.

The remainder of the paper proceeds as follows. Section 4.2 describes our available data on expectations, Section 4.3 and 4.4 motivate an empirical analysis of the distributional effects of changes in beliefs. Section 4.5 then shows a simple two-period model with belief disagreement and otherwise identical agents to examine the significance of these effects. Section 4.6 concludes.

Literature Review. Retirement puzzle and the life-cycle: An ample body of work has studied the retirement puzzle. As examined by Banks, Blundell, and Tanner (1998), fall in consumption in retiring households as a result of informational shocks during retirement. Medical expenses (De Nardi, French, & Jones, 2010), intergenerational transfers and the importance of the bequest motive (De Nardi, 2004; De Nardi & Fella, 2017) have been found to be the key drivers for saving in retirement. Regarding the effect of aging, Korniotis and Kumar (2011) provide evidence on the

detrimental effects of cognitive aging in investment decisions. Abel (2001) explore the role of the bequest motive and stock prices. In this paper I explore the relationship between beliefs on stocks and this puzzle, as disaving rates in old age may depend on retiree's outlook and subjective perceptions.

Expectations and stock prices: Giglio et al. (2021) document the role of beliefs and how they are reflected in their portfolios and trading activity, while the survey in Choi and Robertson (2020) provides support in favor of several hypothesized factors about financial beliefs and portfolio equity share, and Meeuwis, Parker, Schoar, and Simester (2022) exploit the outcome of the 2016 U.S. election as an informative public signal in order to study the effect of belief disagreement on portfolio choices. On the general effect of investors' beliefs, Adam et al. (2017) find that capital gains are driven by non-rational beliefs of investors, and the work of Jappelli and Padula (2013) and Lusardi, Michaud, and Mitchell (2017) suggests that financial knowledge and literacy have distributional effects. Kuhn, Schularick, and Steins 2020 document the linkage between capital gains and wealth and income inequality.

Portfolio choice and expectations: In Merton 1969, Gomes et al. 2021 the expected return and volatility of assets determine their optimal portfolio share. This is the mechanism through which expectations would enter the model. Vissing-Jørgensen and Attanasio (2003) test several asset-pricing models and argue that having two assets yields helps explaining the equity premium puzzle. Malmendier and Nagel (2011) show that lifetime experience on risky asset returns affect beliefs about future performance and participation in bond and stock market (uses UBS index data). M. K. Brunnermeier and Nagel (2008) document the absence of the wealth effect on the risky asset shares and suggest that changing stock market participation rather than time-varying individual aversion may explain the time-varying risk premia in

the aggregate. My paper also contribute to the literature explaining stock market participation

Egan, MacKay, and Yang (2021) find that expectations play a major role in retirement portfolios. The authors exploit exogenous variation in investment costs to retrieve the distribution of beliefs and risk aversion across investors and find substantial heterogeneity in both risk aversion and beliefs across investors. Moreover, they document that investors beliefs are not rational, overreact to recent news and based on extrapolated past fund returns and from individualized experience based on local economic conditions and employer performance.

Distributional effects of portfolio choices Kuhn et al. (2020) use long-run US data and document the highly persistent differences in portfolio composition and leverage of households along the wealth and that capital gains and losses shift the wealth distribution through an "asset price channel". Factors related to personal experience and advice are related to portfolio equity shares (Choi & Robertson, 2020). Giglio et al. (2021) posit capital gains as frictions for beliefs pass-through response of portfolios. Adam et al. (2017) model capital gain optimism to explore whether agents behave under rational expectations.

Contribution: Compared to similar work (Kacperczyk, Nosal, & Stevens, 2019, Giusto, 2014, and Lei, 2021), my contribution is to examine a portfolio choice problem driven by heterogeneous beliefs in a life cycle model with incomplete markets. My goal is to quantify the importance of the belief channel, and examine how it drives the dynamics of the wealth distribution. I posit an endogenous mechanism for capital risk and contribute to the existing literature by quantifying the channel of subjective expectations and its link to the main determinants of wealth distribution (De Nardi

2004, Benhabib, Bisin, and Zhu 2011, Benhabib, Bisin, and Luo 2017, and De Nardi and Fella 2017).

4.2 Data

UBS Gallup/UBS Poll

I analyze these data and study the responsiveness of investors' perception to new information. The survey ranges from 1996 until 2007 (quarterly 1996-1998, monthly onward) is a sample of a national cross section of head of households or spouse in any household with total savings and investments of \$10,000 or more. The survey covers the personal financial and macroeconomic dimension of investment and investor responses are measured on a five-point scale (very optimistic, somewhat optimistic, neither optimistic nor pessimistic, somewhat pessimistic, very pessimistic). Investors are asked about their optimism about their personal investment goals and also about factors that may affect the overall investment environment, including the performance of the stock market over the next year.

This data set contains an ordinal scale of wealth, age, and education, among others. Prior to 2003, investors reported their expected return of the stock market (although no reference index is defined) and starting in 2001, investors are asked about the return of the own portfolio in the past year and over the next year.

Health and Retirement Study

This is a longitudinal panel study that surveys a representative sample of approximately 20,000 people in America, aged 50 or more. Since 2000, the survey has elicited subjective probabilities pertaining to the return on blue chip stocks. Following Kézdi and Willis (2011), under the assumption of normality, the subjective mean and standard deviation can be identified using questions on stock market performance:

"By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?"

"By next year at this time, what is the percent chance that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average will have gained in value by more than 20 percent compared to what they are worth today?"

This source provides rich data on wealth, portfolios, income, and bequests, among other aspects.

Survey of Consumer Finances

The Survey of Consumer Finance (SCF) is a triennial survey with detailed information on household finances and portfolios that serves as the basis for the Distributional Finance Accounts of the Fed. The SCF asks on a three-rating scale about the future performance of the US economy. This survey does not elicit subjective perceptions. When considering the unconditional correlation found in the UBS index between perceived performance of the stock market and the economy (approximately 0.5), the data from the UBS survey may be reasonably matched with the SCF. Economic expectations, credit attitudes and financial institutions. Miscellaneous opinion variables

Other sources. The RAND American Life Panel (ALP) is a nationally representative longitudinal panel that includes individual characteristics. The module 'Effects of the Financial Crisis' was surveyed from November 2008 to January 2016 for a total of 61 waves, with a monthly frequency starting in May 2009. The survey elicits stock market beliefs through probabilistic statements.

The University of Michigan Survey of Consumers includes one question on the probability of an increase in stock market prices. This monthly series has been

available since June 2002. Categorical information on stock investments, housing and income is available.

4.2.1 Data mapping to the empirical analysis and model. The Gallup/UBS poll is used in a high-frequency identification setup which is to be described in what follows of this paper. As this source allows for a simple characterization of the expected returns on stocks (available from 1996 to 2001) and its unconditional distribution, I used it as a basis for calibrating and analyzing a simple two-period model.

For the multiperiod life-cycle model, the calibration of conditional distributions of beliefs of workers aged 50 or more is possible using the HRS. For younger workers, the corresponding transition matrices will be calibrated using the other available sources.

4.3 Empirical Facts and Analysis

In this section, I document several empirical facts that suggest that beliefs on equity returns have fallen and that stocks remain as one of the main assets in households' portfolio, altogether associated with wealth concentration. A glance at the Distributional Finance Accounts reveals that asset portfolios vary distinctively across wealth profiles.

4.3.1 Descriptive analysis.

Medium-run waves of Optimism and Pessimism. To describe the long-term behavior of beliefs, I consider the sentiment index of M. Baker and Wurgler (2006) as a proxy. This metric is based on market measures orthogonalized to macroeconomic conditions. Notably, Figure 13 shows that episodes of optimism and pessimism may last for years and characterize certain decades. The optimism of the 1990s, the mean reversion of sentiment in the 2000s after the Internet

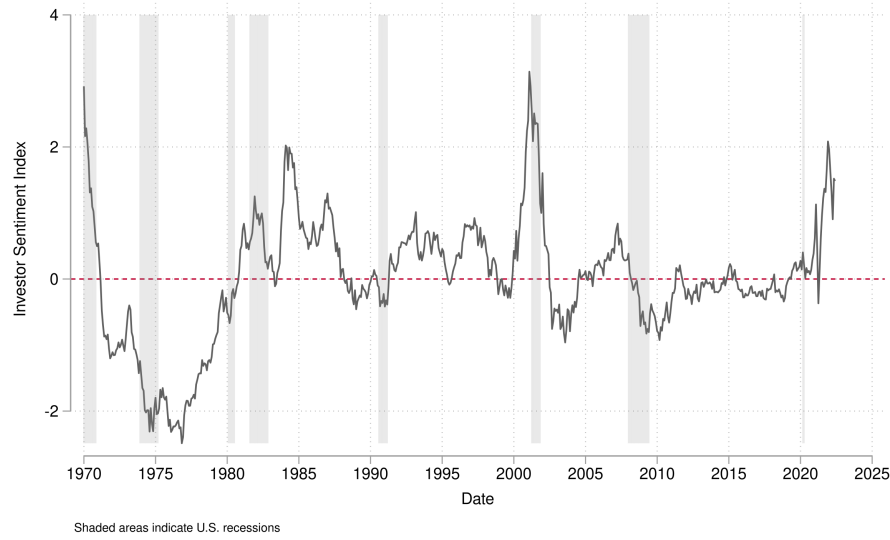


Figure 13. Index of Sentiment Levels, Baker and Wurgler (2006)

Note. This figure shows the first principal component of levels in six measures of sentiment: the closed-end fund discount (CEFD), detrended log turnover (TURN), number of IPOs (NIPO), first-day return on IPOs (RIPO), dividend premium (PDND), and equity share in new issues (S), each standardized and with the effect of macroeconomic conditions removed. Available at <https://pages.stern.nyu.edu/~jwurgler/>

bubble burst, and the lingering post-crisis pessimism of the 2010s suggest that the differential exposure of different cohorts influenced the wealth distribution through asset allocation choices. Previous work has shown that beliefs are reflected in portfolio choices (Giglio et al. 2021, Choi and Robertson 2020) and personal experiences of aggregate shocks affect the risk-taking behavior of individuals (Malmendier & Nagel, 2011).

To conclude, in what remains of this paper, we take the position that changes in beliefs are transitory. Hudomiet, Kézdi, and Willis (2011) find a temporary increase in the population average of expectations and with higher significance on uncertainty right after the stock market crash of 2008. Arguably, as proposed by Dominitz and Manski (2011), population can be thought to be composed of three types of agents in

how they form their expectations: Random-walk type, Persistence type, and Mean-reversion type.

Wealth stock holding concentration. A glance at the distribution of wealth (net worth) of households (panel a), Figure 14) suggests a link between wealth distribution, investor sentiment, and stock holdings.

Although the optimism that characterized the 1990s (as proxied by a prevalent positive Investor Sentiment Index) was associated with higher stockholdings, households in the middle 40th percentile (second row, Figure 14) follow a distinctive pattern in how they "ride the wave" even after the burst of the bubble, which might explain the temporal reversion of the upward trend in wealth concentration by the Top 10th percentile.

For the bottom 50th percentile, housing represents the largest portion of their wealth: between 1989 and 2019, real estate (net of home mortgage) as a share of net worth has soared from 30 percent to 59 percent ¹. Thus, the post-2007 crisis dip of the wealth share and steady decline in aggregate participation on corporate equity shares can be partially explained by the crowding out of housing of stockholdings Cocco (2005). These documented differences may also be due to

4.3.2 Professional forecasters and Investors' beliefs. Individual responses from the Survey of Professional Forecasters administered by the Philadelphia Fed show that long-run expectations on equity have decreased over time, including the implied real return. Notably, the downward trend in expectations is not reversed with the uptick of the 1-year US Treasury Securities that occurred between 2004 and 2007. For the implied equity premium ² which displays high dispersion in

¹Own calculation based on the Fed's DFA data

²For each individual response, the forecast of the real return and the equity premium can be computed using the respondent's inflation and interest rate forecast over the same period.

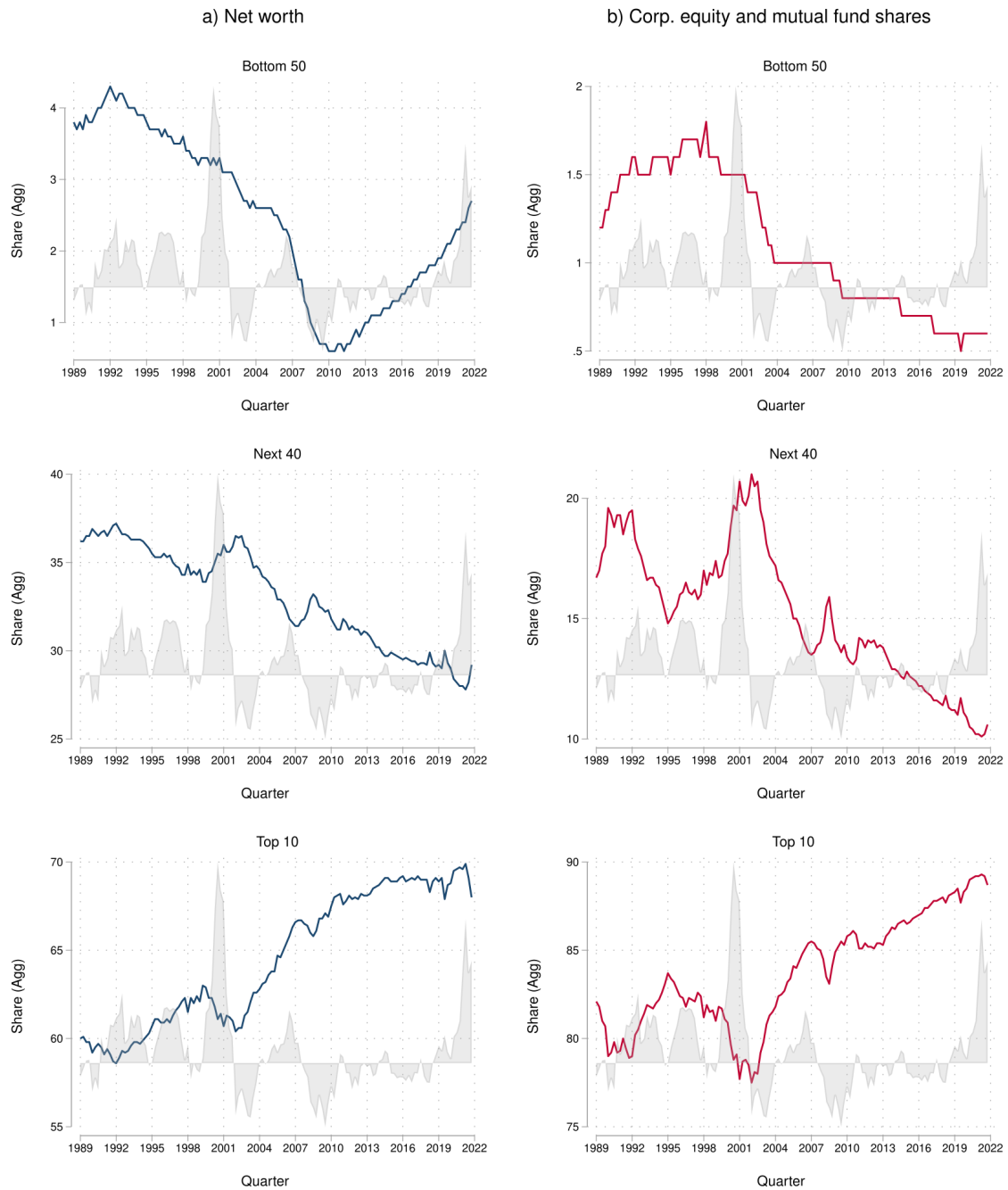


Figure 14. Wealth and Stock holdings (Share of aggregate volume). Fed's Distributional Finance Accounts.

the late 90s and soars after the Great Financial Crisis and the post-pandemic years, suggestive the responsiveness of agents to economic shocks. Although these data may not be relevant to asset pricing, they are indicative of the market sentiment and trends that investors take into account for their portfolio choices.

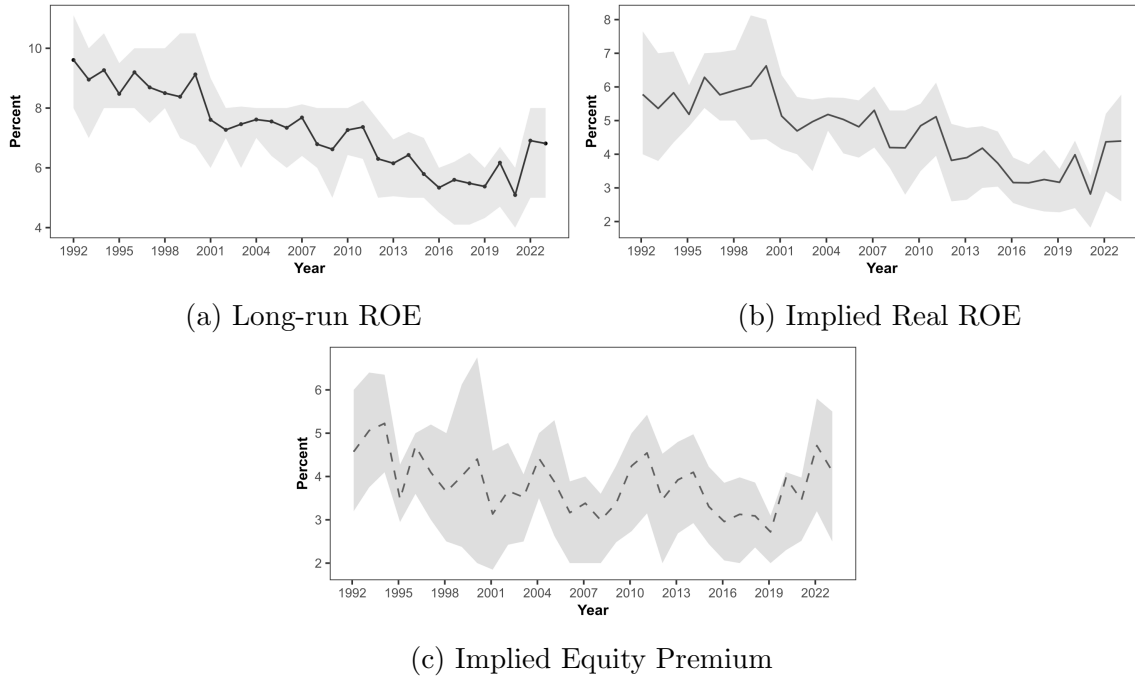


Figure 15. Evolution of long-run mean expectations, SPF Philadelphia Fed.
25-75th percentiles

A similar outlook is observed when we consider investors' responses from the UBS/Gallup survey. According to their self-reported attitude towards the performance of the stock market over the next year, the share of pessimistic agents³ has experienced a small shift after the Dot-com bubble of 2000 and both the mean expected stock return and the equity premium reflect the self-reported attitude.

³For presentation purposes, I collapse the categories "Very pessimistic" and "Pessimistic", and "Optimistic" and "Very optimistic" into one, respectively.

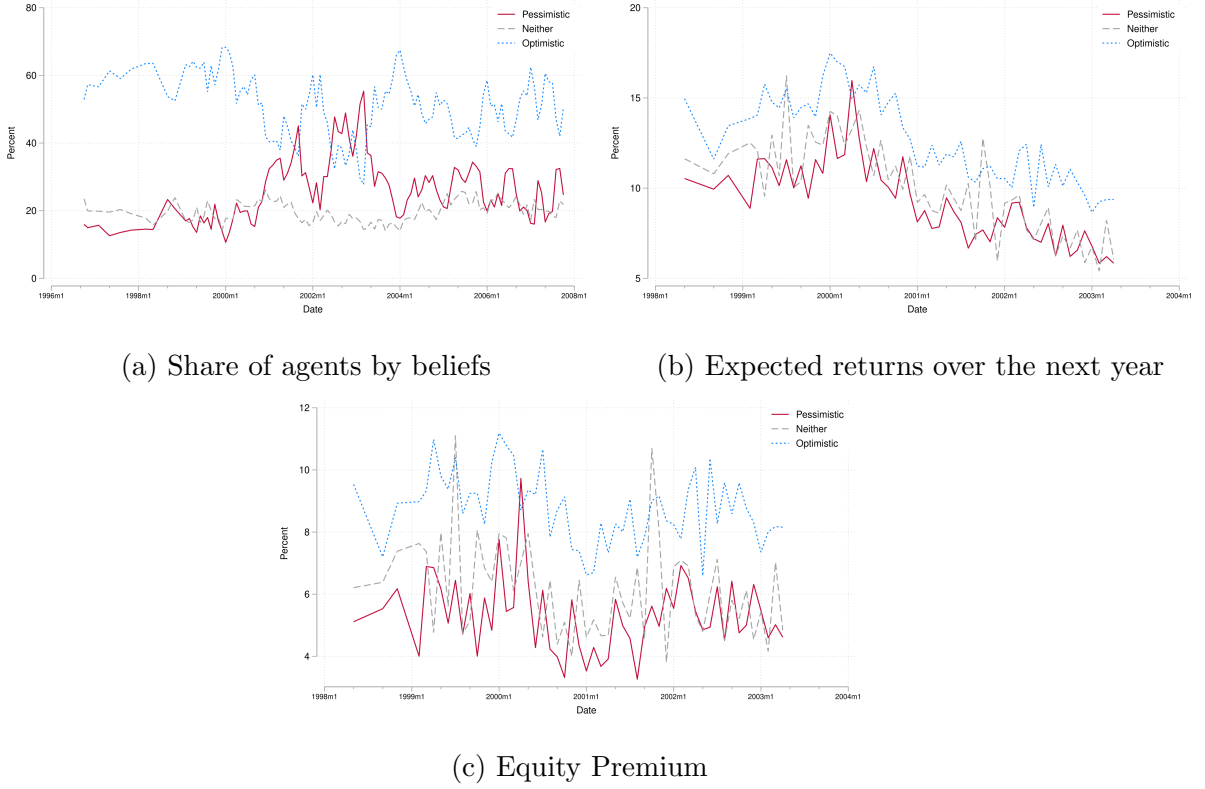


Figure 16. Mean beliefs by type, UBS/Gallup Survey

4.3.3 Stock holdings, bequest motive, and beliefs. Is there an interaction between beliefs and the bequest motive? In the early 2000s, Poterba (2001) posited and tested the "asset market meltdown" hypothesis, which predicted a sharp decline in asset holding associated with the age structure due to baby boomers selling without finding strong evidence in its favor, and Abel 2001 taking up this point argued that the bequest motive influenced asset prices. An inspection of terminal portfolios shows that stocks constitute the highest share of decedents' portfolios and have consistently remained above 30% (panel a) Figure 17) and, while liquid and retirement assets are nearly depleted, the latter is consistent with the standard life cycle hypothesis. From the Survey of Consumer Finances, there is a high correlation between stock holdings and having received receiving an inheritance. In addition,

optimism about economic performance is associated with the reported likelihood of bequeathing assets.⁴ Although differential background risk (Gomes et al., 2021), the positive relationship between health and risky asset shares in retirement (Yogo, 2016), or strategic bequests to reward informal caregivers (Bernheim, Shleifer, & Summers, 1985; French, Jones, & McGee, 2023) explain these facts, terminal portfolios continue to highlight the importance of equity instruments in retirement.

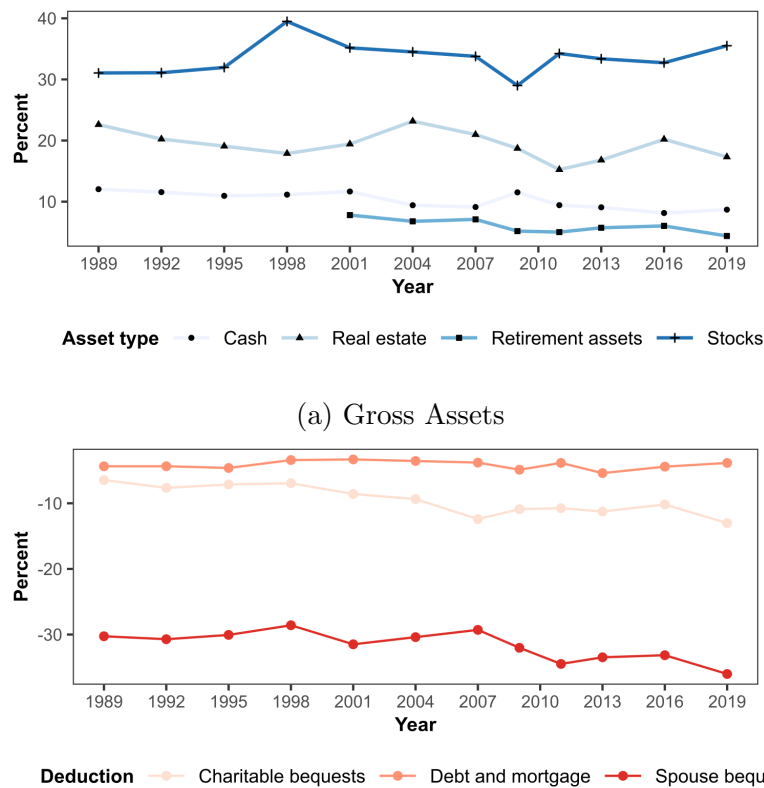


Figure 17. Percent of gross assets, all decedents

4.4 Empirical analysis

In this section, I set out to examine the empirical relationship between beliefs about the stock market and wealth distribution by studying the implications of an

⁴To add annex

exogenous variation in beliefs. I use the "Central Bank Information" (CBI) structural shocks identified according to Jarociński and Karadi 2020, combining high-frequency identification ⁵

First, I analyze investors' attitudes regarding their personal finances and the stock market performance in light of new information. Using responses from the UBS/Gallup data set within two days of the CBI shock, I run an ordered logit model for the ordinal responses:

$$Pr(Y_{jt} = i) = Pr(\kappa_{i-1} < \alpha D_{jt} \times CBI_t + \beta X_{jt} + \gamma Z_{jt} \times CBI_t + u_{jt} < \kappa_i) \quad (4.1)$$

where Y_{jt} is the response of the investor j in time t , D_{jt} is an indicator variable of whether the respondent responded after the realization of the CBI shock CBI_t , X_{jt} is a set of control variables and Z_{jt} a subset of X_{jt} interacting with the shock. The coefficients α, β, γ and cutoffs κ_i are estimated using a Maximum Likelihood Estimator under the assumption that the error term u_{jt} is logit distributed. I report the odds ratio $P(Y \leq k)/P(Y > k)$. Under the null hypothesis, the odd ratio is equal regardless of whether the respondent has observed the CBI shock. Given data availability, this analysis is capturing the effect of changes occurring in the early 2000s.

Having explored the first stage of beliefs changes, we then examine the response of the aggregate wealth distribution using high-frequency data on the wealth distribution by Blanchet, Saez, and Zucman (2022). To this end, and following the implementation of Adämmer (2019) with an externally identified shock I estimate the impulse response function using local projections (Jordà, 2005) of the wealth shares:

$$y_{t+h} = \alpha^h + \beta_h CBI_t + \gamma_h MP_t + u_{t+h}^h \quad (4.2)$$

⁵Based on a 30-min narrow window around the FOMC announcements and using changes in the three-month fed funds futures and in the S&P 500 index. This restriction is grounded on the fact that Jarociński and Karadi 2020 document: in some cases, interest rate and stock prices comove positively, in opposition to the inverse relationship predicted by textbook economics.

Provided that investors revise their expectations after an exogenous information shock on the economic outlook and the stock market, the wealth distribution may respond if agents rebalance their portfolios and adjust their savings and consumption.

4.4.1 Investor optimism and new information. Table 21 provides supporting evidence that investors’ beliefs respond to exogenous information about the economic outlook. Recall that we use only survey responses the deUpon learning a positive Fed information shock, investors are more likely to report being more optimistic about the expected performance of the stock market over the next year. These results support the method used by Jarociński and Karadi (2020), in that the monetary policy shocks identified by the authors are orthogonal to the informational content of the central bank announcement and do not act through a belief channel.

Our results also suggest that active workers are more optimistic and that past portfolio returns are positively correlated with optimistic attitudes. To conclude, we also tested for statistically different responses to CBI shocks across wealth levels⁶. The p-value of these tests shows that for all specifications considered, the null hypothesis of equal responses is rejected. Appendix C.1 presents the results of conditional regressions of the expected equity premium on CBI shocks and other regressors conditional on investors’ attitudes. I find that information shocks about the economic outlook do not induce a revision of the expected premium and that, overall, active workers tend to expect higher equity premia. Together, these results suggest that the beliefs of investors respond differently throughout their life cycle and wealth levels.

4.4.2 Wealth distribution and information shocks. To motivate the discussion, I examine whether exogenous information to households has any relevant distributional effect. The textbook valuation model predicts that a positive shock

⁶Since wealth is reported as an ordinal variable, I interact wealth and year to account for inflation.

Table 21. Ordered logistic regressions: Expected Performance of Stock Market

	(1)	(2)	(3)	(4)	(5)	(6)
CBI shock	1.031*	1.016*	1.568***	1.250***	1.259***	1.516***
	(2.49)	(2.44)	(12.90)	(4.77)	(4.87)	(7.30)
MP shock		0.997	0.994	0.995	0.997	0.997
		(-0.76)	(-1.09)	(-0.88)	(-0.57)	(-0.41)
Business env. index		0.588***	0.605***	0.602***	0.599***	0.652***
		(-8.16)	(-4.96)	(-4.71)	(-5.44)	(-3.99)
Retired = No			0.757***	0.748***	0.747***	0.745***
			(-4.64)	(-4.63)	(-4.65)	(-3.77)
Retired = Don't know / Refused			2.394	3.096	3.124	3.201
			(1.37)	(1.50)	(1.51)	(0.85)
(Retired = No) $\times$ CBI shock			0.970	0.968	0.968	0.959**
			(-1.39)	(-1.73)	(-1.73)	(-3.14)
(Retired = DK / Refused) $\times$ CBI shock			1.065	1.075	1.075	1.209
			(0.38)	(0.46)	(0.46)	(1.10)
Portfolio return (past 12m)						1.012***
						(4.92)
CBI shock $\times$ Portfolio return						1.000
						(-0.83)
Wealth x Shocks	No	No	Yes	Yes	Yes	Yes
Annual Income	No	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes	Yes
Year fixed effect	No	No	Yes	Yes	Yes	Yes
Macro var.	No	No	No	No	Yes	Yes
N	11744	11744	11744	10443	10443	6758
p-val: Post-shock $\times$ Savings $\times$ Year = 0			0	0	0	0

Exponentiated coefficients. CBI shock: Central Bank Information shock

on the outlook on dividends raises stock prices. As shown in the previous section, information shocks affect investor attitudes and we now turn to the distributional effects.⁷ Appendix C.2 shows the IRFs. I include the Business Investment and Sentiment Index to account for an external measure ⁸ which responds simultaneously to the shock. A positive information shock (as in Jarociński and Karadi 2020) results in a transitory medium-run redistribution (right panel Figure C.2.1) which is qualitatively different from a monetary policy shock C.2.2. The response of the top 50% is consistent with the documented fact that wealthier and better educated households exhibit less sluggish behavior (Campbell, 2006).

4.4.3 Subjective expectations on stock returns and the bequest motive. To provide additional evidence for a connection between stock return

⁷The macroeconomic effects have been studied in Jarociński and Karadi 2020, Nakamura and Steinsson 2018

⁸Equity Market Volatility Tracker: Macroeconomic News and Outlook: Business Investment And Sentiment from S. R. Baker, Bloom, and Davis (2023)

expectations and the bequest motive, I examine the Health and Retirement Study. I investigate the relationship between the self-reported percent chance that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average, will appreciate in value, and the self-reported likelihood of leaving bequests. Using HRS exit interviews of decedents, Munnell, Aubry, and Wettstein (2023) find a strong correlation between bequest expectations and actual transfers, and studying the determinants of these expectations can help explain the intergenerational links arising from the bequest motive (De Nardi, 2004). Figure 18 provides illustrates a visualization of the multivariate regression analysis, demonstrating that an increased optimism about stock returns corresponds to greater expectations of leaving behind financial assets.

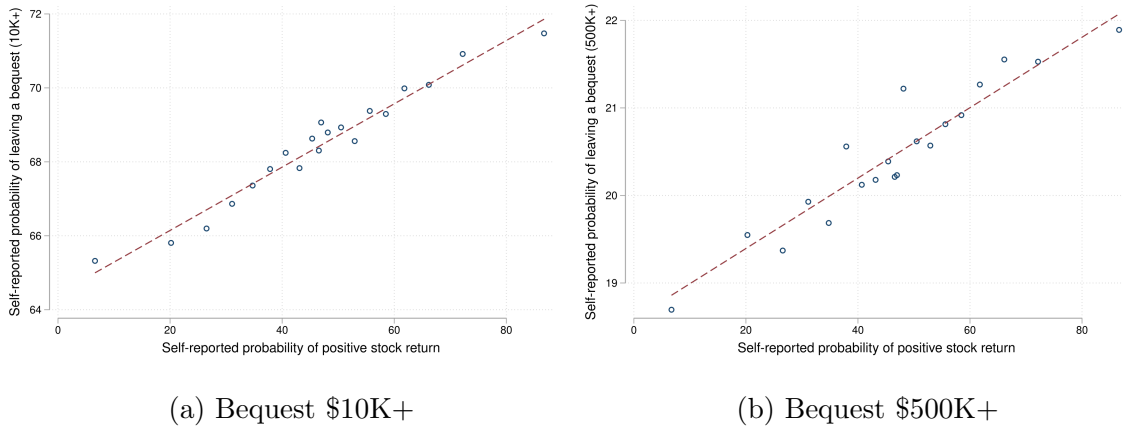


Figure 18. Binned scatterplots: Bequest Expectations and Stock return expectations
Control variables include past returns of NASDAQ index, housing wealth and income (as a fraction of total wealth) and respondent fixed effects.

The appendix table C.4.6 shows several estimates under different specifications showing that the association between these expectations is fairly stable. Appendix C.5 introduces a linear approximation of a retiree with a bequest motive and subjective

beliefs which can be used to identify the effect of subjective beliefs about stock returns on the realized bequest.

4.5 Two-period OLG model

To better understand the role of belief changes about stock markets in shaping the wealth distribution, I analyze a simple two-period model with the basic ingredients, namely, i) the existence of a risk-free asset and a risky asset, ii) subjective beliefs, and iii) stochastic bequest motive. Introducing the portfolio problem allows for weaker restrictions on beliefs ⁹. I assume dogmatic agents as well, that is, retirees preserve their beliefs. I also assume a fixed fraction of young workers ω_y .

The economy lasts for two periods, $t = 0, 1$. There are N_b types of otherwise agents with heterogeneous beliefs. Type i believes that (log) returns on the risky asset follow a normal distribution $\log(R_i^k) \sim \mathcal{N}(\log(R^r) + \mu_i, \sigma_k)$. The mass of agents type i is ω_i with $\sum \omega_i = 1$. Agents of type i rank consumption stream according to

$$U_t^{i,t} = u(c_t^{i,t}) + \beta E^i(u(c_{t+1}^{i,t}) + \beta e(a_{t+2}^{i,t})) \quad (4.3)$$

where $e(a)$ denotes a warm-glow motive. In the initial period, wealth a_t is identical across agents. The maximization problem is given by

$$\begin{aligned} \max_{\substack{c_t^{i,t}, c_{t+1}^{i,t}, \\ k_{t+1}^{i,t}, b_{t+1}^{i,t}, k_{t+2}^{i,t}, b_{t+2}^{i,t}}} \quad & u(c_t^{i,t}) + \beta E^i(u(c_{t+1}^{i,t}) + \beta e(a_{t+2}^{i,t})) \\ \text{s.t.} \quad & c_t^{i,t} + k_{t+1}^{i,t} + b_{t+1}^{i,t} = a_t^{i,t} \\ & a_{t+1}^{i,t} = R_t^s b_{t+1}^{i,t} + R_{t+1}^k k_{t+1}^{i,t} + y_{t+1}^{i,t} \end{aligned}$$

⁹With a single asset, overly optimistic or pessimistic agents might not save

With $u(c_t) = c_t^{1-\sigma}/(1-\sigma)$, and $e(a_t) = A(a_t)^{1-\mu}/(1-\mu)$ and a_t denotes total wealth after earnings, $y_t^{i,t}$ is the agent's earnings in period t : workers earn wages on their labor endowment w_t , and pensioners receive a pension payment which is equal to the product of the replacement rate $\bar{r}$ and past wage w_{t-1} . Returns on risky assets are log-normal with $\log(R^k) \sim \mathcal{N}(\log(R^r) + \mu_k, \sigma_k)$. For the non-stochastic equilibrium I consider, this process is relevant only in that agents acknowledge the uncertainty via their subjective beliefs.

General Equilibrium: A non-stochastic equilibrium is given by an interest rate R_{t+1}^s and wage w_t , allocations $\{c^{i,t}(a_t), b^{i,t}(a_t), k^{i,t}(a_t)\}$, government tax rate τ_l and transfers p_t^{t-1} , and a constant fraction of young agents ω_y

- a) Given their subjective beliefs on aggregate risk, households optimize
- b) Labor and capital earn the their marginal product.
- c) Markets clear:

$$\text{Capital market: } \sum_{i \in \{bel\}} \omega_y k_t^{t,i} + \sum_{j \in \{bel\}} (1 - \omega_y) k_t^{t-1,j} = K_{t+1} \quad (4.4)$$

$$\text{Bond market: } \sum_{i \in \{bel\}} \omega_y b_t^{t,i} + \sum_{j \in \{bel\}} (1 - \omega_y) b_t^{t-1,j} = B_{t+1} \quad (4.5)$$

$$\text{Labor market: } L_t = \omega_y \quad (4.6)$$

$$\text{Agg. const: } \sum_{i \in \{bel\}} \omega_y c_t^{t,i} + \sum_{j \in \{bel\}} (1 - \omega_y) c_t^{t-1,j} + K_{t+1} + G_t = AK_t^\alpha L_t \quad (4.7)$$

- d) The government budget constraint balances every period:

$$G_t = R_t^s B_t - B_{t+1} + (1 - \omega_y) p_t^{t-1} = \tau_l \omega_y w_t$$

- e) Young agents' initial wealth is consistent with the bequeathed assets by the retirees of the previous generation.

Table 22. Aggregate Moments of the Model

	Capital	Labor	Int. rate [†]	Wage	Output	Bonds	Labor tax	Bequest (%) [‡]
Base	0.0649	0.87	1.0600	1.0000	1.2428	0.0071	0.1134	0.56
Alt	0.0225	0.87	1.0924	0.6787	0.9049	0.0064	0.1914	0.55

Notes. TFP = 3.1121. † Annual gross interest rate. ‡ Aggregate bequests as percentage of Output

In this setup, households believe that aggregate risk exists which leads to different consumption and saving decisions.

Calibration: The model period is set 30 years. I set the annual discount factor at $\beta_y = 1.06^{-1}$, so that the model-period discount factor is $\beta = \beta_y^n$. The risk aversion parameter is 2.0, a standard value in the literature. I set the risk-free interest annual rate at 6% which implies an Output-to-Capital ratio of 19 (30 years of output, annual output-to-capital 0.65). Risk premium: 2.08 (1% annual, $R_{t+1}^s \exp(0.01n) - R_{t+1}^s$). I collapse the distribution of beliefs into four types of agents with beliefs μ_{bi} such that the risk premium is given by $R_{t+1}^s \exp(\mu_{bi}n) - R_{t+1}^s$.

	Pre-2001	Post-2001	p	N
Bottom 25th	0.1111	0.1287	.9470	54
Mid 25th	4.3961	3.4181	0.0000	53
Upper-middle	8.2358	6.6700	0.0000	53
Top 75th	24.8441	22.7507	.03518	54

Notes. Pooled by percentile per month

Results. The base calibration suggests that heterogeneous subjective beliefs induce wealth inequality among otherwise identical agents. A pessimistic shift that emulates the 2001-2002 leads in a steep decline in capital and wages (Table 22) and subsequently a substantial increase in interest rates. While the market yield on US 30-yr treasury securities remained close to 5% between 2000 and 2007, the stabilization of the downward trend observed in the 1990s suggests that the pressure on interest rate fueled by beliefs as implied by this framework might have been in place.

Pessimistic retirees save the most as they underestimate the utility of bequeathing stocks. The saving rate and wealth share of overly optimistic workers (Type IV, Table 23)¹⁰ are sensitive to beliefs and interest rate changes, while the pessimistic agents whose beliefs remain unchanged (Type I) are affected through price changes.

Table 23. Model moments by agent type: Base and alternative

	Type	Beliefs		Saving rate			Wealth share		
		Eq. prem. [†]	Share	Workers	Retirees	Total	Workers	Retirees	Total
Base	I	0.001	0.25	7.552	10.811	7.936	21.266	4.413	25.68
	II	0.041	0.25	6.221	7.357	6.269	17.519	2.767	20.29
	III	0.075	0.25	4.525	5.019	4.457	12.741	1.682	14.42
	IV	0.211	0.25	13.808	1.301	12.242	38.884	0.728	39.61
Alt	I	0.001	0.25	6.739	8.078	7.282	31.898	8.542	40.44
	II	0.032	0.25	5.137	5.863	5.325	24.319	5.257	29.58
	III	0.066	0.25	3.525	3.883	3.518	16.686	2.854	19.54
	IV	0.195	0.25	2.094	0.895	1.88	9.915	0.529	10.44

[†] Equity premium (multiplicative)

The model predicts that with more pessimistic agents, capital becomes concentrated within these agents (Table 24). These predictions are consistent with the documented wealth and stock concentration associated with lower expected returns on equity, and the fact that wealthier respondents are more pessimistic Giglio et al. (2021).

Provided there is a change in beliefs, these exercises suggest that waves of pessimism induce higher saving rates and non-negligible distributional effects. The intuition behind this mechanism is that optimists derive a higher expected utility of one unit of capital and optimally do not need to save as much as their pessimistic counterparts. Moreover, the asymmetric effect of belief changes can further exacerbate wealth inequality. The question of whether agents have the correct

¹⁰To examine non-linearities in extremes

Table 24. Capital (stock) holdings: Base and alternative

	Type	Beliefs			Stock holdings
Base	I	0.031	0.001	0.25	17.556
	II	1.22	0.041	0.25	22.503
	III	2.246	0.075	0.25	15.999
	IV	6.316	0.211	0.25	43.942
Alt	I	0.031	0.001	0.25	23.522
	II	0.947	0.032	0.25	37.977
	III	1.982	0.066	0.25	25.091
	IV	5.854	0.195	0.25	13.41

beliefs is absent from this discussion. For a calibrated model with a (multiplicative) premium of 0.015, approximately 60% of the time equity return exceeds the base rate of 6%, which implies that pessimistic agents tend to better more frequently.

4.6 Discussion and Future Research

This paper provides evidence that both short-run fluctuations and long-run changes in beliefs on stock returns have non-negligible effects on the wealth distribution. The empirical evidence and analysis presented in this study align with the perspective that subjective beliefs about stock returns are related to both life-cycle savings and wealth distribution. The rising trend in wealth inequality has been accompanied by concentrated stock holdings, and the final portfolios of decedents indicate that retirees exhaust their cash reserves while maintaining a consistent stock portfolio share, exceeding 30%. Explanations for stock market participation based on preferences do not account for short-term variations, and a declining equity risk premium is expected to reduce the likelihood of individuals investing in stocks. (Gomes et al., 2021).

In our simple counterfactual with a reduction in the expected risk premium, the model predicts a steep reduction in physical capital, production, bond supply, and aggregate bequest, driven by an overall reduction in saving rates. As the expected risk

premium of the most optimistic agents falls, wealth is concentrated among relatively pessimistic agents.

More work on the belief formation process and the relationship between short-run fluctuations and long-run trends is warranted. Our model can be further extended to explore the link between beliefs and the optimality of beliefs M. K. Brunnermeier and Parker (2005) in a boundedly rational setting. Moreover, I leave for future research the study of the beliefs changes on entrepreneurship, and the extent to which this behavioral aspect may crowd out investment in human capital.

APPENDIX A

CHAPTER II APPENDIX

Appendix

A.1 GK (2011) model

A.1.1 Households. There is a continuum of identical households of measure unity. Households consume, save and supply labor. They save by lending funds to financial intermediaries.

There is a constant fraction f of bankers that manage a financial intermediary and $(1 - f)$ workers. With probability θ , a banker stays banker next period. Thus, each period, $(1 - \theta)f$ bankers exit and become workers.

Let C_t and L_t denote consumption and labor respectively. Households preferences are given by

$$\max E_t \sum_{i=0}^{\infty} \beta^i \left[\ln(C_{t+i} - hC_{t+i-1}) - \frac{\chi}{1+\varphi} L_{t+i}^{1+\varphi} \right] \quad (\text{A.1})$$

Household budget constraint

$$C_t = W_t L_t + \Pi_t + T_t + R_t B_t - B_{t+1} \quad (\text{A.2})$$

Let ϱ_t and μ_{jt} be the Lagrange multipliers on the budget constraint and the incentive constraint respectively. The Lagrangian is given by

$$\begin{aligned} \mathcal{L}_t = E_t \sum_{i=0}^{\infty} \beta^i & \left[\ln(C_{t+i} - hC_{t+i-1}) - \frac{\chi}{1+\varphi} L_{t+i}^{1+\varphi} \right] + \\ & \varrho_{t+i} (W_{t+i} L_{t+i} + \Pi_{t+i} + T_{t+i} + R_{t+i} B_{t+i} - B_{t+i+1} - C_{t+i}) + \\ & \mu_{t+i} (V_{jt+i} - \lambda(B_{jt+i+1} + N_{jt+i})) \end{aligned}$$

Households are infinitesimally small and take as given the total deposits of the bank, so that $\mu_{t+i} = 0$

The FOC are then

$$C_t : \quad (C_t - hC_{t-1})^{-1} - E_t \beta h (C_{t+1} - hC_t)^{-1} = \varrho_t$$

$$L_t : \quad \chi L_t^\varphi = W_t \varrho_t$$

$$B_{jt+1} : \quad \varrho_t = \beta \varrho_{t+1} R_{t+1}$$

and the Euler Equation

$$\textbf{Euler Eq.} \quad \tilde{\varrho}_t = \tilde{\varrho}_{t+1}^e \beta R_{t+1}$$

A.1.2 Banks maximization problem. Bankers seek to maximize their expected terminal worth:

$$V_{jt} = \max_{S_{jt}} E_t \sum_{i=0}^{\infty} (1 - \theta) \theta^i \beta^{i+1} \Lambda_{t,t+1+i} N_{jt+1+i} \quad (\text{A.3})$$

$$= \max_{S_{jt}} E_t \Lambda_{t,t+1+i} \beta ((1 - \theta) (\{R_{kt+1} - R_{t+1}\} Q_t S_t + R_{t+1} N_{jt}) + \theta V_{jt+1}) \quad (\text{A.4})$$

subject to

$$\textbf{Law of motion} \quad N_{jt+1} = (R_{kt+1} - R_{t+1}) Q_t S_t + R_{t+1} N_{jt} \quad (\text{A.5})$$

$$\textbf{Incentive constraint} \quad V_{jt} \geq \lambda Q_t S_t \quad (\text{A.6})$$

Let μ_t be the Lagrange multiplier associated with the incentive constraint. The Lagrangian of the bankers' problem:

$$\mathcal{L}_{jt} = V_{jt} + \mu_t (V_{jt} - \lambda Q_t S_t) = (1 + \mu_t) V_{jt} - \lambda \mu_t Q_t S_t$$

Denote $V_{jt}^N = \frac{\partial V_{jt}}{\partial N_t} \equiv \eta_t$, $V_{jt}^S = \frac{\partial V_{jt}}{\partial S_t} \equiv \nu_t Q_t$, and note that $\frac{\partial N_{jt+1}}{\partial S_t} = (R_{kt+1} - R_{t+1})Q_t$. The First Order Condition w.r.t. loans S_{jt} is given by

$$(1 + \mu_t)V_{jt}^S - \lambda\mu_t Q_t = 0$$

$$(1 + \mu_t)E_t\Lambda_{t,t+1}\beta \left((1 - \theta)\frac{\partial N_{t+1}}{\partial S_t} + \theta V_{jt+1}^N \frac{\partial N_{t+1}}{\partial S_t} \right) = \lambda\mu_t Q_t$$

$$(1 + \mu_t)E_t\Lambda_{t,t+1}\beta \{R_{kt+1} - R_{t+1}\} ((1 - \theta) + \theta V_{jt+1}^N) = \lambda\mu_t$$

$$E_t\Lambda_{t,t+1}\beta \{R_{kt+1} - R_{t+1}\} ((1 - \theta) + \theta\eta_{t+1}) = \frac{\lambda\mu_t}{1 + \mu_t} = \nu_t$$

The Envelope Condition is given by:

$$\begin{aligned} V_{jt}^N &= E_t\Lambda_{t,t+1}\beta \left((1 - \theta)\frac{\partial N_{jt+1}}{\partial N_t} + \theta V_{jt+1}^N \frac{\partial N_{t+1}}{\partial N_t} \right) \\ &= E_t\Lambda_{t,t+1}\beta ((1 - \theta) + \theta V_{jt+1}^N) \left[\frac{\partial N_{jt+1}^*}{\partial S_{jt}} \frac{\partial S_{jt}^*}{\partial N_t} + R_{t+1} \right] \\ &= E_t\Lambda_{t,t+1}\beta ((1 - \theta) + \theta V_{jt+1}^N) R_{t+1} + V_{jt}^S \frac{\partial S_{jt}^*}{\partial N_t} \\ \eta_t &= E_t\Lambda_{t,t+1}\beta ((1 - \theta) + \theta\eta_{t+1}) R_{t+1} + \nu_t\phi_t^* \end{aligned} \tag{A.7}$$

where S_{jt}^* is the optimal asset choice of the bank and $\phi_t^* = S_{jt}^*/N_{jt}$ is the leverage ratio.

A.1.3 Firms.

A.1.3.1 Intermediate good firms. Non-financial firms finance capital acquisitions for the next period by obtaining funds from intermediaries:

$$Q_t K_{t+1} = Q_t S_t \tag{A.8}$$

Production is given by

$$Y_t = A_t (U_t \xi_t K_t)^\alpha L_t^{1-\alpha} \tag{A.9}$$

where U_t is the utilization rate of capital chosen by the firm, and ξ_t is the exogenous shock to quality of capital at time t .

Intermediate good firms pay the ex-post return of capital R_{kt+1} to the intermediary.

A.1.3.2 Capital producing firms. At the end of period t , competitive capital producing firms buy capital from intermediate goods producing firms and then repair depreciated capital and build new capital. They then sell both the new and re-furbished capital

Let I_t be gross capital created and $I_{nt} \equiv I_t - \delta U_t \xi_t K_t$ be net capital created, and I_{ss} the steady state investment. The discounted profits for a capital producer are given by

$$\max E_t \sum_{\tau=t}^{\infty} \beta^{T-t} \Lambda_{t,\tau} \left\{ (Q_{\tau} - 1) I_{n\tau} - f \left(\frac{I_{n\tau} + I_{ss}}{I_{n\tau-1}} \right) (I_{n\tau} + I_{ss}) \right\} \quad (\text{A.10})$$

where f denotes flow adjustment costs with, $f(1) = f'(1) = 0$ and $f''(1) > 0$.

Capital producers may earn profits that they rebate to households as lump sums.

A.1.3.3 Retail firms. Final output is a CES composite of a continuum of mass unity of differentiated retail firms. Retailers re-package intermediate output using a CES

A.1.4 Resource constraint and government policy. Government policy is characterized by government consumption G and government intermediation $\tau \psi_t Q_t K_{t+1}$. The aggregate resource constraint is

$$Y_t = C_t + I_t + f \left(\frac{I_{nt} + I_{ss}}{I_{nt-1} + I_{ss}} \right) (I_{nt} + I_{ss}) + G + \tau \psi_t Q_t K_{t+1} \quad (\text{A.11})$$

Capital evolves according to

$$K_{t+1} = \xi_t K_t + I_{nt} \quad (\text{A.12})$$

Government budget constraint is given by

$$G + \tau \psi_t Q_t K_{t+1} = T_t + (R_{kt} - R_t) B_{gt-1} \quad (\text{A.13})$$

where government bonds B_{gt-1} , finance government intermediated assets, $Q_t \psi_{t-1} S_{t-1}$.

Monetary policy is characterized by a simple Taylor rule with interest-rate smoothing, and the link between nominal and real interest rates is given by a Fisher relation:

$$i_t = (1 - \rho)\{i + \kappa_\pi v \pi_t + \kappa_y(\log Y_t - \log Y_t^*)\} + \rho i_{t-1} + \epsilon_t \quad (\text{A.14})$$

$$1 + i_t = R_{t+1} \frac{E_t P_{t+1}}{P_t} \quad (\text{A.15})$$

with i denoting the steady state nominal rate and Y^* the flexible-price equilibrium level of output. Credit policy responds to credit spreads:

$$\psi_t = \psi + \nu E_t [(\log R_{kt+1} - \log R_{t+1}) - (\log R_k - \log R)] \quad (\text{A.16})$$

where ψ is the steady state fraction of government intermediated assets and $(\log R_k - \log R)$ the steady state premium.

A.1.4.1 Credit policy. GK assume that the central bank facilitates lending and its policy is to fund a fraction ψ_t of total intermediate assets. Let $Q_t S_{pt}$ and $Q_t S_{gt}$ denote the value of privately intermediated assets and government-intermediated assets respectively. Then, total value of assets $Q_t S_t$ can be written as

$$Q_t S_t = Q_t S_{pt} + Q_t S_{gt} \quad (\text{A.17})$$

$$= Q_t S_{pt} + \psi_t Q_t S_t \quad (\text{A.18})$$

$$(1 - \psi_t) Q_t S_t = \phi_t N_t \quad (\text{A.19})$$

The central bank issues government debt B_{gt} to households and pays the riskless rate R_{t+1} and lends the funds to non-financial firms at the market lending rate R_{kt+1} . Government intermediation involves an efficiency cost of τ per unit supplied.

A.2 Model: Rational Expectations

Households

$$(C_t - hC_{t-1})^{-1} - E_t \beta h (C_{t+1} - hC_t) = \varrho_t \quad (\text{A.20})$$

$$\chi L_t^\varphi = W_t \varrho_t \quad (\text{A.21})$$

$$\varrho_t = \beta E_t \varrho_{t+1} R_{t+1} \quad (\text{A.22})$$

$$\Lambda_{t,t+1} = \frac{\varrho_{t+1}}{\varrho_t} \quad (\text{A.23})$$

Financial Intermediaries

$$V_{jt} = \nu_t Q_t S_{jt} + \eta_t N_{jt} \quad (\text{A.24})$$

$$= (\nu_t \phi_{jt}^* + \eta_t) N_{jt}, \quad \phi_{jt} = \frac{Q_t S_{jt}}{N_{jt}} \quad (\text{A.25})$$

$$\begin{aligned} \nu_t = E_t \{ & (1 - \theta) \beta \Lambda_{t,t+1} (R_{kt+1} - R_{t+1}) + \\ & \beta \Lambda_{t,t+1} \theta x_{t,t+1} \nu_{t+1} \} \end{aligned} \quad (\text{A.26})$$

$$\eta_t = E_t \{ (1 - \theta) + \beta \Lambda_{t,t+1} \theta z_{t,t+1} \eta_{t+1} \} \quad (\text{A.27})$$

Intermediate goods firm

$$Q_t K_{t+1} = Q_t S_t \quad (\text{A.28})$$

$$Y_t = A_t (U_t \xi_t K_t)^\alpha L_t^{1-\alpha} \quad (\text{A.29})$$

$$P_{mt} \alpha \frac{Y_t}{U_t} = \delta' (U_t) \xi_t K_t \quad (\text{A.30})$$

$$P_{mt} (1 - \alpha) \frac{Y_t}{L_t} = W_t \quad (\text{A.31})$$

$$R_{kt+1} = \frac{[P_{mt+1} \frac{\alpha Y_{t+1}}{\varepsilon_{t+1} K_{t+1}} + Q_{t+1} - \delta(U_{t+1})] \xi_{t+1}}{Q_t} \quad (\text{A.32})$$

Capital producing firms

$$Q_t = 1 + f(.) + \frac{I_{nt} + I_{ss}}{I_{nt-1} + I_{ss}} f'(.) - E_t \beta \Lambda_{t,t+1} \left(\frac{I_{nt+1} + I_{ss}}{I_{nt} + I_{ss}} \right)^2 f'(.) \quad (\text{A.33})$$

Retail firms

$$\pi_t = [(1 - \gamma)(\pi_t^*)^{1-\varepsilon} + \gamma(\pi_{t-1}^{\gamma_p})^{1-\varepsilon}]^{1/1-\varepsilon} \quad (\text{A.34})$$

$$(\varepsilon - 1)a_{1,t} = \varepsilon a_{2,t} \quad (\text{A.35})$$

$$a_{1,t} = f(\pi_t^*, \pi_t^{*e}, \pi_{t+1}^e, a_{1,t+1}^e, \Lambda_{t,t+1}) \quad (\text{A.36})$$

$$a_{2,t} = g(\pi_{t+1}^e, a_{1,t+1}^e, \Lambda_{t+1}) \quad (\text{A.37})$$

$$\vartheta_t = h(\pi^*, \pi_t, \pi_{t-1}, \vartheta_{t-1}), \quad Y_{mt} = \vartheta_t Y_t \quad (\text{A.38})$$

Resource Constraint

$$Y_t = C_t + I_t + f\left(\frac{I_{nt} + I_{ss}}{I_{nt-1} + I_{ss}}\right)(I_{nt} + I_{ss}) + G + \tau\psi_t Q_t K_{t+1} \quad (\text{A.39})$$

Law of motion of capital

$$K_{t+1} = \xi_t K_t + I_{nt} \quad (\text{A.40})$$

Government

$$G + \tau\psi_t Q_t K_{t+1} = T_t + (R_{kt} - R_t)B_{gt-1} \quad (\text{A.41})$$

Monetary policy

$$i_t = (1 - \rho)\{i + \kappa_\pi v \pi_t + \kappa_y (\log Y_t - \log Y_t^*)\} + \rho i_{t-1} + \epsilon_t \quad (\text{A.42})$$

$$1 + i_t = R_{t+1} \frac{E_t P_{t+1}}{P_t} \quad (\text{A.43})$$

Credit policy

$$\psi_t = \psi + \nu E_t [(\log R_{kt+1} - \log R_{t+1}) - (\log R_k - \log R)] \quad (\text{A.44})$$

Exogenous $AR(1)$ processes for TFP, capital quality shocks, monetary policy shocks

A.3 Steady state of the model

A.3.1 Steady-state. The value function is linear on assets and net worth

$$V(N_{jt}) = \nu_t Q_t S(N_{jt}) + \eta_t N_{jt} \quad (\text{A.45})$$

$$= (\nu_t \phi_t^* + \eta_t) N_{jt} \quad (\text{A.46})$$

with

$$\nu_t = E_t \{ (1 - \theta) \beta \Lambda_{t,t+1} (R_{kt+1} - R_{t+1}) + \beta \Lambda_{t,t+1} \theta x_{t,t+1} \nu_{t+1} \} \quad (\text{A.47})$$

$$\eta_t = E_t \{ (1 - \theta) + \beta \Lambda_{t,t+1} \theta z_{t,t+1} \eta_{t+1} \} \quad (\text{A.48})$$

Let $\bar{\phi}$ denote the steady state leverage ratio. In steady state:

$$\bar{\nu} = (1 - \theta) \beta (R_k - R) + \beta \theta \bar{x} \bar{\nu} \quad (\text{A.49})$$

$$\bar{\eta} = (1 - \theta) + \beta \theta \bar{z} \bar{\eta} \quad (\text{A.50})$$

Noting that the growth rate of assets is such that $\bar{x} = \bar{z}$, we can write:

$$\bar{\nu} = \frac{(1 - \theta) \beta (R_k - R)}{1 - \beta \theta \bar{z}} \quad (\text{A.51})$$

$$\bar{\eta} = \frac{(1 - \theta)}{1 - \beta \theta \bar{z}} \quad (\text{A.52})$$

The steady state leverage ratio is

$$\bar{\phi} = \frac{\bar{\eta}}{\lambda - \bar{\nu}} = \frac{(1 - \theta)}{\lambda(1 - \beta \theta \bar{z}) - (1 - \theta) \beta (R_k - R)} \quad (\text{A.53})$$

From the law of motion of aggregate worth (Equation 18), and noting that in steady state $Q = 1$:

$$\bar{z} = (R_k - R) \bar{\phi} + R \quad (\text{A.54})$$

The equation that solves for the steady state leverage ratio is

$$\bar{\phi}\lambda(1 - \beta\theta\bar{z}) - \bar{\phi}(1 - \theta)\beta(R_k - R) = (1 - \theta) \quad (\text{A.55})$$

$$-\bar{\phi}\lambda\beta\theta(\bar{\phi}(R_k - R) + R) + \bar{\phi}(\lambda - (1 - \theta)\beta(R_k - R)) = (1 - \theta) \quad (\text{A.56})$$

$$-\lambda\beta\theta(R_k - R)\bar{\phi}^2 + (\lambda - (1 - \theta)\beta(R_k - R) - \lambda\beta\theta R)\bar{\phi} - (1 - \theta) = 0 \quad (\text{A.57})$$

A.4 Medium-run calibration

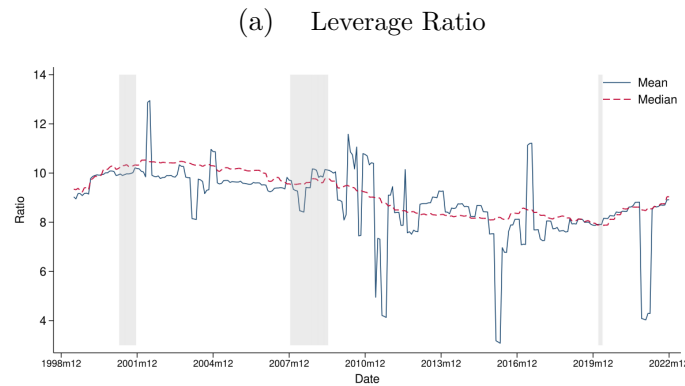
Table A.25. Mean risk premium, relative to 10-yr US Treas. Bond.

	BAA Corp. Bond	30-yr Mort. Rate
Pre-2008	2.061	1.214
2008-2009	3.881	1.446
Post-2009	2.599	0.955
Pre-2008 vs. Post-2009	0.538	-0.259

Notes: Spread over a 10-yr US Treasury Bond. Pairwise comparisons of means with equal variances significant at the 1% level.

A.4.1 Expected Premium. The average implied forecast of the 2010-2019 period released by the Philadelphia Fed Survey of Forecasters is 2.53 and displays a modest downward trend.

Figure A.19. Financial measures: Leverage Ratio



Source: Compustat Quarterly Ratios

A.4.2 Leverage Ratio. The pre-2008 mean industry leverage ratio declined from 9.8 to 8.11 in the post-DFA period. Deleveraging may be driven by regulatory effects or responses of large banks. Table A.26 shows the bank-level change relative to the pre-2007 (inclusive). We target the unconditional mean change across banks of -0.0132.

Fraction of Divertible Assets.

Table A.26. Bank-level estimated changes (relative to pre-2008)

	log. Leverage ratio			log. Price-to-Book ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Period 2008 -2009	0.00795*** (4.95)	-0.0131*** (-7.67)	-0.0174*** (-12.64)	-0.118*** (-29.28)	-0.0865*** (-16.20)	-0.0263*** (-6.11)
Period 2010 - 2014	-0.0231*** (-11.65)	-0.0395*** (-22.06)	-0.0325*** (-22.88)	-0.00185 (-0.43)	-0.0609*** (-11.02)	-0.0435*** (-9.68)
Period 2015 - 2019	-0.0204*** (-8.49)	-0.0601*** (-27.60)	-0.0375*** (-27.67)	0.0236*** (4.64)	-0.0276*** (-4.80)	-0.0190*** (-4.38)
Macro Var	No	Yes	Yes	No	Yes	Yes
Bank-level var	No	No	Yes	No	No	Yes
Observations	50,991	50991	37,883	51,414	51,414	37,883
Number of Banks	1,201	1,201	982	1,201	1,201	982

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Sample Dec 1989 - Dec 2019

- Define the medium-run targets of the average change in the log-deviation of the leverage ratio $\hat{\phi}^{DFA}$, and the risk premium $\hat{R}k^{DFA} - \hat{R}^{DFA}$.
- Code functions for the Rational Expectations and the Restricted Perception model, $\tilde{\lambda} : F_i \rightarrow \mathbb{R}^2$, $i \in \{RE, RP\}$. The functions differ only in the underlying code for the IRFs under RE and learning. The function F_i :
 - * Generates the path of the system up to $T = 20$ quarters, given $\tilde{\lambda}$.
 - * Retrieves the (log. dev.) leverage ratio and the realized premium series, $\hat{w} = [\hat{w}_1 \ \hat{w}_2 \dots \hat{w}_T]'$, $w \in \{\phi, Rpp\}$, where $Rpp \equiv Rk - R$.
 - * Computes the average of each $\hat{w}$, denoted by $\bar{w}^T$ and returns the vector $[\bar{\phi}^T \ \bar{Rpp}^T]'$.
- The calibrated fraction of divertible assets λ'_i , $i \in \{RE, RP\}$ solves:

$$F_i(\lambda'_i) = \begin{bmatrix} \hat{\phi}^{DFA} \\ \hat{R}k^{DFA} - \hat{R}^{DFA} \end{bmatrix}$$

A.5 Calibration results

Table A.27. Structural change: Results

Target avg. change: Realized premium: 30%, Leverage ratio: -2.30%								
Parameter/Value	Description	Base	No MP shocks		MP shocks			
			RE	RPE	RE	RPE	RPE, cg 5%	
		(1)	(2)	(3)	(4)	(5)	(6)	
λ	% Divertible Assets	0.3815	0.4110	0.4147	0.3910	0.3935	0.3940	
$E_{ss}[R_k - R]$	s.s. Risk premium	1.0000	1.0774	1.0886	1.0044	1.0127	1.0149	
ϕ_{ss}	s.s. Leverage Ratio	4.0000	3.7132	3.6854	3.8222	3.8054	3.8048	
η_{ss}	Marg. return on equity	1.5110	1.5112	1.5133	1.4806	1.4833	1.4848	
ν_{ss}	Marg. return on assets	0.0037	0.0040	0.0041	0.0037	0.0037	0.0037	
$\log V/N$	log. FVtN	1.5260	1.5261	1.5284	1.4946	1.4975	1.4989	
$\lambda QS/Y$	Div. Assets-to-Output	2.5447	2.7274	2.7500	2.6075	2.6226	2.6252	
$\text{Corr}(\log V/N, \eta_{t+4})$	Corr. logFVtN and η_{t+4}	0.9973		0.9966	0.6982	0.7604	0.8128	
<i>40-quarter avg. Untargeted moments (%)</i>								
Variable	Description	Data	No MP shocks		MP shocks			
			RE	RPE	RE	RPE	RPE, cg 5%	
$\Delta V/N$	Change log. Franch. Value to Net worth		5.16	6.06	0.17	0.80	0.92	
$\Delta \eta$	Marg. Return on Net worth (% std dev)		32.95	39.16	0.43	4.38	5.16	
ΔQS	Loan growth	1.33	-1.78	-1.79	- 0.63	-0.67	-0.68	
ΔN	Net worth growth	0.57	0.41	0.40	1.56	1.52	1.51	
π	Inflation rate	0.42	-0.04	-0.05	0.01	0.0	0.0	
ΔY	Output growth	0.57	-0.91	-0.97	-0.31	-0.35	-0.35	

Notes: The target moment is the 20-quarter average of the variable in order to match the observed 5-year mean between January 2010 and December 2014.

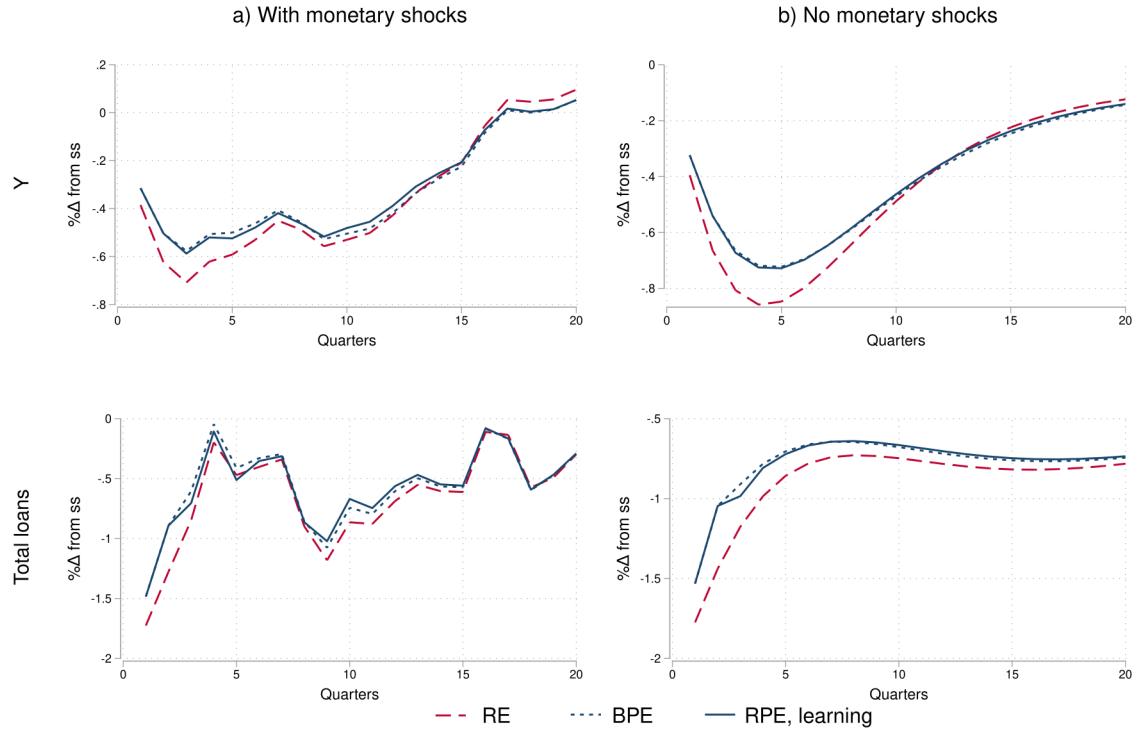
RPE, cg 19%: Restricted Perceptions Equilibrium, with learning and constant gain of 5%. The constant gain is the weight agents attribute to new observations in order to update their beliefs.

Balance sheet data retrieved from FRED, Federal Reserve Bank of St. Louis

Appendix A.6 contains the IRFs corresponding to the transition to the **new** steady state based on column 6, our preferred calibration. Relative to REE and RPE without learning, Figures A.20 and A.21 depict a sluggish behavior of leverage, due to large forecast errors in the early periods (as shown by the spike in quarter 2, panel a) Figure A.21) that affected lending and resulted in slow output recovery. A key difference between RE and RPE transitions is the implied risk premium and that the perceived RPE returns remained above their RE counterpart (Figure A.22), suggesting that agents under-price risk, consistent with our empirical findings.

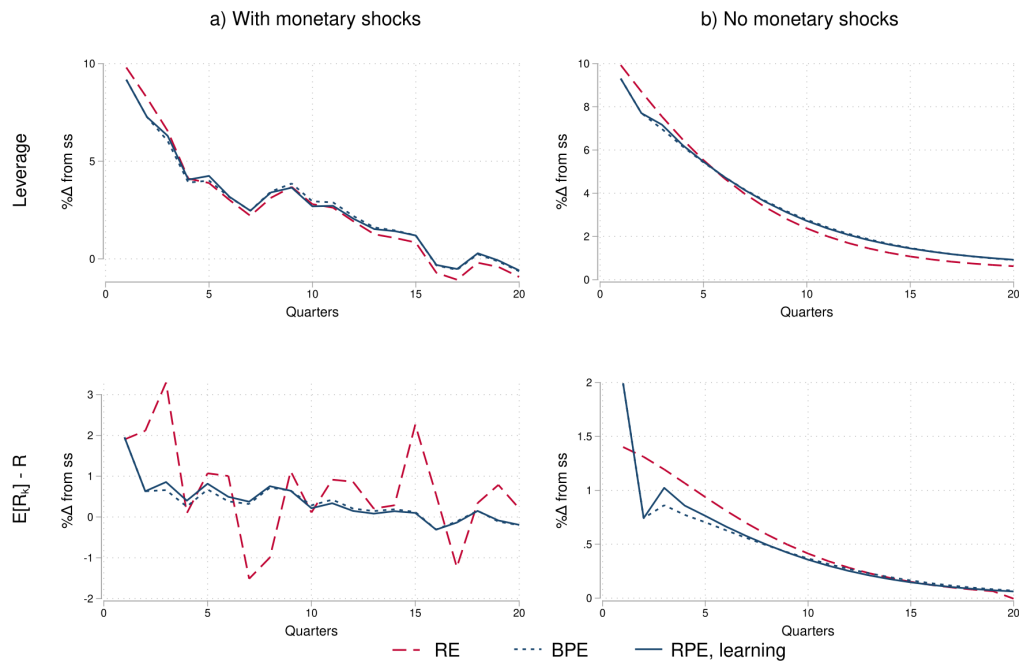
A.6 Structural Change: Impulse Response Functions

Figure A.20. Responses to structural change



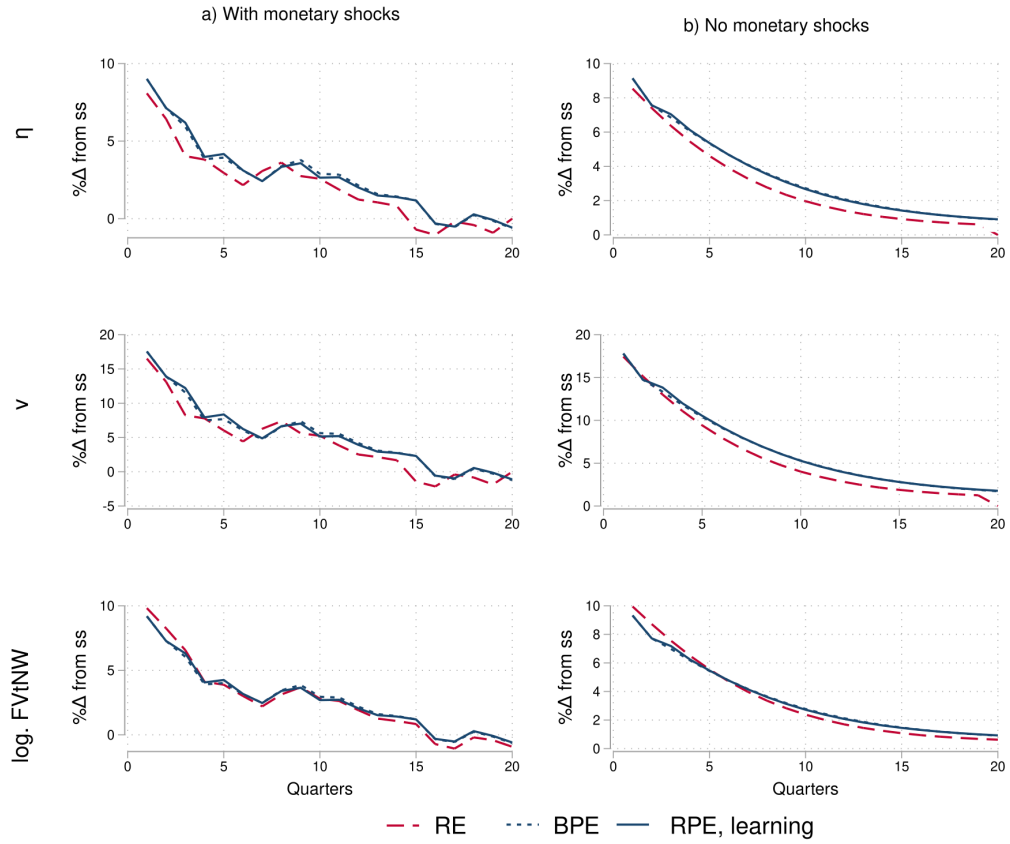
Notes: Impulse Response Functions of the log.deviation of the variables from the **new** steady state value according to the calibration in Column 7 of Table A.27. Panel a) shows the transition to the new steady state while considering externally identified shocks.

Figure A.21. Responses to structural change



Notes: Impulse Response Functions of the log.deviation of the variables from the *new* steady state value according to the calibration in Column 7 of Table A.27. For the expected risk premium, we show the annualized difference of the log. deviations of the risky rate R_k and the risk-free interest rate R .

Figure A.22. Responses to structural change



Notes: Impulse Response Functions of the log deviation of the variables from the *new* steady state value according to the calibration in Column 7 of Table A.27. $\log. FVtNW$: log Franchise Value-to-Net Worth. For the expected risk premium, we show the annualized difference of the log. deviations of the risky rate R_k and the risk-free interest rate R .

A.7 Data Appendix

A.7.1 Compustat Bank. We access the Compustat Bank database on Wharton Research Data Services. The data covers deposit-taking commercial banks. The SIC codes included in the classification are:

6020: Commercial banks

6021: National commercial banks

6022: State commercial banks

6029: NEC Commercial Banks

6035: Savings institutions, Fed-chartered

6036: Savings institutions, not Fed-chartered

A.7.2 Monetary shocks. For the monetary shocks, I use the monetary policy shock and the "central bank information" identified by Jarociński and Karadi 2020. The identification of these shocks is based on a 30-min narrow window around the FOMC announcements and using changes in the three-month fed funds futures and in the S&P 500 index. This restriction is grounded on the fact that Jarociński and Karadi 2020 document: in some cases, interest rate and stock prices comove positively, in opposition to the inverse relationship predicted by textbook economics. The shock data is available at the website of Marek Jarocinski:

<https://marekjarocinski.github.io/jkshocks/jkshocks.html>

APPENDIX B

CHAPTER III APPENDIX

Appendices

B.1 Data Appendix

B.1.1 Bank data. The data was retrieved between June 2022 and September 2022. The main source is the National Banking and Securities Commission (Comisión Nacional Bancaria y de Valores, CNBV) and the files can be accessed via their website

<https://www.cnbv.gob.mx/Paginas/PortafolioDeInformacion.aspx>.

The webpage name and codes of the files (in parentheses) are described below.

- a) Financial Statements (Información de la Situación Financiera): Comprehensive financial data on banks' balance sheet and income statements (File codes: 040-5A-R0 and 040-5B-R0, respectively).
- b) Lending activity at the bank-municipality level (Información de las características de cartera de crédito Consumo no revolvente): Municipality-bank level data is available on (File codes for Payroll loans/Personal loans)
 - Total loan volume (040-33A-R25 / 040-33B-R25)
 - Number of originated loans (040-30B-R26 / 040-33B-R26)
 - Lending rates (040-33A-R63 / 040-30B-R63)

The publisher of these data sets makes the following disclosure: "This report does not yet have the necessary quality of information" (Free Spanish translation from *Este reporte aun no cuenta con la calidad de la información necesaria*)

B.1.2 Financial survey data. The Financial Inclusion Surveys can be retrieved from:

<https://www.inegi.org.mx/programas/enif/2012/>

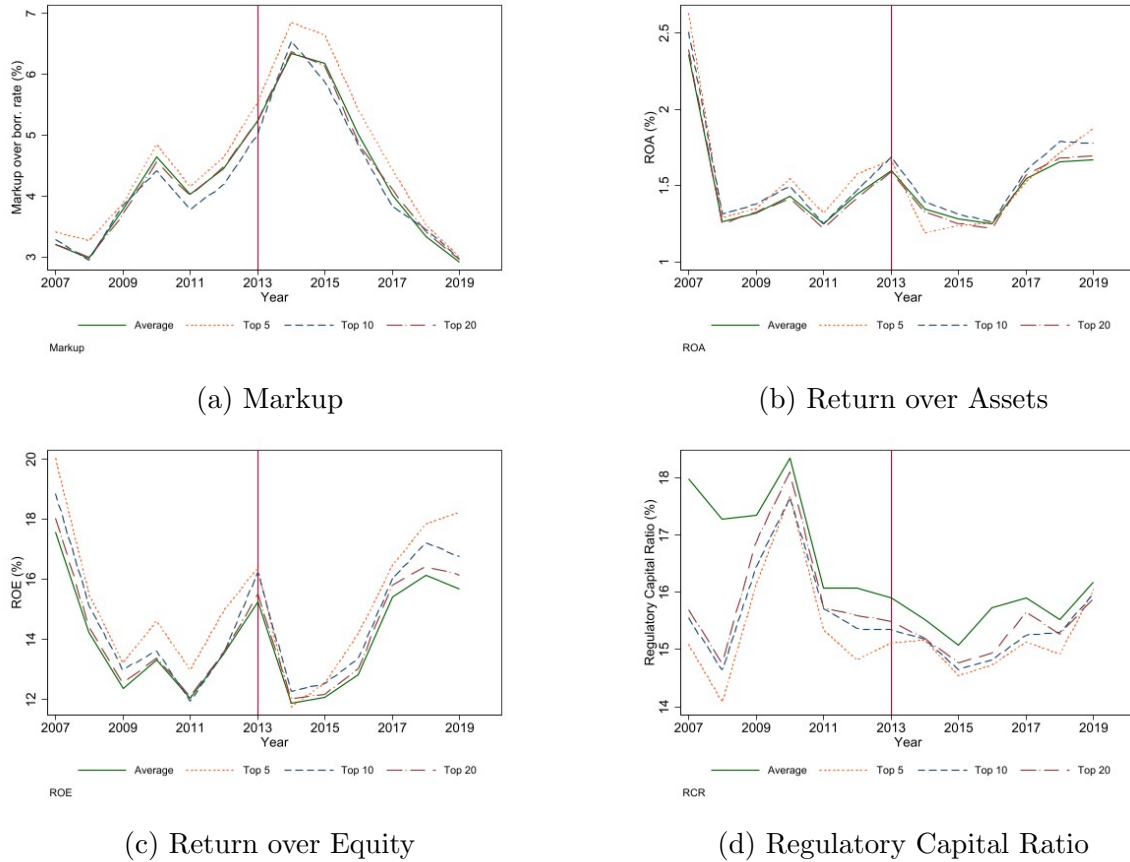
I use the microdata of three waves of Financial Inclusion Surveys (2012, 2015, and 2018) to examine outcomes at the individual-state level. To match the location of the individual, I extract the state code from the identifier of each observation. As the microdata explicitly discloses the region of the observation, I can only verify that the inferred state is part of the revealed region.

B.2 Descriptive evidence

B.2.1 Markups, returns, and regulatory capital. As of December 2010, there were 41 commercial banks and the top 5 banks managed 74% of total assets, whereas in 2019, the number of commercial banks rose to 51 and the top 5 banks held 69% of total assets.

As a primer on market power in the Mexican banking sector, selected performance indicators are presented in Figure B.2.1. Financial intermediation markups arise either from higher revenue in credit markets or trading activities or lower funding costs. As shown in Figure B.2.1a, the markup over the borrowing rates has decreased and converged over time which suggests that competition in the Mexican banking sector increased during the 2010s. Nonetheless, it is worth noting that large banks remained consistently above the (asset-weighted) mean markup.

Figure B.2.1. Markups, Returns, and Regulatory Capital by Bank type



Weighted by Total Assets

Moreover, profitability measures shed light on the drivers of the observed markups. The Return on Assets (ROA) waned to pre-reform levels in the years that followed the implementation of Basel III, and surged back in the later years of the decade. A similar pattern can be observed for the Return over Equity (ROE), although larger banks consistently remained above the average throughout the pre and post-reform period. Equally well-run banks with the same ROA will have different ROE depending on their funding structure. Highly leveraged banks have larger ROE at the expense of the safety of equity holders. Figure B.2.1c suggests that larger banks have a different business model for managing their bank capital as their ROE

remains consistently above the average of the banking industry despite the negligible differences in ROA. Although this facet is not examined in this paper, larger banks might exert similar market power in funding markets: In 2010 the top 5 banks concentrated 76% (74%) of total borrowed funds (assets) and by the end of the decade, this share dropped to 69% (69%).

Another element to be factored into this discussion is the evolution of the Regulatory Capital Ratio (RCR), which is eligible equity as a fraction of risk-weighted assets. Consistent with our previous remarks, the top 5 banks hold lower equity amounts relative to their risk-weighted assets responded differently in the immediate post-reform years as shown by the two-year sustained increase in their RCR, beginning in 2013. By 2010, as the new standards were released by the international committee, bank capitalization reached its maximum. As the minimum RCR set by the new capital rule in Mexico starting in 2013 was 10.5%, clearly the new regulation was non-binding and banks adjusted during the period between 2010 and 2012 under the uncertainty of whether the implementation of the requirements was to be staggered.

Notably, in 2014, average markups reach their maximum value while both ROA and ROE plummeted, which indicates that non-interest expenses (such as administrative and advertising expenses) were important enough to lower these profitability measures¹. The line-up between the maximum markup and the plunge in ROE in 2014 could be attributed to contracts settled in prior periods.

¹Following the banking literature, I estimate the marginal non-interest income derived from a trans-log function (see the supplement to Corbae and D’Erasmus 2021), finding a larger average non-interest expense for top 5 banks (1.64%) than small banks (0.01%). Nonetheless, these estimates are not statistically significant different due to the imprecision of the estimate for small banks. Results not shown.

The differential markup is driven by lower funding costs as the returns on assets do not appear to be bank-size dependent and equity is more profitable for larger banks (Panel c Figure B.2.1). The regulatory capital ratio, although based on eligible capital instruments, is consistent with Panel c, as larger banks hold less bank capital and earn similar returns on their asset portfolio as the other banks in the industry.

B.2.2 Reallocation of credit at the bank level. Banks might shift their portfolios to safer instruments to meet risk-based capital requirements and their target solvency buffer (Cohen and Scatigna 2016 and Corbae and D’Erasmus 2021). In light of capital requirements, standardized risk weights are factors to adjust bank exposures according to their credit risk. These weights are not to be confused with default probabilities, and the lowest risk weight is denoted by 0%. To see why the reallocation of assets is a strategy for capital management, consider a minimum requirement of eligible capital as a fraction of risk-weighted assets of 8%. Suppose a bank holds two assets in equal normalized monetary units with the safer asset having a 0% risk weight and the riskiest, 100%: total risk-weighted assets amount to 1 ($0\% \times 1 + 100\% \times 1$) and the bank must hold 8% units of equity, 0.08. For a given increment in capital requirements to 10%, the bank can hold the initial 0.08 units of equity constant and reduce its holding of the riskier asset to 0.8 units.

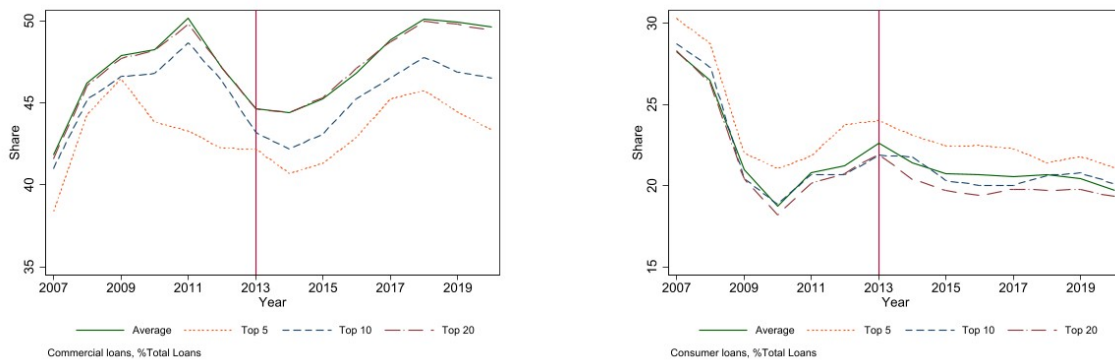
The Mexican regulation sets the risk weight on consumer loans at 75% whereas, for commercial loans, the weight ranges from 0% to 100%. It is worth mentioning that small business loans have an 85% risk weight². Therefore, for a given dollar amount of capital, a bank can increase its regulatory capital ratio by reallocating its lending activity. Figure 7a shows that the Mexican banking industry has shifted towards the

²Article 2 Bis 12-Bis 22, "Disposiciones de Carácter General Aplicables a las Instituciones de Crédito"

pre-reform levels of commercial loans while the share of consumer loans has steadily declined.

Large banks have a distinctive behavior and serve the consumer loan market to a greater extent (see Figure B.2.2). As previously argued, the evolution of the series of return on assets is independent of the bank size and the heterogeneity in the asset portfolio indicates that interest rates and other relevant factors such as risk management equate the overall return of banks.

Figure B.2.2. Participation of Commercial loans and Consumer loans, % of Total loans

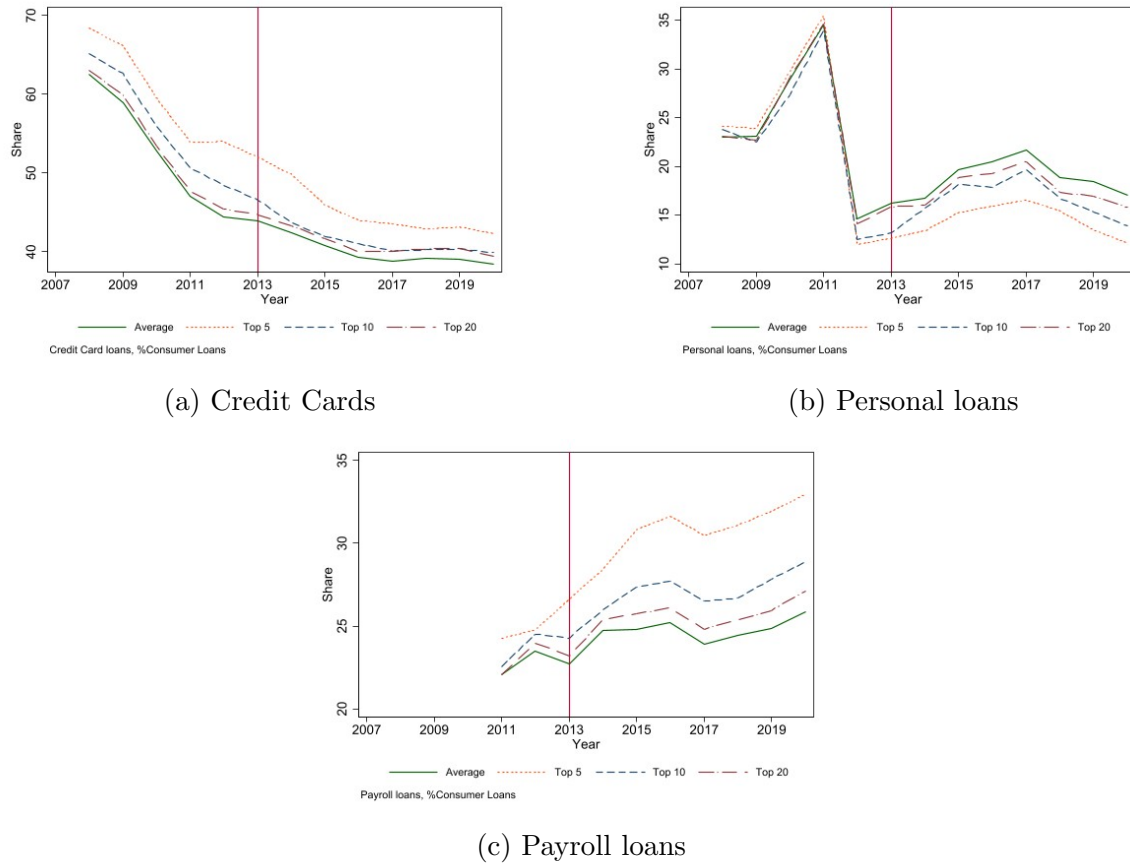


(a) Commercial loans

(b) Consumer loans

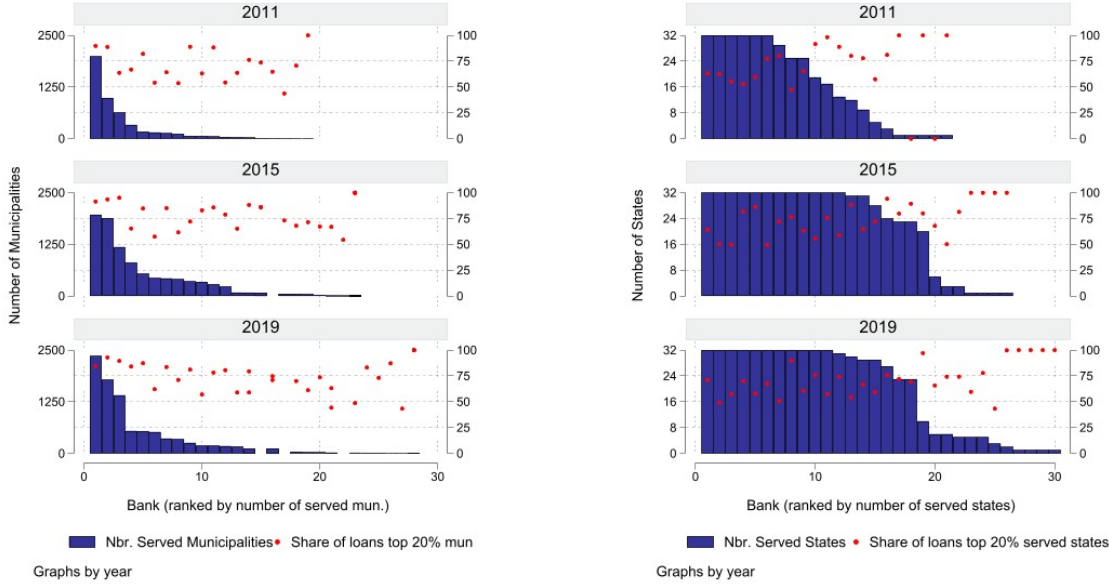
When examining the distribution of consumer loans by type (Figure B.2.3), general trends are evident with a distinguishable pattern for large banks. The share of personal loans (unsecured small consumption loans) began to decline in 2017.

Figure B.2.3. Consumer loans, by type. Average share



B.2.3 Number of serviced municipalities and states. In 2011, 20 banks serviced the (formal) personal loans market and only one bank lent to borrowers from approximately 1,800 municipalities, with the top 20 municipalities receiving around 80% of the bank's total loans. By 2019, 29 banks were in the personal loan market, with three banks each serving more than 50% of total municipalities, although heavily concentrated in 20 locations. On the opposite side, there are regional banks serving local markets as well. Panel b of Figure B.2.4 depicts a similar situation at the state level.

Figure B.2.4. Number of municipalities and state served by each bank



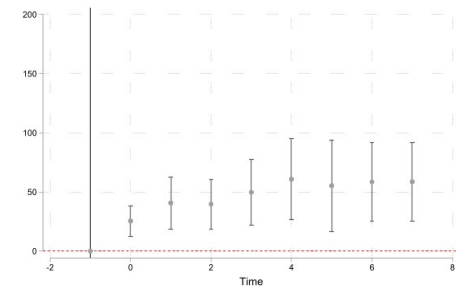
(a) Municipalities and share of top 20% served mun.

(b) States and share of top 20% served mun.

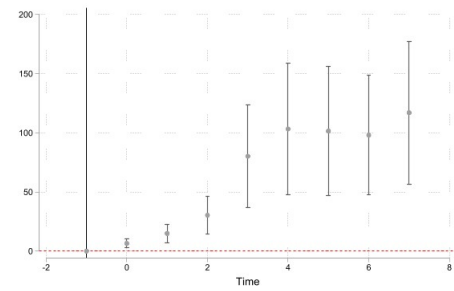
Bank lending data at the municipal level shows that borrowers from municipalities with no bank branch are serviced, suggesting that individuals can shop for loans across markets and that potential spillovers can arise.

B.2.4 Consumer loans market. Having documented the recomposition of consumer loan portfolios at the bank level, I examine consumer credit allocation using data on loan origination, total volume and (loan-weighted average) lending rates aggregated at the municipality level. In light of the capital requirements, risk-weighted assets will be partially driven by the varying nature and riskiness of the different consumer loan types, the dependence of the default risk on the loan contract (Jaffee & Russell, 1976), and spatial heterogeneity (Ji et al., 2021).

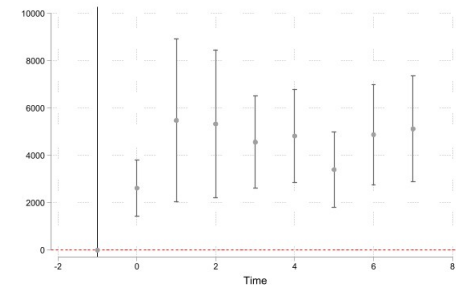
Figure B.2.5. Event Studies: Personal loans and Payroll loans



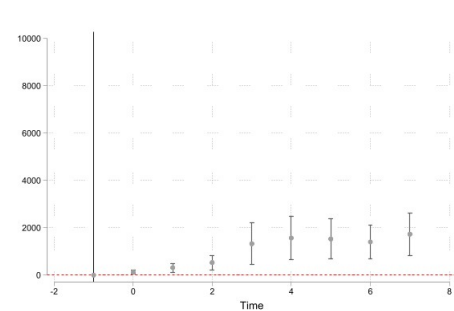
(a) Total real amount: Personal loans



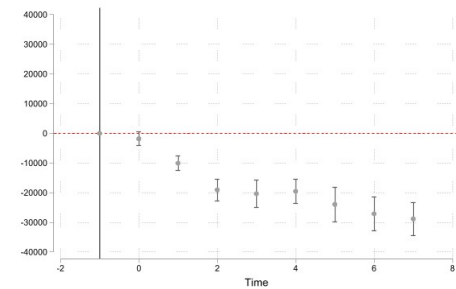
(b) Total real amount: Payroll loans



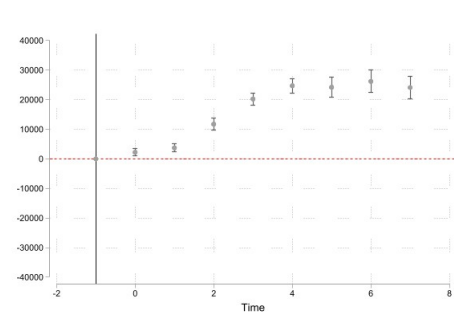
(c) Number of loans: Personal loans



(d) Number of loans: Payroll loans



(e) Average loan size: Personal loans



(f) Average loan size: Payroll loans

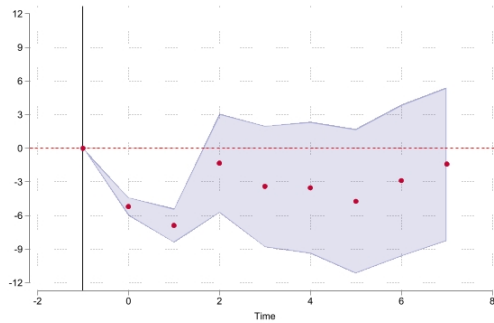
Municipality-fixed effects. Clustered Std. errors at the state level

The volume of (real) loans and count of originated loans have increased over time, with the number of originated personal loans growing at a higher rate which in turn results in lower average real loan size. This fact suggests that improvements

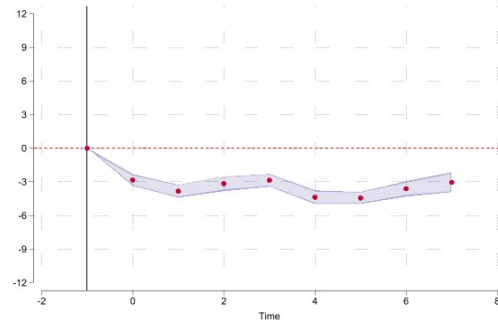
in financial access were driven by higher bank competition through catering to underserved populations by offering smaller loans.

Average lending rates across municipalities, however, changed differently as shown in Figure B.2.6. Payroll loans had a one-time permanent in 2013, personal loans the average lending rate experienced a temporary decline which also resulted in a transitory reduction in the average spread between lending rates of these products. The larger number of originated loans and reduction of the lending rate suggests an expansion of personal loan supply temporarily expanded.

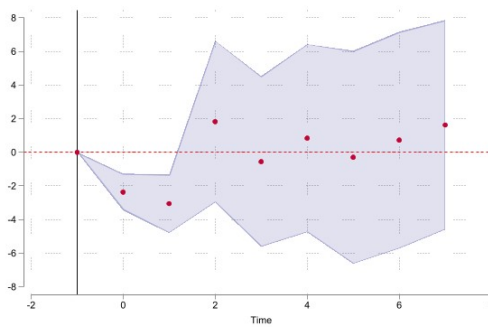
Figure B.2.6. Event Studies: Lending rates Personal loans and Payroll loans



(a) Lending rate: Personal loans



(b) Lending rate: Payroll loans



(c) Lending rate difference

Municipality-fixed effects. Clustered Std. errors at the state level

B.2.5 Average loan size and bank size. I examine the association between changes in capital requirements reform, loan size and bank size. I compute

the average loan size using data on total loan volume by bank b at municipality m and the corresponding number of originated loans. In a similar fashion as in Crawford, Pavanini, and Schivardi (2018) I use the residuals of the regression of the lending rate on personal loans to address the potential issue that unobservable factors at the municipality level drive the bank's lending decisions.

$$\begin{aligned}
AL_{bmt} = & \sum_{j=2011}^{2019} \alpha_j RCR_{b2010} + \gamma_j RCR_{b2010} \times BN_{bl2010} + \\
& \mathbb{1}_{\mathbb{T}} \left(\sum_{j=2011}^{2019} \alpha_j^T RCR_{b2010} + \gamma_j^T RCR_{b2010} \times BN_{bl2010} \right) + \\
& \lambda \hat{\varepsilon}_{ibt} + \delta' X_{mt} + \rho_t + \alpha_b + \varepsilon_{bmt} \quad (\text{B.1})
\end{aligned}$$

where AL_{bmt} is the average personal loan by bank b at location m at time t , RCR_{b2010} is the (total) regulatory capital ratio of bank b by the end of 2010, BN_{bmt} the number of branches of bank b at location m at time t , ε_{ibt} the residual of the regression of the lending rate, X_{it} a set of covariates, including adult population and area of the municipality, ρ_t and α_b are time and bank fixed effects respectively. The indicator variable $\mathbb{1}_{\mathbb{T}}$ takes the value of one when bank b is among the top five banks at time t . I estimate this equation for the period 2011-2019 taking 2013 as the base level, using the gap of the total regulatory capital ratio relative to the minimum requirement of 10%.

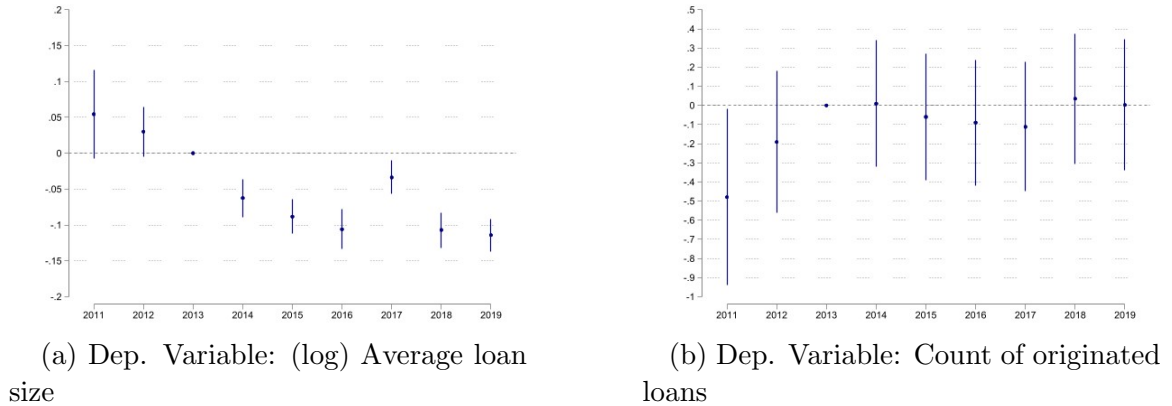
A priori, the relationship between banks' initial regulatory capital ratios, loan size, and bank size is ambiguous. This specification whether the association between the documented series of declining average loan size (Figure B.2.5e) is driven by the capital ratios held by large banks. The inquiry is motivated by the documented differences in loan portfolio composition in Figures B.2.2 and the premise that large

banks have different business models. Equation B.1 tests for this association by estimating the α_j^T s; an increasing pattern would be suggestive of large banks catering to borrowers with larger loans.

As shown in Figure B.2.7a, the average personal loan size at the municipality level is negatively correlated with the initial regulatory capital ratio (gap) for large banks, while no correlation is found for the number of originated personal loans (Figure B.2.7b).

As shown in Appendix B.2.4, the share of personal loans experienced a general downward trend, with the top 5 banks remaining above the average. These results suggest jointly that under the new rule, larger banks expanded by extending smaller loans.

Figure B.2.7. Reduced-form estimates: Coefficient on $\mathbb{1}_{year} \times GAPB_{b2010} \times Top5$



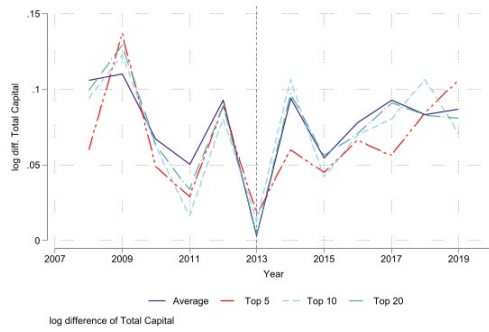
Furthermore, the negative coefficient on the number of the bank's own branches in a given municipality in 2010 (results not shown) suggests that banks expanded onto municipalities with fewer branches. A potential explanation is that after the announcement of the new rule and eventual implementation, banks responded by

reducing their precautionary holding of excess capital and targeting under-served municipalities.

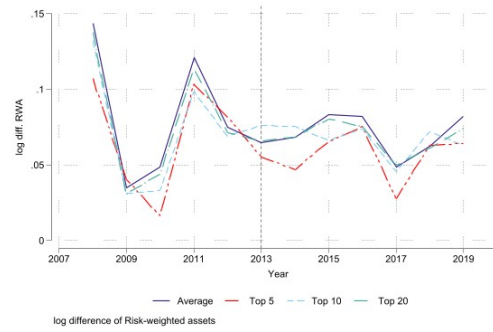
B.3 Components of the Regulatory Capital Ratio

How did banks adjust to the new regulatory framework? Figure B.3.1 shows the log-differenced series of total capital (the numerator of the RCR) and risk-weighted assets (RWA, denominator). The RCR soared to 17 percent in 2009, driven by both an expansion of total capital and a contraction of RWA, while the change in 2012 sets the overall growth rate of the post-reform period. Banks did not change significantly their capital during the first year of the reform and their RWA growth decelerated. It can be seen that rates of change were smaller for larger banks and that, on average, smaller banks expanded both their risk-weighted assets and capital at a higher rate, suggesting that credit supply was not contracted as a means to reduce risk exposures. Figure B.3.1c depicts a similar situation for the CET1 capital especially in the early years of the reform, which justifies the choice of the RCR (rather than the CET1 ratio) which is available for the pre-reform years and correlated with the new measure.

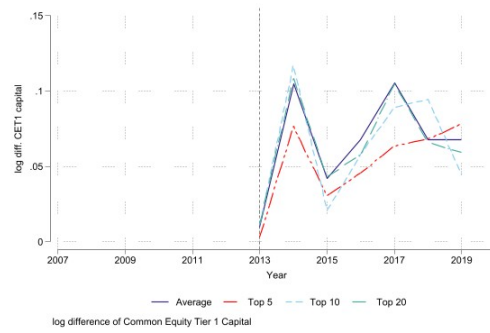
Figure B.3.1. Components of the Regulatory Capital Ratio



(a) Total Capital



(b) Risk-weighted assets



(c) Common Equity Tier 1 Capital Ratio

B.4 Tables

Table B.4.1. Respondent has credit, State level Level

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
<i>Year</i>						
Year=2015	0.0106 [0.030]	0.0179 [0.044]	0.0095 [0.044]	-0.5183*** [0.035]	0.0334 [0.044]	-0.5118*** [0.038]
Year=2018	-0.0235 [0.020]	-0.0306 [0.041]	-0.0227 [0.039]	-0.6361*** [0.036]	0.0046 [0.041]	-0.6217*** [0.040]
<i>Predicted shock</i>						
Pred. credit shock	18.4762*** [0.770]	5.9774 [22.475]	15.8291 [21.488]	79.7495*** [5.602]	16.0853 [21.401]	82.5163*** [5.987]
Year=2015 × Pred. credit shock	0.4946 [0.875]	0.2432 [1.002]	0.4810 [1.017]	-0.3936*** [0.086]	0.3818 [0.975]	-0.5459 [0.397]
Year=2018 × Pred. credit shock	1.4733* [0.636]	1.3151 [0.856]	1.0773 [0.860]	3.8102*** [0.098]	0.6732 [0.891]	3.2612*** [0.445]
<i>State-level characteristics</i>						
Adult population (in millions)		0.0416 [0.024]	0.0314 [0.022]	-0.9867*** [0.120]	0.0299 [0.022]	-1.0710*** [0.133]
Poverty rate, last census		0.0016 [0.003]	0.0003 [0.003]	-0.0566*** [0.003]	0.0003 [0.003]	-0.0581*** [0.004]
Number of branches		0.3622 [0.206]	0.2553 [0.182]	4.9876*** [0.495]	0.2564 [0.180]	5.3700*** [0.557]
Soc. security cov. rate, last census		0.0007 [0.005]	-0.0019 [0.005]	0.0296*** [0.002]	-0.0021 [0.004]	0.0303*** [0.002]
<i>Gender and interactions</i>						
Female			0.0327*** [0.008]	0.0317*** [0.008]	0.0515** [0.020]	0.0506** [0.019]
Year=2015 × Female					-0.0489 [0.031]	-0.0443 [0.030]
Year=2018 × Female					-0.0571 [0.030]	-0.0562 [0.029]
Female × Pred. credit shock					0.3028 [0.715]	0.2860 [0.701]
Year=2015 × Female × Pred. credit shock					0.1023 [0.998]	-0.0308 [0.981]
Year=2018 × Female × Pred. credit shock					0.8303 [0.955]	0.8215 [0.937]
State Fixed Effects	Yes	Yes	Yes	No	Yes	No
State-Year Fixed Effects	No	No	No	Yes	No	Yes
Ind. Employment and Education level	No	No	Yes	Yes	Yes	Yes
F-statistic (subset of parameters)	97.04	114.58	80.72	3.89e+11	68.82	1.45e+11
Number of observations	24587	24587	17685	17685	17685	17685

Unweighted observations. Standard errors clustered on year-state are in brackets

Table B.4.2. Respondent has personal loan

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
<i>Year</i>						
Year=2015	-0.0262 [0.038]	-0.0224 [0.058]	-0.0300 [0.053]	-0.1162 [0.068]	-0.0883 [0.056]	-0.2017** [0.071]
Year=2018	-0.0708* [0.030]	-0.0457 [0.054]	-0.0515 [0.050]	-0.1395* [0.066]	-0.0644 [0.048]	-0.1859** [0.067]
<i>Predicted shock</i>						
Pred. credit shock	9.6709*** [1.574]	27.7060 [22.603]	15.0944 [21.797]	8.4714 [11.171]	15.6731 [22.062]	13.8982 [10.987]
Year=2015 × Pred. credit shock	0.9484 [1.129]	1.2408 [1.312]	1.1437 [1.206]	3.0718*** [0.205]	3.0655* [1.364]	4.8507*** [0.684]
Year=2018 × Pred. credit shock	1.6838* [0.836]	1.8489 [1.068]	1.5285 [0.960]	3.8191*** [0.118]	2.1314* [0.968]	4.5157*** [0.522]
<i>State-level characteristics</i>						
Adult population (in millions)		-0.0822 [0.047]	-0.0726 [0.037]	-1.0770*** [0.228]	-0.0733* [0.036]	-1.2030*** [0.224]
Poverty rate, last census		-0.0008 [0.003]	0.0003 [0.003]	0.0059 [0.007]	0.0003 [0.003]	0.0026 [0.007]
Number of branches		-0.4380 [0.300]	-0.2655 [0.278]	5.4764*** [0.928]	-0.2852 [0.274]	6.0113*** [0.914]
Soc. security cov. rate, last census		-0.0019 [0.005]	0.0006 [0.005]	0.0034 [0.004]	0.0005 [0.005]	0.0052 [0.004]
<i>Gender and interactions</i>						
Female			-0.0164* [0.007]	-0.0154* [0.007]	-0.0183 [0.025]	-0.0140 [0.025]
Year=2015 × Female					0.1249** [0.047]	0.1244* [0.047]
Year=2018 × Female					0.0291 [0.030]	0.0247 [0.031]
Female × Pred. credit shock					0.2130 [0.829]	0.2811 [0.872]
Year=2015 × Female × Pred. credit shock					-4.0941** [1.386]	-4.3688** [1.424]
Year=2018 × Female × Pred. credit shock					-1.2566 [0.980]	-1.3071 [1.025]
State Fixed Effects	Yes	Yes	Yes	No	Yes	No
State-Year Fixed Effects	No	No	No	Yes	No	Yes
Ind. Employment and Education level	No	No	Yes	Yes	Yes	Yes
F-statistic (subset of parameters)	12.34	9.28	8.76	2675.40	8.67	1579.20
Number of observations	7483	7483	6042	6042	6042	6042

Unweighted observations. Standard errors clustered on year-state are in brackets

Table B.4.3. Respondent has payroll loan

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
<i>Year</i>						
Year=2015	-0.0238 [0.030]	-0.0665 [0.040]	-0.0943* [0.046]	-2.7794*** [0.053]	-0.1184* [0.056]	-2.8075*** [0.061]
Year=2018	-0.0281 [0.031]	-0.0607 [0.039]	-0.0881 [0.045]	-2.4514*** [0.050]	-0.0983 [0.051]	-2.4697*** [0.055]
<i>Predicted shock</i>						
Pred. credit shock	9.3510** [2.950]	21.6787 [16.242]	23.5663 [19.051]	423.3635*** [8.523]	21.0619 [19.045]	425.5855*** [8.428]
Year=2015 × Pred. credit shock	0.7912 [0.864]	1.9129* [0.915]	2.2441* [1.079]	-0.2294 [0.116]	2.2755 [1.349]	-0.2441 [0.741]
Year=2018 × Pred. credit shock	0.6381 [0.846]	1.8164* [0.892]	2.0789* [1.030]	-6.5474*** [0.076]	1.8005 [1.126]	-6.8057*** [0.616]
<i>State-level characteristics</i>						
Adult population (in millions)		0.0309 [0.029]	0.0337 [0.030]	-7.7927*** [0.177]	0.0348 [0.030]	-7.8133*** [0.177]
Poverty rate, last census		-0.0006 [0.002]	-0.0014 [0.003]	-0.2642*** [0.005]	-0.0011 [0.003]	-0.2654*** [0.005]
Number of branches		-0.8965** [0.276]	-1.0576** [0.316]	31.1091*** [0.729]	-1.0659*** [0.313]	31.1829*** [0.729]
Soc. security cov. rate, last census		-0.0009 [0.003]	-0.0003 [0.004]	0.1470*** [0.003]	0.0003 [0.004]	0.1475*** [0.003]
<i>Gender and interactions</i>						
Female			-0.0164* [0.007]	-0.0169* [0.008]	-0.0030 [0.036]	-0.0021 [0.036]
Year=2015 × Female					0.0451 [0.053]	0.0414 [0.054]
Year=2018 × Female					0.0168 [0.041]	0.0112 [0.041]
Female × Pred. credit shock					-1.4544 [1.022]	-1.3921 [1.031]
Year=2015 × Female × Pred. credit shock					-0.0126 [1.589]	-0.0898 [1.623]
Year=2018 × Female × Pred. credit shock					0.6209 [1.167]	0.6937 [1.166]
State Fixed Effects	Yes	Yes	Yes	No	Yes	No
State-Year Fixed Effects	No	No	No	Yes	No	Yes
Ind. Employment and Education level	No	No	Yes	Yes	Yes	Yes
F-statistic (subset of parameters)	9.55	2.71	21.25	8574.96	16.57	4018.66
Number of observations	7483	7483	6042	6042	6042	6042

Unweighted observations. Standard errors clustered on year-state are in brackets

Table B.4.4. Respondent has saving account

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
<i>Year</i>						
Year=2015	0.0004 [0.030]	-0.0311 [0.056]	-0.0270 [0.054]	-0.5432*** [0.035]	-0.0649 [0.057]	-0.5030*** [0.049]
Year=2018	0.0643** [0.022]	0.0265 [0.050]	0.0257 [0.048]	-0.6802*** [0.035]	-0.0144 [0.047]	-0.6453*** [0.047]
<i>Predicted shock</i>						
Pred. credit shock	28.7238*** [0.706]	1.6210 [27.366]	26.9697 [25.969]	80.4935*** [5.539]	27.7044 [26.062]	66.9163*** [7.399]
Year=2015 × Pred. credit shock	3.2035** [1.063]	3.4871* [1.414]	2.5120 [1.342]	-2.4870*** [0.125]	2.8651* [1.355]	-2.0131* [0.839]
Year=2018 × Pred. credit shock	0.3785 [0.868]	0.6985 [1.305]	0.5060 [1.176]	1.7582*** [0.089]	1.8353 [1.099]	3.0840*** [0.679]
<i>State-level characteristics</i>						
Adult population (in millions)		0.0178 [0.036]	-0.0143 [0.038]	-0.1317 [0.118]	-0.0127 [0.038]	0.1504 [0.154]
Poverty rate, last census		0.0012 [0.004]	-0.0024 [0.003]	-0.0622*** [0.003]	-0.0022 [0.003]	-0.0543*** [0.004]
Number of branches		0.1780 [0.414]	0.0941 [0.388]	-1.1287* [0.483]	0.1066 [0.383]	-2.3290*** [0.638]
Soc. security cov. rate, last census		0.0058 [0.005]	0.0014 [0.005]	0.0369*** [0.002]	0.0015 [0.005]	0.0330*** [0.002]
<i>Gender and interactions</i>						
Female			-0.0025 [0.009]	-0.0025 [0.009]	-0.0816* [0.036]	-0.0825* [0.036]
Year=2015 × Female					0.0815 [0.055]	0.0751 [0.055]
Year=2018 × Female					0.0862* [0.041]	0.0879* [0.041]
Female × Pred. credit shock					2.1046 [1.493]	2.0892 [1.493]
Year=2015 × Female × Pred. credit shock					-0.6070 [2.060]	-0.3777 [2.080]
Year=2018 × Female × Pred. credit shock					-2.8994 [1.606]	-2.8755 [1.595]
State Fixed Effects	Yes	Yes	Yes	No	Yes	No
State-Year Fixed Effects	No	No	No	Yes	No	Yes
Ind. Employment and Education level	No	No	Yes	Yes	Yes	Yes
F-statistic (subset of parameters)	169.58	509.96	190.83	15682.79	159.46	5076.04
Number of observations	24587	24587	17685	17685	17685	17685

Unweighted observations. Standard errors clustered on year-state are in brackets

Table B.4.5. Respondent had loan application rejected

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
<i>Year</i>						
Year=2015	-0.2112*** [0.060]	-0.2337** [0.071]	-0.2297** [0.080]	-4.5227*** [0.052]	-0.2077* [0.093]	-4.4914*** [0.070]
Year=2018	-0.2152*** [0.033]	-0.2527*** [0.057]	-0.2811*** [0.066]	-4.2435*** [0.052]	-0.2751*** [0.080]	-4.2326*** [0.069]
<i>Predicted shock</i>						
Pred. credit shock	182.5656*** [1.325]	190.8678*** [34.447]	156.2066*** [37.698]	666.7339*** [8.368]	156.0073*** [37.737]	667.1746*** [9.922]
Year=2015 × Pred. credit shock	2.4095 [1.715]	1.7607 [1.755]	1.7006 [1.977]	11.8862*** [0.162]	0.9308 [2.395]	10.8716*** [1.011]
Year=2018 × Pred. credit shock	0.5294 [1.117]	-0.0265 [1.237]	0.3887 [1.535]	8.1090*** [0.146]	0.0162 [2.008]	7.6114*** [1.047]
<i>State-level characteristics</i>						
Adult population (in millions)		0.0528 [0.042]	0.0455 [0.048]	-15.4643*** [0.179]	0.0461 [0.048]	-15.4564*** [0.217]
Poverty rate, last census		-0.0081 [0.005]	-0.0037 [0.006]	-0.3636*** [0.005]	-0.0037 [0.006]	-0.3638*** [0.006]
Number of branches		0.3326 [0.373]	0.8867* [0.438]	63.6141*** [0.733]	0.8846* [0.444]	63.5717*** [0.901]
Soc. security cov. rate, last census		0.0017 [0.007]	0.0082 [0.007]	0.2625*** [0.003]	0.0083 [0.007]	0.2624*** [0.003]
<i>Gender and interactions</i>						
Female			0.0186 [0.011]	0.0177 [0.011]	0.0290 [0.065]	0.0430 [0.066]
Year=2015 × Female					-0.0491 [0.078]	-0.0766 [0.079]
Year=2018 × Female					-0.0143 [0.074]	-0.0266 [0.075]
Female × Pred. credit shock					-0.5515 [1.778]	-0.9541 [1.781]
Year=2015 × Female × Pred. credit shock					1.7127 [2.258]	2.4670 [2.273]
Year=2018 × Female × Pred. credit shock					0.8418 [2.211]	1.1469 [2.227]
State Fixed Effects	Yes	Yes	Yes	No	Yes	No
State-Year Fixed Effects	No	No	No	Yes	No	Yes
Ind. Employment and Education level	No	No	Yes	Yes	Yes	Yes
F-statistic (subset of parameters)	2325.02	4940.93	569.28	6.25e+10	505.20	6.27e+10
Number of observations	24587	24587	17685	17685	17685	17685

Unweighted observations. Standard errors clustered on year-state are in brackets

Table B.4.6. Respondent has used informal credit products

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
<i>Year</i>						
Year=2015	0.0507 [0.031]	0.0317 [0.032]	0.0720* [0.036]	-2.1614*** [0.031]	0.0788* [0.039]	-2.1649*** [0.044]
Year=2018	0.0365 [0.034]	0.0357 [0.032]	0.0702 [0.035]	-2.3144*** [0.031]	0.0743 [0.041]	-2.3180*** [0.045]
<i>Predicted shock</i>						
Pred. credit shock	28.2878*** [2.077]	60.6171*** [16.191]	73.4164*** [21.283]	371.7636*** [4.926]	73.5242*** [21.426]	373.5315*** [6.346]
Year=2015 × Pred. credit shock	-0.1422 [0.911]	0.6938 [0.687]	-0.0471 [0.806]	-5.6316*** [0.104]	-0.3888 [0.997]	-5.9368*** [0.715]
Year=2018 × Pred. credit shock	0.6323 [0.942]	1.3989* [0.602]	0.7821 [0.665]	3.5766*** [0.086]	0.3534 [0.933]	3.1067*** [0.654]
<i>State-level characteristics</i>						
Adult population (in millions)		0.0056 [0.023]	0.0026 [0.028]	-8.3119*** [0.104]	0.0036 [0.028]	-8.3361*** [0.135]
Poverty rate, last census		-0.0019 [0.002]	-0.0026 [0.003]	-0.2190*** [0.003]	-0.0027 [0.003]	-0.2201*** [0.004]
Number of branches		-0.9679*** [0.254]	-0.9215** [0.307]	35.4890*** [0.423]	-0.9220** [0.303]	35.5782*** [0.562]
Soc. security cov. rate, last census		-0.0049 [0.003]	-0.0081 [0.004]	0.1325*** [0.002]	-0.0080 [0.004]	0.1331*** [0.002]
<i>Gender and interactions</i>						
Female			0.0167* [0.008]	0.0161* [0.007]	0.0121 [0.042]	0.0184 [0.042]
Year=2015 × Female					-0.0160 [0.056]	-0.0201 [0.056]
Year=2018 × Female					-0.0105 [0.048]	-0.0167 [0.048]
Female × Pred. credit shock					-0.2155 [1.188]	-0.4083 [1.180]
Year=2015 × Female × Pred. credit shock					0.7608 [1.641]	0.8182 [1.646]
Year=2018 × Female × Pred. credit shock					0.9691 [1.348]	1.1403 [1.344]
State Fixed Effects	Yes	Yes	Yes	No	Yes	No
State-Year Fixed Effects	No	No	No	Yes	No	Yes
Ind. Employment and Education level	No	No	Yes	Yes	Yes	Yes
F-statistic (subset of parameters)	141.75	54.96	39.57	1.19e+11	32.19	8.40e+10
Number of observations	24587	24587	17685	17685	17685	17685

Unweighted observations. Standard errors clustered on year-state are in brackets

APPENDIX C

CHAPTER IV APPENDIX

Appendix

C.1 Ordered Logistic Regressions: Expected equity premium

Table C.1.1. Implied expected equity premium: Pessimistic agents

	(1)	(2)	(3)	(4)	(5)	(6)
CBI shock	1.004 (0.34)	1.246 (0.40)	0.224 (0.09)	0.550 (0.21)	2.101 (0.88)	5.751 (2.01)
$Year > 2000 = 1$	-0.403 (-1.10)	-0.509 (-1.02)	-0.644 (-1.21)	-4.349 (-1.38)	-4.775 (-1.44)	1.973 (1.11)
MP shock	2.803* (2.52)	2.751* (2.42)	1.335 (1.18)	1.399 (1.20)	1.935 (1.70)	3.394** (2.94)
Business env. index		0.192 (0.40)	0.0338 (0.07)	0.0762 (0.15)	0.301 (0.58)	1.169** (2.83)
Retired			ref.	ref.	ref.	ref.
No			1.074** (3.25)	1.910*** (5.17)	1.928*** (5.13)	1.255** (3.41)
Don't know / Refused			-1.284 (-1.26)	-0.403 (-0.34)	-0.303 (-0.27)	-0.751 (-0.73)
Portfolio return (past 12m)						0.136* (2.36)
$Year > 2000 = 1 \times$ Portfolio return (past 12m)						-0.0655 (-1.11)
Constant	5.536*** (17.02)	5.456*** (16.07)	5.908*** (9.60)	10.37*** (3.74)	11.97*** (4.01)	3.911** (2.72)
Wealth x Post-2000	No	No	Yes	Yes	Yes	Yes
Annual Income x Post-2000	No	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes	Yes
Macro var.	No	No	No	No	Yes	Yes
N	11766	11766	11686	11686	11686	8103

Table C.1.2. Implied expected equity premium: Neither

	(1)	(2)	(3)	(4)	(5)	(6)
CBI shock	-3.888 (-1.01)	-4.244 (-1.10)	-5.257 (-1.41)	-5.136 (-1.29)	-3.609 (-0.94)	-6.808 (-1.32)
$Year > 2000 = 1$	-0.698 (-1.78)	-0.555 (-1.01)	-0.801 (-0.85)	-4.617 (-1.08)	-4.677 (-1.08)	-3.501 (-0.54)
PM shock	2.381 (1.66)	2.379 (1.69)	1.908 (1.63)	1.980 (1.43)	2.846 (1.92)	0.459 (0.18)
Business env. index		-0.278 (-0.46)	-0.302 (-0.49)	-0.305 (-0.48)	-0.501 (-0.99)	-0.237 (-0.35)
Retired No			1.442** (2.95)	2.145*** (4.42)	2.144*** (4.46)	1.100* (2.37)
Don't know / Refused			2.049 (0.90)	3.276 (1.41)	3.324 (1.44)	3.787* (2.60)
Portfolio return (past 12m)						0.303*** (4.55)
$Year > 2000 = 1 \times$ Portfolio return (past 12m)						-0.259** (-3.56)
Constant	6.430*** (21.39)	6.543*** (18.53)	6.356*** (5.94)	9.011* (2.16)	9.754* (2.22)	9.160 (1.44)
Wealth x Post-2000	No	No	Yes	Yes	Yes	Yes
Annual Income x Post-2000	No	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes	Yes
Macro var.	No	No	No	No	Yes	Yes
N	8402	8402	8292	8292	8292	5135

Table C.1.3. Implied expected equity premium: Optimistic

	(1)	(2)	(3)	(4)	(5)	(6)
	(1)	(2)	(3)	(4)	(5)	(6)
CBI shock	-3.335 (-0.84)	-4.144 (-1.09)	-5.285 (-1.49)	-4.557 (-1.25)	-4.666 (-1.32)	-4.720 (-1.63)
$Year > 2000 = 1$	-1.056** (-3.43)	-0.664 (-1.41)	0.921 (1.78)	0.273 (0.14)	0.388 (0.20)	3.706 (1.39)
PM shock	0.236 (0.14)	0.383 (0.26)	-0.808 (-0.51)	-0.148 (-0.09)	-0.244 (-0.14)	1.366 (0.92)
Business env. index		-0.763 (-1.34)	-0.451 (-0.82)	-0.354 (-0.63)	-0.0778 (-0.13)	1.276* (2.40)
Retired No			ref. 1.975*** (7.57)	ref. 2.392*** (7.94)	ref. 2.396*** (7.98)	ref. 1.650*** (6.21)
Don't know / Refused			-1.436 (-1.00)	-1.322 (-0.93)	-1.384 (-0.96)	-0.398 (-0.27)
Portfolio return (past 12m)						0.381*** (10.76)
$Year > 2000 = 1 \times$ Portfolio return (past 12m)						-0.254*** (-6.91)
Wealth x Post-2000	No	No	Yes	Yes	Yes	Yes
Annual Income x Post-2000	No	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes	Yes
Macro var.	No	No	No	No	Yes	Yes
N	22411	22411	21819	21819	21819	12135

C.2 Local projections

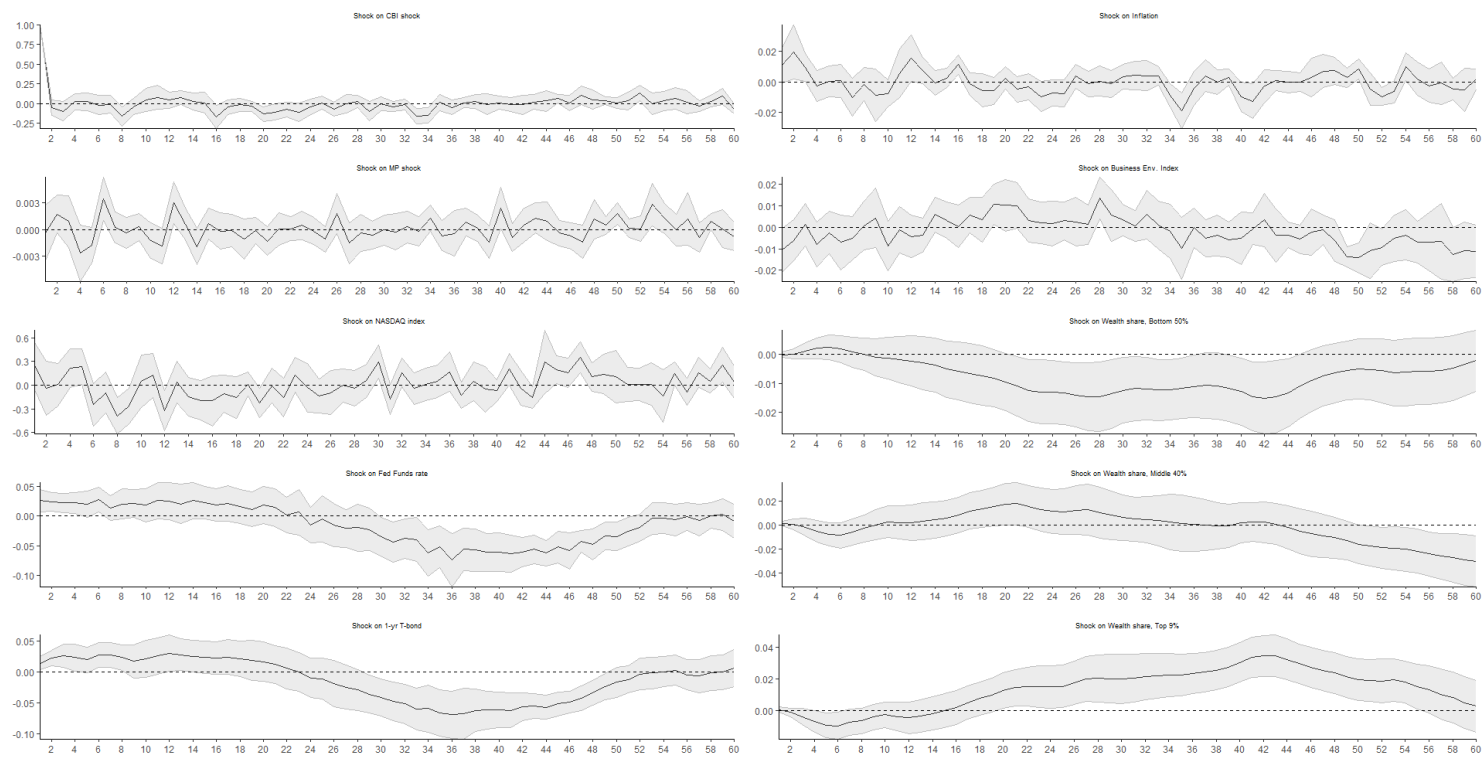


Figure C.2.1. Central Bank Information shock

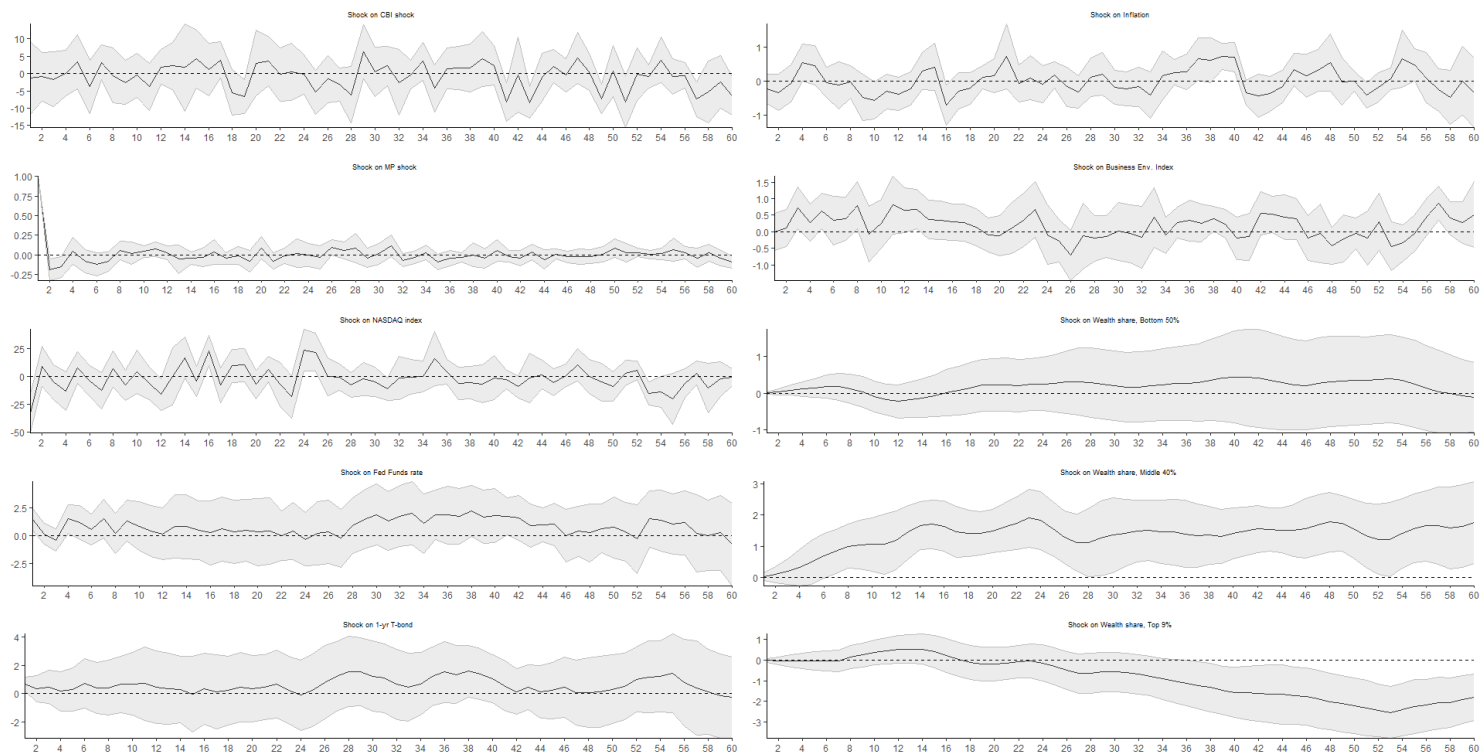


Figure C.2.2. Monetary policy shock

C.3 Logistic Regressions

	(1) (1)	(2) (2)	(3) (3)	(4) (4)	(5) (5)	(6) (6)
Post x CBI shock	1.029*** (3.84)	1.007 (0.72)	0.264*** (-39.71)	0.276*** (-28.40)	0.275*** (-27.35)	1.133* (2.20)
Year ≥ 2000	0.529*** (-9.83)	0.546*** (-13.02)	0.654*** (-6.95)	1.507*** (4.26)	1.308* (2.31)	0.859 (-0.19)
Post x PM shock		0.987* (-2.34)	0.986** (-2.71)	0.986** (-2.91)	0.985*** (-4.59)	0.988** (-2.76)
Business env. index		0.653*** (-4.84)	0.690** (-2.96)	0.709* (-2.50)	0.678*** (-5.64)	0.741** (-3.06)
Retired No			ref. 0.790*** (-4.29)	ref. 0.733*** (-4.97)	ref. 0.734*** (-4.97)	ref. 0.775** (-3.21)
Don't know / Refused			2.826 (1.43)	2.841 (1.15)	2.881 (1.17)	5.340 (0.98)
Retired x Post-shock No x Post x CBI shock			ref. 1.002 (0.18)	ref. 1.003 (0.27)	ref. 1.003 (0.25)	ref. 1.004 (0.27)
Don't know / Refused x Post x CBI shock			1.192 (1.05)	1.181 (0.95)	1.178 (0.93)	1.371 (1.89)
Portfolio return (past 12m)						1.020*** (5.85)
Post x CBI shock x Portfolio return (past 12m)						1.000 (-0.50)
Wealth x Shocks	No	No	Yes	Yes	Yes	Yes
Annual Income	No	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes	Yes
Year fixed effect	No	No	Yes	Yes	Yes	Yes
Macro var.	No	No	No	No	Yes	Yes
N	11744	11744	11744	10443	10443	6758
p-val: Post-shock x Savings x Year = 0			0	0	0	0
Exponentiated coefficients						

Table C.3.4. Investment Target - Next 12 months

	(1)	(2)	(3)	(4)	(5)	(6)
Post x CBI shock	1.006 (0.82)	0.993 (-0.76)	0.340*** (-36.61)	0.385*** (-22.85)	0.384*** (-22.52)	1.142** (3.11)
Year 2000	0.622*** (-7.14)	0.610*** (-7.63)	0.850 (-1.29)	1.402*** (4.66)	1.305* (2.35)	0.366 (-0.86)
Post x PM shock		0.988** (-3.15)	0.992 (-1.41)	0.993 (-1.26)	0.993 (-1.35)	0.993 (-0.91)
Business env. index		0.962 (-0.49)	0.788*** (-3.34)	0.843* (-2.38)	0.857* (-2.12)	0.815* (-2.39)
Retired			ref.	ref.	ref.	ref.
No			0.950 (-0.86)	0.839* (-2.46)	0.840* (-2.45)	0.872 (-1.29)
Don't know / Refused			0.719 (-0.62)	0.717 (-0.61)	0.718 (-0.61)	0.608 (-1.06)
Retired x Post-shock			ref.	ref.	ref.	ref.
No x Post x CBI shock			1.018 (1.36)	1.020 (1.36)	1.020 (1.36)	1.015 (0.76)
Don't know / Refused x Post x CBI shock			1.203 (1.38)	1.201 (1.17)	1.199 (1.16)	1.244** (2.64)
Portfolio return (past 12m)						1.014*** (6.97)
Post x CBI shock x Portfolio return (past 12m)						1.000 (-0.75)
Wealth x Shocks	No	No	Yes	Yes	Yes	Yes
Annual Income	No	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes	Yes
Year fixed effect	No	No	Yes	Yes	Yes	Yes
Macro var.	No	No	No	No	Yes	Yes
N	11744	11744	11744	10443	10443	6758
p-val: Post-shock x Savings x Year = 0			0	0	0	0
Exponentiated coefficients						

Table C.3.5. Investment Target - Next 5 years

C.4 Regressions of the Self-reported probability of leaving bequests

Table C.4.6. Bequest Expectations and Stock Return Expectations

	(1)	(2)	(3)	(4)	(5)
Self-reported prob. of positive stock return	0.0924*** (22.28)	0.0927*** (22.23)	0.0884*** (20.47)	0.0867*** (20.08)	0.0857*** (17.70)
NASDAQ Composite monthly return		-8.055*** (-5.40)	-0.306 (-0.19)	-0.542 (-0.34)	-1.887 (-1.00)
NASDAQ Comp. monthly return $t - 1$		-3.907** (-2.61)	0.674 (0.43)	0.527 (0.34)	0.0892 (0.05)
NASDAQ Comp. monthly return $t - 2$		-5.671*** (-4.00)	0.965 (0.62)	1.739 (1.12)	1.463 (0.78)
Income to Total Wealth			-0.000503** (-2.77)	-0.000451* (-2.45)	-0.000389* (-2.09)
Stock Portfolio to Non-housing Wealth				1.465*** (3.39)	1.507** (3.17)
Value Primary Residence to Total Wealth				0.0136 (0.89)	0.0170 (1.23)
Follows Stock Market (Base Value = Very Closely)					-0.990* (-2.11)
Somewhat Closely					
Not at All					-2.942*** (-5.31)
Don't know					-2.401 (-0.66)
Refused to answer					9.404 (1.13)
Wave Fixed Effect	No	No	Yes	Yes	Yes
Observations	116,043	114,947	109,839	107,445	90,133

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.5 Linear approximation of the bequest motive

For a model with certain life span, with $u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma}$ and $e(a_t) = A \frac{a_t^{1-\mu}}{1-\mu}$ the FOC in the last period are given by

$$k_t^{i,t} \quad (c_t^{i,t})^{-\sigma} \geq A\beta E_t^i R_{t+1}^k (R_t^s b_{t+1}^{i,t} + R_{t+1}^k k_{t+1}^{i,t})^{-\mu} \quad (\text{C.1})$$

$$b_t^{i,t} \quad (c_t^{i,t})^{-\sigma} \geq A\beta R_t^s E_t^i (R_{t+1}^s b_{t+1}^{i,t} + R_{t+1}^k k_{t+1}^{i,t})^{-\mu} \quad (\text{C.2})$$

The policy functions can be written as $c_t^{i,t} = c^{i,t}(a_t)$, $b_{t+1}^{i,t} = b^{i,t}(a_t)$, and $k_{t+1}^{i,t} = k^{i,t}(a_t)$. Guess that $c^{i,t}(a_t) = \gamma_t a_t$, $k^{i,t}(a_t) = (1-\gamma_t)\kappa_t a_t$, and $b^{i,t}(a_t) = (1-\gamma_t)(1-\kappa_t)a_t$

Consider $f(x) = \exp(\log(x((R_t^s(1-\kappa_t) + x\kappa_t)^{-\mu}))$. Then

$$\begin{aligned} f'(x) &= f(x) \left(\frac{1}{x} - \frac{\mu\kappa_t}{R_t^s(1-\kappa_t) + x\kappa_t} \right) \\ f''(x) &= f(x) \left[\left(\frac{1}{x} - \frac{\mu\kappa_t}{R_t^s(1-\kappa_t) + x\kappa_t} \right)^2 + \frac{\mu\kappa_t^2}{(R_t^s(1-\kappa_t) + x\kappa_t)^2} - \frac{1}{x^2} \right] \\ &= f(x) \left[\frac{\mu}{R_t^s(1-\kappa_t) + x\kappa_t} \left(\frac{(1+\mu)\kappa_t^2}{R_t^s(1-\kappa_t) + x\kappa_t} - \frac{2\kappa_t}{x} \right) \right] \end{aligned} \quad (\text{C.3})$$

Expanding around the expected return and taking expectations:

$$\begin{aligned} E^i[R_{t+1}^k (R_t^s(1-\kappa_t) + R_{t+1}^k \kappa_t)^{-\mu}] &\approx \\ [\bar{R}_{t+1}^k (R_t^s(1-\kappa_t) + \bar{R}_{t+1}^k \kappa_t)^{-\mu}] &\left[1 + \frac{\text{Var}^i(R^k)\mu}{2(R_t^s(1-\kappa_t) + \bar{R}_{t+1}^k \kappa_t)} \left(\frac{(1+\mu)\kappa_t^2}{R_t^s(1-\kappa_t) + \bar{R}_{t+1}^k \kappa_t} - \frac{2\kappa_t}{\bar{R}_{t+1}^k} \right) \right] \end{aligned} \quad (\text{C.4})$$

Consider $f(x) = \exp(\log((R_t^s(1-\kappa_t) + x\kappa_t)^{-\mu}))$. Then

$$f'(x) = f(x) \frac{-\mu\kappa_t}{R_t^s(1-\kappa_t) + x\kappa_t}$$

$$f''(x) = f(x) \left(\frac{\mu \kappa_t^2}{(R_t^s(1 - \kappa_t) + x \kappa_t)^2} + \left(\frac{-\mu \kappa_t}{R_t^s(1 - \kappa_t) + x \kappa_t} \right)^2 \right) \quad (\text{C.5})$$

Expanding around the expected return and taking expectations:

$$E^i[(R_t^s(1 - \kappa_t) + R_{t+1}^k \kappa_t)^{-\mu}] \approx (R_t^s(1 - \kappa_t) + \bar{R}_{t+1}^k \kappa_t)^{-\mu} \left[1 + \frac{Var^i(R^k) \mu(1 + \mu) \kappa_t^2}{2(R_t^s(1 - \kappa_t) + \bar{R}_{t+1}^k \kappa_t)^2} \right] \quad (\text{C.6})$$

Retirees bequeath stocks if

$$(\gamma_t a_t)^{-\sigma} = A\beta\{(1 - \gamma_t)a_t\}^{-\mu}(\bar{R}_{t+1}^k)^{1-\mu} \left[1 - \frac{Var^i(R^k) \mu(1 - \mu)}{2(\bar{R}_{t+1}^k)^2} \right] \quad (\text{C.7})$$

$$> A\beta\{(1 - \gamma_t)a_t\}^{-\mu} R_{t+1}^s (\bar{R}_{t+1}^k)^{-\mu} \left[1 + \frac{Var^i(R^k) \mu(1 + \mu)}{2(\bar{R}_{t+1}^k)^2} \right] \quad (\text{C.8})$$

or

$$\bar{R}_{t+1}^k \left[1 - \frac{Var^i(R^k) \mu(1 - \mu)}{2(\bar{R}_{t+1}^k)^2} \right] > R_{t+1}^s \left[1 + \frac{Var^i(R^k) \mu(1 + \mu)}{2(\bar{R}_{t+1}^k)^2} \right] \quad (\text{C.9})$$

$$\bar{R}_{t+1}^k > R_{t+1}^s \left[\frac{(\bar{R}_{t+1}^k)^2 + Var^i(R^k) \mu(1 + \mu)}{(\bar{R}_{t+1}^k)^2 + Var^i(R^k) \mu(1 - \mu)} \right] \quad (\text{C.10})$$

REFERENCES CITED

- Abadie, A., & Kasy, M. (2019). Choosing among regularized estimators in empirical economics: The risk of machine learning. *Review of Economics and Statistics*, 101(5), 743–762.
- Abel, A. B. (2001). Will bequests attenuate the predicted meltdown in stock prices when baby boomers retire? *Review of Economics and Statistics*, 83(4), 589–595.
- Acharya, V. V., & Richardson, M. (2012). Implications of the dodd-frank act. *Annu. Rev. Financ. Econ.*, 4(1), 1–38.
- Adam, K., Marcet, A., & Beutel, J. (2017). Stock price booms and expected capital gains. *American Economic Review*, 107(8), 2352–2408.
- Adämmmer, P. (2019). lpirfs: An r package to estimate impulse response functions by local projections. *The R Journal* (2019), 11(2), 421–438.
- Agarwal, V., Green, T. C., & Ren, H. (2018). Alpha or beta in the eye of the beholder: What drives hedge fund flows? *Journal of Financial Economics*, 127(3), 417–434.
- Aguirregabiria, V., Clark, R., & Wang, H. (2019). *The geographic flow of bank funding and access to credit: Branch networks, local synergies, and competition* (Tech. Rep.). CEPR.
- Airaudò, M., Nisticò, S., & Zanna, L.-f. (2015). Learning, monetary policy, and asset prices. *Journal of Money, Credit and Banking*, 47(7), 1273–1307.
- Akinci, O., & Queralto, A. (2022, April). Credit spreads, financial crises, and macroprudential policy. *American Economic Journal: Macroeconomics*, 14(2), 469–507. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/mac.20180059> doi: 10.1257/mac.20180059
- Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The review of economics and statistics*, 89(4), 701–720.
- Anolli, M., Beccalli, E., & Molyneux, P. (2014). Bank earnings forecasts, risk and the crisis. *Journal of International Financial Markets, Institutions and Money*, 29, 309–335.

- Badertscher, B. A., Burks, J. J., & Easton, P. D. (2018). The market reaction to bank regulatory reports. *Review of Accounting Studies*, 23, 686–731.
- Bai, J., Philippon, T., & Savov, A. (2016). Have financial markets become more informative? *Journal of Financial Economics*, 122(3), 625–654.
- Bajaj, R., Binmore, A., Dasgupta, R., & Vo, Q.-A. (2018). Banks' internal capital markets: how do banks allocate capital internally? *Bank of England Quarterly Bulletin*, Q2.
- Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), 1645–1680.
- Baker, M., & Wurgler, J. (2015, May). Do strict capital requirements raise the cost of capital? bank regulation, capital structure, and the low-risk anomaly. *American Economic Review*, 105(5), 315–20. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/aer.p20151092> doi: 10.1257/aer.p20151092
- Baker, S. R., Bloom, N., & Davis, S. J. (2023). *Equity market volatility tracker: Macroeconomic news and outlook: Business investment and sentiment [emvmacrobus]*. (Retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/EMVMACROBUS>, May 17, 2024.)
- Balasubramanyan, L., Daniel, N. D., Haubrich, J. G., & Naveen, L. (2024). Impact of risk oversight functions on bank risk: Evidence from the dodd-frank act. *Journal of Banking & Finance*, 158, 107049.
- Banks, J., Blundell, R., & Tanner, S. (1998). Is there a retirement-savings puzzle? *American Economic Review*, 769–788.
- Bauer, M. D., Bernanke, B. S., & Milstein, E. (2023). Risk appetite and the risk-taking channel of monetary policy. *Journal of Economic Perspectives*, 37(1), 77–100.
- Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, 22(2), 218–244. Retrieved from <https://www.sciencedirect.com/science/article/pii/S1042957312000344> doi: <https://doi.org/10.1016/j.jfi.2012.07.001>
- Beck, T., Levine, R., & Levkov, A. (2010). Big bad banks? the winners and losers from bank deregulation in the united states. *The Journal of Finance*, 65(5), 1637–1667. Retrieved from <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2010.01589.x> doi: <https://doi.org/10.1111/j.1540-6261.2010.01589.x>

- Begenau, J., Bigio, S., Majerovitz, J., & Vieyra, M. (2020). *A q-theory of banks* (Tech. Rep.). National Bureau of Economic Research.
- Begenau, J., & Landvoigt, T. (2021, 12). Financial Regulation in a Quantitative Model of the Modern Banking System. *The Review of Economic Studies*, 89(4), 1748-1784. Retrieved from <https://doi.org/10.1093/restud/rdab088> doi: 10.1093/restud/rdab088
- Belkhir, M., Naceur, S. B., Chami, R., & Samet, A. (2021). Bank capital and the cost of equity. *Journal of Financial Stability*, 53, 100843.
- Benetton, M. (2021). Leverage regulation and market structure: A structural model of the uk mortgage market. *The Journal of Finance*, 76(6), 2997–3053.
- Benhabib, J., Bisin, A., & Luo, M. (2017). Earnings inequality and other determinants of wealth inequality. *American Economic Review*, 107(5), 593–597.
- Benhabib, J., Bisin, A., & Luo, M. (2019). Wealth distribution and social mobility in the us: A quantitative approach. *American Economic Review*, 109(5), 1623–1647.
- Benhabib, J., Bisin, A., & Zhu, S. (2011). The distribution of wealth and fiscal policy in economies with finitely lived agents. *Econometrica*, 79(1), 123–157.
- Berk, J. B., & Van Binsbergen, J. H. (2016). Assessing asset pricing models using revealed preference. *Journal of Financial Economics*, 119(1), 1–23.
- Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market’s reaction to federal reserve policy? *The Journal of finance*, 60(3), 1221–1257.
- Bernheim, B. D., Shleifer, A., & Summers, L. H. (1985). The strategic bequest motive. *Journal of Political economy*, 93(6), 1045–1076.
- Birn, M., de Bandt, O., Firestone, S., Gutiérrez Girault, M., Hancock, D., Krogh, T., ... others (2020). The costs and benefits of bank capital—a review of the literature. *Journal of Risk and Financial Management*, 13(4), 74.
- Blanchet, T., Saez, E., & Zucman, G. (2022). *Real-time inequality* (Tech. Rep.). National Bureau of Economic Research.
- Bordo, M. D., & Duca, J. V. (2018). *The impact of the dodd-frank act on small business* (Tech. Rep.). National Bureau of Economic Research.
- Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1), 181–213.

- Branch, W. A., & Evans, G. W. (2010). Asset return dynamics and learning. *The review of financial studies*, 23(4), 1651–1680.
- Branch, W. A., & Evans, G. W. (2011). Learning about risk and return: A simple model of bubbles and crashes. *American Economic Journal: Macroeconomics*, 3(3), 159–191.
- Brunnermeier, M., Farhi, E., Koijen, R. S., Krishnamurthy, A., Ludvigson, S. C., Lustig, H., ... Piazzesi, M. (2021). Perspectives on the future of asset pricing. *The review of financial studies*, 34(4), 2126–2160.
- Brunnermeier, M. K., Eisenbach, T. M., & Sannikov, Y. (2012, May). *Macroeconomics with financial frictions: A survey* (Working Paper No. 18102). National Bureau of Economic Research. Retrieved from <http://www.nber.org/papers/w18102> doi: 10.3386/w18102
- Brunnermeier, M. K., & Nagel, S. (2008). Do wealth fluctuations generate time-varying risk aversion? micro-evidence on individuals' asset allocation. *American Economic Review*, 98(3), 713–736.
- Brunnermeier, M. K., & Parker, J. A. (2005). Optimal expectations. *American Economic Review*, 95(4), 1092–1118.
- Burgess, R., & Pande, R. (2005, June). Do rural banks matter? evidence from the indian social banking experiment. *American Economic Review*, 95(3), 780–795. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/0002828054201242> doi: 10.1257/0002828054201242
- Caballero, R. J., & Simsek, A. (2022). Monetary policy with opinionated markets. *American Economic Review*, 112(7), 2353–2392.
- Calluzzo, P., & Dong, G. N. (2015). Has the financial system become safer after the crisis? the changing nature of financial institution risk. *Journal of Banking & Finance*, 53, 233–248.
- Campbell, J. Y. (2006). Household finance. *The journal of finance*, 61(4), 1553–1604.
- Campbell, J. Y., & Shiller, R. J. (2001). *Valuation ratios and the long-run stock market outlook: An update*. National bureau of economic research Cambridge, Mass., USA.
- Carvalho, C., Eusepi, S., Moench, E., & Preston, B. (2023). Anchored inflation expectations. *American Economic Journal: Macroeconomics*, 15(1), 1–47.

- Che, Y.-K., & Sethi, R. (2014). Credit market speculation and the cost of capital. *American Economic Journal: Microeconomics*, 6(4), 1–34.
- Chen, Q., Goldstein, I., & Jiang, W. (2007). Price informativeness and investment sensitivity to stock price. *The Review of Financial Studies*, 20(3), 619–650.
- Choi, J. J., & Robertson, A. Z. (2020). What matters to individual investors? evidence from the horse’s mouth. *The Journal of Finance*, 75(4), 1965–2020.
- Chong, T. T.-L., Lu, L., & Ongena, S. (2013). Does banking competition alleviate or worsen credit constraints faced by small- and medium-sized enterprises? evidence from china. *Journal of Banking & Finance*, 37(9), 3412–3424. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0378426613002240> doi: <https://doi.org/10.1016/j.jbankfin.2013.05.006>
- Clark, R., Houde, J.-F., & Kastl, J. (2021). The industrial organization of financial markets. In *Handbook of industrial organization* (Vol. 5, pp. 427–520). Elsevier.
- Cocco, J. F. (2005). Portfolio choice in the presence of housing. *The Review of Financial Studies*, 18(2), 535–567.
- Cohen, B. H., & Scatigna, M. (2016). Banks and capital requirements: channels of adjustment. *Journal of Banking & Finance*, 69, S56–S69.
- Coimbra, N., & Rey, H. (2024). Financial cycles with heterogeneous intermediaries. *Review of Economic Studies*, 91(2), 817–857.
- Corbae, D., & D’Erasmus, P. (2021). Capital buffers in a quantitative model of banking industry dynamics. *Econometrica*, 89(6), 2975–3023. Retrieved from <https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA16930> doi: <https://doi.org/10.3982/ECTA16930>
- Cornett, M. M., Minnick, K., Schorno, P. J., & Tehranian, H. (2020). An examination of bank behavior around federal reserve stress tests. *Journal of Financial Intermediation*, 41, 100789.
- Coudert, V., & Gex, M. (2013). The interactions between the credit default swap and the bond markets in financial turmoil. *Review of International Economics*, 21(3), 492–505.
- Crawford, G. S., Pavanini, N., & Schivardi, F. (2018, July). Asymmetric information and imperfect competition in lending markets. *American Economic Review*, 108(7), 1659–1701. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/aer.20150487> doi: 10.1257/aer.20150487

- de Clippel, G., & Rozen, K. (2024). Bounded rationality in choice theory: A survey. *Journal of economic literature*, 62(3), 995–1039.
- Degryse, H., Kim, M., & Ongena, S. (2009). *Microeconometrics of banking: methods, applications, and results*. Oxford University Press, USA.
- Delis, M. D., Hasan, I., & Kazakis, P. (2013, 10). Bank Regulations and Income Inequality: Empirical Evidence. *Review of Finance*, 18(5), 1811–1846. Retrieved from <https://doi.org/10.1093/rof/rft039> doi: 10.1093/rof/rft039
- De Nardi, M. (2004). Wealth inequality and intergenerational links. *The Review of Economic Studies*, 71(3), 743–768.
- De Nardi, M., & Fella, G. (2017). Saving and wealth inequality. *Review of Economic Dynamics*, 26, 280–300.
- De Nardi, M., French, E., & Jones, J. B. (2010). Why do the elderly save? the role of medical expenses. *Journal of political economy*, 118(1), 39–75.
- d’Haultfoeuille, X., Gaillac, C., & Maurel, A. (2021). Rationalizing rational expectations: Characterizations and tests. *Quantitative Economics*, 12(3), 817–842.
- Dick-Nielsen, J., Gyntelberg, J., & Thimsen, C. (2022). The cost of capital for banks: Evidence from analyst earnings forecasts. *The Journal of Finance*, 77(5), 2577–2611.
- Dominitz, J., & Manski, C. F. (2011). Measuring and interpreting expectations of equity returns. *Journal of applied econometrics*, 26(3), 352–370.
- Drechsler, I., Savov, A., & Schnabl, P. (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics*, 132(4), 1819–1876.
- Drechsler, I., Savov, A., & Schnabl, P. (2018). A model of monetary policy and risk premia. *The Journal of Finance*, 73(1), 317–373.
- Egan, M., Hortaçsu, A., & Matvos, G. (2017). Deposit competition and financial fragility: Evidence from the us banking sector. *American Economic Review*, 107(1), 169–216.
- Egan, M., Hortaçsu, A., & Matvos, G. (2017, January). Deposit competition and financial fragility: Evidence from the us banking sector. *American Economic Review*, 107(1), 169–216. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/aer.20150342> doi: 10.1257/aer.20150342

- Egan, M., MacKay, A., & Yang, H. (2021). *What drives variation in investor portfolios? evidence from retirement plans* (Tech. Rep. No. w29604).
- Ellison, M., & Pearlman, J. (2011). Saddlepath learning. *Journal of Economic Theory*, 146(4), 1500–1519.
- Evans, D., Evans, G. W., & McGough, B. (2022). The rpes of rbcs and other dsge. *Journal of Economic Dynamics and Control*, 143, 104492.
- Evans, G. W., & Honkapohja, S. (2001). *Learning and expectations in macroeconomics*. Princeton University Press.
- Evans, G. W., & McGough, B. (2020). Adaptive learning in macroeconomics. In *Oxford research encyclopedia of economics and finance*.
- Evans, G. W., & McGough, B. (2021). Agent-level adaptive learning. In *Oxford research encyclopedia of economics and finance*.
- Fafchamps, M., & Schündeln, M. (2013). Local financial development and firm performance: Evidence from morocco. *Journal of Development Economics*, 103, 15-28. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0304387813000138> doi: <https://doi.org/10.1016/j.jdeveco.2013.01.010>
- Falato, A., & Xiao, J. (2023). Expectations and credit slumps. *Available at SSRN 4650869*.
- Farboodi, M., & Veldkamp, L. (2020). Long-run growth of financial data technology. *American Economic Review*, 110(8), 2485–2523.
- Fischer, S., & Merton, R. C. (1984). Macroeconomics and finance: The role of the stock market. In *Carnegie-rochester conference series on public policy* (Vol. 21, pp. 57–108).
- Flannery, M., Hirtle, B., & Kovner, A. (2017). Evaluating the information in the federal reserve stress tests. *Journal of Financial Intermediation*, 29, 1–18.
- Freixas, X., & Rochet, J.-C. (2008a). *Microeconomics of banking*. MIT press.
- Freixas, X., & Rochet, J.-C. (2008b). *Microeconomics of Banking, 2nd Edition* (2nd ed.) (No. 0262062704). The MIT Press.
- French, E., Jones, J. B., & McGee, R. (2023). Why do retired households draw down their wealth so slowly? *Journal of Economic Perspectives*, 37(4), 91–113.

- Galí, J. (2015). *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and Its Applications Second edition* (No. 10495). Princeton University Press.
- Gertler, M., & Karadi, P. (2011). A model of unconventional monetary policy. *Journal of monetary Economics*, 58(1), 17–34.
- Giannone, D., Lenza, M., & Primiceri, G. E. (2021). Economic predictions with big data: The illusion of sparsity. *Econometrica*, 89(5), 2409–2437.
- Giglio, S., Maggiori, M., Stroebe, J., & Utkus, S. (2021). Five facts about beliefs and portfolios. *American Economic Review*, 111(5), 1481–1522.
- Gilchrist, S., & Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American economic review*, 102(4), 1692–1720.
- Giusto, A. (2014). Adaptive learning and distributional dynamics in an incomplete markets model. *Journal of Economic Dynamics and Control*, 40, 317–333.
- Glasserman, P., & Tangirala, G. (2016). Are the federal reserve’s stress test results predictable? *The Journal of Alternative Investments*, 18(4), 82–97.
- Goel, T., Lewrick, U., & Tarashev, N. (2020). Bank capital allocation under multiple constraints. *Journal of Financial Intermediation*, 44, 100844.
- Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8), 2586–2624.
- Gomes, F., Haliassos, M., & Ramadorai, T. (2021). Household finance. *Journal of Economic Literature*, 59(3), 919–1000.
- Gorton, G., & Ordoñez, G. (2020). Fighting crises with secrecy. *American Economic Journal: Macroeconomics*, 12(4), 218–245.
- Goulet Coulombe, P., Leroux, M., Stevanovic, D., & Surprenant, S. (2022). How is machine learning useful for macroeconomic forecasting? *Journal of Applied Econometrics*, 37(5), 920–964.
- Greenstone, M., Mas, A., & Nguyen, H.-L. (2020, February). Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and "normal" economic times. *American Economic Journal: Economic Policy*, 12(1), 200–225. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/pol.20160005> doi: 10.1257/pol.20160005
- Greiner, A., & Semmler, W. (1996). Saddle path stability, fluctuations, and indeterminacy in economic growth. *Studies in Nonlinear Dynamics & Econometrics*, 1(2).

- Harrison, J. M., & Kreps, D. M. (1978). Speculative investor behavior in a stock market with heterogeneous expectations. *The Quarterly Journal of Economics*, 92(2), 323–336.
- Heller, Y., & Winter, E. (2020). Biased-belief equilibrium. *American Economic Journal: Microeconomics*, 12(2), 1–40.
- Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000, March). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American Economic Review*, 90(1), 147–165. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/aer.90.1.147> doi: 10.1257/aer.90.1.147
- Hobijn, B., & Jovanovic, B. (2001). The information-technology revolution and the stock market: Evidence. *American Economic Review*, 91(5), 1203–1220.
- Hoerl, A. (1962). Application of ridge analysis to regression problems. *Chemical Engineering Progress*, 58, 54–59.
- Hoff, K., & Stiglitz, J. E. (2010). Equilibrium fictions: A cognitive approach to societal rigidity. *American Economic Review*, 100(2), 141–146.
- Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *the Quarterly Journal of economics*, 112(3), 663–691.
- Hudomiet, P., Kézdi, G., & Willis, R. J. (2011). Stock market crash and expectations of american households. *Journal of Applied Econometrics*, 26(3), 393–415.
- Hull, J., Predescu, M., & White, A. (2004). The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of banking & finance*, 28(11), 2789–2811.
- Hull, J. C., & White, A. (2000). Valuing credit default swaps ii: Modeling default correlations.
- Irani, R. M., Iyer, R., Meisenzahl, R. R., & Peydro, J.-L. (2021). The rise of shadow banking: Evidence from capital regulation. *The Review of Financial Studies*, 34(5), 2181–2235.
- Jaffee, D. M., & Russell, T. (1976). Imperfect information, uncertainty, and credit rationing. *The Quarterly Journal of Economics*, 90(4), 651–666.
- Jappelli, T., & Padula, M. (2013). Investment in financial literacy and saving decisions. *Journal of Banking & Finance*, 37(8), 2779–2792.

- Jarociński, M., & Karadi, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2), 1–43.
- Jehiel, P. (2018). Investment strategy and selection bias: An equilibrium perspective on overoptimism. *American Economic Review*, 108(6), 1582–1597.
- Ji, Y., Teng, S., & Townsend, R. (2021). *Dynamic bank expansion: Spatial growth, financial access, and inequality* (Working Paper No. 28582). National Bureau of Economic Research.
- Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, 95(1), 161–182.
- Jorgenson, D. W. (2001). Information technology and the us economy. *American Economic Review*, 91(1), 1–32.
- Kacperczyk, M., Nosal, J., & Stevens, L. (2019). Investor sophistication and capital income inequality. *Journal of Monetary Economics*, 107, 18–31.
- Karlan, D., & Morduch, J. (2010). Access to finance. In *Handbook of development economics* (Vol. 5, pp. 4703–4784). Elsevier.
- Kekre, R., & Lenel, M. (2022). Monetary policy, redistribution, and risk premia. *Econometrica*, 90(5), 2249–2282.
- Kézdi, G., & Willis, R. J. (2011). *Household stock market beliefs and learning* (Tech. Rep.). National Bureau of Economic Research.
- Korniotis, G. M., & Kumar, A. (2011). Do older investors make better investment decisions? *The review of economics and statistics*, 93(1), 244–265.
- Kovner, A., & Van Tassel, P. (2022). Evaluating regulatory reform: Banks’ cost of capital and lending. *Journal of Money, Credit and Banking*, 54(5), 1313–1367.
- Kuhn, M., Schularick, M., & Steins, U. I. (2020). Income and wealth inequality in america, 1949–2016. *Journal of Political Economy*, 128(9), 3469–3519.
- Lei, X. (2021). How do stock market experiences shape wealth inequality? *Ratio*, 14, 16.
- Lusardi, A., Michaud, P.-C., & Mitchell, O. S. (2017). Optimal financial knowledge and wealth inequality. *Journal of political Economy*, 125(2), 431–477.
- Maćkowiak, B., Matějka, F., & Wiederholt, M. (2023). Rational inattention: A review. *Journal of Economic Literature*, 61(1), 226–273.

- Malherbe, F. (2020, July). Optimal capital requirements over the business and financial cycles. *American Economic Journal: Macroeconomics*, 12(3), 139-74. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/mac.20160140> doi: 10.1257/mac.20160140
- Malmendier, U., & Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *The quarterly journal of economics*, 126(1), 373–416.
- Manski, C. F. (2004). Measuring expectations. *Econometrica*, 72(5), 1329–1376.
- Manski, C. F. (2018). Survey measurement of probabilistic macroeconomic expectations: progress and promise. *NBER Macroeconomics Annual*, 32(1), 411–471.
- Meeuwis, M., Parker, J. A., Schoar, A., & Simester, D. (2022). Belief disagreement and portfolio choice. *The Journal of Finance*, 77(6), 3191–3247.
- Merton, R. C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *The review of Economics and Statistics*, 247–257.
- Milani, F. (2008). Learning, monetary policy rules, and macroeconomic stability. *Journal of Economic Dynamics and Control*, 32(10), 3148–3165.
- Miles, D., Yang, J., & Marcheggiano, G. (2013). Optimal bank capital. *The Economic Journal*, 123(567), 1–37.
- Morgan, D. P., Peristiani, S., & Savino, V. (2014). The information value of the stress test. *Journal of Money, Credit and Banking*, 46(7), 1479–1500.
- Munnell, A. H., Aubry, J.-P., & Wettstein, G. (2023). Wills, wealth, and race. *Wharton Pension Research Council Working Paper*(2023-16).
- Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: journal of the Econometric Society*, 315–335.
- Nakamura, E., & Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics*, 133(3), 1283–1330.
- Nguyen, H.-L. Q. (2019, January). Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics*, 11(1), 1-32. Retrieved from <https://www.aeaweb.org/articles?id=10.1257/app.20170543> doi: 10.1257/app.20170543

- Poterba, J. M. (2001). Demographic structure and asset returns. *Review of Economics and Statistics*, 83(4), 565–584.
- Rychalovska, Y. (2016). The implications of financial frictions and imperfect knowledge in the estimated dsge model of the us economy. *Journal of Economic Dynamics and Control*, 73, 259–282.
- Simon, H. (1957). *Models of man: Social and rational; mathematical essays on rational human behavior in society setting*. Wiley. Retrieved from https://books.google.com/books?id=_w1gAAAAIAAJ
- Sims, C. A. (2003). Implications of rational inattention. *Journal of monetary Economics*, 50(3), 665–690.
- Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, 71(3), 393–410.
- Suss, J., & Hughes, A. (2023). Bank expectations and prudential outcomes.
- van Wieringen, W. N. (2015). Lecture notes on ridge regression. *arXiv preprint arXiv:1509.09169*.
- Vissing-Jørgensen, A., & Attanasio, O. P. (2003). Stock-market participation, intertemporal substitution, and risk-aversion. *American Economic Review*, 93(2), 383–391.
- Wharton Research Data Services. (2020). *Wharton research data services*. The Wharton School at the University of Pennsylvania.
- Yogo, M. (2016). Portfolio choice in retirement: Health risk and the demand for annuities, housing, and risky assets. *Journal of monetary economics*, 80, 17–34.
- Zhang, B. Y., Zhou, H., & Zhu, H. (2009). Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. *The Review of Financial Studies*, 22(12), 5099–5131.