The Fisher Channel According to HANK:
Unexpected Inflation and the Missing Recession*

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Abstract

This paper argues that the post-pandemic U.S. expansion has been partly sustained by *Fisher-type redistribution* from nominal creditors to nominal debtors. I build a Heterogeneous-Agent New Keynesian model with long-term nominal claims disciplined to two micro targets: the cross-section of net nominal positions (NNP) and the covariance between NNP and marginal propensities to consume (MPCs). Feeding in the realized 2021–22 price-level surprise, the model implies an impact rise in aggregate consumption of about 0.5% and a moderate but persistent increase in inflation of about 0.3pp. A behavioral extension, capturing households' partial awareness of debt devaluation, dampens the impact response yet prolongs the effects. I validate the mechanism using a large U.S. fintech panel (430k households, daily flows), combining cross-sectional variation in baseline exposures with local-projection dynamics: results are consistent with the model and lean towards the behaviorial extension. Finally, I show that an active Fisher channel amplifies conventional monetary policy and reshapes the role of nominal rigidities in its transmission to aggregate demand.

Keywords: Inflation, Redistribution, Household Heterogeneity, Net Nominal Positions, Consumption, HANK, Monetary Policy, Alternative Data, Fintech.

JEL Codes: D12, D14, D31, E21, E52, E58

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1 Introduction

Over the course of 2022, as the Federal Reserve began raising rates at the fastest pace in four decades, many economists across the financial sector, central banks, and academia anticipated an imminent recession.[1] However, not only did a recession fail to materialize, but the U.S. economy also recorded robust growth, with real personal consumption expenditures (PCE) increasing by more than 3% in both 2023 and 2024.

In this paper, I propose that wealth transfer from nominal creditors to debtors driven by unexpected inflation has been sustaining aggregate demand in the post-pandemic period. This idea dates back to Fisher (1933): unexpected inflation reduces the real value of nominal claims.[2] If nominal debtors have a higher marginal propensity to consume (MPC) than nominal creditors (Tobin, 1982), then such a redistribution raises aggregate demand.

In Pallotti (2022), I showed that U.S. households have accumulated substantial nominal assets and liabilities over the past four decades. As first noted by Doepke and Schneider (2006), these nominal positions are distributed asymmetrically across the population. Wealthier, middle-aged, and elderly households hold most of the nominal assets, such as bonds and deposits, while nominal liabilities - especially fixed-rate mortgages - are more prevalent among the young middle class.[3] Consequently, unexpected inflation redistributes wealth away from the former group and towards the latter.

The seminal work by Auclert (2019) incorporated Tobin (1982)'s insight into a Heterogeneous Agent New Keynesian (HANK) framework, in the broader context of the distributional consequences of monetary policy. In this paper, I build a HANK model

[1]For example, a Bloomberg article predicted a 100% likelihood of a recession in 2023 (link). A survey of academics led by the Initiative on Global Markets indicated that, as of June 2022, 70% of respondents believed a recession would start before the end of 2023, with an additional 10% expecting it by 2024Q2 (link). During the press conference following the December 2023 FOMC meeting, Fed Chair Jay Powell reflected on these predictions: "So I think forecasters generally, if you go back a year, were very broadly forecasting a recession for this year (...) that includes Fed forecasters and really essentially all forecasters (...)."

[2]Nominal claims are financial assets and liabilites with a fixed face value, such as bonds or fixed-rate-mortgages.

[3]In the United States, unlike in some countries (e.g. the UK or Spain), more than 95% of outstanding mortgages in 2021 were fixed-rate for the entire duration of the loan, meaning that the nominal payments implied by the contract were completely independent from realized inflation or monetary policy.

specifically designed to match key empirical evidence on the Fisher channel, namely the distribution of net nominal positions (NNP) across households[4] and the empirical covariance between NNP and MPC - a sufficient statistic in Auclert (2019) that standard HANK models have so far struggled to match.

I then use this HANK model to analyze how the "inflation shock" in 2021-2022 has affected aggregate consumption via wealth redistribution. According to the model, shifting wealth from households with lower MPCs holding nominal assets to those with higher MPCs holding nominal liabilities through unexpected inflation has boosted aggregate consumption by around 0.5 percentage points in the 2023, gradually diminishing thereafter. Through a standard New Keynesian Phillips curve, inflation also rose endogenously in response to the wealth redistribution - by about 0.3 percentage points in 2023, with a similar decay over time. Therefore, in a HANK model that matches some key empirical moments for the Fisher channel, unexpected inflation can "feed on itself," even when monetary policy follows a standard Taylor rule. Building on Schnorpfeil et al. (2023), who show that households may be only partially aware of the debt-devaluing effect of inflation, I extend the my HANK model to incorporate a form of cognitive discounting for gains and losses on long-term nominal claims (e.g., fixed-rate mortgages). This behavioral friction dampens the initial consumption response yet imparts a more persistent stimulus to aggregate demand over time.

Empirical evidence supports the model's prediction about consumption responses. I use a very large transactions dataset from a U.S. fintech company covering 2014-2024 and construct a balanced panel of roughly 430,000 households. My sample closely tracks official aggregates (e.g., retail sales and personal income) and mirrors key distributional features (the income distribution, the share of mortgagors, and the distribution of mortgage payments in the Survey of Consumer Finances (SCF)). Over the inflationary episode, households with fixed-rate mortgages increased monthly spending by about \$40 per \$100,000 of outstanding nominal debt; aggregated, this translates into roughly \$53 bn per year (or about 0.3% of PCE). This slightly more modest amount than what my benchmark HANK model predicts coupled with its persistence over the inflationary

[4] NNP is defined as the market value of nominal assets minus the market value of nominal liabilities.

episode leans toward the behavioral extension of the model rather than the purely rational counterpart. Constructing this sample represents a separate contribution of the paper, and to my knowledge, no other study has compiled a comparable dataset that enables analysis of consumption, income, and asset flows at a daily frequency for hundrends of thousands of U.S. households.

I move beyond the current inflationary episode to examine the broader implications of the Fisher channel for monetary policy. I uncover two main findings. First, the presence of an active Fisher channel substantially amplifies the effectiveness of monetary policy, making a standard monetary policy shock nearly 50% more powerful in the model with rational expectations. This arises because unexpected movements in inflation that follow a monetary policy shock transfer wealth from richer, low-MPC households to indebted, high-MPC households. Second, the degree of nominal rigidities proves less central for monetary policy's effectiveness. In standard models, higher nominal rigidities strengthen monetary policy by increasing the impact of policy shocks on the real interest rate. However, the Fisher channel introduces an offsetting effect: when prices are stickier, inflation responds less on impact, reducing the wealth transfer between low-MPC creditors and high-MPC debtors. In my model, the real-rate channel still dominates, so the conventional result holds: stronger nominal rigidity generally increases policy effectiveness. Nevertheless, the Fisher channel quantitatively narrows substantially the gap in outcomes across different levels of nominal rigidity, and allows monetary policy to have meaningful real effects even with completely flexible prices. At the zero lower bound (ZLB), both the real-rate channel and the Fisher channel act in the same direction, thereby substantially reinforcing the "paradox of flexibility" described by Eggertsson and Krugman (2012).

My model builds on a standard HANK framework, in which households face idiosyncratic risk and a borrowing constraint. Agents save and borrow in one account comprising long-term nominal claims whose maturity aligns with the average duration of nominal positions in the economy. I also follow an emerging convention in the HANK literature, adopting a sticky-wage, flexible-price specification as in Auclert et al. (2024a). Under this assumption, the real wage always follows productivity, allowing me to abstract from the impact of inflation on the split between labor and capital income (Lorenzoni and Werning,

2023) and thus focusing solely on how unexpected inflation redistributes nominal wealth. As I show in the paper, this modeling choice is consistent with the recent U.S. experience, as nominal wages largely kept pace with the price level during the latest inflationary episode, unlike in other countries.[5]

Of course, in the model, inflation is an endogenous variable. Recent work has proposed several structural shocks as the main drivers of the post-pandemic inflation surge, including both supply- and demand-side factors (e.g., Bernanke and Blanchard, 2023; Dao et al., 2024; Giannone and Primiceri, 2024). Since my focus lies on how the wealth redistribution caused by unexpected inflation propagated to aggregate demand, it is not strictly necessary for my research question to take a stance on the exact combination of the primitive structural shocks that moved inflation in the first place. Instead, in my model, I simply introduce a shock to the unit of account that replicates exactly the unanticipated rise in the price level observed in 2021-2022, thus reducing the real value of nominal claims and reallocating resources from asset-rich households to indebted ones. By examining the impulse response of consumption and inflation to this *wealth redistribution* shock, I isolate the Fisher channel's contribution to aggregate consumption - relative to a counterfactual where households had only real assets. This approach allows me to concentrate on the redistributive effects of inflation stemming from nominal positions, without necessarily taking a stance on the specific structural origins of the inflation surge within the model.

To organize the empirical evidence, I use two complementary designs. First, a transparent pre/post cross-section a la Mian et al. (2013) regresses household spending growth over the episode on baseline nominal exposures interacted with the cumulative price-level surprise; identification comes from cross-sectional heterogeneity in exposures combined with a common aggregate surprise. This delivers the headline finding: nominal liabilities load positively and precisely on spending, nominal assets load near zero. Second, I trace dynamics in a local-projection framework that regresses horizon-h spending changes on baseline exposures interacted with monthly inflation surprises, including household and calendar-month fixed effects. This design maps more cleanly to model IRFs and shows

[5]In some cases, nominal wage growth exceeded the rise in prices, especially for lower-income groups (Autor et al., 2023).

a liability-driven response that is persistent rather than front-loaded, therefore closer to the behavioral extension than to a purely rational benchmark. Results are robust to alternative pre/post windows, winsorization choices, and control sets. Placebo exercises in pre-inflation windows show no significant liability effect, underscoring that the estimated responses seem activated by the inflation surprise rather than by pre-existing trends.

Because the fintech data contain flows but not stocks, I reconstruct exposures at the household level. On the liability side, I infer mortgage balances from observed payment streams and prevailing rates at origination, and distinguish likely fixed- and adjustable-rate loans using the cadence and sign of payment changes; the resulting balance distributions closely track the one in the Survey of Consumer Finances. On the asset side, I proxy liquid balances by capitalizing interest-income inflows at contemporaneous deposit rates; this matches central quantiles reasonably well but is noisier in the upper tail and, by construction, misses long-duration nominal assets (e.g., bonds). These features - short duration, plus measurement noise - tend to attenuate the asset slope toward zero.

As additional evidence, reported in the appendix, I conduct a cross-county analysis similar to Mian et al. (2013), using county-level spending data from Chetty et al. (2020) alongside data on nominal assets and liabilities from the New York Fed and the IRS Statistics of Income. Once again, counties with more negative net nominal positions - especially those carrying more nominal debt - showed relatively stronger consumption growth after the onset of the inflation shock, although the results are not statistically significant in this case.

Literature Review This paper builds on some of the very first HANK models that included nominal assets, such as Auclert (2019) and Luetticke (2021). Most of the subsequent HANK literature employed either one-period real assets or continuous-time framework (Kaplan et al., 2018), where inflation plays no redistributive role. Recent exceptions include Auclert et al. (2024a), which considers the redistribution between households and the government in the case of nominal bonds, Yang (2022), Kaplan et al. (2023), Angeletos et al. (2024), all which consider the redistributive impacts of unexpected inflation across households. Relative to all of these studies, I develop a model that closely replicates both the distribution of net nominal positions and the covariance between NNP and marginal propensities to consume - a sufficient statistics in Auclert (2019) to evaluate the impact of the Fisher channel on aggregate consumption within a very broad class of environments. Matching both statistics is also what distinguishes my paper from Auclert et al. (2024b), which shows that letting households choose optimal portfolios between nominal and real bonds in a Huggett (1993) model brings the covariance between MPC and NNP closer to empirical estimates. I also build on Auclert et al. (2020) and Auclert et al. (2024a) when incorporating in my baseline HANK model cognitive discounting, reflecting the insight of Schnorpfeil et al. (2023) that households may not be fully aware of the Fisher channel.

I then apply my framework to the specific case of the latest U.S. inflation episode, and test the model's consumption implications using high-frequency alternative data from a fintech company (as in, among others, Diamond and Moretti, 2021; Buda et al., 2023), highlighting the value of fintech data sources for macroeconomic modeling.

Structure of the paper Section 2 presents the HANK model. Section 3 uses it to examine how the wealth redistribution propagated to aggregate consumption and inflation. Section 4 evaluates the strength of the Fisher channel empirically using the fintech data. Section 5 investigates the role of the Fisher channel in amplifying monetary policy and reassesses the importance of nominal rigidities. Section 6 concludes.

2 The Model

Households face idiosyncratic risk and are constrained in their borrowing capacity, deriving utility from consumption and leisure. They save and borrow into a long-term nominal assets modeled as in Woodford (2001): at price Q_t, the asset provides a stream of nominal payments $1, \delta, \delta^2, \ldots$.

The household's problem is given by:

$$\max_{\{c_{it}\}_{t=0}^{\infty}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left(u(c_{it}) - v(n_{it}) \right) \right] \tag{1}$$

$$\text{subject to} \quad P_t c_{it} + Q_t \Lambda_{it} = (1 + \delta Q_t)\Lambda_{i,t-1} + P_t z_{it}, \quad \forall t \tag{2}$$

$$Q_t \Lambda_{it} \geqslant \underline{a} P_t, \quad \forall t \tag{3}$$

where c_{it} is consumption, n_{it} hours worked, Λ_t is the amount of nominal claims and Q_t their price. Net labor income $z_{i,t}$ is given by:

$$z_{it} = \tau_t (w_t e_{it} n_{it})^{1-\theta} \tag{4}$$

Where τ_t is the intercept of the retention function, w_t is the real wage, e_{it} is household-level productivity, and θ is the progressivity parameter. As shown by Heathcote et al. (2017), this rule can approximate particularly well the existing tax structure in the US. Following a convention in the HANK literature (e.g. Auclert et al. (2024a)), households are off their labor supply curve with hours worked n_{it} chosen by the unions and taken by the household as given, as described below. For simplicity, unions follow a uniform allocation rule, with $n_{it} = N_t$.

The borrowing limit a in equation 3 is defined in real terms, so that unexpected inflation effectively relaxes the borrowing constraint. This is a natural starting point, as any more elaborate borrowing constrained defined e.g. in terms of debt-to-income ratio (as in e.g. Paz-Pardo (2021)), or collateral value (as in e.g. Iacoviello (2005)) will also relax when nominal incomes and/or house prices approximately follow the evolution of the price level. As discussed in appendix A.2, this has been broadly the case during the latest inflationary episode in the US. Moreover, in my calibration outlined below I will have virtually no households at the borrowing constraint in the steady state, which makes the particular modeling choice of the borrowing limit relatively unimportant in terms of the implications of the model for aggregate consumption.

The price of the long-term bond Q_t is pinned down by a no-arbitrage condition given the expected path of nominal interest rate i_t:

$$Q_t = \frac{1 + \delta \mathbb{E}_t[Q_{t+1}]}{(1 + i_t)} \tag{5}$$

The ex-post real interest rate r_t faced by households is then simply given by the Fisher equation:

$$1 + r_t = \frac{(1 + i_{t-1})}{(1 + \pi_t)} = \frac{(1 + \delta Q_t)}{Q_{t-1}} \frac{1}{1 + \pi_t} \tag{6}$$

Finally, the utility function belongs to the constant elasticity of substitution (CES) family with intertemporal elasticity σ, i.e. $u(c) = \frac{c^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}}$, while the disutility function from work has a Frisch elasticity of labor supply ϕ, i.e. $v(N) = N^{1+\frac{1}{\phi}}$.

Supply On the supply side, I follow a convention in the HANK literature by adopting sticky wages and flexible prices. As emphasized by Auclert et al. (2023) and Broer et al. (2020), this combination of sticky wages and flexible prices is more in line with empirical evidence, as it does not feature countercyclical profits and large income effects on labor supply. As well known, both of these features are instead typical of flexible wages, sticky price versions of New Keynesian models. More specifically, in my baseline specification there is a representative firm that produces output with a technology which is linear in labor N_t and productivity A_t

$$Y_t = A_t N_t$$

Solving the firm problem yields $\frac{W_t}{P_t} = A_t$: the real wage thus follows productivity, which is constant in the rest of the paper.[6] In other words, price inflation and nominal wage inflation are the same at all times.[7] A constant real wage and no profits are conceptually appealing for my purpose as they allow the model to abstract away from any redistributional effect of unexpected inflation stemming from differential impacts on profits versus labor income (see, e.g. Lorenzoni and Werning (2023)). As discussed in appendix A.2, the real wage has indeed remained approximately constant in the US dur-

[6] The firm problem here is simply given by $\max_{N_t} P_t A_t N_t - W_t N_t$.

[7] As way to see it, $\frac{W_t(1+\pi_t^w)}{P_t(1+\pi_t)} = A_t(1 + g_{At})$, take logs and obtain $\pi_t^w - \pi_t = g_{At} = 0$.

ing the latest inflationary episode, and it actually increased for the bottom half of the distribution (Autor et al. (2023)).

Sticky wages Wages are set by unions subject to a quadratic costs a la Rotemberg (1982). Appendix A.1 describes the union problem following Auclert et al. (2024a), which extends to the heterogeneous agent setting the standard microfoundation of sticky wages from Erceg et al. (2000), showing that it leads in equilibrium to the New Keynesian Wage Phillips Curve (NKWPC) for wage inflation π_t^w:

$$\pi_t^w(1+\pi_t^w) = \kappa^w \left(\mu^w \frac{\gamma N_t^{1/\phi}}{(C_t^*)^{-\sigma}(1-\theta)(Y_t - T_t)/N_t} - 1 \right) + \beta \pi_{t+1}^w (1+\pi_{t+1}^w) \tag{7}$$

Where κ^w denotes the slope of the NKWPC, which is in turn a function of the elasticity of substitution across different union tasks and the costs of adjusting wages, as documented in section A.1. μ^w is the mark-up applied by unions, $T_t = w_t N_t - \int z_{it} di$ are total taxes collected by the government, and C_t^* is a virtual consumption aggregator that captures the aggregate wealth effect on labor supply, defined as:

$$C_t^* = \left(\int \frac{e_{it}^{1-\theta}}{\int e_{it}^{1-\theta} di} c_{it}^{-\sigma} di \right)^{-\frac{1}{\sigma}}$$

Monetary Policy The monetary authority follows a standard Taylor rule for setting the nominal interest rate i_t:

$$i_t = r^* + \phi \mathbb{E} \pi_t + \epsilon_t \tag{8}$$

Where r^* is the steady state real interest rate, ϕ is the coefficient on inflation, and ϵ_t a monetary policy shock.[8]

Government The government issues long-term nominal debt Λ_t^g, which is the counterpart of the net nominal claims held by the household sector. It faces a standard

[8]For simplicity and in keeping with most of the HANK literature, I assume inflation in the steady state to be 0.

intertemporal budget constraint with nominal bonds:

$$P_t\, G_t + Q_t\, \Lambda_t^g = (1 + \delta Q_t)\, \Lambda_{t-1}^g + P_t\, T_t \tag{9}$$

Defining $B_t = \frac{Q_t \Lambda_t^g}{P_t}$ brings us back a more familiar formulation $G_t + B_t = (1 + r_t)\, B_{t-1} + T_t$, where r_t is the ex-post real interest rate given by the Fisher equation 6. In the benchmark version of the model, I assume that government adjust government spending G_t in response to shocks that move its real debt level B_t away from the steady state, with a coefficient γ_G:[9]

$$G_t = G_{ss} - \gamma_G (B_t - B_{ss}) \tag{10}$$

Equilibrium Given initial values for nominal government debt Λ_{t-1}^g, nominal wage W_{t-1}, price level P_{t-1}, a distribution of households over skills e and assets Λ such that the economy starts from its steady state, a general equilibrium is a path for prices $\{P_t$, W_t, π_t, π_t^w, r_t, i_t, $Q_t\}$ and aggregates $\{Y_t$, N_t, C_t, Λ_t^g, G_t, $T_t\}$ such that households optimize, unions optimize, no arbitrage 5 is satisfied, the representative firm optimizes, monetary policy follows the Taylor rule 8, the government satisfies its budget constraint and 10, and markets clear:

$$Y_t = \int c_{it} di + G_t \tag{11}$$

$$\Lambda_t^g = \int \Lambda_{it} di \tag{12}$$

2.1 Calibration

I calibrate the model at a yearly frequency, following conventions in the literature for most of the parameters. The main deviation from the literature consist in relaxing the

[9] As discussed also below in the context of the calibration, the choice of adjusting government spending rather than taxes in response to a deviation of government debt from its steady state level is a conservative one, in order to limit as much as possible the (positive) implications for aggregate consumption stemming from a devaluation of the government nominal debt after unexpected inflation.

borrowing constraint to account for mortgage debt, as typical HANK models are calibrated to account only for consumer credit. Table 1 reports all the parameter values.

Households Both the intertemporal elasticity of substitution σ and the Frisch elasticity of labor supply θ have values well within the ranges of empirical estimates at 0.5 (see also Auclert et al. (2021)). The income process faced by households is also standard and follows an AR(1) process with persistence ρ_e of 0.91 and a standard deviation of the earnings σ_e at 0.92, as in e.g. Auclert and Rognlie (2018). I discretize this process using Rouwenhorst method on a grid of 11 points for e_{it}.

In order to match the empirical distribution of net nominal positions, I set the borrowing limit $\underline{a}$ to 1, which is the average yearly income in the economy. This is a deviation from the literature, as $\underline{a}$ is typically calibrated to zero or to the average quarterly income (see e.g. Kaplan et al. (2018)). The standard calibration in HANK has been motivated by focusing on consumer credit: here, my emphasis in on matching the empirical distribution of NNP, which include also mortgages. The real return is 5% per year as in Auclert et al. (2024a). While high, this allows me to match the distribution of the NNP better, as well as hitting perfectly the covariance between MPC and NNP. The discount factor β clears the asset market at 0.85. Finally, the bond decay parameter δ is set at 0.8 to match the average duration of nominal positions at the end of 2020, which was approximately 4.5 years (Pallotti (2022)).

Supply I set wage markup to 1.1 and the coefficient for wage rigidity to 0.05 following standard values in the literature based on Grigsby et al. (2021).

Policy Government spending represents 20% of GDP. The level of government debt in the steady state is also at 20% of GDP, as it acts as a counterpart to the aggregate Net Nominal Position of the household sector, which was 20% of GDP at the start of the inflation episode (as in Pallotti (2022)). As my focus here is on the redistribution within the household sector, I prefer to capture the distribution of NNP across households and their aggregate position well, rather the actual NNP of the government (which is lower in the data, as foreigners also hold U.S. nominal debt).[10] The responsiveness of government spending to deviation of its debt level from the steady state γ_G is set conservatively at 0.1, implying a small but quite persistent response. Once again, the rationale behind this choice is to limit as much as possible the influence of government actions on the implications of the model for consumption, as my primary focus here is the redistribution of wealth across households. The coefficient for tax progressivity is 0.18, as in Heathcote et al. (2017). Finally, the coefficient on expected inflation in the Taylor rule is set to 1.25.

Solution method I use 500 points on a grid for assets, solving the household problem through the endogenous grid method. The model is solved using the Sequence Space Jacobian method from Auclert et al. (2021).

Calibration

Parameter	Description	Value	Parameter	Description	Value
σ	IES	0.5	κ_w	Slope of wage Phillips curve	0.05
v	Frisch	0.5	μ_w	Wage markup	1.1
$\underline{a}$	Borrowing constraint	-1	ϕ	Taylor Rule coefficient	1.25
θ	Tax progressivity	0.18	B	Government Debt/GDP	0.2
ρ_e	Autocorrelation of earnings	0.91	G	Government spending	0.2
σ_e	Std of log earnings	0.92	γ_G	G response	0.1
β	Discount Factor	0.85	$r*$	Eq. real rate	0.05
δ	Bond decay	0.80	π_{ss}	Steady-state inflation	0

Table 1: Calibration of all the parameters in the model. All values follow standards in the literature, except for the borrowing constraint $\underline{a}$, in order to account for mortgages, and the Governemnt Debt/GDP B in order to match the NNP of households in Pallotti (2022).

2.1.1 Results

Table 2 reports percentiles of the distribution of the net nominal position over labor market income in the model against the ones from the 2019 Survey of Consumer Finances (SCF), following the methodology in Pallotti (2022) in order to compute both the direct

[10] As shown in Pallotti (2022), the rest of the world plays a significant role in financing the large NNP of the government in the US. As my model is a closed economy, I currently abstract from the wealth redistribution from the rest of the world towards the U.S. following unexpected inflation.

and indirect nominal positions in the SCF.[11] Overall, the matching is quite accurate. Both distributions switch from negative to positive NNP between the 50th and the 75th percentiles, and have similar value in the left tail as well as to some extent in the right tail, despite the well known difficulty for the one-account HANK model to capture the very wealthy (e.g. Castaneda et al. (2003)). This relatively good performance in the right tail of the NNP distribution of my model is also driven by the fact that the NNP distribution is not as skewed as the one for overall wealth, which includes also housing, stocks and other real assets.

Net nominal positions in the data and in the model

NNP Quantiles			Consumption CDF
Pct	Data	Model	Model
0.01	-6.8	-7.2	0.0%
0.05	-3.6	-4.8	0.8%
0.1	-2.5	-3.5	2.3%
0.25	-1.1	-2.3	8.7%
0.5	-0.1	-0.9	25.3%
0.75	0.4	0.5	51.3%
0.9	2.2	2.0	74.3%
0.95	4.1	2.9	84.7%
0.99	10	4.6	95.7%

Table 2: Net nominal position over household annual labor income in the 2019 Survey of Consumer Finance vs. in the model. Cumulative distribution function of consumption in the model.

Most importantly, the model can perfectly match the empirical covariance between NNP and MPC at -0.072, which is the most precise estimate among the ones in Auclert (2019). As shown in Auclert (2019), within a very general class of models, this covariance is a sufficient statistics to predict the impact on aggregate consumption of a wealth

[11] As in Doepke and Schneider (2006), I take include nominal positions that are directly held in household portfolios (e.g. mortgages or bonds) as well as those held through investments intermediaries, such as bonds held by a mutual funds where households are shareholders. Moreover, I also take into account indirect nominal positions arising from the households' ownership of equity in firms, which have nominal assets or liabilities on their balance sheets. For details, see Pallotti (2022).

redistribution stemming from a one-off shock to the price level.

Matching well the distribution of NNP as well as the covariance between NNP and MPC comes at the cost of having virtually no people at the borrowing constraint, and thus a lower average MPC in the model, which is 21% per year - in the low range of the empirical estimates. The intertemporal Keynesian cross Auclert et al. (2024a) is therefore less powerful in this model relative to a baseline HANK, and the propagation to the broader economy of any initial impulse to aggregate demand can be interpreted as a lower bound.

3 Wealth Redistribution and its Propagation

I use the model to examine how the wealth redistribution resulting from an inflation shock propagates to aggregate variables, specifically consumption and inflation. I measure the latest inflation shock by comparing the expected path for the price level from the Survey of Professional Forecasters at the end of 2020 with the actual evolution of the price level - which was around 10% higher by the end of 2022.[12]

This shock to the price level has been arguably due to several factors: supply chain disruptions, generous transfers from the government to households, or monetary policy remaining accommodative even after inflation started to exceed 2% year-on-year in April 2021, among others (e.g. Giannone and Primiceri (2024), Bernanke and Blanchard (2023), Dao et al. (2024). Since my interest lies solely in how the redistributive effects implied by this inflation shock (due to the presence of nominal assets and liabilities) propagated to the rest of the economy, it is not strictly necessary to specify within the model the exact combination of underlying structural shocks that caused this spike in the price level in the first place.

Instead, in the model, I directly shock the wealth distribution by simulating a change in the unit of account equal in magnitude to the surprise inflation observed over 2021 and 2022. Through the lens of the model, the only effect comes from the net nominal position Λ becoming less valuable in terms of real consumption c, redistributing resources

[12]Figure 16 shows the actual and expected paths for the price level as of December 2020.

away from asset-rich households and towards indebted ones. Another equivalent way of modeling the change in the unit of account is a one-off MIT shock as a wealth tax, θ_π, on wealth holdings Λ, which results in negative outlays for creditors and a positive subsidy to debtors and to the government (which has a negative net nominal position).

A possible interpretation the impulse response function (IRFs) of consumption and inflation to this wealth redistribution is to compare a *real-asset* economy, hit by the same combination of primitive structural shocks that moved inflation in the first place, to a *nominal-asset* economy where these primitive shocks also had redistributive effects due to the unexpected inflation they generated. In turn, these redistributive effects transmitted to aggregate consumption and inflation according to the IRFs shown below.

Of course, it is entirely feasible within the model to generate inflation (and thus wealth redistribution) also through some primitive structural shocks. We will look at the example of monetary policy shock thorugh the lens of the model in Section 5.

3.1 Impact on aggregates

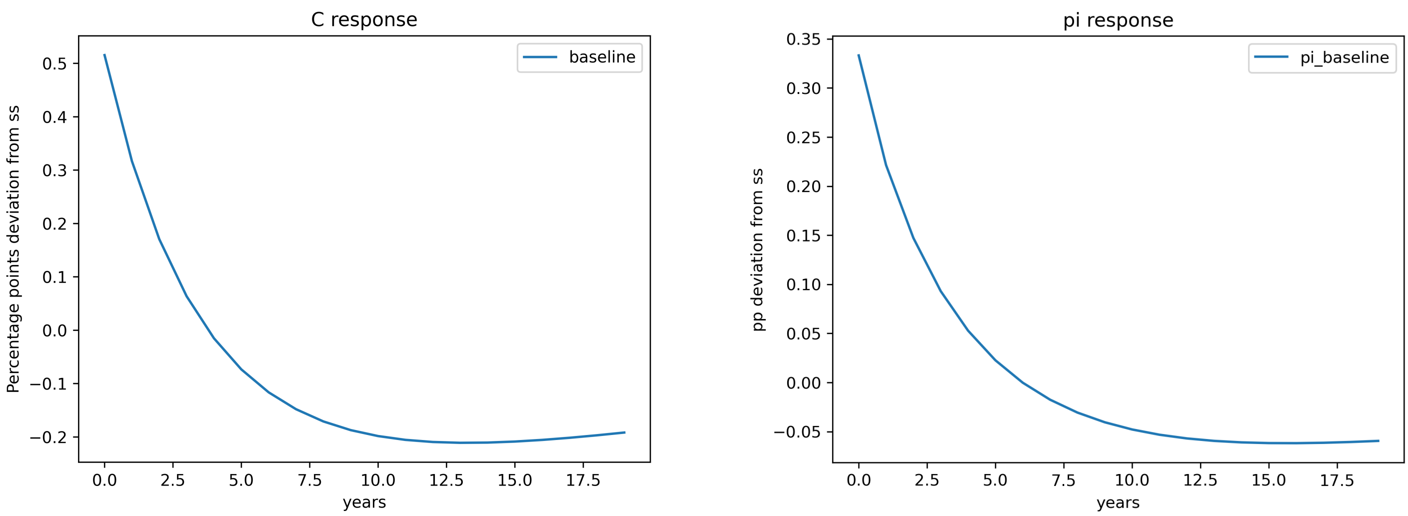

Figure 1: Impulse response functions (IRFs) of consumption and inflation to the wealth redistribution generated by the 2021-2022 inflation shock in the United States according to my HANK model with nominal assets, matching the empirical NNP distribution and the covariance between NNP and MPC in the data.

The right panel of figure 1 depicts the response of aggregate consumption to the inflation shock described above. Consumption rises by 0.5% in the first year and then begins to slowly decline back toward the steady state, ultimately undershooting it. Similarly, through the NKWPC 7, inflation rises by 0.3 pp in the first year, slowly decaying afterwards, as reported in the left panel of figure 1. In this sense, an inflationary shock in a HANK model featuring nominal wealth redistribution tends to ”feed on itself”.

Figure 2 sheds light on the various channels within the model behind the aggregate increase in consumption. The direct impact of the shock (blue dotted line) is initially expansionary, as it redistributes resources from households with low MPC to those with high MPC. After a few years, the direct response of consumption to the shock turns negative. This is due to the fact that while households close to the borrowing constraint have a higher MPC and initially raise their consumption substantially, wealthier households behave more in line with the Permanent Income Hypothesis (Friedman, 1957), cutting their consumption permanently by an amount close to the annuity value of the negative wealth shock. Over time, the consumption behavior of the rich dominates the initial spending spree of indebted households, also because the household sector as a whole has a positive net nominal position.

The initial positive direct effect raises output in the economy (the blue line in the left panel of figure 2), which further boosts consumption through the intertemporal Keynesian cross (Auclert et al., 2024a), as shown by the dotted orange line in the right panel of figure 2. Output increases initially also thanks to a small but persistent rise in government spending due to devaluation of its nominal debt as per equation 10, shown by the green line in the left panel of Figure 2.

The increase in output from both consumption and government spending pushes up inflation according to the New Keynesian Wage Phillips Curve (Equation 7). This rise in inflation due to the wealth redistribution triggers a monetary policy response, raising nominal interest rates according to the Taylor rule (Equation 8) of around 40 basis points, as reported in the left panel of Figure 2. The ex-post real interest rate is negative in the first period, both because of the unexpected inflation and because the price of the long-term bond unexpectedly falls - due to discounting the higher future path of nominal interest rates.

As the negative direct effect on consumption after a few years begins to dominate the

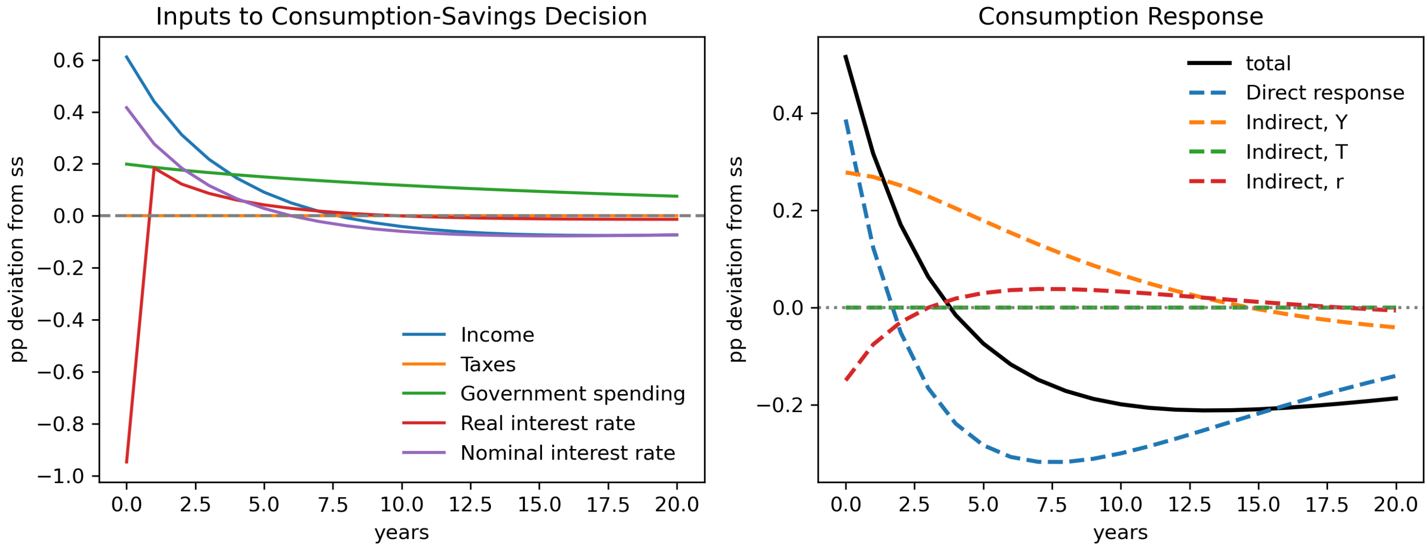

Figure 2: Decomposition of the net effect on consumption reported in the left panel of figure 1 into the direct impact of the redistributive shock, the feedback loop from income to consumption through the intertemporal Keynesian cross, as well as the reactions of government spending and interest rates in the model. Left panel reports the IRFs of the inputs to the household problem, right panel reports each input transmission to aggregate consumption.

positive general equilibrium effect from the intertemporal Keynesian cross, consumption and inflation undershoot their steady-state values. Consequently, monetary policy starts to cut interest rates (marginally) and consumption converges back to its equilibrium level from below. The model suggests that while the effects of wealth redistribution on aggregate quantities are very small after a few years, they are nevertheless very long-lasting, as it takes a several years for the wealth distribution to return back to its ergodic state.

3.1.1 Behavioral frictions

In the simulation discussed above, I assumed that households perfectly understood that unexpected inflation implied a reduction in the present value of their nominal assets or liabilities. However, using data for Germany, Schnorpfeil et al. (2023) show that households are often unaware of the reduction in the real value of their nominal debt induced by the Fisher effect. This is particularly relevant for long-term nominal positions, like mortgages or Treasuries, where the reduction in the real value of cash flows from these instruments happens over long time horizons, and it thus may not be immediately apparent to some households.

To capture this potential friction in the model, I shift from simulating a one-off wealth redistribution to simulating the same wealth over time (retaining the same present value). Concretely, I introduce an inflation tax $\theta_{\pi,t}$ on nominal assets and liabilities that phases off completely after d years.

$$\theta_{\pi,t} = \begin{cases} \frac{\gamma_\pi}{d} & \text{for } t < d \\ 0 & \text{for } t \geqslant d \end{cases}$$

Here, γ_π represents the overall inflation shock described above, and d is the average duration of net nominal positions as of the end of 2020 (five years, as in Pallotti (2022)). Households with negative net nominal positions Λ receive a subsidy equal to $\theta_{\pi,t}\Lambda$, while households with positive net nominal positions have to pay the equivalent tax. This simulates a reduction in the negative cash flow implied by a mixture of short and long term nominal debt, or in the positive cash flow implied by a mixture of short and long-term nominal positions. This tax lasts only d periods, and households form their expectations about the future values of this tax under cognitive discounting, following Gabaix (2020):

$$E_t^B[\theta_{\pi,t+1}] = \theta_{\pi,ss} + \tilde{m}E_t[\theta_{\pi,t+1}] \tag{13}$$

Here, $\theta_{\pi,ss}$ is the steady-state value of this tax, which is zero. The parameter $\tilde{m}$ governs the degree of cognitive discounting regarding the future values of this tax, or in other words the myopia of these households with respect to the future reduction in the value of their nominal assets and liabilities. For $\tilde{m} = 0$, households are fully myopic and every reduction in the real value of their nominal assets or liabilities comes to them as a surprise each period t . For $\tilde{m} \to 1$, the model gets closer to the case of rational expectations in the previous section, where households perfectly anticipate the reduction in the present value of all their future nominal cash flows.[13]

[13] There is a subtlety that makes the exercise in the previous section not perfectly comparable to the current one with $\tilde{m} = 1$, which is that when $\tilde{m} = 1$ households perfectly understand that their future nominal assets, not just their current ones, will be devalued by the tax $\theta_{\pi,t}$, which ceteris paribus encourages them to save less and consume more.

Figure 3 reports the impulse response functions (IRFs) for consumption and inflation in the model for varying degrees of $\tilde{m}$. For $\tilde{m}$ close to one, the effect is similar to the rational expectations case. As we decrease $\tilde{m}$ towards zero, the response of consumption becomes less pronounced on impact but more persistent over time. This occurs because indebted households adjust their consumption positively every time they realize their liabilities have actually a lower value than they expected - without (or only partially) anticipating that this is going to happen again over the next periods. The response of inflation for lower $\tilde{m}$ is more persistent - though broadly similar on impact, since the unions are fully rational and forecast the cumulative deviation of consumption from its steady state when setting wages.

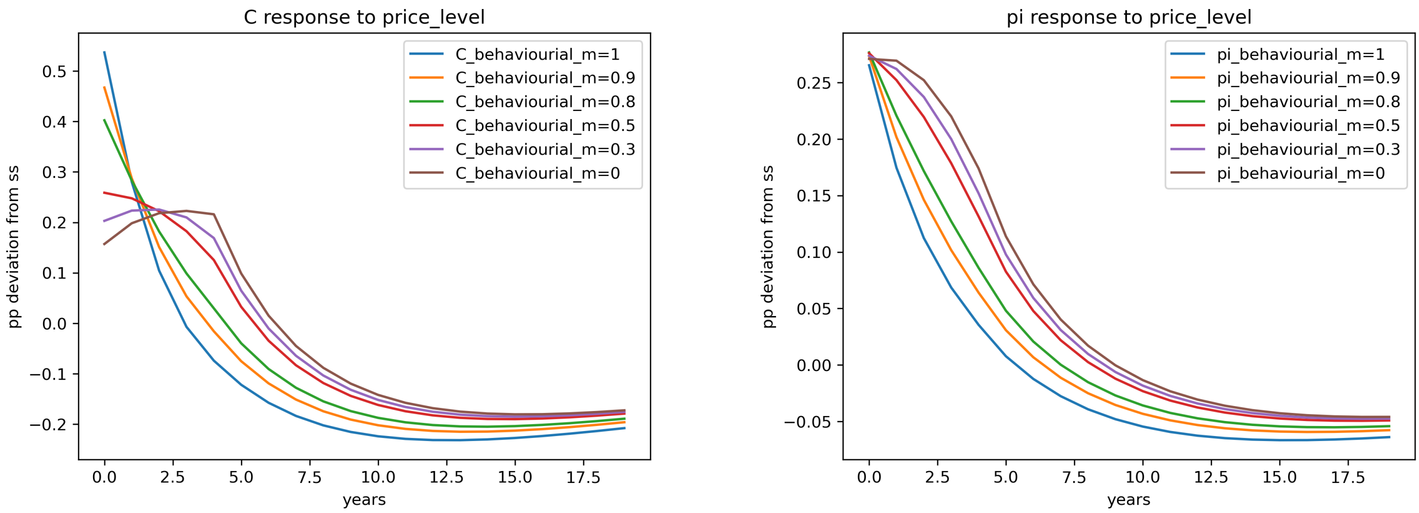

Figure 3: Impulse response functions (IRFs) of consumption and inflation to the wealth redistribution generated by the inflation shock when households exhibit cognitive discounting with respect to the reduction in the real value of their long-term assets and liabilities. A lower $\tilde{m}$ implies more myopia, as in Equation 13.

4 Empirical Evidence

A key prediction from Section 3.1 is that households with more negative net nominal positions (debtors) should increase consumption more following the inflation shock, and vice-versa for households with positive net nominal positions (savers). I test this prediction using a large U.S. fintech transactions dataset (2014-2024) that allows me to construct household-level measures of nominal liabilities (principally fixed-rate mortgage balances) and nominal assets (liquid deposit balances inferred from interest income). I then relate subsequent spending changes to these pre-period exposures. As a complementary check, I replicate the analysis with publicly available data that proxy aggregate nominal assets and liabilities at the county level; those results, which are directionally consistent but less precise, are reported in Appendix C.

4.1 Data description

The dataset covers almost 100 billion transactions for more than 45 million unique users from January 1st 2010 to May 31th 2024.[14] The fintech company supplying the data offers a financial platform to U.S. banks. The data consist of all inflows (e.g., salaries, transfers, refunds) and outflows (e.g., direct debits, credit card spending, cash withdrawals, mortgage payments) of the bank accounts of each user tracked by the fintech. Although it is possible that the users have additional accounts not captured in the dataset, I apply some active filtering to mitigate these concerns. I treat each user as representing a household unit.

Sample selection I construct a panel of users who remain continuously active from January 1, 2014 to the last available month in the data (May 2024). This ensures that I can abstract from entry and exit dynamics and that each user has a sufficiently long transaction history to impute their nominal assets and liabilities at the onset of the inflationary period. To exclude users whose main bank accounts may not be captured by the fintech provider, I further restrict the sample to households performing at least nine transactions per month over the entire period. This restriction allows me to closely match both official U.S. aggregate series (e.g., consumption and income) and the income distribution in the Survey of Consumer Finances (SCF). Increasing the monthly transaction threshold shifts the lower end of the income distribution above that of the SCF.

[14] The exact numbers for the whole sample are 97,869,791,714 transactions and 45,302,620 unique account holders.

Because data collection issues led to a drop in the number of accounts for some users starting in 2022, I additionally limit the sample to households whose total number of accounts does not decline between 2022 and the end of the sample. To mitigate potential contamination from small or medium enterprises (SMEs), I exclude households holding more than eight bank or eight card accounts, as well as those that in any month receive only inflows categorized by the fintech in income classes that are likely SME-related (e.g., ”Restaurants”, ”Electronics/General Merchandise”) rather than typical household income sources (e.g., ”Salary”, ”Interest Income”).

After applying all these restrictions, the final panel consists of 430,760 users who are continuously active each month from January 2014 to May 2024. I further restrict transactions to those denominated in U.S. dollars and apply the fintech provider’s algorithm to remove outliers and duplicates.

4.2 Validating the data against US official statistics[15]

4.2.1 Tracking US Aggregates

The data align closely with official U.S. consumption statistics. Figure 5 shows a comparison between U.S. Census monthly retail sales data with credit and debit card expenditures extracted from the fintech data, showing a tight correspondence at a monthly frequency over a ten-year period. There is reasonable alignment also with Personal Consumption Expenditures (PCE) from the Bureau of Economic Analysis (BEA), even though some items like owners’ equivalent rent or government-financed purchases (e.g., Medicaid) are absent from the fintech data by design, as they do not involve monetary transactions (see figure 23 and figure 24 in the appendix).

Figure 5 similarly illustrates that total inflows in the fintech data closely track the evolution of personal income from the BEA. Discrepancies appear to be driven essentially by seasonal adjustment in the official series and the unadjusted nature of the fintech flows. Overall, these comparisons underscore that the fintech data reliably capture the trends in

[15]This subsection and the related appendix benefited from extensive discussion and feedback in an ongoing project using the same fintech data with Richard Blundell, Vasco Carvalho, Tao Chen, Stephen Hansen and Gianluca Violante.

U.S. consumption and income.

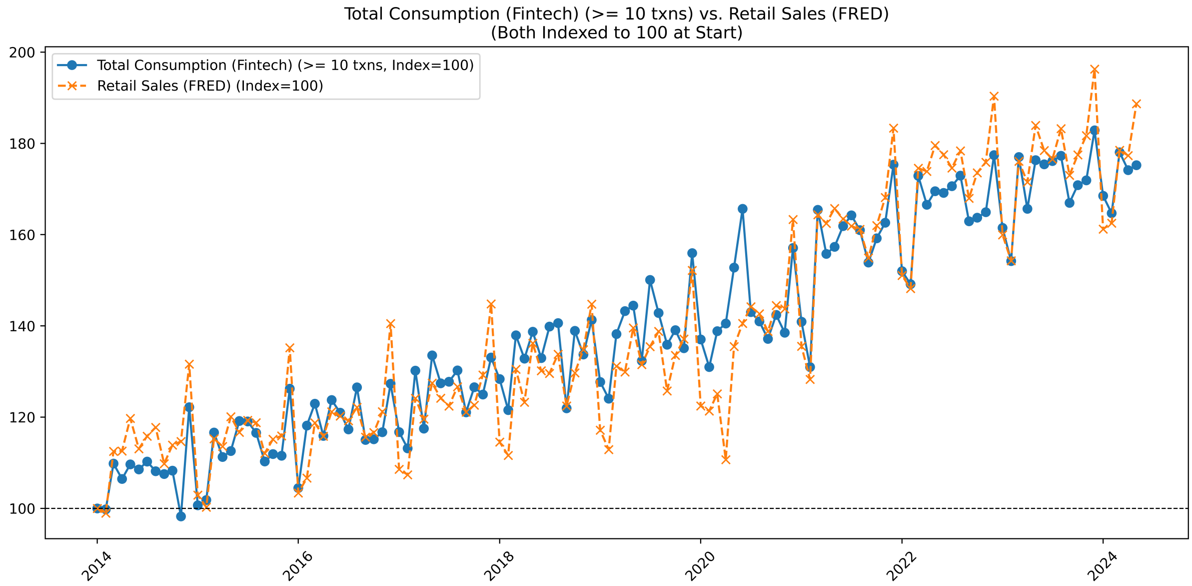

Figure 4: Comparison of our consumption measure in the fintech data with U.S. Retail Sales from January 2014 to May 2024. The fintech data are restricted to a sample of users who performed at least 9 relevant transaction per month during this period, resulting in a panel of 430,760 users. Both values are indexes starting at 100 in January 2014.

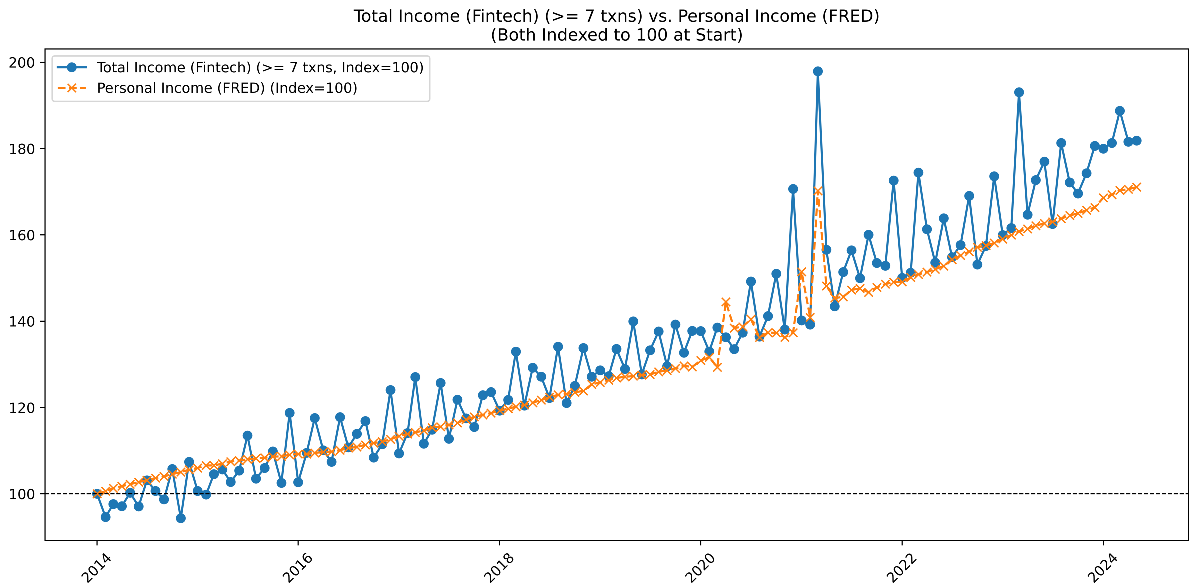

Figure 5: Comparison of total income inflows in the fintech data (not seasonally adjusted) with official U.S. Personal Income (BEA) (seasonally adjusted) from January 2014 to May 2024. The fintech data are restricted to a sample of users who performed at least at least 9 relevant transaction per month during this period, resulting in a panel of 430,760 users. Both values are indexes starting at 100 in January 2014.

4.2.2 Income distribution

Table 3 contrasts the 2021 income distribution derived from the fintech records with the distribution reported in the 2022 Survey of Consumer Finances (SCF), which refers to the same calendar year. For the fintech's sample, total income is the sum of all inflows that the provider's classification algorithm tags as ”Salary/Regular Income”, ”Other Income”, ”Investment/Retirement Income”, or ”Interest Income”. My data understate the very top of the income distribution but track the remainder fairly closely. One structural difference helps explain this pattern: the fintech data record inflows to bank accounts, which can be net of tax withholding and other payroll deductions, whereas the SCF measures self-reported pre-tax income. Some attenuation, especially at the top, is therefore expected.

Appendix B shows analogous comparisons for the 2019 and 2016 SCF waves with similar conclusions. It also documents that tightening the activity requirement (more transactions per month) raises measured income in the lower part of the distribution, while relaxing it lowers income there. Finally, by focusing on wage income - well captured in both datasets - appendix B shows that the same shortfall appears in the upper tail of the distribution. This pattern therefore likely reflects incomplete coverage of very high-income households rather than the omission of certain types of income flows.

Taken together, these results indicate that the transaction-based measure provides a reliable picture of the income distribution for the vast majority of households.

	Fintech		**SCF**	
Income group	Median	Mean	Median	Mean
Bottom 20	24.78	22.73	20.54	19.39
20-39.9	56.70	56.53	43.24	43.17
40-59.9	80.60	80.90	70.26	71.46
60-79.9	111.62	112.50	115.66	117.28
80-89.9	149.86	150.90	189.16	193.37
90-95	188.52	189.76	299.41	307.19
95-99	246.35	254.26	546.94	636.49
Top 1	410.34	461.94	1848.36	3191.79

Table 3: Total Income by percentile: Fintech vs. SCF, 2021 (USD 000)

4.3 Constructing nominal assets and nominal liabilities

4.3 Constructing nominal assets and nominal liabilities

4.3.1 Mortgages

Mortgage payments A key advantage of these data is that one can identify households who are paying down a mortgage. Specifically, I use the fintech's internal algorithm, which classifies transactions based on their descriptions and counterparties, to isolate mortgage-related payments. Among those flagged as mortgage payments, I only retain those exceeding $200 to limit the inclusion of unrelated or incidental charges. Figure 6 shows that the fraction of households marked as mortgagors in my core sample almost perfectly matches the fractions from the 2019 and 2022 Survey of Consumer Finance (SCF).

Conditioning on households with positive mortgage payments, the three diagnostics in the figures below, show close alignment of levels and dispersion across years: (i) the 2015 histogram overlays are similar throughout the interior of the distribution; (ii) the 2018 QQ plot lies near the 45-degree line at all deciles; and (iii) the 2021 ECDFs nearly coincide after truncation at the 99th percentile. The most likely reason for which the fintech series slightly exceeds the SCF is mechanical: bank payments include escrowed property taxes and homeowners/mortgage insurance, whereas the SCF instructs respondents to exclude these components when possible. Overall, the evidence indicates that conditional on having a mortgage, the fintech data reproduce the SCF distribution of monthly payments with a small, interpretable upward shift.

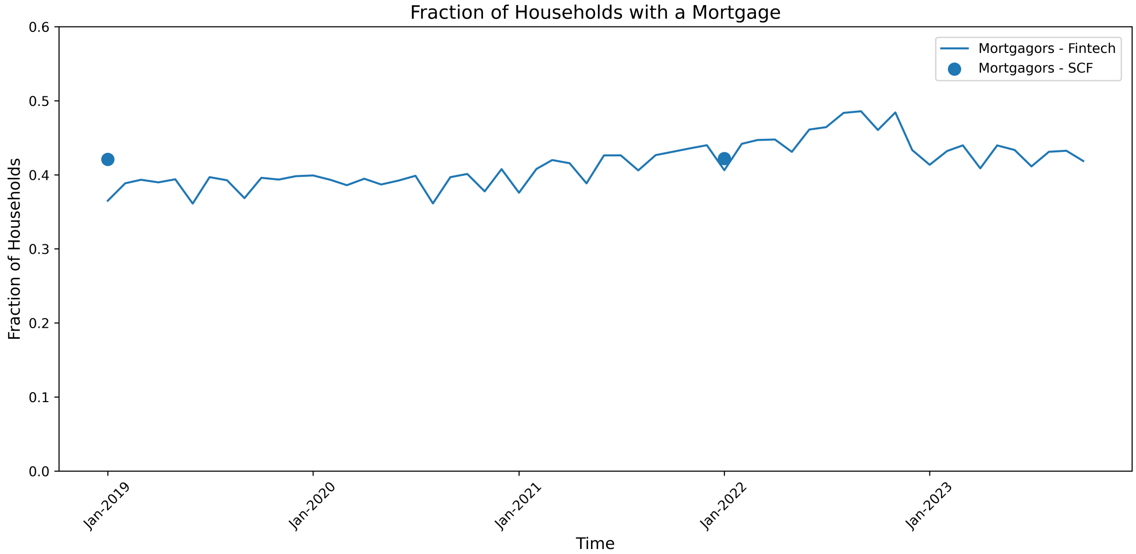

Figure 6: Fraction of households paying down a mortgage each month in the fintech data (January 2019–October 2023) versus the fraction of households carrying mortgage debt in the 2019 and 2022 SCF. The fintech sample includes users with at least 9 transactions per month, yielding about 430,760 households.

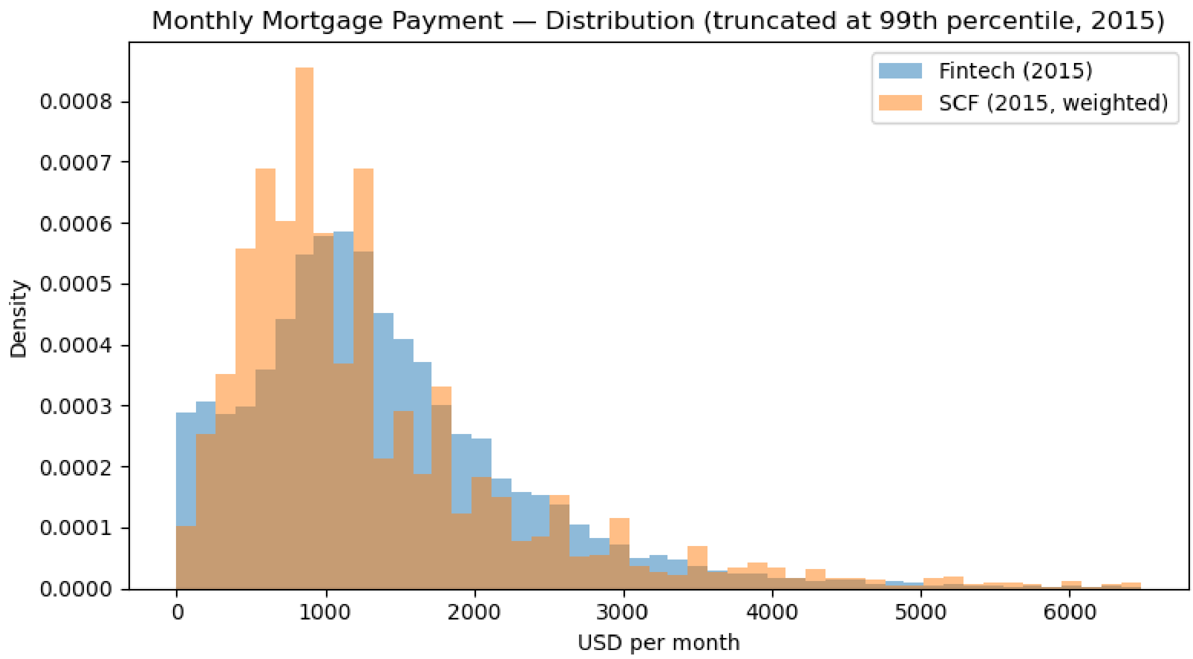

Figure 7: Comparison of mortgage payments in the fintech data with mortgage payments in the SCF for 2015. In the SCF, respondents are asked to exclude insurance and escrow.

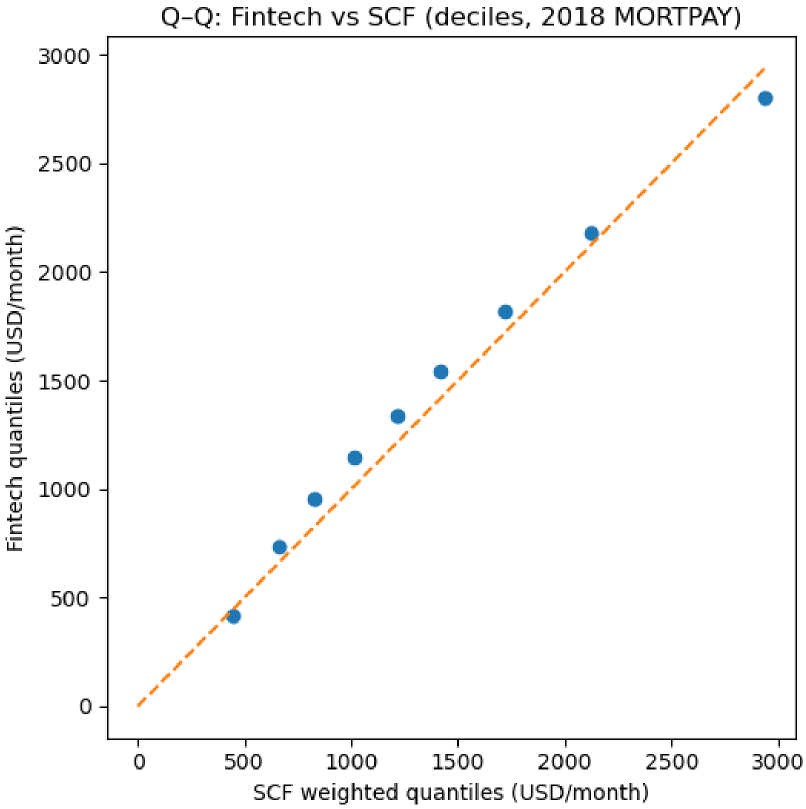

Figure 8: Comparison of mortgage payments quantiles in the fintech data with mortgage payments quantiles in the SCF for 2018. In the SCF, respondents are asked to exclude insurance and escrow.

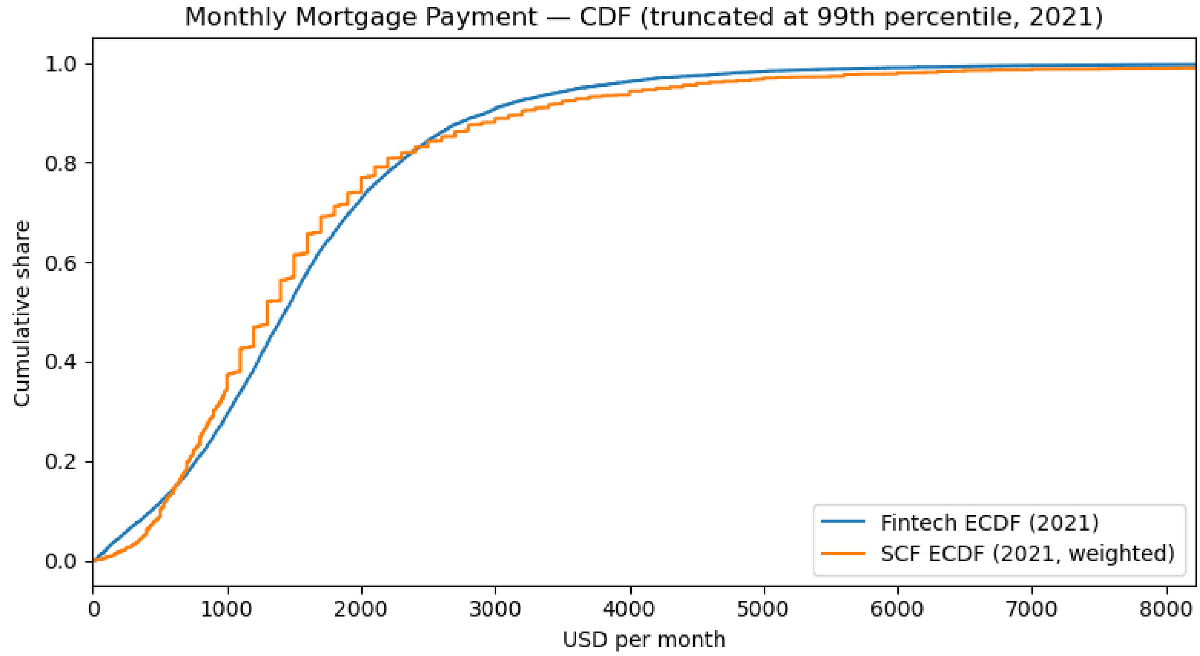

Figure 9: Comparison of the ECDF of mortgage payments in the fintech data with the one in the SCF for 2021. In the SCF, respondents are asked to exclude insurance and escrow.

Constructing Mortgage Payment Streams I transform raw transaction debits categorized as "Mortgage" into household-level payment streams following these steps:

- First, within each household I bucket monthly mortgage debits by rounded payment size (default \$ 400) to reduce fragmentation from escrow drift. Consecutive months in the same bucket are grouped into runs, allowing short gaps ($\leqslant$ 3 months), and I retain only persistent runs ($\geqslant$ 3 months).

- For each run I construct a proxy for principal-and-interest (P&I) payments by scaling the observed debit by an escrow factor (default=0.92) and smoothing it with a rolling median of 3m.

- I then stitch adjacent runs within a household (with a tolerance of gaps of three months) unless the payments jump by more than 50% in either direction, suggesting a major refinancing event has occurred and the new stream should be treated separately.

- Finally, smaller step changes in this smoothed stiched series are flagged when they exceed both a relative and an absolute threshold (default is the maximum between 100 $ and more than 10% of the monthly payment).

ARM/FRM identification To identify likely ARMs, I require most step intervals to fall in semiannual or annual cadence bands and that the direction of payment changes always follows the one of the six-month change in the 1-year Constant Maturity Treasury (CMT) index. The rest of step changes are likely small refinancing events or noise, with those mortgages therefore treated as FRM. This procedure yields a percentage of ARM mortgages over total outstanding mortgages of 3.6%, consistent with empirical evidence from the National Mortgage database from the Federal Housing and Finance Agency (FHFA), according to which ARM in the US have been 4% of the total on average over the period of interest. Further implementation details appear in appendix B.1.

Principal Balance Imputation In what follows, I denote by A_t the estimated proxy for the principal-and-interest payment associated with a given stream in month t, by r_t the monthly interest rate applied in that month, and by n_0 the original mortgage term (in months) at origination or refinancing. According to the National Mortgage Database from the Federal Housing Finance Agency (FHFA), the average mortgage term at origination in the U.S. has been about 26 years over the past two decades, as shown in Figure 20 in Appendix B.1. I therefore take $n_0 = 312$ as the benchmark value. For left-censored mortgages - cases in which households are already observed making mortgage payments during the first three months of 2014, when my panel begins - I assume $n_0 = 156$ (half of the benchmark) for simplicity. Regarding the interest rate r_t, I distinguish between fixed-rate mortgages (FRM) and adjustable-rate mortgages (ARM). For FRM, I use the average rate on 30-year mortgages published by Freddie Mac and available on FRED; for ARM, I use the market yield on U.S. Treasury Securities at the 1-year constant maturity (CMT-1Y), also from FRED, plus a constant spread of 2% for simplicity.

The initial balance is computed as the present value of an annuity:

$$B_0 = \frac{A_0\big(1-(1+r_0)^{-n_0}\big)}{r_0}.$$

I then update the balance on a monthly basis according to:

$$B_{t+1} = \max\big\{B_t(1+r_t) - A_t,\, 0\big\},$$

For both fixed-rate and adjustable-rate mortgages (FRM and ARM), I hold $r_{i,t}$ constant at its initial value $r_{i,0}$ until the first *step* in flow payments is identified. Both rates are converted to their monthly equivalents. If $A_t = 0$ for three consecutive months, I assume the loan has been fully repaid and set $B_t = 0$.

Substantial refinancing events - defined as cases where payments increase by more than 50% - are treated as new loans, as these likely involve either significant cash-out refinancing or prepayment. In such cases, the initial principal balance B_0 is re-estimated following the same procedure described above.

Results Table 4 reports the comparison between the mortgage and home-equity loan balances in the SCF and those inferred from the fintech data. For both 2018 and 2021, the fraction of households without any mortgage debt is aligned across sources at close to 40%. Mean mortgage balances are somewhat lower in the fintech sample - about 12 percent below the SCF in 2018 and nearly matched by 2021 - but the percentiles track remarkably well, suggesting that the imputation procedure recovers the bulk of the observed distribution in survey data. Figures 21 and 22 in Appendix B.1 compare the full distribution of outstanding mortgage in the fintech data with the corresponding weighted distribution from the SCF for 2018 and 2021. The shapes of the two distributions are very similar across years, both exhibiting the expected right-skewness and a comparable upper tail. The fintech data tend to show slightly more mass in the lowest part of the distribution, especially in 2021, consistent with a marginally higher share of small or recently originated loans - but differences remain modest. Overall, the visual evidence supports the quantitative comparison in Table 4, suggesting that the imputation of principal balances reproduces the empirical distribution of household mortgage debt in survey data with reasonable accuracy.

	2018		2021	
Statistic	**SCF**	**Fintech**	**SCF**	**Fintech**
Share with balance > 0	0.421	0.390	0.422	0.401
Mean balance	88,063.63	77,503.24	89,643.42	86,931.71
P10	0.00	0.00	0.00	0.00
P25	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00
P75	125,194.17	111,229.39	129,000.00	139,564.37
P90	278,209.27	256,703.22	268,399.62	299,146.15
P99	725,662.52	640,173.01	780,265.51	707,584.35

Table 4: Mortgage/HELOC balances: SCF vs. Fintech, 2018 and 2021 (USD). Principal balance outstanding in the fintech are imputed as described in section 4.3.1

4.3.2 Liquid assets

I impute balances outstanding based on yearly "interest income" in the fintech and the average interest rate on checking accounts in the US according to the Federal Deposit Insurance Corporation. Comparing this to liquid assets held in the SCF show a relatively good correspondence, especially up to the 60th percentile. Holdings of the top 1% are overestimated, potentially because large flows categorized as "interest income" may be related to other, higher yielding sources than deposits.

Table 5: Deposits in the fintech data versus the SCF by percentile: Fintech vs. SCF, 2021 (USD 000)

	Fintech		SCF	
Liquidity group	Median	Mean	Median	Mean
Bottom 20	0.33	0.37	0.05	0.12
20-39.9	1.73	1.80	1.70	1.70
40-59.9	5.03	5.27	6	6.39
60-79.9	14.20	15.16	20	20.78
80-89.9	37.53	39.22	52	54.54
90-95	82.80	87.63	110	111.05
95-99	235.77	280.53	220	262.86
Top 1	1154.73	4971.78	810	1189.77

4.3.3 NNP

My proxy for each user net nominal position is defined as liquid assets minus the outstanding principal balance on fixed-rate mortgages. In principle, the fintech data also include information on other types of loans and financial assets; however, their classification is less precise, and imputing the corresponding outstanding balances is considerably more difficult. For this reason, I focus exclusively on these two components.

4.4 Empirical evidence

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I present two approaches to test whether households adjusted their consumption in response to the inflation shock as predicted by section 3.

4.5 First approach: pre-post comparison

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Following the approach in Mian et al. (2013), among others, I estimate a cross-sectional relationship between household nominal exposures at the baseline and subsequent spending growth over the inflation episode.

Setup. Figure 28 (in section B.2.1) shows that year-on-year inflation began exceeding 2% in March 2021, surpassing 5% by June 2021. Around this time, the rise in inflation also gained substantial media coverage, as evidenced by Google trends data (Figure 29). The baseline window T_0 is therefore the first quarter of 2021 and the late window T_1 is the corresponding period in 2023, in line with the model in section 3 (robustness to alternative T_0 and T_1 is reported below and in appendix B.2.1). For each household i, I compute average consumption $C_{i,T}$ in each window and consider the absolute change in consumption over the period $\Delta C_i = C_{i,T_1} - C_{i,T_0}$ as well as its log counterpart. I also construct the cumulative price-level surprise between the end of T_0 and the start of T_1:

$$\Pi^s_{\Delta T} \equiv \sum_{t \in (T_0, T_1)} (\pi_t - \pi^e_t).$$

where π_t is realized monthly inflation and π_t^e the ex-ante expected monthly inflation, measured from the Survey of Professional Forecasters as of T_0.

Specification. I regress the spending change on net nominal position NNP_{i,T_0} and, in a decomposition, on nominal liabilities NL_{i,T_0} and nominal assets NA_{i,T_0}. I report estimates in levels, so coefficients are directly interpretable as dollars of spending per unit of nominal exposure per unit price-level surprise:

$$\Delta C_i \;=\; \alpha \;+\; \beta_{NNP} * (NNP_{i,T_0} * \Pi^s_{\Delta T}) \;+\; X'_{i,T_0}\theta \;+\; \varepsilon_{i,T} \tag{14}$$

and

$$\Delta C_i \;=\; \alpha \;+\; \beta_L * (NL_{i,T_0} * \Pi^s_{\Delta T}) \;+\; \beta_A * (NA_{i,T_0} * \Pi^s_{\Delta T}) \;+\; X'_{i,T_0}\theta \;+\; \varepsilon_{i,T} \tag{15}$$

Controls X_{i,T_0} are state fixed effects measured as of T_0. Appendix tables vary T_0, while main-text tables vary T_1.

Results Table 6 and 7 reports the results.[16] The pre/post estimates in levels are consistent with a clear debtor response: liabilities interacted with the cumulative price-level surprise load positively and significantly across late windows. However, both the asset slope and the NNP slope are flat. The most plausible interpretation is that my asset proxy (deposits) (i) has short duration and reprices quickly, (ii) can be reallocated during the inflationary episode, and (iii) is measured with error and has heavy tails, as reported in table 5. Each of these forces attenuates $\hat{\beta}_A$ toward zero. For the NNP, its coefficient $\hat{\beta}_{NNP}$ from the univariate regression 14 can be expressed as (dropping subscripts for simplicity):

$$\hat{\beta}_{NNP} = \frac{\beta_A\big[\,\mathrm{Var}(NA) - \mathrm{Cov}(NA, NL)\big] \;+\; \beta_L\big[\,\mathrm{Cov}(NA, NL) - \mathrm{Var}(NL)\big]}{\mathrm{Var}(NA - NL)}.$$

[16]For computational constraints, I run the regressions on a random sample of 20% of households in the my balanced panel, namely 85,976 users.

As reported in table 15 in appendix B.2.1, $\mathrm{Var}(NA)$ is more than a thousand times larger than $\mathrm{Var}(NL)$, while $\mathrm{Cov}(NA, NL) \approx 0$. This mechanically drives $\hat{\beta}_{NNP}$ toward zero, even though the liability signal is large and significant in the multivariate regression.

Pre/Post — Robustness by late window T_1 (fixed T_0 = Jan–Mar 2021)

	(2022)	(2023)	(2024)
$\hat{\beta}_{NNP}$	0.000***	0.000**	-0.000
	(0.000)	(0.000)	(0.000)
State FE	✓	✓	✓
Winsor (1%)	✓	✓	✓
N	85,976	85,976	85,976
R^2	0.000	0.000	0.000

Table 6: Outcome: ΔC. Entries are dollars of spending per ($NNP \times \Pi^s$). Robust SEs clustered by state.

Pre/Post— Robustness by late window T_1 (fixed T_0 = Jan–Mar 2021)

	(2022)	(2023)	(2024)
$\hat{\beta}_L$	0.005***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)
$\hat{\beta}_A$	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)
State FE	✓	✓	✓
Winsor (1%)	✓	✓	✓
N	85,976	85,976	85,976
R^2	0.002	0.001	0.001

Table 7: Outcome: ΔC. Entries are dollars of spending per ($NL \times \Pi^s$) and ($NA \times \Pi^s$). Robust SEs clustered by state.

Macro interpretation Taking the signal from liabilities and using $\hat{\beta}_L \simeq 0.004$ (units: dollars of ΔC per dollar of L per log-point of surprise), a 10 pp cumulative surprise between 2021Q1 and 2023Q1 and an average fixed-rate mortgage balance of $\bar{L} \simeq \$210{,}000$

imply

$$\Delta C_{\text{mortgagor}} \approx \hat{\beta}_L \times \Pi^s \times \bar{L} \ \approx \ 0.004 \times 0.10 \times 210{,}000 \ \approx \ \$85 \text{ per month.}$$

With roughly 40% of households holding mortgages, this maps to about \$52bn per year, or $\approx$ 0.3% of 2023 PCE, a magnitude that sits between the direct effect predicted by the HANK benchmark (figure 2) and its behavioral variant with high-degrees of cognitive discounting (figure 11). Of course, this empirical estimate should be read as only the debtor-side contribution, being therefore a likely upper bound on the overall effect. Together with the fact that $\hat{\beta}_L$ is stable across windows and slightly larger in 2024, rather than rapidly declining as the benchmark with rational expectations would predict, the empirical evidence seems more consistent with the model with cognitive discounting of section 3.1.1, also inspired by Schnorpfeil et al. (2023) results for Germany.

Placebo test As a falsification, I shift the entire exercise to pre-inflation windows starting in 2018-2020. In those periods, the estimates for NL are never statistically different from zero and very close to zero in terms of point estimates, with the pattern observed in 2021-2024 disappearing. This is consistent with the mechanism being activated by the inflation surprise, rather than by time-invariant differences in spending trends. Appendix B.2.1 reports the results.

4.5.1 Second approach: local projections

The second approach aims at tracing out dynamics more explicitly. I therefore estimate horizon-by-horizon responses of spending growth to the monthly surprise in inflation over the period. The local projection (LP) framework avoids imposing a parametric adjustment path and reports $\{\beta(h)\}_{h=0}^{H}$, similar to Cloyne et al. (2020), among many others. My baseline LP regresses $\Delta_h C_{i,t} = C_{i,t+h} - C_{i,t}$[17] on pre-period exposures NNP_{i,T_0} interacted with the rolling price-level surprise $\pi_t^s = \pi_t - \pi_t^e$, where π_t^e comes from the survey of professional forecasters as of T_0. I also include two-way fixed effects and estimate the

[17] In this regression, C_i, t is seasonally adjusted by estimating a common month factor on the 2014-2019 sample to abstract from the Covid-shock.

following equations:

$$\Delta_h C_{i,t} \;=\; \alpha \;+\; \beta_{NNP(h)} * (NNP_{i,T_0} * \pi_t^s) \;+\; \gamma_i \;+\; \tau_t \;+\; \varepsilon_{i,t+h} \tag{16}$$

and

$$\Delta_h C_{i,t} \;=\; \alpha \;+\; \beta_{L(h)} * (NL_{i,T_0} * \pi_t^s) \;+\; \beta_{A(h)} * (NA_{i,T_0} * \pi_t^s) \;+\; \gamma_i \;+\; \tau_t \;+\; \varepsilon_{i,t+h} \tag{17}$$

The household fixed-effect γ_i absorbs any permanent household-level heterogeneity, while month FE τ_t absorb aggregate shocks. Identification comes from cross-sectional exposure $\times$ common monthly inflation surprise.

Results. Figure 10 reports the results for equation 17. As in Section 4.5, the coefficients for nominal liabilities are orders of magnitude larger than those for nominal assets. While there is month-to-month volatility, the relatively flat impulse response and the presensce of statistically significant responses even twenty months after the initial shock are once again more consistent with the behavioral model with cognitive discounting rather than the full rational-expectations benchmark.

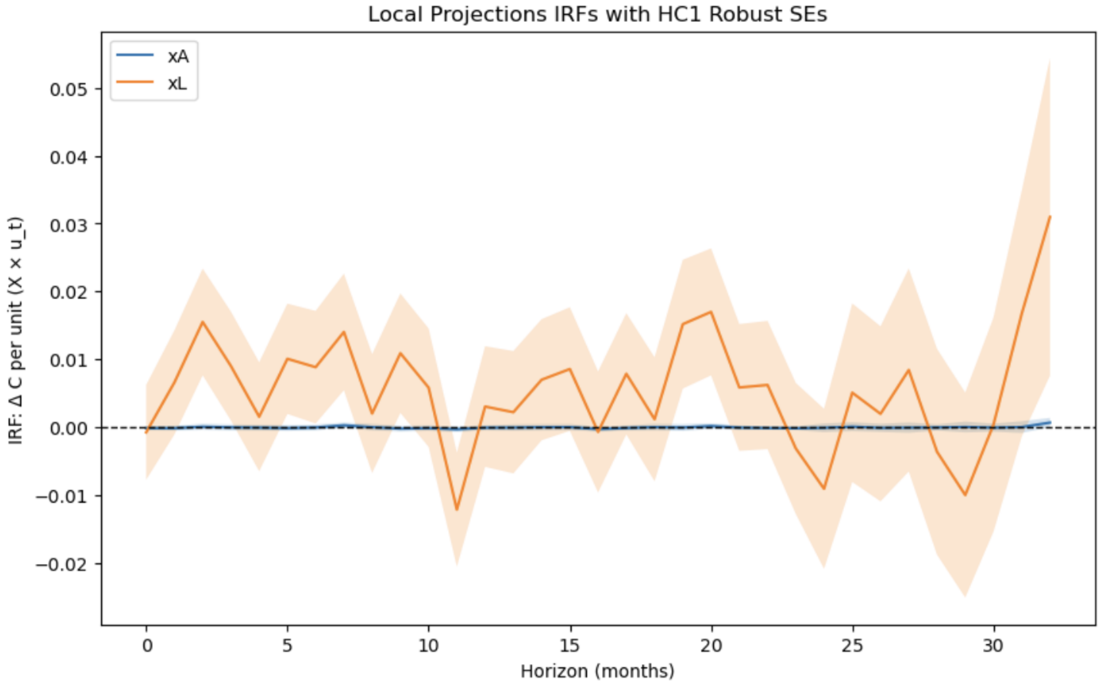


Figure 10: Estimated local projections of $\Delta_h C_{i,t}$ on $(NL_{i,T_0}\pi_t^s)$ and $(NA_{i,T_0}\pi_t^s)$ from equation 17. The solid lines plot point estimates of $\hat{\beta}_L(h)$ and $\hat{\beta}_A(h)$, with shaded 95% confidence intervals (HC1-robust).

4.6 County-level results

4.6 County-level results

Appendix C reports cross-county regressions parallel to the household exercise above (this time, in logs). With full controls, the point estimate on net nominal position to income (NNP/Y) is negative but imprecise (-0.29), the one on nominal liabilities-to-income (NL/Y) is positive and comparatively more precise (0.72) while the nominal asset slope (NA/Y) is near zero. While these point estimates for the net nominal position and nominal liabilities are consistent with the theory, neither is statistically significant.

5 Implications for Monetary Policy

The previous two sections focused on the importance of the Fisher channel in the context of the surprising strength of aggregate demand in the US post-pandemic. In this section, I move beyond the current inflationary episode - studying monetary policy in my HANK model featuring a quantitatively disciplined Fisher channel.

Monetary policy shocks I start by simulating a standard 25 bps expansionary shock with persistence $\rho = 0.7$ as in Kaplan et al. (2018).[18] I trace out the IRFs of consumption and inflation when households and the government have nominal assets, as in my model, and then contrast those IRFs with the case in which all assets are real - as in most baseline HANK models, where unexpected inflation has no redistributive impacts.

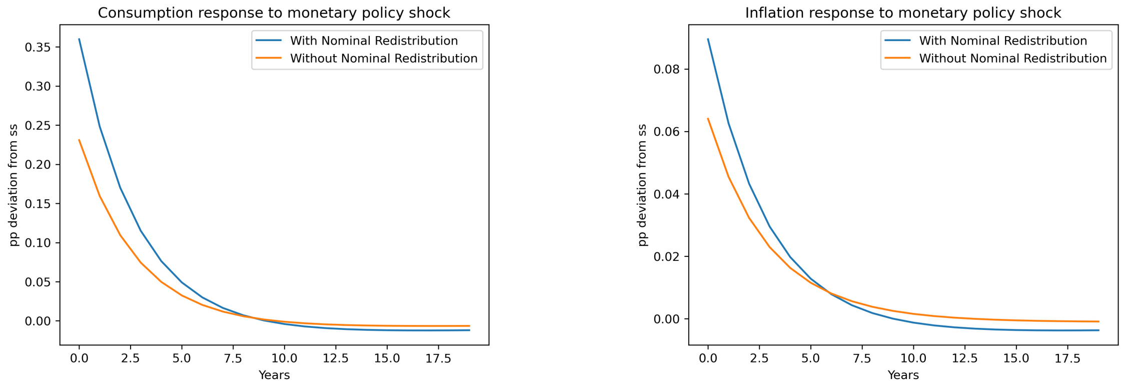


Figure 11: Impulse response functions of consumption and inflation to a standard monetary policy shock with and without an active Fisher channel in the model. In the model with nominal assets, monetary policy is around 50% more powerful as it also induces unexpected wealth redistribution across households.

Figure 11 reports the results. The left panel shows that an active Fisher channel makes monetary policy almost 50% more powerful on impact in its transmission to consumption. The intuition is the same as in the previous section: a persistent monetary policy shock generates some unexpected inflation (reported in the right panel of figure 11) which redistributes resources from wealthy households towards indebted ones with a higher MPC. In turn, this also generates more inflation thorough the standard New Keynesian Wage Phillips Curve 7.[19]

Increasing the degree of activeness of monetary policy through a higher coefficient on

[18] The path for the monetary policy shock is reported in figure 18 in the appendix.

[19] As noticed in section 3.1, the smaller but more persistent cut to consumption by wealthy households - who behave more according to the permanent income hypothesis (Friedman (1957)) - dominates over time the temporary spike in consumption of indebted households. The aggregate consumption IRFs to an expansionary monetary policy shocks therefore mildly undershoots its real-assets counterpart at long horizons.

inflation in the Taylor rule 8 reduces the differences across models with nominal and real assets. Intuitively, in the case of an expansionary monetary shock, the systematic component of monetary policy in case of an higher Taylor coefficient responds more aggressively in the model with nominal assets to counteract the inflationary impact stemming from the Fisher channel. In turn, this limits the differences across the model with nominal and the one with real assets.

Nominal Rigidities and the Effectivness of Monetary Policy In my model, varying the degree of nominal rigidity produces two opposing effects with respect to the impact of monetary policy shocks on consumption. On the one hand, reducing the degree of nominal rigidities implies that the real interest rate responds less to a monetary policy shock, decreasing the effectiveness of monetary policy - in line with conventional wisdom. On the other hand, in my model, less nominal rigidities also lead to a stronger reaction of inflation on impact, which leads to more wealth redistribution from low MPC households to high MPC ones, thus increasing the positive impact of an expansionary monetary policy shock on consumption.[20]

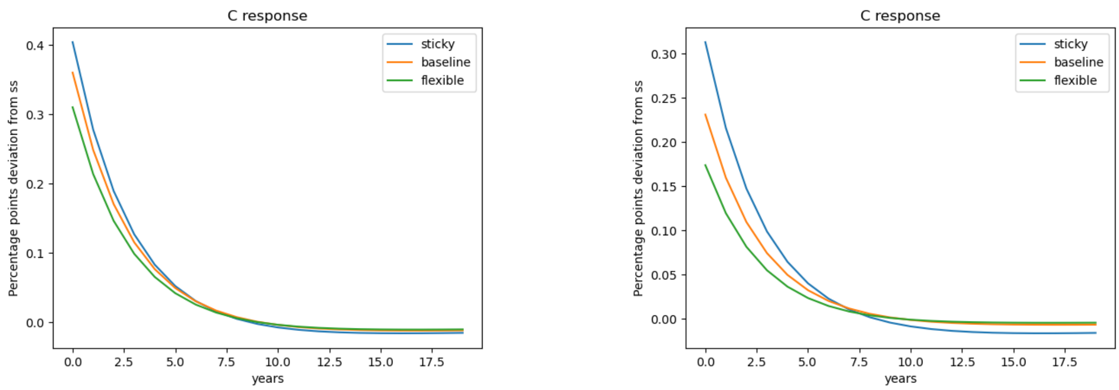
In my benchmark calibration of the model, the first channel through the real-rate still quantitatively dominates the opposing force arising from the Fisher channel. Therefore, consistent with conventional wisdom, monetary policy is still more effective the higher the degree of nominal rigidities. However, the Fisher channel still plays a significant quantitative role in dampening the differences across levels of nominal stickiness.

Figure 12 visualizes this point. The left panel shows the IRF of consumption in my benchmark model to the same monetary policy shock as the one in the previous paragraph, for different calibrations of the slope of the New Keynesian Wage Phillips Curve - i.e. the parameter κ_w in equation 7. Monetary policy is more effective the stickier nominal wages are, but the differences between IRFs are relatively small, due to the counterbalancing effect of the Fisher channel. The right panel of Figure 12 shows the same IRFs of consumption across the same values of κ_w, but in a model with only real assets. The differences in consumption IRFs across different values of κ_w are now much

[20]Clearly, the reverse applies to contractionary shocks.

larger due to the absence of the Fisher channel. As discussed in the previous paragraph, the absence of the Fisher channel also dampens the overall impact of monetary policy on consumption.

For some extreme parameterizations of the model that overstate the covariance between the marginal propensity to consume (MPC) and net nominal positions (NNP), the Fisher channel actually dominates the conventional impact of monetary policy on the real interest rate. This generates a "paradox of flexibility" whereby monetary policy has larger real effects the smaller the degree of nominal rigidity in the model. However, this paradox arises from a different mechanism than the one emphasized by Eggertsson and Krugman (2012), which operates through the effects of unexpected inflation in lowering the real interest rate when the nominal rate is stuck at the zero lower bound (ZLB). In my model, when monetary policy is stuck at the ZLB and the economy faces a demand shock, the Fisher channel will add to the real-rate channel, making the paradox of flexibility identified by Eggertsson and Krugman (2012) more pronounced.



Model with Fisher Channel **Model without Fisher Channel**

Figure 12: Impulse response functions of consumption to a standard monetary policy shock for different degrees of nominal rigidity in the model. Left panel: benchmark model with nominal assets; right panel: model with real assets, where there is no redistribution of wealth generated by inflation. Sticky: $\kappa_w = 0.05$; baseline: $\kappa_w = 0.10$; flexible: $\kappa_w = 0.15$.

6 Conclusions

This paper extends a standard HANK framework to incorporate household balance sheets with nominal assets and liabilities in a way that matches both the empirical distribution of net nominal positions (NNP) and their covariance with marginal propensities to consume. In doing so, it highlights the quantitative relevance of the Fisher channel for macroeconomic outcomes - an effect emphasized first by some seminal papers in the literature (Auclert (2019); Luetticke (2021)) but then often overlooked in models with only real, one-period assets. I further introduce a parsimonious behavioral friction - cognitive discounting of gains and losses on long-duration nominal claims (e.g., fixed-rate mortgages), inspired by the empirical work of Schnorpfeil et al. (2023) - that attenuates households' immediate response to unexpected inflation while making its effects more persistent.

Quantitatively, the baseline full-information model implies that the wealth transfer from creditors to debtors induced by the 2021-2022 inflation shock raised aggregate consumption by about 0.5% on impact, with effects that decay relatively rapidly. The behavioral extension delivers a smaller impact response but a more persistent stimulus. Micro evidence from a large fintech panel is consistent with these mechanisms and leans towards the behavioral extension. Mortgagors increased monthly spending by roughly \$40 per \$100,000 of outstanding fixed-rate debt in 2023, which aggregates to about \$53,bn per year - around 0.3% of PCE, with a similar response in early 2024. In impulse-response form, the local-projection estimates are volatile but show overall a response to nominal liabilities devaluations positive and often statistically significant several months after the initial shock, while the response to nominal assets remain near zero throughout.

Implications are significant. Because unexpected inflation redistributes toward indebted, higher-MPC households, the Fisher channel substantially amplifies monetary transmission: in the model, consumption responses to monetary policy shocks are up to 50% larger under a conventional Taylor rule and rational expectations. Moreover, amplification relies less on nominal rigidities, since redistribution operates even with flexible prices, and at the zero lower bound the Fisher channel magnifies the "paradox of flexibility" (Eggertsson and Krugman, 2012). For macroeconomic analysis and forecasting more generally, the results imply that demand sensitivity during inflationary episodes depends on the cross-section of nominal balance sheets and on how strongly households attend to inflation's balance-sheet consequences.

Overall, the results underscore that the distribution of nominal exposures - and the degree to which households attend to inflation's balance - sheet consequences - are first-order for the dynamics of aggregate demand. Accounting for these mechanisms helps explain the resilience of U.S. consumption in the wake of the recent inflation shock, with the behavioral extension highlighting the possibility that a small tailwind may persists for several years.

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Appendix A Model

A.1 Unions

This sections describes the key steps behind the New Keynesian Wage Phillips Curve 7. It recaps the crucial steps in Auclert et al. (2024a), referring to that paper for further details. As already mentioned in the main text, labor hours n_{it} are not chosen by households, but are determined by labor demand from unions. In the spirit of Erceg et al. (2000), each worker belongs to a union k, which employs a fully representative sample of the population. Each union aggregates individual tasks into $N_{kt} = \int e_{it} n_{ikt} di$. These tasks are combined by a competitive labor packer into aggregate employment according to

$$N_t = \int \left(N_{kt}^{\frac{\epsilon-1}{\epsilon}} dk \right)^{\frac{\epsilon}{\epsilon-1}}$$

and then sold to firms at price W_t.

Adjusting wages has quadratic costs that feed in directly in the utility function, of the form $-\frac{\psi}{2} \int \left(\frac{W_{kt}}{W_{kt-1}} - 1 \right)^2 dk$.

Each union sets a common wage W_{kt} for each efficient unit of labor provided by its members and (for simplicity) asks each member to work the same amount of hours, so $N_{kt} = n_{ikt}$. As noted by Auclert et al. (2024a), a more general rule $n_{it} = n(e_{it}) N_t =$ would be equivalent to redefining the e_{it} to account for the function n. In equilibrium, all unions choose the same wage $W_{kt} = W_t$ and all households work the same amount of hours $n_{it} = N_t$.

W_{kt} is set by each union in order to maximize the average utility of its members, which is given by:

$$\max_{W_{k,t}} \sum_{\tau \geqslant 0} \beta^{\tau+T} \left(\int \{ u(c_{i,t+\tau}) - v(m_{i,t+\tau}) \} d\psi_{i,t+\tau} - \frac{\psi}{2} \left(\frac{W_{k,t+\tau}}{W_{k,t+\tau-1}} - 1 \right)^2 \right)$$

where $\psi_{i,t+\tau}$ is the distribution of households and the maximization is subject to the demand curve for labor:

$$N_{kt} = \left(\frac{W_{kt}}{W_t} \right)^{-\epsilon} N_t$$

Where $W_t = \left(\int W_{kt}^{1-\epsilon} dk \right)^{\frac{1}{1-\epsilon}}$ is the price index for aggregate employment services.

Taking the first-order condition wrt to $W_{k,t}$, applying the envelope theorem to the household problem 1 whereby $\frac{\partial c_{it}}{\partial W_{kt}} = \frac{\partial z_{it}}{\partial W_{kt}}$ (recalling the definition of z_{it} from 4), recognizing that all unions are identical and thus in equilibrium $W_{kt} = W_t$, defining wage inflation $\pi^w = \frac{W_t}{W_{t-1}} - 1$ and rearranging as in Auclert et al. (2024a) we arrive at the New Keynesian Wage Phillips Curve:

$$\pi_t^w (1 + \pi_t^w) = \frac{\epsilon}{\psi} \int N_t \left(v'(n_{it}) - \frac{\epsilon - 1}{\epsilon} \frac{\partial z_{it}}{\partial n_{it}} u'(c_{it}) \right) di + \beta \pi_{t+1}^w (1 + \pi_{t+1}^w) \tag{18}$$

According to 18, the unions set higher wages whenever the average marginal rate of substitution between hours and consumption (
fracv'(n$_{it}$)$u'(c_{it})$ is above the marginal income from extra hour (after tax), marked down by $\frac{\epsilon-1}{\epsilon}$.

Equation 18 can be rewritten in terms of aggregates by noticing that in equilibrium since $n_{it} = N_{kt} = N_t$ we have:

$$\frac{\partial z_{it}}{\partial n_{it}} = (1-\theta)\tau_{it}e_{it}^{1-\theta}\left(\frac{W_t}{P_t}\right)^{1-\theta} N_t^{-\theta} = (1-\theta)\frac{e_{it}^{1-\theta}}{\int e_{it}^{1-\theta}di}\frac{(Y_t - T_t)}{N_t}$$

And therefore:

$$\pi_t^w(1+\pi_t^w) = \frac{\epsilon}{\psi}\left(N_t v'(N_t) - \frac{\epsilon-1}{\epsilon}(1-\theta)(Y_t - T_t)u'(C_t^*)\right) + \beta\pi_{t+1}^w(1+\pi_{t+1}^w)$$

Where $u'(C_t^*)$ is defined as

$$u'(C_t^*) = \int \frac{e_{it}^{1-\theta}u'(c_{it})}{\int e_{it}^{1-\theta}di}di$$

Substituting in for the utility function, we get equation 7.

A.2 Inflation, nominal wages and house prices

Figure 13 compares nominal wages, as measured by the Atlanta Fed Wage Tracker, with the Consumer Price Index (CPI), both normalized to 100 as of December 2020. In contrast to many Euro Area countries, nominal wages in the United States have almost kept pace with CPI. Figure 14 provides a breakdown by wage level, revealing that lower-wage workers experienced faster wage growth. Both figures abstract from productivity growth over the period.

Figure 15 shows the Case-Shiller index for U.S. home prices at the national level, also normalized to 100 as of December 2020. Throughout the inflationary episode, home values increased substantially more than the CPI on average.

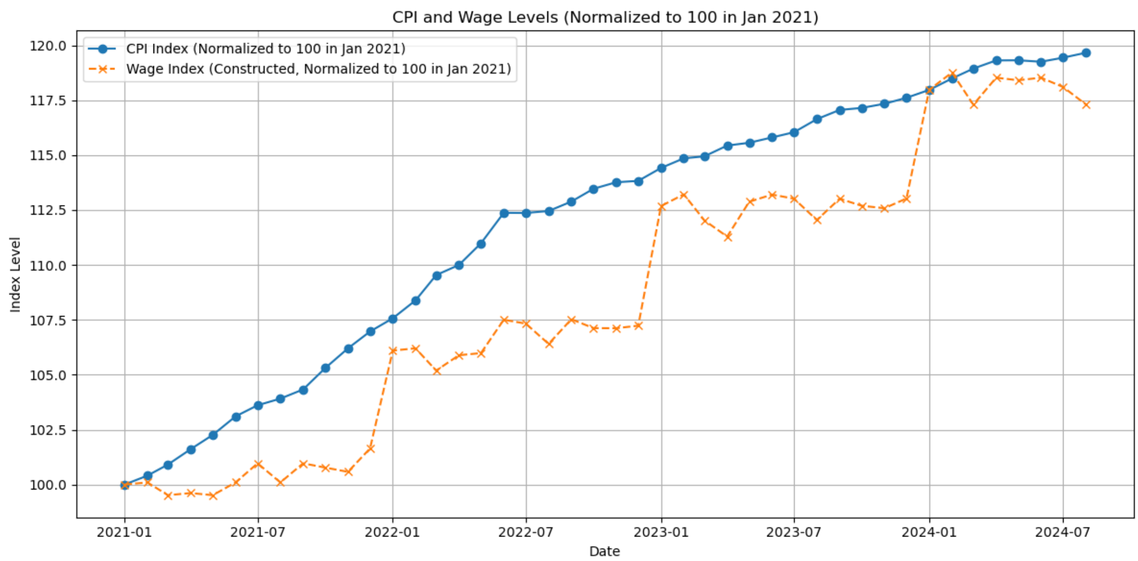

Figure 13: Price-level path for CPI and nominal wages from the Atlanta Fed Wage Tracker, normalized to 100 as of December 2020.

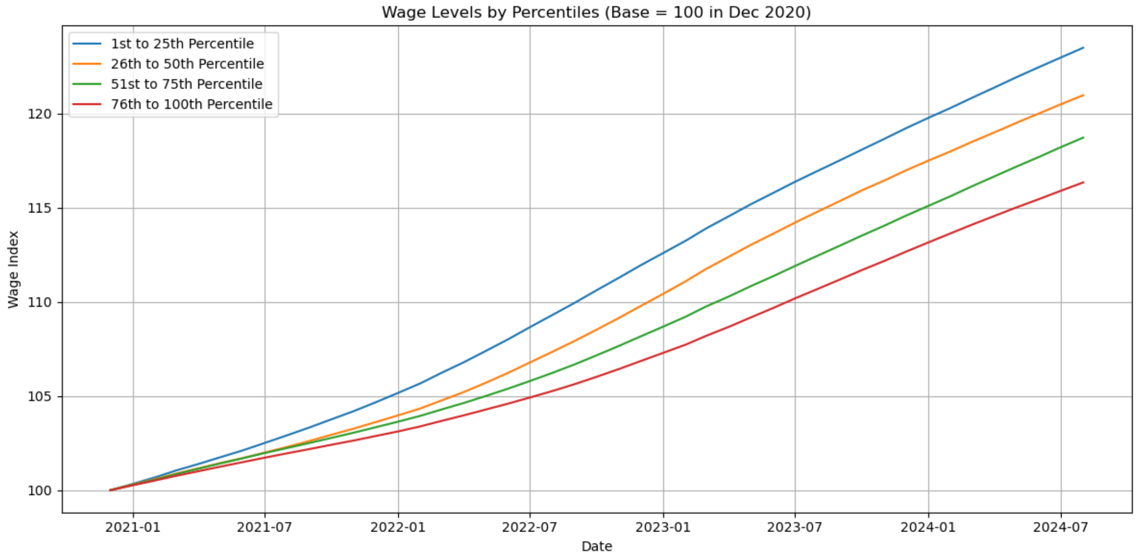

Figure 14: Path for nominal wages constructed from 12-Month Moving Averages Growth Rates from teh Atlanta Fed Wage Tracker for quartiles of the wage distribution, normalized to 100 as of December 2020.

A.3 Inflation shock

Figure 16 reports the gap between the expected path of inflation and its actual realization starting in December 2020. By December 2022, the cumulative difference—covering the period used in this paper — amounted to almost exactly 10%.

Although inflation expectations did adjust upward over this interval, nominal assets and liabilities have an average duration of approximately 5 years. As a result, any upward revision to inflation expectations after December 2020 reduces the ex post surprise only for shorter-term positions. Long-term nominal claims, such as Treasuries or fixed-rate mortgages, are still subject to the entire devaluation implied by unexpectedly high inflation. In contrast, short-term instruments like deposits or consumer credit can be reinvested or refinanced at higher nominal rates, mitigating part of the inflation-induced loss or gain.

Indeed, monetary policy tightening in 2022 may slightly overstate the wealth redistribution calculated here, because higher interest rates reduce the devaluation of short-term nominal positions. However, this effect should be quantitatively small, given the long duration of most nominal exposures and the fact that policy rates rose mainly toward the end of 2022. Moreover, Figure 17 illustrates that the difference between historically expected and actual inflation persisted into 2023–2024, adding around 2.5 additional percentage points at the time of writing. This later development increases the overall redistribution relative to what is analyzed in the paper, offsetting any mitigating effect from interest rate hikes on short-term positions.

A.4 Structural shocks

Figure 18 reports the path of the monetary policy shock considered in the paper, following Kaplan et al. (2018)

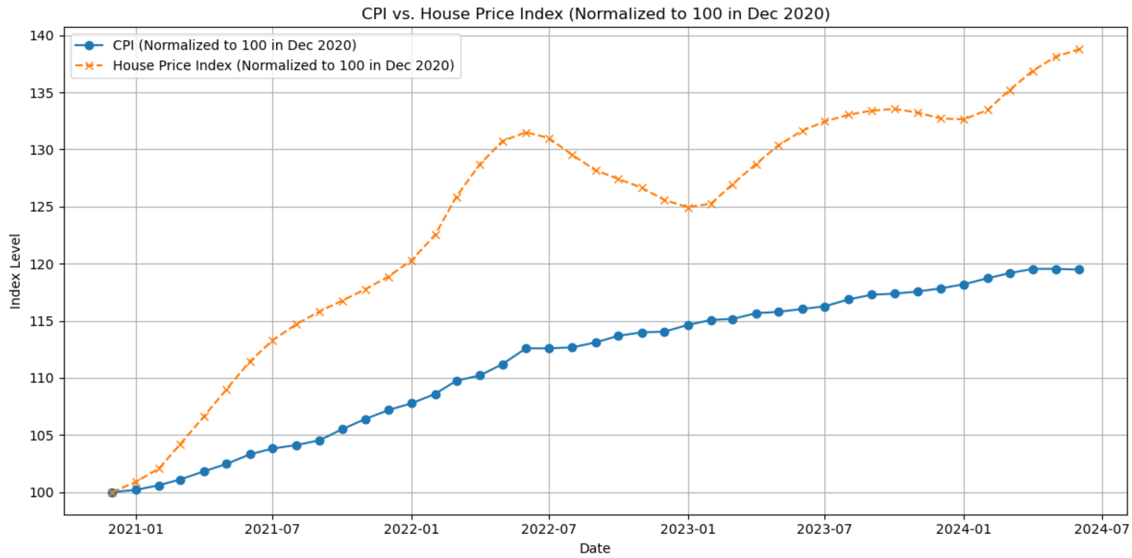

Figure 15: Price-level path for CPI and the Case-Shiller U.S. National Home Price Index from Standard & Poors, normalized to 100 as of December 2020.

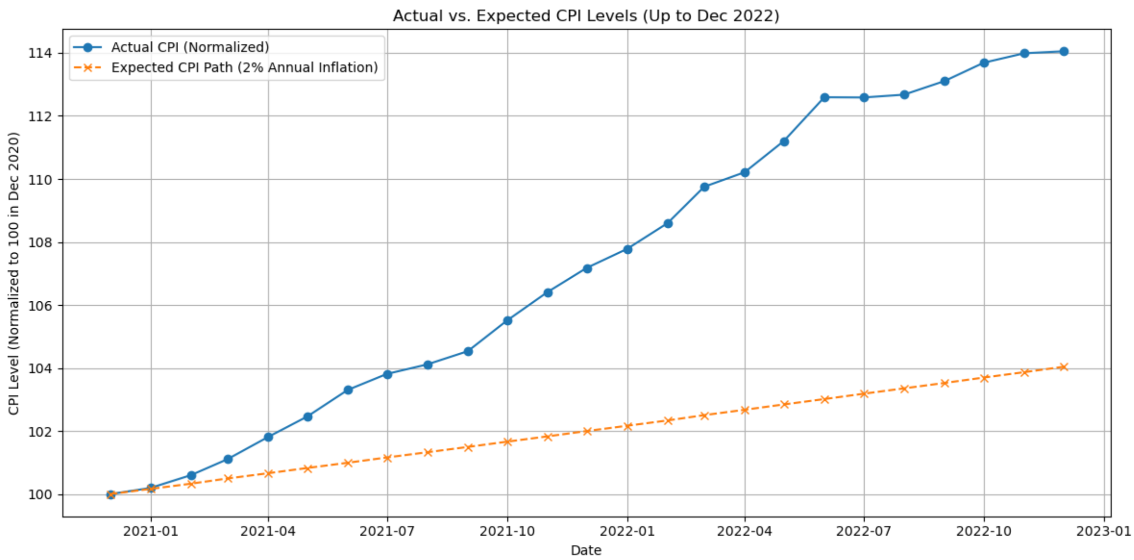

Figure 16: Actual and expected price-level path for CPI from December 2020 to December 2022. Expectations according to the Survey of Professional Forecasters as of December 2020.

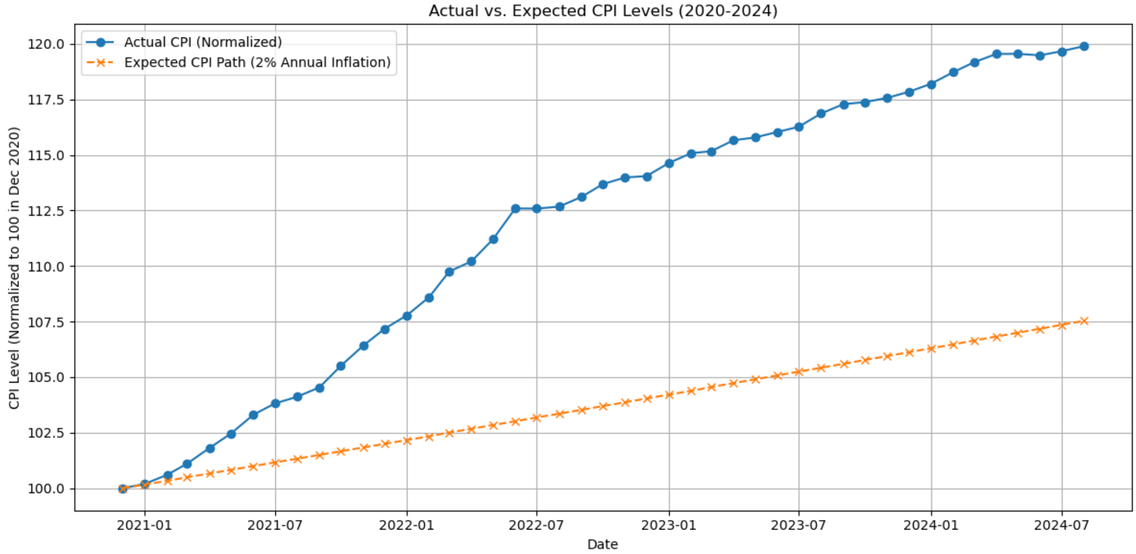

Figure 17: Actual and expected price-level path for CPI from December 2020 to August 2024. Expectations according to the Survey of Professional Forecasters as of December 2020.

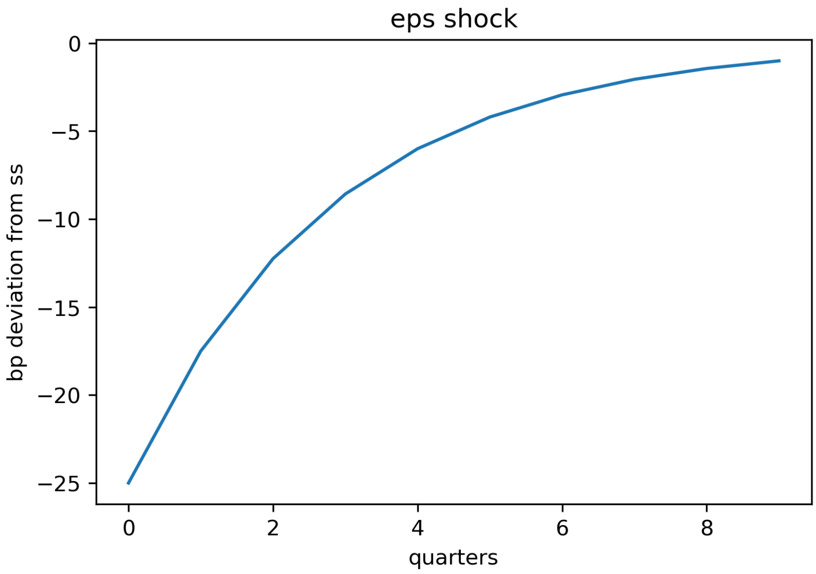

Figure 18: Monetary policy shock with persistence $\rho = 0.7$ as in Kaplan et al. (2018)

Appendix B Fintech data

B.0.1 Are the data missing people or missing income sources?

Two margins could explain the upper-tail gap: incomplete coverage of high-income households or incomplete coverage of their income sources. When I drop the top 3.5% of SCF households by income, the two distributions line up closely in 2021 (Table 8). By contrast, holding the SCF universe fixed but restricting SCF income to sources that are reliably visible in bank inflows (wages, interest and dividends, Social Security and retirement income, unemployment and other transfers) narrows the concept gap yet leaves a substantial shortfall at the top and exaggerates income at the bottom (Table 9). Excluding only the top 2% of SCF households under this restricted concept improves the upper tail further but does not eliminate the bottom overstatement (Table 10); results for alternative trims (1–3%) are reported in the appendix.

Dropping households whose total income is in the top 3.5% of the distribution and comparing the fintech income distribution to the one in the SCF generates a better alignment overall for 2021.

Table 8: Total Income by percentile: Fintech vs. SCF, 2021 (USD 000) - excluding the top 3.5% of households in the SCF

	Fintech		**SCF**	
Income group	Median	Mean	Median	Mean
Bottom 20	24.78	22.73	20.54	19.04
20-39.9	56.70	56.53	42.16	41.96
40-59.9	80.60	80.90	68.10	68.20
60-79.9	111.62	112.50	108.09	110.02
80-89.9	149.86	150.90	164.30	168.58
90-95	188.52	189.76	237.80	241
95-99	246.35	254.26	329.68	338.57
Top 1	410.34	461.94	464.79	462.67

Table 9: Total Income by percentile: Fintech vs. SCF, 2021 (USD 000), SCF only counting wages, interest and dividends, social security and retirement income, unemployment and other transfers

	Fintech		**SCF**	
Income group	Median	Mean	Median	Mean
Bottom 20	24.78	22.73	16.41	14.93
20-39.9	56.70	56.53	38.91	38.85
40-59.9	80.60	80.90	64.85	64.60
60-79.9	111.62	112.50	105.93	106.08
80-89.9	149.86	150.90	162.68	167.03
90-95	188.52	189.76	248.61	252.82
95-99	246.35	254.26	408.11	445.59
Top 1	410.34	461.94	1189.22	1727.18

Excluding the top 2% of households and keeping only those SCF income categories also gives a good match at the top, but it keeps exacerbating the overestimation at the bottom.

Table 10: Total Income by percentile: Fintech vs. SCF, 2021 (USD 000), SCF only counting wages, interest and dividends, social security and retirement income, unemployment and other transfers - excluding the top 2% of households

	Fintech		**SCF**	
Income group	Median	Mean	Median	Mean
Bottom 20	24.78	22.73	16.21	14.18
20-39.9	56.70	56.53	37.83	37.49
40-59.9	80.60	80.90	62.69	62.67
60-79.9	111.62	112.50	102.69	102.92
80-89.9	149.86	150.90	152.95	156.08
90-95	188.52	189.76	217.27	222.14
95-99	246.35	254.26	304.82	316.46
Top 1	410.34	461.94	468.03	466.42

Focusing on wages yields a parallel picture. Using my “Salary/Regular Income” category as the bank-based proxy for wages, I continue to understate upper-tail earnings relative to the SCF (Table 11). Trimming the top 2% of the SCF wage distribution removes the gap at the top (Table 12). Plausible drivers include stock-based compensation and bonuses that bypass checking accounts, self-employment income captured imperfectly by bank descriptors, and net-of-tax measurement in the bank data.

Table 11: Wage income by percentile: Fintech vs. SCF, 2021 (USD 000), Fintech considering ”Salary/Regular Income”

	Fintech		**SCF**	
Income group	Median	Mean	Median	Mean
Bottom 20	7.67	9.50	0	-0
20-39.9	39.71	39.01	12.97	12.82
40-59.9	61.95	62.07	43.24	42.55
60-79.9	87.21	87.97	86.47	88.60
80-89.9	117.62	118.35	144.84	147.87
90-95	146.71	147.67	216.18	223.53
95-99	189.01	195.01	357.78	395.20
Top 1	307.80	344.90	1080.91	1480.55

Table 12: Wage income by percentile: Fintech vs. SCF, 2021 (USD 000), Fintech considering "Salary/Regular Income"- excluding the top 2% of households in the SCF

	Fintech		**SCF**	
Income group	Median	Mean	Median	Mean
Bottom 20	7.67	9.50	0	-0
20-39.9	39.71	39.01	12.97	12.20
40-59.9	61.95	62.07	41.07	40.68
60-79.9	87.21	87.97	81.07	83.57
80-89.9	117.62	118.35	131.87	135.68
90-95	146.71	147.67	194.56	195.27
95-99	189.01	195.01	270.23	279.68
Top 1	307.80	344.90	399.94	403.35

B.1 Imputation of principal balance outstanding

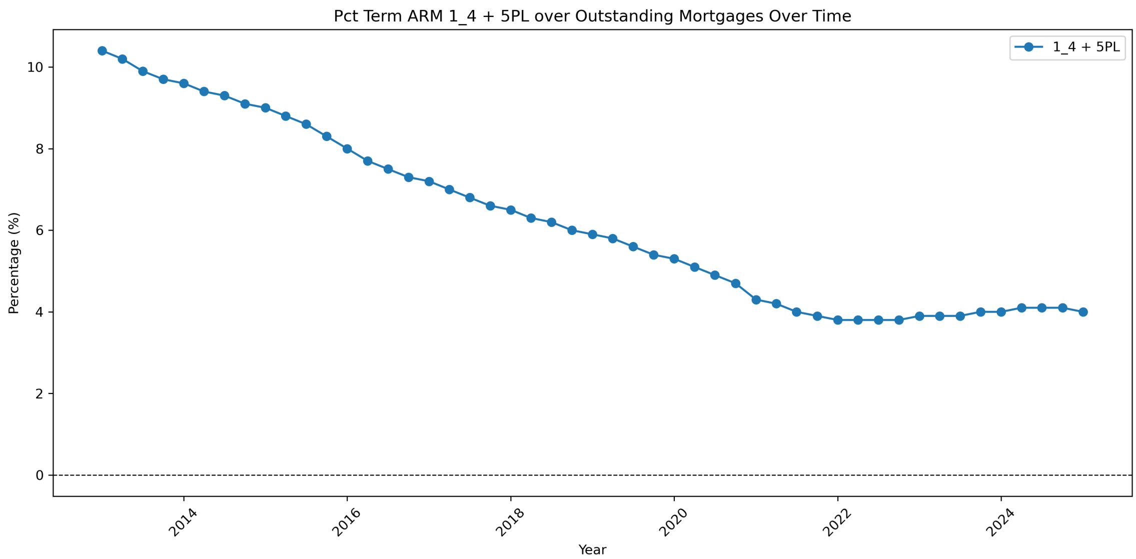

Figure 19: Percentage of Adjustable Rate Mortgages (1/4 and 5+ years) over outstanding mortgages in the US. Source: Federal Housing Finance Agency

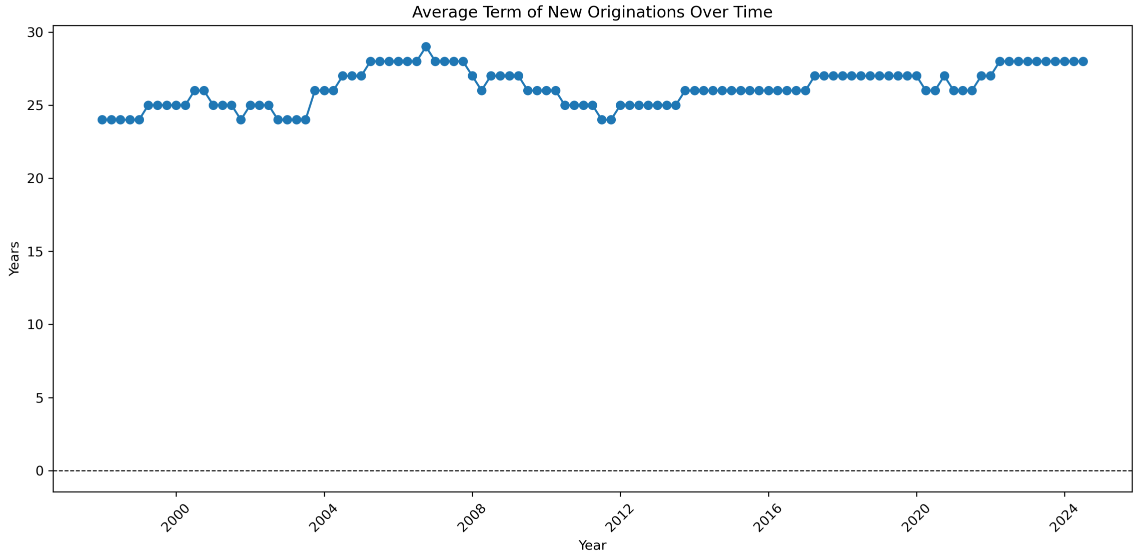

Figure 20: Average Term of Mortages at Origination. Source: Federal Housing Finance Agency

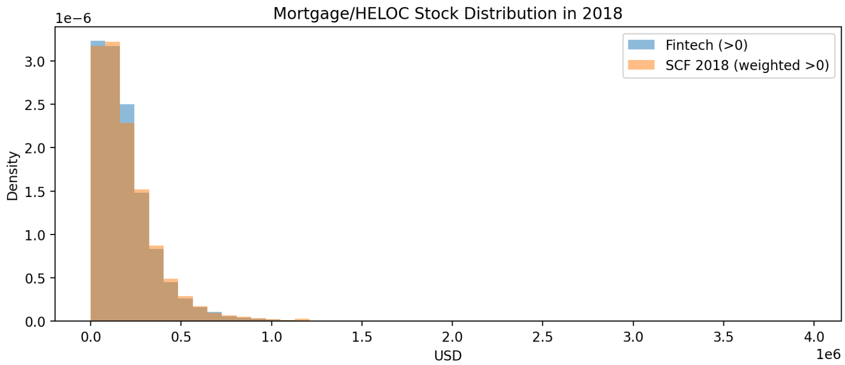

Figure 21: Distribution of Mortgages/HELOC principal balance outstanding, excluding households with 0 balances, SCF versus fintech data, 2018

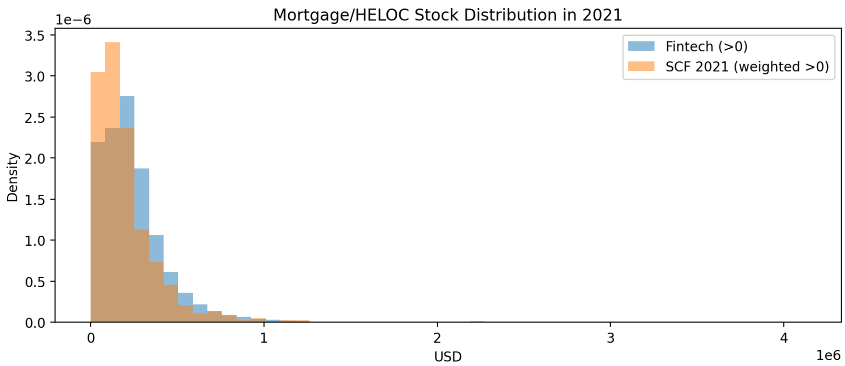

Figure 22: Distribution of Mortgages/HELOC principal balance outstanding, excluding households with 0 balances, SCF versus fintech data, 2021

B.2 Fintech data vs US official aggregates

Figure 23 compares aggregate consumption data from the fintech sample with Personal Consumption Expenditures (PCE) from the BEA. Despite the seasonally adjusted nature of the official data and the inclusion of items like imputed rents—which the fintech data does not capture—the two series align reasonably well. Figure 24 focuses on quarterly goods consumption in the BEA data and shows even closer alignment, since excluding services with imputed components (e.g., housing or medical services) better matches the fintech data's coverage.

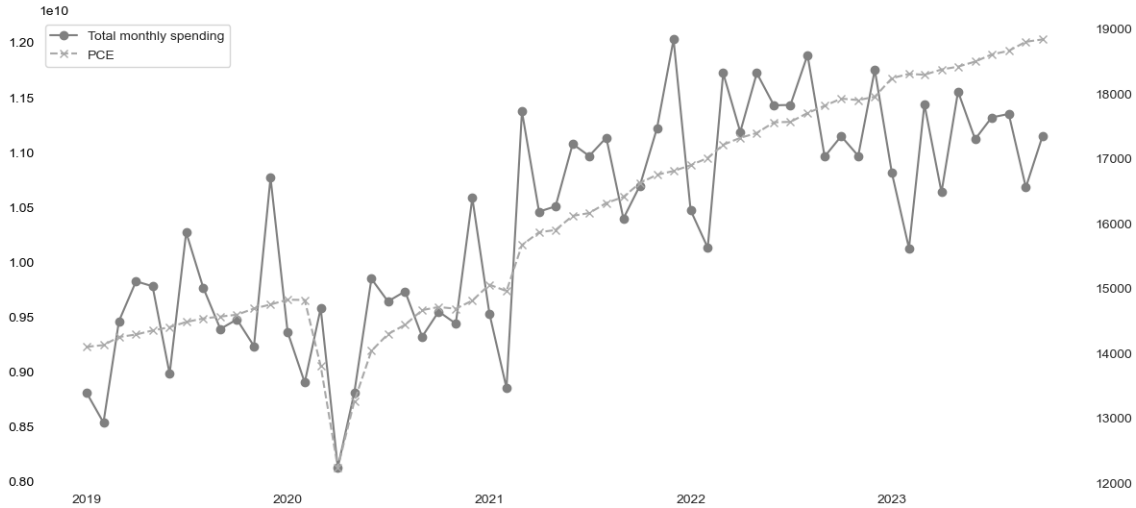

Figure 23: Comparison of official US Personal Consumption Expenditures data with fintech-based aggregate expenditures, January 2019 to October 2023. Note: data for US PCE are seasonally adjusted

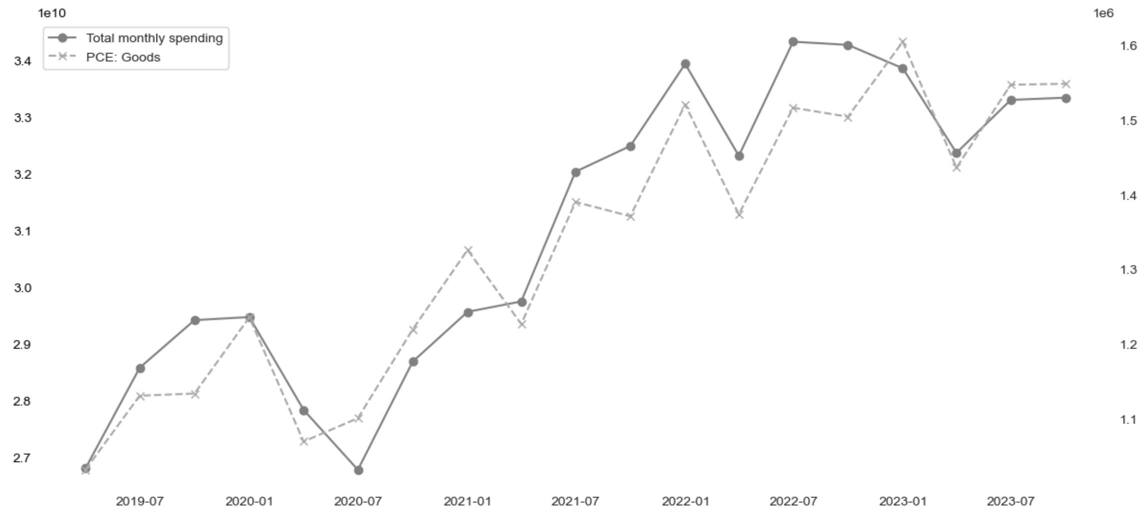

Figure 24: Comparison of official US Personal Consumption Expenditures on Goods with fintech-based aggregate expenditures, January 2019 to October 2023.

Pre/Post — Robustness to baseline T_0 (late window T_1 matched in 2024)

	Jan–Mar	Feb–Apr	Mar–May
$\hat{\beta}_{NNP}$	-0.000	0.000**	0.000*
	(0.000)	(0.000)	(0.000)
State FE	✓	✓	✓
Winsor (1%)	✓	✓	✓
N	85,976	85,976	85,976
R^2	0.000	0.000	0.000

Table 13: Outcome: ΔC. Entries are dollars of spending per $(NNP \times \Pi^s)$. Robust SEs clustered by state.

Pre/Post — Robustness to baseline T_0 (late window T_1 matched in 2024)

	Jan–Mar	Feb–Apr	Mar–May
$\hat{\beta}_L$	0.005***	0.004***	0.003**
	(0.001)	(0.001)	(0.001)
$\hat{\beta}_A$	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
State FE	✓	✓	✓
Winsor (1%)	✓	✓	✓
N	85,976	85,976	85,976
R^2	0.001	0.001	0.000

Table 14: Outcome: ΔC. Entries are dollars of spending per $(NL \times \Pi^s)$ and $(NA \times \Pi^s)$. Robust SEs clustered by state.

B.2.1 Transaction threshold

B.2.2 Decomposition of nominal assets and liabilities

B.2.3 Placebo tests

	Estimate (per log-pt)	s.e.
β_L/Π^s	0.0491	(0.0084)
β_A/Π^s	0.0000	(0.0001)
Second moments (scaled by $(\Pi^s)^2$*; units* $\$^2$		
$\mathrm{Var}(A)$	3.29×10^{11}	
$\mathrm{Var}(L)$	2.32×10^{8}	
$\mathrm{Cov}(A, L)$	-2.84×10^{7}	
(A, L)	-0.003	
$\mathrm{Var}(A - L)$	3.30×10^{11}	
$\hat{\beta}^{LA \Rightarrow NNP}_{NNP}/\Pi^s$	-0.0000	(0.0001)
Direct $\hat{\beta}_{NNP}/\Pi^s$	-0.0000	(0.0001)

Notes: N = 85,976; state FE; winsor 1%; Π^s = 0.098 log-pt.
Numerator shares: $b_A[\mathrm{Var}(A) - \mathrm{Cov}] = -122\%$; $b_L[\mathrm{Cov} - \mathrm{Var}(L)] = +222\%$.

Table 15: From (β_L, β_A) to implied β_{NNP} on the same sample.

Table 16: Pre/Post — Robustness by late window T_1 (fixed T_0=Jan–Mar 2021). Entries show $\hat{\beta}$ with robust SEs (clustered by state). Outcome: ΔC; spec: NNP; controls: none; winsor: 1%.

T1	2019	2020	2021
$\hat{\beta}_{NNP}$	-0.000*** (0.000)	-0.000*** (0.000)	0.000 (0.000)
N	85976	85976	85976
R2	0.000	0.000	0.000

Table 17: Pre/Post — Robustness by late window T_1 (fixed T_0=Jan–Mar 2021). Entries show $\hat{\beta}$ with robust SEs (clustered by state). Outcome: ΔC; spec: (L, A); controls: none; winsor: 1%.

T1	2019	2020	2021
$\hat{\beta}_L$	0.000 (0.000)	0.001 (0.001)	0.001 (0.001)
$\hat{\beta}_A$	-0.000*** (0.000)	-0.000*** (0.000)	0.000 (0.000)
N	85976	85976	85976
R2	0.000	0.000	0.000

Table 18: Pre/Post — Robustness to baseline T_0 (late window T_1 matched in 2024). Entries show $\hat{\beta}$ with robust SEs (clustered by state). Outcome: ΔC; spec: NNP; controls: none; winsor: 1%.

T0	Jan-Mar	Feb-Apr	Mar-May
$\hat{\beta}_{NNP}$	-0.000*** (0.000)	0.000 (0.000)	-0.000 (0.000)
N	85976	85976	85976
R2	0.000	0.000	0.000

Table 19: Pre/Post — Robustness to baseline T_0 (late window T_1 matched in 2024). Entries show $\hat{\beta}$ with robust SEs (clustered by state). Outcome: ΔC; spec: (L, A); controls: none; winsor: 1%.

T0	Jan-Mar	Feb-Apr	Mar-May
$\hat{\beta}_L$	0.001 (0.001)	-0.001 (0.001)	-0.003*** (0.001)
$\hat{\beta}_A$	-0.000*** (0.000)	0.000 (0.000)	-0.000 (0.000)
N	85976	85976	85976
R2	0.000	0.000	0.000

Appendix C Cross-county evidence

For cross-county evidence, I use real-time credit and debit card expenditures at the county level provided by Affinity Solutions and made publicly available by Chetty et al. (2020). Figure 26 presents the time series for the US and compares it with aggregate expenditures from BEA data, showing reasonable alignment. Figure 25 contains an example of the data for the county of Dutchess, NY.

I complement these data on expenditures by constructing a new measure of net nominal position at the county level. I follow a separate procedure for assets and liabilities. For nominal assets, I start from the total nominal assets held by US domestic households as computed in Pallotti (2022), and then assign it proportionally across counties based on each county share of yearly interest income over national interest income - both reported by the IRS Statistics of Income.[21] For nominal liabilities, I use the debt-to-income ratio for each county as of the start of the inflation episode in 2021 Q1, reported by the NY FED, and scale it by income at the county level reported by the IRS Statistics of Income.[22]

The net nominal position of county j is therefore simply:

$$NNP_j = \mathrm{NA}\,\frac{I_j}{I} - \mathrm{DTI}_j\,Y_j, \tag{19}$$

Where NA represents total nominal assets held by U.S. households, I_j yearly interest income in county j, DTI_j and Y_j respectively the debt-to-income ratio and yearly income of county j.

Regression I follow a similar approach as in section 4.4, regressing the log change in consumption at the county level during the inflationary shock on a measure of the county-level NNPs at the start of the period. I scale county-level NNP by its income Y_j. As the daily or weekly values are extremely volatile, as before I take an average of June and July 2021 as a starting point of the inflation episode and of August and September 2023 as the endpoint.[23] The results are robust to alternative specifications for the time interval. Equation 20 below describes my empirical strategy:

$$\Delta \log(C_j) = \alpha + \beta_1 \frac{\mathrm{NNP}_j}{Y_j} + \boldsymbol{\beta}_2 \mathbf{X}_j + \varepsilon_j, \tag{20}$$

I control for a number of confounding factors X_j which may have been relevant to determine the county-level spending growth over the inflationary shock. These include state-level fixed effect, industry composition at the county level (defined as the share in employment for each NAICS 2-digit sectors) and the level of employment in each county at the start of the inflation episode (an average over the first two months, as above).

Results Table 20 reports the results. Consistently with the theory, counties with a more negative NNP tended to exhibit higher spending growth following the onset of the inflationary trend. As before, the first column uses all controls: moving to the right side of the table, these controls are progressively excluded. The magnitude of the coefficient shrinks, and the sign

[21] I thus abstract away from differences in maturity structure of nominal positions across counties and adopt a risk-neutral approach with respect to differential exposure to default risk, assuming this is fully reflected in interest income.

[22] Figure 27 in the appendix illustrates the variation in the debt-to-income ratios at the county level.

[23] Data are seasonally adjusted as in Chetty et al. (2020).

flips once the analysis is not limited to within-State variation and does not control for industry composition.

Table 21 decomposes the NNP/Y at the county level into nominal assets and liabilities, again gradually excluding controls moving to the right side of the table. Consistently with the theory, counties with more nominal debt have seen a larger consumption response - with the estimate close to being statistically significant. The effect of nominal assets is much less precisely estimated, and the point estimate is slightly above zero, in contrast with the theory.

NNP and Spending Growth at the county level

	(1)	(2)	(3)	(4)
NNP/Y	-0.2866 (0.459)	-0.1018 (0.385)	0.1476 (0.295)	0.6640 (0.300)
State FE	✓	✓	✓	
Industry Comp.	✓	✓		
Employment	✓			
N	952	1607	1607	1607
R^2	0.447	0.394	0.371	0.007

Table 20: Results of regression 20 of consumption growth from June-July 2021 to August-September 2023 on NNP/Y (net nominal position relative to income) plus controls, all at the county level. Controls include state-level fixed effect, industry composition at the county level (defined as the share in employment for each NAICS 2-digit sectors) and the level of employment in each county at the start of the inflation episode.

C.1 Data sources for county-level regressions

The data on credit and debit card spending at the county level are freely downloadable here `https://tracktherecovery.org/`. Data on demographic structure at the county level are publicly available from Census at this link `https://www2.census.gov/programs-surveys/popest/datasets/2020-2022/counties/asrh/`. Chart 25 plots county level spending for the county of Dutchess. Chart 26 aggregates up spending for all counties and compare it to Personal Consumption Expenditures according to the BLS. Chart 27 plots the debt to income ratio for U.S. counties according to the NY Fed as of the first quarter of 2021. Figure 28 contains the CPI for the US, while chart 29 reports google searches for inflation in the U.S., showing a pickup around May 2021, coincident with the start of the inflationary period.

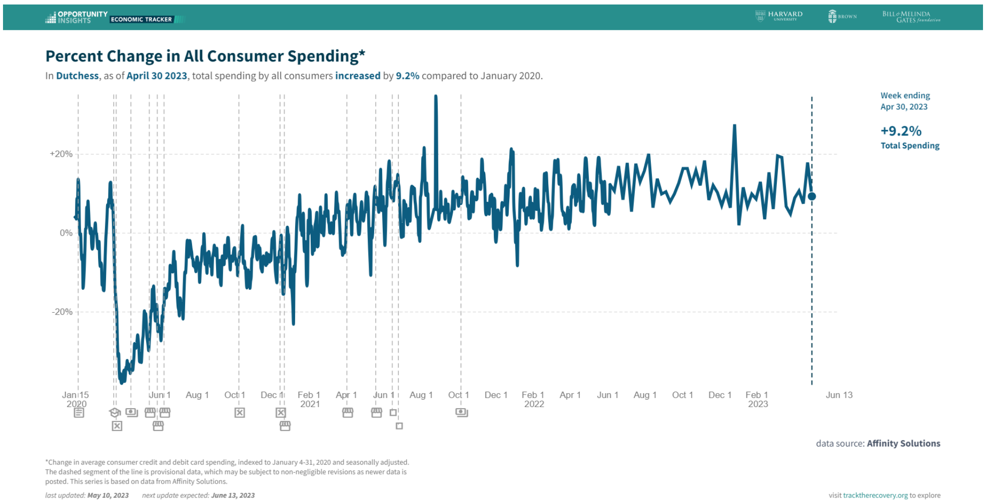

Figure 25: Example for the county of Dutchess of credit and debit card spending from January 1st 2020 to April 30th 2023. Source: https://tracktherecovery.org/.

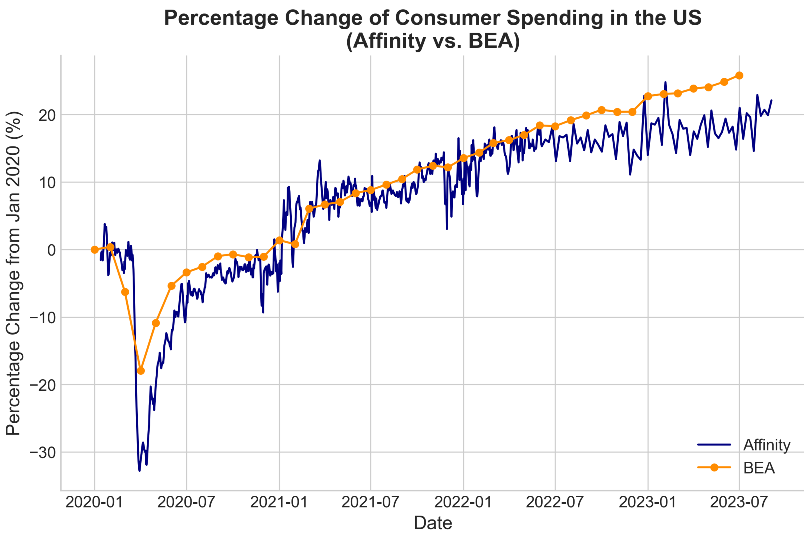

Figure 26: Total consumer spending in the US - Affinity versus BEA Personal Consumption Expenditures.

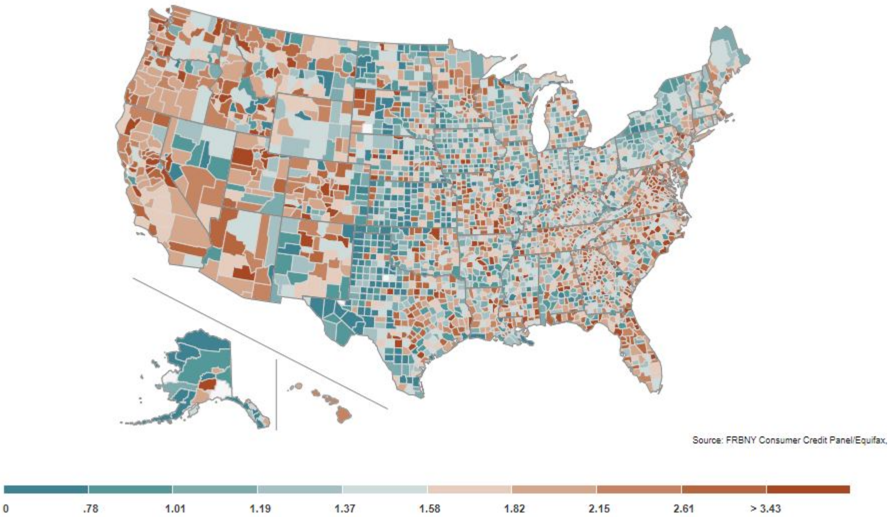

Figure 27: Debt to income ratio for U.S. counties as of 2021Q1. Source: Federal Reserve of New York.

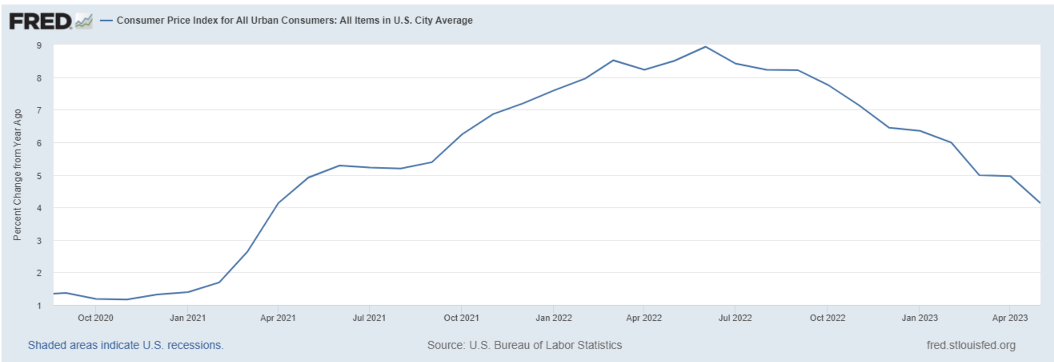

Figure 28: CPI for the US. Source: Fred.

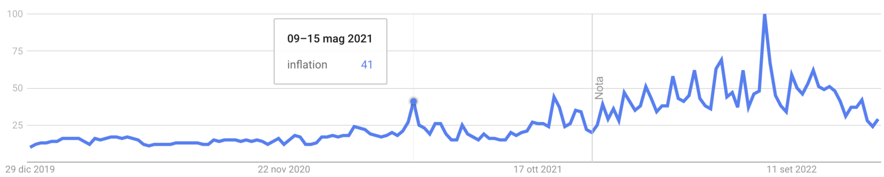

Figure 29: Google searches for inflation in the US. Source: Google Trends.

Nominal assets and liabilities and spending growth at the county level

	(1)	(2)	(3)	(4)
NL/Y	0.7193	0.4640	0.0683	-0.1168
	(0.691)	(0.574)	(0.351)	(0.678)
NA/Y	0.1300	0.277	0.4600	-1.2669
	(0.736)	(0.679)	(0.795)	(0.525)
State FE	✓	✓	✓	
Industry Comp.	✓	✓		
Employment	✓			
N	952	1607	1607	1607
R^2	0.448	0.394	0.372	0.011

Table 21: Results of regression 20 of consumption growth from June-July 2021 to August-September 2023 on NL/Y and NA/Y (respectively, nominal liabilities and nominal assets relative to income) plus controls, all at the county level. Controls include state-level fixed effect, industry composition at the county level (defined as the share in employment for each NAICS 2-digit sectors) and the level of employment in each county at the start of the inflation episode.