The fintech lending channel of monetary policy

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Job Market Paper - November 10, 2023

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Abstract

Technology-based (fintech) lending is a growing segment of the credit market. Yet, there is a question of whether the transmission of monetary policy to fintech lending differs from the non-fintech one. This paper investigates the transmission of monetary policy through a *fintech lending channel*. Using static and dynamic models and a detailed dataset on fintech nonbanks activities in the U.S., I show that fintech lenders tend to accelerate the monetary policy transmission to mortgages rates, while they lessen the pass-through to mortgage volumes. As fintech lending grows at a fast pace, these results are relevant from a policy and regulatory standpoint.

Keywords: Fintech lending, Monetary policy transmission, Nonbanks, Unconventional monetary policy.

JEL classification: E52, E58, G21, G23, O30.

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1 Introduction

Over the past few years, the volume of mortgages provided by technology-based (fintech) lenders has grown significantly. As an example, the market share of fintech lenders in the U.S. government-backed mortgage sector has increased from around 3% in 2012 to approximately 15% of total volumes in 2019. Mortgages play a central role in the transmission mechanism of monetary policy, yet there is a question of whether the transmission of monetary policy to fintech lending differs from the non-fintech one.

The transmission channel for technology-based lending can differ for two reasons: technology, as fintech lenders use automated screening approach and process mortgage applications faster (Buchak et al, 2018; Fuster et al, 2019); funding structure, as fintech lenders are typically nonbanks with a short-term funding structure, mostly credit lines (Jiang, 2019; Kim et al, 2018). The former could accelerate the transmission of policy rates to lending rates and have a more rapid pass-through to lending volumes, facilitated by sophisticated technologies. The latter could instead imply a lower sensitivity of fintech credit to monetary policy developments, as the availability of short-term funding tends to increase in monetary contraction cycles. As shown by Elliott et al (2022) and Xiao (2019), this could lead to a substitution effect of credit supply from banks to nonbanks, of which fintech lenders are a subgroup.

This paper investigates the effect of conventional and unconventional monetary policy shocks on fintech and non-fintech mortgage rates and volumes in the U.S. between 2012 and 2019. I show that fintech lenders tend to accelerate the monetary policy transmission to mortgages rates, while they lessen the pass-through to mortgage volumes. I refer to this novel mechanism as the *fintech lending channel* of monetary policy. The differential impact of changes in monetary conditions cannot be explained by lenders or borrowers' characteristics, nor by time-variant geographical features. The *fintech lending channel* is likely driven by technological advancements that distinguish fintech lenders from other credit providers. Indeed, the differences appear related to the speed of the pass-through rather than to its cumulative magnitude, which, over the medium term, is comparable between the two groups.

For identification, I exploit loan-level data from the U.S. Federal Housing Administration (FHA) and the monetary policy shocks put forward by Swanson (2021) and Bauer and Swanson (2022) over the period 2012-2019. I complement these data with a granular dataset on fintech lenders' balance sheet and funding conditions and with several borrower, county, and macro-level control variables. For the first time in the literature, I use these combined datasets to assess the monetary policy transmission mechanism of fintech lenders in the U.S. My empirical assessment consists in the estimation of alternative panel regression models, which allow me to study both the short-term (1-quarter lag) and the dynamic responses (using panel local projections, Jordà, 2005) of lending rates and volumes.

The classification of fintech and non-fintech lenders for the U.S. mortgage market used in the paper is based on the work of Buchak et al (2018) and Fuster et al (2019). In line with these authors, I define fintech lenders as companies (i) with a significant online presence, and ii) with an almost entirely digital loan application process. More in general, fintech lending can be associated to online mortgage origination. The primary scope of my analysis is to compare fintech (which are typically nonbanks) vs non-fintech lenders (which can be both banks and nonbanks). Therefore, to ensure that results are not driven by the nonbanks nature of fintech lenders, in certain specifications I restrict my analysis to nonbanks only.

While banks core funding instruments are retail deposits, nonbanks (both fintech and non-fintech) rely on a short-term funding structure to originate mortgages. Nonbanks call reports (recently comprehensively described and utilized by Jiang, 2019 and Jiang, et al 2020) offer precious insights on nonbanks activities undisclosed until a few years ago. The combination of loan-level data from the FHA with nonbanks call report data makes the information set on which I base my analysis particularly insightful. This is the first study that exploits nonbanks call report data to assess the differential impact of changes in monetary conditions between fintech and non-fintech lenders. As Jiang (2019), I submitted a FOIA request to several U.S. states and I obtained data from the states of Washington and Massachusetts. Since the information collected from registered/licensed lenders in any state include activities conducted at national level, these data allow for a substantial coverage of the national mortgage origination in the nonbanks sector. For both fintech and non-fintech lenders, I collect information on assets, sources of capital (equity and debt), and warehouse credit lines, including the credit limit of each credit line and the remaining balance at the end of the quarter. Furthermore, to estimate the interest rate paid by each nonbank on their warehouse credit lines, I combine data on the debt facilities outstanding balance with the warehouse interest expense. This allows a first direct comparison of fintech and non-fintech lenders' balance sheets and funding conditions, which feeds into the study of the monetary policy pass-through.

My empirical assessment is composed by three main sections. First, I study the responses of fintech and non-fintech lending to monetary policy shocks by regressing changes in mortgage interest rates and volumes on the monetary policy shocks interacted by a fintech dummy. I control for a set of borrower, macro variables, and I saturate the model with lender and county-time fixed effects. Second, I explore the statistical relationship between monetary policy and the flow of funds to fintech and non-fintech lenders and I assess the potential role of lenders' balance sheet and funding characteristics in the transmission mechanism. To do so, I add to the main regression model described above a set of lender-level control variables. Finally, in the third section, I look at the dynamic responses of mortgage rates and volumes using the local projection framework à la Jordà, 2005. This allows me to assess whether the *fintech lending channel* of monetary policy can be associated to a different distribution of the pass-through over time between fintech and non-fintech lenders and/or to a different cumulative size of the policy transmission.

The main results are as follows. First, I find that, on average, fintech lenders tend to accelerate the pass-through of monetary policy shocks to mortgage rates. As an example, a contractionary monetary policy shock proportional to a 100 basis points move in the fourth contract of the Eurodollar futures (ED4)[1] is estimated to raise the lending rates of fintech lenders by 16 basis points more than the rate of non-fintech ones. This finding provides empirical evidence that technology may reduce frictions and facilitate the transmission of monetary policy (Fuster et al, 2019). Second, the estimates show that fintech lenders lessen the pass-through to mortgage volumes. For instance, a shock proportional to a tightening of 100 basis points in monetary policy generates an aggregate decline in mortgage origination, but an increase of up to 27% in the volumes of fintech loans relative to non-fintech. This result is in line with research on nonbanks, which, in contrast to banks, are better able to provide credit following a monetary contraction (see Elliott et al, 2022 and Xiao, 2019). At the same time, it expands on the existing literature by showing that this effect is stronger for fintech nonbanks. Third, following-up from the previous finding, the short-term debt of nonbank lenders tends to increase

[1]The Eurodollar futures refer to futures on time deposits denominated in U.S. dollars and held in banks outside of the U.S. The fourth contract of the Eurodollar futures can be interpreted as the 1-year ahead view on the 3-month interest rate.

following a tightening in monetary policy conditions. I show that a 100 basis points of monetary policy tightening over a three-year horizon is associated to an increase of close to 50% of nonbanks short-term debt financing. Notably, this result holds for both fintech and non-fintech, without statistically relevant differences between the two groups. These findings are consistent with the literature regarding nonbanks financing during monetary tightening cycles (see Elliott et al, 2022 and Xiao, 2019) and illustrate, for the first time, a comparable effect for the subgroup of fintech nonbanks. Fourth, the inclusion of novel lender-level characteristics into the model (comprising fintech and non-fintech funding conditions and capital and liquidity ratios) do not explain the difference in the monetary policy pass-through between fintech and non-fintech institutions. Even accounting for multiple lender-level control variables in the model, the interaction between fintech and the monetary policy variable remains statically significant and similar in magnitude to my previous estimates. Fifth, the stronger pass-through of monetary policy shocks to fintech mortgage rates vanishes after about three quarters and it is not persistent over time. This new finding shows that fintech appears to accelerate the speed of pass-through (which can be due to automated screening processes, online lending origination and faster pricing), but does not amplify the cumulative magnitude of the transmission over time, which remains comparable between the two groups of lenders. Finally, I show that fintech lenders lessen the response of mortgage volumes to monetary policy even more than other nonbanks lenders (as previously shown), albeit they do so for a limited period of time. Indeed, the difference among the two groups starts converging towards zero from the second quarter after the shock. These findings suggest that fintech institutions are better placed than other nonbank lenders to benefit from the additional flow of funds they receive in periods of monetary policy tightening, exploiting their technological lead and faster mortgage origination process. Nevertheless, over the medium term, the cumulative magnitude of the transmission remains comparable between the two groups of lenders. Overall, the *fintech lending channel* of monetary policy appears to be driven by the technological innovation for which fintech lenders distinguish themselves from other lenders.

This paper contributes to various strands of the literature. First, it contributes to the literature on the transmission mechanism of monetary policy via nonbanks and more generally, via innovative lending processes, such as fintech lending. Previous studies show that banks increase the margins they make on deposits as the Fed funds rate rises, which causes deposits to leave the banking system (Drechsler et al, 2017). Depositors tend to migrate from bank deposits to higher yielding money market fund shares (Xiao, 2020). As a result, nonbanks receive a large amount of funding from money market funds (MMFs) by issuing short-term debt instruments. It has been documented that such increase in funding allows nonbanks to lend more to the real economy relatively to banks in periods of monetary policy tightening (Elliott et al, 2022 and Xiao, 2020). Moreover, Agarwal et al (2023) show that mortgage servicing, by generating non-deposit funds, dampens the effect of monetary policy on shadow bank mortgage lending. I contribute to this literature by assessing whether the transmission of monetary policy differ between non-fintech and fintech nonbanks. Furthermore, I exploit a novel granular dataset on nonbanks call reports which allows me to assess this phenomenon at lender-level. More generally, on the role of technology in the monetary policy transmission mechanism, a recent ECB Working Paper (Dedola et al, 2023) qualitatively assesses how digitalization may change the way the retail and financial sectors respond to monetary policy. The authors hypothesize that digitalisation can enhance the pass-through of monetary policy into prices as lower online price adjustment friction and online competition can increase price flexibility. A recent study by Earnest et al (2023), which looks at the deposit rates offered to depositors, shows that the pass-through of monetary policy is stronger for online banks compared to brickand-mortar banks. Among other findings, the model proposed by De Fiore et al (2023) suggests that big tech credit reacts less than bank credit to a tightening in monetary policy, owing to the lower sensitivity of expected profits on big tech platform ("network collateral") than that of physical collateral typical of secured bank credit (i.e. real estate values). The authors conclude that a higher share of big tech credit reduces frictions in the credit market and makes real activity less impacted by monetary policy developments. Previous studies found that fintech lending may lessen frictions by reducing geographic distance between borrowers and bank branches (Hau et al., 2021) or by offering fast lending processes and elastic adjustments to changes in mortgage demand (Fuster et al, 2019). According to Zhou (2022), the function of fintech lending in the transmission of monetary policy is reinforced by consumers' social networks, and where fintech lending has a high market penetration, the pass-through of interest rates to borrowers is more complete. In contrast, Hasan et al (2023) finds that fintech adoption mitigates monetary policy transmission to real GDP, consumer/housing prices and, in particular, to bank loans growth. I contribute to this literature by quantitively measuring the monetary policy pass-through on mortgage rates and volumes of fintech and non-fintech lenders.

Second, this paper contributes to the literature on the role of technology in mortgage lending (Bartlett et al, 2022; Buchak et al, 2018; Fuster et al, 2019)[2]. Research has focused on two main aspects: (i) the efficiency and swiftness of the lending process, (ii) the enhanced screening and monitoring process. Studies show that, in the U.S. mortgage market, fintech lenders handle mortgage applications 20% quicker than other lenders (Fuster et al, 2019) and charge higher interest rates (Buchak et al, 2018), suggesting that fintech

[2]The literature on fintech lending has been extensively reviewed in a recent work by Berg et al (2021).

borrowers benefit from technology more in terms of convenience than in terms of cost savings. Importantly, the faster lending process does not appear to be associated with laxer screening. In the Federal Housing Administration (FHA) segment, default rates are about 25% lower for fintech borrowers compared to other borrowers (Fuster et al, 2019). Additionally, default rates on loans insured by Government-Sponsored Enterprises (GSEs) reveal non-significant variations between fintech and non-fintech borrowers (Buchak et al, 2018). Given the enhanced lending process offered by fintech lenders, Fuster et al, 2019 assert that technology may reduce frictions and facilitate the transmission of monetary policy. I add to this literature by testing this prediction on U.S. mortgages rates.

Third, my paper relates to the literature that investigates the role of lender's characteristics such as size, capital, liquidity and cost of funding measures as potential factors affecting the monetary policy transmission (see, for instance, Kashyap and Stein, 2000, Jiménez et al, 2012 and 2014). Using a detailed dataset on nonbanks activity, I add to this literature by studying if and how balance sheet characteristics and funding conditions affect the monetary policy transmission through non-fintech and fintech nonbank lending.

The rest of the paper proceeds as follows. Section 2 provides an overview of the nonbanks FHA's market. Section 3 describes the fintech and non-fintech loan-level data utilized in the analysis and the monetary policy variables. Section 4 describes the data on lenders' characteristics and additional data that I use. Section 5 reports the specifications, baseline results and robustness tests. Section 6 explores the potential role of lenders' balance sheet and funding structure in the monetary policy transmission mechanism. Section 7 reports the dynamic response of fintech and non-fintech lending to monetary policy shocks. Section 8 concludes.

2 The nonbanks' FHA market: an overview

I analyse how monetary policy shocks affect mortgage rates and volumes using home loans insured by the Federal Housing Administration (FHA) in the U.S.[3] Data come from the U.S. Department of Housing and Urban Development and concern loans that are insured by the government and issued by approved lenders. The FHA program is addressed to borrowers with weak credit history and/or with small down payment and that in general may have difficulties to obtain conventional mortgages.[4] Because of the insurance coverage, if a borrower defaults on a mortgage, the FHA pays the outstanding amount that the borrower owes. In turn, to join the program, borrowers pay an upfront and annual insurance premiums and need to meet certain eligibility criteria (such as a minimum credit score of 500 out of 850).

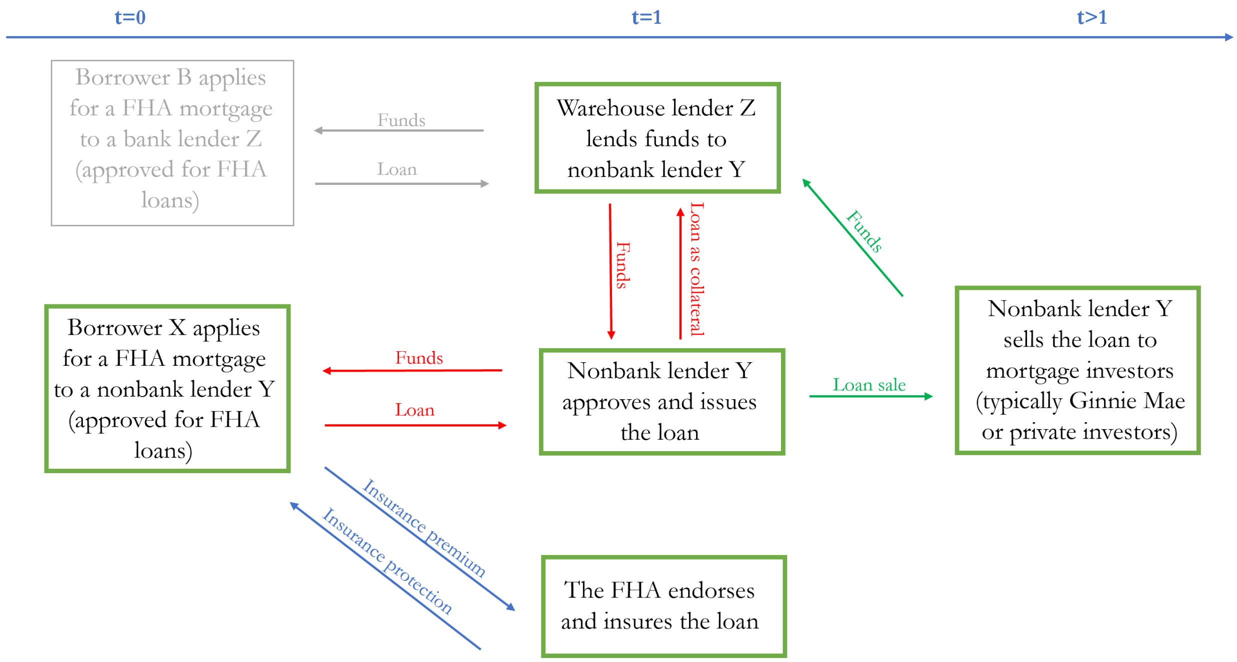
In recent years, about three-quarter of the FHA mortgages were issued by nonbanks (Kim et al, 2018), with an increasing share being issued by fintech lenders. This section provides an overview of the origination process of loans insured by the FHA, with the aim to facilitate the assessment of monetary policy transmission mechanism in this market segment. Valuable insights on the role of nonbanks in the FHA segment are offered by Kim et al (2018).

Figure 1 summarizes the process of loan origination and disposition. At time t=0, borrowers apply for a FHA mortgage. Borrowers are required to meet certain eligibility criteria to be considered for the loan. In t=1 (roughly two months after the process started), if the

[3] On average, between 2012 and 2019, the FHA's market share of new home purchase mortgage was about 20% (Congressional Research Service, 2022).

[4] For a detailed description of FHA home insured loans and history of the FHA program see Jones (2015).

Figure 1: Stylized representation of nonbanks' FHA market



Source: Author's elaborations on Jiang (2019) and Kim et al (2018).
Notes: The figure summarizes the process of loan origination and disposition. At time t=0, borrowers apply for a FHA mortgage. In t=1 (roughly two months after the process started), if the application is successful, the nonbank lender originates the mortgage which is endorsed and insured by the FHA. Borrowers pay an insurance premium to the FHA. At t=1, to originate the mortgage, nonbanks draw from the available credit lines (with commercial banks or investment banks) and use the originated loan as collateral. Usually within three months from the loan origination date, the loan is sold to a mortgage investor (such as the government-owned corporation Ginnie Mae) and the warehouse lender receives the fund back (see Jiang, 2019 and Kim et al, 2018).

application is successful, the nonbank lender originates the mortgage which is endorsed and insured by the FHA. Borrowers pay an insurance premium to the FHA. Up to this point, the process is similar between banks and nonbanks lenders. What differentiates the latter is the financing of mortgage origination. Nonbanks rely on a short-term funding structure, mostly based on warehouse credit lines (with commercial banks or investment banks), while banks core funding instruments are retail deposits. Therefore, at t=1, to originate the mortgage, nonbanks draw from the available credit lines and use the originated loan as collateral. Usually within three months from the loan origination date, the loan is sold to a mortgage investor (such as the government-owned corporation Ginnie Mae) and the warehouse lender receives the fund back (see Jiang, 2019 and Kim et al, 2018).

The difference in the funding structure between banks and nonbanks could imply a different monetary policy pass-through for these two types of lenders. In the following sections, after having focused on the transmission of monetary policy through rates and volumes of loans originated by fintech and non-fintech lenders, I complement the analysis with information on warehouse credit line usage and costs.

3 Fintech and Non-Fintech mortgage data and monetary policy measures

In this section, I provide the definition of fintech lenders, and I describe my sample of fintech and non-fintech lenders and related data. In addition, I illustrate the monetary policy measures used in the analysis.

3.1 Fintech and Non-Fintech mortgage lenders classification and data

The classification of fintech and non-fintech lenders for the U.S. mortgage market used in the paper is based on the work of Buchak et al (2018) and Fuster et al (2019). Fintech lenders are defined as companies (i) with a significant online presence, and ii) with an almost entirely digital loan application process. In other words, fintech lenders provide borrowers with a digital loan application process that enables interaction with loan officers only at a late stage of the process (usually at closing). In addition to the fintech classification, each lender (fintech and non-fintech) is classified as either a nonbank (non-depository taking lender) or a traditional bank.

Using FHA mortgages (described in the previous section) and following the classification of fintech and non-fintech lenders in Buchak et al (2018) and Fuster et al (2019), my sample includes about 2.5 million single family fixed rate mortgages issued by 230 non-fintech banks and 188 nonbanks (179 non-fintech and 9 fintech) over the period January 2012-June 2019. Among the selected fintech lenders, some account for a sizable portion of the overall mortgage volumes.[5] [6] [7]

The FHA data have a monthly frequency and include a number of information at loan level, such as the interest rate charged, the loan amount, the county where the insured property is located and the name of the lender that provided the loan (which allowed me to identify and classify each lender).

[5]The largest fintech lender in the U.S., Quicken Loans, held around 5% of the mortgage market in 2016, putting it in second place after Wells Fargo in terms of mortgage originators in the country. About 0.9% and 0.6% of the market were accounted for, respectively, by other fintech lenders like Guaranteed Rate and Movement Mortgage (see Table 1 in Fuster et al, 2019).

[6]While Buchak et al (2018) and Fuster et al (2019) do not exclude a priori the possibility of fintech *banks*, they include in their analysis fintech *nonbanks* only. However, in the past few years *banks* began providing more digital loan application processes. Indeed, Fuster et al (2019) note that, in 2017, some *banks* started offering online pre-approval. In addition, Buchak and co-authors provide updates to classifications of fintech lenders as of 2019 including some *banks* that were classified as non-fintech as of 2017 and that became fintech by 2019. My sample includes fintech nonbanks only, but in future extensions the same analysis can be performed on fintech banks too.

[7]The actual period of my analysis is January 2012-June 2019. However, I use FHA data from March 2012 to August 2019 as the date reported is the "endorsement date" (i.e. the effective date for mortgage acceptance by the FHA for endorsement) and FHA loans usually take on average more than 50 days to close.

Table 1 - Summary statistics: interest rate charged and amount borrowed

Interest rate charged

	Non-fintech Interest rate			
	Obs.	Mean	Median	SD
2012	367,283	3.78	3.75	0.34
2013	314,801	3.78	3.75	0.53
2014	252,102	4.22	4.25	0.34
2015	320,159	4.02	4.00	0.39
2016	324,686	3.83	3.75	0.41
2017	302,201	4.21	4.25	0.43
2018	254,197	4.82	4.88	0.52
2019	242,892	4.49	4.50	0.67

	Fintech interest rate			
	Obs.	Mean	Median	SD
2012	12,686	3.81	3.75	0.34
2013	14,643	3.88	3.75	0.49
2014	21,808	4.22	4.25	0.29
2015	37,549	4.01	3.99	0.32
2016	50,388	3.77	3.75	0.33
2017	46,547	4.18	4.12	0.35
2018	44,914	4.78	4.75	0.48
2019	48,894	4.39	4.38	0.60

Amount borrowed

	Non-fintech Amount US$K			
	Obs.	Mean	Median	SD
2012	367,283	168.49	147.28	93.15
2013	314,801	176.20	155.25	95.90
2014	252,102	172.78	155.04	88.62
2015	320,159	186.36	166.92	92.87
2016	324,686	195.24	176.74	94.40
2017	302,201	201.11	184.10	95.31
2018	254,197	204.58	188.52	95.51
2019	242,892	214.18	200.64	97.65

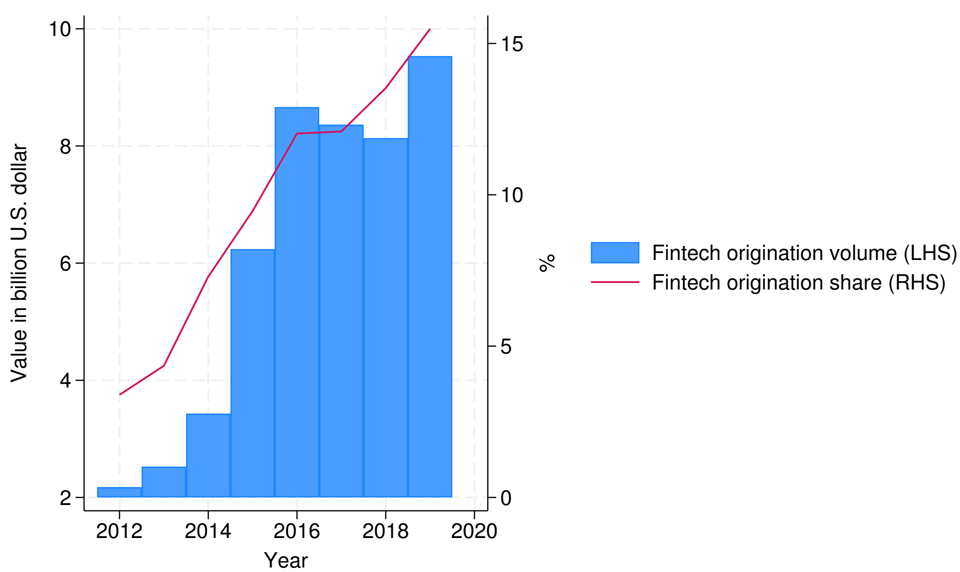
	Fintech Amount US$K			
	Obs.	Mean	Median	SD
2012	12,686	171.31	150.67	96.30
2013	14,643	172.25	151.20	97.76
2014	21,808	157.19	142.36	82.85
2015	37,549	166.13	149.83	87.81
2016	50,388	171.94	157.10	89.08
2017	46,547	179.60	163.98	93.98
2018	44,914	181.12	164.96	93.62
2019	48,894	194.94	180.46	96.37

Source: Author's calculation on U.S. Department of Housing and Urban Development data.
Notes: The data refer to single-family fixed rate purchase mortgages insured by the Federal Housing Administration between January 2012 and June 2019 for the sample of selected non-fintech and fintech lenders. *Observations* refer to the number of mortgages issued by non-fintech and fintech lenders in my sample.

Fintech and non-fintech mortgage lenders, over time, charged customers interest rates that ranged on average from 3.7% to 4.8% and lent an average amount that varied from US$157,000 to US$214,000 (Table 1). The loan volumes issued by fintech lenders expanded significantly, growing four times in the period 2012 to 2019 (Figure 2). While the increase is primarily the result of new fintech lenders entering the market over time (particularly starting in 2017), the upward trend in volumes is meaningful at lender-level.[8] As a share of total volumes, fintech increased from about 3% in 2012 to about 15% in 2019 (Figure 2).

To evaluate the role of borrowers' characteristics when assessing the transmission mechanism of monetary policy, I complement the FHA data with data from the Home Mortgage Disclosure Act (HMDA). Such dataset is the most detailed and publicly available source of information on the U.S. mortgage market. The data are reported on a yearly basis[9] and include information on the borrower such as ethnicity, race, sex, and income.

Figure 2: Fintech origination over time



Source: Author's calculation on U.S. Department of Housing and Urban Development data.
Notes: The data refer to single-family fixed rate purchase mortgages insured by the Federal Housing Administration over the period 2012-2019, after matching observations across datasets.

[8]It refers to the sample after matching observations across datasets.

[9]Monthly data are available within the Federal Reserve System.

Table 2 - Summary statistics: borrowers' riskiness

	Non-fintech	Fintech
Borrower's Average Income (US$K)	67	69
Borrower's Median Income (US$K)	61	63
	Non-fintech	Fintech
Average Loan to Value Ratio (%)	96	95
Median Loan to Value Ratio (%)	97	97

Source: Author's calculation on HMDA data for the sample of selected non-fintech and fintech lenders. Notes: Data for *Average Income* refer to the 2012-2019 sample. Data for *Loan to Value Ratio* are available for 2018-2019 only.

While the FHA and HMDA databases have different observations frequency (monthly and yearly, respectively), the former is a subset of the latter. Matching the two sources provides me with a significantly larger amount of information at lender/county level, as well as a better control for mortgage market developments outside of FHA insured products.

Table 2 reports selected statistics at borrower-level. I measure the borrower's riskiness by looking at the average borrower's income and the loan to value ratio for the FHA loan. On average, the income of fintech borrowers is $2000 higher than non-fintech ones, while the loan to value ratio is 97% for both groups.[10] Overall, on average, the borrowers' riskiness is similar across fintech and non-fintech borrowers. Yet, all model specifications will include controls for borrowers' income.

[10] The loan to value ratio is very high as the FHA program is specifically addressed to borrowers with weak credit history and/or with small down payment.

3.2 Monetary policy measures

This subsection describes the monetary policy measures used in the analysis. To assess the impact of monetary policy developments on fintech lending there are two key conditions that monetary policy variables need to satisfy: (1) being exogenous to other factors (e.g., macroeconomic developments) and (2) being comprehensive enough to incorporate all policy actions, including unconventional measures largely utilized in the post 2007-2008 great financial crisis.

The monetary policy shocks estimated by Swanson (2021) and Bauer and Swanson (2022), which I use in my paper, address both points: along with addressing the endogeneity of monetary policy, the approach enables estimation of the unexpected changes in the three most relevant policy tools lately employed by the Federal Reserve—the policy rate (federal funds rate), forward guidance and large-scale asset purchases (LSAPs). The approach put forward by Swanson (2021) expands on the high-frequency method used by Gürkaynak et al (2005). Swanson (2021) first collects the 30-minute responses of asset prices to FOMC announcements from July 1991 to June 2019, then determines the first three principal components of these responses, and finally rotates the principal components into factors that can more directly be associated to corresponding monetary policy shocks. Following Bauer and Swanson (2022), I aggregate the first and second measures (policy rate and forward guidance) into a single variable which I refer to as "target/path". The aggregation allows to parsimoniously capture the main features of both types of monetary policy surprises and to simplify their interpretability. Moreover, Bauer and Swanson (2022) further adjust the estimated policy shocks to minimize their potential endogeneity with macro time series. In a second stage estimation, they regress the policy surprises on economic and financial variables that pre-date the announcements and appear to have some predictive power on the policy shocks. By taking the residuals of this second-stage regression, the policy variables are more likely to be capturing policy innovations more neatly. In addition, expanding on Bauer and Swanson (2022) methodology, I perform a similar second-stage analysis on the LSAP variable, utilizing the same macro regressors identified by the authors. As a result, I obtain two time series of monetary policy shocks from January 2012 to June 2019: (i) the “target/path” series which captures unexpected changes in the policy rate and forward guidance and, (ii) the large-scale asset purchases (LSAPs) series. While the “target/path” shocks constitute the key focus of my analysis, to prevent bias from omitted variable I always account for LSAPs innovations as well.

To facilitate the coefficients' interpretability in the regression analysis, the policy shocks are rescaled in order to be proportional to a 100 basis point move in ED4 for the ”target/path” and to a 100 basis point move in the ten-year U.S. Treasury rate for the LSAPs variable. This simple rescaling does not affect the variables distribution and it is only functional to a better interpretability of my results.

I apply three types of robustness tests to the baseline policy variables used throughout the paper. The first one consists in the recalibration of the monetary policy shocks on a shorter sample, from 2012q1-2019q2 (rather than the 1991-2019 sample used in Swanson, 2021), consistently with the timeframe of my regression analysis. Secondly, I exclude the LSAPs variable and only utilise the ”target/path” policy variable. Finally, I test an alternative measure of monetary policy shocks using the approach proposed by Bu et al (2021), which relies on heteroscedasticity-based partial least squares estimates combined with Fama-MacBeth style cross-section regression analysis.

4 Nonbanks lender-level data and additional data

This section describes (i) lender-level characteristics that may affect the monetary policy transmission and (ii) national- and county-level macro and market controls.

4.1 Nonbanks call reports data

For the first time in the literature, I complement mortgages and monetary policy data with a novel and granular dataset on fintech lenders' balance sheet and funding conditions to assess the monetary policy transmission mechanism of fintech lenders in the U.S.

As shown in Section 2, the process of loan origination in the nonbanks FHA mortgage market is composed by various steps. The warehouse credit lines and interest rates that lenders pay are a crucial step of the process. Therefore, to evaluate if and how characteristics of both fintech and non-fintech lenders affect the monetary policy transmission, I supplement the analysis using nonbanks call report data. Since 2011, nonbanks that conduct mortgage origination under a state license or state registration need to file call reports on a quarterly basis (Jiang, 2019). The filing must be compiled for each state in which the mortgage origination is conducted. As Jiang (2019), I submitted a FOIA request to several U.S. states and I obtained data from the states of Washington and Massachusetts. Given the information collected from registered/licensed lenders in any state include activities conducted at national level, these data allow for a substantial coverage of the national mortgage origination in the nonbanks sector.[11]

[11] According to Jiang (2019), data from the states of Washington and Massachusetts cover about 80% of total mortgage origination in the nonbanks sector. My main source of data comes from the state of Wahington and when necessary, I complement them with the data from the state of Massachusetts.

Nonbanks call reports offer precious insights on nonbanks activities undisclosed until a few years ago. This is the first direct comparison of fintech and non-fintech lender balance sheets and warehouse credit lines based on these novel data. For each nonbank lender in my sample for which data are available, I collect information on assets, sources of capital (equity and debt), and warehouse credit lines, including the credit limit of each credit line and the remaining balance at the end of the quarter.

Furthermore, to estimate the interest rate paid by each nonbank on their warehouse credit lines, I combine data on the debt facilities outstanding balance with the warehouse interest expenses as follows:

$$\text{Credit lines interest rate}_{i,q} = \frac{E_q}{(0.5 \times B_q + 0.5 \times B_{q-1}) \times (0.25)}$$

where the credit lines interest rate of lender i in quarter q is a function of the warehouse interest expense (E) and of the outstanding balance on debt facilities (B). Since the warehouse interest rate is typically quoted at a given spread to the LIBOR rate (see Jiang, 2019), I then subtract the 1-month LIBOR rate to my estimates:

$$\text{Net credit lines interest rate}_{i,q} = \text{Credit lines interest rate}_{i,q} - \text{1-month LIBOR}_q$$

I obtain data for 105 non-fintech lenders and 7 fintech lenders from my initial nonbanks sample. Table 3 reports several summary statistics for the sample of non-fintech (column 1) and fintech (column 2) lenders. Column 3 reports the p-value for the two-sample t-test with unequal variances. The median equity over total assets is 17% for both groups. The median short-term assets over short-term liabilities, which is about 108-109%, is again similar across the two groups. In terms of warehouse funding usage, the median non-fintech lender utilizes about 54% of the available line of credit, while the median fintech utilizes about 57% of the available funding. Furthermore, the median interest rate paid on the warehouse funding is 10 basis point cheaper for fintech lenders relatively to non-fintech. The last section of Table 3 reports information on the warehouse period for the state of Washington only. The average number of days loans are warehoused before being sold is 19 for both groups, while the median pull-through ratio (i.e. the number of loan issued divided by the number of applications) is 57% for non-fintech and 45% for fintech. Despite most values look comparable and fairly close between fintech and non-fintech lenders, two sample t-tests with unequal variances point to a rejection of the null hypothesis of equal means between the two groups for some of the aforementioned indicators. For this reason, I will introduce some of these variables as controls in the regression analysis presented in subsequent sections.

4.2 National and county-level data

To account for macro and market dynamics, I supplement the loan-level data and the monetary policy measures with several national and county-level variables. First, I collect, from Bloomberg, the monthly VIX index as measure of market volatility, the monthly ISM purchasing managers' index as measure of the U.S. economic activity, the monthly U.S. breakeven inflation (at various horizons) as proxy for inflation expectations and inflation risk premia and U.S. Treasury yields at various horizons as proxies of risk-free rates in the economy. Second, I take the quarterly employment and wages data for the largest U.S. counties from the U.S. Bureau of Labour Statistics.

Table 3 - Summary statistics - Lenders' characteristics and warehouse credit lines

	(1)				(2)				(3)
	Non-fintech				Fintech				T-test
	Obs.	Mean	Median	SD	Obs.	Mean	Median	SD	p-value
Assets & liabilities									
Ln(total assets)	2,841	18.73	18.82	2.31	177	20.41	20.47	1.62	<0.01
Ln(total liabilities)	2,841	18.48	18.63	2.37	177	20.00	20.33	1.89	<0.01
Capital & Liquidity									
Equity over total assets (%)	2,837	20.13	16.69	13.08	177	27.73	16.57	23.25	<0.01
Short-term assets over short-term liabilities (%)	2,504	130.55	108.34	377.08	169	133.25	109.25	62.45	0.76
Short-term assets over total assets (%)	2,145	80.23	86.42	18.57	145	78.68	84.11	15.33	0.25
Loan servicing									
Servicing fees earned (first mortgages) over total assets (%)	2,199	0.72	0.49	0.77	173	0.88	0.50	0.83	0.02
Servicing fees earned (other mortgages) over total assets (%)	155	0.07	0.01	0.18	33	1.29	1.60	0.66	<0.01
Subservicing fees earned over total assets (%)	333	0.14	0.03	0.24	35	0.02	0.02	0.01	<0.01
Capital structure & warehouse funding usage									
Total Liabilities over total equity (%)	2,837	571.36	498.74	375.10	177	487.83	503.58	328.60	<0.01
Short-term liabilities over total liabilities (%)	2,504	92.14	96.74	14.27	169	95.50	97.35	4.75	<0.01
Credit lines utilized over total assets (%)	2,100	75.03	71.01	44.53	159	57.32	67.03	29.18	<0.01
Credit lines utilized over credit limit (%)	2,227	54.09	54.25	19.62	159	55.17	57.02	21.06	0.53
Warehouse funding cost									
Credit lines interest rate (estimated) (%)	2,093	3.00	2.97	1.21	159	2.71	2.87	1.26	<0.01
Credit lines interest rate minus LIBOR (estimated) (%)	2,093	2.09	2.12	1.23	159	1.68	1.88	1.09	<0.01
Warehouse period, state-specific (Washington state)									
Days in warehouse before the loan is sold	990	19.63	18.50	15.35	56	20.54	19.00	7.83	0.44
Pull-through ratio (%)	1,009	57.19	56.59	32.62	63	44.93	45.38	17.65	<0.01

Source: Author's elaborations on nonbanks call reports data. Notes: This table reports summary statistics of nonbanks call reports data for the sample of non-fintech (column 1) and fintech (column 2) nonbanks used in my analysis. Column 3 reports the p-value for the two-sample t-test with unequal variances. Data are reported at a quarterly frequency. The sample period is 2012q1 – 2019q2.

5 The responses of fintech and non-fintech mortgage lending to monetary policy shocks

In this section, I study the responses of fintech and non-fintech mortgage lending rates and volumes to monetary policy shocks in the U.S. First, I study the effects of monetary policy surprises on fintech and non-fintech loan rates and volumes. Subsequently, I report some robustness tests.

I assess whether fintech mortgage lending rates and volumes respond differently to monetary policy shocks than non-fintech ones by using regression analysis. All regression models are estimated in changes with quarterly frequency on a sample that starts in 2012 and ends in 2019. Since the data do not allow to track individual borrowers over time, I aggregate loan-level data at lender-county-quarter level (with a total of 2150 counties in the largest specification).

5.1 Specifications

The baseline regression model is the following:

$$\begin{aligned} \Delta \mathrm{X}_{l,c,q} = \beta_1 \mathrm{Fintech}_l + \beta_2 \mathrm{MPS}_{q-1} + \beta_3 \mathrm{Fintech}_l \times \mathrm{MPS}_{q-1} + \beta_4 \Delta \mathrm{Z}_{q-1} + \\ + \beta_5 \mathrm{Fintech}_l \times \Delta \mathrm{Z}_{q-1} + \epsilon_{l,c,q} \end{aligned} \tag{1}$$

where X is the either the average lending rate or the log of volumes (of loans originated by lender l in county c in quarter q); *Fintech* is an indicator variable equal to one for fintech lenders; monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks and *MPS* refers to the target/path monetary policy shock; Z is a vector of macro controls that includes the VIX, as a proxy for uncertainty and market volatility, the U.S. five-year breakeven inflation rate, as a proxy for inflation expectations and inflation risk premia, the ISM Purchasing Managers' Index as measure of the U.S. economic activity, the ten-year U.S. treasury yields as a proxy of risk-free rates in the economy, and the LSAPs monetary policy shock, as a measure of unconventional monetary policy shock via large-scale asset purchases. In addition, in all specifications, I control for (i) a measure of the lender's size using the log of total loan origination (not only FHA) in the given year and (ii) the borrower's income as a measure of borrower's riskiness. All data have quarterly frequency, except total loan origination which is at annual level. All variables are lagged by one quarter, except the ten-year U.S. treasury yields which is contemporaneous. I saturate the model with different combinations of fixed effects which include county, lender, time and county-time fixed effects.

In equation (1), a contractionary monetary policy shock is indicated by a positive surprise in the federal funds rate or forward guidance factor, which I define as *MPS target/path*. If fintech strengthens the transmission of monetary policy surprises to mortgage rates, I expect a positive sign for the fintech interactions with the federal fund rates and forward guidance variable. Coefficients of opposite signs would indicate that fintech dampens the transmission of monetary policy relative to the standard lending channel. With respect to fintech lending volumes, a negative coefficient associated to the fintech interaction with the *MPS target/path* policy variable would signal a stronger policy transmission.

5.2 Main results

Table 4 reports the results of estimating various versions of equation (1) where the dependent variable is the quarterly change in the average lending rates. Panel A shows estimates for the full sample of lenders (banks and nonbanks). From columns 1 to 4, I saturate the model with several fixed effects. The most restrictive specification is reported in column 4, where lender and county-quarter-year fixed effects are included to account both for time-invariant lender-level characteristics and time-variant county-level characteristics. Panel B reports estimates for nonbanks only, while Panel C also excludes the largest fintech lender from the sample.[12] Similarly to Panel A, these subsequent blocks show estimates including various degree of fixed effects in the model. Robust standard errors are applied to all specifications.

The sign of the monetary policy shock is as expected: following a contractionary monetary policy shock to the policy rate or a hawkish forward guidance, the average lending rate increases. I find that a shock proportional to a 100 basis points tightening in the *MPS target/path* translates on average into approximately 7-24 basis points increase in the average lending rates with a one quarter lag (column 1 in Table 4). These results are comparable in size to the ones estimated by Bauer and Swanson (2022) for the 30-year yield responses to monetary policy surprises.

I now turn to the interaction of the monetary policy variable with the fintech dummy in Table 4. The results indicate that, relative to non-fintech lenders, the pass-through of a *target/path* shock is stronger for fintech mortgage rates. According to my estimates, a 100 basis points move in the *MPS target/path* variable is estimated to raise fintech lending rates by an additional 14-28 (column 1 in Table 4), on top of the impact discussed above, implying an aggregate 21-52 basis points increase in fintech lending rates.

In the most restrictive specifications of Panels A and B, these results lose significance, suggesting that some demand side effects play a role in driving the results. However,

[12]Panels B and C allow me to confirm whether the results are not driven by the nonbanks nature of fintech lenders or by the largest fintech lender.

the stronger transmission of monetary policy to fintech rates holds in the most restrictive specification in Panel C, i.e. where the largest fintech lender is excluded from the fintech sample. This finding suggests that most fintech lenders do react differently than non-fintech ones in setting their interest rates following a monetary policy shock. This result is consistent with the hypothesis that technology can accelerate the transmission of monetary policy.

Table 5 shows results of estimating equation (1) to study the responses of mortgage volumes to monetary policy shocks. As above, Panel A reports estimation for the full sample of lenders (banks and nonbanks). From columns 1 to 4, the model is saturated with several fixed effects. The most restrictive specification is reported in column 4, where lender and county-quarter-year fixed effects are included to account both for time-invariant lender-level characteristics and time-variant county-level characteristics. Panel B reports estimates for nonbanks only, while Panel C also excludes the largest fintech lender from the sample. Similarly to Panel A, these subsequent blocks show estimates including various fixed effects in the model. Robust standard errors are applied to all specifications.

As expected, following a contractionary monetary policy shock to the policy rate or a hawkish forward guidance, there is a decrease in mortgage origination. I find that a shock proportional to a 100 basis points tightening in the *MPS target/path* translates into approximately a 43-45% decrease in the average volumes originated with a one quarter lag (column 1 in Table 5).

Table 4 - The responses of mortgages rates to monetary policy shocks

	(1)	(2)	(3)	(4)
	← Lending Rate$_{l,c,q}$ →			
	Panel A: All lenders			
Change in MPS	0.072***			
	(0.017)			
Change in MPS × Fintech	0.214***	0.058	0.045	0.055
	(0.037)	(0.037)	(0.037)	(0.037)
N	274,557	274,557	274,557	274,557
R^2	0.305	0.353	0.376	0.449
	Panel B: Nonbanks only			
Change in MPS	0.215***			
	(0.022)			
Change in MPS × Fintech	0.140***	0.046	0.019	0.031
	(0.040)	(0.039)	(0.040)	(0.041)
N	175,345	175,345	175,345	175,345
R^2	0.303	0.341	0.367	0.452
	Panel C: Excluding the largest fintech			
Change in MPS	0.236***			
	(0.022)			
Change in MPS × Fintech	0.283***	0.200***	0.182***	0.150**
	(0.060)	(0.059)	(0.061)	(0.062)
N	153,269	153,269	153,269	153,269
R^2	0.303	0.340	0.365	0.449
Control Variables	yes	yes	yes	yes
Control Variables Interactions	yes	yes	yes	yes
County Fixed Effects	yes	yes		
Lender Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes			
Quarter-Year Fixed Effects		yes	yes	
County-Year Fixed Effects			yes	
County-Quarter-Year Fixed Effects				yes

Notes: The sample period is 2012q1 – 2019q2. *All lenders* refer to the full sample. *Nonbanks only* refer to the sample of non-depository lenders only. *Excluding the largest fintech* refer to the sample of non-depository lenders excluding the largest fintech lender. Estimation is performed at lender-county-quarter level. All regression models are estimated in changes with quarterly frequency. The dependent variable is the quarterly change in the average lending rate of loans originated by lender l in county c. Monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks: the target/path monetary policy shock (MPS). Fintech is an indicator variable equal to one for fintech lenders. The *Control Variables* are VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate, the LSAPs monetary policy shock, the borrower's income and a measure of lender size (in level). Robust standard errors are reported in parentheses.

Table 5 - The responses of mortgage volumes to monetary policy shocks

	(1)	(2)	(3)	(4)
	← Lending Volumes$_{l,c,q}$ →			
	Panel A: All lenders			
Change in MPS	-0.450***			
	(0.045)			
Change in MPS × Fintech	0.705***	0.784***	0.737***	0.741***
	(0.100)	(0.099)	(0.101)	(0.101)
N	274,557	274,557	274,557	274,557
R^2	0.081	0.101	0.121	0.225
	Panel B: Nonbanks only			
Change in MPS	-0.446***			
	(0.055)			
Change in MPS × Fintech	0.717***	0.797***	0.766***	0.810***
	(0.106)	(0.105)	(0.108)	(0.108)
N	175,345	175,345	175,345	175,345
R^2	0.076	0.098	0.123	0.245
	Panel C: Excluding the largest fintech			
Change in MPS	-0.433***			
	(0.056)			
Change in MPS × Fintech	0.453***	0.578***	0.589***	0.603***
	(0.147)	(0.145)	(0.149)	(0.152)
N	153,269	153,269	153,269	153,269
R^2	0.072	0.094	0.118	0.237
Control Variables	yes	yes	yes	yes
Control Variables Interactions	yes	yes	yes	yes
County Fixed Effects	yes	yes		
Lender Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes			
Quarter-Year Fixed Effects		yes	yes	
County-Year Fixed Effects			yes	
County-Quarter-Year Fixed Effects				yes

Notes: The sample period is 2012q1 – 2019q2. *All lenders* refer to the full sample. *Nonbanks only* refer to the sample of non-depository lenders only. *Excluding the largest fintech* refer to the sample of non-depository lenders excluding the largest fintech lender. Estimation is performed at lender-county-quarter level. All regression models are estimated in changes with quarterly frequency. The dependent variable is the quarterly change in the log volume of loans originated by lender l in county c. Monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks: the target/path monetary policy shock (MPS). Fintech is an indicator variable equal to one for fintech lenders. The *Control Variables* are VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate, the LSAPs monetary policy shock, the borrower's income and a measure of lender size (in level). Robust standard errors are reported in parentheses.

Turning to the interaction of the monetary policy variables with the fintech dummy in Table 5, I find that on average fintech lenders seem to reduce the pass-through of a *target/path* shock on mortgage volumes. More precisely, I find that a shock proportional to a tightening of 100 basis points in monetary policy generates an aggregate decline in mortgage origination, but an increase of up to 27% in the volumes of loans originated by fintech relative to non-fintech (column 1 in Table 5). This result is consistent with the literature that shows that nonbanks tend to provide more credit after a monetary contraction relatively to banks (see, for instance, Elliott et al, 2022 and Xiao, 2019), and this seems to be particularly true for fintech nonbanks. The results hold in all sample, also in the most restrictive specifications. When county-quarter-year fixed effects are included, the estimates change only marginally and they remain highly significant statistically.

Overall, the results suggest that fintech lenders tend to intensify the transmission of the monetary policy pass-through to mortgage rates. I find, instead, statistically strong evidence that all fintech lenders reduce the pass-through of monetary policy shocks on mortgage volumes.

As robustness checks, I obtain similar results using the *target/path* shock recalibrated exclusively on the 2012q1-2019q2 sample and excluding the LSAPs variable from the specification (Table A1 in Appendix). Similarly, results are consistent using as alternative monetary policy variable the unified measure of Fed monetary policy shocks proposed by Bu et al (2021) (Table A2 in Appendix).

In additional robustness tests (not reported, but available upon request), (i) I weight observations based on the number of mortgages that are issued in county c by lender l in quarter q, (ii) I incorporate additional county controls by adding employment and wages data at county level to the baseline regression model to control for cyclical developments across counties and, (iii) I use the number of new loans as dependent variable rather the new mortgage volume. Across all specifications, the main results are confirmed. Finally, results do not change when I address the potential collinearity concerns related to the 10-year U.S. Treasury rate (which features as a control variable in my baseline model), and the monetary policy shocks. Treasury rates are, indeed, affected by unexpected monetary policy changes, while at the same time incorporating an "expected" policy outcome ahead of FOMC decision. To separate the two components ("expected" and "unexpected" policy shocks), I regress changes in the 10-year U.S. Treasury rate on the *target/path* monetary policy shock and on the *LSAPs* variable. I then utilise the residual of this first-stage regression in the baseline model as a substitute for the 10-year U.S. Treasury rate variable.

6 The role of funding flows and nonbank lenders' characteristics in the monetary policy transmission

In the previous section, I show that fintech lenders lessen the transmission of monetary policy to mortgage volumes, while, under some conditions, they increase the monetary policy transmission to mortgages rates. In this section, I explore the potential role of lenders' balance sheet and funding structure in explaining the differential impact of changes in monetary conditions on lending.

First, I assess how monetary policy developments impact the flow of funds to fintech and non-fintech lenders. Second, I add to the variables in model (1) some lender-level control variables. This allows me to assess if and how balance sheet characteristics and funding conditions affect the monetary policy transmission through fintech and non-fintech lending.

The lender-level data that I use in my analysis is limited to nonbanks. Therefore, from this point onwards, the comparison of fintech and non-fintech is assessed within the nonbank sector.

6.1 Fintech and non-fintech funding flows

Previous studies show that banks increase the margins they make on deposits as the Fed funds rate rises, which causes deposits to leave the banking system (Drechsler et al, 2017). Depositors tend to migrate from bank deposits to higher yielding money market fund shares (Xiao, 2020). As a result, nonbanks receive a large amount of funding from money market funds (MMFs) by issuing short-term debt instruments. It has been documented that such increase in funding allows nonbanks to lend more to the real economy relatively to banks in periods of monetary policy tightening (Elliott et al, 2022 and Xiao, 2020). For these reasons, I am interested in assessing whether fintech and non-fintech short-term debt respond to monetary policy developments. Differently from previous studies, I exploit a novel granular dataset on nonbanks call reports which allows me to assess this phenomenon at lender-level. I estimate the following specification:

$$\begin{aligned}\Delta ln(\text{Short-Term Debt})_{l,q} = \beta_1 Fintech_l + \beta_2 \text{MPS}_q + \beta_3 Fintech_l \times \text{MPS}_q + \\ + \beta_4 Z_{l,q} + \beta_5 Fintech_l \times Z_{l,q} + \epsilon_{l,q}\end{aligned} \tag{2}$$

where the dependent variable is the quarterly change in the log of short-term debt of lender l in quarter q. Following Xiao (2020), the monetary policy measure is the 3-year cumulative changes[13] in the *target/path* monetary policy shock as measured by Swanson

[13] Xiao (2020) shows that when the Fed funds rate increases in year 0, the rise in nonbanks deposits is persistent and reaches its peak in year 3.

(2021) and Bauer and Swanson (2022) series of shocks. Fintech is an indicator variable equal to one for fintech lenders. I control for a number of macro factors (VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index and U.S. ten-year Treasury rate), a time trend and the interest rate paid on the warehouse funding at lender level as measure of funding cost. Table 6 reports results of estimating equation (2).

Table 6 - Monetary policy and fintech and non-fintech short-term debt

	(1)	(2)
	$\leftarrow \Delta\ln(\text{Short-Term Debt})_{l,q}$	$\rightarrow$
Change in MPS	0.472**	0.523***
	(0.194)	(0.197)
Change in MPS × Fintech	0.072	-0.009
	(0.213)	(0.211)
N	1,805	1,805
R^2	0.063	0.135
Control Variables		yes
Control Variables Interactions		yes
Lender Fixed Effects	yes	yes

Notes: The dependent variable is the quarterly change in the log of short-term debt of lender l in quarter q. The monetary policy measure is the 3-year cumulative changes in the target/path monetary policy shock (MPS) as measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks. Estimation is performed at lender-quarter level. A time trend is also included in the specification. Fintech is an indicator variable equal to one for fintech lenders. The control variables (in changes with quarterly frequency) are: VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate and the interest rate paid on the warehouse funding. The sample period is 2012q3 – 2019q2. Robust standard errors are reported in parentheses.

The estimates show that the short-term debt of nonbank lenders tend to increase following a tightening in monetary policy. I find that 100 basis points of monetary policy tightening over a three-year horizon is associated to an increase of close to 50% in short-term debt financing for nonbanks. The analysis does not show significant differences between non-fintech and fintech nonbanks, suggesting the two groups behave similarly.

To summarize, these findings confirm what has been documented in the literature regarding nonbanks financing during monetary tightening cycles. This result holds for both fintech and non-fintech, without statistically relevant differences between the two.

6.2 The role of lenders' characteristics

In the literature, lender's characteristics such as size, capital, liquidity and cost of funding measures have often been investigated as potential factors affecting the monetary policy transmission (see, for instance, Kashyap and Stein, 2000, Jiménez et al, 2012 and 2014). I add to the literature by studying if and how balance sheet characteristics and funding conditions affect the monetary policy transmission through non-fintech and fintech nonbank lending.

In this section, I introduce a set of lender-level control variables which I add to model (1): (i) the equity to assets ratio (as measure of capital), (ii) the short-term assets to short-term liabilities ratio (as measure of liquidity), (iii) the interest paid on the warehouse funding (as measure of funding cost) and (iv) the short-term liabilities to total liabilities (as measure of reliance on short-term funding). The regression equation is:

$$\begin{aligned}\Delta \mathrm{X}_{l,c,q} = \alpha_l + \alpha_{c,q} + \beta_1 \mathrm{Fintech}_l + \beta_2 \mathrm{Fintech}_l \times \mathrm{MPS}_{q-1} + \beta_3 \mathrm{Fintech}_l \times \Delta \mathrm{Z}_{q-1} + \\ + \beta_4 \Delta \mathrm{W}_{l,q} + \beta_5 \mathrm{Fintech}_l \times \Delta \mathrm{W}_{l,q} + \epsilon_{l,c,q}\end{aligned} \tag{3}$$

where X is the either the average lending rate or the log of volumes (of loans originated by lender l in county c in quarter q); *Fintech* is an indicator variable equal to one for fintech lenders; monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks and *MPS* refers to the target/path monetary policy shock; Z includes macro control variables similar to equation (1) and W includes balance sheet characteristics and funding conditions at lender-level. In addition, in all specifications, I control for the lender's total asset as measure of lender size, the borrower's income as a measure of borrower's riskiness, and I include lender and county-quarter-year fixed effects. In order to rule out the possibility that a single large lender drives the model output, I report estimates for the sample of nonbanks excluding the largest fintech lender (Tables 7 and 8).

Table 7 shows results of estimating equation (3) where the dependent variable is the change in the mortgage interest rate. I expect higher nonbanks funding costs to be generally associated to higher mortgage rates. The results show that there is, indeed, a positive relationship between the funding cost and the interest rate charged, although not statically significant. I find, instead, a positive and statically significant relation when interacting the funding cost variable with the fintech dummy (for an increase in the funding cost spread to LIBOR rates of 1%, the lending rate charged by fintech lenders increase by an additional 0.02%, column 3 in Table 7). Results are not statically significant when testing for capital, liquidity and short-term debt measures.

In general, controlling for lender's characteristics and funding condition does not alter the main results from Section 5. The coefficients associated to monetary policy pass-through remain statistically significant and comparable in magnitude to previous estimates (a 100 basis points move in the *MPS target/path* variable is estimated to raise fintech lending rates by 28 basis points more than non-fintech ones, column 4 in Table 7).

With respect to changes in mortgage volumes, results are reported in Table 8. Consistently with the literature on banks, I find that liquid lenders are less prone to originate mortgages to new borrowers (see for instance Jiménez et al, 2012). This seems to be particularly true for fintech nonbanks (see column 2 in Table 8).

Table 7 - Lenders' characteristics and the responses of mortgage rates to monetary policy shocks

	Excluding the largest fintech lender			
	(1)	(2)	(3)	(4)
	← Lending $\text{Rate}_{l,c,q}$ →			
Change in MPS × Fintech	0.166**	0.174**	0.277***	0.284***
	(0.067)	(0.075)	(0.082)	(0.087)
Equity over total assets		0.028		0.015
		(0.032)		(0.032)
Equity over total assets × Fintech		0.025		-0.042
		(0.165)		(0.168)
ST assets over ST liabilities		-0.010		-0.009
		(0.008)		(0.008)
ST assets over ST liabilities × Fintech		0.044		0.036
		(0.046)		(0.060)
Credit lines interest rate minus LIBOR			0.003	0.003
			(0.002)	(0.002)
Credit lines interest rate minus LIBOR × Fintech			0.023***	0.023***
			(0.008)	(0.008)
ST liabilities over total liabilities			0.001	-0.004
			(0.028)	(0.029)
ST liabilities over T. liabilities × Fintech			-0.094	-0.042
			(0.118)	(0.151)
N	94,839	94,839	94,839	94,839
R^2	0.433	0.433	0.433	0.433
Control Variables	yes	yes	yes	yes
Control Variables Interactions	yes	yes	yes	yes
Lender Fixed Effects	yes	yes	yes	yes
County-Quarter-Year Fixed Effects	yes	yes	yes	yes

Notes: The sample period is 2012q1 – 2019q2. *Excluding the largest fintech* refer to the sample of non-depository lenders excluding the largest fintech lender. Estimation is performed at lender-county-quarter level. The dependent variable is the quarterly change in the average lending rate of loans originated by lender l in county c. Monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks: the target/path monetary policy shock (MPS). Fintech is an indicator variable equal to one for fintech lenders. The *Control Variables* are VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate, the LSAPs monetary policy shock and the borrower's income. The lender-level control variables are in level. All specifications include the lender's total asset as measure of lender size. Robust standard errors are reported in parentheses.

Table 8 - Lenders' characteristics and the responses of mortgage volumes to monetary policy shocks

	Excluding the largest fintech lender			
	(1)	(2)	(3)	(4)
	← Lending Volumes$_{l,c,q}$ →			
Change in MPS × Fintech	0.473***	0.341*	0.453**	0.481**
	(0.166)	(0.189)	(0.200)	(0.215)
Equity over total assets		-0.055		-0.118
		(0.080)		(0.081)
Equity over total assets × Fintech		0.223		-0.010
		(0.364)		(0.366)
ST assets over ST liabilities		-0.064***		-0.044**
		(0.020)		(0.021)
ST assets over ST liabilities × Fintech		-0.221*		-0.154
		(0.129)		(0.172)
Credit lines interest rate minus LIBOR			0.019***	0.021***
			(0.005)	(0.005)
Credit lines interest rate minus LIBOR × Fintech			0.042**	0.041**
			(0.019)	(0.019)
ST liabilities over total liabilities			0.281***	0.232***
			(0.066)	(0.068)
ST liabilities over T. liabilities × Fintech			0.246	-0.013
			(0.298)	(0.397)
N	94,839	94,839	94,839	94,839
R^2	0.258	0.258	0.259	0.259
Control Variables	yes	yes	yes	yes
Control Variables Interactions	yes	yes	yes	yes
Lender Fixed Effects	yes	yes	yes	yes
County-Quarter-Year Fixed Effects	yes	yes	yes	yes

Notes: The sample period is 2012q1 – 2019q2. *Excluding the largest fintech* refer to the sample of non-depository lenders excluding the largest fintech lender. Estimation is performed at lender-county-quarter level. The dependent variable is the quarterly change in the log volume of loans originated by lender l in county c. Monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks: the target/path monetary policy shock (MPS). Fintech is an indicator variable equal to one for fintech lenders. The *Control Variables* are VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate, the LSAPs monetary policy shock and the borrower's income. The lender-level control variables are in level. All specifications include the lender's total asset as measure of lender size. Robust standard errors are reported in parentheses.

Funding conditions are also statistically relevant. Higher funding costs and a larger reliance on short-term debt are associated with larger increases in mortgage volumes. For a 1% increase in the funding cost, mortgage volumes increase by 2% and for a 1% increase in the ratio of short-term liabilities over total liabilities, mortgage volumes increase by 0.28% (column 3 in Table 8). These estimates suggest that nonbanks, and fintech in particular, are able to attract funding via issuing higher yielding short-term notes, allowing them to increase mortgage origination. This is consistent with the flow of funds from banks to nonbanks described in Elliott et al, 2022 and Xiao, 2020.

When all lender-level control variables are included (column 4 in Table 8), the interaction between fintech and the monetary policy variable remains positive and statically significant. This result indicates that fintech lenders reduce the pass-through of monetary policy shocks on mortgage volumes even when accounting for lender's characteristics.

Taking together the results of the fintech and non-fintech funding flows and the results including lender-level characteristics, I show that fintech lenders, similarly to other nonbanks lenders, increase their short-term debt in periods of monetary policy tightening, which allows them to lend more to the real economy relatively to banks. Yet, controlling for lenders funding conditions, and for their capital and liquidity ratios, does not seem to explain the difference in the monetary policy pass-through between fintech and non-fintech institutions. The *fintech lending channel* of monetary policy cannot be explained by factors related to balance sheet or funding characteristics. Alternative factors, which have been proposed in the literature (see Dedola et al, 2023) and are not directly accounted in my model, could be related to technology and digitalisation (as greater price flexibility can accelerate the pass-through of monetary policy to prices) or competition (as prices may become more flexible as a result of online competition, making them more responsive to monetary policy). In the next section, by looking at the dynamic responses of mortgages rates and volumes to monetary policy shocks, I test whether the differences in the pass-through are persistent over time or whether they tend to reconverge in subsequent periods.

7 The dynamic response of fintech and non-fintech lending to monetary policy shocks

As shown in the previous section, controlling for the funding flows and lender's characteristics does not explain the difference in the monetary policy pass-through between fintech and non-fintech institutions. In this section, I look at the dynamic responses of mortgage rates and volumes to assess whether the *fintech lending channel* of monetary policy can be associated to a different distribution of the pass-through over time between fintech and non-fintech lenders (e.g., potentially driven by technological advancements) and/or to a different cumulative size of the transmission (which might indicate more structural causes).

The empirical assessment consists in the estimation of the responses of fintech and non-fintech rates and volumes to monetary policy shocks using panel local projections (Jordà, 2005). Differently from the previous sections, this approach allows for the estimation of dynamic responses of the variables of interest over time. The specification is as follows:

$$\mathrm{X}_{c,q+h} - \mathrm{X}_{c,q-1} = \alpha^h + \beta^h \mathrm{target/path}_q + \sum_{j=1}^{J} \gamma_j Z_{c,q-j} + \sum_{k=1}^{K} \delta_k Y_{c,q-k} + \epsilon_{c,q+h} \tag{4}$$

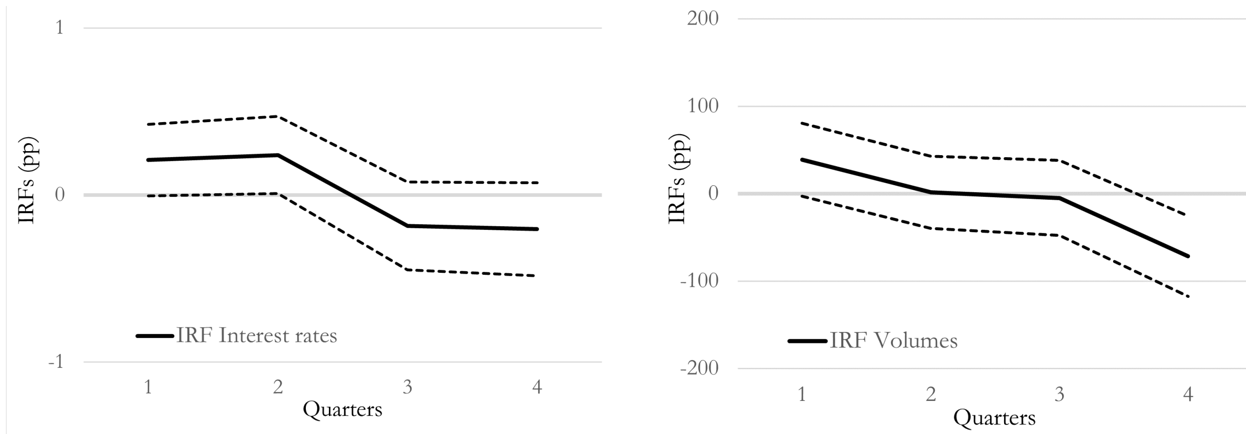
where X is either the average lending rate or the log of mortgage volumes (of loans originated by fintech or non-fintech lenders in county c in quarter q) and h≥ 0 indexes the forecast horizon. I estimate the impulse response functions from the sequence of the coefficients on the *target/path* shock, $\{\beta^h\}_{h=0}^{H}$, for fintech and non-fintech. The vector Z of controls includes: the dependent variable, the *LSAPs* monetary policy shock and the ten-year U.S. treasury yields. The vector Y of controls includes the VIX, the US five-year breakeven inflation rate, and the ISM Purchasing Managers' Index. I set the number of lags to J=1 quarter and K=2 quarters and the horizon of the impulse response functions to H=4 quarters. I use robust standard errors [14] and I saturate the model with county fixed effects. All estimations are performed at quarterly frequency.

Figure 3 reports the difference in the impulse responses for fintech and non-fintech lenders. Panel A reports estimations for the responses of the mortgage interest rates to the monetary policy shocks up to four quarters. Panel B reports estimation for the responses of the mortgage volumes. A positive coefficient indicates that the impulse response function in a given quarter is larger for fintech compared to non-fintech.

Starting from Panel A, I find a positive and significant coefficient with one-quarter lag between fintech and non-fintech, which confirms the result obtained from the static model in Section 5. The difference remains significant and similar in size after two quarters, while it decreases and turns slightly negative four quarters after the shock. The stronger pass-through of monetary policy shocks to fintech mortgage rates vanishes after about three quarters and it is not persistent over time. Fintech appears to accelerate the speed of pass-through, but does not amplify the cumulative magnitude of the transmission over time, which remains comparable between the two groups of lenders.

[14] Montiel Olea and Plagborg-Møller (2021) show that Eicker–Huber–White heteroscedasticity-robust standard errors are sufficient for lag-augmented local projections.

Figure 3: Impulse response functions



Panel A: Lending Rates

Panel B: Lending Volumes

Notes: I estimate the impulse response functions from the sequence of the coefficients on the *target/path* shock, $\{\beta^h\}_{h=0}^{H}$, for fintech and non-fintech in equation (4). The figure reports the difference in the impulse responses for fintech and non-fintech lenders. Estimation is performed at county-quarter level. The samples are restricted to nonbanks only and the fintech sample excludes the largest fintech lender. The dependent variable is either the average lending rate or the log of mortgage volumes (of loans originated by fintech or non-fintech lenders in county c in quarter q). Confidence intervals at 90% levels are estimated assuming a covariance of zero between the two series of parameters, which is the most conservative assumption. Monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks: the target/path monetary policy shock. The controls are VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate, the LSAPs monetary policy shock and dependent variable. I use robust standard errors and I saturate the model with county fixed effects. The sample period is 2012q1 − 2019q2.

Panel B of Figure 3 shows a comparable behaviour for mortgage volumes. The response of mortgage origination between fintech and non-fintech differs for one quarter after the shock (in line with the findings from Section 5), while it converges towards zero in following quarters. As previously discussed, this suggests that fintech lending decreases by less than non-fintech lending in times of monetary policy tightening, albeit for a limited period of time.

The impulse response function analysis shows that fintech lenders accelerate rather than amplify the pass-through of monetary policy shocks on lending rates. This could be due to the technology advancements of fintech lenders, such as automated screening processes, online lending origination and faster pricing (see Buchak et al, 2018 and Fuster et al, 2019). Furthermore, the analysis shows that fintech lenders lessen the response of mortgage volumes to monetary policy even more than other nonbanks lenders, albeit for a limited period of time. These findings suggest that fintech institutions are better placed than other nonbank lenders to benefit from the additional flow of funds they receive in periods of monetary policy tightening, exploiting their technological lead and faster mortgage origination process. Overall, the *fintech lending channel* of monetary policy appears to be driven by the technological innovation for which fintech lenders distinguish themselves from other lenders.

8 Concluding remarks

Technology-based (fintech) lending is a growing segment of the credit market. Yet, there is a question of whether the transmission of monetary policy to fintech lending differs from the non-fintech one. This paper investigates the effect of conventional and unconventional monetary policy shocks on fintech and non-fintech mortgage rates and volumes in the U.S. between 2012 and 2019. I refer to this new transmission mechanism as the *fintech lending channel*.

The main findings show that fintech lenders tend to accelerate the monetary policy transmission to mortgages rates, while they lessen the pass-through to mortgage volumes. The differential impact of changes in monetary conditions cannot be explained by lenders or borrowers' characteristics, nor by time-variant geographical features. The *fintech lending channel* is likely driven by technological advancements that distinguish fintech lenders from other credit providers. Indeed, the differences appear related to the speed of the pass-through rather than to its cumulative magnitude, which, over the medium term, is comparable between the two groups.

The analysis offers a first in-depth assessment of the monetary policy transmission mechanism via fintech lending, which, given its increasing share, will help policymakers to adequately calibrate their interventions. Moreover, a better understanding of the *fintech lending channel* and of new forms of technology-based lending will facilitate policy considerations related to macro-prudential and financial stability assessments.

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9 Appendix

Table A1 -

The responses of mortgages rates and volumes to monetary policy shocks

	(1) Lending Rate	(2) Lending Volumes
	Panel A: All lenders	
Change in MPS × Fintech	0.057**	0.508***
	(0.028)	(0.077)
N	274,557	274,557
R^2	0.449	0.225
	Panel B: Nonbanks only	
Change in MPS × Fintech	0.047	0.542***
	(0.030)	(0.082)
N	175,345	175,345
R^2	0.452	0.245
	Panel C: Excluding the largest fintech	
Change in MPS × Fintech	0.105**	0.313***
	(0.046)	(0.117)
N	153,269	153,269
R^2	0.449	0.237
Control Variables Interactions	yes	yes
Lender Fixed Effects	yes	yes
County-Quarter-Year Fixed Effects	yes	yes

Notes: The sample period is 2012q1 – 2019q2. *All lenders* refer to the full sample. *Nonbanks only* refer to the sample of non-depository lenders only. *Excluding the largest fintech* refer to the sample of non-depository lenders excluding the largest fintech lender. Estimation is performed at lender-county-quarter level. All regression models are estimated in changes with quarterly frequency. The dependent variable, in column 1, is the quarterly change in the average lending rate of loans originated by lender l in county c and, in column 2, is the quarterly change in the log volume of loans originated by lender l in county c. Monetary policy is measured by Swanson (2021) and Bauer and Swanson (2022) series of shocks (the target/path monetary policy shock - MPS) recalibrated exclusively on the 2012q1-2019q2 sample. Fintech is an indicator variable equal to one for fintech lenders. The *Controls* are VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate, the borrower's income and a measure of lender size (in level). Robust standard errors are reported in parentheses.

Table A2 -

The responses of mortgages rates and volumes to monetary policy shocks

	(1) Lending Rate	(2) Lending Volumes
	Panel A: All lenders	
Change in BRW × Fintech	0.049*	0.745***
	(0.029)	(0.083)
N	274,557	274,557
R^2	0.449	0.225
	Panel B: Nonbanks only	
Change in BRW × Fintech	0.076**	0.688***
	(0.031)	(0.090)
N	175,345	175,345
R^2	0.452	0.245
	Panel C: Excluding the largest fintech	
Change in BRW × Fintech	0.084*	0.320**
	(0.048)	(0.131)
N	153,269	153,269
R^2	0.449	0.237
Control Variables Interactions	yes	yes
Lender Fixed Effects	yes	yes
County-Quarter-Year Fixed Effects	yes	yes

Notes: The sample period is 2012q1 – 2019q2. *All lenders* refer to the full sample. *Nonbanks only* refer to the sample of non-depository lenders only. *Excluding the largest fintech* refer to the sample of non-depository lenders excluding the largest fintech lender. Estimation is performed at lender-county-quarter level. All regression models are estimated in changes with quarterly frequency. The dependent variable, in column 1, is the quarterly change in the average lending rate of loans originated by lender l in county c and, in column 2, is the quarterly change in the log volume of loans originated by lender l in county c. The monetary policy variable is the unified measure of the Fed monetary policy shocks constructed by Bu et al (2021); the BRW shocks is the policy shock estimate as measured at the frequency of the FOMC meetings. Fintech is an indicator variable equal to one for fintech lenders. The *Controls* are VIX, U.S. five-year breakeven inflation rate, ISM Purchasing Managers' Index, U.S. ten-year Treasury rate and LSAPs monetary policy shock, the borrower's income and a measure of lender size (in level). Robust standard errors are reported in parentheses.