State-Dependent Pass-Through from Monetary Policy to Lending Rates

*

Federico Puglisi †

This version: November 26, 2022

[Please click here for the latest version]

Abstract

The efficacy of monetary policy depends crucially on the extent to which bank lending rates respond to changes in policy rates. This paper documents that this response is state-dependent. I show empirically that the key state variable is the skewness of the cross-sectional distribution of lending rates across banks prior to the change in the policy rate. High initial skewness leads to a stronger response of (i) bank lending rates and (ii) economic activity to monetary policy. I develop a model of imperfect competition among banks that accounts for this empirical finding. A key feature of the model is that borrowers face search and switching frictions. A higher degree of dispersion among lending rates increases borrowers' expected returns to search. In these circumstances, strategic behaviour by banks leads to higher responsiveness of lending rates to policy rate changes. Through this channel, the model can also reconcile my finding that conventional monetary policy has stronger effects on economic activity the more skewness there is in bank lending rates.

JEL classification: E43, E44, E52, G21, l16.

Keywords: Monetary Policy, State-Dependent efficacy, Lending Rates responsiveness, Skewness-based State Dependence, Bank Imperfect Competition, Borrowers' Search and Switching Frictions, Strategic Price Complementarities.

*I especially thank my advisor Martin Eichenbaum for his continuous guidance and help with this research project. I am grateful to Lawrence Christiano, Giorgio Primiceri, and Guido Lorenzoni for their comments and fundamental support as part of my dissertation committee. I also thank Mattew Rognlie, Matthias Doepke, Jane Olmstead-Rumsey, Kristina Manysheva, and all the seminar participants at Northwestern University for their useful comments and discussions. All errors are my own.

†Northwestern University, Department of Economics. Email: federicopuglisi@u.northwestern.edu)

1 Introduction

The efficacy of monetary policy crucially hinges on the way the financial system reacts to its interventions. In this paper, I focus on the extent to which bank lending rates respond to changes in monetary policy rates.[1]

In the first part of the paper, I establish two key empirical results. First, I document the state-dependence of the response of lending rates to monetary policy based on the skewness of the initial distribution of lending rates. Second, the effects of monetary policy on output are also larger the higher is the initial skewness.

In the second part of the paper, I develop a model of imperfect competition among banks that accounts for these empirical findings. In this model, borrowers face search and switching frictions. In addition, banks are strategic and compete over prices (i.e., Bertrand competitors). Other things equal, borrowers prefer to stick to their current lender. However, if they observe that their lender offered particularly unfavorable rates in the recent past, they expect large gains from searching for a new lender. The more skewed is the distribution of lending rates the larger is the mass of borrowers searching. Banks respond to this larger pool of potential customers by competing more intensely on prices. As a result, a higher cross-sectional skewness in initial lending rates leads to a larger response of lending rates to policy rate changes. The stronger response in lending rates, in turn, leads to a stronger response of economic activity to monetary policy.

The recent literature on monetary policy state-dependence has focused on the role of refinancing costs on house mortgagees' refinancing decisions (Berger et al. (2021), Eichenbaum et al. (2022)). My paper focuses on the supply side of bank loan markets. The state variable that I emphasize affects commercial and consumer durables in addition to housing loan markets. My theoretical model builds on the literature studying bank competition and cost pass-through. Existing models of state-dependent price stickiness feature adjustment costs on the side of price-setting banks. In contrast to the existing literature, I emphasize the importance of customer search and switching frictions on banks' pricing strategies.[2]

My analysis proceeds in two steps. In the empirical portion of the paper, I construct a comprehensive Macro-Banking dataset featuring different levels of dis-aggregation and granularity. The dataset contains (i) quarterly bank-level data on assets, liabilities, income, and expenses, (ii) monthly branch-level data on advertised lending rates for several loan products (new auto loans 50K, motor-home loans 150K etc.), and (iii) quarterly loan-level data on house mortgage loans (loan and borrower characteristics). I complement this data with information on output, unemployment, personal income, consumer and home price indexes, and wage indexes at the national, state, county, and MSA levels. Using this dataset, I investigate how the response of bank lending rates to changes in monetary policy depends

[1] Policy rates are here to be intended as the set of rates that central banks can either set (e.g. Interest Rate on Excess Reserves) or influence directly through open market operations (e.g. Federal Funds Rare)

[2] Driscoll and Judson (2013) show evidence that menu-cost frictions do not fit lending rate data well.

on the level of the initial cross-sectional skewness of lending rates. I do so using a local projection framework allowing for state-dependent responses (Tenreyro and Thwaites (2016); Ramey and Zubairy (2018)). Following the recent literature on the estimation of monetary policy effects, I address endogeneity issues by focusing on the response to monetary policy rate shock. I identify these shocks using high-frequency changes in money market interest rates in a narrow window around monetary policy announcements (see e.g. Bauer and Swanson (2022), more discussed in Section V). My results provide strong evidence that the response of lending rates and output to monetary policy shocks is increasing in the initial level of the cross-sectional skewness of lending rates. In particular, a 1-standard deviation higher initial cross-sectional skewness of lending rates is associated with a roughly 70% stronger response of lending rates and output to monetary policy over the first 10 months.

In the theoretical portion of the paper, I develop a model that can account for this empirical finding. The model analyses the behavior of imperfectly competitive banks when there is customer segmentation due to (i) loan product differentiation, (ii) search, and (iii) switching frictions. The latter features temper the degree of strategic price complementarity among banks. In what follows, I provide a sketch of the key features and implications of the model. Consider an environment in which there are two banks. For simplicity, I assume the loan duration is one period and borrowers are not risky. In reality, banks tend to cater to either a niche or a more general pool of clients. To capture this fact, I suppose that one bank has a bigger pool of customers than the other. The two banks have an advantage within their respective pool of clients: each period, customers know their bank's new rate for free. However, customers need to pay a search cost to know the rate offered by the other bank. All customers, know the rates charged by all banks in the previous period.[3]. Customers use previous interest rates to estimate the returns from search and switching to a competitor bank.[4] I denote by "high-rate" and "low-rate" bank, the bank that has the higher and lower rate, respectively, at the beginning of the period.

The model timing is as follows. First, borrowers decide whether to stay with their initial bank or pay the search cost and know the rate offered by the other bank. Second, monetary policymakers set the policy rate. Third, Banks set their lending rates. Third, banks decide their lending rates. Finally, borrowers make their loan decisions. The customers of the low-rate bank never have an incentive to search. However, expected returns to search of high-rate banks' customers are increasing in the gap between the initial rates of the two banks. The higher is that gap, the stronger is the incentive of the low-rate bank to poach customers from the high-rate bank. As a consequence, the high-rate bank has more of an incentive to prevent its competitor from poaching its customers.

The incentives of the low-rate bank to poach customers are also increasing in the mass of the high-rate bank customers that are searching. The rationale is that the low-rate bank trades off the loss (gain) in profits on its current customers (intensive margin) with the profit gain (loss) from poaching

[3]Stylized way to represent inattentive clients getting information from friends, media, etc with a time lag.

[4]Borrowers are assumed to have a simple random walk model in mind where lending rates evolve as a linear function of banks' cost of funds which are themselves evolving as random walks.

customers from the competition (extensive margin). Define price complementarity as the responsiveness of the interest rate offered but its competitors. In my model price complementarity is increasing in the initial lending rates gap and in the initial mass of the high-rate bank clients. Monetary policy shifts the marginal cost to a bank of producing a loan. When the central bank decreases the policy rate, both banks decide how much to change their lending rates. I show that banks change their lending rates more the higher is the beginning-of-period gap in lending rates and the mass of initial consumers of the high-rate bank. The larger is the change in lending rates, the stronger is the effect of monetary policy on output in any general equilibrium model will be. This feature of the model is consistent with my empirical results.

According to my model, there is an asymmetry in the way the interest rate gap between the high and low-rate banks responds to increases and decreases in the policy rate. When the central bank decreases the policy rate, the high-rate bank responds by more than the low-rate bank. The reason is that the marginal costs of losing a customer for the high-rate bank are larger than the marginal benefit of gaining one for the low-rate bank. As a result, the gap in the end-of-period rates becomes smaller than the beginning-of-period one. Because the gap is smaller the mass of borrowers searching in the next period is smaller. So a new decrease in the policy rate generates a weaker response of lending rates than the previous decrease. Now suppose that the central bank increases the policy rates. The low-rate bank has to increase its rate to maintain profitability, thus attenuating the competitive pressure on the high-rate bank. So the high-rate bank will increase its lending rate by more because fewer customers on search can now be poached.

I finally test empirically my model's implication of the high-rate bank responding more than the low-rate bank to a monetary policy shock. My results show that when skewness is 1 standard deviation higher, the high-rate bank responds on average by roughly 50 % more than the low-rate bank to a 1% exogenous change in the monetary policy rate. This result quantifies the qualitative prediction of the model and further strengthens the evidence that the cross-sectional skewness of lending rates plays a crucial role in the way banks react to monetary policy rate changes.

The paper is organized as follows. Section II discusses the related literature and contribution. Section III describes the dataset constructed for the empirical analysis. Section IV presents motivating evidence on the properties of the lending rate cross-sectional distributions using two specific types of loans as examples. Section V sets out the econometric model and the identification strategy used in the empirical analysis. Section VI presents the empirical results. Section VII builds the theoretical framework proposed to rationalize the empirical findings. Section VIII collects conclusions and future directions of work.

2 Related Literature

This paper lies at the intersection of three broad strands of literature: the Banking literature on (i) the responsiveness of bank rates to monetary policy and (ii) household refinancing decisions, the Macro-finance literature on the role of pricing frictions and heterogeneity in the financial sector in the amplification of macroeconomic shocks and finally on the Industrial Organization literature studying (i) price competition in presence of customer inertia due to search and switching frictions and (ii) cost pass-through. I bring together insights of these strands to explore a novel form of state-dependence in the strategic pricing behavior of banks with implications for the effectiveness of monetary policy.

Banking Literature on Lending Rates Pass-Through. The study of lending rates pass-through has long traditions in the banking literature together with its counterpart, the deposit rates pass-through. The standard approach (Monti-Klein Model, (Monti (1972); Klein (1971)) assumes banks follow a marginal cost pricing model where monetary policy plays a role by shifting banks funding costs. Starting with the empirical contributions of Hannan and Berger (1991); Neumark and Sharpe (1992); Sharpe (1997); De Bondt (2005) evidence has been shown of a limited and heterogeneous pass-through in bank retail rates (both deposit and lending rates)[5] Bank interest rates are characterized by a lower time variation than money market rates and their behavior shows various degrees of asymmetry and non-linearity (Borio and Fritz (1995); Mojon (2000); Sander and Kleimeier (2000); Hofmann and Mizen (2004); Gambacorta and Iannotti (2007); Driscoll and Judson (2013)).[6]. One sub-strand of literature has documented the evolution of the pass-through and its causes (Hristov et al. (2014); Illes et al. (2015); von Borstel et al. (2016); Holton and Rodriguez d'Acri (2018); Zentefis (2020); Altavilla et al. (2020)), another has focused more on the sources of the heterogeneity in pass-through due to (i) balance sheet constraints (Bernanke and Blinder (1988); Kashyap and Stein (1995); Van den Heuvel (2002); Brunnermeier and Sannikov (2016)), (ii) deposit market power (Drechsler et al. (2017)) and finally (iii) loan market power (Scharfstein and Sunderam (2016)) all three recently considered jointly in Wang et al. (2022), and further adjustment costs (Hannan and Berger (1991); Elyasiani et al. (1995); Hofmann and Mizen (2004); Kopecky and Van Hoose (2012)) and asymmetric information (Berger and Udell (1995); Degryse and Van Cayseele (2000); Allen and Gale (2001); Gambacorta and Mistrulli (2014)). This paper contributes to this literature along three dimensions. First, by extending the focus to an ample variety of consumer durable loans in addition to house mortgage loans, and by considering advertised lending rates in addition to realized actual loan rates.[7] Advertised loan rates allow to abstract from borrower-specific characteristics and focus on the competitive, as it turns out also state-dependent, forces driving bank rates responses to monetary policy. Second, most of the

[5]See also Cottarelli and Kourelis (1994); Angeloni and Ehrmann (2003); Mojon (2000) for similar evidence in the Euro-Area. See De Bondt (2005); Gambacorta and Mizen (2019) for systematic surveys of empirical works on bank rates pass-through.

[6]see Fuertes and Heffernan (2009) for a pre-GFC survey of the early works on the topic

[7]The results are then compared to more standard data sources present in my dataset such as Bank Call Reports and House Mortgage level data.

papers in the literature focus on either bank-specific or demand-specific heterogeneity in lending rates pass-through, this paper contributes to the debate by offering a source of variation at the intersection of the two. Intuitively, a bank with branches in two different counties with the same demand schedule will differentiate its response in lending rates across the two branches depending on its potential to poach customers from other banks in each of the two counties.

Macro-Finance Literature. This paper mostly relates to three strands of this vast literature.

Heterogeneity in Financial Intermediaries. This recent strand of literature studying the role played by *ex-ante* or *ex-post* heterogeneity in financial intermediaries as in (see e.g. Coimbra and Rey (2021); JRios Rull et al. (2020); Jamilov and Monacelli (2021); Rojas (2020); Begenau and Landvoigt (2021); Bianchi and Bigio (2022); Bellifemine et al. (2022) on the amplification of macroeconomic shocks is part of the broader literature on heterogeneous agents (see e.g. Buera and Moll (2015); Kaplan et al. (2018); Auclert (2019); Ottonello and Winberry (2020); Auclert et al. (2020a;b); Kekre and Lenel (2020); Kaplan et al. (2020); Ravn and Sterk (2021); Baqaee et al. (2021); Bigio and Sannikov (2021); Bilbiie (2021). This paper shares the view that different types of heterogeneity produce different, yet quantitatively important aggregate amplification effects of macroeconomic shocks. It contributes by documenting a new channel of state-dependence in the reaction of lending rates to monetary policy shocks based on the heterogeneity banks face in terms of own- and cross-price demand elasticity.

Modelling Banking Competition. While most of the literature on the topic has been focusing on monopolistically Competitive environments á la Dixit-Stiglitz (see e.g. Gerali et al. (2010)) and its generalizations, this paper mostly relates to the handful of studies introducing competitive environments where banks are non-atomistic and strategic (see e.g. Corbae et al. (2013); Aliaga-Díaz and Olivero (2010); Cuciniello and Signoretti (2015); Corbae and D'Erasmo (2021); Villa (2022)). When the competitive market structure is characterized by a finite number of large entities, these entities internalize their effect on aggregate demand and competitors' pricing rules. This, in turn, produces significant additional variation in mark-ups and amplification in lending rates responses to macro-shocks. This paper revives and shares the emphasis on the importance of focusing on imperfect competition and strategic price complementarities and contributes along two dimensions. It is the first paper to study an environment featuring state-dependent and heterogeneous local demand elasticities in a Bertrand competition game between two banks. Also, it stresses the important conditioning effect of monetary policy on bank strategic interactions (easing shocks increase the room to decrease rates and compete and vice versa).

Customer Capital and Deep Habits Tangentially, this paper also reinforces the aggregate effects of *customer capital*. Gourio and Rudanko (2014) first make this point for non-financial firms by showing its important effects on the level and volatility of their investments, profits, value, sales, and markups, most importantly on the timing of their responses to shocks. The present study also relates to the models featuring "Deep Habits" Ravn et al. (2006); Gilchrist et al. (2017) in borrowers Vives (2001); Aliaga-Díaz and Olivero (2010) and depositors demand functions Kravik and Mimir (2019);

Polo (2021). These latter studies stress the importance of deep habits' static and dynamic effects on banks' interest rate-setting decisions. This paper complements this view by showing that such effects might give rise to state-dependent responses. It also adds to the literature by showing how search frictions are a complementary yet different source of demand stickiness with respect to switching costs, normally considered to be the main source of deep habits.[8]

Price Stickiness. Time-dependent or state-dependent stickiness in firms pricing decisions is at the root of monetary policy non-neutrality (Taylor (1980), Calvo (1983), Rotemberg and Saloner (1987), Reis (2006), Golosov and Lucas Jr (2007), Nakamura and Steinsson (2010), Midrigan (2011), Alvarez and Lippi (2014)).[9]. In both types, every period only a subset of firms change their prices following a macroeconomic shock due to exogenous or endogenous price-adjustment frictions. In recent works, pricing frictions are further combined with information frictions (on the firms' side, (see e.g. Alvarez et al. (2011; 2017a)) or with strategically engaged firms (see e.g. Mongey (2021)). The theoretical framework proposed in this paper similarly features a state-dependent form of price stickiness. Yet, while those works normally retrieve the sources of state-dependence on the *price-setters* side, here they arise from search and switching frictions on the *price-taker* (borrowers) side. In the model developed in this paper, price stickiness emerges as price-setters (banks) anticipate the effects of such frictions in terms of borrower inertia and compete more or less intensely depending on the mass of consumers searching for lenders. Last, this paper shares the view of Alvarez et al. (2016) that higher-order moments of the cross-sectional distribution of prices carry important information for predicting the strength of an economy's response to nominal shocks. In particular, Alvarez et al. (2016) prove that the ratio of the kurtosis of the size distribution of *current* price changes and their frequency is a sufficient statistic for the output response to a monetary shock. Differently, this paper provides empirical evidence that the skewness of the *past* distribution of interest rates acts as a relevant state-variable for the lending rate pass-through of monetary policy shocks.

Industrial Organization Literature: Customer Inertia, Competition, and Cost Pass-Through.

Competition with Customer Inertia. The theoretical framework proposed in this paper builds on the IO literature on Cournot/Bertrand/Stackelberg Competition in presence *customer inertia* arising from *switching costs* (pioneered by Klemperer (1987), Beggs and Klemperer (1992) or Nilssen (1992) and more recently extended to account for network externalities (Irina and Christian (2011), Weiergraeber (2022)), firm heterogeneity (Biglaiser et al. (2013; 2016)), interaction with market structure (see e.g. Fabra and García (2015) for High vs Low Concentration Markets and Lam (2015) for the case of two-sided markets) or product innovation (Salies (2012)).[10]) and search costs (first considered as separate form switching costs in Moshkin and Shachar (2000); Waterson (2003). Wilson (2012)

[8] Notice search frictions are different from frictions arising from processing the information as in the "rational inattention" Sims (2003); Moscarini (2004); Sims (2006); Moscarini (2004); Woodford (2009); Matějka and McKay (2015)

[9] As shown by Auclert et al. (2022) or Alvarez et al. (2017b) the two models exhibit similar patterns to macroeconomic shock as long as the shock is small

[10] Klemperer (1995) and Farrell and Klemperer (2007) provide extensive surveys on the effects of switching costs in various theoretical and empirical settings.

is the first to model them jointly in order to distinguish their respective effects on consumer behavior, competition, and welfare). This literature stresses how search and switching costs fundamentally create a dichotomy between existing locked-in and new customers. Thanks to switching costs firms can extract *rents* from their locked-in consumers. As the present value of acquiring a new *locked-in customer* is high, firms will compete strongly on new consumers entering the market. This dichotomy explains the empirical observation of teasing prices for new customer acquisition followed by increasing prices once those customers are locked-in. This paper contributes by adding a *signaling channel* into the consumer problem. If the previous period distribution of interest rates is considerably skewed a greater proportion of consumers will *have a signal* that it is profitable to search and switch to a new lender. These consumers will be considered as potential new customers by competitor suppliers and in equilibrium, all banks will compete more to poach them. This channel combined with Search and Switching costs delivers a novel form of state-dependence in customer inertia which, in turn, determines a form of state-dependence in cost-pass-through of banks. In addition, the model also illustrates that if firms face pools of customers that are different in size and price elasticity, then equilibria featuring both cross-sectional asymmetric prices and cost-pass-through may arise.[11]

Cost Pass-Through. Finally, this paper also broadly relates to the strand of literature studying specifically the pass-through of shocks to firms' marginal costs to prices. Building on the foundational framework of Shubik and Levitan (1980) recent empirical works have shown how a higher degree of product differentiation may lead to lower cost pass-through (see e.g. Kim and Cotterill (2008); Loy and Weiss (2019); Pless and van Benthem (2019); Bittmann et al. (2020)).[12]. This paper marginally contributes to the literature by showing evidence of skewness-based state-dependence of the cost pass-through in the banking sector, a feature that was still unexplored both theoretically and empirically.[13]

Other Literature. The empirical estimation builds on the literature on the identification (Kuttner (2001a); Gürkaynak et al. (2005); Swanson (2021)) and estimation (Christiano et al. (1999); Jorda (2005); Gertler and Karadi (2015); Ramey (2016); Nakamura and Steinsson (2018); Miranda-Agrippino and Ricco (2021); Jarociński and Karadi (2020); Plagborg-Møller and Wolf (2021)) of Monetary Policy shocks. A more detailed discussion is left to Section IV.

[11] On the empirical side, search and switching costs have been receiving a lot of attention in recent years (see e.g. Dube et al. (2006); Gamble et al. (2009); Cabral (2016); González and Miles-Touya (2018); Illanes (2017); Luco (2019); Buso and Hey (2021); Anell et al. (2021); Heiss et al. (2021) and more specifically for the financial industry, see e.g. Yankov (2018); Li and Netessine (2020); Wang and Yang (2020)). First, in both physical and online markets search and switching costs are highly predictive of brand loyalty or consumer inaction. Second, when considered jointly, search costs have a more prominent role than switching costs in consumer decisions. Lowering search rather than switching costs delivers the highest proportion of customers switching to the best alternative in a given market. See the appendix for more details.

[12] See Arkolakis and Morlacco (2017) for a theoretical note on variable demand elasticities, cost pass-through and markups.

[13] Examples of the cost pass-through empirical literature focusing on the effects of search and switching costs in the banking sector (see e.g. Sharpe (1990); Ausubel (1991); Degryse and Van Cayseele (2000); Brown and Hoffmann (2016); Brunetti et al. (2020); Allen and Li (2020)) will be discussed in the next sections and in the appendix.

3 Data

The empirical analysis of this paper is carried out at three different levels of dis-aggregation: State-Bank level, County-Branch level, and MSA-Loan level. The exposition proceeds in three steps. First, it introduces the various types of data by category: Macroeconomic or Banking data. Second, it describes how the three datasets are compiled. Third, it explores some of the main properties of the main variables of interest in the analysis. This third step will be carried out using the County-Branch level dataset, as this is the dataset used to expose the flagship results of the empirical portion of the paper.

3.1 Macroeconomic Data

. The macroeconomic data is here introduced according to its level of dis-aggregation. Four levels of dis-aggregation are considered: national, state, county, and MSA levels.

3.1.1 National-Level

At the National level, I collect information on (i) economic activity, namely Real GDP, Industrial Production, and Unemployment, (ii) prices, namely GDP Deflator, Consumer Price Index (CPI), Commodity Price Index, House Price Index, and (iii) financial variables, namely S&P 500, Excess Bond Premium (Gilchrist and Zakrajšek (2012)), Treasury Rates at 1,2, 10 years maturity and the Federal Funds Rate. All data is publicly available from FRED. These variables are conventionally employed in the Monetary literature for the empirical identification of exogenous monetary policy rate changes at the aggregate level (see e.g. Christiano et al. (1999); Gertler and Karadi (2015); Ramey (2016); Caldara and Herbst (2019); Swanson (2021)).

3.1.2 State-Level

I collect information on Personal Income and GDP at a quarterly frequency from the Bureau of Economic Analysis (BEA)[14]. Real Personal income is obtained by deflating Nominal Personal Income through the aggregate US CPI. I obtain state-level indexes of CPI inflation from Hazell et al. (2020). In their paper, the authors reconstruct state-level price indices at a monthly frequency based on the price micro-data the BLS collects to construct the US aggregate CPI. The sample period is from 1978 to 2018. I complement this data with information on GDP by industry as a measure of the industry mix by state. Finally, I collect state-level house price and rent indexes quarterly from FRED.

[14]GDP is only available from 2005. In absence of GDP, Personal Income is used as a proxy for economic activity.

3.1.3 County-Level and MSA-Level

At the county and MSA level, I collect data from the Bureau of Labour Statistics (BLS) on employment, labor force, and unemployment rates from Local Area Unemployment Statistics (LAU), together with wage data from Current Employment Statistics (CES), and the Quarterly Census of Employment and Wages (QCEW). I further collect house price data publicly available from Zillow (Link)[15]

3.2 Banking Data

Banking data is also introduced ordered by increasing levels of dis-aggregation. Data is available at three levels of dis-aggregation: bank-, branch- and loan-level. Throughout the paper, the terms bank, depository, and financial institution will be used interchangeably to refer to all entities issuing loans in the US (servicing institutions or brokers are hence excluded from this definition).

3.2.1 Bank-Level Data

I collect bank-level information on Balance Sheet and Income Statement quantities from the Call Reports filed by financial institutions quarterly. This data is publicly available and retrieved from Wharton Data Service.[16] I further collect information on Bank Holding Companies from Federal Financial Institutions Examination Council (FFIEC). Finally, I collect information on the number of branches and total deposit volume by depository institution at the county level from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposit Statistics (SOD). This data is used to compute a proxy of market concentration by county. In both the Call Reports and SOD datasets, each institution is assigned with either an RSSDID and/or an FDIC certificate (CERT) number, which are, respectively, the unique identifiers of the Federal Reserve Census of financial institutions or of the FDIC census of financial institutions. The SOD data also have a specific unique identification number for each branch (UNINBR).

3.2.2 Branch-Level Data

The core of the empirical analysis crucially relies on this data. I collect branch-level information for over 7500 financial institutions (including banks, credit unions, savings and loan associations, and others) in the U.S. The data is obtained from the private vendor S&P 500 Global Market Insights. The data provider surveys more than 96000 branches at a monthly frequency and gathers information on a variety of deposit and loan products such as CDs, checking accounts, saving accounts, money markets, or loans for new and used auto purchases, personal loans, HELOCs, and mortgages. For each category of loan or deposit, the dataset contains several characteristics like term length, dollar tier,

[15] As argued in Chodorow-Reich et al. (2021) Zillow's house price data represents a good substitute for other confidential or private sources of housing data at dis-aggregated geographical levels in the US.

[16] This data is pre-processed following Drechsler et al. (2017).

and, importantly, the offered interest rate at the survey date. For each branch, information on their holding financial institution (connected with either the RSSDID or the CERT number), location, and level of autonomy are also available (i.e. whether they have the right to set their own interest rates offered to the public). For each branch, the FDIC UNINUMBR is also included in the data.

3.2.3 Loan-Level Data

We finally use the public dataset available under the House Mortgage Disclosure Act from Freddie Mac's Single-Family Loan-Level Dataset. The collection contains loan-level origination and monthly loan performance data on all fully amortizing fixed-rate Single-Family mortgages that Freddie Mac acquired from private lenders with origination dates from 1999. Loans are 15-, 20-, 30-, and 40-year fixed-rate mortgages with either verified or waived documentation (i.e. "full documentation"),[17] "Relief refinance" mortgages, and "Home Possible" Mortgages originated on or after March 1, 2015. The loan origination information in the dataset includes data about (i) borrowers' observables such as FICO score, Debt-to-Income ratio or the number of borrowers, (ii) loan characteristics such as maturity, age, Loan-to-value ratio, prepayment penalties, purpose (new loan, cash-out and no-cash-out refinancing), location of issuance and of the property insuring the loan, among others; (iii) type of originator of the loan. The loan performance information in the dataset includes the monthly loan balance, delinquency status, actual Loss data components of Net Sale Proceeds, Expenses (such as Legal Costs or Maintenance and Preservation Costs), MI Recoveries, Non-MI Recoveries, Zero Balance Removal UPB, and certain information up to and including termination event.[18].[19]

3.3 Matching Macroeconomic and Banking Data

The empirical analysis uses three newly constructed datasets from the items described above. The first dataset is at the state-bank level and quarterly frequency. The second dataset is at the branch-county level and monthly frequency, and the third dataset is at the Loan-MSA level at a quarterly frequency.

3.3.1 State/Bank Level dataset

This dataset is compiled by matching State-Level Macro data with Bank level data from the Call Reports. National-level macro data will be matched using simply the time index. For each bank, several variables of interest are created building on information from the Call Reports. First and most importantly, I create average realized interest rates on various loan categories by taking the ratio of Interest Income on the specific loan category and the corresponding total balance-sheet volume (e.g.

[17]Generally, Freddie Mac requires that Sellers of mortgage loans document or verify loan application information about the Borrower's income, assets, and employment.

[18]Possible termination events are: Prepaid or Matured (Voluntary Payoff), Third Party Sale, Short Sale or Charge Off, Repurchase prior to Property Disposition, REO Disposition, Note Sale, Reperforming Loan Sale

[19]Appendix A contains a more detailed description of all data items and sources.

the average realized interest on Commercial and Industrial Loans, C& I Loans, is computed as the ratio of Interest Income from C& I Loans and Total Volume of C&I Loans). This is an imperfect measure of interest rates, although widely used in the literature in the absence of more precise sources of information. Second, I create measures of bank financing costs by taking the ratio of total interest expense and the total volume of interest-carrying liabilities (e.g. demand deposits, time deposits, or debt securities). Third, I compute the ratio of total loan loss provisions over total loans as a proxy variable for banks' expectations of future losses and defaults on the loan portfolio. Finally, I compute measures of profitability such as the return on assets, return on loans or return on equity according to their standard definition. The match with State Level macro-variables is performed using the information contained in the FDIC summary of deposit data. Bank Call Reports and Summary of deposits are merged based on the RSSDID and/or CERT identifier. Each bank is assigned to the states in the U.S. in which it has at least one branch. For each state and quarter, the first four moments of the cross-sectional distribution of lending rates of the same loan category are hence computed using the total branch deposit volume as weights. For instance, the mean of the cross-sectional distribution of C&I lending rates in state s is computed as the average lending rate weighted by the total bank deposit volume in state s divided by the total volume of deposits across all branches in the state.

3.3.2 Branch/County-level dataset

This dataset is compiled by first matching county-level macro data with state and national level data using the QCEW County-MSA-CSA Crosswalk file from the BLS.[20] Using the information on branches location, the branch-level data is hence matched with the county/state/national macro data. Using the information on the Financial Institutions holding each branch, the branch-level data is hence matched with Call Reports data. For each loan category contained in the branch-level data, the first four moments of the cross-sectional distribution of lending rates are computed at the county, state, and national levels. These moments are computed either using equal weights $\frac{1}{N}$ or weighted by deposit volume. Recall that in the branch-level data, only a subset of branches has the right to set interest rates, the other branches either follow the near rate-setting branch of the same bank or the rate-setting directives centrally planned by the bank headquarters. Using an equally weighting scheme hence amounts to weighting each rate-setting branch by the number of branches that follow its set rates over the total amount of branches. For instance, for county c and month t, the variance of the cross-sectional distribution of offered lending rates for the new auto loans category is computed as the average squared deviations from the county mean of the lending rate observations in county c and month t with either weights $\frac{1}{N}$ or weighted by the share of average branch deposit volumes over total deposit volume in the county. The state and national versions of the first four moments of the

[20]The procedure is slightly more involved as in the history some counties have been merged, or changed name, a preliminary step to the merging based on the cross-walk file is hence the reconstruction of the history of counties mergers and changes of the denomination.

cross-sectional distribution are computed following the same approach. [21] This dataset will be hence available in two forms. In the first form, the minimal observation unit is the county/level. All variables available at higher levels of disaggregation will be hence averaged to obtain a unique observation for the county. In its second form, the minimal unit of information will be the branch level. In this case, for each branch and month, all the branch-level variables will be kept at the branch level. Branches belonging to the same institution will share the same institution-level information. Branches of the same county and state will share the same observation of, respectively, county.

3.3.3 MSA/Loan-level dataset

Similarly to the County-Level macro data, MSA Macro data are matched with county and state-level macro data using the QCEW County-MSA-CSA Crosswalk file from the BLS. Loan level data is aggregated at the quarterly level.[22]. State/County/MSA data is also aggregated at the quarterly level. National data is matched to the dataset by time index. Loan-level data is matched with MSA/County/State macro data using the information on the location of the issuance available for each loan in the dataset. Loan-level data is also matched with bank-level information from the Call Reports information using RSSDID and/or CERT and/or the name of the private lender issuing the loan when available. These are realized lending rates, and as such, the interest rates include the bank's consideration of borrowers and loan type characteristics. Following Hurst et al. (2016), I parse out the effects of the latter two factors using a time-varying regression model including most of the borrowers and loan observable characteristics obtained in the dataset. As it will become clear in the following sections, the focus of the paper is on competition over interest rates among banks. Intuitively, absent any borrower or loan type heterogeneity, the lending rates offered by different banks should be all the same when there is high competition and should be increasingly differing as competition decreases. The focus of the paper is precisely on the forces that drive interest rates other than borrower and loan type characteristics. For this reason, the lending rates in this dataset are residualized, and the primary lending rates utilized in the empirical analysis come from the Branch-Level Data described in the previous subsection. The Branch Level Rates are indeed advertised rates, in other words, they are the rates that a specific branch provides as base quotes before sitting at the bargaining table with a specific borrower. As for the branch-level data, using the residualized lending rates, the first four moments of the MSA cross-sectional distribution of mortgage rates are created. In this case, again, two weighting schemes are used, either assigning an equal weight of $\frac{1}{N}$ or weighting by the ratio of loan

[21] As argued in Drechsler et al. (2017), banks may have a high deposit market share in one county but not equally high loan market share in the same county, a more precise weighting scheme would ideally use the loan volumes by branch for the specific category of loans, unfortunately however this information is not available at the branch level. Loan level data at the annual frequency would be available from the House Mortgage Disclosure Act data, but this would be only on house mortgage loans and not on consumer durable loans

[22] Although the data would be available at the monthly level in its row form, quarterly aggregation is a common choice in the papers carrying empirical analysis on the Freddie Mac data such as Eichenbaum et al. (2022) or Scharfstein and Sunderam (2016) and is here kept for comparability reasons

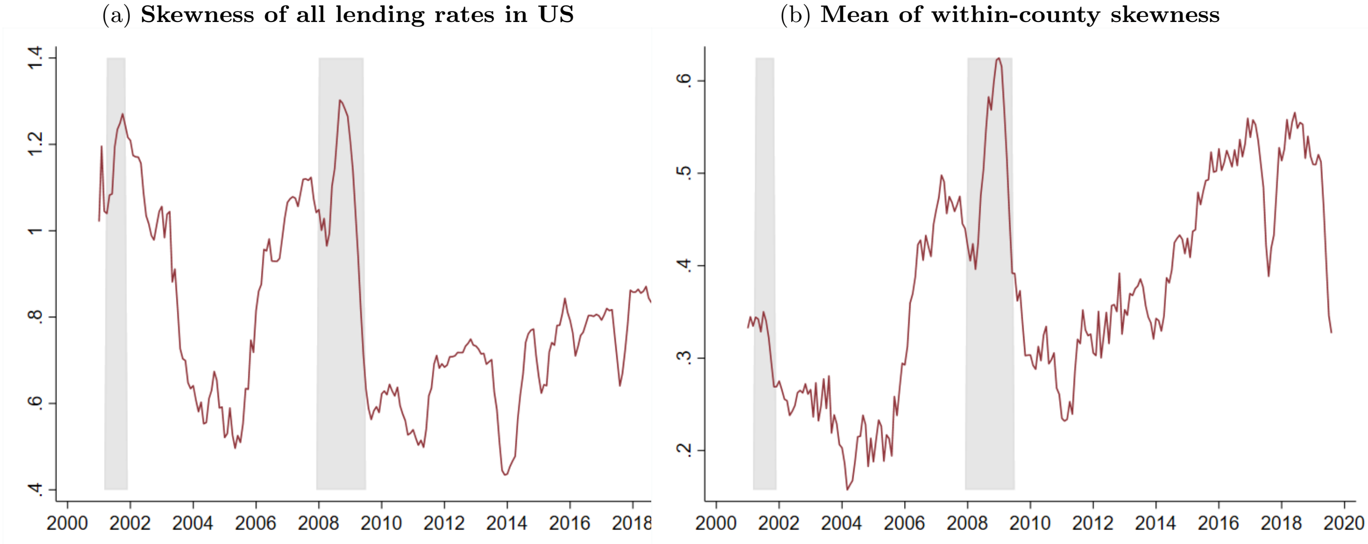
volume to total MSA loan volume. The main empirical analysis will be carried out based on the Branch Level data aggregated to the county level using the equal-weighted scheme (with the caveat above). In the following subsection, some of the cross-county and time series properties of the cross-sectional skewness of lending rates will be introduced and studied.

4 Motivating Evidence

In this section, I show that, even after controlling for borrower and loan characteristics, there is still a great deal of variation across the lending rates set within a given month, location and loan category[23]. I establish this fact first by using advertised lending rates from the County/Branch level data. Since these are the base rates that each branch advertises or reports to the public, they are not specific to any particular borrower characteristic. In what follows, I show that the cross-sectional distribution of lending rates at each point in type is highly dispersed and particularly asymmetric. This is a pervasive feature of the data across many different loan products. In this section, I will show two examples of loan products. Figure 1 below shows the two measures of cross-sectional skewness in lending rates for a specific category of loans, namely the loans for purchasing Personal Recreational Vehicles.[24] Panel (a) shows the skewness of the cross-sectional distribution of the pool of all lending rates offered by branches in the US for each point in time.

Figure 1: Personal Recreational Vehicle Advertised Lending Rates.

(a) **Skewness of all lending rates in US** (b) **Mean of within-county skewness**



Notes: Panel (a) shows the skewness of the cross-section of all lending rates advertised by all surveyed branches in the US for Personal Recreational Vehicle Loans. Panel (b) shows the mean of the cross-section of within-county measures of skewness for the same type of loans. NBER recession dates in grey.

[23]Examples of loan categories considered are: Home E.L.O.C. 81-90% LTV, 30Yr Fxd Mtg 175K, Auto-new, Boat-Used

[24]Similar Loan Products both in the sector of consumer durable and house mortgage loans yield very similar results.

Panel (b) instead focuses on the within-county skewness and shows the average of all skewness measures computed within-county at each point in time.[25] Within each county and month, any conventional banking model with homogeneous banks would predict that all banks should advertise the same lending rate for the same loan[26] This is not the case. The within-county skewness in advertised lending rates is always relatively high over the years covered in the dataset.[27] A conventional explanation for geographic dispersion in lending rates is market concentration. But market concentration does not change considerably from month to month, so it is unlikely that market concentration per-se can explain the time-series volatility of cross-sectional skewness.

A second prominent feature of the lending rates distribution is that its skewness is always positive or, in figurative terms, it has a *long* and *fat* right tail. This means that (i) the distribution is highly asymmetric, (ii) there is a relatively big mass of banks that is able to offer exceptionally high rates while staying "in business". This data feature appears at the county level as much as at the state and national levels. Two main stylized facts can be observed from Panel(a). First, the time series fluctuates considerably between the values of 0.3, which corresponds to an almost symmetric distribution, to above 1, which is conventionally considered as a rule of thumb value for a *"highly"* asymmetric distribution. Second, the time series shows considerable volatility over time. Panel (b) shows that the whole distribution of within-county skewness measures shifts considerably across time in a similarly volatile way. Combining Panel (a) and Panel (b), two observations can be made. First, the variation in the aggregate national skewness is not driven by a subset of counties having exceptionally high rates but rather by all counties shifting up or down in their skewness measures. In other words, the right tail of the cross-sectional distribution of lending rates grows in mass and length due to the single within-county tails growing in length and mass as opposed to a few counties charging particularly high rates as a whole. Second, the variation in the mean county skewness, as captured by Panel (b), exhibits some inconsistencies with the business cycle: (i) it grew considerably during the great financial crisis, but it did not grow as much during the 2001 recession (ii) at the end of each of the recessions it also decreased considerably, (iii) contrary to the post-2001 recession period, the mean county skewness stayed low for a considerable amount of time after the great financial crisis. These latter three facts combined suggest (i) that the cross-sectional skewness of lending rates is not a proxy of the business cycle but rather carries important independent information for the state of the economy, (ii) it seems correlated with the stance of monetary policy decreasing with the two post-crisis easing periods, increasing with the tightening monetary policy applied in the build-up of the great financial crisis and finally remaining relatively low in the following period. In addition, the higher the peak of the skewness reached within each crisis, the steeper the descent following a monetary policy tightening. These observations seem

[25](i.e. first, for each county, the within-county skewness is computed, and then for each month, the mean across counties is computed)

[26]Note that the S&P Global market Insights Ratewatch Data purposely surveys branch over *standardized* loans, that is loan products that are standard in their characteristics and amounts over the US territory.

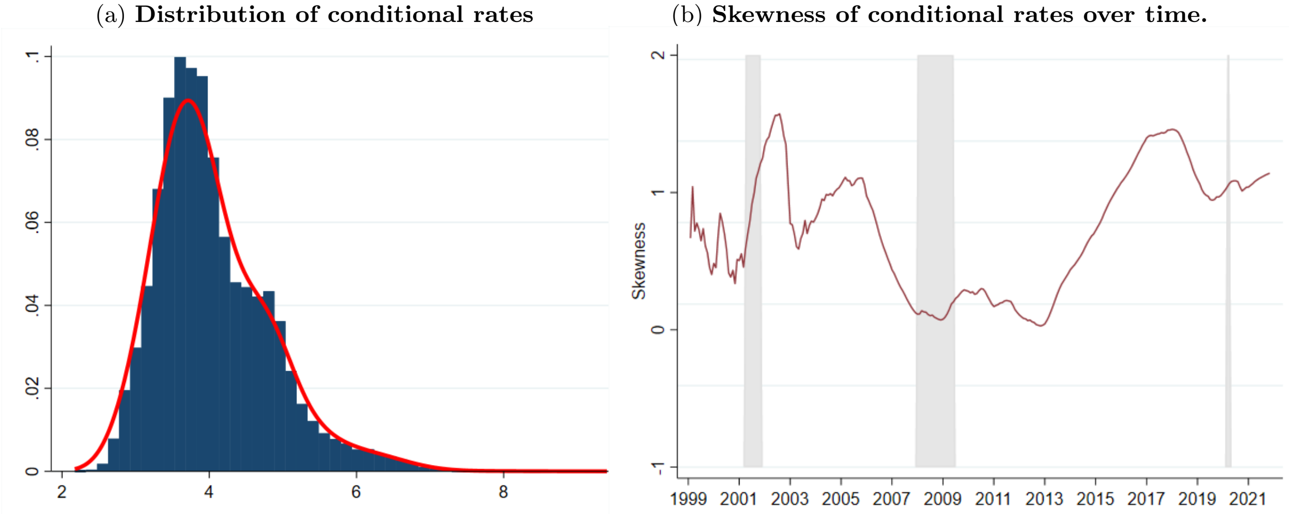
[27]Rule of thumb is to consider as low skewness levels around 0 and as high skewness levels around 1.

to suggest that there might be scope for an inverse direction of causality between the cross-sectional skewness of lending rates and the strength of monetary policy, which motivates the empirical analysis of this paper.

In Figure 2, I use instead the mortgage loan-level data from Freddie Mac. Contrary to the previous figure, these are lending rates on actual loans issued by banks to their clients. In this case, the raw rates do include information on the specific borrower and loan characteristics. To partial out the effect of the latter two factors, I employ non-parametric methodology by Hurst et al. (2016) and to residualize the observed rates with respect to all borrower and loan observables.[28] Panel (a) shows the resulting cross-sectional distribution of residualized lending rates on 30-Year House Mortgages for the Minneapolis-St. Paul-Bloomington MSA originated in January 2019. Panel (b) shows the time series of the cross-sectional skewness for the same loan category and MSA. Again, Panel (a) shows that after controlling for borrowers' and loan characteristics, there is still a great deal of variation across lending rates within the same month and county. Panel (b) exhibits the cross-sectional skewness of the same lending rates for the same MSA over time.

Figure 2: 30Y Mortgage Rates. Minneapolis-MSA. January 2019

(a) **Distribution of conditional rates** (b) **Skewness of conditional rates over time.**



Notes: This figure is based on interest rates on 30Y House Mortgage Loans purchased by Freddie Mac. Panel A displays the distribution of rates after partialling out the effects of Borrower and Loan characteristics (following non-parametric methodology by Hurst et al. (2016)). Panel B displays the time series of the skewness of the distribution displayed in Panel A. Source: Freddie Mac Single Family Loan Level Dataset and author computations.

Two main observations suggest scope for analyzing the cross-sectional skewness of lending rates as a relevant state variable. First, the cross-sectional distribution of residualized rates for a given period, MSA, and loan category displays a long right fat tail, i.e. high cross-sectional skewness. Second, the same cross-sectional skewness controlled for bank characteristics also exhibits significant variation

[28] e.g. FICO score, Debt to Income ratio, etc.

over time, as shown in Figure 1 Panel B. This evidence combined suggests the following questions: are borrowers more prone to search or switch to different lenders more when they observe a skewed distribution of lending rates in the recent past? And, how do banks react to a shock in their marginal lending cost, such as a monetary policy rate shock, when many borrowers are prone to search and switch? In the empirical sections of the paper, I will test the hypothesis that the within-county cross-sectional skewness of lending rates is indeed a relevant state-variable proxying the mass of borrowers searching in the next period and influencing the behavior of banks following a new monetary policy shock.

5 Empirical Model

The following two sections present, respectively, the econometric framework and empirical results of the paper documenting the presence of state-dependence in the response of economic activity and lending rates to changes in the monetary policy rate based on the level of the initial cross-sectional skewness of lending rates. Building on Jorda (2005)'s Local projection framework, I will estimate the response of various outcome variables to an exogenous monetary policy shock. Local projections are widely used for the empirical estimation of monetary policy responses in the literature. The approach amounts to the following regression specification:

$$y_{t+h} = \alpha_h + \beta_h X^{MP} + \gamma_h X^{Controls} + \varepsilon_t^h \qquad \text{for } h = 0, 1, 2, ... \tag{1}$$

where y is the variable whose response to monetary policy we are interested in, X^{MP} is a variable capturing monetary policy changes, and $X^{Controls}$ is a vector of relevant controls.[29] Typically monetary policy is highly endogenous which implies that X_t^{MP} is correlated with the error term ε_t^h resulting in a biased estimate of β_h^1. One of the most popular approaches to these issues is to rely on proxy variables that identify the exogenous variation in monetary policy, i.e. monetary policy shocks. In particular, I use high-frequency proxies, which are variables constructed starting from the change in the price of highly liquid financial instruments in a narrow window around the FOMC announcement. The underlying assumption required for the use of these proxies for the estimation of responses to monetary policy is that financial market prices already correctly predict and incorporate the endogenous response of monetary policy to the economy before the FOMC announcement. Any price change happening during the FOMC announcement captures the exogenous unpredictable variation in monetary policy. More on this literature in the next section. If the model monetary policy shock is well identified, then β_h will be an estimate of how much y changes at t+h following an increase in X^{MP}, i.e. $\beta_h = \frac{y_{t+h}}{X^{MP}}$. The complete impulse response function will be hence the vector $\beta_h{}_{h=0}^{HMAX}$ where HMAX is the maximum horizon of the response function we are interested in.

[29] Note that the variable $X^{Controls}$ doesn't have a t index because it includes lags of the outcome variable y, of the main regressor X^{MP} and other potentially relevant control variables (contemporaneous and lagged)

The focus of this paper is (i) to test if $\beta_h{}_{h=0}^{HMAX}$ changes with the level of the cross-sectional skewness of lending rates before the monetary policy change happens (i.e. in t-1), (ii) to estimate the direction of change which is a priori unclear, (iii) finally to quantify the magnitude of the change. I extend the econometric framework to allow the impulse response to varying with the level of the cross-sectional skewness of lending rates prior to the monetary policy shock. As a result, the outcome variable response to monetary policy is allowed to be dependent on the state of the cross-sectional skewness, i.e. state-dependent. To do so, I estimate a regression of the following form:

$$y_{t+h} = \alpha_h + \beta_h^0 X^{MP} + \beta_h^1 \left[X_t^{MP} \times \mu_{t-1}^3\right] + \delta_h \mu_{t-1}^3 + \gamma_h X^{Controls} + \varepsilon_t^h \qquad \text{for } h = 0, 1, 2, ... \tag{2}$$

where $\left[X^{MP} \times \mu^3\right]$ is an interaction term between the monetary policy variable X_t^{MP} and the cross-sectional skewness of lending rates μ_{t-1}^3 prior to the new monetary policy innovation, i.e. in (t-1). The non-interacted term $\delta_h \mu_{t-1}^3$ is added to the specification to avoid bias in β_1 due to potential direct relationships between y and μ_{t-1}^3. Under this new specification the response of y to X^{MP} is now $\frac{\partial y_{t+h}}{X_t^{MP}} = \beta_h^0 + \beta_h^1 \mu_{t-1}^3$. If the model is well identified and β_h^1 is positive, then the response of y to X_t^{MP} at horizon h is increasing in μ_{t-1}^3. On the contrary, if β_h^1 is negative, then the response of y to X_t^{MP} at horizon h decreases in μ_{t-1}^3. Finally, if β_h^1 is found to be not statistically different from 0, then the response of y to X_t^{MP} at horizon h will not depend on μ_{t-1}^3. As argued in Balli and Sørensen (2013), if we have a monetary policy proxy capturing identifying the exogenous variation in X_t^{MP} then the interaction term between the proxy and μ_{t-1}^3 will also work for an unbiased estimation of β_h^1. Importantly all terms entering the interaction terms are subtracted of their long-run mean. This is done to capture the impact of short-run variations in the cross-sectional distribution of lending rates on the strength of the responses to monetary policy. Consequently, β_h^1 should be interpreted as the average response of the outcome variable y at horizon h to a monetary policy change depending on the distance of the long-run skewness from its long-run mean over time. Tangentially, this procedure allows controlling for biases in the coefficients due to co-variation between the interaction terms and the other linear terms of the regression as explained in Balli and Sørensen (2013).

The regression equation 2 would be typically estimated using aggregate data about GDP, CPI, etc. This amounts to roughly 25 years of data (at either quarterly or monthly frequency) if one focuses on the last two recent decades and excludes the latter Covid crisis from the sample. These are hardly enough observations. In addition, using aggregate data does not allow testing whether the cross-sectional skewness of the distribution of lending rates at the local regional level plays a role. In order to include the latter consideration, the framework is further extended for use in a panel dataset by adding an s subscript to each variable.

$$y_{s,t+h} = \alpha_h + \beta_h^0 X^{MP} + \beta_h^1 \left[X_t^{MP} \times \mu_{s,t-1}^3\right] + \delta_h \mu_{s,t-1}^3 + \gamma_h X_s^{Controls} + \varepsilon_{s,t}^h \qquad \text{for } h = 0, 1, 2, ... \tag{3}$$

The only change with respect to the regression equation 2 is that now at each time t, there is a separate observation of each of the left and right-hand-side variables for each region of the US (state, county, or MSA depending on the dataset used). Note that the coefficients β_h^0 and β_h^1 do not vary across regions, meaning they will capture the average regional response of the relevant outcome variable to X_t^{MP}. The following subsections present a brief literature review of the strand dealing with the estimation of Monetary Policy Shock responses and the complete empirical model used with a complete description of the controls used and the specification of the interaction terms.

5.1 Robust specification

Three different datasets are used in this analysis. Recall from Section 3 that the first dataset is a state-quarterly level dataset obtained by merging national- and state-level macro indicators of economic activity with banking variables from the Call Reports. The second dataset is at the county/monthly level. It merges the national and county macro aggregates available with the branch-level data from the proprietary S&P Global Market Insights Ratewatch database. Finally, the third dataset is at the MSA/Quarterly level and will encompass macroeconomic information at the national and MSA level with loan-level data on the Single-Family Home Mortgages as contained in the public dataset of Freddie Mac. The second dataset will be the one used in the analysis in the main text the results of the other two datasets will be discussed briefly at the end of this section and left to the appendix. As discussed in the previous section, the methodology chosen is local projection, and the identification is achieved through high-frequency proxies (Bauer and Swanson (2022)). As shown by Plagborg-Møller and Wolf (2021) for impulse response estimation, the approach, in population, is equivalent to estimating VARs. The choice is here made in order (i) to have a more flexible structure for the estimation of panel regression with instrumental variable and interaction terms and (ii) to be robust to misspecification of the model in hand. The general form of the local projection equation is as follows:

$$\begin{aligned}
\mathrm{y}_{s,t+h} \;=\; & \alpha_{s,h} + \beta_h^0 X_t^{MP} + \beta_h^1 \left[X_t^{MP} \times \mu_{t-1,s}^3\right] + \beta_h^2 \left[X_t^M P \times \mu_{t-1,s}^1\right] + \beta_h^3 \left[X_t^{MP} \times \mu_{t-1,s}^2\right] + \qquad (4)\\
+ \;& \rho_{1,h}\mu_t^1 + \rho_{2,h}\mu_t^2 + \rho_{3,h}\mu_t^3 + \gamma_h X_{BANK,t} + \delta_h X_{s,t} + \delta_h X_{US,t} + \\
+ \;& B(L)_h \left[X_t^{MP} + X_t^{MP} \times \mu_{t-1,s}^3 + X_t^M P \times \mu_{t-1,s}^1 + X_t^{MP} \times \mu_{t-1,s}^2\right] + \\
+ \;& C(L)_h \left[\mu_t^1 + \rho_{2,h}\mu_t^2 + \rho_{3,h}\mu_t^3\right] + D(L)_h \left[X_{BANK,t} + \delta_h X_{s,t} + \delta_h X_{US,t}\right] + \varepsilon_{s,t,h}
\end{aligned}$$

where t is the time index, and s is the region index (state, county, or MSA depending on the dataset). Compared to equation 3, the final specification extends into two directions. First, two new interaction terms are added: the interaction $\left[X_t^M P \times \mu_{t-1,s}^1\right]$ between the monetary policy proxy $X_t^M P$ and the demeaned first moment of the cross-sectional distribution of lending rates in county s $\mu_{t-1,s}^1$ and the interaction term $\left[X_t^{MP} \times \mu_{t-1,s}^2\right]$ the monetary policy proxy $X_t^M P$ and the demeaned first moment of the cross-sectional distribution of lending rates in county s $\mu_{t-1,s}^2$. The cross-sectional skewness of lending rates at the regional level covaries with the mean and variance. These two terms are added in order to control for such variation. Second, the full set of controls is spelled out in this specification. Since the regression is at the regional level, controls for bank-specific balance sheet variables and for county-level macros are added in addition to the usual controls at the national level. The next paragraphs will discuss in more detail the choices for each of the variables in the specification.

5.2 Outcome Variables

The outcome variable will be the Real Personal Income for the first state-bank level dataset, unemployment and lending Rates for the county-branch level dataset and finally, unemployment, refinancing rates, and mortgage interest rates for the MSA-Loan Level dataset. At the state-level personal income is the only variable available with a long enough time-series.[30] At the county and MSA level, unemployment is the only available proxy for Economic Activity at the monthly and quarterly frequency. For the branch-level data, the average advertised rate by county/loan category will be used. As discussed in the data section, the branch-level dataset contains information on various categories of loans, such as new auto loans, new personal recreational vehicles, or new boat loans, together with the more conventional house mortgage loans at maturities of 3,5, and 10 years or home equity loans. County/category fixed effects will be used. Finally, for the MSA-Loan level, data lending rates of house mortgages will be used. In this case, for each county and time, the average lending rates by maturity will be used.

5.3 Main Regressors

The monetary policy shock variable X_t^{MP} is the high-frequency proxy proposed in Bauer and Swanson (2022). Similarly to the previous literature, the proxy is similarly constructed from price changes over narrow windows around FOMC announcements. Differently from previous literature, the proxy is orthogonalized with respect to the public information about the economic and inflation outlook at the time of the FOMC announcement. Following are its interaction terms, respectively, the cross-sectional skewness, mean, and variance of lending rates computed at the county level in the previous period (quarter or monthly, depending on the frequency of the dataset). Alike skewness, the cross-sectional variance and mean entering the interaction terms will be also demeaned by their long-run mean over time.

[30]It is used in place of state-level output, which is not available at quarterly frequency starting from 2005. Personal Income and Output have a high correlation across the overlapping sample.

5.4 Other Regressors

Finally, the specification is saturated with controls at the bank level, county-, and national- levels. The controls at the bank level are computed as the county average of three main balance-sheet variables. The average is weighted by the local presence in the county as measured by the volume of deposits of the branches in the county by bank.[31] The main controls used are average interest rate expense, return on assets, and loan loss provisions. The first variable controls for idiosyncratic variation in banks' cost of funds which might introduce confounding variation in the lending rate behavior across counties. The return on assets variable is capturing bank-specific idiosyncratic variation in lending rates due to capital constraints on the banking side. As bank returns increase, so does their net worth and hence relaxes capital and regulation constraints limiting the issuance of new loans. Finally, the Loan Loss Provision variable controls for banks' heterogeneous expected future probability of default on loans. Intuitively the more banks expect future losses, the more they will increase lending rates. As a consequence, controlling for this expectation is essential to isolate banks' responses to monetary policy. The county-level controls are the unemployment rate, and the log of total wages available at the MSA level and matched to the county closest to the MSA level by definition. Counties for which total wages are not available are assigned with the mean state-level wage average. House price indexes are also available and used at the county level to control for housing market factors which might vary heterogeneously across counties. Finally, at the national level, four main variables are used consistent with the analysis in Bauer and Swanson (2022) namely the US aggregate unemployment rate, the log of CPI index, the 2-year Treasury rate, and the Excess Bond Premium as in Gilchrist and Zakrajšek (2012). These are among the usual variables used in Local Projection and VAR estimations of monetary policy effects.

5.5 Identifying Variation

In each of the three data panels, both cross-county and time-variation can be used. The empirical exercise is meant to test whether counties in a state characterized by particularly high levels of cross-sectional skewness of lending rates with respect to their long-run mean experienced a stronger pass-through in the following monetary policy movements. Both county and time variation is hence used. Recall that the relevant variable is the nationwide monetary policy shock X_t^{MP}. At each point in time, different counties will have their cross-sectional skewness differentially far from their long-run county mean. Counties with an initial cross-sectional skewness that is further away from the long-run mean

[31]This information is available from the FDIC Summary of Deposits dataset presenting information on the number, location, and total deposit volume of each branch of US and Foreign Banks in the US. An alternative weighting could be through the volume of loans by bank and county as available from the House Mortgage Disclosure Act Data. This data is however only concerning house mortgage loans, while the analysis of the paper is instead devoted to C&I and consumer durable loans in addition to house mortgage loans. I hence adopt the first weighting scheme for the main results and use the second as robustness. In the appendix, there are also results using the simple number of branches by county or simple unweighted averages by county. The resulting time series do not vary much across different weighting schemes.

vary in the response of their economic activity and lending rates to monetary policy shocks. At the same time, each county will also be differentially far from its long-run mean at different points in time. As a result, its activity measures and lending rates will respond differently to the monetary policy shock. This specific time variation will also allow identifying the differential effect of skewness over the responsiveness of economic activity and lending rates to monetary policy.

6 Empirical Results

This section presents the main empirical results of the paper, obtained using the branch/county Level dataset at the monthly frequency. The following subsection presents the results obtained using unemployment as a measure of economic activity. The following subsection focuses instead on the transmission of monetary policy through lending rates. Finally, the last part of the section provides an extensive summary description of the extended battery of robustness checks and results obtained using the other data-sets. The result tables are contained in Appendix C.

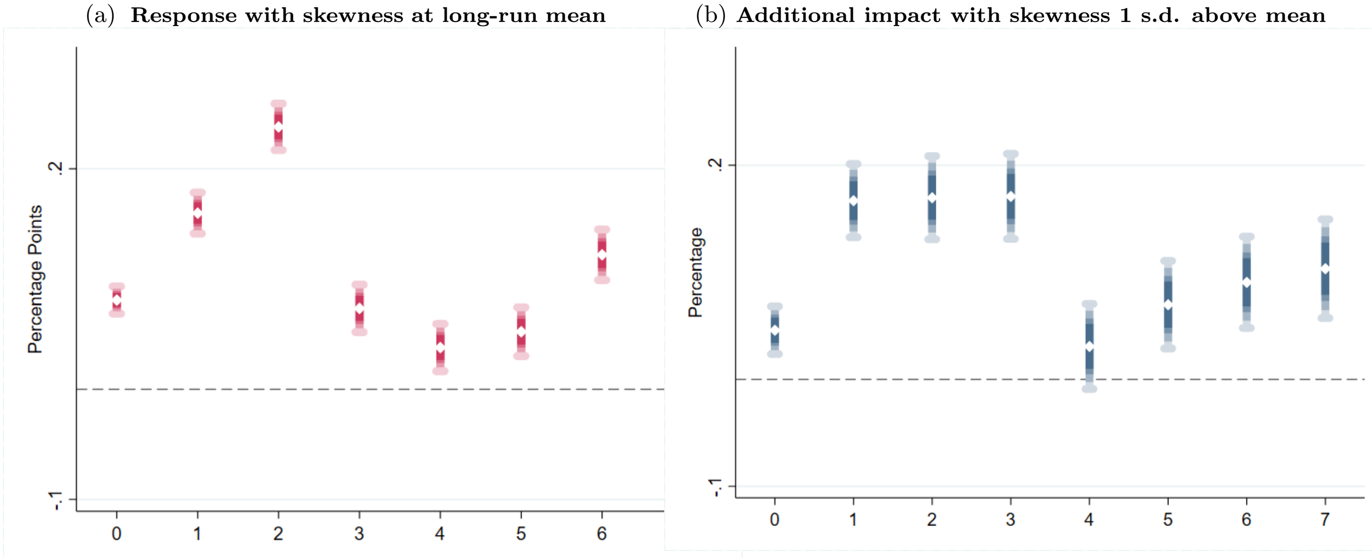
6.1 Economic Activity

The results of the regression analyzing the response of economic activity are presented first. The analysis focuses on the short-run response of unemployment to monetary policy, namely the first 10 months.[32] Figure 3 shows the baseline results from estimating the regression equation 3. Table 1 below presents instead the estimation results of the robust regression equation 4 which includes interaction terms controlling for the first and second moment of the cross-sectional distribution. For clarity, the table only reports the main coefficients of interest, the reader should note, however, that all controls spelled out in the previous section are present. The dependent variable is the county/month total civilian unemployment rate. Each table column reports the set of estimated coefficients at horizon h. Each row reports the right-hand side variable that the estimated coefficient belongs to. In other words, the first row reports the set of coefficients β_h^0 for $h = 1, 2, ..., 10$. The second one reports β_h^1 for $h = 1, 2, ..., 10$. And so on. The unemployment rate is expressed in percentage points. The monetary policy shock is in percentage points, and three moments part of the interaction terms displayed are standardized. This implies that the coefficient β_h^0 represents the change in percentage points of unemployment due to a 1 percentage point positive monetary policy shock at horizon h. This response increases by β_h^1 when the skewness is one standard deviation above the long-term regional mean.

[32] This is because branch-level data presents important gaps and structural breaks in the time series at the county/category level, which prevents inference on longer horizons.

Figure 3: Response of Unemployment to a Monetary Policy Shock

(a) **Response with skewness at long-run mean** (b) **Additional impact with skewness 1 s.d. above mean**



Notes: Panel (a) shows the impulse response of Unemployment to a 100 b.p. monetary policy shock when within-county beginning-of-period cross-sectional skewness of lending rates is at the long-run mean. Panel (b) shows the additional impact of the same monetary policy shock when the within-county beginning-of-period cross-sectional skewness of lending rates is 1 standard deviation above its long-run mean. 95 confidence intervals are displayed.

Table 1: Response of Unemployment to a Monetary Policy Shock, robust specification

Month	0	1	2	3	4	5	6	7	8	9	10
X_t^{MP}	0.04***	0.28***	0.36***	0.26***	0.21***	0.23***	0.37***	0.49***	0.56***	0.57***	0.19***
	(4.96)	(20.15)	(24.02)	(17.23)	(13.41)	(14.27)	(21.92)	(26.25)	(29.86)	(31.73)	(11.42)
$\left[X_t^{MP} \times \mu_{t-1}^3\right]$	0.04***	0.12***	0.11***	0.09***	-0.05**	0.02	0.04*	0.09***	0.05**	0.02	0.02
	(3.12)	(6.67)	(5.50)	(4.58)	(-2.38)	(0.91)	(1.91)	(3.54)	(2.00)	(0.67)	(1.01)
$\left[X_t^{MP} \times \mu_{t-1}^1\right]$	0.09***	-0.04***	-0.11***	-0.02*	-0.03**	-0.00	-0.18***	-0.18***	-0.17***	-0.28***	-0.05***
	(14.53)	(-4.12)	(-10.29)	(-1.71)	(-2.44)	(-0.26)	(-14.68)	(-13.21)	(-12.38)	(-21.11)	(-3.81)
$\left[X_t^{MP} \times \mu_{t-1}^2\right]$	-0.00	0.04*	-0.02	-0.11***	-0.03	-0.11***	0.07**	-0.05	0.02	0.08**	-0.04
	(-0.12)	(1.70)	(-0.65)	(-3.80)	(-1.06)	(-3.77)	(2.39)	(-1.38)	(0.53)	(2.45)	(-1.48)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	121832	110059	107270	104565	99944	97147	95369	91929	90388	88241	85016
R^2	0.969	0.939	0.928	0.929	0.931	0.928	0.920	0.909	0.907	0.920	0.933

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first line of the above table reports the estimated values and t statistic for the coefficients of the monetary policy shock variable alone at each month h. As shown by the first estimate, unemployment, on average, grows by 0.04 percentage points in the first month after a monetary policy shock of 1 percentage point (p.p.). The increase in the following month is 0.28 percentage points, 0.36 in the second month, and so on. Recall that the interaction terms in the specification are defined as the product between the monetary policy shock variable and the distance from the long-run mean of the first three moments of the cross-sectional distribution of interest rates. The collection of the first-row coefficients, hence, represents the impulse response function of unemployment to a monetary policy shock of 1 p.p. when the interaction terms are at 0, i.e. when all three moments are at their long-run mean. In terms of significance, the impulse response function is significantly different from 0. In addition, the response is positive, in line with conventional monetary policy theory. An exogenous increase in the monetary policy rate has contractionary effects on the economy. As it is possible to observe, the contemporaneous response in t, not unexpectedly, is very close to 0. Indeed unemployment tends to have a lagged reaction to monetary policy shocks. In the following 7 months, unemployment increases by a quarter of a percentage point each month, reaching a peak of half of a percentage point in the eighth month. By the end of the horizon, the response decreases while remaining positive.

The second row contains the first core result of the paper. The coefficients of the second row represent the change in the response of unemployment to monetary policy shocks when the skewness is one standard deviation above its long-run mean. The results reported in this second row answer the three main empirical questions of the paper: (i) is the initial cross-sectional skewness of lending rates a relevant state variable for the responsiveness of economic activity to monetary policy shocks, (ii) if yes, is the responsiveness increasing or decreasing in the skewness, (iii) by how much is it increasing or decreasing. We answer the first question by performing an F-Test on the set of coefficients of the second row for each horizon h. The null hypothesis is that the coefficients are jointly not statistically different from 0. The F-Test performed rejects the null hypothesis providing evidence that the initial cross-sectional skewness of lending rates does indeed impact the responsiveness of unemployment to monetary policy shocks. Questions (ii) and (iii) can be directly inspected by looking at the results of the table. As regards question (ii), the coefficients of the second row are all significantly positive. This implies that a 1 standard deviation increase of the cross-sectional skewness of lending rates above the long-run mean predicts an increase in the responsiveness of unemployment to a monetary policy change. Finally, as regards question (iii), the magnitudes of the coefficients in the second row are roughly 1/3 of the coefficients in the first row for the first 4 horizons while becoming 1/10 after the fifth horizon. This suggests that skewness has a solid but short-lived increasing effect on the responsiveness of unemployment to monetary policy shocks. Indeed in the first three months, the response of unemployment for counties that are 1 standard deviation above their long-run mean tends to double in the month the monetary policy shock hits, be 1/3 higher in the following three months, and 1/10 higher up to month 8 where the coefficient becomes insignificant.

The last remark concerns the last two rows of the regression table presented. The third row represents the coefficients on the interaction terms between the monetary policy shock and the distance from the long-run mean of, respectively, the first and the second moments of the initial cross-sectional distribution of lending rates. As it is possible to observe, the coefficients multiplying interaction with the first moment are all highly significant and negative. This implies that when the interest rates are particularly high, to begin with, a positive monetary policy shock is going to be less effective on average. On the opposite, when the interest rates are meager with the respect to the long-run average, then unemployment is estimated to respond more to a monetary policy shock. For the last row interaction term considered, the conclusions are different. Almost no coefficient in the last row is significantly different from 0. In addition, both sign and magnitude are relatively dispersed. This implies that overall the second moment doesn't seem to play a role in how economic activity responds to monetary policy shocks. Overall these results suggest the presence of an important form of state-dependence in the responsiveness of unemployment to monetary policy shocks. First, this response is highly state-dependent on the properties of the initial distribution of interest rates (initial, i.e. prior to the change in monetary policy). Second, the response of unemployment is increasing in the cross-sectional skewness of the distribution. Recall that, as shown in Section 3, the cross-sectional skewness of lending rates is mainly positive. This implies that whenever the distribution is particularly skewed with respect to its long-run mean, the response of following monetary policy shocks to skewness is negative.

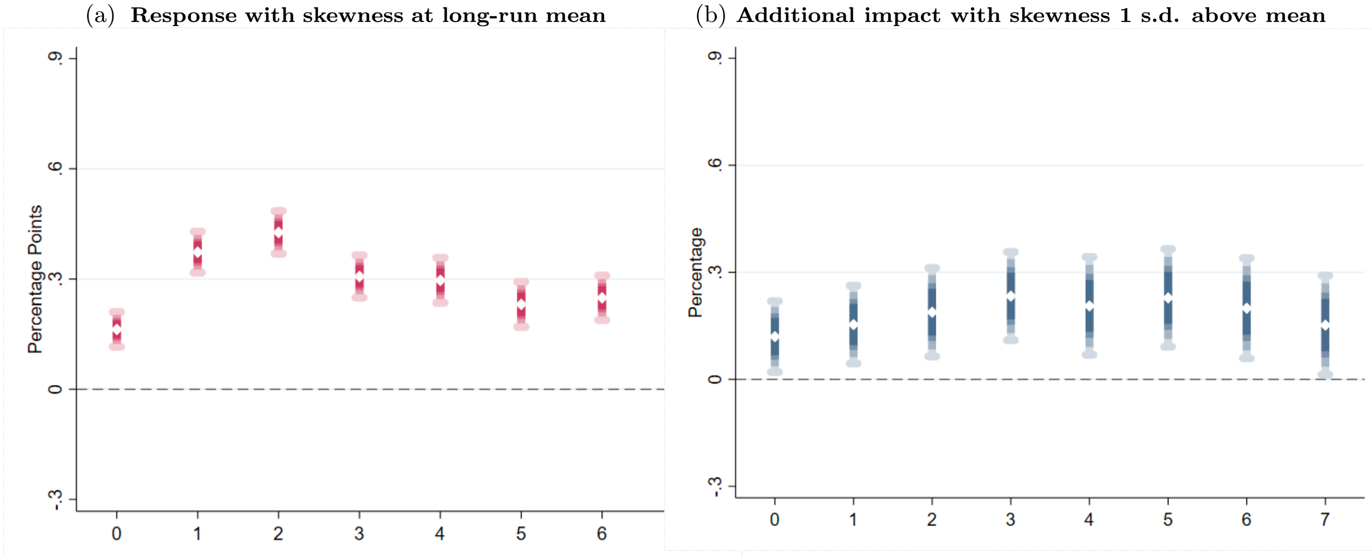
What is driving this result? High positive skewness in the cross-sectional distribution of lending rates indicates a distribution with a particularly long and fat right tail: i.e, a considerable mass of banks charges high lending rates with respect to the rest of the banks in the distribution. The natural candidate driver of the results presented above is hence to be searched in the way lending rates themselves respond to monetary policy when the initial distribution is particularly skewed. The following subsection will present the results of the local projection of lending rates onto the exact specification of the table just presented.

6.2 Lending Rates

The local projections estimated in this subsection vary with respect to the ones in the previous subsection along two dimensions. First, the outcome variables are now the nominal lending rates offered by each branch in the dataset in county s and month t for the category of loan f. The panel regression, in this case, has an additional dimension with respect to the one used in the previous subsection, the loan category. The outcome variable, in this case, is going to be for each month and category of loan the within-county average lending rate. Symmetrically the regressors represented as the moments of the distribution will be computed at the county/month and category level. For instance, when the outcome variable is the mean monthly lending rate for county s and loan category f, the corresponding skewness interaction term will be computed as the product of the monetary policy shock and the cross-sectional skewness of the distribution of lending rates in county s and loan category f. Figure 4 shows the baseline results from estimating the regression equation 3. Table 2 below presents instead the estimation results of the robust regression equation 4 which includes interaction terms controlling for the first and second moment of the cross-sectional distribution.

Figure 4: Response of Lending Rates to a Monetary Policy Shock

(a) **Response with skewness at long-run mean** (b) **Additional impact with skewness 1 s.d. above mean**



Notes: Panel (a) shows the average impulse response of lending rates to a 100 b.p. monetary policy shock when within-county beginning-of-period cross-sectional skewness of lending rates is at the long-run mean. Panel (b) shows the additional impact of the same monetary policy shock when the within-county beginning-of-period cross-sectional skewness of lending rates is 1 standard deviation above its long-run mean. 95 confidence intervals are displayed.

Table 2: Response of Lending Rates to a Monetary Policy Shock, robust specification

Month	0	1	2	3	4	5	6	7	8	9	10
X_t^{MP}	0.22***	0.34***	0.48***	0.44***	0.37***	0.23***	0.29***	0.55***	0.38***	0.44***	0.52***
	(8.44)	(10.84)	(13.62)	(11.87)	(8.95)	(5.55)	(6.67)	(12.54)	(8.62)	(8.87)	(10.12)
$\left[X_t^{MP} \times \mu_{t-1}^3\right]$	0.15***	0.12**	0.22***	0.20***	0.18***	0.17***	0.24***	0.12*	0.16**	0.00	-0.00
	(3.73)	(2.48)	(3.95)	(3.37)	(2.91)	(2.59)	(3.40)	(1.77)	(2.34)	(0.06)	(-0.03)
$\left[X_t^{MP} \times \mu_{t-1}^1\right]$	-0.13***	-0.04**	-0.17***	-0.28***	-0.31***	-0.15***	-0.27***	-0.22***	-0.18***	-0.30***	-0.32***
	(-6.14)	(-2.03)	(-6.72)	(-9.33)	(-9.16)	(-4.01)	(-7.27)	(-5.38)	(-4.67)	(-7.56)	(-7.90)
$\left[X_t^{MP} \times \mu_{t-1}^2\right]$	0.04	0.09	-0.21***	-0.02	-0.05	0.14	-0.16*	-0.00	-0.23**	-0.34***	-0.13
	(0.73)	(1.25)	(-2.73)	(-0.18)	(-0.53)	(1.32)	(-1.67)	(-0.00)	(-2.45)	(-3.29)	(-1.16)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	123775	111611	108658	105835	101058	98156	96266	92717	91096	88863	85569
R^2	0.974	0.967	0.963	0.956	0.950	0.947	0.942	0.937	0.935	0.931	0.927

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In interpreting the result of this table, it is important to note that the coefficients of the regression equation are not allowed to vary across loan categories. This implies that they are estimates of the average responsiveness of lending rates across all loan categories. Likely, lending rates belonging to some loan categories will be more responsive, and lending rates belonging to other loan categories will be less responsive. In the appendix, two subsets of the dataset will be considered. In the first subset, only Loans for consumer durable goods are used. In the second subset, only loans for housing-related mortgages are considered (house purchase and home equity).

Similarly to the previous table, the first row represents the impulse response function of lending rates to an exogenous monetary policy rate change when the first three moments of the initial lending rate distribution are at their long-run mean. Similarly to the previous table, the impulse response function of lending rates is highly significant and positive, in line with textbook monetary responses of lending rates. The average lending rate responds with an increase of 0.22 percentage points on impact to a 1 percentage point monetary policy shock. In the following three months, its response grows to almost 0.5 percentage points. The peak response is reached in the seventh month with signs of decline after. Compared to the response of unemployment, lending rates seem both to respond faster to monetary policy and to peak sooner. Moving to the second row of the table, the estimated coefficients in this row constitute the core takeaway of the analysis. The significance, sign, and magnitude of those coefficients are evidence of the role played by the initial cross-sectional skewness of lending rates on the response of lending rates themselves to monetary policy shocks. As above, I test the significance of the coefficients by running an F-Test for each horizon. The test rejects the null hypothesis confirming that the cross-sectional skewness plays indeed, a crucial role in the responsiveness of lending rates to monetary policy. The sign of all coefficients is positive. This implies that, everything else equal, if the state of the cross-sectional distribution at the moment in which a monetary policy shock hits is particularly skewed, the shock will have a higher impact on lending rates. Finally, as concerns the magnitude of the estimates, the coefficients in the second row are roughly between 1/2 and 1 of the coefficients in the first row. This means that whenever the cross-sectional skewness is 1 standard deviation above its long-run mean, the responsiveness of lending rates to a 1 percentage point monetary policy shock increases by between 50% and almost 100% depending on the horizon considered. Similarly to the previous table, the effect of the cross-sectional skewness also appears to be front-loaded. The most effect comes from the first 5/6 months while declining in strength in the 9th and 10th months.

Analyzing the last two rows of the table, similar conclusions with respect to the previous subsection can be reached. First, the row containing the coefficients of the interaction term with the first moment of the cross-sectional distribution is again all significant and negative. In this case, this might suggest the presence of mean reversion forces in lending rates. The response of lending rates tends to dampen when lending rates are much higher than their long-run mean and vice-versa. This might, in turn, explain the negative and significant coefficients of the corresponding third row in the previous table 1. As lending rates tend to respond less to a new monetary policy shock when their level is already high, the pass-through of monetary policy to the real economy also dampens through the textbook interest rate channel.

The main takeaway of this subsection is in line with the one of table 1. The average responsiveness of lending rates at the local branch-month level is state-dependent, and the third moment is the relevant state variable. If prior to a new monetary policy shock, the cross-sectional distribution of lending rates is particularly skewed (1 standard deviation above its mean), the following monetary policy shock will have 50% to 100% more impact on lending rates on average. In the following subsection, a battery of robustness checks along several dimensions will be discussed in order to characterize the solidity of this result.

6.3 Robustness

The robustness of the two main results presented above is tested along several dimensions: an increased set of interaction terms to control various possible confounding factors, different monetary policy proxies, alternative estimation methodology and clustering of the standard errors, and aggregate moments.

6.3.1 Increased Set of Interaction Terms

First, I augment the set of interaction terms to account for potentially confounding factors. I consider interaction terms between the monetary policy proxy and: (i) a dummy variable capturing the periods in which the zero lower bound is binding (identified as periods in which the Federal Funds Rates close to zero), (ii) a dummy variable capturing the NBER monthly recession dates, (iii) a dummy variable capturing local recessions at the county level (identified as two consecutive quarters of negative growth in the county measure of unemployment), (iv) a proxy of the bank market concentration at the county level (computed as the Herfindal Index based on data on the deposit volume by branch from the FDIC Summary of Deposits data). The four interaction terms are either introduced separately or altogether. The results are contained in Appendix C. Overall the significance, sign, and magnitude of all coefficients presented in the previous subsections remain to large extent unchanged. It is worth noting that among all terms only the interaction term between the monetary policy shock and the zero lower bound seems relevant. Indeed the whole collection of the coefficients multiplying this interaction term is significant and negative. This seems to suggest that the basic responsiveness of lending rates and unemployment to monetary policy is considerably dampened during zero lower bound periods. On the other hand, the coefficient on the local recession variable is positive, although less significant. This, in turn, suggests that during recessionary periods monetary policy is more effective on the economy, in line with the results of Tenreyro and Thwaites (2016).

6.3.2 Different High-frequency Proxy

In order to test the robustness of the results with respect to the choice of the high-frequency proxy, I re-estimate the baseline specification augmented with the interaction terms outlined above using the monetary policy shock measure from Jarociński and Karadi (2020). The authors of the paper note that the change in prices in a narrow window around the FOMC announcement might be driven by two shocks: (i) a pure monetary policy shock and a central bank information shock. Central banks might have either privileged or more accurate information about the state of the economy. When monetary policy rates are changed, markets might infer part of the privileged information and react accordingly. For instance, following a decrease in the monetary policy rate, markets might learn that the central bank expects more deteriorated economic conditions. The monetary policy shock measure constructed in Jarociński and Karadi (2020) parses out this latter effect. In this robustness check the latter measure is substituted to the one from Bauer and Swanson (2022) used in the main specification. As shown in appendix C, the results are essentially unchanged.

6.3.3 Internal Instrument vs Two Stage Least Squares

While the baseline results presented above adopt an internal instrument approach, where the proxy is directly introduced in the specification, an alternative approach would be to run a two-stage least square regression. In this case, X_t^{MP} in the baseline specification is the interest rate on the 2Y treasury rate, in line with the empirical literature on monetary policy using instrumental variables. The proxy hence instead used as an external instrument to estimate unbiased coefficients for X_t^{MP} and its interaction terms. The results, also in appendix C, show that the main result remains robust to this approach.

6.3.4 Bank specific average interest expense

Throughout the paper, the direct responsiveness to a monetary policy shock has been analyzed. One might, however, be concerned with the fact that different banks have different cost structures. If this is the case when monetary policy changes, the average cost of funds might change differently across banks. According to textbook banking models, this would imply a heterogeneous response of lending rates to monetary policy. If different banks populate different counties, part of the results presented might be driven by this latter source of heterogeneity. In the baseline specification, I control for this source of heterogeneity by introducing a variable capturing bank average interest rate expense into the specification. However, in this robustness, I substitute such variable directly to X_t^{MP} and run a two-stage least square local projection using the high-frequency proxy form Bauer and Swanson (2022) as an external instrument. The interpretation of the coefficients varies slightly. In this case, a positive significant coefficient on X_t^{MP} implies that the outcome variable y changes positively and significantly following an exogenous increase of 1 p.p. in the average interest rate expense of the institution owning the branch of the observation. Note that the regression is here at the bank/month/branch level rather than at the county level. The results are mainly robust. One main difference with the baseline results should be noted. The first row of coefficients, i.e. the coefficients on the non-interacted term X_t^{MP}, is much higher than in the baseline specification. This is reassuring because, as shown by Drechsler et al. (2017) among others, a big component of the banks' average cost of funds is constituted by deposit rates, which are much less responsive than lending rates to monetary policy due to bank market power in retail deposit markets. In my results, an increase of 1 percentage point of the interest expense by the bank owning the branch of observation results in a higher than 1 pass-through to lending rates. The relationship between the first and second rows is quantitatively very similar to the baseline results. In counties in which the cross-sectional skewness of lending rates is particularly high, lending rates tend to react 50% to 100% more to an exogenous increase in banks' average interest expense caused by monetary policy.

6.3.5 Robustness with respect to aggregate skewness

The baseline specification relates the county unemployment and county average lending rate to the county-specific cross-sectional skewness of lending rates. As shown at the end of section 3, however, part of the county variation in skewness correlates with the aggregate cross-sectional skewness at the national level. In order to inspect which one is the primary driver of the result, we augment the set of interaction terms with one more term interacting the baseline monetary policy proxy with the national average cross-sectional skewness of lending rates. The results show that the coefficients multiplying the simple monetary policy shocks and the interaction with the local cross-sectional skewness are largely unchanged under this new specification. On the other hand, the coefficients on the latter interaction term between the monetary policy shock and the national cross-sectional skewness are highly volatile, ranging from significant negative values for the first two horizons to significantly positive values in the latter two horizons, which makes any inference challenging to make. This seems to suggest that the driving force is the local-level cross-sectional skewness.

6.3.6 State/Quarterly Dataset

As mentioned in Section 4, this paper further tests the robustness of the presented results on two additional datasets. The first dataset contains state-level information on Personal Income, Inflation and Home Price Indexes, and bank-level information on interest rates. For lack of other sources, the interest rates in this dataset are computed as the ratio between Interest Income by Loan category (from the Call Reports - Income statement) and the corresponding Loan volume by loan category (from the balance sheet section of call reports). Because only a few large banks have branches in more than two states, while most banks have territorial presence only in 1 or 2 states, the bank-level information is allocated to different states depending on their local presence in terms of branches by deposit volume. The interest rate distributional moments are hence computed at the state level by using the branch deposit volume as weights. The dataset expands the range of analysis along two dimensions: (i) it allows to study the state-dependent effects of monetary policy on Real Personal Income rather than on unemployment, (ii) it allows to study the cross-sectional moments of C& I loans, largely absent in the other two datasets. The local projection specification is essentially the same with respect to the one presented in the previous section with the only difference being that the regional control variables are now at the state level rather than at the county level. The results in the appendix show that the response of Real Personal Income to standard monetary policy shock is indeed negative and significant. A 1 percentage point monetary policy shock increases Real Personal Income by roughly 1 percentage point at the peak. The set of local projection coefficients on the interaction between monetary policy and cross-sectional skewness in the initial distribution of lending rates at the state level is also significant and roughly 1/4 of the response to the monetary policy shock alone. This implies that, whenever the cross-sectional skewness is 1 standard deviation higher than its state-level long-run mean, monetary policy is 33% more effective on Real Personal Income than otherwise.

6.3.7 Loan/Quarterly Dataset

The last battery of robustness checks is performed using the loan-level dataset from Freddie Mac. In this case, I restrict the attention to two outcome variables, the average lending rate by loan category (maturity, house value, etc) and county, and the refinancing rates computed as the volume of existing loans that are refinanced with respect to the previous period. Differently from the baseline results, lending rates are in this dataset the actual rates charged by the issuing banks on existing loans rather than the advertised rates. This means that an important part of the interest rate determination is here played by the borrower- and loan-specific characteristics. I control for this by residualizing all lending rates through a time-varying regression on all borrower and loan type characteristics observable in the dataset. This procedure is first used in Hurst et al. (2016). If the model is well identified and there are no omitted variables the so residualized rates become homogeneous rates charged on a riskless borrower and shortest-term loan. The results from running the local projections specifications on these data show largely consistent estimates with the evidence presented above. Both new lending rates and refinancing rates respond more to a monetary policy shock if the initial cross-sectional skewness of lending rates is higher.

6.3.8 Refinancing Channel

The results in Eichenbaum et al. (2022) show that for the special case of house mortgage loans it is important to account for the Refining Channel of Monetary Policy, as measured by the average interest rates gap between lending rates on existing loans and new lending rates offered in the current period. I add this additional control in my regression specification for the MSA/Loan level Dataset. The results show my results are largely robust to the inclusion of this control.

7 Theoretical Framework

The objective of this section is to develop a Bertrand Competition framework to rationalize the main empirical takeaway of the paper. Within the Industrial Organization Literature, the lending rate pass-through of monetary policy can be viewed as a specific case of a cost-price-pass-through mechanism, where monetary policy shocks map into exogenous shifts in banks' marginal cost of producing a loan and lending rates are the prices affected by these shocks. The purpose of the model is threefold. First, it represents a theoretical effort to identify a parsimonious set of *ingredients* necessary in order to capture the state-dependence of the cost pass-through, while abstracting from bank ex-ante heterogeneity in marginal costs and demand ex-ante heterogeneity in price elasticity. The task is not trivial as usually the heterogeneity in the cost pass-through is obtained through the sources we are here abstracting from.

Second, it aims at micro-funding the observed skewness-based state-dependence with a novel mechanism arising from the combination of search and switching costs on the demand side and the strategic complementarity in the bank pricing decisions. Third, the framework will be used to derive sharp theoretical implications for the cross-sectional heterogeneity and time-variation of the cost-pass-through following different combinations of skewness and monetary policy shocks signs and magnitudes: high vs low skewness states with positive vs negative and large vs small monetary policy shocks. In general, the model is to be viewed as a potential substitute for other state-dependent pricing frictions, such as menu costs, largely used to model firms' price-setting behavior.

7.1 Environment and Timeline

I consider a static Bertrand Competition Game Γ among two banks. The two banks produce differentiated loans and compete in interest rates. Loan differentiation is modeled through a Hotelling structure: bank H loans and bank L loans sit at the two extremes of a line on the interval $[0, 2]$. Each potential borrower will be sitting at a specific point on the interval. The distance from 0 captures how much he/she dislikes the characteristics of bank H the distance from 2 represents how much he/she dislikes the characteristics of bank L. Each borrower derives gross utility v from taking out a loan. This utility is exogenous and fixed. The net utility of getting a loan from either bank will be:

$$\begin{aligned} U &= v - z - r_t^H \qquad \text{if loan from bank H} \\ U &= v - (2 - z) - r_t^L \qquad \text{if loan is from bank L} \end{aligned}$$

A borrower with distance z from bank H and $(2 - z)$ from bank L will take out a loan from bank H iff $v - z - r_t^H \geq v - (2 - z) - r_t^L$.

Each period a cohort of new customers will be in need of a new loan. They first have to learn the interest rate that is offered by banks and then decide whether and from which bank to take the loan. Each cohort of customers has already a relationship with either of the two banks. I refer to the bank H(L)'s courtyard as the pool of borrowers in the cohort that have a relationship with bank H(L). Borrowers' have to pay a search cost to learn current interest rates but they can learn the newly offered interest rate of the bank they have a relationship with for free. The timeline is hence as follows. First borrowers decide whether they pay the search cost or not. Then banks observe borrowers' decisions and set their interest rates. Following this, borrowers observe the interest rates and decide whether to apply for a loan. At the beginning of each period, borrowers can observe the equilibrium prices that prevailed in the previous period and this is the only information that they have. Finally, borrowers are heterogeneous in their search and switching frictions. Customers have heterogeneous search costs uniformly distributed over the interval $[0, \bar{\theta}]$. They also have heterogeneous switching costs that are distributed over the $[0, \bar{\Psi}]$ interval.

7.2 First Stage Borrowers Decision to Search

At the beginning of the period borrowers need to decide whether to just wait and observe the new interest rate offered by their courtyard bank or pay the search cost in advance and observe also the other bank's interest rate. In order to take this decision they need to evaluate what are the expected gains from searching. The decision of borrower j belonging to bank H's courtyard will be :

$$\begin{aligned} \text{Search} \quad \text{if} \qquad & \mathbb{E}\left[v - z_j - r_t^H\right] < \mathbb{E}\left[\max\{v - z_j - r_t^H, v - (2 - z_j) - r_t^L\} - \theta\right] && (5) \\ \text{Don't Search} \quad \text{if} \qquad & \mathbb{E}\left[v - z_j - r_t^H\right] \geq \mathbb{E}\left[\max\{v - z_j - r_t^H, v - (2 - z) - r_t^L\} - \theta_j\right] && (6) \end{aligned}$$

Where θ_j is the search cost for borrower j. The decision rule for borrowers of courtyard L will be the same. Recall that borrowers learn their z only after they pay the search cost hence ex-ante they just formulate their expectation to be:

$$\mathbb{E}\left[z\right] = \mathbb{E}\left[(2 - z)\right] = 1 \tag{7}$$

As for the interest rates, recall that borrowers do observe the previous period's equilibrium interest rates. For simplicity I assume they have a simple random walk forecasting model in mind, i.e.:

$$\begin{aligned} r_t^H &= \gamma c_t \\ c_t &= c_{t-1} + \varepsilon_t^{MP} \end{aligned}$$

I assume that $\mathbb{E}\left[\varepsilon_t^{MP}\right] = 0$. This combined with the random walk forecasting model above amounts to borrowers having simple naive expectations

$$\mathbb{E}\left[r_t^i\right] = r_{t-1}^i \qquad \text{for } i = H, L \tag{8}$$

Combining 7 and 8 with 5 the search decision will be defined by the following policy function:

$$\begin{aligned} &\text{Search} \quad \text{if} \quad && \theta_j < r^H_{t-1} - r^L_{t-1} && (9)\\ &\text{Don't Search} \quad \text{if} \quad && \theta_j \geq r^H_{t-1} - r^L_{t-1} && (10)\\ & && && (11) \end{aligned}$$

Without loss of generality assume $r^L_{t-1} < r^H_{t-1}$, i.e. bank L identifies the bank charging the lower rate in the previous. Now recall that search costs are uniformly distributed over the interval $\left[0, \bar{\theta}\right]$.

Remark 7.1. *Borrowers belonging to bank L's courtyard will not decide to search.*

Remark 7.2. *Borrowers who search will observe both r^H_t and r^L_t, and z. Borrowers who don't search will only observe their own courtyard r^i_t and z (2-z).*

7.3 Third Stage Borrowers' Decision to Borrow

The third stage decision is presented before the banks' decision because banks know how many borrowers on aggregate decide to search given the past interest rates r^H_{t-1} and r^L_{t-1} and also know the distribution of switching costs z over loan characteristics. Borrowers' are price-takers. In the third stage, they observe the interest rates and their realized z and decide whether to take a loan or not. If they paid the search cost in the first period then they will also have to decide from whom to take the loan. Consequently, their decision rule will be (for the borrower of courtyard H):

$$\begin{aligned} &\text{Take loan} && \text{iff} && v \geq z_j + r^H_{t-1} && \text{if no search in stage 1}\\ &\text{Don't take loan} && \text{iff} && v < z_j - r^H_{t-1} && \text{if no search in stage 1}\\ &\text{Take loan from Bank H} && \text{iff} && v - z_j - r^H_{t-1} \geq \max\{v - (2 - z_j) - r^L_{t-1}, 0\} && \text{if search in stage 1}\\ &\text{Take loan from Bank L} && \text{iff} && v - (2 - z_j) - r^L_{t-1} > \max\{v - z_j - r^H_{t-1}, 0\} && \text{if search in stage 1}\\ &\text{Don't take loan} && \text{iff} && \max\{v - z_j - r^H_{t-1}, v - (2 - z_j) - r^L_{t-1}\} < 0 && \text{if search in stage 1} \end{aligned}$$

Intuitively the borrower will choose whether to borrow or not from his/her bank if he/she didn't search in the previous period. The borrower might still decide not to borrow if the sum of r and z is too high with respect to v. On the other hand, if the borrower did pay the search cost in the previous period then the bank offering the lowest cost for the borrower will capture that borrower.

Remark 7.3. *Banks will compete only over customers that paid the search cost in the first stage.*

7.4 Demand Derivation and Properties

The key addition to the standard Bertrand Competition Game is to incorporate Search and Switching frictions into borrowers' demand. Imagine in county H there is a continuum of agents on the [0,1]. λ_H customers are in Bank H's courtyard and $\lambda_L = 1 - \lambda_H$ are customers of Bank L. The aim is to now construct the aggregate demand that bank H and bank L face. As specified by Remark 7.3 bank H (L) demand will be made of two components: (i) the demand of customers that did not search and belong to H (L) courtyard and the mass of customers that searched from either courtyard. I assume each loan to be of value 1. This means that for banks the demand will purely vary with the number of borrowers that select to search and or to switch. Let's start with the first stage decision. Recall customers have heterogeneous search costs drown each period from a uniform distribution $[0, \bar{\theta}]$. Recall from 7.2 the mass of borrowers deciding to search comes purely from the bank that was charging the higher rate in the previous period, in this case, bank H. The total mass of consumers of courtyard H not searching will be derived as:

$$X_t^{H,NS} = \lambda_H \int_0^{\bar{\theta}} \frac{1}{\bar{\theta}} \mathbb{1}_{\{\theta \geq r_{t-1}^H - r_{t-1}^L\}} d\theta = \lambda_H \frac{1 - (r_{t-1}^H - r_{t-1}^L)}{\bar{\theta}} \tag{12}$$

The total mass of consumers of courtyard H searching will be the residual:

$$X_t^{H,S} = \lambda_H \frac{(r_{t-1}^H - r_{t-1}^L)}{\bar{\theta}} \tag{13}$$

I will redefine these expressions as:

$$X_t^{H,S} = \lambda_H \left[1 - S(r_{t-1}^H - r_{t-1}^L)\right] = \lambda_H \left[1 - S\right] \tag{14}$$

$$X_t^{H,NS} = \lambda_H \left[S(r_{t-1}^H - r_{t-1}^L)\right] = \lambda_H \left[S\right] \tag{15}$$

For bank L, given Remark 7.2 the mass of borrowers will be:

$$X_t^{L,S} = 0 \tag{16}$$

$$X_t^{L,NS} = \lambda_L \tag{17}$$

In the third stage, consumers observe the new interest rates r_t^H and r_t^L (either one or two interest rates depending on whether they paid the search cost in the first period) and their z_j. Recall z_js are uniformly distributed over the $[0, \bar{\Psi}]$ interval. The final demands faced by each of the two firms will have the following structure.

$$
\begin{aligned}
X_t^{H,S}(r_t^H, r_t^L) &= \lambda_H [1-S] \int_0^{\Psi} \frac{1}{\Psi} \mathbb{1}_{\{v-z-r_t^H \geq v-(2-z)-r_t^L\}} dz = \lambda_H [1-S] \left[1 + \frac{r_t^L - r_t^H}{2}\right] && (18)\\
X_t^{H,NS}(r_t^H) &= \lambda_H [S] \int_0^{\Psi} \frac{1}{\Psi} \mathbb{1}_{\{v-z-r_t^H \geq 0\}} dz = \lambda_H [S] \left[v - r_t^H\right] && (19)\\
X_t^{L,S}(r_t^H, r_t^L) &= \lambda_H [1-S] \int_0^{\Psi} \frac{1}{\Psi} \mathbb{1}_{\{v-z-r_t^H < v-(2-z)-r_t^L\}} dz = \lambda_H [1-S] \left[1 + \frac{r_t^H - r_t^L}{2}\right] && (20)\\
X_t^{L,NS}(r_t^L) &= \lambda_L \int_0^{\Psi} \frac{1}{\Psi} \mathbb{1}_{\{v-z-r_t^L \geq 0\}} dz = \lambda_L \left[v - r_t^L\right] && (21)
\end{aligned}
$$

where $X_t^{H,S}$ is the part of demand faced by bank H by potential borrowers of bank H's courtyard who paid the search cost; $X_t^{H,NS}$ is the part of demand faced from bank H by potential borrowers from bank H's courtyard who didn't pay the search cost; $X_t^{L,S}$ is the part of demand faced by bank L by potential borrowers of bank H's courtyard who paid the search cost and finally $X_t^{L,NS}$ is the part of demand faced from bank L by potential borrowers from bank L's courtyard who didn't pay the search cost. We are now ready to derive the respective total demands faced by bank H and bank L.

$$
\begin{aligned}
X_t^H(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L) &= \lambda_H [S] \left[v - r_t^H\right] + \lambda_H [1-S] \left[1 + \frac{r_t^L - r_t^H}{2}\right] && (22)\\
&= \lambda_H [1 + S[v-1]] - \left[\lambda_H S + \frac{1}{2}\lambda_H(1-S)\right] r_t^H + \left[\frac{1}{2}\lambda_H(1-S)\right] r_t^L && (23)\\
X_t^L(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L) &= \lambda_L \left[v - r_t^L\right] + \lambda_H [1-S] \left[1 + \frac{r_t^H - r_t^L}{2}\right] && (24)\\
&= \lambda_L [v] - \left[\lambda_L + \frac{1}{2}\lambda_H(1-S)\right] r_t^L + \left[\frac{1}{2}\lambda_H(1-S)\right] r_t^H && (25)
\end{aligned}
$$

It is easy to see that the obtained demand system is hence linear in interest rates.

7.5 Profit Function

In the second stage, banks observe the demand derived in the previous subsection and decide their prices. I assume each bank offers one type of loan with one interest rate and a fixed marginal cost of producing it $c_t = c_{t-1} + \varepsilon_t^{MP}$. The cost of funds is shifted around by monetary policy. A positive monetary policy shock ε_t^{MP} will increase banks' marginal cost of producing a loan, and a negative monetary policy shock will decrease banks' marginal cost of funds. The profit function of banks H and L will hence be :

$$\begin{aligned}
\pi^H(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L) &= \left[r_t^H - c_t\right]\left[X_t^L(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L)\right] \\
\pi^L(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L) &= \left[r_t^L - c_t\right]\left[X_t^L(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L)\right]
\end{aligned}$$

Each bank's maximization problem will be :

$$\begin{aligned}
&\max_{r_t^H} \quad \pi^H(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L) \\
&\max_{r_t^H} \quad \pi^H(r_t^H, r_t^L, r_{t-1}^H, r_{t-1}^L)
\end{aligned}$$

Notice from the latter maximization program that each bank is internalizing and best responding to the interest rate setting rule of the other bank.

7.6 Equilibrium Prices and Cost Pass-Through

The equilibrium in pure strategies to the Bertrand-Nash game can be defined as the set of prices r_t^H and r_t^L for which neither of the two banks has a profitable deviation. The equilibrium interest rates will be a function of the parameters $(\lambda_L, \lambda_H, r_{t-1}^L, r_{t-1}^H)$. While the exact specification is left to the appendix, here is their general form:

$$\begin{aligned}
r_t^{A*} &= f^H(\lambda_L, \lambda_H, r_{t-1}^L, r_{t-1}^H) + g^H(\lambda_L, \lambda_H, r_{t-1}^L, r_{t-1}^H)c_t \qquad (26) \\
r_t^{B*} &= f^L(\lambda_L, \lambda_H, r_{t-1}^L, r_{t-1}^H) + g^L(\lambda_L, \lambda_H, r_{t-1}^L, r_{t-1}^H)c_t \qquad (27)
\end{aligned}$$

The focus of this paper will be on the response of lending rates to monetary policy shocks. This will amount to studying the functions $g^H(.)$ and $g^L(.)$ of the above expressions.

7.7 Results

The model produces three main results which will be outlined in three propositions.

Proposition 7.4. *:*

(1) $\left[\frac{1}{2}\lambda_H(1-S)\right] < \left[\lambda_H S + \frac{1}{2}\lambda_H(1-S)\right] \Leftrightarrow \frac{1}{2} < \frac{\partial r_H}{\partial c} < 1$

(2) $\left[\frac{1}{2}\lambda_H(1-S)\right] < \left[\lambda_H S + \frac{1}{2}\lambda_H(1-S)\right] \Leftrightarrow \frac{1}{2} < \frac{\partial r_L}{\partial c} < 1$

The above proposition contextualizes the presented game into the wider class of Bertrand Competition Games with Linear demand. The lower bound $\frac{1}{2}$ would be the counterpart partial derivative if no borrower was searching and banks could just behave as monopolists. On the other hand, 1 would be the cost-pass-through if all borrowers were searching and banks would hence behave as standard Bertrand competitors and pass-through any cost shock 1 to 1. In this case, banks are facing heterogeneous demands part of which they can behave as perfect Bertrand competitors and part as local monopolists. The resulting cost-pass-through derivative will be hence in between the two values.

The following proposition is the central result validating the model for the purpose is built for.

Proposition 7.5. $\frac{\partial r_i}{\partial c}$ *is increasing in* $\left(r_{t-1}^H - r_{t-1}^L\right)$.

The proposition shows how both banks tend to have a stronger pass-through when the distribution of interest rates is more dispersed at the beginning of the period. Recalling the previous discussion, as the gap among t-1 interest rates increases more and more borrowers of bank H courtyard will find it convenient to search. This will increase the coefficient which multiplies the opponents' bank rate in the demand function which in turn implies that the price complementarity among the two banks increases. The build intuition let's start with a situation in which banks are local monopolists. In this case, an increase of 1% in c_t will cause an increase of $\frac{1}{2}$% in the equilibrium interest rates of both banks. Now let's imagine that banks can compete on a small group of customers both banks will make an extra effort and pass-through more of the change in the monetary policy shock due to heightened complementarity among the two banks. As this group of borrowers increases so does the pass-through of monetary policy. Notice that the derivative will be also an increasing function of λ_H. Take again the limit of $\lambda_H \to 0$ then Bank L will again just behave as a monopolist because the net gain from acquiring any small fraction of Bank H courtyard is less than the net loss of charging a lower interest rate on customers from own L courtyard.

The third proposition explores the model implications for how the cost-pass-through of the two banks.

Proposition 7.6. $\lambda_L > \lambda_H \mathbb{S}\left(r_{t-1}^H - r_{t-1}^L\right) \Rightarrow \frac{\partial r_H}{\partial c} > \frac{\partial r_L}{\partial c}$.

The cost-pass-through will be different between the two firms. When the mass of consumers not searching for the other bank's rates is such that the L mass is higher than the H mass then the cost-pass-through of Bank H will be higher than Bank L. The intuition for this result is that when the two banks have non-symmetric pools of customers on which they can behave as local monopolists the bank with the higher pool of non-searching customers will behave closer to a monopolist and hence be less responsive to a cost shock. On the opposite, the bank with the lower pool of local monopoly customers will be closer to a symmetric Bertrand competitor with perfect pass-through.

7.8 Empirical Test of Proposition 3

In this subsection, the baseline specification of equation 3 is augmented with an additional term in order to test the theoretical implication driven by proposition 3. While Proposition 2 implies that with high skewness (the r_t^H is more distant from r_t^L and λ_H/λ_L is higher) both banks tend to pass-through more of a change in the monetary policy rate to a change in their respective lending rates, Proposition 3 goes beyond and characterizes how the responses of the two banks compare to each other when skewness is high: banks that are ex-ante charging the higher rate will pass-through more of the change in the monetary policy rate in the following period. In order to test this latter implication the specification is augmented with a triple interaction term between (i) Monetary Policy shock, (ii) Cross-sectional skewness of lending rates, and (iii) a dummy variable that takes value one when the branch has its lending rates in the upper half of the distribution (above median). Naturally, while the results in Section 5 are based on a county/month panel, these results are instead based branch/month unit of observation. Table 3 reports the estimated results for the two main terms of interest, the interaction term between monetary policy and skewness and the interaction terms between monetary policy, skewness, and high-rate bank dummy. Intuitively the first term provides the additional response of all banks to monetary policy when the beginning-of-period cross-sectional skewness is 1 standard deviation above its long-run mean. The second term provides the additional impact of banks that were in the upper half of the lending rate distribution in the previous period. Table 3 below presents the results.

Table 3: Responsiveness of High vs Low Rate Bank to a 100 b.p. monetary policy shock when skewness is high

Month	0	1	2	3	4	5	6	7	8	9	10
High Skewness	-0.01	-0.01	0.03	0.04*	0.06**	0.08***	0.42***	0.45***	0.38***	0.09***	0.20***
	(-0.69)	(-0.39)	(1.25)	(1.89)	(2.35)	(3.40)	(16.37)	(17.43)	(14.81)	(3.41)	(7.91)
High Rate Bank & High Skewness	-0.06*	-0.04	0.01	0.13***	0.15***	0.13***	0.10***	0.07*	0.09**	0.20***	0.14***
	(-2.56)	(-1.24)	(0.40)	(3.46)	(3.91)	(3.31)	(2.61)	(1.69)	(2.21)	(4.90)	(3.52)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	2317536	2200605	2139583	2080359	2028567	1983506	1943036	1898621	1860857	1823443	1784944
R^2	0.977	0.968	0.961	0.955	0.950	0.946	0.943	0.940	0.938	0.936	0.934

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first-row coefficients represent the increase, for each horizon h in the responsiveness of lending rates to the same monetary policy shocks when the skewness is 1 standard deviation above the mean. The second row represents the additional responsiveness in the lending rates to monetary policy changes when both the initial cross-sectional skewness of lending rates is one standard deviation higher than its long-run mean and the branch was charging a high rate in the previous period. In line with the theoretical prediction of the model, all coefficients are overall significant and positive. Whenever the cross-sectional skewness of lending rates is higher, all banks do indeed respond more to a monetary policy shock, but among them, the ones that respond the most are the ones in the tail of the distribution.

8 Conclusion and Future Research

In this paper, I show that the efficacy of monetary policy in shaping economic outcomes crucially depends on the way financial intermediaries respond to it. I document empirically that this response is state dependent. The key state variable is the skewness of the cross-sectional distribution of lending rates across banks at the local level prior to the change in the policy rate.

Contrary to conventional wisdom, I show that, even after controlling for borrower and loan type characteristics the cross-sectional distribution of lending rates exhibits a highly asymmetric shape as measured by the third moment of the distribution, i.e. the cross-sectional skewness. The cross-sectional skewness of lending rates exhibits high-frequency variation both within regions, i.e. states, counties, and MSAs, and across time. Building on a comprehensive dataset matching macroeconomic and banking variables at various levels of dis-aggregation I show that high initial cross-sectional skewness leads to a (i) roughly 70% stronger response of bank lending rates and a roughly 25% stronger response of economic activity to monetary policy.

I develop a model of imperfect competition among banks that accounts for this empirical finding. Banks experience increases (decreases) in their funding costs after an easing (tightening) of monetary policy and strategically compete over borrowers through the interest rates (i.e. they are Bertrand competitors). A key feature of the model is that borrowers face search frictions and switching frictions. Because both searching for a new lender and switching to a new lender is costly, borrowers tend to remain loyal to their *home bank*, i.e. the bank they have a past relationship with. However, if they receive a signal that the returns from searching overcome the cost of searching and switching they will start exploring offers from other banks. A higher degree of skewness among lending rates prior to a new monetary policy shock increases borrowers' expected returns to search. Whenever a larger mass of borrowers is on the search for new lending rates offers banks will know that are larger than usual portion of customers will be easier to poach and the price complementary among interest rates will increase In these circumstances, strategic behavior by banks leads to higher responsiveness of lending rates to policy rate changes. Through this channel, the model can also reconcile my finding that conventional monetary policy has stronger effects on economic activity the more skewness there is in bank lending rates. A further implication of the model is that the banks starting with a higher rate at the beginning of the period will adjust their interest rates more following a new monetary policy shock. When tested empirically this implication is strongly sustained by the data.

Two important policy implications are in order. First, whenever local lending markets exhibit low skewness on average, the response of lending rates to a change in monetary policy will be dampened, and so will the transmission to economic activity. This was the case after periods of many consequent monetary policy easings. Monitoring the cross-sectional skewness of the distribution of lending rates would improve the predictability of monetary policy outcomes therefore a lower discrepancy between the intended and actual outcomes of a new monetary policy decision. Second, policies that reduce borrowers' search and switching frictions could reduce the variability of monetary policy outcomes. This paper fosters the development of a new line of study taking more seriously the role of the organization and market structure of financial intermediaries in the amplification of macroeconomic shocks. In future work, I intend to extend the theoretical model from a duopoly to an oligopoly, and from static to dynamic. Following, I will introduce this model into a quantitatively realistic macro-banking model in order to study its interaction with the other financial frictions already emphasized by the long literature on financial intermediation and more short-lived literature on heterogeneous financial intermediaries.

References

Knut Are Aastveit, Gisle Natvik, and Sergio Sola. Economic uncertainty and the influence of monetary policy. *Journal of International Money and Finance*, 76(C):50–67, 2017.

Viral Acharya, Bjorn Imbierowicz, Sascha Steffen, and Daniel Teichmann. Does the lack of financial stability impair the transmission of monetary policy? *Journal of Financial Economics*, 138(2): 342–365, 2020.

Tobias Adrian and Nina Boyarchenko. Intermediary leverage cycles and financial stability. Staff Reports 567, Federal Reserve Bank of New York, 2015.

Tobias Adrian and Hyun Song Shin. Liquidity and leverage. *Journal of Financial Intermediation*, 19 (3):418–437, 2010. Risk Transfer Mechanisms and Financial Stability.

Sumit Agarwal, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. Regulating consumer financial products: Evidence from credit cards. *The Quarterly Journal of Economics*, 130(1): 111–164, 2015.

Sumit Agarwal, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, Tomasz Piskorski, and Amit Seru. Policy intervention in debt renegotiation: Evidence from the home affordable modification program. *Journal of Political Economy*, 125(3):654 – 712, 2017.

Sumit Agarwal, John Grigsby, Ali Hortacsu, Gregor Matvos, Amit Seru, and Vincent Yao. Searching for approval. NBER Working Papers 27341, National Bureau of Economic Research, Inc, 2020.

Roger Aliaga-Díaz and María Pía Olivero. Macroeconomic implications of "deep habits" in banking. *Journal of Money, Credit and Banking*, 42(8):1495–1521, 2010.

Franklin Allen and Douglas Gale. *Comparing financial systems.* MIT press, 2001.

Jason Allen and Shaoteng Li. Dynamic competition in negotiated price markets. Staff working papers, Bank of Canada, 2020.

Jason Allen, Robert Clark, and Jean-FranÃ§ois Houde. Search frictions and market power in negotiated-price markets. *Journal of Political Economy*, 127(4):1550 – 1598, 2019.

Jason Allen, Robert Clark, Shaoteng Li, and Nicolas Vincent. Debt-relief programs and money left on the table: Evidence from canada's response to covid-19. *Canadian Journal of Economics/Revue canadienne d'Ã©conomique*, 55(S1):9–53, 2022.

Carlo Altavilla, Lorenzo Burlon, Mariassunta Giannetti, and Sarah Holton. Is there a zero lower bound? The effects of negative policy rates on banks and firms. *Journal of Financial Economics*, 2019.

Carlo Altavilla, Fabio Canova, and Matteo Ciccarelli. Mending the broken link: Heterogeneous bank lending rates and monetary policy pass-through. *Journal of Monetary Economics*, 2020.

Fernando Alvarez and Francesco Lippi. Price setting with menu cost for multiproduct firms. *Econometrica*, 82(1):89–135, 2014.

Fernando Alvarez, Hervé Le Bihan, and Francesco Lippi. The real effects of monetary shocks in sticky price models: a sufficient statistic approach. *American Economic Review*, 106(10):2817–51, 2016.

Fernando Alvarez, Francesco Lippi, and Luigi Paciello. Monetary shocks in models with observation and menu costs. *Journal of the European Economic Association*, 16(2):353–382, 05 2017a.

Fernando Alvarez, Francesco Lippi, and Juan Passadore. Are state-and time-dependent models really different? *NBER Macroeconomics Annual*, 31(1):379–457, 2017b.

Fernando E Alvarez, Francesco Lippi, and Luigi Paciello. Optimal price setting with observation and menu costs. *The Quarterly journal of economics*, 126(4):1909–1960, 2011.

Dean F. Amel, Arthur B. Kennickell, and Kevin B. Moore. Banking market definition: evidence from the Survey of Consumer Finances. Technical Report 2008-35, Board of Governors of the Federal Reserve System (U.S.), 2008.

Mary Amiti, Oleg Itskhoki, and Jozef Konings. International shocks, variable markups, and domestic prices. *The Review of Economic Studies*, 86(6):2356–2402, 2019.

Steffen Andersen, John Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai. Sources of inaction in household finance: Evidence from the danish mortgage market. *American Economic Review*, 110 (10):3184–3230, 2020.

Anders Anell, Jens Dietrichson, Lina Maria Ellegard, and Gustav Kjellsson. Information, switching costs, and consumer choice: Evidence from two randomised field experiments in swedish primary health care. *Journal of Public Economics*, 196:104390, 2021.

Ignazio Angeloni and Michael Ehrmann. Monetary transmission in the euro area: early evidence. *Economic Policy*, 18(37):469–501, 2003.

Joshua D. Angrist, Óscar Jordá, and Guido M. Kuersteiner. Semiparametric Estimates of Monetary Policy Effects: String Theory Revisited. *Journal of Business & Economic Statistics*, 36(3):371–387, July 2018.

Costas Arkolakis and Monica Morlacco. Variable demand elasticity, markups, and pass-through. Technical report, Yale University, 2017.

Adrien Auclert. Monetary policy and the redistribution channel. *American Economic Review*, 109(6): 2333–67, June 2019.

Adrien Auclert, Bence Bardóczy, and Matthew Rognlie. Mpcs, mpes and multipliers: A trilemma for new keynesian models. Working Paper 27486, National Bureau of Economic Research, July 2020a.

Adrien Auclert, Matthew Rognlie, and Ludwig Straub. Micro jumps, macro humps: Monetary policy and business cycles in an estimated hank model. Working Paper 26647, National Bureau of Economic Research, January 2020b.

Adrien Auclert, Rodolfo D Rigato, Matthew Rognlie, and Ludwig Straub. New pricing models, same old phillips curves? Technical report, National Bureau of Economic Research, 2022.

Lawrence M. Ausubel. The failure of competition in the credit card market. *The American Economic Review*, 81(1):50–81, 1991.

Emanuele Bajo and Massimiliano Barbi. Financial illiteracy and mortgage refinancing decisions. *Journal of Banking & Finance*, 94(C):279–296, 2018.

Hatice Ozer Balli and Bent E Sørensen. Interaction effects in econometrics. *Empirical Economics*, 45 (1):583–603, 2013.

Anindya Banerjee, Victor Bystrov, and Paul Mizen. How do anticipated changes to short-term market rates influence banks' retail interest rates? evidence from the four major euro area economies. *Journal of Money, Credit and Banking*, 45(7):1375–1414, 2013.

Anindya Banerjee, Victor Bystrov, and Paul Mizen. Structural factor analysis of interest rate pass through in four large euro area economies. Lodz Economics Working Papers 1/2019, University of Lodz, Faculty of Economics and Sociology, 2019.

David Baqaee, Emmanuel Farhi, and Kunal Sangani. The supply-side effects of monetary policy. Working Paper 28345, National Bureau of Economic Research, January 2021.

Regis Barnichon and Christian Matthes. Functional Approximation of Impulse Responses. *Journal of Monetary Economics*, 99(C):41–55, 2018.

Guglielmo Barone, Roberto Felici, and Marcello Pagnini. Switching costs in local credit markets. *International Journal of Industrial Organization*, 29(6):694–704, 2011.

C Basten and M Mariathasan. How banks respond to negative interest rates: Evidence from the swiss exemption threshold (no. 6901). *CESifo Group Munich*, 2018.

Michael D. Bauer and Eric T. Swanson. A Reassessment of Monetary Policy Surprises and High-Frequency Identification. NBER Working Papers 29939, National Bureau of Economic Research, Inc, April 2022.

Juliane Beganau, Saki Bigio, Jeremy Majerovitz, and Matias Vieyra. A Q-Theory of Banks. Technical Report 21-44, Bank of Canada, September 2021.

J Begenau and T Landvoigt. Financial Regulation in a Quantitative Model of the Modern Banking System. *The Review of Economic Studies*, 89(4):1748–1784, 12 2021.

Alan Beggs and Paul Klemperer. Multi-period competition with switching costs. *Econometrica*, 60(3): 651–666, 1992.

Marco Bellifemine, Rustam Jamilov, and Tommaso Monacelli. HBANK: Monetary Policy with Heterogeneous Banks. CEPR Discussion Papers 17129, C.E.P.R. Discussion Papers, March 2022.

Andrea Beltratti, Matteo Benetton, and Alessandro Gavazza. The role of prepayment penalties in mortgage loans. *Journal of Banking & Finance*, 82(C):165–179, 2017.

Martin Beraja, Andreas Fuster, Erik Hurst, and Joseph Vavra. Regional Heterogeneity and the Refinancing Channel of Monetary Policy*. *The Quarterly Journal of Economics*, 134(1):109–183, 09 2018.

Allen Berger and Gregory Udell. Relationship lending and lines of credit in small firm finance. *The Journal of Business*, 68(3):351–81, 1995.

David Berger, Konstantin Milbradt, Fabrice Tourre, and Joseph Vavra. Mortgage prepayment and path-dependent effects of monetary policy. *American Economic Review*, 111(9):2829–78, September 2021.

Ben S Bernanke and Alan S Blinder. Credit, Money, and Aggregate Demand. *American Economic Review*, 78(2):435–439, May 1988.

Ben S Bernanke and Mark Gertler. Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic perspectives*, 9(4):27–48, 1995.

Ben S. Bernanke and Kenneth N. Kuttner. What explains the stock market's reaction to federal reserve policy? *The Journal of Finance*, 60(3):1221–1257, 2005.

Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, 1:1341–1393, 1999.

Javier Bianchi and Saki Bigio. Banks, liquidity management, and monetary policy. *Econometrica*, 90 (1):391–454, 2022.

Saki Bigio and Yuliy Sannikov. A model of credit, money, interest, and prices. Working Paper 28540, National Bureau of Economic Research, March 2021.

Gary Biglaiser, Jacques Crémer, and Gergely Dobos. The value of switching costs. *Journal of Economic Theory*, 148(3):935–952, 2013.

Gary Biglaiser, Jacques CrÃ©mer, and Gergely Dobos. Heterogeneous switching costs. *International Journal of Industrial Organization*, 47:62–87, 2016.

Florin Bilbiie. Monetary Policy and Heterogeneity: An Analytical Framework. Technical report, Working Paper, 2021.

Thomas Bittmann, Jens-Peter Loy, and Sven Anders. Product differentiation and cost pass-through: industry-wide versus firm-specific cost shocks. *Australian Journal of Agricultural and Resource Economics*, 64(4):1184–1209, 2020.

John C Bluedorn, Christopher Bowdler, and Christoffer Koch. Heterogeneous bank lending responses to monetary policy: new evidence from a real-time identification. *47th issue (February 2017) of the International Journal of Central Banking*, 2018.

Jean Boivin and Marc P. Giannoni. Has monetary policy become more effective? *The Review of Economics and Statistics*, 88(3):445–462, 2006.

Jean Boivin, Michael Kiley, and Frederic Mishkin. How has the monetary transmission mechanism evolved over time? In Benjamin M. Friedman and Michael Woodford, editors, *Handbook of Monetary Economics*, volume 3, chapter 08, pages 369–422. Elsevier, 1 edition, 2010.

Claudio E. V. Borio and Wilhelm Fritz. The response of short-term bank lending rates to policy rates: a cross-country perspective. BIS Working Papers 27, Bank for International Settlements, May 1995.

M. Bottero, C. Minoiu, J. Peydró, A. Polo, A. Presbitero, and E. Sette. Expansionary Yet Different: Credit Supply and Real Effects of Negative Interest Rate Policy. CEPR Discussion Paper DP14233, Centre for Economic Policy Research, January 2020.

Martin Brown and Matthias Hoffmann. Relationship banking in the residential mortgage market? evidence from switzerland. *Swiss Journal of Economics and Statistics*, 152(1):23–48, 2016.

M. Brunetti, R. Ciciretti, and Lj. Djordjevic. Till mortgage do us part: Mortgage switching costs and household's bank switching. *Journal of Banking & Finance*, 119:105904, 2020.

Marianna Brunetti, Rocco Ciciretti, and Lj. Djordjevic. The determinants of household's bank switching. *Journal of Financial Stability*, 26(C):175–189, 2016.

Markus Brunnermeier and Lasse Pedersen. Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6):2201–2238, 2009.

Markus K. Brunnermeier and Yuliy Sannikov. A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421, February 2014.

Markus K Brunnermeier and Yuliy Sannikov. The i theory of money. Technical report, National Bureau of Economic Research, 2016.

Markus K Brunnermeier, Thomas M Eisenbach, and Yuliy Sannikov. Macroeconomics with financial frictions: A survey. *National Bureau of Economic Research*, 2012.

Johannes Bubeck, Angela Maddaloni, and José-luis Peydró. Negative monetary policy rates and systemic banks' risk-taking: Evidence from the euro area securities register. *Journal of Money, Credit and Banking*, 52(S1):197–231, 2020.

Francisco J. Buera and Benjamin Moll. Aggregate implications of a credit crunch: The importance of heterogeneity. *American Economic Journal: Macroeconomics*, 7(3):1–42, July 2015.

Ariel Burstein, Vasco M Carvalho, and Basile Grassi. Bottom-up markup fluctuations. Technical report, National Bureau of Economic Research, 2020.

Irene Maria Buso and John Hey. Why do consumers not switch? An experimental investigation of a search and switch model. *Theory and Decision*, 91(4):445–476, November 2021.

Luis Cabral. Dynamic pricing in customer markets with switching costs. *Review of Economic Dynamics*, 20:43–62, 2016.

Dario Caldara and Edward Herbst. Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svars. *American Economic Journal: Macroeconomics*, 11(1):157–92, 2019.

Guillermo A Calvo. Staggered prices in a utility-maximizing framework. *Journal of monetary Economics*, 12(3):383–398, 1983.

John Y Campbell. Household finance. *The journal of finance*, 61(4):1553–1604, 2006.

Fabio Canova and Luca Gambetti. Structural changes in the us economy: Is there a role for monetary policy? *Journal of Economic Dynamics and Control*, 33(2):477–490, 2009.

Santiago Carbo-Valverde, Timothy Hannan, and Francisco Rodriguez-Fernandez. Exploiting old customers and attracting new ones: The case of bank deposit pricing. *European Economic Review*, 55 (7):903–915, 2011.

Agnese Carella and Valentina Michelangeli. Information or persuasion in the mortgage market: the role of brand names. Temi di discussione (Economic working papers) 1340, Bank of Italy, Economic Research and International Relations Area, 2021.

Gerald Carlino and Robert H. DeFina. The differential regional effects of monetary policy: evidence from the u.s. states. Working Papers 97-12, Federal Reserve Bank of Philadelphia, 1997.

Geraldo Cerqueiro, Steven Ongena, and Kasper Roszbach. Collateralization, bank loan rates, and monitoring. *Journal of Finance*, 71(3):1295–1322, 2016.

Gabriel Chodorow-Reich, Adam M Guren, and Timothy J McQuade. The 2000s housing cycle with 2020 hindsight: A neo-kindlebergerian view. Technical report, National Bureau of Economic Research, 2021.

Lawrence J Christiano, Martin Eichenbaum, and Charles L Evans. Monetary policy shocks: What have we learned and to what end? *Handbook of Macroeconomics*, 1:65–148, 1999.

Lawrence J. Christiano, Roberto Motto, and Massimo Rostagno. Risk shocks. *American Economic Review*, 104(1):27–65, January 2014.

LJ Christiano, M Eichenbaum, and C Evans. The effects of monetary policy stocks. evidence from the flow of funds. *The Review of Economics and statistics*, 7811:16–34, 1996.

Stijn Claessens and Luc Laeven. What drives bank competition? some international evidence. *Journal of Money, Credit and Banking*, 36(3):563–583, 2004.

Nuno Coimbra and HÃ©lÃšne Rey. Financial cycles with heterogeneous intermediaries. Working paper, LSE, December 2021.

Dean Corbae and Pablo D'Erasmo. Capital buffers in a quantitative model of banking industry dynamics. *Econometrica*, 89(6):2975–3023, 2021.

Dean Corbae and Ross Levine. Competition, stability, and efficiency in the banking industry. *Manuscript, University of Wisconsin*, 2022.

Dean Corbae, Pablo D'erasmo, et al. A quantitative model of banking industry dynamics. *Federal Reserve Bank of Philadelphia Working Paper*, 14, 2013.

Charlene Cosandier, Filomena Garcia, and Malgorzata Knauff. Price competition with differentiated goods and incomplete product awareness. *Economic Theory*, 66(3):681–705, October 2018.

Carlo Cottarelli and Angeliki Kourelis. Financial structure, bank lending rates, and the transmission mechanism of monetary policy. *Staff Papers (International Monetary Fund)*, 41(4):587–623, 1994.

Vincenzo Cuciniello and Federico M. Signoretti. Large Banks, Loan Rate Markup, and Monetary Policy. *International Journal of Central Banking*, 11(3):141–177, June 2015.

Vasco Cúrdia and Michael Woodford. Credit frictions and optimal monetary policy. *Journal of Monetary Economics*, 84:30–65, 2016.

Gabe J. De Bondt. Interest rate pass-through: Empirical results for the euro area. *German Economic Review*, 6(1):37–78, 2005.

Ferre De Graeve, Olivier De Jonghe, and Rudi Vander Vennet. Competition, transmission and bank pricing policies: Evidence from belgian loan and deposit markets. *Journal of Banking & Finance*, 31(1):259–278, 2007.

Davide Debortoli, Jordi GalÃ, and Luca Gambetti. On the Empirical (Ir)relevance of the Zero Lower Bound Constraint. In *NBER Macroeconomics Annual 2019, volume 34*, NBER Chapters, pages 141–170. National Bureau of Economic Research, Inc, June 2019.

Hans Degryse and Patrick Van Cayseele. Relationship lending within a bank-based system: Evidence from european small business data. *Journal of Financial Intermediation*, 9(1):90–109, 2000.

Selva Demiralp, Jens Eisenschmidt, and Thomas Vlassopoulos. Negative interest rates, excess liquidity and bank business models: Banks' reaction to unconventional monetary policy in the euro area. Technical report, Working Paper, 2017.

Florian Deuflhard. Quantifying inertia in retail deposit markets. Technical Report 223, Leibniz Institute for Financial Research SAFE, 2018.

Sebastian Di Tella and Pablo Kurlat. Why are banks exposed to monetary policy? *American Economic Journal: Macroeconomics*, 13(4):295–340, October 2021.

Douglas W Diamond and Philip H Dybvig. Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, 91(3):401–419, June 1983.

Michael Dinerstein, Liran Einav, Jonathan Levin, and Neel Sundaresan. Consumer price search and platform design in internet commerce. *American Economic Review*, 108(7):1820–59, 2018.

Hendrik Döpper, Alexander MacKay, Nathan Miller, and Joel Stiebale. Rising markups and the role of consumer preferences. *Available at SSRN 3939126*, 2021.

Itamar Drechsler, Alexi Savov, and Philipp Schnabl. The Deposits Channel of Monetary Policy*. *The Quarterly Journal of Economics*, 132(4):1819–1876, 05 2017.

Itamar Drechsler, Alexi Savov, and Philipp Schnabl. A model of monetary policy and risk premia. *The Journal of Finance*, 73(1):317–373, 2018.

Itamar Drechsler, Alexi Savov, and Philipp Schnabl. Banking on deposits: Maturity transformation without interest rate risk. *The Journal of Finance*, 76(3):1091–1143, 2021.

John C. Driscoll and Ruth Judson. Sticky deposit rates. Finance and Economics Discussion Series 2013-80, Board of Governors of the Federal Reserve System (U.S.), 2013.

Jean-Pierre Dube, Guenter J. Hitsch, and Peter Rossi. Do switching costs make markets less competitive? 2006 Meeting Papers 514, Society for Economic Dynamics, 2006.

William Dudley. The recovery and monetary policy. Speech 89, Federal Reserve Bank of New York, 2012.

Mark Egan, Ali Hortaçsu, and Gregor Matvos. Deposit competition and financial fragility: Evidence from the us banking sector. *American Economic Review*, 107(1):169–216, January 2017.

Gauti B Eggertsson, Ragnar E Juelsrud, Lawrence H Summers, and Ella Getz Wold. Negative nominal interest rates and the bank lending channel. Working Paper 25416, National Bureau of Economic Research, January 2019.

Martin Eichenbaum, Nir Jaimovich, and Sergio Rebelo. Reference prices, costs, and nominal rigidities. *American Economic Review*, 101(1):234–62, February 2011.

Martin Eichenbaum, Sergio Rebelo, and Arlene Wong. State-dependent effects of monetary policy: The refinancing channel. *American Economic Review*, 112(3):721–61, March 2022.

Glenn Ellison and Sara Fisher Ellison. Search, obfuscation, and price elasticities on the internet. *Econometrica*, 77(2):427–452, 2009.

Elyas Elyasiani, Kenneth J Kopecky, and David Van Hoose. Costs of adjustment, portfolio separation, and the dynamic behavior of bank loans and deposits. *Journal of Money, Credit and Banking*, 27 (4):955–974, 1995.

Henrik Erikson and David Vestin. Pass-through at mildly negative policy rates: The swedish case. *Sveriges Riksbank Staff Memo*, pages 1–32, 2019.

Natalia Fabra and Alfredo García. Market structure and the competitive effects of switching costs. *Economics Letters*, 126(C):150–155, 2015.

Joseph Farrell and Paul Klemperer. Coordination and lock-in: Competition with switching costs and network effects. *Handbook of industrial organization*, 3:1967–2072, 2007.

Jesús Fernández-Villaverde, Samuel Hurtado, and Galo Nuno. Financial frictions and the wealth distribution. Technical report, National Bureau of Economic Research, 2019.

Ana-Maria Fuertes and Shelagh A. Heffernan. Interest rate transmission in the UK: a comparative analysis across financial firms and products. *International Journal of Finance & Economics*, 14(1): 45–63, 2009.

Andreas Fuster, L. Goodman, D. Lucca, L. Madar, L. Molloy, and Paul Willen. The rising gap between primary and secondary mortgage rate. *FRB NY Econ. Policy Rev.*, 19:17–39, 01 2013.

Leonardo Gambacorta. Inside the bank lending channel. *European Economic Review*, 49(7):1737–1759, 2005.

Leonardo Gambacorta and S. Iannotti. Are there asymmetries in the response of bank interest rates to monetary shocks? *Applied Economics*, 39(19):2503–2517, 2007.

Leonardo Gambacorta and Paolo Emilio Mistrulli. Bank heterogeneity and interest rate setting: What lessons have we learned since lehman brothers? *Journal of Money, Credit and Banking*, 46(4): 753–778, 2014.

Leonardo Gambacorta and Paul Mizen. 369Inside the Bank Box: Evidence on Interest-Rate Pass-Through and Monetary Policy Transmission. In *The Oxford Handbook of the Economics of Central Banking*. Oxford University Press, 04 2019. ISBN 9780190626198.

Leonardo Gambacorta and Hyun Song Shin. Why bank capital matters for monetary policy. *Journal of Financial Intermediation*, 35:17–29, 2018. Banking and regulation: the next frontier.

Amelie Gamble, E. Asgeir Juliusson, and Tommy GÃ€rling. Consumer attitudes towards switching supplier in three deregulated markets. *Journal of Behavioral and Experimental Economics (formerly The Journal of Socio-Economics)*, 38(5):814–819, 2009.

Georgios Georgiadis. Towards an explanation of cross-country asymmetries in monetary transmission. *Journal of Macroeconomics*, 39(PA):66–84, 2014.

Andrea Gerali, Stefano Neri, Luca Sessa, and Federico M. Signoretti. Credit and banking in a dsge model of the euro area. *Journal of Money, Credit and Banking*, 42(s1):107–141, 2010.

Mark Gertler and Peter Karadi. Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76, January 2015.

Mark Gertler and Nobuhiro Kiyotaki. Chapter 11 - financial intermediation and credit policy in business cycle analysis. In Benjamin M. Friedman and Michael Woodford, editors, *Handbook of Monetary Economics*, volume 3, pages 547–599. Elsevier, 2010.

Mark Gertler, N. Kiyotaki, and A. Prestipino. Wholesale banking and bank runs in macroeconomic modeling of financial crises. In *Handbook of macroeconomics*, volume 2, chapter Chapter 16, pages 1345–1425. Elsevier, 2016.

Mark Gertler, Nobuhiro Kiyotaki, and Andrea Prestipino. A Macroeconomic Model with Financial Panics. *Review of Economic Studies*, 87(1):240–288, 2020.

Simon Gilchrist and Egon Zakrajšek. Credit spreads and business cycle fluctuations. *American economic review*, 102(4):1692–1720, 2012.

Simon Gilchrist, Raphael Schoenle, Jae Sim, and Egon Zakrajšek. Inflation dynamics during the financial crisis. *American Economic Review*, 107(3):785–823, 2017.

Isabel Gödl-Hanisch. Bank concentration and monetary policy pass-through. Technical report, FDIC Center for Financial Research Paper No. 2022-06, June 2022.

Mikhail Golosov and Robert E Lucas Jr. Menu costs and phillips curves. *Journal of Political Economy*, 115(2):171–199, 2007.

Sílvia Gonçalves, Ana María Herrera, Lutz Kilian, and Elena Pesavento. When do state-dependent local projections work? *CEPR Discussion Paper No. DP17265*, 2022.

Xulia González and Daniel Miles-Touya. Price dispersion, chain heterogeneity, and search in online grocery markets. *SERIEs: Journal of the Spanish Economic Association*, 9(1):115–139, 2018.

Marvin Goodfriend and Bennett McCallum. Banking and interest rates in monetary policy analysis: A quantitative exploration. *Journal of Monetary Economics*, 54(5):1480–1507, 2007.

Charles Goodhart. Why do the monetary authorities smooth interest rates? *SPECIAL PAPER-LSE FINANCIAL MARKETS GROUP*, 1996.

Gita Gopinath and Oleg Itskhoki. Frequency of price adjustment and pass-through. *The Quarterly Journal of Economics*, 125(2):675–727, 2010.

Francois Gourio and Leena Rudanko. Customer capital. *Review of Economic Studies*, 81(3):1102–1136, 2014.

Jiří Gregor, Aleš Melecký, and Martin Melecký. Interest rate pass-through: A meta-analysis of the literature. *Journal of Economic Surveys*, 35(1):141–191, 2021.

Refet S Gürkaynak, Brian Sack, and Eric Swanson. Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking*, 1(1), May 2005.

Timothy Hannan and Robert M. Adams. Consumer switching costs and firm pricing: Evidence from bank pricing deposit accounts. *Journal of Industrial Economics*, 59(2):296–320, 2011.

Timothy Hannan and Allen Berger. The rigidity of prices: Evidence from the banking industry. *American Economic Review*, 81(4):938–45, 1991.

Timothy Hannan, Elizabeth K. Kiser, Robin A. Prager, and James McAndrews. To surcharge or not to surcharge: An empirical investigation of atm pricing. *The Review of Economics and Statistics*, 85 (4):990–1002, 2003.

Jonathon Hazell, Juan Herreño, Emi Nakamura, and Jón Steinsson. The slope of the phillips curve: Evidence from u.s. states. Working Paper 28005, National Bureau of Economic Research, October 2020.

Zhiguo He and Arvind Krishnamurthy. Intermediary asset pricing. *American Economic Review*, 103 (2):732–70, April 2013.

Florian Heider, Farzad Saidi, and Glenn Schepens. Life below Zero: Bank Lending under Negative Policy Rates. *The Review of Financial Studies*, 32(10):3728–3761, 02 2019.

Florian Heider, Farzad Saidi, and Glenn Schepens. Banks and negative interest rates. *Annual Review of Financial Economics*, 13(1):201–218, 2021.

Florian Heiss, Carmine Ornaghi, and Mirco Tonin. Inattention vs switching costs: An analysis of consumers' inaction in choosing a water tariff. DICE Discussion Papers 366, Heinrich Heine University DÃŒsseldorf, DÃŒsseldorf Institute for Competition Economics (DICE), 2021.

Charles Hodgson and Gregory Lewis. You can lead a horse to water: Spatial learning and path dependence in consumer search. Cowles Foundation Discussion Papers 2246, Cowles Foundation for Research in Economics, Yale University, 2020.

Boris Hofmann. Non-linear base rate pass-through in banks' and building societies' retail rates. Technical report, Citeseer, 2002.

Boris Hofmann and Paul Mizen. Interest rate pass-through and monetary transmission: Evidence from individual financial institutions' retail rates. *Economica*, 71(281):99–123, 2004.

Boris Hofmann, Anamaria Illes, Marco Lombardi, and Paul Mizen. The impact of unconventional monetary policies on retail lending and deposit rates in the euro area. BIS Working Papers 850, Bank for International Settlements, 2020.

Bengt Holmstrom and Jean Tirole. Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, 112(3):663–691, 1997.

Sarah Holton and Costanza Rodriguez d'Acri. Interest rate pass-through since the euro area crisis. *Journal of Banking & Finance*, 96(C):277–291, 2018.

Nikolay Hristov, Oliver Hülsewig, and Timo Wollmershäuser. The interest rate pass-through in the euro area during the global financial crisis. *Journal of Banking & Finance*, 48(C):104–119, 2014.

Alberto Humala. Interest rate pass-through and financial crises: do switching regimes matter? the case of argentina. *Applied Financial Economics*, 15(2):77–94, 2005.

Erik Hurst, Benjamin J. Keys, Amit Seru, and Joseph Vavra. Regional redistribution through the us mortgage market. *American Economic Review*, 106(10):2982–3028, October 2016.

Gastón Illanes. Switching costs in pension plan choice. Working paper, Northwestern University, 2017.

Anamaria Illes, Marco Lombardi, and Paul Mizen. Why did bank lending rates diverge from policy rates after the financial crisis? Discussion Papers 2015/05, University of Nottingham, Centre for Finance, Credit and Macroeconomics (CFCM), 2015.

Vasso Ioannidou and Steven Ongena. "time for a change": Loan conditions and bank behavior when firms switch banks. *Journal of Finance*, 65(5):1847–1877, 2010.

Suleymanova Irina and Wey Christian. Bertrand Competition in Markets with Network Effects and Switching Costs. *The B.E. Journal of Economic Analysis & Policy*, 11(1):1–58, September 2011.

Rajkamal Iyer and Manju Puri. Understanding bank runs: The importance of depositor-bank relationships and networks. *American Economic Review*, 102(4):1414–45, 2012.

Rajkamal Iyer, Manju Puri, and Nicholas Ryan. A tale of two runs: Depositor responses to bank solvency risk. *Journal of Finance*, 71(6):2687–2726, 2016.

Rustam Jamilov and Tommaso Monacelli. Bewley banks. *Available at SSRN 3732172*, 2021.

Marek Jarociński and Peter Karadi. Deconstructing monetary policy surprises-the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43, April 2020.

Urban Jermann and Vincenzo Quadrini. Macroeconomic effects of financial shocks. *American Economic Review*, 102(1):238–71, February 2012.

Gabriel Jiménez, Steven Ongena, José-Luis Peydró, and Jesús Saurina. Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102(5):2301–26, May 2012.

Gabriel Jiménez, Steven Ongena, José-Luis Peydró, and Jesús Saurina. Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82(2):463–505, 2014.

Oscar Jorda. Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182, 2005.

V. JRios Rull, T. Takamura, and Y. Terajima. Banking Dynamics and Capital Requirements. Technical report, manuscript, 2020.

Charles Kahn, George Pennacchi, and Ben Sopranzetti. Bank consolidation and the dynamics of consumer loan interest rates. *The Journal of Business*, 78(1):99–134, 2005.

Greg Kaplan, Benjamin Moll, and Giovanni L. Violante. Monetary policy according to hank. *American Economic Review*, 108(3):697–743, March 2018.

Greg Kaplan, Kurt Mitman, and Giovanni L. Violante. The Housing Boom and Bust: Model Meets Evidence. *Journal of Political Economy*, 128(9):3285–3345, 2020.

Anil Kashyap and Jeremy Stein. The impact of monetary policy on bank balance sheets. *Carnegie-Rochester Conference Series on Public Policy*, 42(1):151–195, 1995.

Anil Kashyap and Jeremy C. Stein. What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428, June 2000.

Rohan Kekre and Moritz Lenel. Monetary Policy, Redistribution, and Risk Premia. Working Papers 2020-02, Becker Friedman Institute for Research In Economics, 2020.

Robert Kelly and David Byrne. Bank asset quality and monetary policy pass-through. ESRB Working Paper Series 98, European Systemic Risk Board, July 2019.

Benjamin Keys, Devin Pope, and Jaren C. Pope. Failure to refinance. *Journal of Financial Economics*, 122(3):482–499, 2016.

Donghun Kim and Ronald W. Cotterill. Cost pass-through in differentiated product markets: The case of u.s. processed cheese. *The Journal of Industrial Economics*, 56(1):32–48, 2008.

Moshe Kim, Doron Kliger, and Bent Vale. Estimating switching costs: the case of banking. *Journal of Financial Intermediation*, 12(1):25–56, 2003.

Ruby P Kishan and Timothy Opiela. Bank size, bank capital, and the bank lending channel. *Journal of Money, Credit and Banking*, 32(1):121–41, 2000.

Nobuhiro Kiyotaki and John Moore. Credit Cycles. *Journal of Political Economy*, 105(2):211–248, April 1997.

Michael A. Klein. A theory of the banking firm. *Journal of Money, Credit and Banking*, 3(2):205–218, 1971.

Paul Klemperer. The competitiveness of markets with switching costs. *The RAND Journal of Economics*, 18(1):138–150, 1987.

Paul Klemperer. Competition when Consumers have Switching Costs: An Overview with Applications to Industrial Organization, Macroeconomics, and International Trade. *The Review of Economic Studies*, 62(4):515–539, 10 1995.

Matthew Klepacz. Price setting and volatility: Evidence from oil price volatility shocks. *International Finance Discussion Paper*, 1316, 2021.

Kenneth J Kopecky and David D Van Hoose. Imperfect competition in bank retail markets, deposit and loan rate dynamics, and incomplete pass through. *Journal of Money, Credit and Banking*, 44 (6):1185–1205, 2012.

Erling Motzfeldt Kravik and Yasin Mimir. Navigating with nemo. Technical report, Staff Memo, 2019.

Elizaveta Krylova, Matthieu Darracq Pariés, Diego Moccero, and Claudia Marchini. The retail bank interest rate pass-through: The case of the euro area during the financial and sovereign debt crisis. Technical Report 155, ECB WP, September 2014.

Kenneth Kuttner. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics*, 47(3):523–544, 2001a.

Kenneth Kuttner and Patricia C. Mosser. The monetary transmission mechanism: some answers and further questions. *Economic Policy Review*, 8(May):15–26, 2002.

Kenneth N Kuttner. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of monetary economics*, 47(3):523–544, 2001b.

Claudia Kwapil and Johann Scharler. Interest rate pass-through, monetary policy rules and macroeconomic stability. *Journal of International Money and Finance*, 29(2):236–251, 2010.

Claudia Kwapil, Johann Scharler, et al. Limited pass-through from policy to retail interest rates: empirical evidence and macroeconomic implications. *Monetary policy and the Economy Q*, 4:26–36, 2006.

James M. Lacko and Janis K. Pappalardo. The failure and promise of mandated consumer mortgage disclosures: Evidence from qualitative interviews and a controlled experiment with mortgage borrowers. *The American Economic Review*, 100(2):516–521, 2010.

W. Lam. Switching costs in two-sided markets. LIDAM Discussion Papers CORE 2015024, UniversitÃ© catholique de Louvain, Center for Operations Research and Econometrics (CORE), 2015.

Jun Li and Serguei Netessine. Higher market thickness reduces matching rate in online platforms: Evidence from a quasiexperiment. *Management Science*, 66(1):271–289, 2020.

Ming-Hua Liu, Dimitri Margaritis, and Alireza Tourani-Rad. Monetary policy transparency and pass-through of retail interest rates. *Journal of Banking & Finance*, 32(4):501–511, 2008.

Ming Chien Lo and Jeremy Piger. Is the response of output to monetary policy asymmetric? evidence from a regime-switching coefficients model. *Journal of Money, Credit and Banking*, 37(5):865–886, 2005.

Jens-Peter Loy and Christoph Weiss. Product differentiation and cost pass-through. *Journal of Agricultural Economics*, 70(3):840–858, 2019.

Fernando Luco. Switching costs and competition in retirement investment. *American Economic Journal: Microeconomics*, 11(2):26–54, May 2019.

Alexander MacKay and Marc Remer. Consumer inertia and market power. *Available at SSRN 3380390*, 2022.

Ulrike Malmendier and Young Han Lee. The bidder's curse. *American Economic Review*, 101(2): 749–87, April 2011.

Ana maria Fuertes and Shelagh A. Heffernan. Bank heterogeneities in the interest rate transmission mechanism. working paper, 2006 finance faculty working paper series, 2006.

Filip Matějka and Alisdair McKay. Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review*, 105(1):272–98, 2015.

Sophocles Mavroeidis. Identification at the zero lower bound. *Econometrica*, 89(6):2855–2885, 2021.

Alisdair McKay and Johannes F Wieland. Lumpy durable consumption demand and the limited ammunition of monetary policy. *Econometrica*, 89(6):2717–2749, 2021.

Caterina Mendicino, Federico Puglisi, and Dominik Supera. Beyond zero: Are policy rate cuts still expansionary? Working paper, Available at SSRN 4015500, February 2022.

Karel Mertens and Morten O. Ravn. The dynamic effects of personal and corporate income tax changes in the united states. *American Economic Review*, 103(4):1212–47, June 2013.

Atif Mian, Kamalesh Rao, and Amir Sufi. Household Balance Sheets, Consumption, and the Economic Slump*. *The Quarterly Journal of Economics*, 128(4):1687–1726, 09 2013.

Virgiliu Midrigan. Menu costs, multiproduct firms, and aggregate fluctuations. *Econometrica*, 79(4): 1139–1180, 2011.

Silvia Miranda-Agrippino and Giovanni Ricco. The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, Forthcoming, 2021.

Frederic S. Mishkin. The Channels of Monetary Transmission: Lessons for Monetary Policy. NBER Working Papers 5464, National Bureau of Economic Research, Inc, February 1996.

Benoit Mojon. Financial structure and the interest rate channel of ecb monetary policy. Working Paper Series 40, European Central Bank, 2000.

Simon Mongey. Market structure and monetary non-neutrality. Technical report, National Bureau of Economic Research, 2021.

Mario Monti. *Deposit, credit and interest rate determination under alternative bank objective function.* North-Holland/American Elsevier, 1972.

Giuseppe Moscarini. Limited information capacity as a source of inertia. *Journal of Economic Dynamics and control*, 28(10):2003–2035, 2004.

N. Moshkin and R. Shachar. Switching costs or search costs? Working papers, Tel Aviv, 2000.

Emi Nakamura and Jon Steinsson. Monetary non-neutrality in a multisector menu cost model. *The Quarterly journal of economics*, 125(3):961–1013, 2010.

Emi Nakamura and Jón Steinsson. High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330, 2018.

Emi Nakamura and Dawit Zerom. Accounting for incomplete pass-through. *The review of economic studies*, 77(3):1192–1230, 2010.

David Neumark and Steven Sharpe. Market structure and the nature of price rigidity: Evidence from the market for consumer deposits. *The Quarterly Journal of Economics*, 107(2):657–680, 1992.

Tore Nilssen. Two kinds of consumer switching costs. *The RAND Journal of Economics*, 23(4):579–589, 1992.

Galo Nuño and Carlos Thomas. Bank leverage cycles. *American Economic Journal: Macroeconomics*, 9(2):32–72, April 2017.

Pablo Ottonello and Thomas Winberry. Financial heterogeneity and the investment channel of monetary policy. *Econometrica*, 88(6):2473–2502, 2020.

Joe Peek and Eric S. Rosengren. Bank lending and the transmission of monetary policy. *Conference Series ; [Proceedings]*, 39:47–79, 1995.

Gert Peersman and Frank Smets. Are the effects of monetary policy in the euro area greater in recessions than in booms? Working Paper Series 52, European Central Bank, 2001.

Anil Perera and Jayasinghe Wickramanayake. Determinants of commercial bank retail interest rate adjustments: Evidence from a panel data model. *Journal of International Financial Markets, Institutions and Money*, 45(C):1–20, 2016.

Mitchell Petersen and Raghuram Rajan. The benefits of lending relationships: Evidence from small business data. *Journal of Finance*, 49(1):3–37, 1994.

Mikkel Plagborg-Møller and Christian K. Wolf. Local Projections and VARs Estimate the Same Impulse Responses. *Econometrica*, 89(2):955–980, March 2021.

Mikkel Plagborg-Møller and Christian K Wolf. Local projections and vars estimate the same impulse responses. *Econometrica*, 89(2):955–980, 2021.

Jacquelyn Pless and Arthur A. van Benthem. Pass-through as a test for market power: An application to solar subsidies. *American Economic Journal: Applied Economics*, 11(4):367–401, October 2019.

Alberto Polo. Imperfect pass-through to deposit rates and monetary policy transmission. Technical report, Bank of England, 2021.

Giorgio E. Primiceri. Time Varying Structural Vector Autoregressions and Monetary Policy. *Review of Economic Studies*, 72(3):821–852, 2005.

Valerie Ramey. Macroeconomic shocks and their propagation. In *Handbook of Macroeconomics*, volume 2, chapter Chapter 2, pages 71–162. Elsevier, 2016.

Valerie A. Ramey and Sarah Zubairy. Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data. *Journal of Political Economy*, 126(2):850–901, 2018.

Morten Ravn, Stephanie Schmitt-Grohe, and MartÃn Uribe. Deep habits. *Review of Economic Studies*, 73(1):195–218, 2006.

Morten O Ravn and Vincent Sterk. Macroeconomic Fluctuations with HANK & SAM: an Analytical Approach. *Journal of the European Economic Association*, 19(2):1162–1202, 2021.

Ricardo Reis. Inattentive Producers. *The Review of Economic Studies*, 73(3):793–821, 07 2006.

Fernández Rojas. Monetary policy, bank heterogeneity and the marginal propensity to lend. Technical report, Boston University, 2020.

Christina Romer and David Romer. Does monetary policy matter? a new test in the spirit of friedman and schwartz. In *NBER Macroeconomics Annual 1989, Volume 4*, pages 121–184. National Bureau of Economic Research, Inc, 1989.

Julio Rotemberg and Garth Saloner. The relative rigidity of monopoly pricing. *American Economic Review*, 77(5):917–26, 1987.

Glenn D. Rudebusch. Do measures of monetary policy in a var make sense? *International Economic Review*, 39(4):907–931, 1998.

B Sack. Does the fed work gradually? a var analysis. *Federal Reserve Board of Governors, FEDS Working Paper*, 17, 1998.

Evens Salies. Product innovation when consumers have switching costs. In *Handbook on the Economics and Theory of the Firm*, chapter 31. Edward Elgar Publishing, 2012.

Harald Sander and Stefanie Kleimeier. Asymmetric adjustment of commercial bank interest rates in the euro area: implications for monetary policy. In *University of Groningen's Conference on "Financial Structure, Bank Behaviour, and Monetary Policy in the EMU", Groningen*. Citeseer, 05 2000.

Harald Sander and Stefanie Kleimeier. Convergence in euro-zone retail banking? what interest rate pass-through tells us about monetary policy transmission, competition and integration. *Journal of International Money and Finance*, 23(3):461–492, 2004. Banking, Development and Structural Change.

Emiliano Santoro, Ivan Petrella, Damjan Pfajfar, and Edoardo Gaffeo. Loss aversion and the asymmetric transmission of monetary policy. *Journal of Monetary Economics*, 68(C):19–36, 2014.

David S. Scharfstein and Adi Sunderam. Market power in mortgage lending and the transmission of monetary policy. Mimeo, HBS, 2016.

Johann Scharler. Do bank-based financial systems reduce macroeconomic volatility by smoothing interest rates? *Journal of Macroeconomics*, 30(3):1207–1221, 2008.

Steven Sharpe. Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance*, 45(4):1069–87, 1990.

Steven A. Sharpe. The effect of consumer switching costs on prices: A theory and its application to the bank deposit market. *Review of Industrial Organization*, 12(1):79–94, 1997.

Mengze Shi. A theoretical analysis of endogenous and exogenous switching costs. *Quantitative Marketing and Economics (QME)*, 11(2):205–230, June 2013.

Martin Shubik and Richard Levitan. *Market Structure and Behavior*. Harvard University Press, Cambridge, MA and London, England, 1980.

Christopher A Sims. Implications of rational inattention. *Journal of monetary Economics*, 50(3): 665–690, 2003.

Christopher A Sims. Rational inattention: Beyond the linear-quadratic case. *American Economic Review*, 96(2):158–163, 2006.

Jeremy C. Stein. An adverse-selection model of bank asset and liability management with implications for the transmission of monetary policy. *The RAND Journal of Economics*, 29(3):466–486, 1998.

Joseph E. Stiglitz and Andrew Weiss. Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3):393–410, 1981.

James H. Stock and Mark W. Watson. Disentangling the Channels of the 2007-09 Recession. *Brookings Papers on Economic Activity*, 43(1 (Spring):81–156, 2012.

Eric T. Swanson. Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118(C):32–53, 2021.

John B Taylor. Aggregate dynamics and staggered contracts. *Journal of political economy*, 88(1):1–23, 1980.

Silvana Tenreyro and Gregory Thwaites. Pushing on a string: Us monetary policy is less powerful in recessions. *American Economic Journal: Macroeconomics*, 8(4):43–74, October 2016.

Mauricio Ulate. Going negative at the zero lower bound: The effects of negative nominal interest rates. *American Economic Review*, 111(1):1–40, January 2021.

Skander Van den Heuvel. Does bank capital matter for monetary transmission? *Economic Policy Review*, 8(May):259–265, 2002.

Michiel van Leuvensteijn, Christoffer Kok SÃžrensen, Jacob A. Bikker, and Adrian A.R.J.M. van Rixtel. Impact of bank competition on the interest rate pass-through in the euro area. *Applied Economics*, 45(11):1359–1380, April 2013.

Alessandro T Villa. Credit misallocation and macro dynamics with oligopolistic financial intermediaries. unpublished, 2022.

Xavier Vives. Competition in the Changing World of Banking. *Oxford Review of Economic Policy*, 17 (4):535–547, 12 2001.

Julia von Borstel, Sandra Eickmeier, and Leo Krippner. The interest rate pass-through in the euro area during the sovereign debt crisis. *Journal of International Money and Finance*, 68(C):386–402, 2016.

Olivier Wang. Banks, low interest rates, and monetary policy transmission. Working Paper Series 2492, European Central Bank, November 2020.

Yifei Wang, Toni M. Whited, Yufeng Wu, and Kairong Xiao. Bank market power and monetary policy transmission: Evidence from a structural estimation. *The Journal of Finance*, 77(4):2093–2141, 2022.

Zongrun Wang and Mei Yang. Effective allocation of financial services intensity and its impact on channel competition. *Managerial and Decision Economics*, 41(8):1473–1492, 2020.

Michael Waterson. The role of consumers in competition and competition policy. *International Journal of Industrial Organization*, 21(2):129–150, 2003.

Stefan Weiergraeber. Network Effects And Switching Costs In The U.S. Wireless Industry. *International Economic Review*, 63(2):601–630, May 2022.

Chris M. Wilson. Market frictions: A unified model of search costs and switching costs. *European Economic Review*, 56(6):1070–1086, 2012.

Michael Woodford. Information-constrained state-dependent pricing. *Journal of Monetary Economics*, 56:S100–S124, 2009.

Vladimir Yankov. In search of a risk-free asset: Search costs and sticky deposit rates. *Available at SSRN 2044882*, 2018.

Alexander K. Zentefis. Bank net worth and frustrated monetary policy. *Journal of Financial Economics*, 138(3):687–699, 2020.

State-Dependent Pass-Through from Monetary Policy to Lending Rates

Supplementary Material – Online Appendix

A Extended Literature Review

This paper contributes to three main strands of literature. First it relates to the very recent work uncovering state-dependent effects of Monetary Policy. Two my knowledge only two works are involved in this study, namely Berger et al. (2021) and Eichenbaum et al. (2022). The two papers study how prepayment and refinancing decisions on house mortgages lead to state-dependent efficacy of monetary policy. Consumers face a cost in refinancing or prepaying their mortgage which implies they keep their mortgage as it is unless the gains/savings in terms of interest expense from refinancing and/or prepaying their existing mortgage are sufficiently high. This implies that when monetary policy shifts interest rates down only a fraction of the consumers locked in sufficiently high rates will move.[33] The state-dependence comes from the fact that if the distribution of the spreads between the existing and new rates has a high mean a lot of consumers will refinance otherwise only a few will. As a result successive shocks decreasing interest rates will result in almost all consumer refinancing, which in turn decreases the efficacy of next monetary policy shocks going in the same direction. My paper notably innovates in this literature in three different ways. First it relates monetary policy state-dependence to the supply rather than the demand side of Loan Markets by focusing on frictions affecting banks strategic pricing decisions. The two channels are complementary yet reinforcing. If banks do not face incentives from poaching customers from their competition, lending rates would respond by less to monetary policy intervention which in turn implies that less borrowers will have incentives from refinancing. Second the form of state-dependence outlined in this paper works in both the directions of an easing and a tightening of monetary policy. Banks whose rates are standing in the tail of the distribution are constrained by their competition to keep their rates lower than they otherwise would be, as monetary policy shifts marginal costs up, this constrained is progressively released hence leading to an expansion of the distribution up. Third it shows how not only the mean of the past distribution of interest rates is a relevant variable for the evaluation of the monetary policy pass-through but higher order moments of the same distribution carry equally important information. Last the channel outlined in this paper carries also to consumer loans and Commercial and Industrial Loans.

In a similar flavour to Beraja et al. (2018) regional heterogeneity is a key driver in the amplification of monetary policy effects. In their paper the authors argue that regional heterogeneities in the distribution of housing equity significantly impacts the response of refinancing decision following interest rates cuts. Central Banks should hence track the regional distribution of equity over time. Similarly this paper argues that the regional heterogeneity in the cross-sectional distribution of lending rates drives the banks response to successive interest rates. Differently from their paper, I document how the regional heterogeneity in the local market structure of banking industry gives rise to endogenous time-varying intensity in bank price competition and I show its effects on following monetary policy pass-through interest not only for house mortgage decisions but also for several other types of loans.

The channel outlined in this paper is related to the literature arguing for the importance of bank's market power in bank's pricing decisions and hence on monetary policy pass-through. Notable recent examples are Gödl-Hanisch (2022), Scharfstein and Sunderam (2016), Corbae and Levine (2022), Wang (2020) and Wang et al. (2022). By using the same branch-level source of data used in this paper, the author is able to disentangle the importance of bank concentration and bank capitalization showing that both channels together with their interaction are greatly important for the monetary policy pass-through. In line with this work, this paper shows that market power plays an important

[33] a similar loss in monetary policy efficacy working through lumpy consumer spending on durable goods has been proposed by McKay and Wieland (2021).

role in the determination of loan rate pass-through on a broad set of data outside the shared dataset. In contrast with that work this paper focuses on a type of variation that cannot be explained according to standard model of bank market power. Indeed in the model used in that work features local monopolistic competition and bank capital constraints. This would imply that conditional on the level of binding capital constraint the same bank would have the same pass-through across time in a specific region. This is counterfactual with the main stylized fact documented in this paper of asymmetric local Skeweness across time. Also again conditional on the level of bank capital the mark-up is a constant multiplier over the policy rate. Finally that model would not explain why the Skewness of interest rates in a certain period would affect the. I am reconciling this three new factors by endogenizing the local bank demand elasticity to own and competition interest rates through Information and Switching costs on the consumer side. Through this mechanism I am able to explain a considerable portion of the variation of bank cross-branch time-variation in the pass-through of monetary policy to lending rates. Importantly this literature would imply that the history of previous monetary policy shocks is irrelevant for the current pass-through of the current monetary policy shock. On the contrary this paper argues that the a sequence of monetary policy easing interventions could have the effect of squeezing the distribution into being less dispersed and more symmetric and could hinder the pass-through of the next monetary policy interventions.
Broadly this paper is related to literature coming from three different fields. First it contributes to the Macro-Finance literature studying how frictions in the financial markets impact the transmission and amplification of macroeconomic shocks and in particular monetary policy shocks. Second it contributes the Industrial Organization literature studying frictions in firms' competition arising from the presence of consumers' switching costs, brand loyalty and product differentiation. Third it is also related to the banking literature analyzing the micro-structure of the banking sector and credit markets and their macroeconomic effects. In general this paper aims at drawing a novel connection between the theory and evidence on competition in presence of customer's frictions (second), bank's asymmetric and heterogeneous behaviour (third), and space/time varying pass-through of monetary policy (first). It does so by introducing state-dependence in customer's switching decisions and showing how this implies an interesting interaction with monetary policy shocks leading to powerful dynamics in banks competition over clients ultimately impacting the effectiveness of monetary policy on credit markets.

Macro-Banking Literature on Bank Rates pass-through. Letting aside the papers mentioned above, within this literature the paper relates to various strands. First it relates to the literature studying the lending rates pass-through of monetary policy. The theoretical foundations for interest pass-through models are set in the pioneering works of Monti (1972); Klein (1971), the so called Monti-Klein model, which set the microfundations of interest rate setting as a profit-maximization of a firm tacking deposits and issuing loans. The standard approach is to assume banks follow a marginal cost pricing model, where monetary policy gets transmitted by shifting the latter cost. Starting with the empirical contributions of Hannan and Berger (1991); Neumark and Sharpe (1992); Sharpe (1997) evidence has been shown of limited or incomplete pass-through to bank retail rates (both deposit and lending rates).[34] Bank interest rates are characterized by a lower variance than money market rates, which suggests that banks typically do not fully adjust retail rates when market rates change. The conventional view on the topic regarded bank balance sheet characteristics such as size (Kashyap and

[34]See also Cottarelli and Kourelis (1994); Angeloni and Ehrmann (2003); Mojon (2000) for the similar evidence in the Euro-Area. See De Bondt (2005); Gambacorta and Mizen (2019) for systematic surveys of empirical works on bank rates pass-through.

Stein (1995)), liquidity (Stein (1998),Kashyap and Stein (2000)), capitalization (Peek and Rosengren (1995); Kishan and Opiela (2000)) as the main driver explaining heterogeneity and fluctuation in the response of banks to monetary policy interventions.[35] Since its onset this literature underlined strong evidence of stickiness in pass-through from monetary policy rates to bank rates (De Bondt (2005)) both on the liability side (deposits) and asset side (assets) accompanied with asymmetries and non-linearities (Borio and Fritz (1995); Mojon (2000) find asymmetries in the sign of the change in the wholesale rates, Sander and Kleimeier (2000); Hofmann and Mizen (2004); Driscoll and Judson (2013) for asymmetries in bank responses depending on the relative position with respect to the long run cointegrating relationship, finally Gambacorta and Iannotti (2007) show evidence of asymmetries in the response to monetary policy shocks depending on the sign of the shock.).[36] and explored the role of potential explanations due to adjustment costs (Hannan and Berger (1991); Elyasiani et al. (1995); Hofmann and Mizen (2004))[37], competition and market concentration (Borio and Fritz (1995), Claessens and Laeven (2004), Kahn et al. (2005), De Graeve et al. (2007), van Leuvensteijn et al. (2013)), managerial efficiency (maria Fuertes and Heffernan (2006)), relationship lending (Berger and Udell (1995); Degryse and Van Cayseele (2000); Allen and Gale (2001); Gambacorta and Mistrulli (2014)), affiliation to large bank conglomerates with sizeable internal capital markets (Gambacorta (2005), Bluedorn et al. (2018)), borrowers collateral value (Cerqueiro et al. (2016)), capital and default risk (Gambacorta and Shin (2018); Acharya et al. (2020)), search costs Yankov (2018), asset quality (Kelly and Byrne (2019)), exposure to monetary policy due to maturity mismatch and liquidity premia (Drechsler et al. (2018), Di Tella and Kurlat (2021)) at the bank level, and more on aggregate on the degree of financial development (Cottarelli and Kourelis (1994), financial instability regimes (Humala (2005)).[38][39] More recently von Borstel et al. (2016), Illes et al. (2015), Hristov et al. (2014), Krylova et al. (2014) Holton and Rodriguez d'Acri (2018) document a more or less significant fall in the average pass-through relative to the pre-crisis period, Zentefis (2020) shows that the pass-through of monetary policy to loan rates can break down when banks have too little capital to compete with each other in a Salop model, finally Altavilla et al. (2020) provides a comprehensive account of cross-country time variation in the monetary policy pass-through in the Euro-Area.[40] Recently a literature flourished studying the effects of Lending and Deposit Rates transmission when interest rates are around or below zero reaching mixed evidence (Debortoli et al. (2019), Mendicino et al. (2022), Altavilla et al. (2019),

[35]Wang et al. (2022) identify four main bank related transmission channels: the reserve and capital constraint channel (Bernanke and Blinder (1988); Kashyap and Stein (1995)), the bank capital channel (Van den Heuvel (2002); Brunnermeier and Sannikov (2016)), deposit market power (Drechsler et al. (2017)) and finally loan market power (Scharfstein and Sunderam (2016)) in which banks reduce markups to mitigate effects of monetary policy.

[36]see Fuertes and Heffernan (2009) for a pre-GFC survey of the early works on the topic

[37]Goodhart (1996); Sack (1998); Kuttner (2001b); Hofmann (2002); Banerjee et al. (2013) provide evidence of banks smoothing their responses to monetary policy shocks based on their expectations on the future path of interest rates, Kopecky and Van Hoose (2012) formalize this point theoretically in a Monti-Klein model augmented with quadratic adjustment costs.

[38]Focusing on the volume of granted loans rather than on interest rates Jiménez et al. (2012) or risk-taking Jiménez et al. (2014) provide strong evidence of interactions between monetary policy and bank capitalization and risk-taking behaviour.

[39]Variation in the strength of pass-through was also detected as a function of the maturity of the loan, see e.g. Sander and Kleimeier (2004); De Bondt (2005); Kwapil et al. (2006) on short vs long term loans to firms.

[40]See Gregor et al. (2021) for a meta-analysis of the literature comparing pass-through estimates across different types of loans (corporate, house, consumer loans) different geographical regions and different time periods.

Eggertsson et al. (2019), Ulate (2021)).[41][42] Now as pointed out in Scharler (2008); Kwapil and Scharler (2010) limited interest rate pass-through might interfere with the stabilizing role of monetary policy and might even lead to a breaking of the Taylor Principle, hence understanding the variables affecting is of crucial importance to understand the workings of monetary policy. Most of this literature has been focusing on cross-country heterogeneity in order to identify the effects of bank specific factors (Balance Sheet, Market Power, Risk) or sectoral/aggregate factors (market concentration). Using its unique combined County/MSA - Branch/Loan level dataset this paper is able to abstract from identification concerns arising from country-specificity by exploiting instead variation over different loan categories, loan characteristics and borrower's characteristics across regions of the same country. More importantly previous work focuses on the differences in bank or sectoral characteristics in order to explain heterogeneity in the monetary policy pass-through. Both categories of factors and their interactions hardly explain why there would be variation in the pass-through of a monetary policy interventions across similar regions populated by similar banks in the same given period. In this paper I explore an entire novel dimension that intrinsically has more degrees of freedom i.e. the heterogeneity in local bank specific demands. It's interaction with bank strategic price behaviour gives rise to heterogeneous local skewness in the bank rates distribution which in turn plays a relevant role in explaining the heterogeneity of monetary policy pass-through across space and time. The evidence and mechanism outlined in this paper proposes to look at a completely different set of characteristics that are at the same time bank and region specific, i.e. the degree of information and switching costs of the local bank demands (specific bank in specific region) which give rise to heterogeneous and time-varying demand interest rate elasticities. In the theoretical framework developed in the second part of the paper the composition and micro-structure of local bank demands are shown to have significant asymmetric impact on the bank pass-through. Intuitively all this work focuses on the factors affecting a higher cost of funds for banks while completely overlook the effects of demand stickiness. The level of activity in searching for better rates and the intensity of switching does play a crucial role in bank pricing models and should hence be accounted for.

Evolution of Monetary Policy Pass-Through over time. Several studies have been focusing on the evolution of the monetary policy pass-through within a Monetary Union, (Kuttner and Mosser 2002; Boivin and Giannoni 2006; Canova and Gambetti 2009; Primiceri 2005; Boivin et al. 2010, see e.g.). The evidence on the degree of pass-through is however rather mixed. So far two main sources of time variation have been identified: the business cycle phase and the Zero Lower Bound. As for the first earlier studies such as Peersman and Smets (2001); Lo and Piger (2005) claim it is more effective, later studies such as Tenreyro and Thwaites (2016) claim that is less effective. As for the Zero-Lower bound the same mixed evidence have been found (Eggertsson et al. 2019; Debortoli et al. 2019, see e.g.). Recently a third relevant state has been argued for, i.e. the level of the uncertainty of the economy Aastveit et al. (2017). Despite the evidence of strength of the pass-through one element is in common across all this studies: data seems to suggest that the effectiveness of monetary policy is state-dependent. The current paper shares this view of the literature and aims to contribute by adding a new source of state-dependence, but it is different from previous studies as it aims at providing a mechanism that can explain both high frequency and low frequency variation in the strength monetary

[41] More literature regards broadly the reaction of the bank lending channel in negative territory (Demiralp et al. (2017), Basten and Mariathasan (2018), Bottero et al. (2020), Bubeck et al. (2020), Heider et al. (2019), Erikson and Vestin (2019), Heider et al. (2021))

[42] See e.g. Hofmann et al. (2020), Banerjee et al. (2019) for further studies on the effects of funding costs and lending rates of unconventional monetary policy shocks.

policy pass-through, together with its geographical variation.

Heterogeneity of Monetary Policy Pass-Through across Geographical Regions. There is a very sparse literature documenting the heterogeneity of monetary policy pass-through across different geographical regions. In particular Carlino and DeFina (1997), Perera and Wickramanayake (2016), Liu et al. (2008) and Georgiadis (2014), provides evidence that policy transparency, financial structure, literature, labor market rigidities and industry mix help explain such heterogeneity. As shown in Hurst et al. (2016) and Beraja et al. (2018) for the housing mortgage market, geographical asymmetries in the pass-through may have important yet unintended implications in terms of in terms of inequality of welfare effects of monetary policy.

Macro-Finance Literature More generally this paper is related to the well established line of study of financial frictions and their role in the amplification of macroeconomic shocks.[43] The literature of financial frictions dates back to the seminal works of Bernanke et al. (1999) and Kiyotaki and Moore (1997) and has shown several channels through which financial markets produce amplification of macroeconomic shocks, (Goodfriend and McCallum 2007; Brunnermeier and Pedersen 2009; Gerali et al. 2010; Gertler and Kiyotaki 2010; Adrian and Shin 2010; Jermann and Quadrini 2012; He and Krishnamurthy 2013; Christiano et al. 2014; Brunnermeier and Sannikov 2014; Gertler and Karadi 2015; Adrian and Boyarchenko 2015; Cúrdia and Woodford 2016; Nuño and Thomas 2017; Drechsler et al. 2017; Egan et al. 2017; Gertler et al. 2016; Fernández-Villaverde et al. 2019; Gertler et al. 2020; Bigio and Sannikov 2021; Drechsler et al. 2021; Beganau et al. 2021, see e.g.).[44] More closely to related to this paper is the literature studying the role played by the heterogeneity in financial intermediaries, ex-ante as in , or ex-post as in (Coimbra and Rey 2021; JRios Rull et al. 2020; Jamilov and Monacelli 2021; Rojas 2020; Begenau and Landvoigt 2021; Bianchi and Bigio 2022; Bellifemine et al. 2022, see e.g.) and more broadly the heterogeneous agents literature as in (Buera and Moll 2015; Kaplan et al. 2018; Auclert 2019; Ottonello and Winberry 2020; Auclert et al. 2020a;b; Kekre and Lenel 2020; Kaplan et al. 2020; Ravn and Sterk 2021; Baqaee et al. 2021; Bigio and Sannikov 2021; Bilbiie 2021, see e.g.) . This paper shares the view of the literature that both ex-ante and ex-post heterogeneity produce quantitatively important aggregate amplification effects of macroeconomic shocks. It contributes to the literature by documenting a new channel of state-dependence of prices reaction to MC shocks based on the heterogeneity firms face in terms of own and cross price demand elasticity. Within this literature only a handful of papers analyze the amplification effects when banks are non-atomistic[45] and feature strategic behaviour by internalizing either their effect on aggregate demand or their effect on other banks' pricing rules ((Vives 2001; Aliaga-Díaz and Olivero 2010; Cuciniello and Signoretti 2015; Corbae and D'Erasmo 2021, see e.g.)). This paper revives and shares the emphasis of strategic behaviour and price complementarities do have high amplification effects in the economy. In particular it contributes in two different ways. First through a theoretical model featuring state-dependent and heterogeneous local demand elasticities and second by studying a Bertrand competition type of game across banks. It also adds by analyzing the interference of monetary policy in the strategic interaction among banks. Empirically it documents how the heterogeneity in local level skeweness of the lending

[43]The basic theoretical forces underlying these friction have their roots asymmetric information costs that induce problems of adverse selection and moral hazard both on the asset (Stiglitz and Weiss (1981)) and liability side (Diamond and Dybvig (1983)), Holmstrom and Tirole (1997), Stein (1998)

[44]See Brunnermeier et al. (2012) for a survey of the macro literature on financial frictions.

[45]A large part of the literature assumes Monopolistic Competition which in turn means banks do not internalize the effect of their lending or deposit rates on the market.

rates carries important information for the transmission of monetary policy shocks as predicted by the theoretical framework. This paper also stresses the important aggregate effects of customer capital as a state variable. Gourio and Rudanko (2014) is the first to make this point for firms in general by showing this has important effects on firms' level and volatility of investment, profits, value, sales and markups, most importantly the timing of their responses to shocks. Deep habits literature Ravn et al. (2006)

Identification and Econometric Modeling. The identification strategy adopted in this paper for the estimation of monetary policy effects draws from the large empirical literature on high frequency proxies starting from the seminal works of Rudebusch (1998) Kuttner (2001a) who pioneered the idea of extracting the exogenous component of monetary policy movements by looking at the financial markets response to Monetary Policy announcements. The literature developed through the contributions of Bernanke and Kuttner (2005), Gürkaynak et al. (2005) and Gertler and Karadi (2015) among others up to the most recent contributions from Jarociński and Karadi (2020) Nakamura and Steinsson (2018) Bauer and Swanson (2022) focusing on disentangling Information and Pure Monetary policy effects in high frequency proxies. This paper improves the understanding of this type of identification by showing how it remains robust in the study of monetary policy effects over sub-national geographical units such as counties and MSAs, dis-aggregated targets such as loans of a specific category or in a specific area and state-dependent effects.[46]

Local Projections represent an ideal framework for the empirical question at hand. It's simple linear structure allows for the study of state-dependence of monetary policy impulse responses in a panel environment with high degree of dis-aggregation. While first example of the methodology can be traced back to Christiano et al. (1996) and Romer and Romer (1989), the widespread use of local projections for the study of monetary policy effects is due to the seminal work of Jorda (2005). Following its contribution several different works have As recently proven in Plagborg-Møller and Wolf (2021) given an identification strategy, Local Projections estimate the same impulse responses as VARs as the number of lags goes to infinity. Even in finite sample with a finite number of lags the two methodologies deliver the same result for the horizon corresponding to the minimum between the two lag orders. The bias-efficiency trade-off stays however for horizons longer than the lag structure of either of the two methodologies. Local Projections are less prone to mis-specification bias while VARs are more efficient in long run estimation. Given the nature of the question at hand we select the first over the second.

More closely to this paper, Local Projections have been popular in the study of the dependence of monetary policy responses on the state of the economy. Among others Santoro et al. (2014), Tenreyro and Thwaites (2016), Angrist et al. (2018), Barnichon and Matthes (2018) and Mavroeidis (2021) and Klepacz (2021).[47] In line with these studies, this paper shows evidence of state-dependence in the responses to monetary policy. It contributes to the literature by providing an entire new dimension of state-dependence based on the micro-structure of bank competition. Notably, contrary to the other suggested state variables, this dimension is able to reconcile the joint time and space variation of monetary policy effects in the US.

[46] The use of instrumental variables in the identification of policy shocks is not limited to local projections nor to monetary policy. See Mertens and Ravn (2013) for an early example of Fiscal Policy shocks identified in a VAR model through external instruments. Stock and Watson (2012) use external instrument identification strategies to disentangle the various channels of the 2007-2008 Recession.

[47] See Ramey and Zubairy (2018) for an example of state-dependent local projections applied to the study of fiscal multipliers. See Gonçalves et al. (2022) for a more rigorous consideration of the asymptotic validity of state-dependent local projections.

The High frequency identification and Local Projections methodology are only one of the many ways adopted by the literature to study the macroeconomic effects of monetary policy shocks, see Ramey (2016) for a wonderful critical survey of literature on the topic comparing various identification and econometric models, their performance and robustness of the results.
Among the transmission channels of monetary policy as outlined for instance in the early work of Mishkin (1996) the literature has well understood the important role of the so called "credit channels". Contributions focused on this latter channel such as Bernanke and Gertler (1995), Gertler and Karadi (2015) and Caldara and Herbst (2019) have found strong evidence of amplification caused by frictions in credit and more generally financial markets. Notably this line of work focuses on aggregate frictions mainly arising from balance sheet constraints or asymmetric information. This paper contributes to this literature by showing how certain frictions characterizing the demand in this market combined with bank strategic pricing in these markets can lead not only aggregate but also heterogeneous amplification of the monetary policy pass-through.

Industrial Organization Literature on Switching Costs. The theoretical framework proposed in the second part of the paper is mainly related to strand studying Bertrand Competition environments in presence of Switching Costs and Product differentiation. The literature has its roots in the pioneering works of Klemperer (1987), Beggs and Klemperer (1992) or Nilssen (1992) who incorporate consumers characterized by costs of switching across different suppliers of goods into the three main workhorse models of competition (Cournot, Bertrand and Stackelberg). The literature is mainly focused on the rationalization of phenomena regarding the industrial organization certain sector, for instance the emergence of teasing rates offered by telecom companies to lock-in customers in the first year followed by consistently higher prices in the following years. Switching costs might be very different in nature Nilssen (1992) describes transactional vs learning switching costs for when one switches to a new product/supplier with a learning curve, or endogenous vs exogenous switching costs ((Shi 2013, e.g. see)) Recent contributions extended the baseline model to account for instance for Network Externalities (Irina and Christian (2011), Weiergraeber (2022)), Heterogeneity ((Biglaiser et al. 2013; 2016, e.g. see)), interaction with market structure (see e.g. Fabra and García (2015) for High vs Low Concentration Markets and Lam (2015) for the case of two-sided markets) or with product innovation (Salies (2012)).[48] This literature stresses how switching costs fundamentally create a dichotomy between existing locked-in consumers and new consumers. Because of switching costs Firms can extract monopolistic rents from their consumers but their competition on new consumers is much higher exactly because the lock-in has an incredible value for the firm in the following years. The contribution of this paper to the literature is to look at what happens once part of the switching cost is connected to an information cost. Customers not only do not switch easily to other products because cost of adjusting to the feature of the new product but importantly also because they don't want to sustain the cost of informing themselves about price and characteristics of other products in every period. However if they receive a signal form past prices that competition decreased incredibly its prices on a competitive product they will be incentivized to re-enter the market and firms will have to look at them as new customers (so low price to lock them in).

Industrial Organization on Price Competition. The theoretical model is most similar in its key insights to two different strands of literature. First to the literature exploring the relevance of search

[48] Klemperer (1995) and Farrell and Klemperer (2007) Provide extensive surveys on switching costs in various theoretical and empirical settings.

costs in the class of switching costs. Second the literature analysing cost pass-through in enviroments characterized by heterogeneous and variable demand price elasticities.
To my knowledge there is only a handful of papers relating Search Costs as part of the Switching costs, namely Moshkin and Shachar (2000); Waterson (2003). The key insight of this two works is that a consumer doesn't hold perfect knowledge of the competitor products and hence before switching has to sustain the cost of searching for alternative products to the one he/she is currently using. More recently Wilson (2012) develops a unified model of switching and search cost in order to analyze qualitatively the interaction between this two types of costs and identify them in empirical estimations. On the empirical side Heiss et al. (2021) provide empirical evidence of this latter fact by showing how consumer inattention plays a big role in the choice between two water tariffs. Consumer inertia in switching is not due to learning or transactional costs of switching but rather by the fact that consumers are not informed and do not actively inform themselves of the alternatives. In another study using data from an online grocery retail market González and Miles-Touya (2018) estimate that around two thirds of the consumers using the platform do not compare prices across different supermarkets. Finally Gamble et al. (2009) compare three different deregulated markets in Sweden namely the market for electricity, landline telecom, and home insurance. They find that the differences in consumer inertia not switching to the best option can be pinned down by loyalty, information search costs, and expected economic benefits. Luco (2019) compares Retirement Fund choices using cross-sectional heterogeneity between new potential customers and those already attached to a specific fund in order to isolate search and transactional costs. For the same market in Chile Illanes (2017) estimates a dynamic demand model with switching costs finding that prices are twice as high with respect to the no-switching cost case. Finally Buso and Hey (2021) shows that the reluctance to switch supplier has been shown to affect not only the energy market but also other important economic sectors such as health insurance and investment for retirement. Search and switching costs appear to be the main factors that deter consumers from switching to the best supplier. Now according to Dube et al. (2006) analysis switching costs might actually decrease prices rather than increasing them. This paper shares the view and provides a theoretical framework in which they might have both roles depending on the trade-off between extensive and intensive margin. If the value of poaching new customers is higher then the value of extracting rents from existing loyal customers then prices will be decreasing in the switching costs else they will be increasing in them. A conclusion similar in spirit is also reached in a theoretical dynamic setting by Cabral (2016). In a Swedish randomized experiment where 1.2 million people where sent pamphlets on alternative primary healthcare providers in the area, Anell et al. (2021) document an increase of 10-14% in the percent of switchers, providing further evidence that Information costs do play a big role in Consumer inertia and switching decisions. Second the paper also focuses mainly on the cost price pass-through of shocks to the first. This is similar to the theoretical analysis of this paper that focusing on the pass-through of monetary policy shocks, viewed as a shifter of banks fixed marginal cost of producing a loan to their interest rates. The theoretical foundation model to study this dates back to Shubik and Levitan (1980) but only in the very last years the empirical literature has focused on this problem showing how more differentiation in products leads to lower cost-pass-through. Mapping this to my model when more consumers are on the lookout for a new bank, differentiation decreases and hence the loan pass-through increases and viceversa ((Kim and Cotterill 2008; Loy and Weiss 2019; Pless and van Benthem 2019; Bittmann et al. 2020, e.g. see)).[49] In this respect my model is most similar to Cosandier et al. (2018) like their it is a Bertrand duopoly with differentiated

[49] See Arkolakis and Morlacco (2017) for a theoretical note on variable demand elasticities, cost pass-through and markups.

goods giving rise to asymmetric own and cross-price elasticities. Now while in their analysis they concentrate on the equilibrium price outcomes when the share of informed consumers varies I analyze a framework in which the share of informed consumers comes endogenously from a search cost decision based on previous year prices. On top the share of informed consumers is asymmetric. As only one of the consumers of the two firms decides to become informed. Third I focus on the cost-pass through analysis of equilibrium prices rather than on prices alone. Now note that the model is the first to the authors knowledge able to reconcile increasing price dispersion on online markets. In my model this also happens while this also explains time varying Skewness.....

Industrial Organization and Banking Literature on Consumer Inertia and Rates Pass-Through. Finally this paper is related with the IO-Banking literature studying specifically the effects of Market Power arising from customers' inertia (also referred to as brand loyalty, stickyness). The literature dates back to the seminal work of Sharpe (1990) who identify switching costs to be one of the main reasons for consumer inertia and sets the theoretical foundations for the study of the interaction between bank pricing strategies and switching costs. Empirically the topic has been first explored both as concerns deposit rates Sharpe (1997), Hannan et al. (2003) Hannan and Adams (2011), Carbo-Valverde et al. (2011) and lending rates Ausubel (1991)[50], Petersen and Rajan (1994), Degryse and Van Cayseele (2000), Ioannidou and Ongena (2010), Barone et al. (2011), Fuster et al. (2013), Brown and Hoffmann (2016), Deuflhard (2018), Brunetti et al. (2020), Allen and Li (2020), Andersen et al. (2020).[51] The fundamental take-away of this literature is that banks internalize and exploit consumer inertia in their pricing decisions. Two are the main outcomes shown. First Banks tend to react less than 1 to 1 to a shock affecting their marginal cost. Second Banks tend to offer very low rates to potential new customers in order to attract them from the competition and very high rates on existing already locked-in customers tacking advantage of their switching costs. As stressed previously by the IO literature, part of the consumer inertia is also due to search costs faced by consumers whenever they need to look for a substitute product. In the context of the banking literature this has been recently explored by Allen et al. (2019) who estimate that around 50% of the surplus extracted by banks is actually due to search costs, while only 28% can be associated with discrimination, 22% with inefficient matching.[52] According to the Survey of Consumer Finances Amel et al. (2008) report that the average household borrower lives within 4 miles from lender. In another study based on qualitative interviews and a controlled experiment Lacko and Pappalardo (2010) report that that the mean borrower only checks 2 mortgage providers before making the choice. Focusing more on the importance of search costs Li and Netessine (2020) and Wang and Yang (2020) show respectively that higher market thickness on the supply side of the mortgage market requires higher search intensity hence resulting

[50]On credit Card Rates

[51]Kim et al. (2003) estimates the average switching cost to be 4.1%, about one-third of the market average interest rate on loans. More than a quarter of the customer's added value is attributed to the lock-in phenomenon generated by these switching costs. About a third of the average bank's market share is due to its established bank-borrower relationship.

[52]The effects of switching costs on consumer decisions are studied more generally in the Household Finance literature see for instance Iyer and Puri (2012); Iyer et al. (2016); Brunetti et al. (2016) for Household deposit account switching or Campbell (2006); Agarwal et al. (2015; 2017); Scharfstein and Sunderam (2016); Keys et al. (2016); Beltratti et al. (2017); Bajo and Barbi (2018); Carella and Michelangeli (2021); Allen et al. (2022) documenting and exploring households inertia in refinancing and/or switching house/mortgage loans (Keys documents 20% fail to refinance when profitable main determinants are financial literacy & education, age, location). Agarwal et al. (2020) explore the role of searching costs on household refinancing decisions. Further see Dudley (2012) and Fuster et al. (2013) for report also partial pass-through of unconventional monetary policy interventions, they consider several explanations such as origination costs, capacity constraints and market concentration but do not find a single factor driving the empirical fact. See Mian et al. (2013) for a notable example of the relevance of household mortgage decisions in the post-2007 crisis US.

in less search, and higher transparency might actually increase rather than decrease bank profits.[53] Ellison and Ellison (2009); Dinerstein et al. (2018) in a theoretical exercise of platform design identify a similar trade-off faced by online retail platform between lowering consumer search costs and lowering prices. Yankov (2018) finds that most of the pass-through of monetary policy in the deposit market can be attributed to search costs. Search Costs in turn are correlated with age and financial illiteracy. [54]

Macro Literature on Price Stickyness. Price stickyness is at the root of monetary policy non-neutrality. It is conventionally classified as time-dependent (Taylor (1980), Calvo (1983)) or state-dependent (Rotemberg and Saloner (1987), Reis (2006), Golosov and Lucas Jr (2007), Nakamura and Steinsson (2010), Midrigan (2011), Alvarez and Lippi (2014)).[55]. In both types of models firms do not adjust price neither immediately nor necessarily after every macroeconomic shock due to time or menu cost frictions. These models have been employed in understanding the observed variation in mark-ups (Burstein et al. (2020)) or in the pass-through of exogenous aggregate shocks (Nakamura and Zerom (2010); Gopinath and Itskhoki (2010); Amiti et al. (2019)). In a few works, namely Alvarez et al. (2011; 2017a), pricing frictions were hence further combined with Information frictions, as intended in the Rational Inattention literature. On the other hand only one paper, Mongey (2021), analyzes the impact of menu-costs in a model where firms are not monopolistically competitive but rather strategically engaged. In the same spirit the theoretical framework proposed in this paper drows its power from the fact that firms can anticipate each other responses and have an impact both on the market and on the opponents business. Differently from that paper, here however the stickyness is not micro-funded through fixed costs on the bank-side but rather through inaction on the customer side, which in turn stategically implies price inaction. Similarly to Alvarez et al. (2016) in this paper for Skweness as being a statistic that carries information on the degree of stickiness of bank interest rates after the next monetary policy shock. Differently from that paper however, here the Skewness is not computed on contemporary price adjustment but rather represent a state variable capturing what is the relevant mass of potential churners in the next period.[56] Andersen et al. (2020) suggests the idea that informational costs might be at the heart of consumers refinancing inertia. This paper shares this perspective, but differently from previously cited papers on the topic combines it with strategic behaviour of firms and state-dependence. Banks are not sticky in their interest rates because of their own information costs, but because their customers have high information costs, which they will not pay unless they receive a sufficiently strong signal that they would benefit from it. Tangentially to this literature a handful of paper focuses in particular on consumer inertia and its impact on firms price competition. In particular Döpper et al. (2021) shows evidence that the 25% rise in mark-ups observed in consumer products between 2006 and 2019 can e attributed for almost 50% to the reduction in consumers price elasticity. MacKay and Remer (2022) shows how consumer inertia arising from consumer Information/Switching costs, Brand Loyalty or Habit formation create important dynamic rather than static effect on firms pricing decisions.

[53] Hodgson and Lewis (2020) push forward this arguments but developing a spatial learning gives rise to path dependence, as each new search decision depends on past experiences through the updating process

[54] Another cause of consumer inertia is inattention, either rational or behavioural. See for instance Malmendier and Lee (2011) for a notable example of apparent irrationality of consumers overbidding behaviour on online auctions

[55] As shown by Auclert et al. (2022) or Alvarez et al. (2017b) the two models exhibit similar patterns to macroeconomic shock as long as the shock is small

[56] A few works analyze the effects of reference prices on the dynamics of inflation (Eichenbaum et al. (2011)) documenting that firms seem to be changing prices weekly but those are part of a pre-set schedule of prices conditional on the state of the economy and of the market, the schedule however only gets changed a few times.

B Empirical Robustness: Local Projection Equation

In this section the details of the various robustness checks performed on the empirical part of the analysis are provided. The general extended specification of the empirical model is as follows:

$$
\begin{aligned}
\text{Outcome Variable}_{t+h,s} \;=\;& \alpha + \underline{\boldsymbol{\beta_1}}\textbf{MP Shock}_t + \underline{\boldsymbol{\beta_2}}\left[\textbf{MP Shock}_t \times \textbf{Skewness}_{t-1,s}\right] + \\
+\;& \boldsymbol{\beta_3}\left[\textbf{MP Shock}_t \times \textbf{Mean}_{t-1,s}\right] + \boldsymbol{\beta_4}\left[\textbf{MP Shock}_t \times \textbf{Variance}_{t-1,s}\right] \\
+\;& \boldsymbol{\beta_5}\left[\textbf{MP Shock}_t \times \textbf{County Recess}_{t,s}\right] + \boldsymbol{\beta_6}\left[\textbf{MP Shock}_t \times \textbf{ZLB}_{t,s}\right] \\
+\;& \boldsymbol{\beta_7}\left[\textbf{MP Shock}_t \times \textbf{Bank Concentration (HHI)}_{t,s}\right] \\
+\;& \boldsymbol{\beta_8}\left[\textbf{MP Shock}_t \times \textbf{Aggregate Skewness US}_{t,s}\right] \\
+\;& \sum_{k=1}^{3}\rho_{1,k}\text{MP Shock}_{t-k} + \sum_{k=1}^{3}\rho_{2,k}... \\
+\;& \sum_{k=0}^{3}\rho_{1,k}\text{Mean}_{t-k} + \sum_{k=1}^{3}\rho_{2,k}\text{Var.}_{t-k} + \sum_{k=1}^{3}\rho_{2,k}\text{Skew}_{t-k} \\
+\;& \sum_{k=1}^{3}\rho_{2,k}\text{County Rec.}_{t-k} + \sum_{k=1}^{3}\rho_{2,k}\text{ZLB}_{t-k} + \sum_{k=1}^{3}\rho_{2,k}\text{Concentr.}_{t-k} \\
+\;& \sum_{k=0}^{3}\gamma_k X_{BANK,t-k} + \sum_{k=0}^{3}\mu_k X_{s,t-k} + \sum_{k=0}^{3}\delta_k X_{US,t-k} + \varepsilon_{s,t}
\end{aligned}
$$

The first four interaction terms are the ones included in the baseline specification. Following we have in the order: (i) an interaction of the monetary policy shock and an indicator variable of county specific recession taking value one whenever the county is whithin a period of 3 consecutive negative growth periods of unemployment (ii) the interaction between the monetary policy shock and an indicator variable representing the years of the zero lower bound, (iii) an interaction of the monetary policy shock and an indicator of local bank concentration computed as the Herfindal index over branch level deposit volumes reported by banks at the county level (as contained in the FDIC dataset) (iv) finally an interaction term of the monetary policy shock with the Aggregate Skewness at the US level in order to control for aggregate national-level moments of the cross-sectional distribution of lending rates. The local projection will be estimated at the county/month level. Errors are clustered at the county and loan category level.

C Empirical Robustness: Results

In this section the estimation results from the various robustness checks are provided. For each table the title reports the relevant dependent variable and the first columns report the estimated results for the relevant interaction terms. Overall the cross-sectional skewness at the county level ha significantly high predictive power over on the strength of pass-through of new monetary policy rate changes.

Table C1: Lending Rates with Variance Only

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.24***	0.37***	0.51***	0.48***	0.42***	0.26***	0.32***	0.57***	0.40***	0.43***	0.53***
	(8.73)	(11.65)	(14.47)	(12.66)	(10.05)	(6.27)	(7.48)	(13.07)	(9.23)	(8.60)	(10.31)
Var	0.13**	0.16**	-0.08	0.11	0.06	0.23**	-0.01	0.08	-0.12	-0.33***	-0.11
	(2.32)	(2.53)	(-1.13)	(1.44)	(0.71)	(2.51)	(-0.17)	(0.95)	(-1.40)	(-3.33)	(-1.13)
Mean	-0.13***	-0.04**	-0.18***	-0.29***	-0.32***	-0.15***	-0.27***	-0.22***	-0.18***	-0.29***	-0.32***
	(-6.02)	(-2.04)	(-6.94)	(-9.59)	(-9.40)	(-4.11)	(-7.19)	(-5.45)	(-4.68)	(-7.16)	(-7.72)
County Rec	-0.00**	-0.00	0.00***	0.01***	0.00***	0.01***	-0.00***	0.00	-0.00	-0.01***	-0.01***
	(-2.00)	(-0.13)	(4.12)	(4.55)	(4.05)	(4.08)	(-2.77)	(0.76)	(-1.14)	(-7.35)	(-4.46)
ZLB	-0.01***	-0.00	-0.01***	-0.01***	-0.01***	-0.00*	-0.00***	-0.01***	-0.00**	0.00	0.00
	(-6.01)	(-0.36)	(-4.80)	(-7.26)	(-3.71)	(-1.81)	(-2.67)	(-4.33)	(-2.53)	(0.03)	(1.23)
Concentr.	0.00	0.00	0.00**	0.00	0.00	-0.00	-0.00	0.00	0.00	0.00*	0.00***
	(0.94)	(0.96)	(2.24)	(0.26)	(0.89)	(-1.15)	(-1.53)	(0.45)	(1.33)	(1.88)	(2.68)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	121832	110059	107270	104566	99946	97149	95371	91931	90389	88242	85018
R^2	0.974	0.967	0.962	0.956	0.949	0.946	0.941	0.937	0.934	0.930	0.926

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C2: Lending Rates with Aggregate Moments

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.13***	0.21***	0.35***	0.38***	0.22***	0.23***	0.16***	0.38***	0.26***	0.44***	0.53***
	(4.29)	(5.63)	(8.69)	(7.89)	(4.33)	(4.29)	(2.96)	(7.51)	(4.88)	(6.74)	(8.20)
Skew β_1	0.20***	0.21***	0.22***	0.24***	0.17**	0.22***	0.25***	0.14*	0.17**	0.13*	0.08
	(4.79)	(4.04)	(3.61)	(3.72)	(2.54)	(3.13)	(3.41)	(1.96)	(2.36)	(1.74)	(1.00)
Mean	-0.11*	0.06	-0.13*	-0.38***	-0.27***	-0.08	-0.53***	-0.09	-0.20**	-0.41***	0.05
	(-1.91)	(0.80)	(-1.73)	(-4.27)	(-2.91)	(-0.85)	(-5.96)	(-0.92)	(-2.09)	(-3.99)	(0.48)
Var	0.01	-0.00	-0.17*	-0.12	-0.05	-0.00	-0.03	0.02	-0.29**	-0.08	-0.40***
	(0.18)	(-0.01)	(-1.69)	(-1.11)	(-0.49)	(-0.03)	(-0.28)	(0.14)	(-2.37)	(-0.64)	(-3.10)
County Rec	-0.13***	-0.04	0.16***	0.23***	0.30***	0.25***	-0.25***	-0.04	-0.25***	-0.56***	-0.39***
	(-3.00)	(-0.76)	(2.84)	(3.13)	(4.06)	(3.17)	(-3.09)	(-0.45)	(-2.65)	(-6.11)	(-4.30)
ZLB	-0.17***	0.12**	-0.22***	-0.46***	-0.19**	-0.26***	-0.17*	-0.30***	-0.13	-0.21**	-0.05
	(-3.28)	(1.97)	(-3.35)	(-5.48)	(-2.41)	(-3.12)	(-1.93)	(-3.77)	(-1.61)	(-2.27)	(-0.52)
Concentr.	0.04	0.05	0.03	0.05	-0.04	-0.16	-0.14	0.04	0.11	0.14	-0.02
	(0.91)	(0.67)	(0.25)	(0.46)	(-0.44)	(-1.43)	(-1.12)	(0.37)	(0.86)	(1.38)	(-0.18)
US Skew	-0.15**	-0.15**	-0.20**	0.10	0.01	0.05	0.16	0.29*	0.51***	-0.14	0.02
	(-2.52)	(-2.25)	(-2.01)	(0.71)	(0.04)	(0.32)	(1.00)	(1.85)	(3.57)	(-0.97)	(0.14)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	111609	102513	99782	96405	92946	90621	88056	85511	83839	81382	79445
R^2	0.976	0.970	0.965	0.958	0.953	0.950	0.944	0.941	0.938	0.934	0.932

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lending Rates with Time Fixed Effects. Clustering at Time Level

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Skew	1.14**	0.98*	1.15**	0.99**	1.16**	1.34***	1.29***	1.03**	1.16**	0.90*	0.81*
	(2.27)	(1.96)	(2.25)	(2.06)	(2.32)	(2.82)	(2.77)	(2.32)	(2.31)	(1.80)	(1.67)
County Rec.	-0.85	-0.71	-0.59	-0.66	-0.77	-0.62	-0.40	-1.15**	-0.71	-0.33	-0.54
	(-1.54)	(-1.15)	(-1.13)	(-1.22)	(-1.59)	(-1.10)	(-0.78)	(-2.15)	(-1.43)	(-0.62)	(-0.90)
ZLB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
concentr.	-0.37	-0.54	-0.58	-0.78	-0.47	-0.61	-0.77	0.02	-0.09	-0.13	-0.34
	(-0.86)	(-1.05)	(-1.12)	(-1.55)	(-0.82)	(-1.10)	(-1.47)	(0.04)	(-0.29)	(-0.42)	(-0.99)
Mean	-0.86*	-0.66	-0.97*	-1.07*	-1.06*	-1.27**	-1.17*	-0.87	-1.13*	-0.78	-1.01*
	(-1.74)	(-1.29)	(-1.81)	(-1.96)	(-1.85)	(-2.23)	(-1.95)	(-1.38)	(-1.74)	(-1.34)	(-1.65)
Var	-0.61	-0.50	-0.63	-0.62	-0.85	-0.52	-0.87*	-0.55	-0.68	-0.69	-0.72
	(-1.25)	(-1.03)	(-1.10)	(-1.29)	(-1.61)	(-0.98)	(-1.69)	(-0.99)	(-1.20)	(-1.23)	(-1.18)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	123962	111776	108880	106049	101259	98372	96469	92949	91273	89048	85752
R^2	0.573	0.574	0.572	0.567	0.568	0.567	0.565	0.566	0.564	0.564	0.564

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Unemployment

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.04***	0.28***	0.36***	0.26***	0.21***	0.23***	0.37***	0.49***	0.56***	0.57***	0.19***
	(4.96)	(20.15)	(24.02)	(17.23)	(13.41)	(14.27)	(21.92)	(26.25)	(29.86)	(31.73)	(11.42)
Skew	0.04***	0.12***	0.11***	0.09***	-0.05**	0.02	0.04*	0.09***	0.05**	0.02	0.02
	(3.12)	(6.67)	(5.50)	(4.58)	(-2.38)	(0.91)	(1.91)	(3.54)	(2.00)	(0.67)	(1.01)
Mean	0.09***	-0.04***	-0.11***	-0.02*	-0.03**	-0.00	-0.18***	-0.18***	-0.17***	-0.28***	-0.05***
	(14.53)	(-4.12)	(-10.29)	(-1.71)	(-2.44)	(-0.26)	(-14.68)	(-13.21)	(-12.38)	(-21.11)	(-3.81)
Var	-0.00	0.04*	-0.02	-0.11***	-0.03	-0.11***	0.07**	-0.05	0.02	0.08**	-0.04
	(-0.12)	(1.70)	(-0.65)	(-3.80)	(-1.06)	(-3.77)	(2.39)	(-1.38)	(0.53)	(2.45)	(-1.48)
County Rec.	-0.00***	-0.00***	-0.00***	0.00	-0.00***	-0.00***	-0.00***	-0.00***	-0.01***	-0.00***	-0.00
	(-4.41)	(-11.35)	(-11.53)	(1.11)	(-7.89)	(-11.58)	(-11.15)	(-2.66)	(-10.75)	(-7.38)	(-0.13)
ZLB	0.00***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(5.11)	(-12.73)	(-17.25)	(-23.94)	(-19.78)	(-17.64)	(-20.03)	(-17.06)	(-9.85)	(-12.83)	(-11.46)
Concentr.	0.00	-0.00	0.00	-0.00	0.00	0.00***	0.00	0.00	-0.00	-0.00	-0.00
	(1.49)	(-0.41)	(1.27)	(-0.37)	(1.27)	(2.62)	(0.39)	(0.40)	(-1.07)	(-0.96)	(-0.24)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	121832	110059	107270	104565	99944	97147	95369	91929	90388	88241	85016
R^2	0.969	0.939	0.928	0.929	0.931	0.928	0.920	0.909	0.907	0.920	0.933

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lending Rates. TSLS (Instrumenting Treasury 2Y with HF Proxy)

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.09***	0.17***	0.22***	0.26***	0.28***	0.29***	0.32***	0.32***	0.29***	0.31***	0.32***
	(16.97)	(29.00)	(32.41)	(34.03)	(35.92)	(37.95)	(40.13)	(36.51)	(30.11)	(32.34)	(32.15)
Skew	0.34***	0.15***	0.03	0.45***	0.35***	0.11*	0.39***	0.53***	0.47***	0.98***	0.98***
	(9.85)	(4.13)	(0.68)	(9.87)	(6.52)	(1.94)	(6.69)	(8.01)	(7.00)	(13.52)	(13.36)
Mean	-0.09***	-0.09***	-0.06***	-0.11***	-0.11***	-0.11***	-0.08***	-0.12***	-0.11***	-0.08***	0.01
	(-8.18)	(-8.07)	(-4.60)	(-8.01)	(-7.05)	(-7.04)	(-4.45)	(-6.47)	(-6.11)	(-4.05)	(0.32)
Var	-0.21***	-0.17***	0.25***	0.00	0.16***	0.17***	0.28***	0.17**	0.31***	0.23***	0.36***
	(-5.75)	(-4.17)	(5.56)	(0.08)	(2.81)	(2.78)	(3.97)	(2.45)	(4.11)	(2.92)	(4.24)
County Rec	-0.01***	0.01***	0.00	-0.01**	0.00	-0.01**	0.01**	0.00	0.01*	0.01**	0.00
	(-3.19)	(2.67)	(1.17)	(-1.97)	(0.73)	(-2.22)	(2.15)	(0.18)	(1.88)	(2.20)	(0.83)
ZLB	0.01	-0.01***	-0.00	-0.01*	-0.05***	-0.05***	-0.05***	-0.04***	-0.03***	-0.03***	0.02**
	(1.33)	(-2.68)	(-0.72)	(-1.86)	(-8.05)	(-6.63)	(-7.10)	(-5.74)	(-3.88)	(-3.78)	(2.06)
Concentr.	-0.00	0.02	0.03	0.02	0.04	0.02	0.01	0.02	0.02	0.04	-0.00
	(-0.01)	(1.17)	(1.57)	(0.75)	(1.44)	(0.82)	(0.21)	(0.66)	(0.88)	(1.43)	(-0.15)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	98955	91574	89291	86453	83539	81538	79402	77111	75668	73602	71895
R^2	0.976	0.970	0.965	0.958	0.953	0.949	0.943	0.940	0.936	0.932	0.928

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lending Rates. With County & Time Fixed Effects

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Skew	0.08*	0.04	0.10*	0.11*	0.05	0.18***	0.16**	0.08	0.07	-0.14**	-0.12*
	(1.95)	(0.92)	(1.87)	(1.91)	(0.75)	(3.14)	(2.39)	(1.24)	(1.17)	(-2.26)	(-1.83)
Mean	-0.06*	0.12***	-0.00	-0.06	-0.09	0.01	-0.18***	0.00	-0.14**	-0.12*	-0.04
	(-1.65)	(2.78)	(-0.09)	(-1.33)	(-1.59)	(0.24)	(-3.25)	(0.06)	(-2.25)	(-1.93)	(-0.60)
Var	0.01	0.08	-0.19**	-0.10	-0.10	-0.03	-0.22**	-0.08	-0.17*	-0.12	-0.13
	(0.08)	(1.18)	(-2.38)	(-1.24)	(-1.08)	(-0.34)	(-2.31)	(-0.77)	(-1.79)	(-1.16)	(-1.15)
County Rec	-0.22***	-0.05	0.11	0.05	0.21**	0.23**	0.04	-0.18*	0.02	0.09	0.09
	(-3.82)	(-0.77)	(1.52)	(0.53)	(2.41)	(2.30)	(0.41)	(-1.68)	(0.24)	(0.90)	(0.81)
ZLB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Concentr.	0.11**	0.05	0.08	0.08	0.06	-0.06	-0.07	0.06	0.23**	0.33***	0.08
	(2.57)	(0.88)	(0.99)	(0.96)	(0.74)	(-0.59)	(-0.70)	(0.69)	(2.33)	(3.74)	(0.97)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	123775	111611	108658	105835	101058	98156	96266	92717	91096	88863	85569
R^2	0.976	0.971	0.967	0.962	0.958	0.957	0.954	0.951	0.950	0.948	0.946

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lending Rates. Jarocinski & Karadi MP Shock (Gertler and Karadi HF Shock separating MP from Info shock)

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.17***	0.20***	0.23***	0.13***	0.37***	0.34***	0.25***	0.17***	-0.02	0.29***	0.22***
	(6.11)	(6.44)	(6.74)	(3.38)	(8.36)	(7.13)	(4.84)	(3.19)	(-0.39)	(4.87)	(3.46)
Skew	0.08**	0.10**	0.11**	0.17***	0.16***	0.16**	0.22***	0.13*	0.11	-0.02	0.11
	(2.10)	(2.38)	(2.25)	(3.30)	(2.62)	(2.50)	(3.25)	(1.82)	(1.47)	(-0.21)	(1.43)
Mean	-0.08*	0.05	-0.21***	-0.26***	-0.22***	-0.07	-0.35***	-0.14	-0.13	-0.32***	-0.11
	(-1.68)	(0.79)	(-3.12)	(-3.52)	(-2.63)	(-0.85)	(-3.91)	(-1.51)	(-1.48)	(-3.62)	(-1.07)
Var	0.11*	-0.01	-0.12	-0.11	0.04	-0.02	-0.11	0.17	-0.16	0.04	-0.13
	(1.78)	(-0.07)	(-1.51)	(-1.27)	(0.43)	(-0.16)	(-1.01)	(1.47)	(-1.41)	(0.38)	(-1.08)
County Rec	0.00	0.00	-0.00	0.00***	0.00***	0.00***	0.00	0.01***	0.00	-0.00	-0.00
	(0.42)	(0.54)	(-1.21)	(3.12)	(4.00)	(3.86)	(0.23)	(4.03)	(1.05)	(-1.29)	(-0.95)
ZLB	-0.00***	0.00***	-0.00***	-0.00**	-0.01***	-0.01***	-0.00*	-0.00	0.00	-0.00*	0.01***
	(-3.58)	(2.82)	(-2.86)	(-2.51)	(-4.90)	(-3.76)	(-1.73)	(-0.52)	(0.53)	(-1.74)	(3.39)
Concentr.	-0.00	0.00	0.00**	0.00	-0.00	-0.00*	-0.00	-0.00	-0.00	0.00	0.00
	(-0.66)	(0.10)	(1.98)	(0.93)	(-1.39)	(-1.75)	(-1.54)	(-1.43)	(-0.13)	(0.30)	(0.96)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	108685	100467	98395	95671	92305	90058	87564	85097	83481	81073	79183
R^2	0.978	0.971	0.965	0.958	0.952	0.947	0.940	0.935	0.930	0.925	0.921

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lending Rates. Instrumenting Bank Average Cost of Funds (Average by County).

Month	0	1	2	3	4	5	6	7	8	9	10
MP	0.93***	2.86***	4.07***	1.36***	1.27***	0.02	-0.56	1.62**	1.12**	1.35*	1.36
	(2.74)	(4.10)	(5.47)	(2.82)	(3.25)	(0.04)	(-0.81)	(2.46)	(2.44)	(1.70)	(1.49)
Skew	1.41**	2.14	1.35	2.11**	1.34**	1.49**	2.11*	0.58	0.37	-0.89	-0.51
	(2.13)	(1.10)	(1.21)	(2.09)	(1.96)	(2.20)	(1.69)	(0.46)	(0.58)	(-0.74)	(-0.51)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	123775	111611	108658	105835	101058	98156	96266	92717	91096	88863	85569
R^2	0.893	0.766	0.739	0.798	0.838	0.832	0.769	0.831	0.841	0.814	0.814

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lending Rates. Interaction With Skewness, and with Skeweness and Dummy for High Rate Banks. (Testing Proposition 3 of Model)

Month	0	1	2	3	4	5	6	7	8	9	10
MP	-0.13***	0.30***	0.24***	-0.02	0.16***	0.04***	-0.24***	-0.21***	-0.20***	-0.31***	0.07***
	(-13.23)	(25.65)	(17.59)	(-1.60)	(10.42)	(2.78)	(-13.49)	(-12.21)	(-11.30)	(-16.49)	(3.92)
Skew	-0.01	-0.01	0.03	0.04*	0.06**	0.08***	0.42***	0.45***	0.38***	0.09***	0.20***
	(-0.69)	(-0.39)	(1.25)	(1.89)	(2.35)	(3.40)	(16.37)	(17.43)	(14.81)	(3.41)	(7.91)
H Skew H Rate	-0.06*	-0.04	0.01	0.13***	0.15***	0.13***	0.10***	0.07*	0.09**	0.20***	0.14***
	(-2.56)	(-1.24)	(0.40)	(3.46)	(3.91)	(3.31)	(2.61)	(1.69)	(2.21)	(4.90)	(3.52)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	2317536	2200605	2139583	2080359	2028567	1983506	1943036	1898621	1860857	1823443	1784944
R^2	0.977	0.968	0.961	0.955	0.950	0.946	0.943	0.940	0.938	0.936	0.934

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Specification in First Differences

Month	0	1	2	3	4	5	6
MP shock (β_0)	0.12***	0.21***	0.15***	0.18***	0.12**	-0.09**	0.03
Skewness (β_1)	0.11***	0.12***	0.15***	0.19**	0.19*	0.04	0.23***
Mean (β_2)	0.01	-0.04	0.01	0.04	0.05	0.15***	0.14***
High Concentr	-0.01	-0.11**	-0.16***	-0.19**	-0.25***	-0.21**	-0.09
Avg Loss Prov.	-0.00	0.02***	0.07***	0.11***	0.20***	0.28***	0.31***
Avg Cost Funds	0.06***	0.12***	0.13***	0.14***	0.14***	0.11***	0.09***
Controls	✓	✓	✓	✓	✓	✓	✓
N	87571	85278	82615	78734	76673	74387	72787
R^2	0.084	0.132	0.159	0.128	0.143	0.167	0.166

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Std. Errors clustered at the County/Category level.