Learning from Prices, Credit Cycles and Macroprudential Policies

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Abstract

This paper incorporates information frictions in a credit cycle model, in which agents learn from prices. We find that learning from prices amplifies boom-bust dynamics. As a result, this influences the role of macroprudential policies that impact aggregate outcomes such as credit spreads. In a boom, macroprudential policy leads to higher credit spreads to discourage borrowing. Higher credit spreads then create more pessimism through learning from prices relative to a framework without macroprudential policy. In comparison, macroprudential policy leads to lower credit spreads in a downturn. This results in more optimism through learning from prices, counteracting the effect of tighter macroprudential policy. Our findings suggest that although macroprudential policies effectively curb the credit cycle, they might not be optimal if macroprudential policies are excessively tight. The overall impact of learning from prices depends on firms' leverage.

JEL classification: E32, E44, G1, G12

Keywords: Credit Cycles, Macroprudential Policies, Information Frictions, Financial Stability, Learning from Prices, Firm Leverage

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1 Introduction

Credit spreads and bond prices offer important information about changes in the economy. Empirically, it has been well documented that an increase in credit growth is related to a higher probability of a financial crisis and lower economic growth in the future (Gilchrist and Zakrajšek (2012), López-Salido et al. (2017), Mian et al. (2017)). This generates boom-bust crisis cycles. In current studies, the amplification mechanisms of credit cycles have been attributed to frictions in financial intermediation (He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014)), as well as the role of beliefs (Bordalo et al. (2018)). Recent studies have also integrated both the financial intermediation and sentiments channels (Maxted (2020), Krishnamurthy and Li (2020)) in macro-finance models by introducing behavioral frictions such as diagnostic expectations.

In this paper, we depart from the above literature by introducing information frictions and examining how learning from prices affects credit cycle dynamics. As economic agents learn from prices in the credit market, it has the potential to shift their expectations, resulting in larger fluctuations in macroeconomic activities. Here, we build on recent work that highlight how wedges in beliefs of economic agent (Ilut and Saijo (2021), Angeletos and Lian (2022)) can propagate business cycles. For instance, Chahrour and Gaballo (2021) shows that changes in house prices could result in rational waves of optimism and pessimism, highlighting the role of price-based learning in asset markets.

To examine the effect of learning from prices in credit markets, we propose a model in which economic agents (firms and lenders) form expectations about the state of the economy by observing aggregate variables such as credit spreads. Credit spreads refer to the difference in yields between different debt securities and government securities of comparable maturities. As credit spreads reflect the current sentiment of the economy, credit spreads themselves can provide an informational role in generating business fluctuations in our model. The key ingredient of our paper is to focus on the impact of economic agents that respond to credit spreads and how learning from credit spreads, and bond prices could generate and amplify changes in economic activity. We do not rely on any assumptions about the frictions in financial intermediation and the type of beliefs.

Our model follows Bordalo et al. (2021) by modifying a standard heterogeneous firm model (Khan and Thomas (2008), Arellano et al. (2019)) in which economic agents respond to total factor productivity (TFP) news. Compared to the previous literature, the main difference in our model is that the expectations of economic agents are derived not only from signals of productivity (TFP) shocks but also from credit spreads. In our model with imperfect information, agents observe two separate signals: each signal for productivity and credit spreads. We then isolate the impact due to learning from prices by comparing with a counterfactual, in which agents only observe the signal of productivity and not the signal generated by credit spreads. The difference between the two models will allow us to identify the impact of learning from prices.

Consistent with the classical works of Minsky (1977) and Kindleberger (1978), which highlight how sentiments create financial instability, we find that learning from prices impacts expectations, leading to boom-bust credit cycles. This build on earlier work from Bhattacharya et al. (2015), which show how individuals' expectations of investment profitability and economic growth impact their borrowing decision, and ultimately the extent of default. In our model with learning from credit spreads, we show similarly that borrowers and lenders are overly optimistic when they learn from prices in an economic boom. When there is a positive TFP shock, low credit spread leads to higher optimism as agents associate low credit spreads with good times. With higher optimism, firms over-borrow and over-invest.

How would this impact the firm's probability of default in the next period? A-priori, the impact is unclear. With a simultaneous increase in capital and borrowing, we have two competing forces at work. First, we have the investment channel. Over-investment in the current period will increase output in the next period, resulting in a corresponding lower probability of default. On the other hand, there is also a borrowing channel. Over-borrowing in the current period suggests that firms will need to repay more debt, leading to a higher probability of default in the next period. Whether the investment or borrowing channel will dominate depends on the firm's initial leverage. In this paper, we show that as firms learn from credit spreads in an economic boom, high leverage firms with high initial borrowing will experience a higher probability of default in the next period relative to low leverage firms. Consequently, the effect of learning from prices on firms is dependent on the balance sheet of individual firms.

We now turn to an economic downturn. When firms learn from prices during a negative TFP shock, high credit spreads lead to more pessimism as agents associate high credit spreads with bad times. Therefore, firms under-invest and under-borrow. Again, we have tension between the investment channel and the borrowing channel. The investment channel leads to a further reduction in output and a higher probability of default during the next period. With the borrowing channel, firms have a lower probability of default during the next period as they borrow less and have lesser debt. When there is learning in an economic downturn, we find that the borrowing channel dominates the investment channel overall. We find that when the economy recovers, high leverage firms benefit from under-borrowing while low leverage firms lose out from under-investment.

As learning from prices amplifies boom-bust cycles, they could affect the role of regulation such as macroprudential policies in our model. Macroprudential policies seek to ensure the systemic stability of the financial system (Hanson et al. (2011)) and come in different forms, such as caps on loan-to-value ratios, limits on credit growth, as well as several countercyclical capital and reserve requirements. In this paper, we follow Jeanne and Korinek (2019), Bianchi (2011) and model macroprudential policies in the form of a tax on debt. This will be able to discourage over-borrowing during booms. Consequently, an increase in tax rate will reduce bond prices and increase credit spreads during booms. As information comes from market prices in our model, financial policies that influence credit spreads could affect the beliefs of economic agents. In turn, this could impact several outcomes, such as macroeconomic aggregates and social welfare. Thus, it will be interesting to examine the interaction between learning from prices and macroprudential policies.

In our model with learning from prices, macroprudential policies influence credit spreads and, as a result, affect the expectations of economic agents. We show that macroprudential policies can either benefit or harm firms depending on the level of leverage. Recent studies such as Anderson and Cesa-Bianchi (2020) have highlighted the importance of a firm's leverage on changes in interest rate. Here, we highlight how leverage could influence the passthrough of macroprudential policies through learning.

In a scenario of perfect information and economic growth, macroprudential policies lead to higher credit spreads (relative to a model without macroprudential policies). For instance, higher credit spreads lead to more pessimism as agents learn from prices. This leads to under-investment and under-borrowing. Due to the interaction between macroprudential policies and learning from prices, there is a fall in credit growth. This is consistent with empirical evidence globally (Richter et al. (2019), Gómez et al. (2020)).

However, when a recession begins, under-borrowing before the recession due to learning from prices benefits high-leverage firms, which is consistent with the fact that macroprudential policies curb the credit cycle by preventing a more severe downturn. By contrast, with macroprudential policies, under-investment harms low-leverage firms due to learning from prices. This suggests that macroprudential policies are not beneficial to firms with low leverage levels as they under-invest.

We also consider the case in which firms learn from prices during a recession. A perfect information scenario with macroprudential policies leads to lower credit spreads in a downturn (relative to no macroprudential policies). As such, after learning from lower credit spreads, firms become relatively more optimistic in a model with macroprudential policies compared to a model without macroprudential policies. This leads to higher optimism which encourages over-borrowing and over-investment. Over-investment in a downturn curbs the downturn and spurs the economy. In this case, macroprudential policy is beneficial to the economy.

Nonetheless, when the economy reverts to its normal state, over-borrowing during the downturn due to over-optimism generates higher leverage for all firms. This leads to a higher probability of default and higher credit spreads for all firms. Hence, although macroprudential policy is effective in a recession, it could become harmful as the economy recovers back to normal times.

Consequently, we show that the optimal tax rate for macroprudential policies for the learning from prices model should be lower than the counterfactual. A higher tax rate leads to higher credit spreads in a boom and lower credit spreads in a downturn. While macroprudential policies are useful, having an excessive tax will be undesirable. This is attributed to the trade-offs between the benefits of a reduction in the probability of a financial crisis, against the benefits of having more investment in an economy.

Related Literature. This paper contributes to several strands of literature. First, it contributes directly to the study of credit cycles. Empirical studies have highlighted that credit contains valuable information about the likelihood of future crises. This occurs across different countries during time periods (Schularick and Taylor (2012), Krishnamurthy and Muir (2017)). Consequently, crises are predictable (Greenwood et al. (2020)). Earlier studies have showed that this relationship could be explained by financial frictions (Aikman et al. (2015)), household demand (Mian and Sufi (2018)), household debt (Jordà et al. (2016)), limited commitment (Gu et al. (2013)) leading to a self-reinforcing feedback loop.

Our model instead accounts for the fact that learning in financial markets matters. Through learning, we find that changes in the beliefs of economic agents do amplify the effects of positive and adverse shocks. In studying the role of expectations in credit cycles, we build on the recent work that examines how limited cognitive abilities (De Grauwe and Macchiarelli (2015)), diagnostic expectations (Bordalo et al. (2021)) generate self-fulfilling credit cycles.

Next, it contributes to the study of price-based learning. Since the seminal work of Lucas Jr (1972), a large body of literature in macroeconomics and finance have explored the role of learning. Recent work include how firms learn from their own transactions in input and output market (Hellwig and Venkateswaran (2009)), house prices (Chahrour and Gaballo (2021)), forecasts of corporate profits (Falato and Xiao (2020)) and past default rate (Greenwood et al. (2019)). Moreover, studies such as Benhima (2019) have also highlighted the role of dispersed information when there are booms and busts in the economy.

To the best of our knowledge, this paper is among the first to examine the role of learning from credit spreads and how it impacts macroprudential policies. We also show how learning from credit spreads could impact the welfare of the economy. Here, we build on recent work such as Amador and Weill (2010) that has examined how releasing public information can increase uncertainty and reduce welfare.

Finally, it is related to the literature on macroprudential policies.[1] In examining systemic risk and macroprudential policies, most studies have focused on the role of banks and externalities (Acharya (2009)). More recently, Akinci and Queralto (2022) study the role of macroprudential policies in managing credit risk using a macroeconomic model with occasionally binding constraints in banks and endogenous issuance in equity. Moreover, there is no consensus on whether macroprudential policies could benefit the economy. While empirical studies have highlighted that credit have reduced after the imposition of macroprudential policies (Akinci and Olmstead-Rumsey (2018), Cerutti et al. (2017)), the welfare effect is uncertain. For instance, research by Benigno et al. (2013) show that having a macroprudential tax could reduce welfare as it reduces average consumption in a two-sector production economy with a collateral constraint.

We differ from models in the related literature discussed above by studying the relationship between macroprudential policies and the beliefs of economic agents. Our paper suggests that the impact of macroprudential policies is highly dependent on the firm's financial position. In this paper, we show that the balance sheet of the firms' matters. Hence, we argue that a complete analysis must incorporate information frictions and the firm's balance sheet.

The remainder of the paper is organized as follows. Section 2 provides some motivating evidence. In Section 3, we present the credit cycle model with learning. Section 4 provides some quantitative analysis involving our model, while Section 5 discusses the mechanisms that generate boom-bust dynamics. We discuss the impact of macroprudential policies in Section 6. Finally, Section 7 concludes.

2 Motivating Evidence

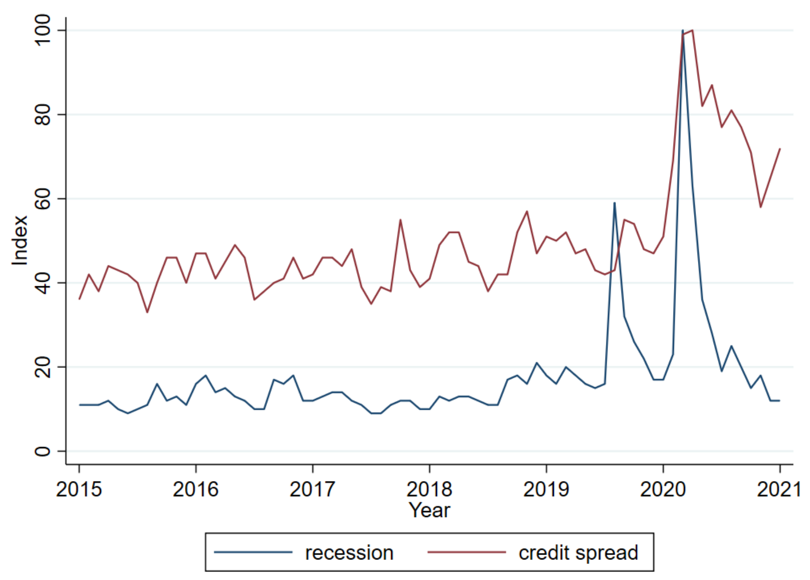
How do individuals form beliefs about the future economy? One way is through credit markets. As highlighted by Stein (2021), an increase in credit market sentiment suggests that individuals are overly-optimistic, resulting in exuberant sentiment. Hence, credit spreads can influence future forecasts of economic growth.

In this section, we provide some motivating evidence that beliefs in the credit markets matter. First, we show that the level of interest in credit markets is highly correlated with economic growth. Figure 1 presents the search volume of the terms "recession" and "credit spread" based on Google Trends. Here, we can see that the search interest of these terms has a high degree of co-movement, with a peak during early 2020 when there

[1] See Claessens (2015) for a review of tools used in macroprudential policies.

was a global recession driven by the COVID-19 pandemic.

Figure 1: Google Trends



Notes: This figure presents the global search interest of the terms "recession" and "credit spread" in Google Trends. This is based on the time period 2015 to 2021.

More formally, to test whether credit spreads provide additional information to the beliefs of individuals, we consider the following empirical specification:

$$x_{t+h} - F_t x_{t+h} = c + \beta_1 (F_t x_{t+h} - F_{t-1} x_{t+h}) + \beta_2 spr + \epsilon_t \tag{1}$$

Following Coibion and Gorodnichenko (2015), x_{t+h} is the actual GDP growth at time period $t+h$, $F_t x_{t+h}$ is the forecast of GDP growth of time period $t+h$ at time period t, and $F_{t-1} x_{t+h}$ is the forecast of GDP growth of time period $t+h$ at time period $t-1$. Hence, we are regressing year-ahead GDP forecast errors against average forecast revisions. Relative to Coibion and Gorodnichenko (2015), we introduce the variable credit spreads spr into the regression.

Our main coefficient of interest is the coefficient for credit spreads β_2. This will allow us to examine whether credit spreads can provide additional information in forecasting future GDP growth. We estimate Equation (1) based on a combination of quarterly data between 1986 to 2019. We use BAA-Treasury spread based on Moody's ratings for the credit spread. We use real GDP growth provided by the Federal Reserve Economic Data (FRED) for GDP growth. Finally, our forecasts rely on quarterly data from the Survey of Professional Forecasters.

Table 1 presents our regression estimates. Column 1 shows the results without considering credit spreads. Here, we find that $\hat{\beta}_1 = 1.463$ and is statistically significant at the 1

Table 1: Regression Results for Credit Spreads as signals

Dependent Variable:	$x^*_{t+h} - F_t x_{t+h}$ (1)	$x^*_{t+h} - F_t x_{t+h}$ (2)
$F_t x_{t+h} - F_{t-1} x_{t+h}$	1.463***	0.543
	(0.518)	(0.362)
spr		-1.476***
		(0.140)
Observations	133	133
Adjusted R^2	0.0901	0.475

Notes: Robust standard errors are in parenthesis. *, ** and *** denotes significance level at 10%, 5% and 1% respectively.

percent level. This is consistent with the evidence that there exist information rigidities in forecasting GDP growth.

Next, Column 2 presents the results with credit spreads. Here, we find that $\hat{\beta}_1 = 0.543$ and is no longer statistically significant even at the 10 percent level. On the other hand, $\hat{\beta}_2 = -1.476$ and is statistically significant at the 1 percent level. Hence, credit spreads are negatively correlated with forecast errors. In particular, an increase in credit spreads is associated with forecasts that are too pessimistic relative to its realization. This suggests that credit spreads provide additional information in the formation of individuals' expectations of GDP growth. We now turn to our model.

3 Outline of Model

Following Bordalo et al. (2021), we modify a standard heterogeneous firm model (Khan and Thomas (2008), Arellano et al. (2019)) in which economic agents respond to total factor productivity (TFP) news. Unlike the previous literature, the key difference in our model is that the expectations of economic agents are derived not only from signals of TFP shocks but also from credit spreads.

The model is in discrete time. There are three time periods ($t = 1, 2, 3$). During each period, a mass of firms with different productivities choose whether to default or not. If they do not default, they will decide how much labor to employ, how much to invest and whether they should issue equity or borrow. Given their expectations of the firms' productivity, deep-pocket lenders will lend to these firms, with the price of debt reflecting the firm's probability of default. In terms of notation, $'$ indicates future values.

We proceed by first presenting the firms' problem under perfect information. We then solve for the equilibrium credit spreads through lenders. Finally, we introduce learning from prices and characterize the structure of information frictions in our model.

3.1 Firms

Firms are risk neutral and they act competitively. With TFP z, a firm chooses capital k and labor n according to the following production function:

$$y = zk^{\alpha}n^{\gamma}, \quad \alpha + \gamma < 1 \tag{2}$$

such that the log of TFP follows the AR (1) process:

$$logz' = \rho_z logz + \epsilon'_z, \quad \epsilon'_z \sim N(0, \sigma_z^2), \quad 0 < \rho_z < 1 \tag{3}$$

Through the following process, firms invest in capital k through investment i:

$$k' = i + (1 - \delta)k, \quad 0 < \delta < 1 \tag{4}$$

Investments incur quadratic adjustment costs with index $n_k > 0$

$$AC(i, k) = \frac{n_k}{2}\left(\frac{i}{k}\right)^2 k \tag{5}$$

Firms are financed from both debt and equity. Within the period, the sequence of actions is as follows:

1. Firms first decide whether to default on their debt.
2. If the firm chooses to default, it will liquidate its net capital stock and hand them to the lender in the current period. After one period, it will then start with zero capital and debt.
3. If the firm chooses not to default and repay its debts, it will need to decide how many workers to employ at wage W and how much investment to make to produce output y. In addition, it will make its financing decisions with regard to the amount of equity and one-period debt to issue.

Should the firm choose not to default, it makes the following profits during each time period:

$$\pi = y - Wn - AC(i, k) - \phi \tag{6}$$

where ϕ refers to the fixed production cost. Here, profits are defined as the difference between the output and the total cost (total wages, adjustment cost for investments and fixed production cost). We assume that there are no taxes, but our key findings remain unchanged if taxes are included.

The current dividend paid by the firm is as follows:

$$d = y - Wn - AC(i,k) - \phi + q(z,k',b')b' - i - b \tag{7}$$

where b refers to the firm's borrowing (debt). Here, dividends refer to profits earned by the firm plus new debt (b') priced by the schedule (q) minus the current investment (i) and current debt (b).

To create a meaningful tradeoff between capital and debt, there will be equity issuance by the firm when $d < 0$. Similar to Bordalo et al. (2021), this is associated with an issuance cost $IC(d) = I(d < 0)(\eta_f + \eta_d|d|)$. $I(d < 0)$ is an indicator variable when dividends are negative, $\eta_f > 0$ relates to the fixed cost of issuance, while $\eta_d > 0$ the variable cost of issuance.

Given an exogenous risk-free rate R and corresponding discount rate $\frac{1}{1+R}$, firms seek to maximize the expected discounted sum of current and future payoffs. Hence, the problem for the firm can be written recursively as follows. When the firm enters the current period, the value of the firm is given by:

$$V(z,k,b) = max[V_D, V_{ND}(z,k,b)] \tag{8}$$

where V_D refers to the continuation value of defaulting and $V_{ND}(z,k,b)$ refers to the continuation value of not defaulting. We let $V_D = 0$ as when the value function is less than zero, firms will default. When firms default, they will not receive anything and exit the economy with zero payoff.

$V_{ND}(z,k,b)$ is determined recursively as follows:

$$V_{ND}(z,k,b) = max\{d - IC(d) + \frac{1}{1+R}E[V(z',k',b'|z)\} \tag{9}$$

$V_{ND}(z,k,b)$ depends on the current level of dividends, issuance cost, and discounted future value of the firm. It is a function of 3 state variables z,k,b. Note that the current decisions of the firm will impact the current credit spread and, by extension, the probability of default in the next period. Intuitively, firms borrow today and pay back tomorrow. During the next period, firms will receive the actual productivity level z. Thereafter, they will decide whether to default or not.

3.2 Lenders

Lenders are risk neutral and have deep pockets. To be willing to lend to the firms, lenders require an expected return equal to the risk-free rate R.

First, we note that if a firm defaults on its debt b, the lender will obtain the recovery rate.

$$\mathcal{R} = \gamma \frac{(1-\delta)k}{b}$$

Here, γ is an exogenous proportion of the firm's capital stock that will be obtained by the lender when the firm goes into liquidation, $(1-\delta)k$. Hence, the price of debt is determined as follows:

$$q(z, k', b') = \frac{1}{1+R} E[1 - df(1 - \mathcal{R})]\} \tag{10}$$

where df refers to the probability of default. Hence, firms with a higher probability of default will be offered a lower bond price as lenders demand higher interest rates.

We can then back out the interest rate spread of the bond relative to the risk-free rate:

$$S(z, k', b') = \frac{1}{q(z, k, b)} - (1+R) \tag{11}$$

This shows that the expectations of the probability of default is directly related to credit spreads. A higher probability of default relates to lower bond prices and, consequently, higher credit spreads.

We further discuss how the state variables z, k, b for the firm's value will impact the probability of default. First, a low probability of z will lead to a higher probability of default. With an AR(1) process, if the current productivity z is low, the probability of future z being low will be higher. Next, a low level of k in the current period will result in a higher probability of default. A low level of k in the current period means output y will be reduced. Hence, firms will choose lesser capital for the next period as they have lesser resources during this period. As a result of choosing lesser capital during this period, firms know that in the next period, they will be endowed with lesser resources, and consequently, there will be a higher probability of default. Finally, high b in the current period means that firms must repay more debt. Hence, they will need to spend more resources on debt in the next period, suggesting lesser resources to increase their output, resulting in a higher probability of default.

In sum, low z, low k, and high b in the current period will result in a high probability of default. Hence, High-leverage firms (with low k and high b) will have a higher probability of default.

3.3 Information Frictions and Learning from Prices

We now introduce information frictions. In our model, there are two types of firms and lenders. The first type of firms and lenders (Type A agents) has perfect information, while the second type of firms and lenders (Type B agents) face information frictions and learn from prices and signals.

Timing. We define Period 1 as the short run and Period 2 as the medium run. In each period, firms make decisions based on the information that is available to them. In Period 3, all firms collect their payoffs and exit the market.

In Period 1, Type B agents face information frictions about the productivity level, z. In contrast, Type A agents do not face any information frictions and observe the actual value of z. In Period 2, both Type A and Type B firms face perfect information. The purpose of perfect information in Period 2 is to examine the consequence of actions due to learning from prices in Period 1.

Information Structure. We first focus on Type A firms (i.e, those with perfect information). In each period, Type A firms are endowed with capital k and borrowing b, as well as information of the current level of productivity z. Given these variables, Type A firms first choose the amount of capital (k') and borrowing (b') in Period 2, given the bond price schedule $q_A(z, k', b')$.

For Type B agents, they do not observe the actual value of z. Instead, they observe two signals and then form expectations about the actual productivity:

$$s_1 = z + \epsilon_1 \tag{12}$$

$$s_2 = q_A(z, k', b') + \epsilon_2 \tag{13}$$

The first signal s_1 is a direct signal on productivity, which is an additive sum of z and noise ϵ_1. The second signal s_2 is a signal that is derived from observing $q_A(z, k', b')$ generated by Type A agents. Based on signals s_1 and s_2, Type B agents update their expectations about z using Bayesian learning.

Following Hellwig and Venkateswaran (2009) and Chahrour and Gaballo (2021), with information of capital and borrowing, firms can pin down z from signal $q_A(z, k', b')$. Consequently, we can rewrite s_2 to be as follows:

$$s_2' = z + \epsilon_2 \tag{14}$$

Given their prior beliefs (E_{prior}), we can use Bayesian updating to obtain the following posterior expectations ($E_{posterior}$) for Agent B:

$$E_{posterior} = (1 - g_1 - g_2)E_{prior} + g_1 s_1 + g_2 s_2' \tag{15}$$

whereby g_1 and g_2 refers to the Kalman gain from observing the signals s_1 and s_2' respectively.

To isolate the impact of learning from prices (credit spreads), we introduce two different models for Type B agents: the learning from prices model and the counterfactual model. In the learning from prices model, firms observe both signals ($g_1, g_2 > 0$). In the counterfactual model, agents only observe the signal for productivity and not the signals to credit spreads ($g_1 > 0, g_2 = 0$). Hence, the difference between the learning from prices model and the counterfactual model for Type B agents would be the impact of learning from prices.

The learning from prices model and the counterfactual model generates different posterior expectations. These are denoted as $E(z|g_1 > 0, g_2 > 0)$ and $E(z|g_1 > 0, g_2 = 0)$ respectively. As the differences in posterior expectations lead to different capital and borrowing decision rules, the impact of learning from prices can lead to over (or under) borrowing and investment. Consequently, Type B firms start with different levels of k and b in Period 2. In our model, we allow both Type A and B firms to face perfect information in Period 2. The purpose of perfect information in Period 2 is to examine the consequences of over (or under) borrowing and investment in Period 1 due to learning from prices.

4 Quantitative Analysis

4.1 Calibration

The model is calibrated at a quarterly frequency. The first four parameters in Table 2 are set to conventional values. We use the TFP process in Arellano et al. (2019) for a model with quarterly frequency, and follow calibration targets from Falato and Xiao (2020). In particular, we jointly target mean investment, leverage, profits to assets, and the default rate.

Certain parameters affect some moments more. The capital adjustment cost η_k affects mean investment, while the equity issuance cost η_d affects mean leverage. A higher capital adjustment cost reduces the incentive to invest and lowers investment. A higher value of η_d increases leverage as firms will substitute away from equity financing by borrowing more. In addition, the fixed cost ϕ affects the default rate as a higher value of ϕ induces more default. Lastly, the recovery rate γ affects all moments jointly.

Table 2: Parameters Used in the Model

Externally Calibrated Parameters:			
Depreciation Rate	δ	0.025	Standard
Risk Free Rate	r^f	0.04	Standard
Capital Revenue Elasticity	α	0.25	Bloom et al. (2018)
Labor Revenue Elasticity	ν	0.5	Bloom et al. (2018)
Autocorrelation of TFP Process	ρ_z	0.9	Arellano et al. (2019)
SD of TFP Process	σ_z	0.1	Arellano et al. (2019)
Kalman gain of s_1	g_1	0.5	See text
Kalman gain of s_2	g_2	0.5	See text
Internally Calibrated Parameters:			
Capital Adjustment Cost	η_k	3.24	Investment rate (mean)
Equity Issuance Cost	η_d	0.12	Leverage (mean)
Fixed Operating Cost	ϕ	0.2	Default rate (mean)
Recovery Rate	γ	0.16	Profits to Asset (mean)

Notes: This table shows the parameter values used for the calibration of the model.

Table 3: Calibrated Moments in the Model

	Data	**Model**
Investment Rate (mean)	0.018	0.026
Leverage (mean)	0.267	0.265
Default Rate	0.013	0.013
Profits to Asset (mean)	0.053	0.029

Notes: This table shows the targeted moments for the model.

Because our TFP process is obtained externally, we set g_1 and g_2 to be 0.5 each, such that the total Kalman gain is 1. A Kalman gain of one with the calibrated TFP process will deliver realistic output dynamics. In contrast, if the Kalman gain is too small, the TFP process needs to be more volatile, generating unrealistic moments for Type A firms.

We solve the model using value function iterations with taste shocks as in Dvorkin et al. (2021). The purpose of taste shocks is to improve the convergence properties of value function iterations and smooth the decision rules. Table 3 shows the calibrated moments in the model. The model matches the empirical counterparts fairly well.

4.2 Decision Rules

In this section, we examine the decision rules. Figures 2 and 3 present the decision rules of the firm when faced with a positive shock and negative shock, respectively. In both figures, we compare the outcome of the learning from prices model with the counterfactual model.

When there is a positive shock, Type A firms generate low credit spreads. Low credit spreads, in turn, lead to a favorable signal (s_2) observed by Type B firms. As such, beliefs for the Type B firms become more optimistic in the case where $g_2 > 0$, compared to the case in which $g_2 = 0$. When there is a negative shock, Type A firms generate high credit spreads. This leads to an unfavorable signal (s_2) observed by Type B firms. Hence, beliefs for the Type B firms become more pessimistic in the case in which $g_2 > 0$, compared to the case in which $g_2 = 0$.

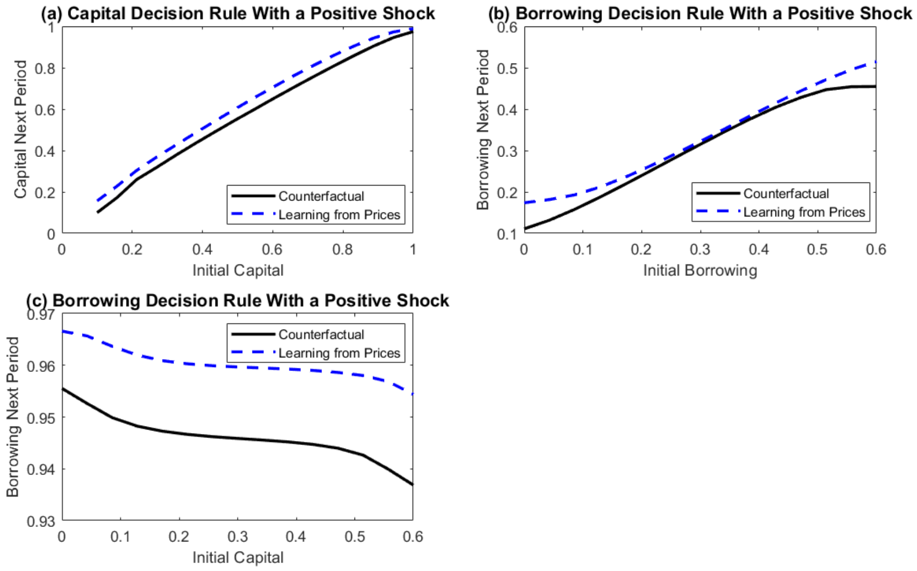
We first examine capital. In Figures 2 and 3, Panel (a) plots the decision rule of capital next period against the initial capital. In general, Type B firms choose a higher level of capital in the next period when they have higher initial capital. Nonetheless, Type B firms are more responsive in the learning from prices model. Relative to the counterfactual model, the capital chosen next period from the learning from prices model will be higher when there is a positive shock (Figure 1) and lower when there is a negative shock (Figure 2). This is because Type B firms are overly optimistic in good times and overly pessimistic in bad times in the model with learning from prices.

Next, we turn to borrowing. The decision rule for borrowing in the next period against the initial borrowing is presented in Panel (b) in Figures 2 and 3. In both models, firms choose a higher level of borrowing in the next period when they have higher initial borrowing. Again, we find that individuals in the learning from prices model are more responsive. Compared to the counterfactual model, the borrowing chosen next period from the learning from prices model will be higher when there is over-optimism (in good times) and lower when there is over-pessimism (in bad times).

Finally, Panel (c) in Figures 2 and 3 shows the decision rule for borrowing in the next period against the initial capital. We find that firms choose a lower level of borrowing in the next period when they have higher initial capital. This is because firms do not need to rely on external financing when they have high capital. Moreover, across all states of initial capital, the borrowing chosen next period for the learning from prices model is higher when there is a positive shock and lower when there is a negative shock.

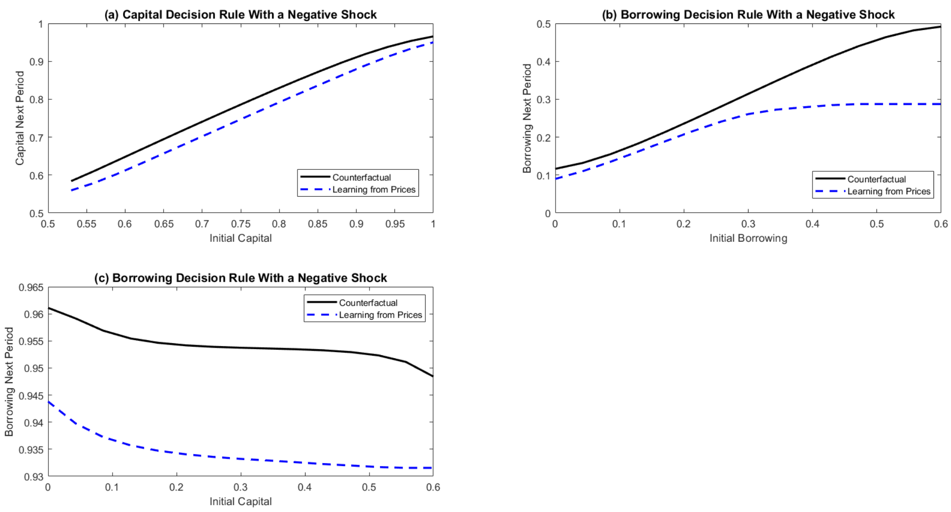
In sum, relative to the counterfactual model, firms choose higher levels of capital and borrowing in the next period when there is over-optimism in the learning from prices model. In comparison, they choose lower levels of capital and borrowing in the next period when there is over-pessimism in the learning from prices model.

Figure 2: Decision Rules with Positive Shock



Notes: This figure presents the decision rules for Type B firms in the learning from prices model and counterfactual model when there is a positive shock. Panel (a) shows the decision rule based on capital next period and initial capital, Panel (b) shows the decision rule based on capital next period and initial capital, while Panel (c) shows the decision rule based on borrowing next period and initial capital.

Figure 3: Decision Rules with Negative Shock

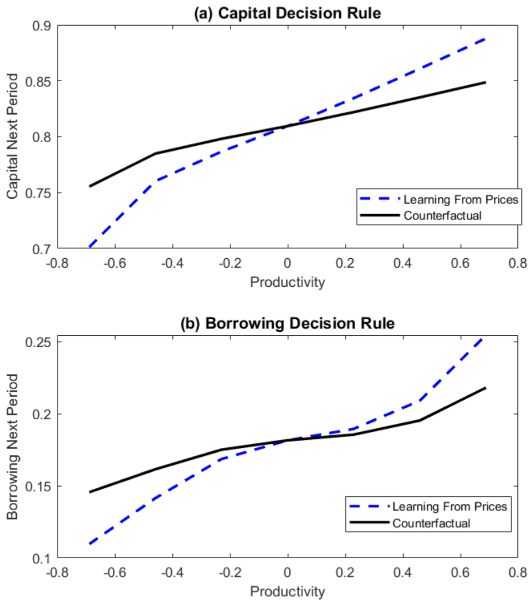


Notes: This figure presents the decision rules for Type B firms in the learning from prices model and counterfactual model when there is a negative shock. Panel (a) shows the decision rule based on capital next period and initial capital, Panel (b) shows the decision rule based on capital next period and initial capital, while Panel (c) shows the decision rule based on borrowing next period and initial capital.

Figure 4 compares the decision rules of the learning from prices model with the counterfactual model across different productivity levels. In Panel (a), we show that with higher productivity, firms choose higher capital in the learning from prices model compared to the counterfactual model. Similarly, we find in Panel (b), firms borrow more in the learning from prices model relative to the counterfactual model with higher productivity.

Hence, agents in the learning from prices model are more responsive to changes in productivity as compared to the counterfactual model. In good times (when there is higher productivity), firms invest more and borrow more as they are more optimistic. In bad times (when there is lower productivity), firms disinvest and borrow less as they are more pessimistic.

Figure 4: Decision Rules under Different Productivity Levels



Notes: This figure presents the decision rules for Type B firms in the learning from prices model and counterfactual model based on changes in productivity. Panels (a) and (b) shows the capital and borrowing decision rule respectively.

4.3 Effects of Over-investment and Over-borrowing on the Probability of Default

As the bond price $q(z, k', b')$ depends on the choice of investment and borrowing next period, over-investment and over-borrowing (under-investment and under-borrowing) due to over-optimism (over-pessimism) directly impact the bond prices, and consequently the probability of default. In this section, we examine how default decisions with different leverage levels interact with over-borrowing and over-investment due to learning from prices.

Firms investing more creates more resources and decrease the probability of default next period. This leads to a lower credit spread and a higher bond price. In contrast, when firms borrow more, they are required to repay a higher level of debt the next period, increasing the probability of default. This results in a higher credit spread and a lower bond price.

Consequently, we have two opposing forces at work: the investment channel and the borrowing channel. When the firm over-invest and over-borrow, the over-investment effect leads to a lower probability of default, while the over-borrowing effect leads to a higher probability of default the next period. Hence, the probability of default ultimately depends on whether the investment or borrowing effects dominate.

Each firm's default decision depends on the actual value of productivity in the next period. We first define z^* as the productivity cutoff that satisfies the default threshold according to the following equation:

$$z^* k'^{\alpha} n'^{\gamma} - b' + \frac{1}{1+R} V(z'', k', b') = 0 \tag{16}$$

Here, the default decision is based on the following cutoff: default if $z' < z^*$. In other words, when z in the next period is less than z^*, the firm will choose to default. This occurs with a probability of $\Phi(z^*|z)$, where Φ denotes the conditional cumulative probability distribution of z', and default otherwise.

From Equation (16), it is evident that the default decision depends on k' and b'. Hence, it depends on the firm's level of leverage. For example, consider high-leveraged firms with high k' and low b'. For Equation (16) to hold, z^* will have to be higher. With a higher cutoff, this implies a higher probability of default. Intuitively, this is due to limited resources. Lower capital implies lesser resources to spend in the next period, while a high level of debt implies higher repayment. Hence, the productivity cutoff and the probability of default will be relatively higher.

We now study the probability of default through the following illustration. Figure 5 Panel (a) plots the distribution of future productivity process z_{t+1}, with the productivity cutoff denoted as z^*. As highlighted earlier. if the next period's productivity is above z^*, the firm continues to operate. Otherwise, the firm defaults. What happens when the firm over-borrows due to learning from prices? The productivity cutoff will increase from z^* to z^{**} as the firm receives fewer resources after repaying more debt. Thus, the shaded area under the curve between z^* and z^{**} shows the increase in the probability of default due to over-borrowing.

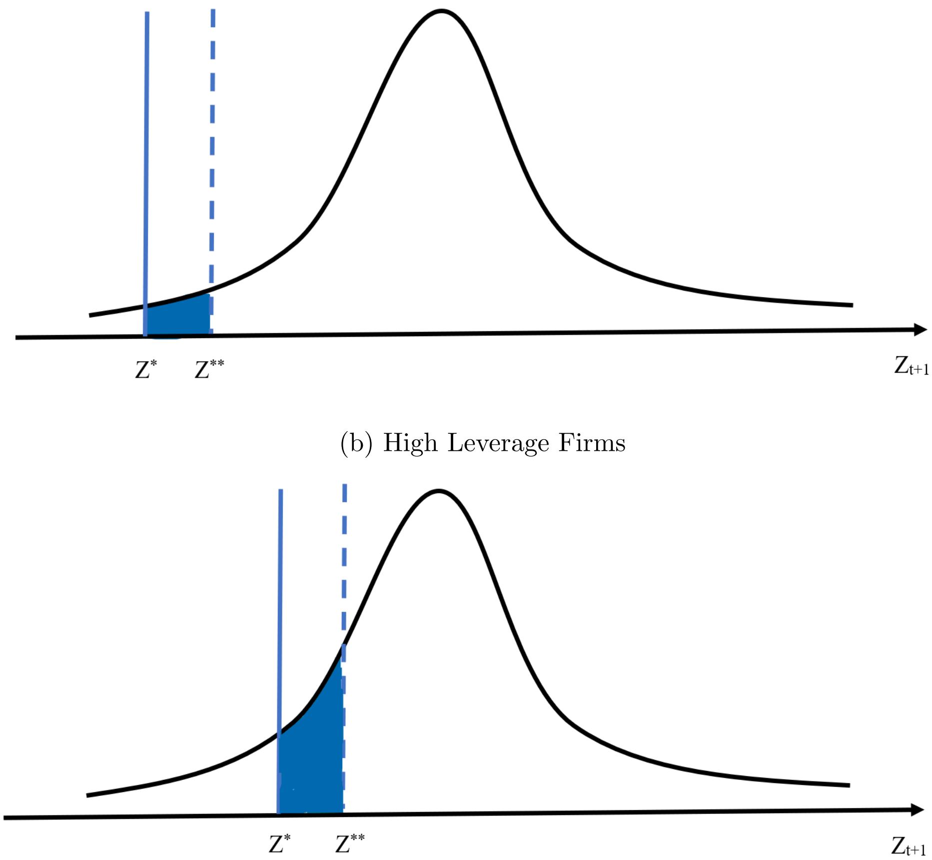
We now turn to a firm that has relatively higher leverage. Higher leverage implies higher initial debt for repayment and lesser capital, which implies fewer resources. Consequently, the productivity cutoff z^* for these firms will be higher than for low leverage firms. This is illustrated in Figure 5 Panel (b), which shows that z^* is further to the right than its counterpart in Figure 5 Panel (a). Consider an identical increase in over-borrowing due to learning from prices. Like the previous example, z^* increases by an identical amount to z^{**}. However, in this case, due to higher leverage, there is a larger increase in the probability of default given by the shaded area under the curve. This example shows that the borrowing effect dominates relatively more for high-leverage firms. Hence, over-borrowing leads to a higher probability of default despite over-investment.

In sum, the balance sheet matters. The effects of over-borrowing and over-investment on firms are highly dependent on the firms' leverage.

Figure 5: Distribution of Future Productivity and its Cut-off Level for Default Decisions

(a) All Firms

(b) High Leverage Firms



Notes: This figure presents the distribution of z_{t+1} and its associated cut-offs z^* and z^{**}. z^* is associated with the counter-factual model while z^{**} is associated with the learning from prices model with over-borrowing. Panel (a) is for all firms, while Panel (b) is for high leverage firms only.

5 Boom-bust Credit Cycles

This section discusses the mechanisms of learning from prices that generate boom-bust dynamics. We examine how firms' decisions based on learning from prices could impact the probability of default and, consequently, bond prices and spreads across different time periods. The outcome of learning from prices is highly dependent on the state of the economy.

To improve the tractability of our analysis, we consider two following cases. First, we consider an economic upturn (boom in Period 1), followed by a recession (bust in Period 2). Second, we consider a recession (bust in Period 1), followed by a recovery (boom in Period 2).

5.1 Learning from Prices Before a Recession

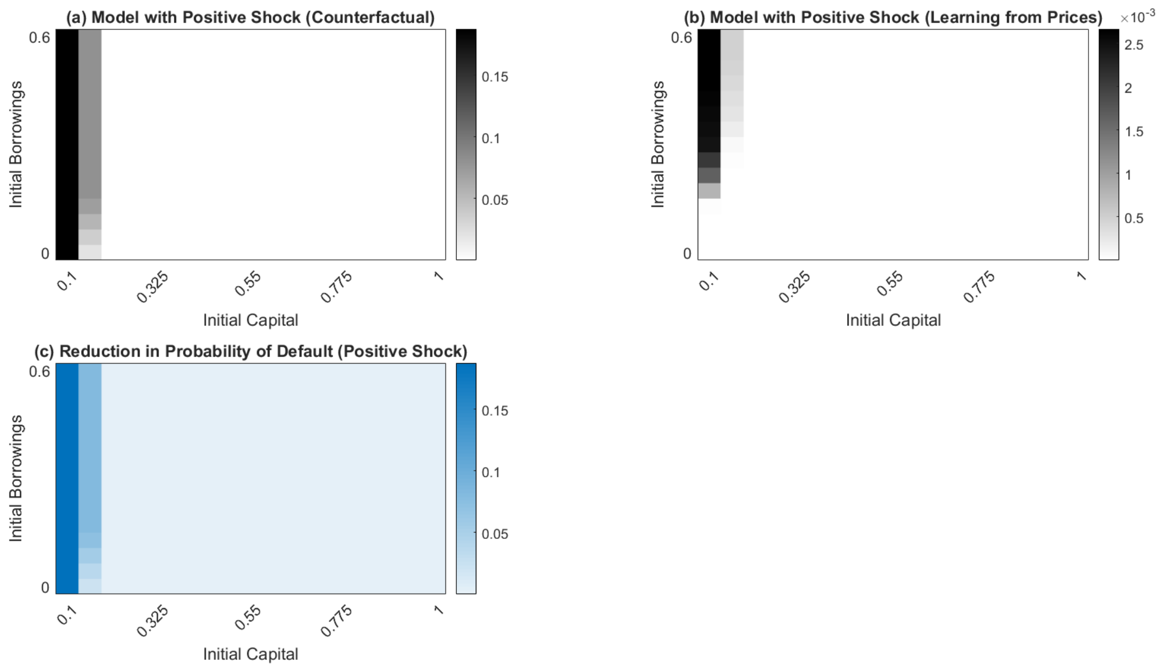
Boom in Period 1 with Learning from Prices. Suppose the economy is booming in Period 1. Type A agents (i.e those with perfect information), will choose more capital and borrowings. Next, we consider Type B agents (i.e those with information frictions). In the model with learning from prices, firms and lenders will observe that the spreads have decreased. Economic agents become more optimistic due to learning from credit spreads (relative to the counterfactual). As agents are more optimistic, they invest relatively more. Hence, there is a lower probability of default in the model with learning from credit spreads relative to the counterfactual model.

To examine the role of the balance sheet in impacting the probability of default, we focus on the different initial levels of borrowing and capital. The heterogeneous effects will allow us to understand better how changes in leverage (defined as the ratio between borrowings and capital, b/k) play a role across different models. Here, we find a reduction in the probability of default in the learning from prices model, especially when firms have higher leverage. When initial leverage is high, higher investment in Period 1 (compared to the counterfactual) leads to more resources in Period 2, lowering the probability of default when firms repay their debt.

Figure 6 compares the probability of default between the counterfactual model and learning from prices model when there is a positive shock in Period 1. The vertical and horizontal axes denote the initial level of borrowings and capital in Period 1, respectively. For each initial level of borrowings and capital, Panel (a) presents the probability of default for the counterfactual model, while Panel (b) presents the probability of default for the learning from prices model. In both models, we find that the probability of default increases when there is higher borrowing and lower capital. In addition, the learning from prices model has a lower probability of default compared to the counterfactual model.

This is shown in Panel (c), which computes the difference in the probability of default between the learning from prices model and the counterfactual model.

Figure 6: Probability of Default (Boom in Period 1)

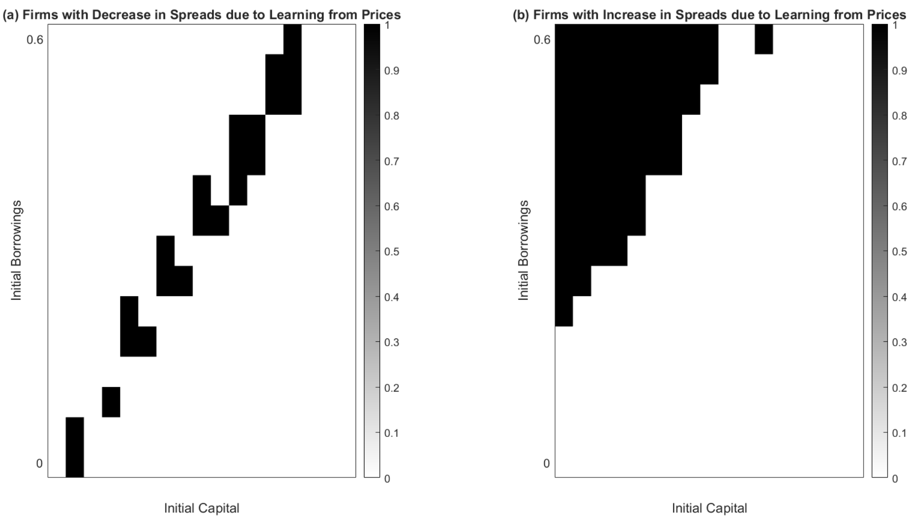


Notes: This figure presents the effects of learning from prices on the probability of default in Period 1. All panels correspond to the model with a positive shock to z. The horizontal and vertial axes denote initial capital and borrowings in Period 1. Panel (a) presents the probability of default in a model without learning from prices. Panel (b) presents the probability of default in a model with learning from prices. Panel (c) presents the differences in the probability of default between the learning from prices model and the counterfactual model.

Recession in Period 2. Now consider a negative shock in Period 2, which follows a positive shock in Period 1. When there is a good shock in Period 1, credit spreads in the learning from prices model are higher than that of the counterfactual model. This is because firms invest more and borrow more due to over-optimism in Period 1. This leads to a lower probability of default in the short run. However, when there is a bad shock in Period 2, firms will aggressively deleverage. The outcome in the medium run depends on firms' leverage level.

Figure 7 presents our findings for Period 2. In Panel (a), the outcome is an indicator variable for firms who experience a decrease in credit spreads in Period 2 due to their actions from learning from prices in Period 1. Here, we find that firms with relatively lower leverage enjoy a decrease in bond spreads. Higher investment from Period 1 leads to more resources in Period 2. As these firms have lower leverage, they do not need to repay a high level of debt. This leads to even more investment in Period 2, which further lowers their probability of default.

Figure 7: Impact on firms when there is recession in Period 2



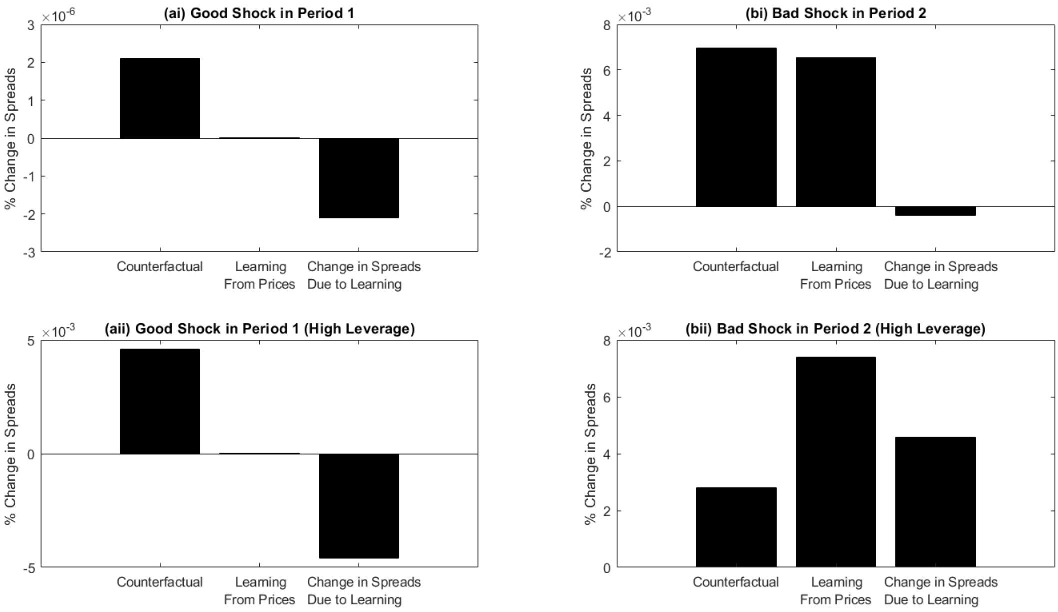
Notes: This figure presents the medium run effects (Period 2) of learning from prices. We conduct an exercise in which there is a positive shock in Period 1 and a negative shock in Period 2. The horizontal and vertial axes denote initial capital and borrowings in Period 1. In Panel (a), the outcome is an indicator variable equal to one if firms experience a decrease in credit spreads. In Panel (b), the outcome is an indicator variable equal to one if firms experience an increase in credit spreads.

In comparison, our findings highlight that firms with high leverage in the learning from prices model will be worse off in Period 2. In Panel (b), the outcome is an indicator variable for firms who have a higher bond spread in Period 2 due to their actions of learning from prices in Period 1. We find that firms with low initial capital and high initial borrowings experienced a decrease in bond prices. Recall that in Period 1, these firms over-invest relative to the counterfactual model. In addition, these firms also over-borrow. As such, these firms are required to pay off a higher level of debt when they enter Period 2. Hence, this curtails their investment in Period 2 due to high initial leverage in Period 1. Even if they were to increase their investment in Period 2, high-leverage firms would be required to borrow more to finance this increase in investment. Hence, high-leverage firms will be worse off in Period 2, due to over-borrowing in Period 1. This leads to a high bond spread in Period 2, and thus, a higher probability of default in Period 3.

Next, we simulate the model economy for 100,000 periods and drop the first 20,000 simulations to obtain an ergodic distribution. Using the simulated data, we examine the changes in credit spreads for two types of firms: average leverage and high leverage. The former refers to firms with average simulation values for borrowing and capital, while the latter refers to firms in the top 10 percentile for leverage ratio.

Based on our simulations, Figure 8 presents the changes in credit spreads between the learning from prices model and the counterfactual model during these two time periods

Figure 8: Changes in Spreads for Boom in Period 1 and Bust in Period 2



Notes: This figure presents the changes in credit spreads due to learning based on our simulation results. The changes in credit spreads are obtained from taking the difference between the learning from price model and counterfactual model. Panel (ai) and Panel (bi) focus on firms with average leverage, while Panel (aii) and Panel (bii) relate to firms with high leverage. We examine the impact of a good shock for Period 1 in Panel (ai) and (aii), as well as the impact of a bad shock for Period 2 in Panels (bi) and (bii).

when there is a good shock (boom) in Period 1 and a bad shock (bust) in Period 2.

We first examine the impact on the good shock (boom) in Figure 8 Panels (ai) and (aii). Panel (ai) shows that for the average firm, the level of spreads in the learning from prices model is close to zero. In comparison, the counterfactual model has higher spreads. Consequently, the changes in spreads due to learning from prices are negative. This occurs because, with a good shock in Period 1, firms become overly optimistic and over-invest, resulting in spreads being excessively low in the model with learning from prices. We then consider firms with high leverage in Panel (aii). In Panel (aii), we show that firms with high leverage behave similarly to the average firm, though the magnitude is larger. Hence, firms with high leverage are more responsive to learning from prices.

Next, we turn to the impact of the bad shock in Period 2. In Panel (bi), we find that for both the counterfactual and learning from prices model, there is an increase in bond spreads for the average firm. Nonetheless, the increase in bond spreads is larger for the counterfactual model relative to the learning from prices model. Hence, the changes in spreads due to learning from prices are also negative in the second period. As these firms invest more in the first period (when there is a good shock), they benefit from their investments. Nonetheless, this is driven primarily by firms with low leverage.

In Panel (bii), we focus on the impact of high-leverage firms in Period 2. Unlike firms with low leverage, high-leverage firms in the counterfactual model experienced a smaller increase in spreads relative to firms in the model with learning from prices. Hence, the changes in spreads due to learning from prices are positive in the second period. With learning from prices, high-leverage firms are worse off when there is a recession because they over-borrow in the first period, and the probability of default increases in the second and third periods.

5.2 Learning from Prices During a Recession

Next, we consider a negative shock in the economy in Period 1 and examine the implications of learning from prices in a recession. In this case, the model with learning from prices predicts a higher probability of default. In a downturn, economic agents of Type A borrow less and invest less. This generates higher credit spreads and lower bond prices. When economic agents of Type B learn from higher credit spreads, this generates more pessimism as credit spreads are higher. This leads to relatively lower investment and lesser resources in Period 2 relative to the counterfactual. This results in a higher probability of default in Period 2.

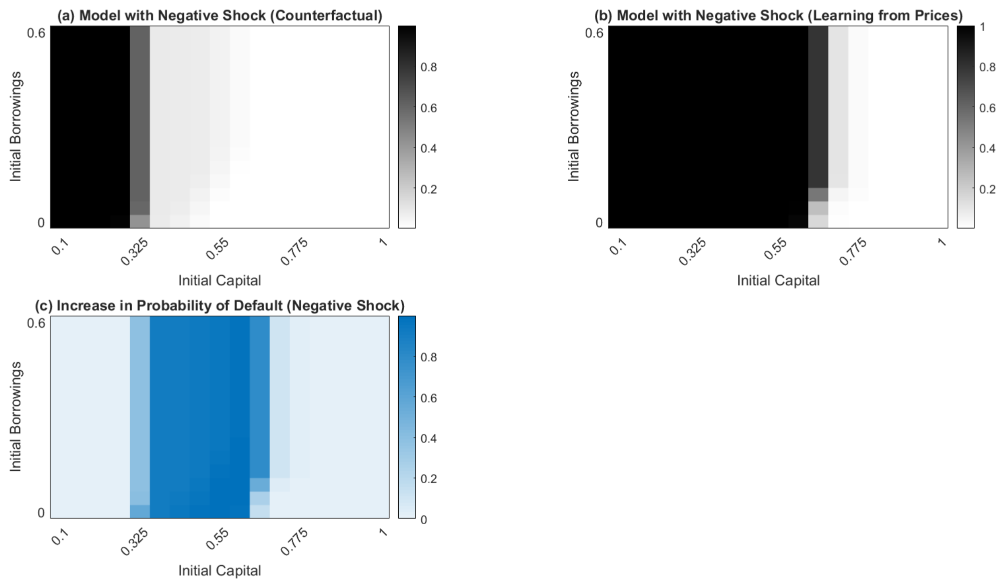
Figure 9 compares the probability of default between the counterfactual model and learning from prices model when there is a negative shock in Period 1. At each initial level of capital and borrowing, Panels (a) and (b) present the probability of default for the counterfactual model and learning from prices model, respectively. In both panels, we find that the probability of default increases with higher leverage.

We find that firms in the model with learning from prices have a higher probability of default. This is reflected in Panel (c), which shows differences in the probability of default between the two models. When capital is low (between 0 to 0.3), firms in both models have a high probability of default. Nonetheless, more firms in the learning from prices model experience an increase in the probability of default when capital is between 0.3 to 0.6. Hence, the main difference comes from the role of leverage.

We now examine the impact of a positive shock in Period 2, which follows a negative shock in Period 1. Figure 10 presents our findings for Period 2. In Panel (a), the outcome is an indicator variable for firms who experienced a decrease in spreads in period 2 due to their actions from learning from prices in Period 1. We find that high-leverage firms experience a decrease in spreads.

In Panel (b), the outcome is an indicator variable for firms who have an increase in spreads in Period 2 due to their actions from learning from prices in Period 1. Here, we find that firms with relatively lower leverage end up with lower bond prices. Hence, the

Figure 9: Probability of Default (Bust in Period 1)



Notes: This figure presents the effects of learning from prices on the probability of default in Period 1. All panels correspond to the model with a negative shock to z. The horizontal and vertial axes denote initial capital and borrowings in Period 1. Panel (a) presents the probability of default in a model without learning from prices. Panel (b) presents the probability of default in a model with learning from prices. Panel (c) presents the differences in the probability of default between the learning from prices model and the counterfactual model.

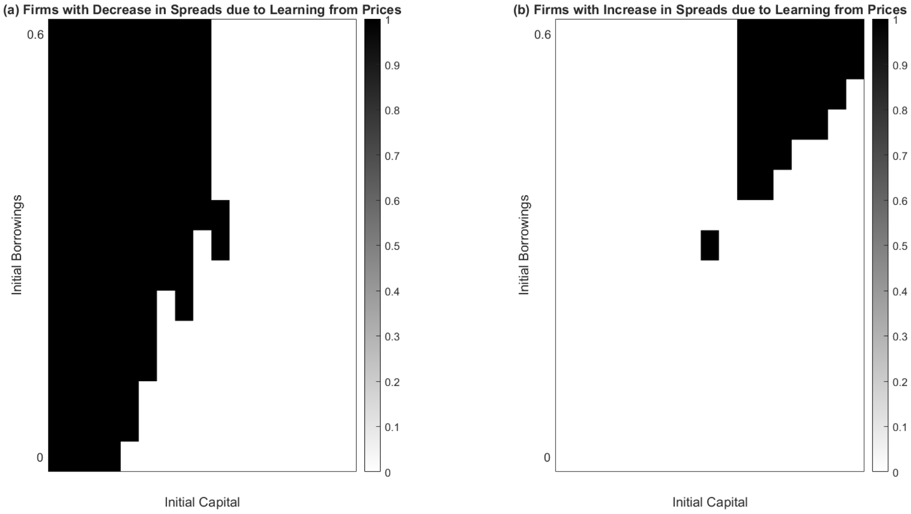
heterogeneous balance sheets of firms play a vital role.

We now examine specific cases of firms with average and high leverage based on our simulations. Based on our simulations, Figure 11 presents the changes in credit spreads between the learning from prices model and the counterfactual model when there is a bad shock (bust) in Period 1 and a good shock (boom) in Period 2

Panels (ai) and (aii) compare the changes in spreads between the two models when there is a recession in Period 1. From Panel (ai), we show that with learning from prices, the spreads are much higher than that of the counterfactual model for the average firm. This is because, under perfect information, spreads are much higher when there is a bad shock in Period 1. With higher observed spreads, individuals become more pessimistic and under-invest, leading to higher spreads when they learn from prices. The effects are more pronounced for firms with high leverage. For firms with high leverage, Panel (aii) show that the differences are significantly larger in terms of magnitude.

In Panels (bi) and (bii), we examine the impact of the positive shock in Period 2. Here, we find that when the economy recovers, credit spreads fall more significantly for the learning from prices model as compared to the counterfactual model. This occurs for the average firm (Panel (bi)), as well as firms with high leverage ((Panel (bii)). Hence, without any policy intervention, firms experience an increase in spreads in Period 1 (when

Figure 10: Impact on firms when there is boom in Period 2



Notes: This figure presents the medium run effects (Period 2) of learning from prices. We conduct an exercise in which there is a negative shock in Period 1 and a positive shock in Period 2. The horizontal and vertial axes denote initial capital and borrowings in Period 1. In Panel (a), the outcome is an indicator variable equal to one if firms experience a decrease in credit spreads. In Panel (b), the outcome is an indicator variable equal to one if firms experience an increase in credit spreads.

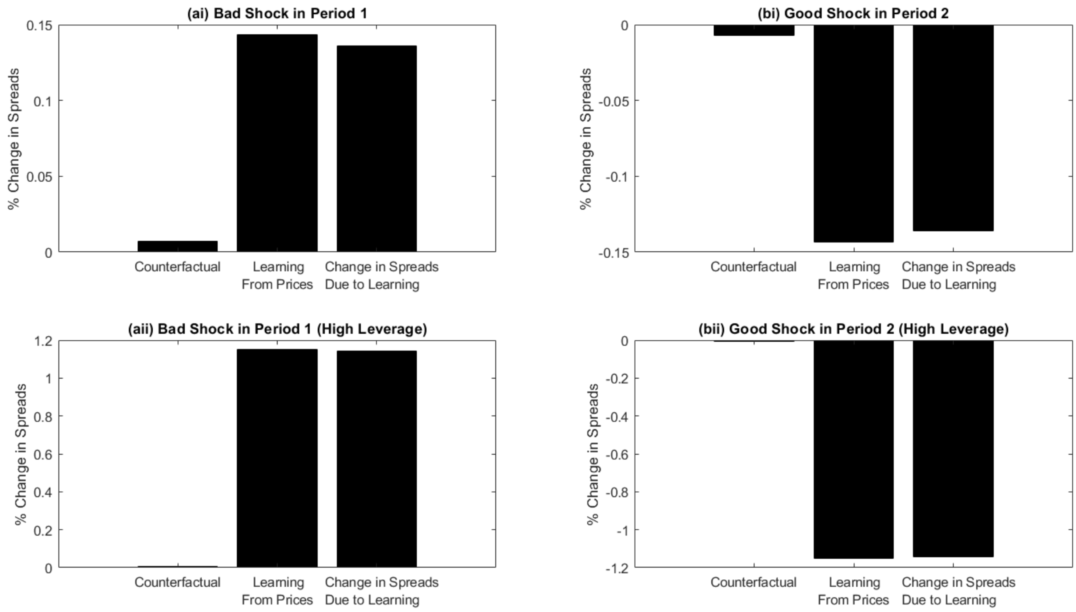
there is a bad shock), and experience a decrease in spreads in Period 2 (when there is a positive shock) due to learning from prices.

5.3 Key Takeaways

The model with learning from prices amplifies boom-bust cycles. A boom generates over-optimism, leading to over-borrowing and higher investment. When the economy enters a recession in Period 2, over-borrowing leads to a higher probability of default for high-leverage firms. In comparison, low-leverage firms exhibit a lower probability of default due to learning from prices.

We also consider a different exercise in which we simulate a recession in Period 1 to examine the effects of learning from prices in a recession during the short run. In this case, learning from prices generates over-pessimism and predicts a higher probability of default in the short run. However, when the economy recovers in Period 2, firms are better off as they enjoy a lower probability of default.

Figure 11: Changes in Spreads for Bust in Period 1 and Boom in Period 2



Notes: This figure presents the changes in credit spreads due to learning based on our simulation results. The The changes in credit spreads are obtained obtained from taking the difference between the learning from price model and counterfactual model. Panel (ai) and Panel (bi) focus on firms with average leverage, while Panel (aii) and Panel (bii) relate to firms with high leverage. We examine the impact of a bad shock for Period 1 in Panel (ai) and (aii), as well as the impact of a good shock for Period 2 in Panels (bi) and (bii).

6 Implications of Macroprudential Policy

Macroprudential policies curb the credit cycle and affect prices, such as credit spreads. Consequently, macroprudential policies have the potential to impact the decisions of firms as they learn from prices. This section examines the impact of macroprudential policies in a model with learning from prices. In particular, we compare the impact of learning from prices with macroprudential policies vis-a-vis without macroprudential policies. Like the previous section, we consider how macroprudential policies affect outcomes when agents learn from prices before and during a recession.

6.1 Overview of Macroprudential Policy

Macroprudential policies relate to financial policies that seek to ensure the financial system's stability. Reducing disruptions in credit can reduce the financial system's sensitivity to shocks. Among others, macroprudential policy tools include caps on loan-to-value ratios, limits on credit growth, as well as several countercyclical capital and reserve requirements. (Claessens (2015))

In this paper, macroprudential policy is modeled as debt taxes τ^b, such that the firm's dividend satisfies

$$d = y - Wn - AC(i,k) - \phi + (q(z,k',b') - \tau^b)b' - i - b \tag{17}$$

The introduction of τ^b lowers the effective bond price, increases credit spreads, and discourages borrowing during normal times. As firms lower borrowings during normal times, they decrease investment simultaneously. Due to lower investment, firms face a higher probability of default and a higher credit spread during normal times.[2]

The main purpose of macroprudential policy aims to prevent huge losses and defaults during a downturn. Because firms decrease their borrowings during normal times, they face less default risk when a recession is realized in the next period. Hence, macroprudential policy substantially lowers the probability of default during a recession by discouraging firms from over-borrowing during normal times. Consequently, macroprudential policies lower credit spreads in a recession at the cost of increasing credit spreads in a boom. It will be interesting to examine how learning from prices (through credit spreads) and macroprudential policy interact in a credit cycle model.

Macroprudential Policy and its Signal Structure. As macroprudential policies increase financial stability, we can rewrite Equation (13) to be as follows:

$$s_2' = \alpha z + e_2 \tag{18}$$

whereby $\alpha < 1$. This is the key difference relative to the learning from prices model without macroprudential policy. First, consider an environment with perfect information. Credit spreads are higher during normal times with macroprudential policy. As a result, upon observing higher credit spreads in normal times ($z > 0$), Type B firms become less optimistic. Posterior expectations will then be given by

$$E_{posterior} = (1 - g_1 - g_2)E_{prior} + g_1 z + g_2 \alpha z \tag{19}$$

Hence, $\alpha < 1$ captures the decrease in optimism due to macroprudential policy. By contrast, consider a recession that corresponds to $z < 0$. Then, credit spreads are lower due to macroprudential policy. Lower credit spreads lead to less pessimism for Type B firms. As such posterior expectations become relatively more optimistic. This is satisfied when $\alpha < 1$ and $z < 0$ jointly. In order to isolate the effects of learning from prices due

[2] Equivalently, an increase in tax rate can be interpreted as an increase in capital requirements. Using changes in bank capital requirements in the United Kingdom, Meeks (2017) showed empirically that an increase in capital requirement resulted in a decrease in lending and a subsequent increase in credit spreads.

to macroprudential policy, we compare the cases in which $\alpha = 1$ (learning from prices with no macroprudential policy), and $\alpha < 1$ (learning from prices with macroprudential policy). Without loss of generality, we set α to be 0.5 in our analysis.

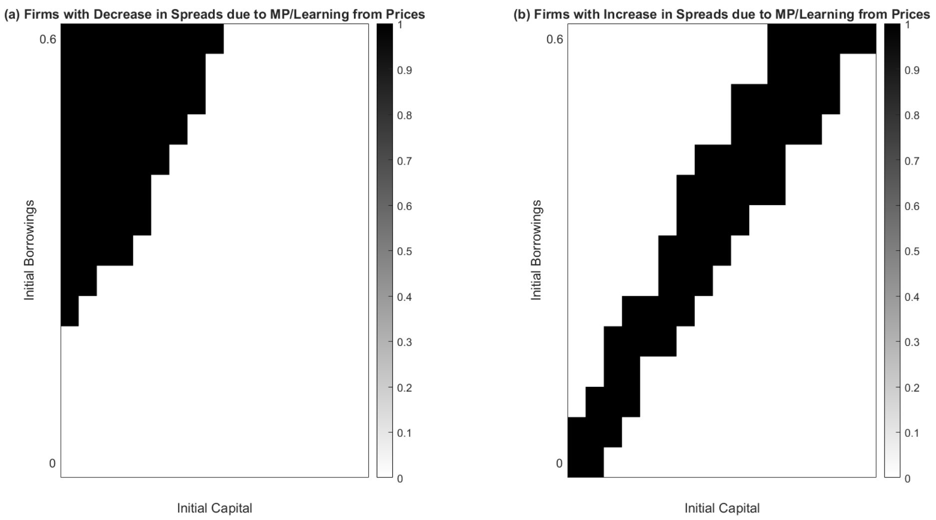
6.2 Macroprudential Policy and Learning from Prices Before a Recession

Boom in Period 1, Learning from Prices and Macroprudential Policy.

We first consider the case where the economy is in a boom in Period 1. With a positive TFP shock in Period 1, bond prices will increase, and credit spreads will decrease. Nonetheless, with macroprudential policies, bond prices will be lower, and credit spreads will be higher due to taxes imposed on borrowings during good times.

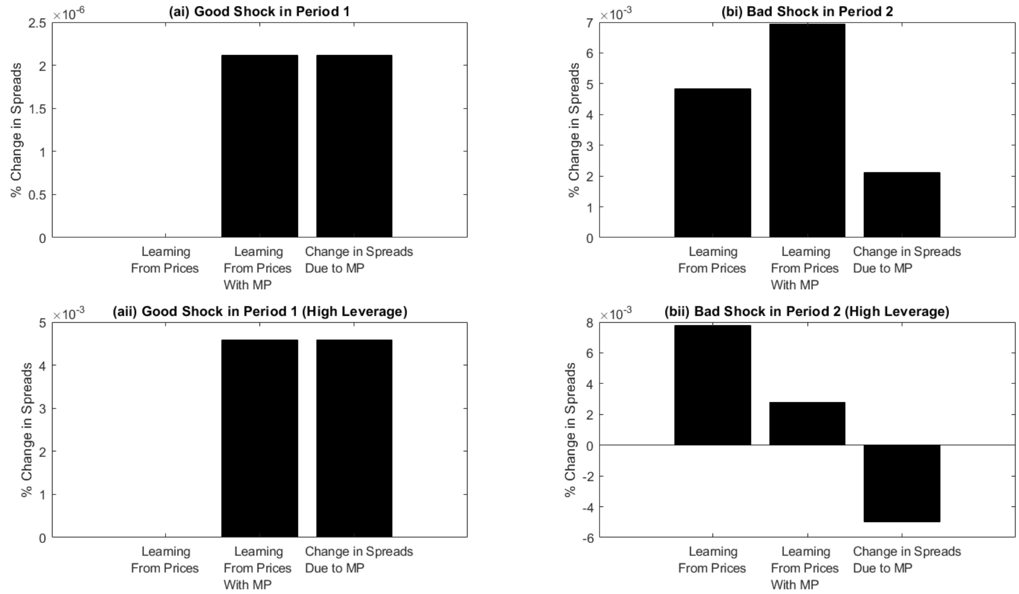
Higher credit spreads result in more pessimism in the economy. Hence, the model with macroprudential policies generates lower borrowing and investment due to learning from prices. Due to the lower level of investment in Period 1, the model with macroprudential policy predicts a higher level of default in the short run. This is because lower investment brings over lesser resources to Period 2. As such, for a given level of debt repayment, all firms face a higher probability of default in Period 2.

Figure 12: Impact on firms when there is macroprudential policy and bust in Period 2



Notes: This figure presents the medium run effects (Period 2) of learning from prices due to macroprudential policy. We conduct an exercise in which there is a positive shock in Period 1 and a negative shock in Period 2. The horizontal and vertial axes denote initial capital and borrowings in Period 1. In Panel (a), the outcome is an indicator variable equal to one if firms experience a decrease in credit spreads. In Panel (b), the outcome is an indicator variable equal to one if firms experience an increase in credit spreads.

Figure 13: Impact of Macroprudential Policy for Boom in Period 1 and Bust in Period 2



Notes: This figure presents the changes in credit spreads due to the presence of macroprudential policies in learning from prices model. The changes in credit spreads are obtained from taking the difference between the learning from prices model with macroprudential policies and the learning from prices model without macroprudential policies. Based on our simulation results, Panel (ai) and Panel (bi) focus on firms with average leverage, while Panel (aii) and Panel (bii) relate to firms with high leverage. We examine the impact of a good shock for Period 1 in Panel (ai) and (aii), as well as the impact of a bad shock for Period 2 in Panels (bi) and (bii).

Recession in Period 2. Now consider a recession in Period 2. Figure 12 Panel (a) reports the results when the outcome is an indicator variable if firms face lower credit spreads due to macroprudential policy, while Panel (b) reports the results when the outcome is an indicator variable for higher credit spreads. We find that firms with higher leverage are associated with decreased credit spreads due to macroprudential policy and learning from prices. By contrast, firms with lower leverage experience an increase in spreads. This suggests that firms with different leverage levels benefit from macroprudential policies differently.

As discussed earlier, with learning from prices, credit spreads are higher in a boom due to macroprudential policy. This results in more pessimism as compared to the model without macroprudential policies. Hence, all firms invest less and borrow less. The effect of lower borrowing in Period 1 benefits the high-leverage firms when a negative shock arrives in Period 2. Hence, this leads to an even lower credit spread in a recession. As a result, macroprudential policy benefits high-leverage firms.

However, more pessimism in Period 1 limits the low-leverage firms from investing more. When a negative shock arrives in Period 2, these firms experience an increase in the probability of default and higher credit spreads due to lower investment in Period 1.

Hence, macroprudential policy leads to negative consequences for low-leverage firms.

To examine the role of macroprudential policies in the learning from price model, we compare changes in credit spreads with and without macroprudential policies from our simulation results. Similar to our discussion in the previous section, we focus on changes in credit spreads for 2 types of firms: average leverage and high leverage. The former refers to firms with average simulation values for the leverage ratio, while the latter refers to firms in the top 10 percentile for the leverage ratio.

We first examine what happens when there is a good shock in Period 1. Figures 13 Panels (ai) and (aii) present changes in spreads for the average firm and firms with high leverage, respectively. In both panels, we find that with macroprudential policies, the spreads are larger in Period 1, with a greater magnitude experienced by high-leverage firms. This is attributed to learning from prices. As firms learn from prices during economic growth, they become more pessimistic with macroprudential policies, generating lower borrowing and investment. Due to the lower level of investment in Period 1, the model with macroprudential policy generates higher spreads in Period 1.

It has been widely documented that with macroprudential policies, there would be lower investments and borrowings. In this paper, we add to the literature by showing that firms are more pessimistic due to the interaction between learning from prices and macroprudential policies, resulting in a larger fall in investments and borrowings. Hence, learning from prices acts as an amplification mechanism.

Next, we consider a recession in Period 2. Figures 13 Panels (bi) and (bii) present changes in spreads for the average firm and firms with high leverage, respectively. In both panels, we find that while credit spread increases for the model without macroprudential policies, the spread decreases for the model with macroprudential policies. This result in the spreads being lowered for the firms with macroprudential policies. Therefore, firms are better off with macroprudential policies.

We find that firms with higher leverage are associated with decreased credit spreads due to macroprudential policy and learning from prices. By contrast, firms with lower leverage experience a decrease in bond prices. This suggests that firms with different levels of leverage benefit differently from macroprudential policy.

6.3 Macroprudential Policy and Learning from Prices During a Recession

Bust in Period 1, Learning from Prices and Macroprudential Policy.

Next, we consider the case where agents learn from prices during a recession. Earlier studies have highlighted the asymmetric effects of macroprudential policies during credit cycle upturns and downturns (De Schryder and Opitz (2021)). In our model, bond prices will decrease with a negative TFP shock in Period 1, and credit spreads will increase. As macroprudential policies curb the credit cycle during a recession, bond prices will be higher, and credit spreads will be lower in the model with macroprudential policies compared to a model without macroprudential policies.

In this case, macroprudential policy benefits the economy as it reduces the probability of default. In the model with macroprudential policies, lower credit spreads and higher bond prices lead to more optimism due to learning from prices. This generates higher borrowing and investment. With a higher level of investment in Period 1, the model with macroprudential policy predicts a lower level of default in the short run. This is because higher investment leads to more resources in Period 2. Even though firms also borrow more, higher investment is more valuable during a recession as it prevents default in the next period. Hence, the benefit of investment outweighs the costs of over-borrowing when a firm enters Period 2.

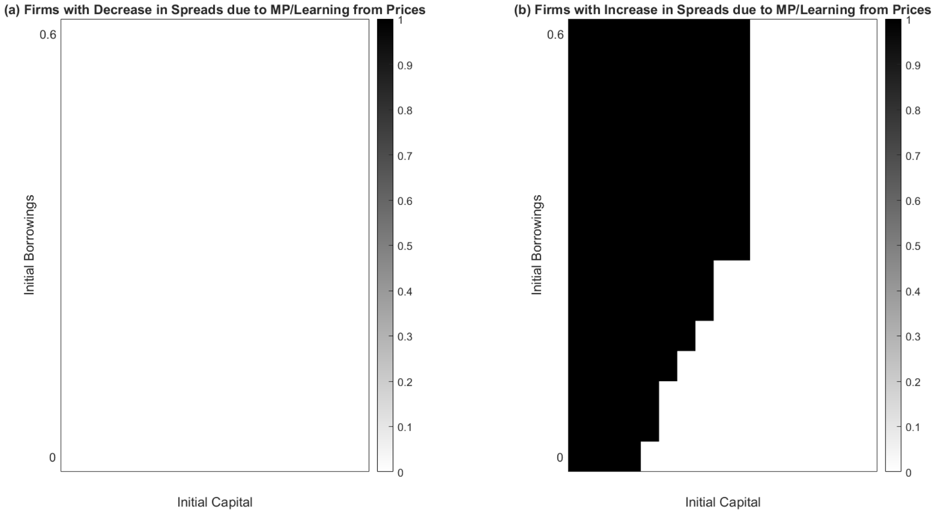
Reverting to Normal Times in Period 2.

Now consider the effects of macroprudential policy in Period 2 when the economy reverts to normal times. Overoptimism, due to lower credit spreads and macroprudential policy in Period 1, leads to over-borrowing compared to the baseline model. This leads to increased leverage and higher credit spreads for all firms.

Figure 14 Panel (a) reports the results when the outcome is an indicator variable for firms with lower credit spreads, while Panel (b) reports the results when the outcome is an indicator variable for firms with higher credit spreads. We find that most firms, regardless of the initial level of leverage, experience a decrease in bond price and an increase in credit spreads in the model with learning from prices and macroprudential policy. This suggests that when the economy reverts to its normal state after a recession, macroprudential policy might be harmful in a framework where individuals learn from prices.

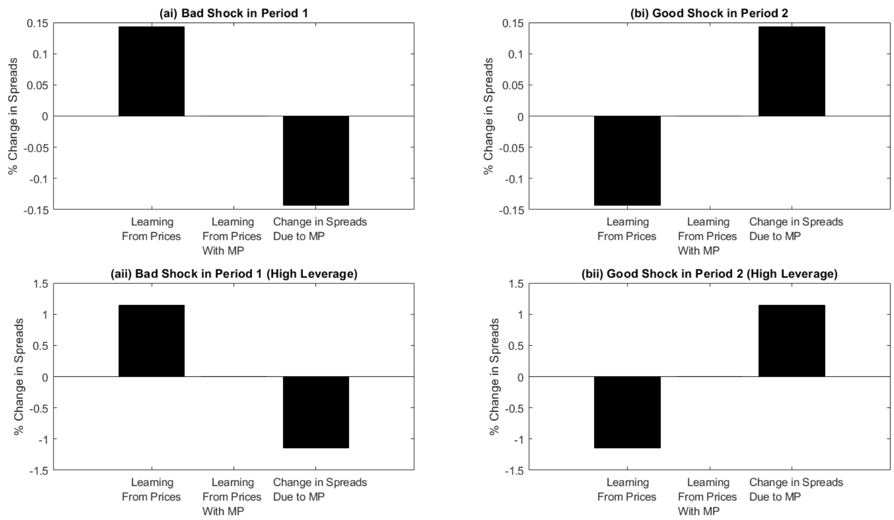
When a Type B firm borrows and invests more in Period 1, this leads to more resources in Period 2 and higher debt repayment. Consequently, how this affects credit spreads in Period 2 depends on the initial level of leverage in Period 1. In this case, regardless of the initial level of leverage, all firms are required to repay off higher debt levels accumulated

Figure 14: Impact on firms when there is macroprudential policy and boom in Period 2



Notes: This figure presents the medium run effects (Period 2) of learning from prices due to macroprudential policy. We conduct an exercise in which there is a negative shock in Period 1 and a positive shock in Period 2. The horizontal and vertial axes denote initial capital and borrowings in Period 1. In Panel (a), the outcome is an indicator variable equal to one if firms experience a decrease in credit spreads. In Panel (b), the outcome is an indicator variable equal to one if firms experience an increase in credit spreads.

Figure 15: Impact of Macroprudential Policy for Bust in Period 1 and Boom in Period 2



Notes: This figure presents the changes in credit spreads due to the presence of macroprudential policies in learning from prices model. The changes in credit spreads are obtained from taking the difference between the learning from prices model with macroprudential policies and the learning from prices model without macroprudential policies. Based on our simulation results, Panel (ai) and Panel (bi) focus on firms with average leverage, while Panel (aii) and Panel (bii) relate to firms with high leverage. We examine the impact of a bad shock for Period 1 in Panel (ai) and (aii), as well as the impact of a good shock for Period 2 in Panels (bi) and (bii).

from Period 1. As such, there are fewer resources for all firms in Period 2. This lowers investment in Period 2. Moreover, to increase investment, firms will borrow even more in Period 2. This generates higher credit spreads for all firms. Essentially, this is due to over-borrowing in Period 1 due to lower spreads due to macroprudential policy.

We turn to our simulation results and compare changes in credit spreads for the model with learning from prices and without macroprudential policies in Figure 15. With a negative TFP shock in Period 1, bond prices will decrease, and credit spreads will increase. As macroprudential policies curb the credit cycle during a recession, bond prices will be higher and credit spreads will be lower in the model with macroprudential policies. This is illustrated in Figures 15 Panels (ai) and (aii). Panel (ai) presents the changes in spreads for the average firm, while Panel (aii) presents the changes in spreads for firms with high leverage. In both panels, we find that with macroprudential policies, the spreads are lower in Period 1, with greater magnitude experienced by high-leverage firms.

In this case, macroprudential policy is beneficial to the economy as it reduces credit spreads and, consequently, the probability of default. In the model with macroprudential policies, lower credit spreads and higher bond prices lead to more optimism due to learning from prices compared to the baseline model. As a result, the model with macroprudential policies generates higher borrowing and investment due to learning from prices relative to the baseline model.

Now consider the effects of macroprudential policy in Period 2 when the economy reverts to normal times. Figures 15 Panels (bi) and (bii) examine the impact on credit spreads in period 2. Panel (bi) presents the changes in spreads for the average firm, while Panel (bii) presents the changes in spreads for firms with high leverage.

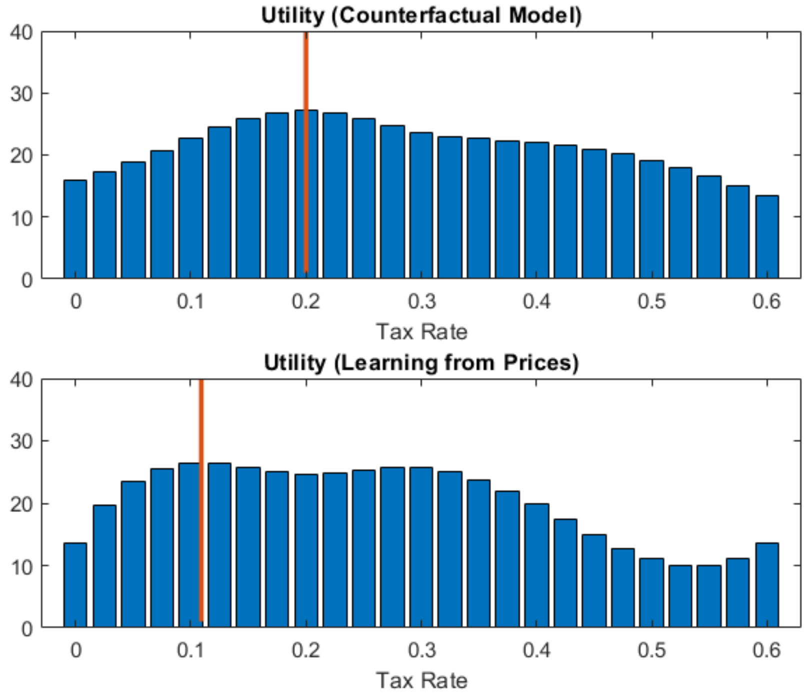
In both panels, we find that while credit spread decreases for the model without macroprudential policies, the spread for the model with macroprudential policies remains relatively unchanged. This result in the spreads being higher for the firms with macroprudential policies. Therefore, with macroprudential policies, firms are worse off when the economy recovers.

7 Optimal Macroprudential Policy

Lastly, we study the optimal policy problem of a financial regulator who chooses the tax rate in an environment with information frictions. By imposing a tax on credit spreads, the financial regulator seeks to maximize the present value of the households' utility. We simulate the model with different levels of tax rates for 100,000 periods and drop the first 20,000 periods.

Figure 16 compares the utility gains of the counterfactual model and the learning from prices model based on changes in the tax rate. Panel (a) shows that utility increases as the tax rate increases in the counterfactual model. This is consistent with the conventional wisdom that macroprudential policies benefit the economy. The red vertical line gives the optimal tax rate that maximizes the present value of households' utility.

Figure 16: Optimal Tax Rate



Notes: This figure presents the lifetime discounted utility in models with macroprudential policy. The top panel shows the model without learning from prices. The bottom panel shows the model with learning from prices. The vertical red line denote the level of optimal tax that maximizes household's lifetime discounted utility.

Figure 16 Panel (b) shows that in the learning from prices model, as the tax rate increases, utility increases at a faster rate before declining. Furthermore, utility declines steeply as the tax rate increases to about 0.5. Macroprudential policy becomes less beneficial as tax rate increases in the model with learning from prices. Here, the optimal macroprudential policy tax rate is 0.11, which is lower than that of the counter-factual model. This is due to the negative consequences of the interaction between macroprudential policy and learning from prices as highlighted in the previous section.

8 Conclusion

We have presented a model of credit cycles in which economic agents learn from prices. Our model finds that learning from credit spreads can amplify boom-bust dynamics. We find that firms with different levels of leverage benefit differently from the mechanism of learning from prices.

We further examine the interaction between learning from prices and macroprudential policy since the latter affects market prices. We find that firms with different levels of leverage benefit differently from macroprudential policy. Moreover, we find that these effects are state-dependent. In particular, macroprudential policies tend to be more harmful when the economy reverts to normal times after a recession.

Consequently, financial regulations that impact credit spreads could influence the beliefs of firms and investors. Under a framework of information frictions, our findings suggest that although macroprudential policies effectively curb the credit cycle, they might not be optimal if macroprudential policies are excessively tight.

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