North American Journal of Economics and Finance 73 (2024) 102173

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

journal homepage: www.elsevier.com/locate/najef

Reassessing the inversion of the Treasury yield curve as a sign of U.S. recessions: Insights from the housing and credit markets

Ujjal K. Chatterjee [a,*], Aras Zirgulis [b], Maik Hüttinger [c], Joseph J. French [d]

[a] *Department of Economics and Management, University of Trento, Trento, Italy*
[b] *Department of Economics, ISM University of Management and Economics, Vilnius, Lithuania*
[c] *Department of Economics, Law and Society, ESSCA - School of Management, France*
[d] *School of Management, Asian Institute of Technology, Khlong Nueng, Pathum Thani, Thailand*

ARTICLE INFO

JEL classification:
E23
E37
E32
R11
R30

Keywords:
Treasury yield curve
Recessions
House Prices
Residential Investment
Bank Liquidity Creation
Credit Spreads
Receiver Operating Curve

ABSTRACT

Is yield curve inversion a reliable recession signal? Prior research on forecasting recessions investigates the role of the slope of the yield curve, housing, banking, and corporate credit spreads in isolation, without fully considering their interconnectedness. Therefore, we conduct a comprehensive investigation into the ability of house prices, residential investment, bank aggregate liquidity creation (LC) and credit (BC), and corporate credit spreads to forecast recessions. For the 1973–2023 sample, after accounting for the slope of the yield curve, our in- and out-of-sample results show that: i) house prices and credit spreads signal recessions—house prices decline, and credit spreads rise ahead of recession quarters; ii) residential investment's recession forecasting ability is not as robust as house prices; iii) the recession forecasting ability of LC or BC diminishes when we include other indicators. These findings provide important insights into the interconnectedness among economic indicators and their relationship with recessions. Importantly, we demonstrate that the inversion of the yield curve alone is not the surest sign of a recession. For a recession to occur, house prices must decline, and corporate credit spreads must significantly increase.

1. Introduction

Identifying recession indicators is crucial for policymakers, investors, and other stakeholders. Furthermore, the impacts of rising monetary policy rates, an inverted yield curve, and the likelihood of a recession have become critical issues in macroeconomics. As of June 23, 2023, based on the slope of the Treasury yield curve, the U.S. Federal Reserve sets recession probability within a year at a staggering 67.3 %.[1] Despite this high likelihood of a recession, a more restrictive monetary policy aimed at controlling inflation has been implemented. The implication is that the slope of the Treasury yield curve cannot be the only recession predictor. We therefore investigate the forecasting of recessions using variables such as house prices, residential investment, corporate bond credit spreads, and bank aggregate liquidity creation, along with a comprehensive set of other known recession-predictive variables. Our motivation for this study is as follows.

* Corresponding author.
E-mail addresses: ujjal.chatterjee@unitn.it (U.K. Chatterjee), arazir@ism.lt (A. Zirgulis), maik.huettinger@essca.fr (M. Hüttinger), joseph@ait.ac.th (J.J. French).

[1] Prob_Rec.pdf (newyorkfed.org).

https://doi.org/10.1016/j.najef.2024.102173
Received 17 August 2023; Received in revised form 26 March 2024; Accepted 25 April 2024
Available online 28 April 2024

The Treasury yield curve offers valuable information about the economy's future states (Estrella & Hardouvelis, 1991; Chauvet & Potter, 2005), but its macroeconomic responsiveness can vary due to changing market dynamics and other reasons. While important, the yield curve does not capture all aspects of the economy; complementary indicators like house prices, credit conditions, and the health of the banking sector may provide additional insights into the potential for a recession. While inversion of the yield curve historically precedes recessions, it does not reveal the specific triggers or causes behind them. Economic downturns can arise from a range of factors like external shocks, financial crises, or asset bubbles, not entirely captured by the yield curve. Consequently, we aim to reassess the yield curve's recession forecasting power.

In the existing empirical literature, investigations into housing, banking, and credit-supply conditions are often conducted in isolation to examine their individual recession forecasting ability. For instance, Favara, Gilchrist, Lewis, and Zakrajsek (2016) show that corporate credit spreads, such as excess bond premium (EBP hereafter) forecast recessions. On the one hand, the housing literature (e.g., Ghent & Owyang, 2010; Bluedorn, Decressin, & Terrones, 2016; Aastveit, Anundsen, & Herstad, 2019) finds different results: some studies suggest that residential investment, rather than house prices, forecasts recessions, while others show that house prices forecast recessions. In contrast, the banking literature (e.g., Berger & Bouwman, 2017; Chatterjee, 2018) shows that bank economic output, as measured by bank liquidity creation (LC hereafter), forecasts crises and recessions.

Nevertheless, while housing, banking, and credit-supply conditions may individually forecast recessions, the housing/credit crisis of 2007–2009 underscored the interdependency of these factors. Importantly, while forecasting recessions is crucial, deriving policy implications considering the endogeneity among recession predictors is more important. Therefore, this study aims to address the gap in the existing literature by incorporating several important recession predictors shown in Table 1 and deriving policy implications. Our empirical approach is as follows: i) we investigate what indicators, besides the slope of the yield curve, were important for forecasting recessions in the past. This analysis involves analyzing shorter time-series data to closely match the period investigated in the earlier studies; ii) then, we extend the data to the most current available to reassess the leading indicators; iii) finally, in a vector-autoregression framework, considering endogeneities among recession predictors, we endeavor to derive monetary policy implications.

Our primary findings based on both the in- and out-of-sample results are as follows. Our results show that house prices and EBP have recessions forecasting ability for at least four quarters ahead of recessions – house prices fall and EBP expands before recessions. While residential investment forecast recessions and it also falls before recessions, after accounting for other predictors its predictability is not robust. As for LC and other predictors, such as oil prices and bank credit (BC), they have shorter forecast horizons relative to house prices and EBP. Importantly, our findings indicate that an inverted yield curve alone does not signal an imminent recession. A recession requires a combination of falling house prices and a significant increase in corporate credit spreads. Our contribution to the literature is as follows.

First, our study offers substantial empirical support for the potential mechanisms that link booms and busts in asset prices, including housing, availability of credit, and the real economy, as explored in several recent papers. Burnside Craig & Martin Eichenbaum & Sergio Rebelo (2016) examine factors driving boom-bust cycles in housing markets, attributing booms to optimistic expectations and supply constraints, with declines occurring upon downward revisions of expectations, amplified by loose lending standards. Baker, Bloom, and Davis (2016) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) demonstrate how heightened uncertainty can lead to deferred investment and hiring decisions, potentially dampening housing investment during downturns. Caballero and Simsek (2020) develop a model where an increase in uninsurable entrepreneurial risk facing households leads to higher precautionary savings and lower spending, generating a demand-driven recession. Simultaneously, the higher risk makes households prefer safer assets, raising risk premiums and depressing speculative asset prices. The model can produce periods of low output, spending, and asset prices driven purely by changes in perceived risks rather than fundamentals. Giglio, Stroebel, Utkus, and Stephen, (2021) document how household beliefs, influenced by individual experiences, can shape investment choices, potentially

Table 1
Recessions (USREC) Predictors.

Variable	Description	Related Literature
TS	Treasury term spreads	TS is diff in yields of 10Y and 3 M Treasuries (Estrella & Hardouvelis, 1991)
ΔFED	Change in the effective Federal Funds rate	
MKT	Stock Market Excess Returns	
VOL	Stock Market Excess Volatility	
ΔILR	Log diff. of stock market Liquidity	Amihud (2002), Næs, Skjeltorp, and Ødegaard (2011), Chatterjee (2016)
ΔLC	Log diff. of bank liquidity creation	Berger and Bouwman (2017), Chatterjee (2018)
ΔLC^{ON}	Log diff. of bank on-balance sheet liquidity creation	
ΔLC^{OFF}	Log diff. of bank off-balance sheet liquidity creation	
EBP	Corproate Credit Spreads	Favara et al. (2016)
ΔOIL	Change in WTI oil prices	Bluedorn et al. (2016); Christensen, Eriksen, and Møller (2019)
ΔRRPP	Log diff. of Real Residential Property Prices	
ΔRINV	Log diff. of residential investment	Aastveit et al. (2019)
ΔBDMargin	Change in Brokers and Dealers Margin	Liu and Moench (2016)
UNRATE	Unemployment rate	
UMCESNT	U.S. Consumer Sentiment	
ΔBC	Log diff. of Bank Credit, sum of (i) Treasury, Agency, and other securities, and (ii) loans and leases	Not used in the literature

amplifying asset price cycles. Beaudry and Prices (2006), Blanchard, L'Huillier, and Lorenzoni (2013), Ilut and Schneider (2014), and Basu and Bundick (2017) highlight shocks to consumer demand, sentiment, and beliefs as drivers of business cycles. These mechanisms intertwine with investment and housing demand fluctuations, with overly optimistic beliefs fueling booms and revisions leading to busts, while loose credit can amplify cycles. Thus, shifts in credit conditions and lower house prices may signal impending recessions.

Secondly, our research directly contributes to the housing literature, contradicting the view that residential investment is a reliable leading indicator of recessions (as argued by Leamer, 2007,2015; Ghent & Owyang, 2010). Instead, we demonstrate that house prices, which are highly correlated with consumption (Benjamin, Chinloy, & Jud, 2004, Campbell & Cocco, 2007, Bostic, Gabriel, & Painter, 2009), provide better forecasts for recessions.

This research also makes a significant contribution to the banking literature that focuses on the role of banks in economic development, as exemplified by works by Bencivenga and Smith (1991), Levine and Zervos (1998), and Kashyap, Rajan, and Stein (2002). However, our findings suggest that LC or BC, after accounting for other indicators, does not serve as a reliable predictor of recessions. Thus, our results are consistent with the findings in the literature (e.g., Bernanke and Lown (1991)) that highlight the absence of a credit crunch in the relationship between bank lending and economic activities.

Our findings have the following policy implications. We demonstrate that the effectiveness of monetary policy decisions depends on two crucial components of the economy – the housing and credit markets. If house prices remain stable and corporate credit spreads do not widen substantially, raising policy rates could be an effective strategy to temper inflationary pressures without triggering a recession. Policymakers may consider these results while formulating economic policies to ensure stability and sustainable economic growth.

The remainder of the paper proceeds as follows. Section 2 describes data sources and characteristics; Section 3 presents the main empirical results along with policy implications; and Section 4 summarizes.

2. Data and sample construction

Our U.S. quarterly sample starts from the first quarter of 1973 through the first quarter of 2023. Our primary dependent variable is the NBER dated recession indicators (USREC hereafter).[2] Unless mentioned otherwise, our data are obtained from either the U.S. Bureau of Economic Analysis or from the ArchivaL Federal Reserve Economic Database (ALFRED). All stock market variables are computed using the Center for Research in Security Prices (CRSP) common stocks data.[3] If we have monthly data, we compute quarterly variables by averaging the monthly data over a three-month period starting from January of each year.[4] Initially, we utilize data from 1984 to 2016 for bank aggregate liquidity creation (LC) due to data availability constraints from the Federal Deposit Insurance Corporation (FDIC) call report data. This data is unavailable before 1984 and extends until 2016. To ensure robustness, we also analyze bank credit (BC) from 1973 to 2023, starting from the first quarter of 1973 due to the unavailability of EBP data before this period.

The recession forecasting literature (e.g., Estrella & Hardouvelis, 1991, Estrella & Mishkin, 1998, Harvey, 1988,1989) has shown that the Treasury term spreads (TS) contains leading information about the probability of recessions, where TS is computed as the difference in the yields on the 3-month Treasury-bill and the 10-year Treasury bond index. TS is our benchmark recession forecasting variable, and we include other indicators to investigate their marginal recession forecasting ability.

As for the housing variables, we use the house prices and residential investment data. The house prices data is the Real Residential Property Price index (RRPP hereafter), and the data includes all types of dwellings in the U.S. in both existing and new houses. House prices are adjusted for inflation, and we use the log difference of house prices, and the corresponding recession forecasting variable is ΔRRPP. Aastveit et al. (2019) show that residential investment forecasts recessions, and hence we use the log difference of residential investment (ΔRINV) as another recession forecasting variable. As for the credit spreads measures, following Favara et al. (2016), we include EBP, the corporate bond credit spreads measures that are computed from unsecured nonfinancial corporate bonds' trading data and these measures are based on Gilchrist and Zakrajšek (2012).[5]

As for the banking variables, first, we use the measures proposed in Berger and Bouwman (2009). Their LC measure accounts for bank on– and off-balance sheet activities. The LC measures are computed for virtually all commercial banks in the U.S. We obtain LC, LC^{ON} and LC^{OFF}, bank aggregate, on–, and off-balance sheet liquidity creation data, respectively, from Christa Bouwman website.[6] We include the log differences of those measures as recession predictors, and they are represented as ΔLC, ΔLC^{ON} and ΔLC^{OFF}, respectively. Berger and Bouwman (2017) show that LC contains leading information about recessions and crises. Chatterjee (2018) further finds that bank on-balance-sheet liquidity creation (LC^{ON}) best forecasts recessions among the above bank liquidity creation measures, and hence we primarily focus on ΔLC^{ON}, while the other two measures are used to ensure robustness. In addition to LC, we use bank

[2] NBER based Recession Indicators for the United States from the Peak through the Period preceding the Trough (USRECQP) | FRED | St. Louis Fed (stlouisfed.org).

[3] Disagreements have effects on macroeconomic outcomes, and asset prices may reflect these disagreements (Burnside et al., 2016; Caballero & Simsek, 2020, Giglio et al., 2021, among others). Indeed, Carlin, Longstaff, and Matoba (2014) demonstrate the relationship between disagreements and asset prices. Thus, we include prices of corporate and Treasury bonds, stocks, and houses as potential recession predictors.

[4] While the macro variables and some micro variables are available in real-time, some of our data such as bank liquidity creation may not be updated in real-time. Thus, due to data limitations, our analysis is not in real-time.

[5] We thank Simon Gilchrist for proving the data.

[6] We thank Christa Bouwman for providing the bank on–, off- and aggregate liquidity creation data.

credit (BC), which is the sum of (i) Treasury, Agency, and other securities, and (ii) loans and leases since LC data is unavailable beyond the sub-sample period of 1984–2016.

2.1. Other recession forecasting variables

Following Bluedorn et al. (2016) we use changes in West Texas crude oil prices (ΔOIL) as another predictor. We also use brokers and dealers' margin account balance (BDMargin), consumer sentiment (UMCESNT), unemployment rate (UNRATE) following Liu and Moench (2016). Additionally, we use other predictors such as the changes in the Federal funds rate (ΔFED), stock market returns (MKT), and stock market volatility (VOL) following the recession forecasting literature (Estrella & Hardouvelis, 1991, Estrella & Mishkin, 1998). We further include stock market illiquidity (ILR) since it is found in the literature (e.g., Chatterjee, 2016) that ILR forecasts recessions. ILR is computed as per the literature (e.g., Amihud, 2002).[7] We use the log difference of ILR (ΔILR) in our analysis.

Finally, we use the Survey of Professional Forecasters' (SPF) mean recession probability estimates to compare our model-implied recession probabilities with that of SPF as per the literature (e.g., Rudebusch & Williams, 2009). The SPF data are obtained from the Federal Reserve Bank of Philadelphia. We next conduct both ADF (Dickey & Fuller, 1979) unit-root and KPPS (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) stationarity tests to investigate whether variables are stationary. The transformed variables to attain stationarity are reported with a prefix 'Δ'. Table 1 presents the predictor variables used in this study.[8]

3. Empirical results

We first investigate whether the variables that are found to be individually important predictors of recessions are indeed important when we investigate them concurrently based on the existing literature. This leads us to examine the 1984–2016 sub-sample since LC data is available for that period only. Next, we assess whether the results hold for a longer sample from 1973 to 2023 where we have data for bank credit.

We estimate the probability of recessions using the following probit model as per the literature (e.g., Estrella & Hardouvelis, 1991, Estrella & Mishkin, 1998):

$$P(X_t = 1) = \Phi(\alpha + \beta^* V_{t-l}) \tag{1}$$

where V is a vector of predictor variables that includes TS, EBP, ΔRRPP, ΔLC, etc., and l is the number of lags used and represents the forecast horizon. The dependent variable (X_t) is a binary variable, which is "1″ if the economy is in a recession quarter and '0' otherwise. Models are evaluated based on Pseudo-R-Squared value, which is defined as

$$\text{PseudoR}^2 = 1 - \left[\frac{\log(L_u)}{\log(L_c)}\right]^{-\left(\frac{2}{n}\right)\log(L_c)} \tag{2}$$

where L_u is the likelihood of the full model and L_c is the likelihood of the intercept only model.

However, the recession forecasting literature (e.g., Liu & Moench, 2016; Aastveit et al., 2019) argues that the probability estimates by probit models are rarely exactly zero or one, and hence a cutoff should be used in such a way that a predicted probability above the cutoff is classified as a recession. Thus, in addition to Pseudo-R-Squared values, we assess each model's accuracy by the receiver operating characteristic (ROC). For Model 1, ROC plots the mapping of the false positive rate, $\text{FPR}_1(\tau)$, and the true positive rate, $\text{TPR}_1(\tau) = \text{TPR}_1(\text{FPR}_1(\tau))$, across different values of the threshold parameter τ (see e.g. Berge & Jordà, 2011; Aastveit et al., 2019; for further details). Next, we summarize the forecast performance of Model 1 implied by the ROC curve by finding the area under the curve (AUROC) as follows:

$$AUROC_1 = \int_{\tau=0}^{1} \text{TPR}_1(\tau) FPR_1'(\tau) d\tau \tag{3}$$

Any model with AUROC value of greater than 0.5 is better than a random guess. The reason is that a random guess would have on average an equal number of true and false positives that corresponds to an AUROC value of 0.5. If we have two Models 1 and 2, the accuracy of one model over the other is evaluated by computing a Wald type of test statistics following the literature (e.g., DeLong, DeLong, & Clarke-Pearson, 1988):

[7] While there are other measures of stock market liquidity, Amihud's illiquidity ratio (ILR) (Amihud, 2002) is found to be the best predictor of recessions and real GDP. The illiquidity ratio of a stock is computed as: $ILR_{i,t} = \frac{1}{D_{i,t}}\sum_{d=1}^{D_{i,t}} |R_{i,d,t}|/VOL_{i,d,t}$, where $|R_{i,d,t}|$ and $VOL_{i,d,t}$ are absolute returns, the dollar volume of security i on date d, respectively and $D_{i,t}$ is the number of days over which ILR is calculated. The measure is a proxy for stock illiquidity. Stocks must have share prices of more than \$5 and less than \$1000 and be traded for 20 days in a month to be included in the sample. An equally weighted quarterly average liquidity of all stocks is stock market liquidity and it is denoted as ILR. Note that ILR measures illiquidity.

[8] Correlation results, which shows that there are no multicollinearity issues, are available upon request.

$$\mathrm{W}_{\mathrm{AUROC}} = \frac{(AUROC_1 - AUROC_2)}{\mathrm{se}\,((AUROC_1 - AUROC_2)} \tag{4}$$

To assess whether Model 1 is preferred to Model 2, we compare $\mathrm{W}_{\mathrm{AUROC}}$ to the relevant critical value from a standard normal distribution and report the results for two-sided tests.

In Table 2, we present the results using the Eq. (1) and 1984–2016 data. For parsimony, we report the results for relevant and important predictors, omitting others as their inclusion does not have any meaningful impact on the model fitness.[9] We show the results for up to four quarters prior to recessions as is standard in literature (e.g., Rudebusch & Williams, 2009; Aastveit et al., 2019). We observe that TS contains leading information about recessions for all forecasting horizons. The coefficient of TS is negative and statistically significant at the 1 % level throughout the forecast horizons, which is consistent with the literature (e.g., Estrella & Mishkin, 1998).

Looking next at the coefficients of ΔRRPP, we find that the sign of ΔRRPP is negative and statistically significant at the 1 % level throughout the forecast horizons. That is, house prices fall before recessions at least four quarters prior to recessions. In contrast, we find that ΔRINV does not have robust recession forecasting ability at forecast horizons lower than three quarters. Consistent with the findings in Favara et al. (2016) we find that EBP contains information about future recessions for up to four quarters prior to recessions: EBP rises before recessions.

Moving next to the coefficients of ΔLC^{ON}, we find that those are statistically significant at least at the 10 % level of significance for up to three quarters ahead of recessions. However, the sign of the coefficients of ΔLC^{ON} is positive at the three-quarter forecast horizon, and then those turn negative and remain negative at forecast horizons lower than three quarters. Thus, we conclude that ΔLC^{ON} may be a good predictor of recessions at shorter forecast horizons. The inclusion of bank off-balance sheet or aggregate liquidity creation, ΔLC^{OFF} and ΔLC, respectively, does not change our conclusion about the relationship between bank liquidity creation and recessions. Since ΔLC^{OFF} and ΔLC are investigated in the out-of-sample tests, we do not report the in-sample results for brevity.

Furthermore, we find that other predictors such as ΔFED, ΔILR, MKT, ΔOIL have recession forecast horizons that are lower than two quarters. The results suggest that stock market returns, liquidity, and oil prices fall before recessions and provide an early warning of increased recession probabilities.

Comparing the AUROC and Pseudo-R-Squared values, we find that both generally agree with each other – AUROC rise with higher Pseudo-R-Squared values. Note that both AUROC and Pseudo-R-Squared values are high, given the shorter time-series data with three recessions, one of which was the 2007–2009 housing/credit crisis-driven recession. Since we are not classifying any predictor variable at this stage of the analysis, we do not compute AUROC gains. Overall, the above results demonstrate that TS, ΔRRPP, and EBP are important predictors of recessions for up to four quarters ahead of recession quarters. Next, we conduct pseudo-out-of-sample tests to ensure that the in-sample results hold.

3.1. Out-of-sample tests

In this section, we conduct pseudo-out-of-sample tests. In particular, we identify the variable that has the best prediction performance of recession forecasts after accounting for TS. The baseline model is the TS model since the literature shows that TS is a robust predictor of recessions (Estrella & Hardouvelis, 1991). We then augment the baseline model with other predictors. The estimation period is from 1984 through 2004—this selection ensures that we include at least two recessions for robust parameter estimates. Next, we forecast the recession probabilities recursively for the 2005–2016 period following the recession forecasting literature (e.g., Aastveit et al., 2019). We evaluate the forecast accuracies by examining the AUROC gains of a given model relative to its competing models.

First, we identify the best recession predictor, and this is a purely classification exercise. Next, we investigate larger encompassing models with several predictors. Specially, we are interested in investigating whether ΔRRPP adds to the baseline TS model since house prices are not investigated in the existing literature at an aggregate U.S. level. We are further interested in investigating whether ΔRRPP adds to the recession forecasting power of a larger parsimonious model with a number of predictors. Finally, we evaluate whether the Survey of Professional Forecasters (SPF) mean recession probability estimates are better than those for our models. Since the SPF mean forecasts are available for up to four quarters ahead of recession quarters, we conduct out-of-sample tests for the same forecast horizons. The out-of-sample forecast results are presented in Table 3.

In Table 3 Panel A, we show the out-of-sample AUROC values of the baseline TS model. Next, we show the AUROC gains of different models that augment the baseline TS model with other predictors. Looking at the row 1, column 1, we observe that the TS model has an AUROC value of 0.845 for a four-quarter forecast horizon, and the AUROC value is greater than 0.5 signifying that TS is an excellent predictor of recessions —- a random guess would have on average an equal number of true and false positives resulting in an AUROC value of 0.5. Looking at the row 2, column 1, we find that the ΔRRPP augmented TS model has an AUROC value of 0.895, which is the highest among the AUROC values of all the models we present in Table 3 Panel A. Thus, we evaluate other models in Table 3 Panel A relative to this model.

In row 1, column 2, we show that the AUROC gain of the parsimonious TS model is negative and is statistically significant as per the test-statistics in Equation (3). Thus, ΔRRPP as an additional predictor improves the performance of the baseline TS model. The results for three- to one-quarter forecast horizons are qualitatively similar to those for the four-quarter ahead forecasts.

[9] Results for all variables are available upon request.

Table 2

In-sample Probit Estimates of Recessions with a Large Set of Predictors This table presents the probit results for forecasting recessions using the probit model $P(X_t = 1) = \Phi(\alpha + \beta^* V_{t-l})$, where ΔOIL is the log difference of West Texas oil prices; ΔILR is the log difference of stock martket illiquidity (ILR); VOL is stock market volatility; ΔBDMargin is the log difference of brokers and dealers margin account balance; other variables are described earlier. Errors are corrected for heteroscedasticity adjustments. Z-statistics are in the parenthesis; intercepts are not reported for parsimony. *, ** and *** denote significance at the 10 %, 5 % and 1 % levels, respectively. We do not report coefficient estimates of some predictors that are not statistically significant across the forecast horizon for parsimony. Quarterly sub-sample 1984:Q1-2016:Q2.

Forecasting recessions with a set of predictors				
Forecast Horizon:	Four-Quarter	Three-Quarter	Two-Quarter	One-Quarter
TS	−1.97	−3.89	−1.78	−0.85
	(−4.56)***	(−2.45)***	(−3.38)***	(−2.77)***
ΔRRPP	−36.70	−98.88	−91.48	−38.07
	(−2.98)***	(−2.88)***	(−2.77)***	(−3.36)***
ΔRINV	−19.57	−37.02	−32.24	−27.56
	(−1.88)*	(−2.28)*	(−0.63)	(−0.42)
ΔFED	−0.55	−0.99	−1.87	−2.05
	(−0.79)	(−1.64)	(−2.67)***	(−2.22)***
MKT	−0.17	−0.49	−0.27	−0.24
	(−1.21)	(−2.30)**	(−2.57)***	(−1.88)*
VOL	68.21	111.61	−41.04	−43.10
	(0.82)	(1.03)	(−0.62)	(−0.40)
ΔILR	−34.43	37.85	13.79	28.83
	(−1.84)**	(1.44)	(1.63)	(3.63)***
EBP	1.38	3.79	1.88	2.01
	(2.66)***	(3.81)***	(2.97)***	(3.74)***
ΔOIL	0.066	0.017	−0.04	−0.02
	(1.54)	(1.23)	(−2.16)**	(−2.08)**
ΔLC^{ON}	13.47	34.54	−31.38	−13.50
	(0.69)	(1.73)*	(−1.65)*	(−1.73)*
ΔBDMargin	1.08	−1.18	−3.39	−1.74
	(0.62)	(−0.98)	(−2.18)**	(−1.36)
Pseudo-R-Sq.	0.71	0.82	0.76	0.79
AUROC	0.983	0.995	0.987	0.990

Table 3

Out-of-Sample Tests This table presents the out-of-sample tests results for different models. Panel A Presents out-of-sample AUROC and AUROC gains of competing recession indicators; all models are compared to the two variable TS + ΔRPPP model since this model has the highest AUROC in all horizons. Panel B presents out-of-sample results for models that are self-explanatory; all models are compared to Model B. SPF stands for the survey of professional forecaster's mean recession probability estimates. The variables are described earlier. Models are evaluated based on AUROC (Area Under the Receiver Operating Characteristic) values as described in the text; Estimation period 1984:Q1-2004:Q4 and evaluation period 2005:Q1-2016:Q2. *, ** and *** denote significance at the 10 %, 5 % and 1 % levels, respectively.

Panel A: Out of sample AUROC Classification

Forecast Horizons:	Four-Quarter		Three-Quarter		Two-Quarter		One-Quarter	
	AUROC	AUROC Gain	AUROC	AUROC Gain	AUROC	AUROC Gain	AUROC	AUROC Gain
TS	0.845	−0.050**	0.802	−0.153***	0.691	−0.206***	0.596	−0.371***
TS + ΔRRPP	0.895	–-	0.955	–-	0.897	–-	0.967	–-
TS + ΔRINV	0.666	−0.229***	0.852	−0.103***	0.849	−0.048***	0.925	−0.042***
TS + ΔLC^{ON}	0.843	−0.052***	0.812	−0.143***	0.740	−0.157***	0.753	−0.214***
TS + ΔLC^{OFF}	0.821	−0.074***	0.794	−0.161***	0.717	−0.180***	0.748	−0.219***
TS + ΔLC	0.837	−0.058***	0.816	−0.139***	0.733	−0.164***	0.701	−0.266***
TS + EBP	0.883	−0.012	0.843	−0.112***	0.863	−0.134***	0.864	−0.103***
TS + MKT	0.864	−0.031***	0.801	−0.154***	0.796	−0.101***	0.826	−0.141***
TS + ΔOIL	0.712	−0.183***	0.783	−0.172***	0.762	−0.135***	0.813	−0.164***

Panel B: Forecasting recessions with a larger set of predictors

Forecast Horizons:		Four-quarter		Three-quarter		Two-quarter		One-quarter	
Models	Predictor Variables	AUROC	AUROC Gain	AUROC	AUROC Gain	AUROC	AUROC Gain	AUROC	AUROC Gain
Model A	TS, ΔOIL, EBP, MKT, ΔRINV, ΔLC^{ON}	0.874	−0.049***	0.822	−0.144***	0.868	−0.105***	0.971	−0.021***
Model B	TS, ΔOIL, EBP, MKT, ΔRINV, ΔLC^{ON}, ΔRRPP	0.923	–-	0.966	–-	0.973	–-	0.992	–-
SPF		0.555	−0.328***	0.836	−0.130***	0.942	−0.031***	0.971	−0.021***

Examining the model in row 3, column 1, where the baseline model is augmented with ΔRINV, we find that ΔRINV may not add to the recessions forecasting ability of the parsimonious TS model at the four-quarter forecast horizon. However, looking at the other columns of row 3, we observe that ΔRINV is an excellent recession forecasting variable at forecasting horizons three-quarter or lower. This result is in accordance with the out-of-sample results found in Aastveit et al. (2019) that residential investment is a good predictor of recessions at forecast horizons lower than four-quarter. However, the AUROC gain of this model relative to the ΔRRPP-augmented TS model is negative and statistically significant across all forecast horizons. That is, ΔRRPP is a better predictor of recessions than ΔRINV.

Among the bank liquidity creation variables from rows 4 through 6, ΔLC^{ON} appears to have the best performance across forecast horizons and the result is in accordance with the results in Chatterjee (2018) that bank on balance sheet liquidity creation is possibly a better predictor.

In rows 7 through 9, columns 1 and 2, we observe that the EBP-augmented TS model has similar performance as the ΔRRPP-augmented TS model for the four-quarter forecast horizon. However, the results for forecast horizons from three- to one-quarter, we find that ΔRRPP is a better predictor relative to EBP. As for ΔOIL and MKT, we further find that none of these two-variable forecast recessions better than ΔRRPP. Overall, these results suggest that once we account for TS, ΔRRPP is the best predictor of recessions.[10]

While identification of a predictor is important, we next investigate whether one can have higher AUROC values by combining different predictor variables. In particular, we investigate the marginal impact of house prices on a forecasting model in terms of AUROC gains.

In row 1, column 1 of Table 3 Panel B, we show the AUROC value of Model A that contains the following predictor variables: TS, ΔOIL, EBP, MKT, ΔRINV, and ΔLC^{ON}. We omit ΔLC^{OFF} and ΔLC in Model A, which is based on the Table 3 Panel results that ΔLC^{ON} is a better bank liquidity creation variable for forecasting recessions. We find that the AUROC value of Model A is approximately 0.874. Looking at row 2, column 1, we show the AUROC value of Model B, where we have included ΔRRPP as an additional predictor. We find that for a four-quarter forecast horizon, Model B has an AUROC value of approximately 0.923. The difference in the AUROC gain of Model A relative to Model B is negative and statistically significant at the 1 % level. The result thus implies that the inclusion of ΔRRPP makes the parsimonious Model A more accurate. By comparing the AUROC gains of Models A across other forecast horizons, we find that the results are qualitatively like the results we obtain for the four-quarter forecast horizon. These results are in accordance with the in-sample recession prediction results that house prices are an important predictor of recessions after accounting for other variables.

Finally, we investigate the performance of Model B relative to the mean SPF estimates of recession probabilities. To do so, we compute the AUROC values of the mean SPF probability estimates at each forecast horizon, and the corresponding AUROC values are shown in the last row of Table 3 Panel B. By comparing the AUROC gains of Model B relative to the SPF estimates for the four-quarter forecast horizon, we find that Model B is better. These results indicate that the professional forecasters may not have included the variables we investigate in their forecasting models. We further show that the results are qualitatively similar for other forecast horizons. The results are consistent with the results in Rudebusch and Williams (2009) that the mean SPF estimates are inferior to that of the baseline TS model at longer forecast horizons. However, we show that the mean SPF estimates are also inferior to Model B estimates at shorter forecast horizons.

3.2. Robustness: Analysis with a longer time-series data

To ensure the robustness and relevance of the above results, we investigate these relationships using a longer sample period from 1973:Q1 to 2023:Q1, which includes six recessions. Any study (e.g., Favara et al., 2016; Ghent & Owyang, 2010; Aastveit et al., 2019; Berger & Bouwman, 2017; Chatterjee, 2018) that contains the 2007–2009 period in the pseudo-out-of-sample forecasts and investigates banking, credit, and housing related variables is likely to perform well since the crisis was driven by those factors. In addition, out-of-sample tests are "black box" techniques that are not able to evaluate whether a forecasting variable is related to recessions negatively or positively: out-of-sample tests just fit the data well. Thus, we focus on in-sample analysis since the literature (e.g., Inoue & Kilian, 2005) suggests that in-sample tests of predictability are more reliable and not subject to the choice of pseudo-out-of-sample predictions bias.

This extended dataset naturally excludes bank liquidity creation due to the lack of data availability. Instead, we utilize bank credit (BC), which accounts for the total credits provided by U.S. commercial banks to the economy. In Table 4, we present the in-sample results. For brevity, we report the results for relevant and important predictors since the inclusion of those predictors do not have any meaningful impact on the model fitness.

Table 4 Panel A shows that residential investment is positively related to recessions at the four-quarter forecast horizon and unrelated to recessions in other forecast horizons. These results are consistent with our previous findings, indicating that residential investment fits the data well at four-quarter forecast horizons, even though it suggests that residential investment should grow before recessions. However, this result is inconsistent with the existing literature (e.g., Ghent & Owyang, 2010; Aastveit et al., 2019). The potential reason is that their sample contained the 2007–2009 crisis period driven by housing, whereas our sample provides a more diverse and comprehensive analysis.

On the other hand, TS and EBP remain important predictors of recessions, conforming to the earlier literature on those two recession indicators. Regarding house prices, they do predict recessions for all forecast horizons greater than one quarter. Additionally,

[10] For brevity, we do not show that results for other recession predictor variables since the AUROC values are too low relative to the models shown here, but the results are available on request.

Table 4

Robustness: Forecasting Recessions with a longer time-series data This table presents the in- and out-of-sample results for a larger time-series data. Panel A Presents in-sample results, where errors are corrected for heteroscedasticity adjustments. T-statistics are in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. We do not report coefficient estimates of some predictors that are not statistically significant across the forecast horizon for parsimony. Quarterly sample 1973:Q1-2023:Q1. Panel B presents in-sample results for the sub-sample of 1973–2005, which excludes the 2007–2009 crisis, where we show parsimonious models to save space. Panel C presents out-of-sample AUROC and AUROC gains of competing recession indicators; all models are compared to the model with the highest AUROC. Results for the housing, Credit, and bank indicators are shown for parsimony. Estimation period 1973:Q1-2015:Q4 and evaluation period 2016:Q1-2023:Q1.

Panel A: Forecasting recessions with a set of predictors

Forecast Horizon:	Four-Quarter	Three-Quarter	Two-Quarter	One-Quarter
TS	−1.52	−1.04	−0.89	−0.63
	(−5.40)***	(−5.66)***	(−5.61)***	(−3.44)***
ΔRRPP	−40.58	−39.20	−26.98	−19.55
	(−3.08)***	(−3.19)***	(−1.96)*	(−1.66)*
EBP	1.40	1.37	0.99	0.96
	(4.25)***	(3.84)***	(2.90)***	(2.56)***
ΔRINV	5.77	4.74	−1.05	−6.16
	(2.12)**	(0.97)	(−0.20)	(−1.52)
ΔBC	30.16	−2.41	−15.46	−43.35
	(1.50)	(−0.13)	(−0.89)	(−2.28)***
MKT	0.15	0.01	−0.06	−0.17
	(2.10)**	(0.11)	(−0.87)	(−2.82)***
UMCESNT	−0.0	−0.02	−0.03	−0.04
	(−0.42)	(0.84)	(−1.89)*	(−2.38)***
ΔOIL	0.06	0.05	0.00	−0.01
	(1.91)*	(1.91)*	(−0.17)	(−0.21)
ΔFED	−0.16	−0.16	−0.23	−0.22
	(1.95)*	(1.61)	(−1.81)*	(−2.32)***
UNRATE	−0.14	−0.03	−0.07	−0.04
	(−1.42)	(−1.76)*	(−1.19)	(−1.01)
Pseudo-R-Sq.	0.59	0.63	0.59	0.61
AUROC	0.96	0.97	0.96	0.95

Panel B: In-Sample Forecasting recessions excluding the 2007–2009 Crisis (1973–2005 Sub-sample)

Forecast Horizon:	Four-Quarter	Three-Quarter	Two-Quarter	One-Quarter
TS	−0.75	−0.88	−0.72	−0.31
	(−4.19)***	(−4.40)***	(−4.94)***	(−1.89)***
ΔRINV	−3.44	−5.46	−3.35	−17.46
	(−0.53)	(−0.94)	(−0.61)	(−3.07)***
EBP	0.69	0.92	1.08	1.57
	(2.00)**	(2.44)***	(2.41)***	(3.08)***
ΔRRPP	11.72	−0.15	−38.01	−66.08
	(0.58)	(−0.01)	(−1.84)*	(−3.01)***
ΔBC	31.46	24.85	−0.43	−10.28
	(1.24)	(1.20)	(−0.02)	(−0.36)
Pseudo-R-Sq.	0.35	0.44	0.43	0.51
AUROC	0.93	0.96	0.96	0.97

Panel C: Out of sample AUROC Classification

Forecast Horizons:	Four-Quarter		Three-Quarter		Two-Quarter		One-Quarter	
	AUROC	AUROC Gain	AUROC	AUROC Gain	AUROC	AUROC Gain	AUROC	AUROC Gain
TS	0.892	−0.042***	0.881	−0.071***	0.822	−0.102***	0.722	−0.172***
TS+ΔRRPP	0.934	–-	0.952	–-	0.923	−0.001	0.888	−0.006
TS+ΔRINV	0.903	−0.031***	0.922	−0.03***	0.913	−0.011***	0.883	−0.011***
TS+ΔBC	0.893	−0.041***	0.885	−0.067***	0.823	−0.101***	0.753	−0.141***
TS+EBP	0.905	−0.029***	0.915	−0.037***	0.924	–-	0.894	–-

we note that the coefficients on TS, EBP and housing prices are the largest when forecasting four quarters ahead. Given the benefits to policymakers of identifying recessions early these variables are particularly useful in designing policy actions. Bank credit, on the other hand, seems to be unrelated to recessions for most forecast horizons and the results are consistent with our findings earlier.

In Fig. 1, we present the in-sample probability of recession estimates to visually inspect how the model aligns with past recessions. The plot shows that while TS is an important recession predictor, after accounting for other variables, the probability of a recession in

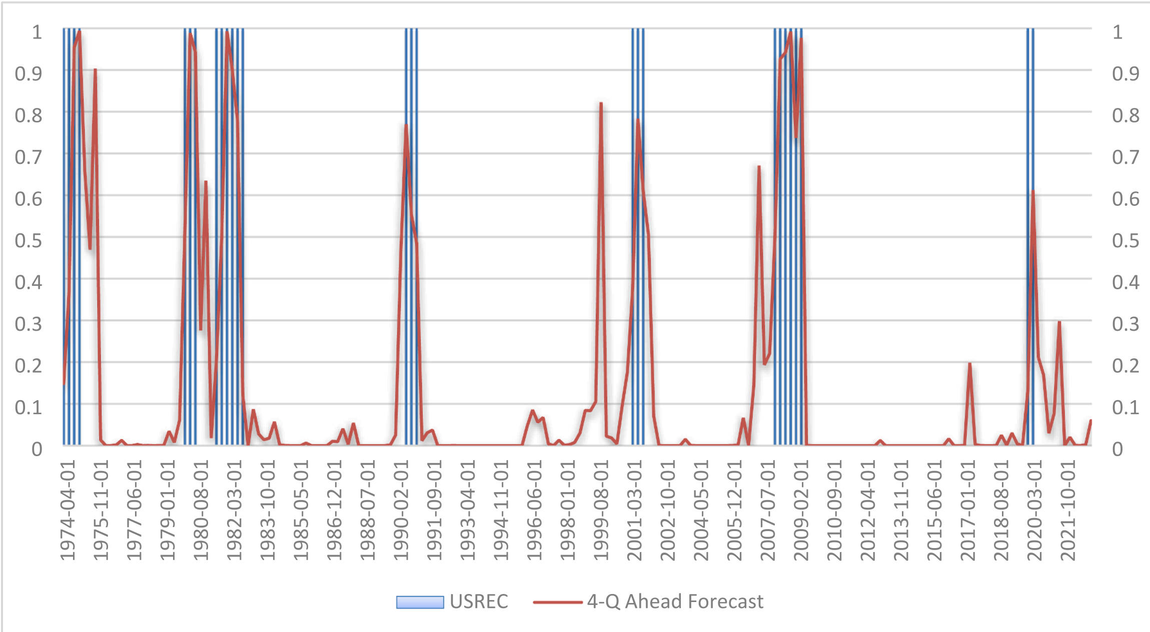

Fig. 1. Robustness: In-sample Probability of Recessions with a longer time-series data This plot presents the in-sample probability of recession estimates four quarters ahead of recessions. Quarterly sample 1973:Q1-2023:Q1.

2023:Q1 is below 10 %. This value is far lower than the approximate recession probability estimated by the Federal Reserve Bank based solely on TS.[11] Thus, the results based on the 1973–2013 data suggest two key points: 1) TS is not a sure sign of an upcoming recession. 2) Credit market conditions should deteriorate, and house prices should fall before we see another recession without a crisis.

However, given the currently resilient house prices, credit conditions, in general, do not foretell any upcoming recession. Resilient house prices can be attributed to a combination of factors that have shaped the housing market. One crucial factor is the implementation of tighter lending policies by financial institutions and regulatory bodies following the financial crisis of 2007–2009. These policies were put in place to mitigate the risks associated with mortgage lending and to prevent a similar housing market collapse.

Another contributing factor to the current housing market conditions is the limited supply of available housing inventory. The demand for housing has been consistently high, but the supply has not kept pace, leading to a situation where housing prices remain stable or even experience growth. Despite these specific factors supporting the strength of house prices, our results suggest that it is essential to consider the broader picture of credit conditions. Credit conditions encompass various economic indicators related to the availability and cost of credit, including interest rates, credit availability, borrowing trends, and overall credit market sentiment. However, at present, we have not observed any deterioration in the credit market.

To ensure robustness, we exclude the 2007–2009 crisis and investigate the relationship for the 1973–2005 sub-sample. In-sample results presented in Table 4 Panel B, where we do not use all the predictors for parsimony, show that along with TS, EBP remains an important predictor of recessions for all forecast horizons. In contrast, we find that housing prices and residential investment have a shorter recession forecast horizon, and house prices, rather than residential investment, seem to be a better predictor. As for bank credit, we do not find any evidence that it has recession forecasting ability. Overall, these results generally conform to the earlier results.

As an additional robustness check, we forecast recessions out-of-sample for the period 2016:Q1-2023:Q1 using data from 1973 to 2015 for model estimates. That is, we aim to forecast recessions prior to, during, and after the COVID-19 recession quarters. The corresponding results in Table 4 Panel C show that besides TS, EBP and ΔRRPP are the other two important recession forecasting variables. Overall these results generally conform to our in-sample results. Next, we conduct an additional analysis where we use a measure of uncertainty to forecast recessions based on prior studies.

It is widely acknowledged in the literature that uncertainty plays a crucial role in business cycles (e.g., Beaudry & Prices, 2006; Blanchard et al., 2013; Ilut & Schneider, 2014; Basu & Bundick, 2017; Baker et al., 2016). Bloom et al. (2018) further argue that microeconomic uncertainty increases during recessions. While we have used a number of uncertainty measures in our study, for robustness, we incorporate "economic policy uncertainty" (EPU), as defined by Baker et al. (2016), as a measure of policy uncertainty and examine its forecasting ability for recessions. Our findings suggest that while EPU may serve as a useful indicator for short-term recession predictions, it lacks predictive power for recessions beyond one quarter. When corporate credit spread (EBP) is considered,

[11] Unreported out-of-sample recession probability estimates for the 2nd quarter of 2023 to 1st quarter of 2024 are lower than 10%. This result is available on request.

even for a shorter forecast horizon, EPU contains no information about recessions. A possible explanation is that financial market variables such as EBP better capture uncertainty about the future health of the economy.[12]

3.3. Monetary policy implications

In this section, we examine how unexpected shocks to previously identified recession predictor variables impact the probability of a recession, with the goal of linking recession forecasting to the policy implications. To achieve this, we employ a standard vector-autoregression (VAR) framework, and instead of USREC, we use GDP_GAP, which is 100*(Real Gross Domestic Product-Real Potential Gross Domestic Product)/Real Potential Gross Domestic Product.[13] Since USREC represents a negative state of GDP, we expect the impulse responses of GDP_GAP to be inversely related to those for USREC.

Thus, we estimate a VAR model with the following endogenous variables: CPI, GDP_GAP, ΔFED, ΔRRPP, ΔBC, TS, and EBP, where CPI is consumer price index. As demonstrated earlier, most of these variables are crucial predictors of recessions. To ensure completeness, we also incorporate ΔBC to account for the impact of the banking sector. Additionally, we include ΔFED and CPI to consider monetary policy changes and inflation, both of which can have significant effects on the economy over time.

To adequately capture the dynamics, we use four lags of each endogenous variable. This choice is based on in-sample results, which indicate that the primary recession indicators are related to recessions for at least four quarters.[14] Moreover, we strive to maintain a parsimonious VAR model by not including an excessive number of variables with four lags each. Having too many endogenous VAR variables with numerous lags can lead to less reliable estimates, as it increases the variables-to-sample period ratio. Fig. 2 displays the accumulated impulse responses of GDP_GAP for orthogonalized Cholesky shocks to selected variables.

We find that GDP_GAP is indeed negatively impacted by monetary policy: a one standard deviation positive Cholesky shock to ΔFED in the present quarter reduces GDP_GAP by approximately 1.0 *percentage points* after 10 quarters. In contrast, positive shocks to housing variables exhibit a positive relationship with GDP_GAP, with house prices having a greater impact than residential investment. As for bank credit or the Treasury term spread, they have a minimal impact. Notably, EBP has the highest negative impact on GDP_GAP: a one standard deviation positive Cholesky shock to EBP in the present quarter reduces GDP_GAP by approximately 2.5 *percentage points* after 10 quarters.

The above results are consistent with our recession forecasting findings. Notably, they highlight that the effectiveness of monetary policy decisions depends on two crucial components of the economy: the housing and credit markets. In Fig. 2, the results aptly demonstrate that if house prices do not decline and corporate credit spreads do not widen, higher policy rates may be a viable strategy for curbing inflation.

4. Summary and conclusions

This study addresses the importance of identifying recession indicators for policymakers and stakeholders. It recognizes the recent discussions on the impact of rising monetary policy rates, an inverted yield curve, and the likelihood of a recession. While the yield curve is valuable, it does not capture all aspects of the economy, necessitating the investigation of complementary indicators like house prices, credit conditions, and the health of the banking sector.

The existing literature has explored housing, banking, and credit-supply conditions in isolation to study their individual recession forecasting abilities without analyzing policy implications. This study contributes to the literature by analyzing these indicators together and highlights that house prices and corporate credit spreads are strong predictors of future recessions. In contrast, residential investment's predictability is less robust when accounting for other predictors. The study also finds that bank liquidity creation (LC) and bank credit (BC) have shorter forecast horizons and may not be reliable recession indicators.

The implications of the study's findings for monetary policy are that policymakers should closely monitor widening of corporate credit spreads and/or the decline of house prices as potential signals of an impending recession, in addition to the yield curve inversion. Measuring bank economic output through LC or BC may not be as reliable for recession forecasting. Overall, the research contributes valuable insights to the housing and banking literature, providing a comprehensive analysis of various indicators for predicting recessions beyond the yield curve's signals.

CRediT authorship contribution statement

Ujjal K. Chatterjee: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Aras Zirgulis:** Conceptualization. **Maik Hüttinger:** Conceptualization. **Joseph J. French:** Writing – original draft, Writing – review & editing, Conceptualization, Formal analysis.

[12] These results are available upon request.

[13] We thank an anonymous referee for this invaluable suggestion.

[14] The standard VAR lag-length criteria suggest different optimal lag lengths, ranging from three to six quarters. For instance, the Akaike Information Criterion (AIC) suggests an optimal lag length of 6 quarters. However, we prefer four quarters for the stated reason.

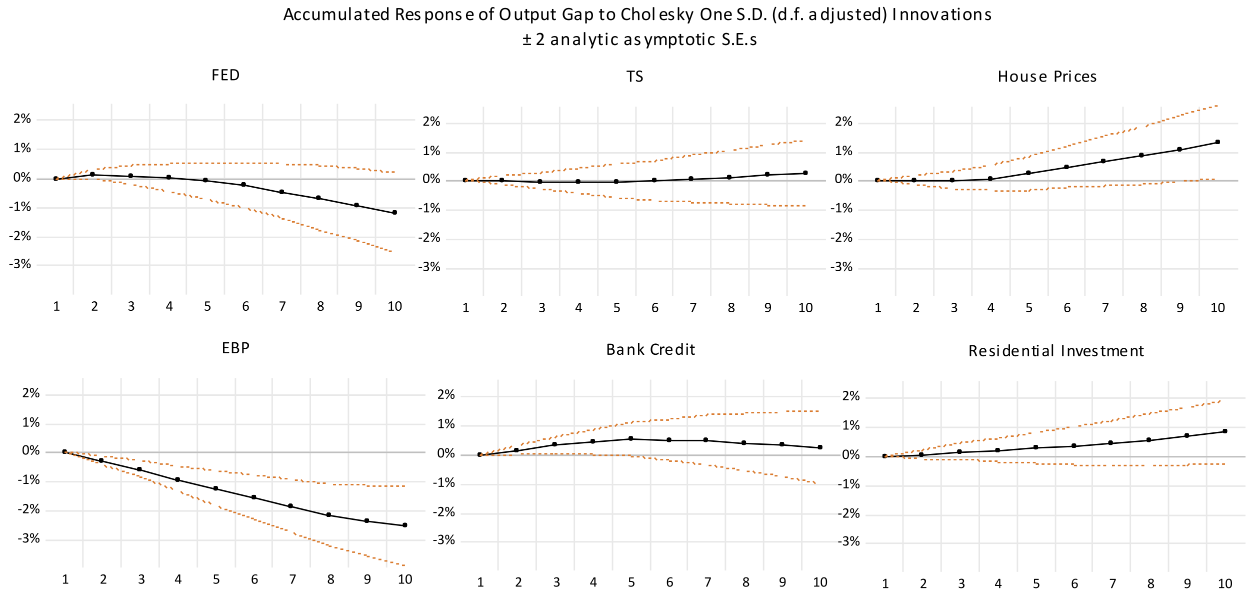

Fig. 2. Response of U.S. GDP Gap for Shocks to Housing and Credit Conditions This plot presents the impulse responses of GDP Gap in a VAR (4) model. with the following endogenous variables: CPI, GDP_GAP, ΔFED, ΔRRPP, ΔBC, TS, and EBP; CPI is consumer price index, GDP_GAP is 100*(Real Gross Domestic Product-Real Potential Gross Domestic Product)/Real Potential Gross Domestic Product; other variables are described earlier. The impulse responses are for Cholesky shocks with the ordering of the variables as shown. Quarterly sample 1973:Q1-2023:Q1. Responses are shown in *percentage points*.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Aastveit, K. A., Anundsen, A. K., & Herstad, E. I. (2019). Residential investment and recession predictability. *International Journal of Forecasting, 35*, 1790–1799.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets, 5*, 31–56.

Baker, R., Bloom, N., & Davis, J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593–1636.

Basu, S., & Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica, 85*(3), 937–958.

Beaudry, P. P., Franck Stock Prices, News, and Economic Fluctuations American Economic Review 96 4 1293-1307 2006 10.1257/aer.96.4.1293.

Bencivenga, V. R., & Smith, B. D. (1991). Financial intermediation and endogenous growth. *The Review of Economic Studies, 58*, 195–209.

Benjamin, J. D., Chinloy, P., & Jud, G. D. (2004). Real estate versus financial wealth in consumption. *The Journal of Real Estate Finance and Economics, 29*, 341–354.

Berge, T., & Jordà, O. (2011). Evaluating the classification of economic activity into recessions and expansions. *American Economic Journal: Macroeconomics, 3*(2), 246–277.

Berger, A. N., & Bouwman, C. H. S. (2009). Bank liquidity creation. *The review of financial studies, 22*, 3779–3837.

Berger, A. N., & Bouwman, C. H. S. (2017). Bank liquidity creation, monetary policy, and financial crises. *Journal of Financial Stability, 30*, 139–155.

Bernanke, B., & Lown, C. S. (1991). The credit crunch. *Brookings Papers on Economic Activity, 22*(2), 205–248.

Blanchard, J., L'Huillier, P., & Lorenzoni, G. (2013). News, noise, and fluctuations: An empirical exploration. *American Economic Review, 103*(7), 3045–3070.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). 2018; "Really uncertain business cycles". *Econometrica, 86*(3), 1031–1065.

Bluedorn, J. C., Decressin, J., & Terrones, M. E. (2016). Do asset price drops foreshadow recessions? *International Journal of Forecasting, 32*, 518–526.

Bostic, R., Gabriel, S., & Painter, G. (2009). Housing wealth, financial wealth, and consumption: New evidence from micro data. *Regional Science and Urban Economics, 39*, 79–89.

Burnside, C., Martin, E., Sergio, R. 2016. Understanding Booms and Busts in Housing Markets, Journal of Political Economy, University of Chicago Press, vol. 124(4), pages 1088-1147.

Caballero, R., & Simsek, A. (2020). A risk-centric model of demand recessions and speculation. *The Quarterly Journal of Economics, 135*(3), 1493–1566.

Campbell, J. Y., & Cocco, J. F. (2007). How do house prices affect consumption? Evidence from micro data. *Journal of monetary Economics, 54*, 591–621.

Carlin, B. I., Longstaff, F. A., & Matoba, K. (2014). Disagreement and asset prices. *Journal of Financial Economics, 114*(2), 226–238. https://doi.org/10.1016/j.jfineco.2014.06.007

Chatterjee, U. K. (2018). Bank liquidity creation and recessions. *Journal of Banking and Finance, 90*, 64–75. https://doi.org/10.1016/j.jbankfin.2018.03.002

Chatterjee, U. K. (2016). Do stock market trading activities forecast recessions, Economic Modelling, 59, 370-386-75. https://doi.org/10.1016/j.econmod.2016.08.007.

Chauvet, M., & Potter, S. (2005). Forecasting recessions using the yield curve. *Journal of Forecasting, 24*, 77–171.

Christensen, C., Eriksen, J. N., & Møller, S. V. (2019). Negative house price co-movements and US recessions. *Regional Science and Urban Economics, 77*, 284–1228. https://doi.org/10.1016/j.regsciurbeco.2019.06.007

DeLong, E. R., DeLong, D. M., & Clarke-Pearson, D. L. (1988). Comparing the areas under two or more correlated receiver operating characteristic curves: A nonparametric approach. *Biometrics, 44*(3), 837–845. https://doi.org/10.2307/2531595

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*, 427–431.

Estrella, A., & Hardouvelis, G. A. (1991). The term structure as a predictor of real economic activity. *The journal of Finance, 46*, 555–576.

Estrella, A., & Mishkin, F. S. (1998). Predicting US recessions: Financial variables as leading indicators. *Review of Economics and Statistics, 80*, 45–61.

Favara, G., Gilchrist, S., Lewis, K. F., & Zakrajsek, E. (2016). Recession risk and the excess bond premium. *Board of Governors of the Federal Reserve System (US)*.

Ghent, A. C., & Owyang, M. T. (2010). Is housing the business cycle? Evidence from US cities. *Journal of Urban Economics, 67*, 336–351.

Giglio, S. M., Stroebel, M., Utkus, J., & Stephen,. (2021). „Five Facts about Beliefs and Portfolios. *American Economic Review, 111*(5), 1481–1522.

Gilchrist, S., & Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review, 102*, 1692–1720.

Harvey, C. R. (1988). The real term structure and consumption growth. *Journal of Financial Economics, 22*, 305–333.

Harvey, C. R. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analysts Journal, 45*, 38–45.

Ilut, C. L., Schneider, M., Ambiguous business cycles. The American Economic Review, 2014, 104(8): 2368-2399.

Inoue, A., & Kilian, L. (2005). In-sample or out-of-sample tests of predictability: which one should we use? *Econometric Reviews, 23*(4), 371–402. https://doi.org/10.1081/ETC-200040785

Kashyap, A. K., Rajan, R., & Stein, J. C. (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of finance, 57*, 33–73.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics, 54*, 159–178.

Leamer, E. E. (2015). Housing really is the business cycle: What survives the lessons of 2008–09? *Journal of Money, Credit and Banking, 47*, 43–50.

Leamer, E.E. 2007. Housing is the business cycle. National Bureau of Economic Research.

Levine, R., & Zervos, S. (1998). Stock markets, banks, and economic growth. *American Economic Review, 88*, 537–558.

Liu, W., & Moench, E. (2016). What predicts US recessions? *International Journal of Forecasting, 32*(4), 1138{1150.

Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2011). Stock market liquidity and the business cycle. *The Journal of Finance, 66*, 139–176.

Rudebusch, G. D., & Williams, J. C. (2009). Forecasting recessions: The puzzle of the enduring power of the yield curve. *Journal of Business & Economic Statistics, 27*, 492–503.