Real Credit Cycles*

Pedro Bordalo† — *University of Oxford*
Nicola Gennaioli‡ — *Universita Bocconi*

Andrei Shleifer§ — *Harvard University*
Stephen J. Terry¶ — *Boston University*

December 2020

(First draft July 2019)

Abstract

We assess whether belief overreaction to standard TFP shocks may produce observed boom-bust credit cycles. We incorporate diagnostic expectations into a workhorse business cycle model with heterogeneous firms and risky debt. A realistic degree of diagnosticity, estimated from the forecast errors of managers of US listed firms, produces significant fragility of the economy during good times. This helps account for countercyclical credit spreads and for credit cycles at both the firm and aggregate levels. Lax financial conditions predict future increases in spreads, low bond returns, and investment drops. Spread increases of the magnitude observed during 2008-9 obtain from modest negative TFP shocks. Our results indicate that diagnostic expectations may offer a realistic and parsimonious way to produce financial reversals in conventional business cycles models.

*We thank audiences at FRB Minneapolis, Yale Finance, Harvard Business School Finance, NBER Behavioral Macro, Stanford SITE Uncertainty, NHH, the European Central Bank, Boston University, Harvard Economics, NBER Impulse and Propagation Mechanisms, Queen Mary University of London, the Econometric Society, and CREi-UPF, as well as our discussant Alp Simsek, for valuable comments and suggestions.

†pedro.bordalo@sbs.ox.ac.uk
‡nicola.gennaioli@unibocconi.it
§shleifer@fas.harvard.edu
¶stephent@bu.edu

1 Introduction

Developed economies experience recurrent boom-bust cycles in financial and economic activity. In the US, buoyant credit markets - measured by low credit spreads - tend to be followed by a financial tightening, in which credit spreads rise, investment growth drops, and GDP growth declines (López-Salido et al., 2017). In panels of developed countries, rapid credit expansions (Schularick and Taylor, 2012) and growth of private debt (Mian et al., 2017; Greenwood et al., 2020) forecast declines in real economic activity.

According to a longstanding hypothesis (Minsky, 1977; Kindleberger, 1978), these boom-bust cycles are driven by non-rational beliefs. During good times, the argument goes, investors are too optimistic, so credit and investment overexpand. Subsequently, beliefs cool off, credit markets tighten, real activity declines, and default rates increase. In this mechanism, inflated expectations and their disappointment play a key role. Two sets of facts are consistent with this view. First, credit booms predict low and even negative returns on corporate bonds and bank stocks (Baron and Xiong, 2017; Greenwood and Hanson, 2013). This finding is consistent with overoptimistic pricing of credit risk in the boom. Second, there is direct evidence from expectations data. When credit spreads are low, credit analysts forecast spreads to be too low in the future (Bordalo et al., 2018), and stock analysts are systematically too optimistic about the future profitability of risky firms (Gulen et al., 2019). This evidence suggests that beliefs overreact to current conditions, becoming too optimistic in good times and too pessimistic in bad times. Can such overreaction produce the boom-bust fluctuations of financial and real aggregate activity observed in reality, and can it shed light on the nature of economic fragility?

We address this question by presenting a workhorse real business cycle (RBC) model in which investors overreact to total factor productivity (TFP) news. We modify a standard heterogeneous firm model (Bachmann et al., 2013; Khan and Thomas, 2008) by a single parameter that regulates the overreaction of beliefs. We estimate the model using firm-level data, which crucially includes data on managers' expectations about their firms' profitability. We show that a realistic degree of overreaction generates dynamics that match qualitatively, and to a good extent quantitatively, the cycles in spreads, bond returns, and investment at both the firm and aggregate levels. The rational expectations model estimated on the same data can neither match the expectations data nor produce credit cycles. A single parameter controlling the extent of belief overreaction offers a promising and parsimonious way to obtain realistic boom-bust credit cycles in standard business-cycle models.

The paper proceeds as follows. In Section 2 we present novel evidence based on microdata that directly connects expectations to credit spreads, bond returns, and investment at the firm level. We first show that managers' expectations of their firms' profits overreact to current conditions:

they are too optimistic in good times and too pessimistic in bad times. In turn, excess optimism about a firm's future profits measured from expectations data predicts a one year-ahead increase in the firm's credit spread, low realized returns on the firm's bonds, and a decline in its investment growth. Overreacting beliefs appear to be directly linked to firms' financial and real cycles.

In Section 3 we present our formalization of non-rational beliefs, based on diagnostic expectations (DE) (Bordalo et al., 2018). This model is founded in the psychology of selective recall. The idea is that, because good news increases the objective likelihood of good future outcomes, good news also causes good outcomes to be top of mind and thus overweighted in beliefs. In our setting an implication of diagnostic beliefs is as follows:

$$\mathbb{E}_t^{\theta}\left(A_{t+1}\right) = \mathbb{E}_t\left(A_{t+1}\right) + \theta\left[\mathbb{E}_t\left(A_{t+1}\right) - \mathbb{E}_{t-1}\left(A_{t+1}\right)\right], \tag{1}$$

where A_{t+1} is future TFP, $\mathbb{E}_t\left(\cdot\right)$ is the rational expectation at time t, and $\theta \geq 0$ is a diagnosticity parameter. When $\theta = 0$ expectations are rational. When $\theta > 0$ agents overreact to news, becoming too optimistic after good news and too pessimistic after bad news.

DE have several advantages relative to other formulations such as mechanical extrapolation or adaptive expectations. First, they are forward-looking and are therefore not directly vulnerable to the Lucas (1976) critique. Second, DE account better for survey evidence on the expectations of financial analysts (Bordalo et al., 2019) and macroeconomic forecasters (Bordalo et al., 2020). Third, the diagnosticity parameter θ has already been estimated using such data, and this set of external estimates offers an important out of sample check for our results.

To assess whether DE yield realistic aggregate credit cycles, in Sections 4 and 5 we build and estimate an RBC model in which firms are subject to idiosyncratic and common TFP shocks, both of which follow AR(1) processes. Each firm optimally decides whether to default, how much labor to hire, how much to invest subject to adjustment costs, as well as how much equity and how much debt to issue. Deep-pocketed risk neutral lenders provide credit. Both managers and lenders hold identical diagnostic expectations. We mostly focus on a partial equilibrium setting: labor is infinitely elastic at an exogenous fixed wage. We later endogenize wages. We structurally estimate the model by matching moments on firm-level profitability, spreads, debt, investment, and, crucially, forecast errors. The estimated degree of diagnosticity $\theta \sim 1$ is in the ballpark of previous estimates (Bordalo et al., 2019, 2020; Pflueger et al., 2020; d'Arienzo, 2020). Despite its nonlinearity and the overidentified estimation with more target moments than parameters, our DE model captures both the volatilities of, and to a large degree the correlations between, real variables, beliefs, and financial outcomes in the firm data. To assess the role of overreacting expectations on macro outcomes, we also estimate and simulate a rational expectations (RE) model with θ fixed at 0, which does not match predictable forecast errors at the firm level.

Two key properties emerge from the analysis. First, the DE model matches untargeted macro moments significantly better than the RE model, including the observed countercyclicality of credit spreads. This is a robust implication: overreaction magnifies the volatility of beliefs of investors and firms, but such excess volatility disproportionately affects the supply of credit. Fluctuations in credit demand are dampened by diminishing returns and bankruptcy costs. In good times overoptimistic investors are willing to supply all the extra capital demanded at a lower spread. In bad times the reverse is true. In the RE model, beliefs are less volatile and shifts in credit demand are relatively more important, generating procyclical spreads.

Second, under DE, but not under RE, the reaction of aggregate investment to a given TFP shock is highly nonlinear. In good times, even a small negative TFP shock causes a large drop in aggregate investment, which is not the case when the same shock hits in normal times. Fragility during good times occurs because overoptimism and hence excess debt issuance is followed by a strong downward revision of beliefs when the adverse shock hits. Debt is then sharply repriced and investment is cut. In this sense, DE offer a belief-based theory of the "financial shocks" evident in macro-financial data (Gilchrist and Zakrajšek, 2012) by generating non-fundamental increases in the cost of credit caused by the waning of optimism.

In Section 6 we assess the ability of this mechanism to account for observed credit cycle facts. Using simulated data, we first show that the DE model yields predictable boom-bust dynamics in investment and credit spreads and also predictable bond returns at both the aggregate (López-Salido et al., 2017; Greenwood and Hanson, 2013) and the firm levels. The RE model can generate some reversals in spreads from mean reversion in productivity but cannot account for any of the other facts. Although our DE model, unlike the RE model, generates these predictable credit cycles, we also note that recurrent aggregate credit cycles in the data are quantitatively larger than those accounted for by our parsimonious supply-driven DE model, suggesting room for additional mechanisms to play a role. For example, factors such as shifts in aggregate demand (Farhi and Werning, 2020), time-varying capacity utilization (King and Rebelo, 1999), or sharp cuts to firm-level employment in bad times (Ilut et al., 2018) could all amplify the magnitude of the predictable reversals in our DE model by reacting to reversals in beliefs.

We also ask how large a TFP shock is required in our model to produce the massive increase in credit spreads observed during 2007-09 and investigate the macroeconomic implications of such a shock. Although our model does not capture some features of the crisis, such as the gradual inflation of house prices and the role of financial intermediaries, we view this exercise as a "stress test" of its ability to produce large financial crises. The result from this exercise is surprising: the empirically observed TFP decline of 1.5% is exactly sufficient to justify the observed increase in credit spreads in 2007-09. Moreover, it generates drops in aggregate investment, credit, and in earnings expectations that are quantitatively consistent with the data. The RE model does not produce these large macroeconomic movements with the same TFP shock. The belief reversals of our model appear to capture important elements of large-scale crises.

In Section 7 we report two robustness exercises. First, we simulate a version of the model in which only firms have diagnostic expectations while lenders hold rational expectations. In this model, credit cycles are dampened, consistent with the centrality of an overreacting supply of capital for our findings. Second, we endogenize the real wage by adding to the model a labor choice with convex effort cost. As expected, endogenous wage adjustments dampen financial volatility: in good times real wages increase, reducing the incentives of firms to lever up and invest. This effect, however, does not eliminate increased fragility after good times, which remains sizable even with fully flexible wages.

Our paper is related to two strands of work in macroeconomics. A large literature studies financial frictions as amplifiers of economic shocks (Bernanke and Gertler, 1989; Bernanke et al., 1999; Kiyotaki and Moore, 1997). Some of this work views prolonged recessions after financial booms as the result of fire sales (Shleifer and Vishny, 1992; Lorenzoni, 2008; Stein, 2012; Dávila and Korinek, 2017), intermediary leverage/bank runs (Brunnermeier et al., 2012; He and Krishnamurthy, 2019; Eggertsson and Krugman, 2012; Guerrieri and Lorenzoni, 2017), demand externalities (Farhi and Werning, 2016; Korinek and Simsek, 2016), and slow reallocation of excess-capital toward more productive sectors Rognlie et al. (2018). This work adopts rational expectations, so it cannot account for predictable expectations errors. To capture non-fundamentals driven crises, this work often relies on "financial shocks" to required returns or collateral constraints, or multiple equilibria (Gu et al., 2013). Arellano et al. (2019) analyze the 2008 crisis by adding uncertainty shocks to a standard business cycle model. This helps account for the decline in debt purchases, output, and labor during the Great Recession, despite the relative stability of TFP.

Relative to this work, we introduce diagnostic expectations in a standard RBC model with financial frictions and also estimate the model using information from expectations micro data. We show that realistic overreaction generates substantial financial shocks and credit cycles from small TFP shocks. It will be interesting for future work to combine diagnostic expectations with the amplification mechanisms above. There are some early attempts. Maxted (2020) introduces diagnostic expectations into He and Krishnamurthy (2019)'s model. Krishnamurthy and Li (2020) also jointly consider beliefs and intermediation within this type of framework. Farhi and Werning (2020) analyze demand externalities in a model with extrapolative expectations.

A second strand of work studies departures from rationality, often in the form of partial information and inattention. This work typically does not consider belief overreaction and does not study credit cycles. Coibion and Gorodnichenko (2015) link macroeconomic forecast errors to information rigidities as in Woodford (2003). Kohlhas and Walther (2020) model asymmetric attention paid to distinct macroeconomic variables. Kozlowski et al. (2017) links belief dynamics to the persistence of the Great Recession. Angeletos et al. (Forthcoming) relies on dispersed information and overextrapolation about macroeconomic outcomes. Falato and Xiao (2020) models imperfect information and learning about corporate profits. Adam et al. (2017) models asset price booms relying on subjective price beliefs by investors. Schaal and Taschereau-Dumouchel (2020) models herding and dispersed information in a setting that generates boom-bust dynamics. Bianchi et al. (2020) measures macro belief distortions using professional forecaster data. Bhandari et al. (2019) and Jaimovich and Rebelo (2007) study the impact of other belief distortions on business cycles in quantitative macro models without financial frictions.

Finally, behavioral finance has studied the role of beliefs in credit cycles, but without assessing quantitatively the promise of this approach. Bordalo et al. (2018) offers a stylized model of credit cycles with diagnostic expectations. Greenwood et al. (2019) builds a model in which credit markets extrapolate from recent default history, so that crises are slow moving. Richter and Zimmermann (2020) studies bank profits and the occurrence of banking crises with behavioral beliefs. Fostel and Geanakoplos (2014) and Simsek (2013) emphasize belief heterogeneity.

2 Evidence on Firm-Level Credit Cycles

If aggregate credit cycles are produced by overreacting beliefs, the same mechanism should produce credit cycles at the firm level. When a firm goes through good times, overreaction should cause excess optimism about its future prospects. When such optimism is systematically disappointed, there should be: i) a predictable increase in the firm's credit spread, ii) predictably low returns on the firm's bonds, and iii) a predictable drop in the firm's investment. This section shows that such predictable firm-level cycles indeed occur, even after controlling for macro shocks. In Section 5 we use this firm-level variation to estimate our model and see whether it can account for boom-bust cycles in the macroeconomy.

We use micro data on firm-level forecasts from the IBES manager guidance database. This panel records, for an individual firm-fiscal year, the prediction offered by the firm's management for their own company's profits or earnings over the next year. We exploit bundled forecasts, i.e., predictions made concurrently with the release of the current year's financials, in a sample spanning the 1999-2018 period. The data from US public firms links to the Compustat database providing the standard firm financial information. To study firm-level credit spreads, we use the Mergent Fixed Income Securities Database (FISD), which contains issuance information on individual securities. We obtain data on bond returns using the FINRA's Trade Reporting and Compliance Engine (TRACE) dataset, which contains detailed information on secondary market transactions from bond dealers. The combined FISD-TRACE bond return sample covers the years 2003-2018. Appendix B provides more information on the data sources, our sample construction, descriptive statistics, etc.

Table 1: Predictable Forecast Errors

	(1)	(2)	(3)	(4)
	Fcst. Error_{t+1}	Fcst. Error_{t+1}	Fcst. Error_{t+1}	Fcst. Error_{t+1}
Forecast_t	-0.242***			
	(0.030)			
Profits_t		-0.043***		
		(0.021)		
Investment_t			-0.455***	
			(0.065)	
Debt Issuance_t				-0.040***
				(0.007)
Firm Effect	X	X	X	X
Time Effects	X	X	X	X
Years	1999-18	1999-18	1999-18	1999-18
Firm-Years	9664	9664	9664	9664

Notes: The table reports estimates of specifications on the merged Compustat - IBES Guidance sample at the firm-fiscal year level. Forecasts are earnings guidance, profits are earnings, investment is tangible capital expenditures, debt issuance is end-of-period net debt, and forecast errors are actual earnings minus manager guidance at a 1-year horizon. All series are relative to firm tangible capital stocks at the beginning of the year. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of future forecast errors is 0.784, the standard deviation of forecasts is 0.925, the standard deviation of profits is 1.031, the standard deviation of investment is 0.233, and the standard deviation of debt issuance is 3.803. For all series, 0.01=1% relative to a firm's tangible capital stock.

To begin, we assess whether expectations of firm profitability overreact to current conditions. We regress next year's firm-level forecast errors, defined as realized minus predicted profits, on current-year firm-level financial outcomes. Under rational expectations, the manager's forecast errors should be unpredictable based on any information available to the firm when the forecast is made. In contrast, if beliefs about the firm's earnings overreact, displaying overoptimism during good times and undue pessimism during bad times, then future forecast errors should be negatively correlated with current firm-level fundamentals.

Table 1 reports the results. Each specification includes firm and time effects, identifying solely off of within-firm variation not driven by common shifts across firms. In column (1), we see that firms making high forecasts of earnings for next year experience more negative earnings surprises on average. In column (2), firms with higher profits today are systematically disappointed next year. In column (3), firms investing more today issue overly optimistic forecasts. Column (4) reports that firms issuing more debt today are also disappointed next year. The magnitudes are meaningful. For example, a one-standard deviation higher firm investment rate, about 23% higher, is on average associated with 23% $\times$ 0.455 $\approx$ 11% stronger disappointment in earnings next year. The evidence on managers' beliefs is consistent with belief overreaction, confirming the findings obtained by Gennaioli et al. (2016) using different data.[1,2]

A series of checks in the empirical Appendix B establishes robustness in the conclusions from Table 1 to a range of different sample and specification choices. We exclude the Great Recession in Table B2, to check whether these patterns are driven by a single episode. Motivated by the arguments in Bertomeu et al. (2020) that forecast manipulation is more common in firms that report fewer forecasts, in Table B3 we drop firms with fewer than five years of earnings guidance. We exclude firms with high-yield debt in Table B4 to verify that our findings are not driven only by the riskiest firms. We also control flexibly for firm-level trends, running regressions in first differences in Table B5. In all cases, we continue to find statistically precise evidence consistent with belief overreaction with small differences in magnitudes.

Building on this analysis, we next assess whether the overreaction of beliefs is associated with firm-level credit cycles. Table 2 estimates a range of specifications on our sample combining data on firm financials, earnings forecast errors, and bond returns. Columns (1), (3), and (5) report OLS regressions. Firms with lower forecast errors – lower profits relative to expectations – experience lower bond returns, higher spread growth, and lower investment growth, with varying degrees of precision in our OLS estimates across outcomes. This pattern of results is, however, consistent with rational expectations because future news can drive all of these outcomes.

To check whether periods of *overoptimism* predict low bond returns, rising spreads, and declining investment, we run an IV regression. In the first stage, which is an analogue of the results from Table 1 for this sample, we regress future forecast errors on current investment. This allows us to identify times of excess optimism (pessimism) as those in which investment is so high (low) that it ex-ante predicts future negative (positive) forecast errors. Investment is a good first-stage predictor because, as shown in Gennaioli et al. (2016), it reflects the manager's beliefs without being affected by the measurement error that may contaminate survey expectations.

In the second stage, we regress bond returns, the change in credit spreads, and investment growth on the forecast errors predicted in the first stage. This IV strategy reveals whether the predictable reversal of expectations itself predicts reversals of firm-level conditions, a result that

[1] The recent literature on overreaction stresses the predictability of forecast errors from forecast revisions (Bordalo et al., 2020, 2019; Coibion and Gorodnichenko, 2015). Since manager profit forecasts are released less frequently, and for fewer horizons, we do not have enough data to perform this type of revision-based analysis.

[2] Bouchaud et al. (2019) study equity analysts' short-term earnings forecasts which, while correlated with manager forecasts, display a form of underreaction. Both the variable forecasted and the incentives involved are distinct in their sample.

Table 2: Linking Forecast Errors and Firm Credit Cycles

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$Return_t$	$Return_t$	Δ $Spread_t$	Δ $Spread_t$	Δ $Investment_t$	Δ $Investment_t$
Estimation	OLS	IV	OLS	IV	OLS	IV
Fcst. $Error_t$	0.001	0.007*	-0.004***	-0.011***	0.009	0.485***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.007)	(0.061)
First Stage		Fcst. $Error_t$		Fcst. $Error_t$		Fcst. $Error_t$
$Investment_{t-1}$		-0.562***		-0.562***		-0.562***
		(0.105)		(0.105)		(0.105)
Years	2003-18	2003-18	2003-18	2003-18	2003-18	2003-18
Firm-Years	2852	2852	2852	2852	2852	2852
Time Effects	X	X	X	X	X	X
First Stage F		28.94		28.94		28.94

Notes: The table reports estimates of specifications on the merged Compustat - IBES - FISD/TRACE sample at the firm-fiscal year level. The top panel plots OLS and IV second-stage estimates. The bottom panel, where relevant, reports IV first-stage estimates. Columns (3)-(4) control for lagged spreads, and columns (5)-(6) control for current profits in the second stage. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of the bond return is 0.014, the standard deviation of spread growth is 0.024, the standard deviation of investment growth is 0.090, the standard deviation of the forecast error is 0.438, and the standard deviation of lagged investment is 0.133. For all series, 0.01=1% relative to a firm's tangible capital stock.

is not consistent with rationality. Columns (2), (4), and (6) present the second-stage estimation results. In all these specifications, we control for time effects.[3] We find that periods for which beliefs about a firm are predictably overoptimistic and hence subsequently disappointed, controlling for macro shocks, also display disappointing returns on the firm's bonds, an increase in its credit spread, and a decline in investment.[4] The magnitudes are meaningful. For example, in column (2) a firm predictably disappointed with a one standard deviation lower forecast error sees its bond returns fall by $0.007 \times 0.438 \approx 0.3$ percentage points on average, a sizable decline relative to the standard deviation of around 1.4 percentage points for bond returns in our sample.

Can mean reversion in fundamentals account for the spread and investment reversals we observe? In the spread regressions in columns (3)-(4) we control for the lagged spread and in the investment regressions in columns (5)-(6) for current profits, so the results suggest otherwise.[5]

[3]If we add firm effects the results are confirmed directionally but we lose power in our first-stage regressions due to a smaller cross-sectional dimension due to the requirement that we also need firm-level credit spreads.

[4]In Appendix B we also check that these firm-level cycles are not driven by highly risky firms, which may display a stronger reaction to macro shocks. We thus repeat the exercise in Table B7 for the subset of investment grade firms, excluding all firms with high-yield debt. Our results are confirmed.

[5]The lagged spread and current profit controls, while reassuring, are not necessary for our results. Table B6 in the empirical Appendix B reproduces Table 2 without such controls, with little resulting change in our estimates.

Note also that such concerns are not relevant for realized bond returns, which should be unpredictable.[6]

To summarize, overreacting expectations are directly linked to reversals in bond returns, in spreads, and in investment at the firm level. Can this mechanism, once aggregated up, account for aggregate credit cycles? To address this question, Section 3 presents our formulation of expectations and shows in a stylized setting how it yields the firm-level cycles documented here. In Section 4 we incorporate these expectations into a standard heterogeneous firm RBC setting.

3 Diagnostic Expectations and Neglected Risk

3.1 Diagnostic Expectations

Diagnostic expectations are a model of belief formation that describes how probabilistic assessments depart from the Bayesian benchmark, accounting for a large and robust body of evidence that started with Kahneman and Tversky in the 1970s. As originally argued in Gennaioli and Shleifer (2010), the assessed probability of an event reflects its accessibility in memory:[7] an agent who receives new information selectively recalls outcomes that are historically most associated with the news and fails to recall outcomes that are less associated with it. Because judgments overweight what is top of mind, they overreact to news.

Bordalo et al. (2018) apply this principle to a dynamic setting in which an agent forecasts a variable X_t, say TFP, on the basis of its history. The true distribution is Markovian, denoted by $f\left(X_{t+1}\,|X_t\right)$, and stored in the agent's memory. Under DE, the agent's beliefs follow the distorted distribution:

$$f^{\theta}\left(X_{t+1}\,|X_t\right) \propto f\left(X_{t+1}\,|X_t\right)\left[\frac{f\left(X_{t+1}\,|X_t\right)}{f\left(X_{t+1}\,|\mathbb{E}_{t-1}\left(X_t\right)\right)}\right]^{\theta} \qquad (2)$$

where $\theta \geq 0$ and $\mathbb{E}_{t-1}\left(X_t\right)$ is the expectation of X_t conditional on information at $t-1$, computed using the memory database. The likelihood ratio measures the diagnosticity of outcome X_{t+1} on the basis of news at t, namely the increase in its probability relative to the case of neutral news $X_t = \mathbb{E}_{t-1}\left(X_t\right)$. θ captures the extent to which memory focuses on such diagnostic outcomes. When $\theta = 0$ there are no memory distortions, so expectations are rational.

Equation (2) simplifies the general DE formulation in two ways. First, it assumes that X_t is perfectly observable. Bordalo et al. (2019, 2020) allow for information frictions such as dispersed

[6]Here we implicitly rule out time variation in required returns. Models of time varying risk aversion are unable to account for the predictable negative excess returns on high yield bonds (Greenwood and Hanson, 2013) and are also not consistent with data on expectations of returns (Greenwood and Shleifer, 2014). Finally, data on earnings expectations outperform these models in accounting for stock price volatility (Bordalo et al., 2019).

[7]Bordalo et al. (Forthcoming (a)) present experimental evidence for the link between memory and probability assessments.

information about X_t. Second, Equation (2) captures overreaction to current news only. Other applications of DE allow for overreaction to a longer streak of news (Bordalo et al., 2019; d'Arienzo, 2020; Maxted, 2020). These features are psychologically plausible and can match persistent belief distortions, such as slowly brewing asset price bubbles (Bordalo et al., Forthcoming (b)). The specification of Equation (2) focuses our analysis on the basic overreaction mechanism.

DE offer multiple advantages relative to other models of non-rational expectations used in macroeconomics and finance. First, they are forward-looking: updating in (2) depends on the true data generating process $f(X_{t+1} | X_t)$. This is important not only methodologically from a traditional macro perspective (Lucas, 1976) but also in accounting for survey data. Belief revisions by professional forecasters are more aggressive for more persistent macroeconomic and firm-level variables (Bordalo et al., 2020, 2019; Afrouzi et al., 2020; Azeredo da Silveira et al., 2020). Forward-looking beliefs also reconcile, in a setting with dispersed information, the well-known sluggishness of consensus forecasts with overreacting individual-level forecasts (Bordalo et al., 2020; Coibion and Gorodnichenko, 2015). Finally, the forward-looking nature of DE accounts for the fact that overreaction is stronger for longer-term outcomes, which are truly more uncertain (d'Arienzo, 2020). The sensitivity of beliefs to the underlying data generating process is not achieved in mechanical models of belief formation such as adaptive or extrapolative expectations.

Second, in DE departures from rationality are disciplined by a single parameter θ. This parameter has now been estimated in different settings, ranging from financial analysts forecasting firm-level earnings (Bordalo et al., 2019), to professional forecasters predicting macroeconomic variables (Bordalo et al., 2020), to beliefs inferred from prices about interest rates (d'Arienzo, 2020), to stock price volatility (Pflueger et al., 2020). These estimates point to a value of θ between 0.5 and 1.5, providing a valuable external benchmark to discipline our quantitative exercise and assess its reliability.

3.2 Diagnostic Expectations and Supply-Driven Bond Pricing: A Toy Model

A stylized example illustrates how diagnosticity generates predictability of forecast errors and the boom-bust cycles documented in Section 2. Suppose that a firm seeks to roll over a fixed amount b of one period bonds by selling them to deep-pocketed risk-neutral lenders. Lenders demand a constant expected return R, which we normalize to one.

Debt is defaultable. If at t lenders believe that default in the next period occurs with probability δ_t^θ, they charge the firm an interest rate $\widehat{R}_t = \frac{1}{1-\delta_t^\theta}$. The spread paid by the firm is then given by:

$$\widehat{R}_t - 1 \equiv s_t = \frac{\delta_t^\theta}{1-\delta_t^\theta}. \tag{3}$$

Intuitively, s_t increases in the probability of default δ_t^θ perceived by investors. Suppose now that the firm defaults at time t if and only if its productivity is sufficiently low, $A_t < A^*$, where A^* is a given threshold. Suppose further that TFP follows an AR(1) process in logs, $\ln A_t = \rho \ln A_{t-1} + \varepsilon_t$, where $\rho \in (0,1)$ and ε_t is Gaussian with mean zero and variance σ^2. From Equation (2), at time t the diagnostic lenders *perceive* next period productivity to be Gaussian with mean:

$$\mathbb{E}_t^\theta \left(\ln A_{t+1}\right) = \rho \ln A_t + \theta \rho \varepsilon_t, \tag{4}$$

and variance σ^2. Relative to the rational benchmark, DE are too optimistic after good news $\varepsilon_t > 0$, and too pessimistic after bad news $\varepsilon_t < 0$. Beliefs exaggerate recent news but, because news is on average zero, they on average revert to rationality in one period. The perceived probability of default is then:

$$\delta_t^\theta = \Phi \left[\frac{\ln A^* - \mathbb{E}_t^\theta \left(\ln A_{t+1}\right)}{\sigma}\right], \tag{5}$$

where $\Phi(\cdot)$ is the standardized Gaussian CDF, which is too low after good news and too high after bad news.

In this stylized model, predictability of forecast errors follows directly from Equation (4):

$$Cov\left[\ln A_{t+1} - \mathbb{E}_t^\theta \left(\ln A_{t+1}\right), \ln A_t\right] = -\theta\rho\sigma^2 < 0.$$

High current productivity is associated with good news and thus with excessive optimism. As a result, when productivity is high forecasts are overoptimistic and hence systematically disappointed. This mechanism can account for the predictability of forecast errors in Table 1. By contrast, forecast errors are not predictable under RE with $\theta = 0$.

The model also has implications for the path of credit spreads. Substituting δ_t^θ (Equation 11) in (3) and linearizing the expression with respect to expectations about productivity around their long run zero mean yields:

$$s_t \approx s_\infty - s\mathbb{E}_t^\theta \left(\ln A_{t+1}\right), \tag{6}$$

where $s_\infty > 0$ is the long run spread and $s > 0$. The spread drops when creditors are more optimistic about future productivity. Inserting (4) above we obtain:

$$s_t \approx s_\infty (1-\rho) + \rho s_{t-1} - s\rho(1+\theta)\varepsilon_t + s\theta\rho^2\varepsilon_{t-1}. \tag{7}$$

Under RE, with $\theta = 0$, spreads mirror TFP and follow an AR(1) process with persistence ρ. Under DE, with $\theta > 0$, there are two differences. First, TFP shocks are amplified: after a positive TFP shock, beliefs become too optimistic and the spread drops too much. Second, part of the effect of current news reverts next period, as optimism wanes and the spread increases, as shown by the term $s\theta\rho^2\varepsilon_{t-1}$. According to Equation (7) the reversals in spreads documented in Table 2 conflate fundamental mean reversion in TFP (the term ρs_{t-1} in (7)), and waning of past optimism (the term $s\theta\rho^2\varepsilon_{t-1}$). Thus, after controlling for past spreads s_{t-1}, predictable reversals in spreads should capture reversals in beliefs.

Finally, the model generates predictability in bond returns. To see this, note that excess returns are predictable whenever the spread s_t differs from its RE counterpart s_t^*, obtained by setting $\theta = 0$ in Equation (7). The distortion in spreads is given by:

$$s_t - s_t^* \approx -s\rho\theta\varepsilon_t + s\theta\rho^2\varepsilon_{t-1}. \tag{8}$$

When current expectations are overly optimistic, $\theta\varepsilon_t > 0$, bonds are overpriced. As a result, bond returns tend to be predictably low. The converse holds when expectations are pessimistic.

In sum, DE for lenders can generate the firm-level boom-bust cycles in expectations, spreads, and returns documented in Section 2. Can they account for macro credit cycles as an overreaction to macro TFP shocks? To address this question, we next introduce a fully-fledged model with aggregate as well as idiosyncratic TFP shocks in which the demand for credit as well as real investment also adjust to TFP news.

4 RBC Model with Diagnostic Firms and Lenders

Firms with different and persistent productivities decide whether to default, hire labor, invest, issue equity, and borrow subject to capital adjustment costs. Credit is supplied by a continuum of risk neutral lenders. The only difference relative to a workhorse neoclassical model with firm heterogeneity and risky debt (Khan and Thomas, 2008; Arellano et al., 2019; Gilchrist et al., 2014), is that firms and lenders form expectations diagnostically.

Our main analysis is partial equilibrium. The risk-free rate R and the wage rate W are taken as given. In Section 7 we endogenize the wage. This is useful because overoptimistic beliefs may boost the demand of labor and hence the real wage, which could dampen the cycle. We instead maintain fixed the risk-free rate R, for two reasons. First, consumption-based models of required returns make predictions on expectations of returns that are inconsistent with measured expectations (Greenwood and Shleifer, 2014). Second, and related, the cyclical changes in the risk-free rate generated by consumption-based models are counterfactual relative to those observed in the data (Winberry, 2017; Cooper and Willis, 2015).[8]

[8] Recent work in quantitative macroeconomics studying firm heterogeneity (Khan and Thomas, 2008; Bachmann et al., 2013; Winberry, 2017) emphasizes that general equilibrium stochastic discount factor movements do not necessarily lead to a dampening of business cycle nonlinearities or investment dynamics if they are structured to produce realistic countercyclicality of real interest rates, while the traditional stochastic discount factor does in fact dramatically dampen investment dynamics through procyclical real interest rates. Our fixed real interest rate assumption here strikes a middle ground between these alternatives and is consistent with the evidence that the real interest rate is not particularly cyclical (Winberry, 2017; Cooper and Willis, 2015).

Time is discrete. We use $'$ to denote future values and $_{-1}$ to indicate lagged values. Uppercase letters refer to macro or common values, lowercase letters refer to idiosyncratic objects.

4.1 Firms

The generic firm has micro-level TFP z and is subject to macro level TFP A. It uses capital k and labor n as inputs to produce output according to a decreasing returns technology

$$y = Azk^{\alpha}n^{\nu}, \qquad \alpha + \nu < 1.$$

The log of micro TFP follows the AR(1) process

$$\log z' = \rho_z \log z + \varepsilon'_z, \quad \varepsilon'_z \sim N(0, \sigma_z^2), \quad 0 < \rho_z < 1 \;, \tag{9}$$

while the log of macro TFP follows a similar process with

$$\log A' = \rho_A \log A + \varepsilon'_A, \quad \varepsilon'_A \sim N(0, \sigma_A^2), \quad 0 < \rho_A < 1 \;. \tag{10}$$

Firms invest i in capital k with one-period time to build

$$k' = i + (1-\delta)k, \qquad 0 < \delta < 1.$$

Investment entails quadratic adjustment costs $AC(i,k) = \frac{\eta_k}{2}\left(\frac{i}{k}\right)^2 k$ indexed by $\eta_k > 0$.

Firms act competitively. In each period, the timing of events is as follows. First, each firm decides whether to default on its debt. If a firm defaults, its assets net of deadweight default costs are recovered by lenders, and the firm restarts with zero capital and debt after one period. If a firm repays, it hires labor at wage W and chooses how much to invest, how much equity to issue, and how much one-period debt to issue. Firms maximize the expected discounted sum of current and future payouts, where the discount rate $(1+R)^{-1} < 1$ reflects the exogenous risk-free rate R.

The firm's current dividend d is given by:

$$d = (1-\tau)\left[y - Wn - AC(i,k) - \phi\right] + q^{\theta}(s, k', b')b' - i - b + \tau(R + \delta k). \tag{11}$$

If $d < 0$ the firm issues equity which following Gomes (2001) is associated with the issuance cost $IC\,(d) = I\,(d < 0)\,(\eta_f + \eta_d\,|d|)$, where $\eta_f > 0$ is the fixed and $\eta_d > 0$ is the variable cost of issuance. The firm's profits are given by its output minus the wage bill, the adjustment cost, and a fixed production cost $\phi > 0$, net of the corporate income tax rate $\tau \in (0,1)$. The firm then raises additional resources by issuing new debt b' priced by the schedule q^{θ}, incurs the investment cost i, and repays its current debt b. Finally, the firm receives tax rebates for capital depreciation and interest expenses on debt.[9] This formulation of dividends and specification of firm fundamentals is standard (Strebulaev and Whited, 2012).

To decide whether to default and how much to borrow and invest, the firm forms beliefs about its future productivity. To assess default risk and interest rates, lenders must do the same. Firms and lenders form identical expectations diagnostically. Given the AR(1) processes (9) and (10), and given Equation (2), diagnostic beliefs over micro and macro TFP are described by the lognormal processes:

$$\log z'|(\log z, \varepsilon_z) \sim N\left[\rho_z(\log z + \theta\varepsilon_z), \sigma_z^2\right] \tag{12}$$

$$\log A'|(\log A, \varepsilon_A) \sim N\left[\rho_A(\log A + \theta\varepsilon_A), \sigma_A^2\right]. \tag{13}$$

When $\theta > 0$ the agent forecasts future productivity by overweighting current news, as if the true productivity process follows an ARMA (1,1).[10] $\theta > 0$ is the only difference between our model and a workhorse business cycle model.

When forming beliefs about a firm, diagnostic agents consider four state variables: its current micro TFP z, macro TFP A, the micro shock ε_z and the macro shock ε_A. We collect these exogenous states in the vector $s = (z, \varepsilon_z, A, \varepsilon_A)$. A firm is also identified by two endogenous states, its inherited capital stock k and debt b. Given an overall state (s, k, b), the firm defaults if its diagnostically expected value from doing so is greater than its perceived value without defaulting, and it repays otherwise. If the firm repays, it hires labor, invests, and borrows so as to maximize the sum of the current and diagnostically expected discounted future payouts, taking into account the possibility of default in the future.

This problem can be written in a recursive fashion. Upon entering the current period, the value of the firm is given by:

$$V^\theta(s, k, b) = \max\left[V_D^\theta(s), V_{ND}^\theta(s, k, b)\right], \tag{14}$$

where $V_{ND}^\theta(s, k, b)$ is the continuation value from not defaulting and $V_D^\theta(s)$ is the continuation from defaulting. Condition $V_{ND}^\theta(s, k, b) < V_D^\theta(s)$ identifies states in which the firm optimally defaults. The continuation value from not-defaulting is recursively determined as:

$$V_{ND}^\theta(s, k, b) = \max_{k', b', n}\left\{d - IC(d) + \frac{1}{1+R}\mathbb{E}^\theta\left[V^\theta(s', k', b')|s\right]\right\}. \tag{15}$$

If the firm does not default, it optimally hires labor n, sets future capital k' and debt b' so as to maximize its current dividend plus its diagnostically expected discounted future value

[9] For computational simplicity, we assume the rebate is on average equal to the cost of debt R.

[10] Another approach to capture extrapolation is Fuster et al. (2010)'s Natural Expectations, in which long lags in the data generating process are neglected by agents who end up overestimating short-term persistence in processes with long-term mean reversion. In the current AR(1) setting, such beliefs would be indistinguishable from RE.

$V^\theta(s', k', b')$.[11] The labor choice n is statically optimized, leaving only the intertemporal choices of k' and b'.

If the firm defaults, its assets k net of deadweight costs are claimed by lenders during a period of reorganization in which no production occurs. The firm then restarts with zero debt and assets:

$$V_D^\theta(s) = \left\{ 0 + \frac{1}{1+R} \mathbb{E}^\theta \left[V(s', 0, 0) | s \right] \right\}. \tag{16}$$

In particular, after defaulting a firm must borrow in order to invest.

Equations (14), (15), and (16) determine both the optimal firm default policy by $df^\theta(s, k, b)$ and, for those firms which choose not to default with $df^\theta(s, k, b) = 0$, the policies for endogenous states $k'^\theta(s, k, b)$ and $b'^\theta(s, k, b)$.

4.2 Lenders

Firms borrow from risk-neutral deep-pocketed lenders who require an expected return equal to the risk-free rate R. If a firm (s, k, b) defaults on its debt b, the lender receives the recovery rate

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

which reflects, net of tax, an exogenous fraction γ of the liquidation value $(1 - \delta)\, k$ of the firm's capital stock. The remaining fraction $1 - \gamma$ is a deadweight loss.

The price of debt $q^\theta(s, k', b')$ adjusts endogenously so that the diagnostically expected bond return is equal to the risk free rate R :

$$q^\theta(s, k', b') = \frac{1}{1+R} \mathbb{E}^\theta \left[1 + df^\theta(s', k', b') \left(\mathcal{R}(k', b') - 1 \right) | s \right]. \tag{17}$$

To equalize expected bond returns across firms, riskier firms promise a higher interest rate. Thus, the firm's interest rate spread relative to the risk-free rate is given by:

$$S^\theta(s, k', b') = \frac{1}{q^\theta(s, k', b')} - (1 + R).$$

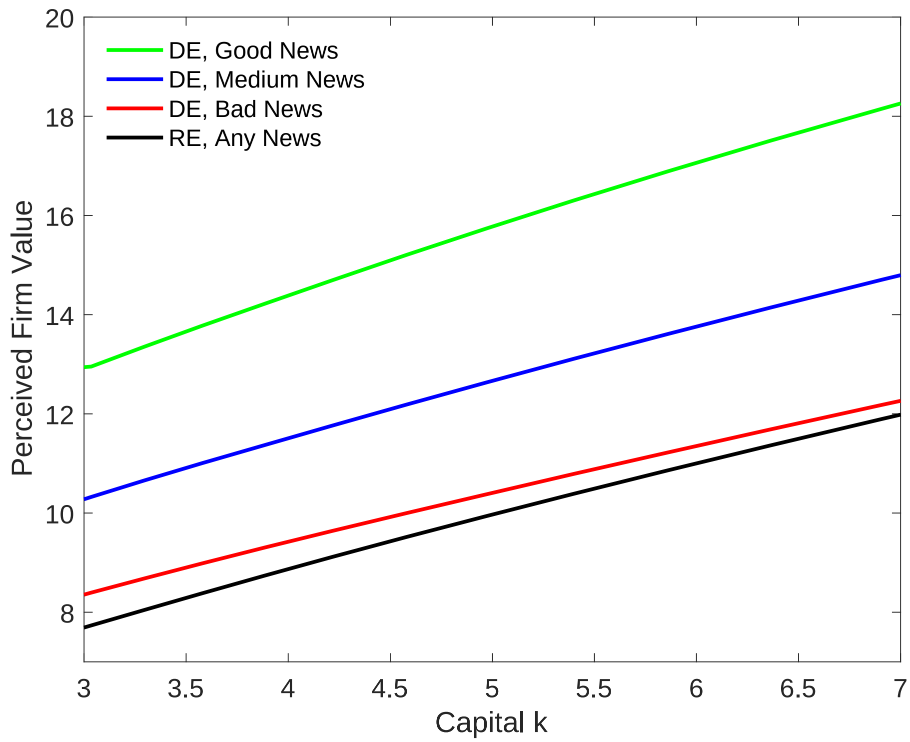
These equations illustrate how diagnosticity affects spreads. On the demand side, diagnosticity affects the firm's default $df^\theta(s, k, b)$, debt $b'^\theta(s, k, b)$, and investment $k'^\theta(s, k, b)$ policies. On the supply side, diagnosticity affects the probability of default perceived by lenders, as captured by the operator $\mathbb{E}^\theta(\cdot)$ in (17). We later analyze how these demand and supply forces separately contribute to macroeconomic fluctuations.

[11] We apply DE to the recursive formulation of the problem, Equation (15). The diagnostic agent believes that productivity follows an ARMA(1,1) and correctly thinks that he will continue to believe the same in the future. The recursive problem is equivalent to an optimal control problem in which the probability distribution of A_{t+s} at time t is the product $\Pi_{j=1}^{s} f^\theta(A_{t+j} | A_{t+j-1}, \epsilon_{t+j-1})$ of the conditional distributions between times t and $t + s - 1$. This distribution has the same mean as the time t diagnostic distribution $f^\theta(A_{t+s} | A_t, \epsilon_t)$ but has larger variance. This is due to overreaction to news (which are zero on average) in the intermediate periods.

4.3 Solving the Model

A solution to the model reflects a set of firm-level policies and values $b'^{\theta}, k'^{\theta}, df^{\theta}, V_{ND}^{\theta}, V_{D}^{\theta}$, and V^{θ} together with a debt price schedule q^{θ}. These objects must jointly satisfy optimization by firms, Equations (14), (15), and (16), as well as the lenders' zero-profit condition in Equation (17).

Figure 1: Firm Value and Diagnosticity



Notes: The figure plots the perceived value function as a function of firm capital k for the estimated DE model and in a comparably parameterized RE model. All lines hold fixed the value of micro TFP z, macro TFP A, macro news ε_A, and the firm's debt b. The first three lines, in the DE model, reflect different realizations of micro TFP news ε_z, with positive news (green line), medium news (blue line), and bad news (red line). The final line, from the RE model with $\theta = 0$, does not depend upon the value of micro TFP news ε_z because micro TFP z is fixed.

We solve the model numerically. In addition to the set of Bellman equations characterizing V^{θ}, V_{ND}^{θ}, and V_{D}^{θ}, the model features a crucial fixed point between firm default policies df^{θ} and credit prices q^{θ} in Equation (17). We employ an iterative approach detailed in Appendix A. First, we guess a firm default rule df^{θ}, computing the implied debt price schedule q^{θ} according to the lenders' zero-profit condition. Then, we solve the Bellman equations for V^{θ}, V_{D}^{θ}, and V_{ND}^{θ} using discretization and policy iteration. If the implied default states, i.e., those with $V_{ND}^{\theta} < V_{D}^{\theta}$, match the set of initial guesses, then the iteration is complete. Otherwise, we compute the newly implied default states and repeat the process. The algorithm we employ is standard within the literature solving quantitative dynamic corporate finance models and follows the implementation in

Strebulaev and Whited (2012). Our numerical approach here is highly computationally intensive, given the presence of four exogenous states, two endogenous states, an endogenous default rule, and a debt-pricing fixed point. However, judicious application of parallelization and an economical approach to storage of micro-level outcomes following Young (2010) and Terry (2017a) allow for solution of the model in several minutes in a desktop computing environment using Fortran.

To illustrate how diagnosticity affects firm-level outcomes, Figure 1 plots cross-sections of the value function in our baseline parameterization with DE ($\theta > 0$) versus RE ($\theta = 0$) as a function of capital k. The green, blue, and red lines in the figure plot the perceived value V^θ for a firm under DE with different realizations of micro TFP news ε_z but otherwise identical states $(z, A, \varepsilon_A, k, b)$. In the comparable curve in black for the RE case, firm value does not depend upon micro TFP news ε_z because the level of the Markov chain z is taken as given.[12] Intuitively, after good news, diagnostic firms are too optimistic, so they value capital more than an otherwise identical firm which recently experienced adverse news. These overoptimistic firms invest and borrow more, an effect that is absent in the RE case. Combined with diagnostic shifts in the supply of capital by lenders, this mechanism proves crucial for generating aggregate effects.

5 Model Estimation

Our model includes seventeen parameters, listed below in Tables 3 and 5. The seven parameters in Table 3 are set to values that are conventional for a model like ours solved at an annual frequency and featuring tangible capital and labor inputs. Given the similarity of the production structure and macro TFP fluctuations, we draw on Bloom et al. (2018) for a range of firm-level and macro TFP parameters. Information on corporate income taxes is obtained from the Congressional Budget Office (CBO, 2017).

We structurally estimate the remaining ten parameters by matching a set of both micro and macro moments. These parameters govern the micro-level TFP process ρ_z and σ_z, adjustment and operating costs η_k and ϕ, lender recovery rates γ, macro volatility σ_A, the equity issuance costs η_f and η_d, and crucially the diagnosticity parameter θ. We also estimate the volatility σ_π of iid measurement noise in profits. Allowing for such measurement noise is useful to capture accounting conventions that may create spurious variability in measured profits regardless of fundamentals.

We structurally estimate these ten parameters through a simulated method of moments (SMM) procedure targeting eighteen moments. Of these, fifteen are firm-level moments: the covariance matrix of investment rates, profits, debt, credit spreads, and, crucially, errors in firm forecasts

[12] The RE curve for perceived firm value lies uniformly below the DE curves in Figure 1. This level shift occurs because diagnostic firms have more volatile expectations of future TFP. Since decreasing returns in production imply convex firm payoffs as a function of TFP, the DE perceived value function lies above that in the RE case due to Jensen's inequality.

Table 3: Externally Fixed Parameters

	Parameter	Value	Explanation	Source
1	δ	0.1	Depreciation rate	Annual solution
2	R	0.04	Risk-free rate	Annual solution
3	α	0.25	Capital revenue elasticity	Bloom et al. (2018)
4	ν	0.50	Labor revenue elasticity	Bloom et al. (2018)
5	ρ_A	0.95	Macro TFP persistence	Bloom et al. (2018)
6	τ	0.20	Corporate income tax	Effective corporate tax rates, CBO (2017)
7	W	0.5	Wage	Normalization

Notes: The table reports the parameter symbol, numerical value, a description, and source information for each of the externally fixed parameters. Outside of the unit-free persistence or normalized parameters, all reported values are in proportional units, e.g. 0.01 = 1%.

of their own profits. We obtain the moments using our combined datasets with firm financials, earnings forecasts, and credit spreads described in Section 2. Just as in Section 2 we focus on idiosyncratic variation, residualizing the underlying series with respect to firm and time effects. We also target three macro moments in the SMM procedure to ensure appropriate scaling of the macro-financial structure of the model: the average credit spread, the average frequency of default, and GDP growth volatility. Table 4 reports the moments we target, including raw covariance values, standard errors clustered at the firm level, and more easily interpretable scaled values in standard deviation or correlation form. Given our use of ten parameters to target eighteen moments, we note at the outset that this is a highly overidentified structural estimation of a nonlinear model. We can therefore exploit a great deal of information but are not in general able to deliver an exact fit.

The key innovation in our estimation exercise is to add moments involving forecast errors and their link to the belief parameter θ. In the RE model with $\theta = 0$, future forecast errors should be unpredictable using any currently available information. In contrast, the DE model with $\theta > 0$ can capture the overreaction whereby expectations are too optimistic in good times and pessimistic in bad times. This yields predictions on the sign and magnitude of forecast errors, offering a good way to pin down θ.

The other moments are conventional, and their choice is natural given the parameters we seek to estimate. Firm profits and their correlations encode information about the productivity process at firms, helping to identify σ_z, ρ_z, and σ_π. Firm investment reflects also the various frictions such as adjustment costs operating at firms, helping to identify η_k. Debt issuance choices, together with credit spreads, aid in the identification of equity issuance costs η_f and η_d. Finally, mean default and spread values encode information about the fixed cost ϕ and recovery rate γ, while GDP growth volatility encodes information about macro shocks σ_A.

Table 4: Target Moments for SMM Estimation

Micro Moments				
Number	Moment	Value	SE	Scaled (SD/Corr)
1	Var(Fcst Error')	0.1359	0.0174	0.3687
2	Cov(Fcst Error' ,Profit)	-0.0057	0.0050	-0.0512
3	Cov(Fcst Error' ,Investment)	-0.0026	0.0010	-0.0974
4	Cov(Fcst Error',Debt')	-0.0425	0.0162	-0.1343
5	Cov(Fcst Error',Spread)	0.0000	0.0001	-0.0088
6	Var(Profit)	0.0922	0.0132	0.3036
7	Cov(Profit,Investment)	0.0053	0.0009	0.2395
8	Cov(Profit,Debt')	0.0245	0.0120	0.0939
9	Cov(Profit,Spread)	-0.0006	0.0001	-0.1626
10	Var(Investment)	0.0053	0.0006	0.0731
11	Cov(Investment,Debt')	0.0111	0.0023	0.1764
12	Cov(Investment,Spread)	-0.0001	0.0000	-0.0729
13	Var(Debt')	0.7363	0.0842	0.8581
14	Cov(Debt',Spread)	-0.0003	0.0002	-0.0317
15	Var(Spread)	0.0001	0.0000	0.0116
Macro Moments				
	Moment	Value	SE	Scaled (SD/Corr)
16	E (Spread)	0.0287	0.0048	0.0287
17	E(Default)	0.0035	0.0008	0.0035
18	Var(GDP Growth)	0.0002	0.0001	0.0141

Notes: The moments were computed on a sample combining information from the Compustat, IBES Manager Guidance, and FISD/Trace Bond databases from 2003-2018, with 2,921 firm-years spanning 387 firms. The reported standard errors for the micro moments are computed using firm-level clustering, and the reported standard errors for the macro moments are computed using a stationary block bootstrap. Scaled values are the associated standard deviation for variances, correlations for covariances, and preserve the mean for expectations. An apostrophe indicates future values. For the micro moments, the forecast error, profit, investment, and debt issuance series are expressed relative to firm tangible capital stocks, while the spread is in proportional units. For the macro moments, the mean spread is the average across years of the mean spread across firms in the FISD/Trace Bond-Compustat merged database, the mean spread is the average across years of the mean default rate across firms in the FISD/Trace-Compustat merged database. The GDP series in annual GDP in chained 2012 dollars.

To estimate the model parameters, we minimize the deviation between the empirical moments in Table 4 and those computed from a comparable unconditional simulation of the model. We weight the moments optimally using the inverse of our estimate of the moment covariance matrix, implying an asymptotically efficient SMM estimator. See Appendix B for a more detailed description of the variable definitions, our sample construction, and our approach to computing the SMM point estimates and standard errors.

As seen in Section 2, one key feature of the micro data is forecast error predictability, which is in particular reflected in the negative correlation between current firm outcomes and future forecast errors in rows (2)-(4) of Table 4. This pattern is at odds with RE and implies meaningfully sized values of $\theta > 0$.

Table 5: Estimated Parameters

Parameter Estimates				
Number	Parameter	Role	Value	SE
1	θ	Diagnosticity	1.069	0.116
2	ρz	Micro persistence	0.722	0.006
3	σz	Micro volatility	0.127	0.011
4	ηk	Capital adjustment cost	3.732	0.196
5	ϕ	Fixed operating cost	0.108	0.021
6	γ	Recovery rate	0.087	0.048
7	σA	Macro volatility	0.007	0.002
8	$\sigma\pi$	Profit noise	0.714	0.068
9	ηf	Equity issuance fixed cost	0.013	0.011
10	ηd	Equity issuance linear cost	0.021	0.005

Notes: The table reports point estimates and standard errors for each of the parameters in our SMM estimation. The moment covariance matrix is based on firm-level clustering in the micro block and a stationary block bootstrap in the macro block. The moment Jacobian is computed numerically. In the SMM estimation, the weighting matrix is optimal, i.e., the inverse of the moment covariance matrix.

Table 5 reports the SMM point estimates and standard errors for our DE model. We later discuss how these values fit the data moments. The diagnosticity parameter $\theta \approx 1$ is in the same ballpark as the values found by Bordalo et al. (2018) using data on professional forecasts of credit spreads ($\theta = 0.9$), by Bordalo et al. (2019) using analyst expectations of US listed firms' long term earnings growth ($\theta = 0.9$), by Pflueger et al. (2020) using stock price-derived measures of risk perception ($\theta = 1$), by d'Arienzo (2020) using bond prices ($\theta = 1$), and by Bordalo et al. (2020) using professional forecasts of several macro series ($\theta = 0.5$). A value of θ close to 1 means that forecast errors are roughly equal to the size of incoming news.

The estimated values governing physical factors such as micro TFP volatility σ_z and capital adjustment costs η_k are close to those from other work calibrating or structurally estimating firm-level shock processes with Compustat data (Gourio and Rudanko, 2014; Terry, 2017b; Khan and Thomas, 2008; Saporta-Eksten and Terry, 2018). The parameters governing financial frictions indicate equity issuance costs η_f, η_d and recovery rates γ comparable to those in Hennessy and Whited (2007). The fixed operating costs ϕ in model units is mainly linked to average default rates and spreads. Finally, the estimated measurement error volatility for profits σ_π suggests that a high degree of noise in accounting conventions is needed to match the covariance of profits and other firm-level outcomes.

Table 6: Estimated Parameters: Constrained Rational Model

Parameter Estimates				
Number	Parameter	Role	Value	SE
1	ρz	Micro persistence	0.794	0.011
2	σz	Micro volatility	0.185	0.010
3	ηk	Capital adjustment cost	3.815	0.491
4	ϕ	Fixed operating cost	0.070	0.011
5	γ	Recovery rate	0.159	0.058
6	σA	Macro volatility	0.007	0.002
7	$\sigma\pi$	Profit noise	0.847	0.052
8	ηf	Equity issuance fixed cost	0.013	0.004
9	ηd	Equity issuance linear cost	0.041	0.031

Notes: The table reports point estimates and standard errors for each of the parameters in our SMM estimation which imposes rational beliefs with θ=0. The moment covariance matrix is based on firm-level clustering in the micro block and a stationary block bootstrap in the macro block. The moment Jacobian is computed numerically. In the SMM estimation, the weighting matrix is optimal, i.e., the inverse of the moment covariance matrix.

Using the same micro and macro moments, we also conduct a constrained SMM structural estimation exercise to estimate the nine parameters of a RE model in which we constrain $\theta = 0$ and eliminate diagnosticity in beliefs. By comparing the performance of this estimated RE model and the estimated DE model, we can assess the consequences of overreacting beliefs. The SMM point estimates and standard errors for the parameters of the RE model are in Table 6. Comparing the DE vs RE parameter estimates, we see that we estimate a lower persistence ρ_z and volatility σ_z of micro TFP shocks in the DE model, because diagnosticity itself amplifies perceived volatility and persistence. We estimate a slightly lower volatility σ_A of aggregate TFP in the RE model than in the DE case, although in both models the standard deviation of the shock is around 0.7% per year. Also, because diagnostic beliefs — by inflating a firm's perceived volatility of TFP shocks in a context where production function-based payoffs are convex — reduce a firm's average incentive to default, we estimate a higher fixed operating cost ϕ in the DE model needed to match the observed default frequency.

Table 7 reports the fit of the micro moments relative to the data for both the estimated DE and RE models. The DE model offers an excellent match of the micro moments, especially taking into account its strong nonlinearity and the overidentified nature of the SMM estimation. The DE model matches both the predictable disappointment of firms after high profits, investment, and debt issuance. Because firms in the DE model respond to both the level and the news in TFP, the correlation of profits with firm investment and debt issuance policies is realistically moderate.

There are two main discrepancies with the data. First the DE model predicts a stronger correlation between firm-level debt and profitability than seen in the data. Second, while the DE model is good at capturing the negative correlation between investment and spreads, it does not capture the negative correlation between profitability and spreads at the micro level. In our model, highly profitable firms, which generally have high micro TFP, choose to issue a lot of debt, endogenously increasing their riskiness. This results in low correlation between spreads and profits in equilibrium, and high correlation between debt and profits. We speculate that an extended version of our model allowing for empirically important costs of debt financing, such as restrictive contractual covenants, would moderate debt movements and improve the already strong fit of our DE model to the data.

As evident from Table 7, the challenges with debt correlations remain, in exaggerated form, in the RE model. Most importantly, the RE model cannot match the high predictability of forecast errors, nor can it generate a meaningful default frequency. This set of results is important: in the DE model, overoptimistic expectations create overindebtedness and hence realistically higher default frequencies than in the RE model in which there is no overexpansion of leverage in response to good shocks. [13]

In Section 6 we show that these differences between the DE and RE models prove critical to account for recurrent credit cycles, both at the aggregate and the firm levels. But first, in Section 5.1 we examine the real side of the macroeconomy and consider nonlinearities in the macro investment response to a TFP shock. In Section 5.2 we simulate the model and analyze its ability to match untargeted but traditional macro correlations, placing particular emphasis on the correlation between credit spreads and economic activity.

5.1 Diagnosticity and the Nonlinear Response of Investment to Shocks

To study the real implications of DE, we simulate the contemporaneous response of macro investment, a real variable that reflects firms' beliefs, to a negative macro TFP shock. We compute

[13] The RE model also features too high a correlation between profitability and investment. In the DE model, this correlation is muted because investment depends, via beliefs, on the TFP shock rather than just on its level.

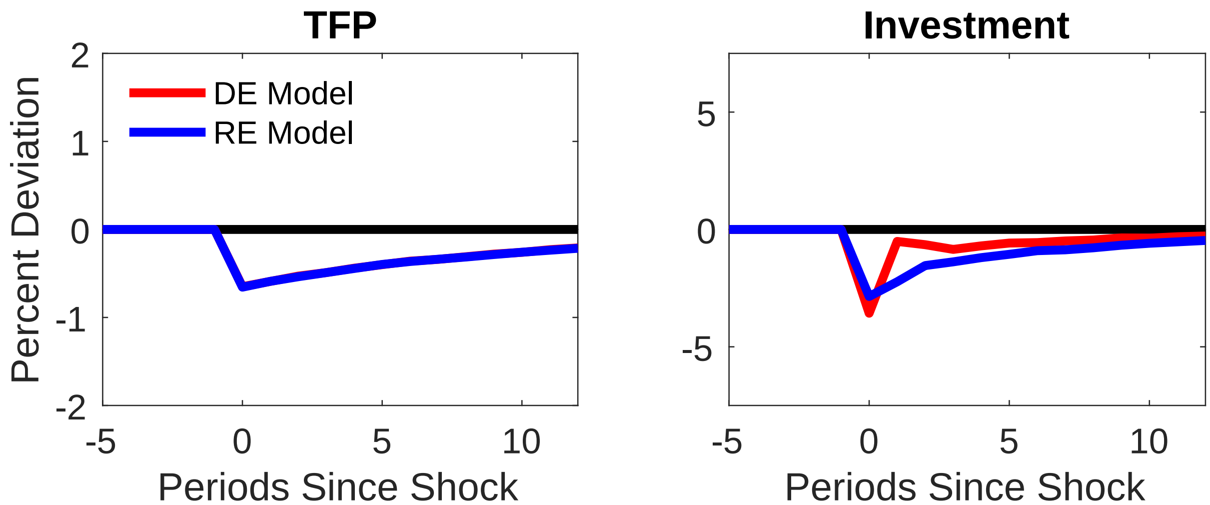
Table 7: Model vs Data Moments

Number	Moment	Data	DE Model	RE Model
	Micro Moments			
1	Std Dev(Fcst Error')	0.3687	0.2687	0.3387
2	Corr(Fcst Error' ,Profit)	-0.0512	-0.0319	-0.0031
3	Corr(Fcst Error' ,Investment)	-0.097	-0.119	-0.002
4	Corr(Fcst Error',Debt')	-0.134	-0.111	-0.002
5	Corr(Fcst Error',Spread)	-0.009	0.008	-0.001
6	Std Dev(Profit)	0.304	0.271	0.361
7	Corr(Profit,Investment)	0.239	0.264	0.343
8	Corr(Profit,Debt')	0.094	0.295	0.369
9	Corr(Profit,Spread)	-0.163	0.006	0.007
10	Std Dev(Investment)	0.073	0.076	0.071
11	Corr(Investment,Debt')	0.176	0.474	0.357
12	Corr(Investment,Spread)	-0.073	-0.064	-0.043
13	Std Dev(Debt')	0.858	0.810	1.197
14	Corr(Debt',Spread)	-0.032	-0.025	-0.027
15	Std Dev(Spread)	0.012	0.009	0.015
	Macro Moments			
	Moment	Data	DE Model	RE Model
16	E (Spread)	0.029	0.018	0.019
17	E(Default)	0.004	0.003	0.001
18	Std Dev(Δ GDP)	0.014	0.014	0.013

Notes: The data column reports the empirical values of the target moments for our SMM exercise. The DE model column reports the target moments at our estimated parameters from the diagnostic expectations model. The RE model reports the target moments at our estimated parameters from the constrained rational expectations model. The empirical moments were computed on a sample combining information from the Compustat, IBES Manager Guidance, and FISD/Trace Bond databases from 2003-2018, with 2,921 firm-years spanning 387 firms. The model moments are based on a simulation of 1,000 firms for 250 years. An apostrophe indicates future values. For the micro moments, the forecast error, profit, investment, and debt issuance series are expressed relative to firm tangible capital stocks. For the macro moments, the mean spread is the average across years of the mean spread across firms, the mean spread is the average across years of the mean default rate across firms.

this response for different initial conditions, captured by TFP shocks of varying magnitudes in the previous period. This exercise allows us to highlight one important consequence of DE: fragility after good times. This nonlinearity or state-dependence is critical to account for boom-bust credit cycles.

Figure 2: Investment Response to a Negative TFP Shock



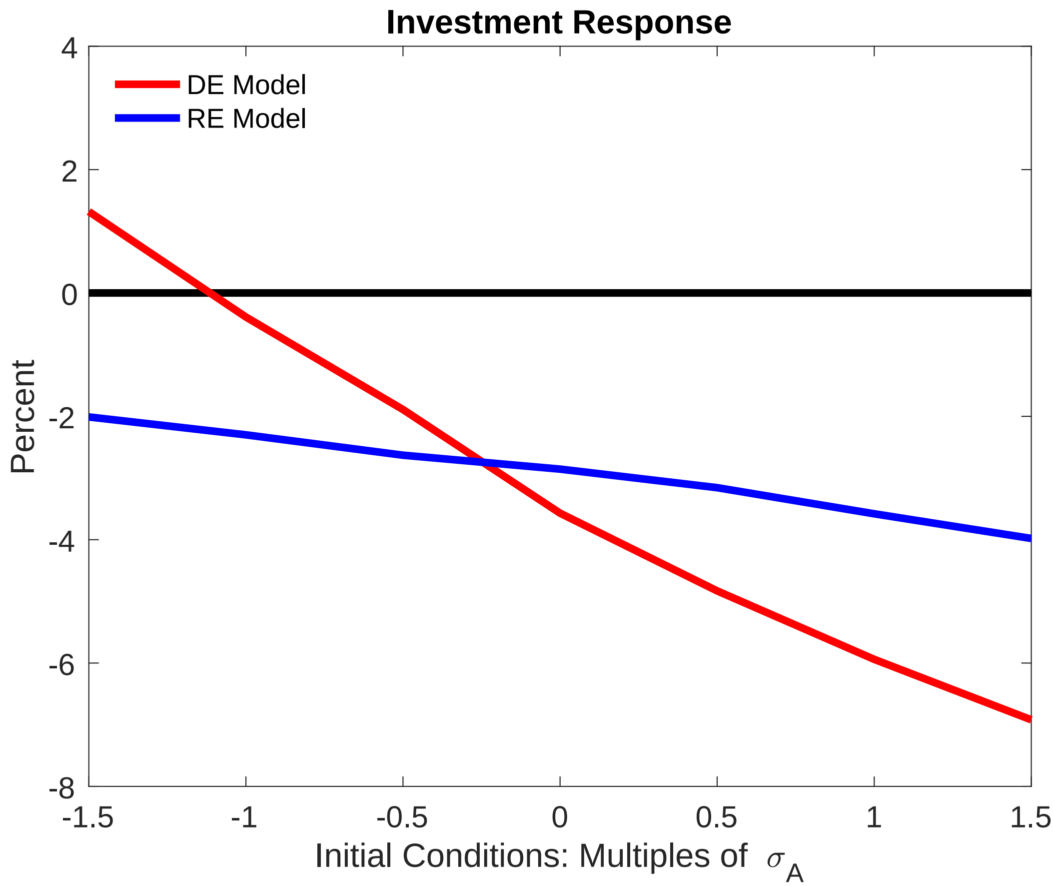
Notes: The figure plots the simulated generalized impulse responses of investment (right panel) to a one-standard deviation negative shock to macro TFP (left panel) occurring at period 0. The DE model (red) and RE model (blue) paths are based on identical shocks to TFP over 10,000 simulated experiments following the Koop et al. (1996) methodology.

Figure 2 plots the average impulse response of investment to a negative shock to macro TFP in both the DE model (red line) and RE model (blue line).[14] These responses reflect "typical times," based on simulated reactions to negative TFP shocks across 10,000 experiments following the methodology of Koop et al. (1996). In normal times, the investment responses to TFP shocks differ only slightly across the DE and RE models. As usual in RBC models, a negative shock to TFP causes a large decline in investment. There is some amplification of the DE model relative to the RE model, but the paths are otherwise fairly similar.

With these baseline responses in hand, we simulate the impact of the same negative shock to macro TFP, varying the initial conditions in a flexible manner. Figure 3 reports the investment response in the DE model (vertical axis, red line) as a function of the magnitude of the previous period's macro TFP shock (horizontal axis), which we control in our experiment. There is a large nonlinearity: the adverse TFP shock is much more damaging for aggregate investment when it occurs in good times, after positive shocks. Intuitively, because during good times expectations are too optimistic, leverage and investment overexpand. When a bad shock hits, the original optimism wanes and reverts to pessimism. The firms are overleveraged, their debt is perceived to be excessively risky, and so they are forced to cut investment. Due to overreacting beliefs, during good times the economy is fragile and prone to crash in response to a negative shock.

[14] The shock is identically sized in the two experiments, as a one standard deviation shock to macro TFP using the parameter estimate $\hat{\sigma}_A$ from the DE model.

Figure 3: Investment Nonlinearity



Notes: The vertical axis in the figure reports the simulated impulse response of macro investment to a one-standard deviation negative shock to macro TFP, and the horizontal axis reports the initial conditions, i.e., the magnitude of the shock to macro TFP in the previous period. Both the DE model (red line) and RE model (blue line) are reported on the figure.

Figure 3 also adds to the same diagram the response of investment in the RE model (blue line). This response is almost the same across different initial conditions, with little excess fragility in good times. Because, under RE, debt and investment are chosen and priced optimally during both good and bad times, a negative shock does not create financial distress in either state.[15]

Fragility in good times is a key feature in the DE model. Recent work on investment dynamics over the business cycle (Bachmann et al., 2013; Winberry, 2017; Bloom et al., 2018) suggests that investment exhibits more sensitivity to shocks during booms than during normal times. Our results show how beliefs play a key role in generating this feature. We next examine the implications of the DE model for business cycle volatility and comovement.

[15]Interestingly, state-dependence in Figure 3 also generates a positive response during bad times under DE, when even a moderate negative shock to TFP can be considered "good news" relative to overpessimistic beliefs. Under RE, the response curve is uniformly negative.

5.2 Diagnosticity and Business Cycle Comovement

Macro business cycle correlations are entirely untargeted in our calibration procedure. We set macro TFP shock persistence to a conventional value in Table 3 and only target the volatility of GDP growth, which simply ensures that the standard deviation of output is comparable to the data. In this sense, the ability of our model to reproduce macro moments is a stringent metric of its explanatory power for business cycles.

Table 8 reports the annual business cycle correlations and volatilities of output, debt, investment, and average credit spreads in the empirical data (top panel), simulated data from the DE model (middle panel), and simulated data from the RE model (bottom panel). The DE and RE model moments are computed based on an identical set of exogenous shocks.

Table 8: Business Cycle Moments

Data					
Correlation	Output	Debt	Investment	Spread	Standard Deviation
Output	1.000	0.891	0.803	-0.105	0.017
Debt		1.000	0.755	-0.169	0.048
Investment			1.000	-0.107	0.053
Spread				1.000	0.01
Diagnostic Expectations Model					
Correlation	Output	Debt	Investment	Spread	Standard Deviation
Output	1.000	0.897	0.484	-0.084	0.014
Debt		1.000	0.690	-0.131	0.012
Investment			1.000	-0.037	0.041
Spread				1.000	0.012
Rational Expectations Model					
Correlation	Output	Debt	Investment	Spread	Standard Deviation
Output	1.000	0.837	0.821	0.368	0.014
Debt		1.000	0.535	0.322	0.006
Investment			1.000	0.300	0.032
Spread				1.000	0.007

Notes: The table reports business cycle correlations (left) and standard deviations (right) from the data (top panel), the diagnostic expectations model (middle panel), and the rational expectations model (bottom panel). The empirical sample is 2003-18 at annual frequency. Real GDP and private nonresidential fixed investment from the US NIPA accounts. Total credit to US non-financial corporations from the BIS. BAA-Treasury spread based on Moody's ratings. The model moments are computed from an unconditional simulation of 250 years. Model quantities refer to total values (output, debt, and investment) or average values (spread) computed from the distribution of firms. Output, debt, and investment are HP-filtered with smoothing parameter 100.

The DE model offers a good account of business cycle moments. It captures well the positive covariance between macro output and debt, the positive covariance between investment and debt, and crucially the negative covariance of spreads with output, debt and investment. It also offers a good account of the standard deviation of macro output and investment. The main difficulty for our DE model lies in capturing the high correlation between investment and output in the data, as well as the high standard deviation of debt. We speculate that a version of diagnostic expectations allowing for slower dynamics in overreaction, as in Bordalo et al. (2019), might generate more variation in debt in the DE model by allowing for credit to shift over multiple years of overreaction.

The RE model makes the counterfactual prediction of procyclical credit spreads and also fails to produce meaningful volatility in debt, investment and spreads compared either to the data or to the DE model. The failure of the RE model to capture countercyclical spreads is due to the fact that it features a strong demand effect. During good economic times, the demand for credit increases relative to its supply, increasing the credit spread. In the DE model, countercyclicality arises because the excess volatility in beliefs caused by $\theta > 0$ mainly influences the supply of credit. On the demand side, diminishing returns and bankruptcy costs limit the extent to which the demand for capital accommodates excess volatility in beliefs. Under DE, procyclical shifts in the supply of credit become more important and generate countercyclical spreads.

The RE model does, however, generate a higher correlation between current output and investment than the DE model, more in line with the data. In the DE model, investment responds both to the level of TFP but also to recent news, increasing the volatility of investment in the direction of the data but bringing down somewhat the contemporaneous correlations between output and investment from its empirical value.

Overall, diagnosticity helps in accounting for cyclical variation in debt, investment, and the countercyclicality of spreads. We next assess the explanatory power of the model for observed financial and real instability.

6 Boom-Bust Cycles in Financial and Real Activity

We show that our model can shed light on two phenomena: recurrent boom-bust credit cycles, as documented in López-Salido et al. (2017) (Section 6.1), and large increases in spreads and financial crises occurring after good times, as described in Krishnamurthy and Muir (2016) (Section 6.2). Our model significantly improves the explanatory power for these cycles due to the fact that in good times DE are too optimistic, which creates fragility and hence subsequent predictable reversals in financial and real activity.

6.1 Recurrent Credit Cycles

We check the ability of our model to account for the cycles in credit spreads and economic activity. We do so both at the macro level, so that we can compare our results to López-Salido et al. (2017), and at the firm level, so we can compare them to our analysis in Section 2.

To do so, we simulate the model for a large number of periods and then use the simulated aggregate data to perform a two-step exercise. First, following López-Salido et al. (2017) we regress spread growth on the lagged spread level.

$$\Delta \text{Spread}_t = \alpha + \beta \text{Spread}_{t-1} + \varepsilon_t.$$

which detects predictable reversals in credit market conditions. Second, we regress macro outcomes of interest at t, X_t, on the predicted spread change $\widehat{\Delta \text{Spread}}_t$ from the first stage:

$$X_t = \delta + \gamma \widehat{\Delta \text{Spread}}_t + \lambda \Delta Y_{t-1} + \eta_t,$$

where following López-Salido et al. (2017) we include lagged output growth ΔY_{t-1} as a control. Table 9 reports $\hat{\beta}$ from the first step in column (1) and $\hat{\gamma}$ from the second step in columns (2)-(4). The top panel reports the coefficients in the simulated DE model, the middle panel reports empirical coefficients directly reproduced from López-Salido et al. (2017), and the bottom panel reports the coefficient obtained from the simulated data of the RE model in which $\theta = 0$.

Consider the top and middle panels. The DE model reproduces salient qualitative features in the data. First, it yields a sizable reversal of spreads in column (1). Second, it yields, in the same direction as the data, that predictable increases in spreads are associated with declines in GDP growth (column (2)), in aggregate investment growth (column (3)), and with lower realized bond returns (column (4)). The quantitative magnitude of the predictable declines in output growth and, to a lesser degree, in investment growth are much lower in the DE model than in the data. The muted shift in output in the DE model is due to the fact that in this RBC model output is entirely supply-driven with predetermined capital and few other mechanisms for contemporaneous responses to revisions in beliefs other than the direct impact of TFP. For example, channels such as variable aggregate demand (Farhi and Werning, 2020), time-varying capacity utilization (King and Rebelo, 1999), sharp labor adjustment in the face of bad news (Ilut et al., 2018), or intermediary financial disruptions (Maxted, 2020; Krishnamurthy and Li, 2020) might all be at work in the data, although they are absent from our DE model.

In the bottom panel we see that the RE model cannot reproduce the observed credit cycles even directionally. In fact, while the RE model obtains meaningful mean reversion in spreads via mean reversion in TFP, it cannot produce any predictability in bond returns (column (4)). The RE model also produces a counterfactual positive response of output and investment to predictable increases in credit spreads.

Table 9: Recurrent Credit Cycles

	(1)	(2)	(3)	(4)
	Diagnostic Expectations Model			
	Δ Spread	Δ Output	Δ Investment	Bond Return
Pred. Δ Spread		-0.512***	-3.64***	-0.010**
		(0.042)	(0.198)	(0.001)
Lagged Spread	-0.304***			
	(0.012)			
Years	7500	7500	7500	7500
	Data (from Lopez-Salido, et al. 2017)			
Pred. Δ Spread		-4.800***	-9.202***	
		(1.134)	(1.346)	
Lagged Spread	-0.248***			
	(0.042)			
Years	1929-2015	1929-2015	1929-2015	
	Rational Expectations Model			
Pred. Δ Spread		0.623***	4.975***	0.000
		(0.107)	(0.239)	(0.000007)
Lagged Spread	-0.218***			
	(0.007)			
Years	7500	7500	7500	7500

Notes: The table reports regressions based on macro data from the simulated diagnostic expectations model (top panel), from empirical regressions directly drawn from Lopez-Salido, et al. (2017) for comparison (middle panel), and from the simulated rational expectations model (bottom panel). Predicted spread growth in columns 2-4 is the predicted value from the regression in column 1. Columns 2-4 control for lagged output growth. In the estimates drawn from Lopez-Salido, et al. (2017), columns 1-2 are from Table II, and column 3 is from Table IV. All standard errors are Newey-West. * = 10% level, ** = 5% level, and ***=1% level.

The ability of the DE model to generate credit cycles comes from the fact that in good times spreads are low because of excess optimism by capital suppliers. A significant chunk of the spread reversal is due to waning of such optimism, and comes with disappointing bond returns, output, and investment. In the RE model, by contrast, spreads are procyclical, so they are low in bad times and predictably increase with TFP mean reversion, which is in turn associated with higher output and investment.

Finally, consider the ability of our model to account for firm-level credit cycles. Table 10 reproduces our IV regression exercise of Table 2 in Section 2, in which predictable future forecast errors are used as an index of overoptimism. The top panel reports the results in the simulated data obtained from the DE model. In line with the estimates of Table 1, in the DE model high investment predicts future negative forecast errors (column (1)), indicating that when investment is high expectations are overly optimistic. In line with the results of Table 2, predictable overoptimism is then associated with lower realized bond returns (column (2)), higher future spreads (column (3)), and lower future investment (column (4)). The regressions for spreads and investment also control for lagged spread and current profits, respectively, to account for fundamental mean reversion, as in Table 2. The magnitudes here are large. Firms that are optimistic, with a predicted forecast error one-standard deviation lower, experience $27 \times 0.121 \approx 3$ percentage points lower bond returns. The RE model cannot reproduce these findings in the bottom panel: because it fails to generate predictability of forecast errors, it does not reproduce the first stage of Table 2.

Overall, DE help account for the evidence on credit cycles thanks to the overreaction of expectations, which creates booms in which the supply of credit overexpands. These expansions are followed by reversals in which optimism wanes, debt is repriced, and real activity contracts.

6.2 The Financial Crisis of 2007-09

We next assess the ability of the DE model to generate the large and sudden increases in credit spreads associated with the Lehman crisis in September 2008. Our model misses some important elements of large crises such as the gradual and persistent inflation of asset prices and the amplification of crashes through financial intermediaries. An asset price bubble can be obtained under DE by introducing information frictions as in Bordalo et al. (Forthcoming (b)), but here we abstract from this aspect to isolate in the sharpest way the role of overreaction. For the same reason, we abstracted from financial intermediaries which are considered in Maxted (2020) and Krishnamurthy and Li (2020).

How large a TFP shock is needed in our model to produce the actual crisis movement in credit spreads? Standard business cycle models have a hard time generating large crises without massive TFP shocks, so they are often enriched with shocks to collateral constraints and uncertainty. By creating fragility after good times, the DE model can produce a crisis-like event with modest TFP shocks alone. We can then ask what the macroeconomic consequences of such a shock are in the context of our model.

To answer these questions, we perform a “ crisis decomposition” exercise. We separate the 2004-2009 period into a “pre-crisis” period, 2004 - 2007, and a “crisis” period, 2008 - 2009 (our model yields neither a gradual path of asset price inflation nor the gradual reduction in spreads during 2004-2007). Credit spreads in the US during the pre-crisis period were low with an average

Table 10: Forecast Errors and Firm Credit Cycles

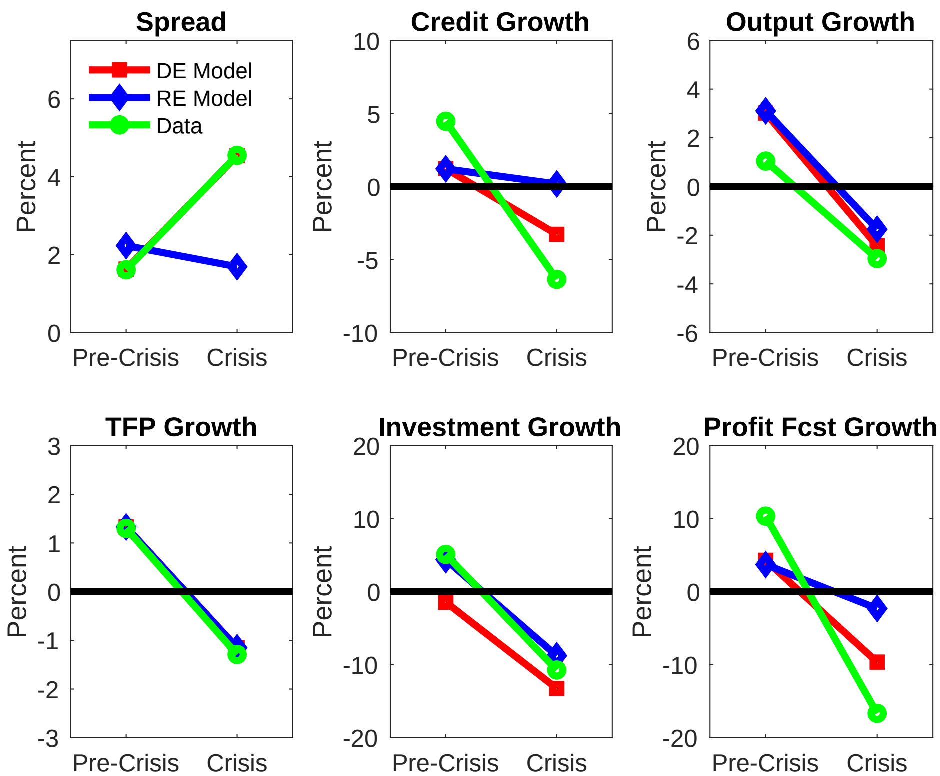
	(1)	(2)	(3)	(4)
Dependent Variable:	Fcst. Error_t	Return_t	Δ Spread_t	Δ Investment_t
Estimation	1st Stage	2nd Stage	2nd Stage	2nd Stage
		Diagnostic Expectations Model		
Fcst. Error_t		0.121***	-1.891***	1.436***
		(0.004)	(0.205)	(0.005)
Investment_{t-1}	-0.703***			
	(0.007)			
Years	500	500	500	500
Firm-Years	500000	500000	500000	500000
Time Effects	X	X	X	X
First Stage F	9635			
		Rational Expectations Model		
Fcst. Error_t		0.209	108.362***	-137.182***
		(0.407)	(10.778)	(0.502)
Investment_{t-1}	0.004			
	(0.007)			
Years	500	500	500	500
Firm-Years	500000	500000	500000	500000
Time Effects	X	X	X	X
First Stage F	0.268			

Notes: The table reports first and second stage IV estimates based on simulated firm-level data from the diagnostic expectations model (top panel) and the constrained rational expectations model (bottom panel). Column 1 reports the first stage, and columns 2-4 report second stage regressions. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. Forecast error is realized minus expected profits normalized by the firm's capital stock. Investment is the investment rate, i.e., capital expenditures normalized by the firm's capital stock. Return is the realized bond return, and spread is the realized bond spread relative to the risk-free rate. Column 3 controls for the lagged spread, and column 4 controls for current profits. For all series, 0.01=1%.

of 1.6%, and jumped to an average level of 4.5% during the crisis period. We then ask: what TFP pattern is needed in our model to go from an initial 1.6% spread to 4.5%?

Figure 4 plots the required TFP shocks, along with their implications for the growth of credit, output, investment, and corporate profit forecasts. The red lines connect the pre-crisis and crisis outcomes generated by the DE model, while the green lines present the data. In the top left panel, the DE model by construction perfectly matches the pre-crisis and crisis spreads. Remarkably, though, the bottom left panel shows that the pattern of TFP growth needed to account for the increase in spreads is virtually *identical* to the TFP growth observed during the period. This overlap is an untargeted feature and shows that in the DE model a moderate 1.5% reduction in TFP growth is able to produce the large observed increase in the average spread.

Figure 4: The Financial Crisis of 2007-09: DE Model vs RE Model



Notes: Each panel plots a macro series from our crisis decomposition exercise, with the data (green), DE model (red), and RE model (blue) included. "Pre-Crisis" is the 2004-07 period, and "Crisis" is the 2008-09 period. In the data, all empirical values are averages drawn from the pre-crisis or crisis periods. Spread is the average spread across firms in our Mergent FISD-TRACE-Compustat sample, credit growth is the growth in total credit to non-financial corporations, real GDP and private nonresidential fixed investment are from NIPA, and profit forecasts are the sum of predicted earnings across all firms in our Compustat-IBES guidance data. In the DE model, we choose the TFP growth series in the bottom left panel in order to exactly match the empirical spread values in the top left panel. We feed the resulting TFP growth series into the RE model to produce the final line in each panel.

The reversal is due to the fragility built during the good times of the pre-crisis period which is in turn capable of producing realistic macro consequences: a large reduction in credit, investment, and output, together with a strong reduction in forecasts of profit growth. These macroeconomic changes in the DE model are not identical to those in the data, but the quantitative fit is noteworthy in light of the simplicity of our model.

We then input the same TFP pattern in the RE model, as also reported in Figure 4. The RE model (blue lines) does not produce any movement in credit spreads, it does not produce deleveraging, nor does it produce the sharp observed downward revision in profit forecasts. Both the DE and RE models feature output growth that declines by similar magnitudes as the data, although the larger drop in investment in the DE model naturally implies a lower path for output growth during the later stages of the recovery. The fact that output differences between DE and

RE are small is expected, since in both neoclassical models the business cycle is driven by the same TFP series.

This exercise shows the potential of DE for accounting for the salient features of the boom-bust cycles in macro-financial aggregates. The realism of the analysis and its fit can be improved by adding ingredients that have likely played a role, such as the housing bubble, intermediary leverage, and the link between household debt and consumption. Boom-bust belief dynamics, however, seem a promising ingredient to generate overexpansion in good times and sharp financial tightening and real contractions after modest TFP shocks.

7 Robustness

We conclude our analysis by reporting the results of two important robustness exercises. First, we evaluate the role of lenders' beliefs in generating fragility in good times. Second, we endogenize wages in general equilibrium, which can dampen volatility. As before, our analysis focuses on the contemporaneous response of macro investment to TFP shocks, and in particular its fragility after good times.

7.1 Demand vs. Supply of Capital

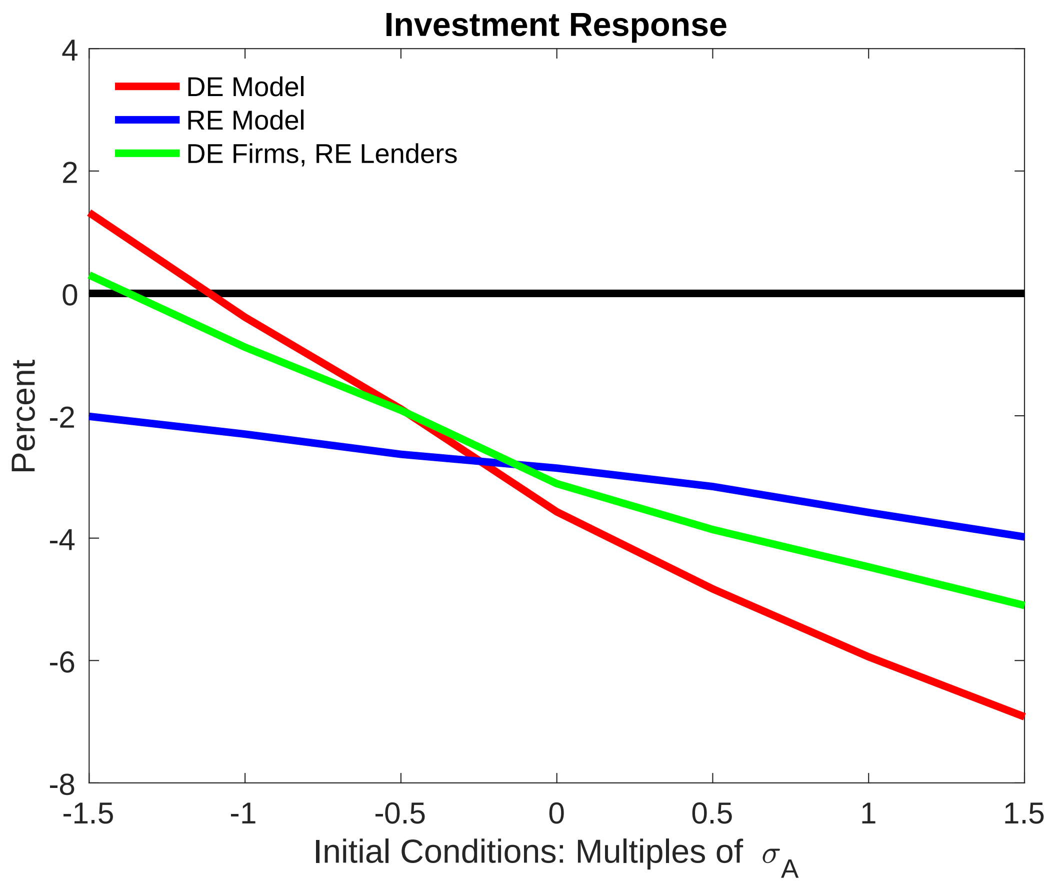
In our model, overreacting beliefs affect both the demand and the supply of credit. Large shifts in the supply of credit are crucial to account for the observed countercyclicality of spreads and for the predictability of bond returns. Here we ask a broader question: what is the role of credit supply in creating real fragility and large drops in investment after good times?

To address this question, we analyze the DE model by assuming that only borrowers are diagnostic. By comparing the outcomes to our baseline results, we can assess the role played by belief overreaction in the supply of credit. This exercise is also interesting as a way to assess the extent to which fragility can be reduced if diagnostic firms are disciplined through rational debt pricing.

We thus run a simulation of the model in which we set $\theta = 0$ for lenders while keeping θ at the estimated value for firms. Figure 5 then reports the response of investment to a negative TFP shock obtained in this exercise (green line), superimposing it on top of Figure 3 reporting the full RE case (blue line) and the full DE case (red line).

Qualitatively, the response of investment displays the nonlinearity typical of the DE model: after good times the economy is fragile, so a given negative TFP shock causes a larger drop in investment than after bad times. Quantitatively, though, shutting down the overreaction of credit supply sharply reduces the magnitude of the effect. The green curve lies about halfway between the full DE and the full RE investment responses. In this respect, diagnostic shifts in the supply

Figure 5: Investment Nonlinearity with Rational Lenders



Notes: The vertical axis in the figure reports the simulated impulse response of macro investment to a one-standard deviation negative shock to macro TFP, and the horizontal axis reports the initial conditions, i.e., the magnitude of the shock to macro TFP in the previous period. The DE model (red line), the RE model (blue line), and a model with DE for firms but RE for lenders (green line) are reported on the figure.

of credit appear to play an important role in creating significant fragility.

7.2 General Equilibrium

Anticipated procyclical wage shifts may dampen movements in the anticipated marginal product of capital and hence push against volatility or nonlinearity in investment. To assess the importance of this mechanism, we now endogenize the wage W, moving towards general equilibrium. We keep the required rate of return R exogenous because, as argued above, empirically realistic countercyclical shifts in real interest rates in this class of heterogeneous firms models are likely to amplify rather than dampen investment dynamics. Moreover, consumption-based models of expected (and required) returns are inconsistent with expectations data.

We allow for disutility from effort by modelling period utility as:

$$U(C,N) = C - \frac{\omega}{1+\frac{1}{\lambda}} N^{1+\frac{1}{\lambda}},$$

where the disutility of labor is governed by $\omega > 0$ and the elasticity of labor supply is given by $\lambda > 0$. The real interest rates are pinned down by the inverse of the household's subjective discount rate $0 < \beta < 1$, i.e., $R = 1/\beta - 1$.

Let $\mu(s,k,b)$ be the cross-sectional distribution of exogenous states s, capital k, and debt b. The macro state is (μ, A, ε_A). Market clearing in the labor market implicitly defines wages $W(\mu, A, \varepsilon_A)$ through

$$\left(\frac{W}{\omega}\right)^{\lambda} = \int n(s,k,b|W) d\mu(s,k,b),$$

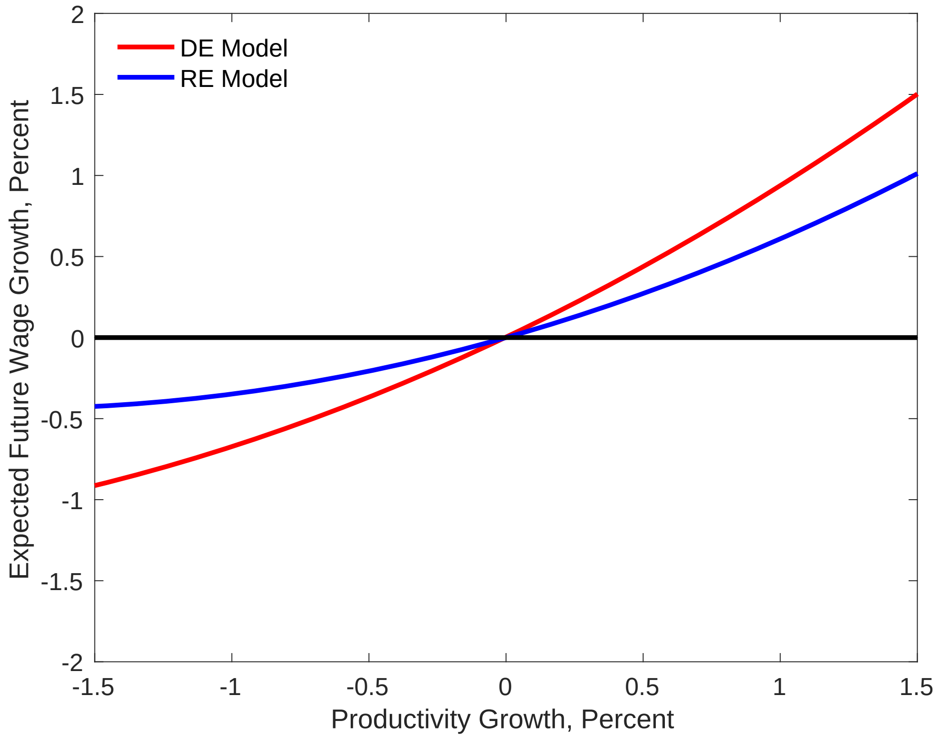
where the left hand side is the household's closed-form labor supply and the right hand side reflects labor demand generated by the current cross-sectional distribution of firm states μ.

As usual in this class of heterogeneous firms models with anticipated macro shocks, general equilibrium creates two computational challenges (Krusell and Smith, 1998). First, the macro state (μ, A, ε_A) is intractable because μ is a distribution. Second, the mapping $W(\mu, A, \varepsilon_A)$ is a complicated implicit object which must be consistent with the firm-level decisions embedded in market clearing.

We follow a novel computational approach tailored to our problem and detailed in Appendix A. To briefly summarize, our approach is to replace the macro state $(\mu_t, A_t, \varepsilon_{At})$ with a history of macro shocks $(A_t, A_{t-1}, ..., A_{t-K})$ up to some truncated lag length, nonparametrically storing predictions of the wage W given each shock history. We then follow an outer loop/inner loop approach, guessing a wage mapping, solving and simulating the model, and updating the wage predictions until convergence. Our solution technique proves tractable and quite accurate in practice, as is also detailed in Appendix A. We parameterize the model based on the estimated values from Table 5. We further assume a conservative Frisch elasticity of labor supply of $\lambda = 0.5$ and choose β to deliver the same fixed 4% annual real interest rate as considered above.

Wages in this equilibrium structure reflect an intratemporal mapping from the macro states to prices, so it might not be immediately clear how our explicitly intertemporal notation of diagnostic expectations interacts with general equilibrium. We make the link explicit in Figure 6, which plots expected future wage growth as a function of current productivity growth in both the DE model (red line) and the RE model (blue line). In the DE model, a positive productivity shock that renders agents overly optimistic increases their perceptions of the future demand for capital and labor and hence future wage growth relative to the RE model. Because perceived future wages affect the future payoff from capital, these anticipated factor price movements dampen investment fluctuations today, a dampening force that is in fact a bit stronger in the DE model than the

Figure 6: Expected Wage Growth



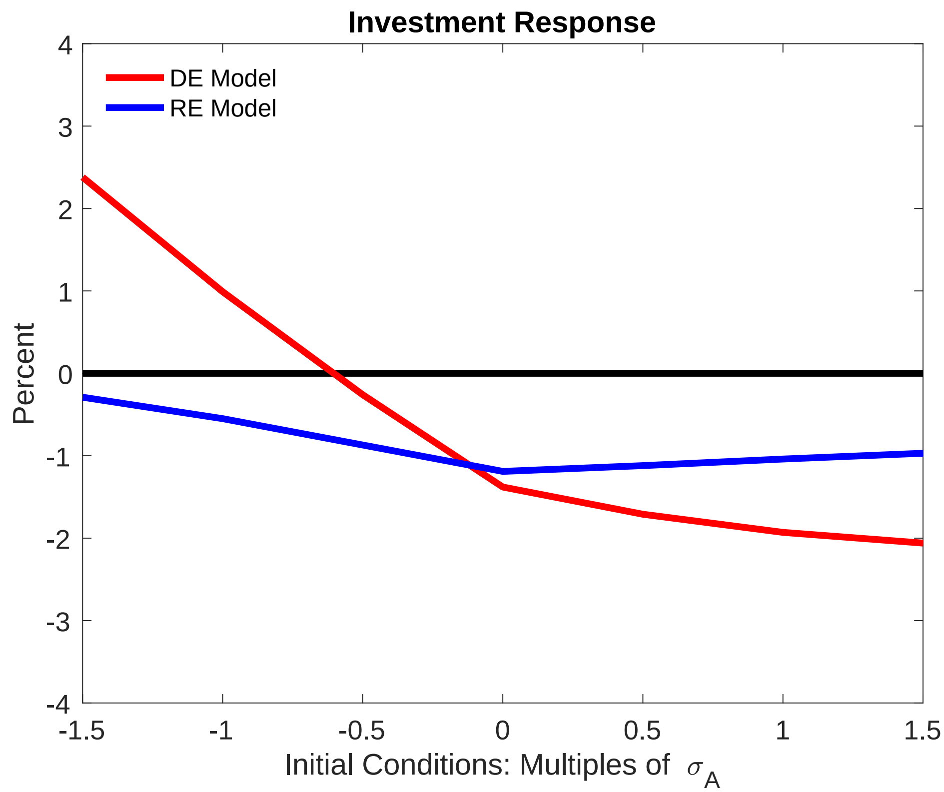
Notes: The figure plots the expected path of wage growth in the next period (vertical axis) given productivity growth today (horizontal axis) in the DE model (red) and RE model (blue).

RE model. Since shifts in the intratemporal price of labor can have a meaningful impact in equilibrium on a firm's perceived intertemporal incentives to invest, we next investigate whether the investment nonlinearities we highlighted above in the DE model survive general equilibrium.

Figure 7, the general equilibrium analogue of Figure 3, reports the response of investment to a negative TFP shock for different initial conditions. The investment response continues to display nonlinearity and in particular the high fragility induced by DE (red line): the negative shock exerts a much larger negative impact in good times. As expected, endogenous wages moderate the quantitative magnitude of the investment response and nonlinearity relative to the partial equilibrium model. However, the nonlinearity remains substantial. The response to a negative TFP shock increases in size by about 40% when arriving after a one standard deviation positive shock rather than in normal times. This increase matches the trough-to-peak growth in empirical investment sensitivity estimated in Bachmann et al. (2013). In the RE model (blue line), by contrast, the general equilibrium feedback working through wages eliminates the (already very insignificant) state-dependence of investment almost entirely.

In sum, even after allowing for fully flexible wages, the DE economy proves more fragile than

Figure 7: Investment Nonlinearity with General Equilibrium



Notes: The vertical axis in the figure reports the simulated impulse response of macro investment to a one-standard deviation negative shock to macro TFP, and the horizontal axis reports the initial conditions, i.e., the magnitude of the shock to macro TFP in the previous period. Both the DE model (red line) and RE model (blue line) are reported on the figure. These results are computed in the general equilibrium model with labor market clearing.

the RE economy in good times, and hence more responsive to negative shocks due to the boom-bust mechanism created by overreacting beliefs.

8 Conclusion

Macroeconomic fragility naturally arises in a canonical business cycle model as a result of micro-founded deviations from rational expectations by individual firms and creditors. Under diagnostic expectations, business cycles prove more volatile, exhibit state-dependent responses of investment, and feature recurrent credit cycles with rapidly worsening credit spreads, deleveraging, and reversals in real outcomes. Such reversals occur after good times with expansion of credit and low spreads. Since a rational expectations model fails to capture these realistic credit cycle dynamics, realistic modeling of expectations may provide a useful tool for understanding macro-financial fluctuations.

References

Adam, Klaus, Albert Marcet, and Johannes Beutel (2017), "Stock price booms and expected capital gains." *American Economic Review*, 107, 2352–2408.

Afrouzi, Hassan, Spencer Kwon, Augustin Landier, Yueran Ma, and David Thesmar (2020), "Overreaction and working memory." Working paper.

Angeletos, George-Marios, Zhen Huo, and Karthik A. Sastry (Forthcoming), "Imperfect macroeconomic expectations: Evidence and theory." *NBER Macroeconomics Annual*.

Arellano, Cristina, Yan Bai, and Patrick J. Kehoe (2019), "Financial frictions and fluctuations in volatility." *Journal of Political Economy*, 127, 2049–2103.

Azeredo da Silveira, Rava, Yeji Sung, and Michael Woodford (2020), "Optimally imprecise memory and biased forecasts." Working paper.

Bachmann, Rüdiger, Ricardo J Caballero, and Eduardo MRA Engel (2013), "Aggregate implications of lumpy investment: new evidence and a dsge model." *American Economic Journal: Macroeconomics*, 5, 29–67.

Baron, Matthew and Wei Xiong (2017), "Credit expansion and neglected crash risk." *The Quarterly Journal of Economics*, 132, 713–764.

Bernanke, Ben and Mark Gertler (1989), "Agency costs, net worth, and business fluctuations." *The American Economic Review*, 79, 14–31.

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

Bertomeu, Jeremy, Iván Marinovic, Stephen J. Terry, and Felipe Varas (2020), "The dynamics of concealment." Working paper.

Bhandari, Anmol, Jaroslav Borovicka, and Paul Ho (2019), "Survey data and subjective beliefs in business cycle models." Working paper.

Bianchi, Francesco, Sydney C. Ludvigson, and Sai Ma (2020), "Belief distortions and macroeconomic fluctuations." NBER working paper 27406.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry (2018), "Really uncertain business cycles." *Econometrica*, 86, 1031–1065.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, Frederik Schwerter, and Andrei Shleifer (Forthcoming (a)), "Memory and representativeness." *Psychological Review*.

Bordalo, Pedro, Nicola Gennaioli, Spencer Yongwook Kwon, and Andrei Shleifer (Forthcoming (b)), "Diagnostic bubbles." *Journal of Financial Economics*.

Bordalo, Pedro, Nicola Gennaioli, Rafael LaPorta, and Andrei Shleifer (2019), "Diagnostic expectations and stock returns." *Journal of Finance*, 74, 2839–2874.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer (2020), "Overreaction in macroeconomic expectations." *American Economic Review*, 110, 2748–82.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2018), "Diagnostic expectations and credit cycles." *The Journal of Finance*, 73, 199–227.

Bouchaud, Jean-philippe, Philipp Krueger, Augustin Landier, and David Thesmar (2019), "Sticky expectations and the profitability anomaly." *The Journal of Finance*, 74, 639–674.

Brunnermeier, Markus K, Gary Gorton, and Arvind Krishnamurthy (2012), "Risk topography." *NBER Macroeconomics Annual*, 26, 149–176.

CBO (2017), "International comparisons of corporate income tax rates." Exhibit 7.

Coibion, Olivier and Yuriy Gorodnichenko (2015), "Information rigidity and the expectations formation process: A simply framework and new facts." *American Economic Review*, 105, 2644–78.

Cooper, Russell and Jonathan Willis (2015), "Discounting: Investment sensitivity and aggregate implications." Working paper.

d'Arienzo, Daniele (2020), "Maturity increasing overreaction and bond market puzzles." Working paper.

Dávila, Eduardo and Anton Korinek (2017), "Pecuniary externalities in economies with financial frictions." *The Review of Economic Studies*, 85, 352–395.

Den Haan, Wouter J (2010), "Comparison of solutions to the incomplete markets model with aggregate uncertainty." *Journal of Economic Dynamics and Control*, 34, 4–27.

Eggertsson, Gauti B and Paul Krugman (2012), "Debt, deleveraging, and the liquidity trap: A fisher-minsky-koo approach." *The Quarterly Journal of Economics*, 127, 1469–1513.

Falato, Antonio and Jasmine Xiao (2020), "The information driven financial accelerator." Working paper.

Farhi, Emmanuel and Iván Werning (2016), "A theory of macroprudential policies in the presence of nominal rigidities." *Econometrica*, 84, 1645–1704.

Farhi, Emmanuel and Ivan Werning (2020), "Taming a minsky cycle." Working paper.

Fostel, Ana and John Geanakoplos (2014), "Endogenous collateral constraints and the leverage cycle." *Annual Review of Economics*, 6, 771–799.

Fuster, Andreas, David Laibson, and Brock Mendel (2010), "Natural expectations and macroeconomic fluctuations." *Journal of Economic Perspectives*, 24, 67–84.

Gennaioli, Nicola, Yueran Ma, and Andrei Shleifer (2016), "Expectations and investment." *NBER Macroeconomics Annual*, 30, 379–431.

Gennaioli, Nicola and Andrei Shleifer (2010), "What comes to mind." *The Quarterly journal of economics*, 125, 1399–1433.

Gilchrist, Simon and Egon Zakrajšek (2012), "Credit spreads and business cycle fluctuations." *American Economic Review*, 102, 1692–1720.

Gilchrist, Simon, Egon Zakrajšek, and Jae Sim (2014), "Uncertainty, financial frictions, and investment dynamics." Working paper.

Gomes, Joao F. (2001), "Financing investment." *American Economic Review*, 91, 1263–85.

Gourio, Francois and Leena Rudanko (2014), "Customer Capital." *Review of Economic Studies*, 81, 1102–36.

Greenwood, Robin and Samuel G Hanson (2013), "Issuer quality and corporate bond returns." *The Review of Financial Studies*, 26, 1483–1525.

Greenwood, Robin, Samuel G. Hanson, and Lawrence J. Jin (2019), "Reflexivity in credit markets." Working paper.

Greenwood, Robin, Samuel G. Hanson, Andrei Shleifer, and Jakob Ahm Sørensen (2020), "Predictable financial crises." NBER working paper 27396.

Greenwood, Robin and Andrei Shleifer (2014), "Expectations of returns and expected returns." *The Review of Financial Studies*, 27, 714–746.

Gu, Chao, Fabrizio Mattesini, Cyril Monnet, and Randall Wright (2013), "Endogenous credit cycles." *Journal of Political Economy*, 121, 940–965.

Guerrieri, Veronica and Guido Lorenzoni (2017), "Credit crises, precautionary savings, and the liquidity trap." *The Quarterly Journal of Economics*, 132, 1427–1467.

Gulen, Huseyin, Mihai Ion, and Stefano Rossi (2019), "Credit cycles and corporate investment." Working paper.

He, Zhiguo and Arvind Krishnamurthy (2019), "A macroeconomic framework for quantifying systemic risk." *American Economic Journal: Macroeconomics*, 11, 1–37.

Hennessy, Christopher A and Toni M Whited (2007), "How Costly is External Financing? Evidence from a Structural Estimation." *Journal of Finance*, 62, 1705–1745.

Ilut, Cosmin, Matthias Kehrig, and Martin Schneider (2018), "Slow to hire, quick to fire: Employment dynamics with asymmetric responses to news." *Journal of Political Economy*, 126, 2011–71.

Jaimovich, Nir and Sergio Rebelo (2007), "Behavioral theories of the business cycle." *Journal of the European Economic Association*, 5, 361–68.

Khan, Aubhik and Julia K Thomas (2008), "Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics." *Econometrica*, 76, 395–436.

Kindleberger, Charles P. (1978), *Manias, Panics, and Crashes: A History of Financial Crises.* John Wiley & Sons.

King, Robert G and Sergio T Rebelo (1999), "Resuscitating real business cycles." *Handbook of macroeconomics*, 1, 927–1007.

Kiyotaki, Nobuhiro and John Moore (1997), "Credit cycles." *Journal of Political Economy*, 105, 211–248.

Kohlhas, Alexandre N. and Ansgar Walther (2020), "Asymmetric attention." Working paper.

Koop, Gary, M Hashem Pesaran, and Simon M Potter (1996), "Impulse response analysis in nonlinear multivariate models." *Journal of Econometrics*, 74, 119–147.

Korinek, Anton and Alp Simsek (2016), "Liquidity trap and excessive leverage." *American Economic Review*, 106, 699–738.

Kozlowski, Julian, Laura Veldkamp, and Venky Venkateswaran (2017), "The tail that wags the economy: Beliefs and persistent stagnation." Working paper.

Krishnamurthy, Arvind and Wenhao Li (2020), "Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment." NBER working paper 27088.

Krishnamurthy, Arvind and Tyler Muir (2016), "How credit cycles across a financial crisis." Working paper.

Krusell, Per and Anthony A Smith, Jr (1998), "Income and wealth heterogeneity in the macroeconomy." *Journal of Political Economy*, 106, 867–896.

López-Salido, David, Jeremy C Stein, and Egon Zakrajšek (2017), "Credit-market sentiment and the business cycle." *The Quarterly Journal of Economics*, 132, 1373–1426.

Lorenzoni, Guido (2008), "Inefficient credit booms." *The Review of Economic Studies*, 75, 809–833.

Lucas, Robert E (1976), "Econometric policy evaluation: A critique." In *Carnegie-Rochester conference series on public policy*, volume 1, 19–46.

Maxted, Peter (2020), "A macro-finance model with sentiment." Working paper.

Mian, Atif, Amir Sufi, and Emil Verner (2017), "Household debt and business cycles worldwide." *The Quarterly Journal of Economics*, 132, 1755–1817.

Minsky, Hyman P (1977), "The financial instability hypothesis: An interpretation of keynes and an alternative to standard theory." *Challenge*, 20, 20–27.

Pflueger, Carolin, Emil Siriwardane, and Adi Sunderam (2020), "Financial market risk perceptions and the macroeconomy." *The Quarterly Journal of Economics*, 135, 1443–1491.

Richter, Björn and Kaspar Zimmermann (2020), "The profit-credit cycle." Working paper.

Rognlie, Matthew, Andrei Shleifer, and Alp Simsek (2018), "Investment hangover and the great recession." *American Economic Journal: Macroeconomics*, 10, 113–53.

Saporta-Eksten, Itay and Stephen J. Terry (2018), "Short-term shocks and long-term investment." Working paper.

Schaal, Edouard and Mathieu Taschereau-Dumouchel (2020), "Herding cycles." Working paper.

Schularick, Moritz and Alan M Taylor (2012), "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008." *American Economic Review*, 102, 1029–61.

Shleifer, Andrei and Robert W Vishny (1992), "Liquidation values and debt capacity: A market equilibrium approach." *The Journal of Finance*, 47, 1343–1366.

Simsek, Alp (2013), "Belief disagreements and collateral constraints." *Econometrica*, 81, 1–53.

Stein, Jeremy C (2012), "Monetary policy as financial stability regulation." *The Quarterly Journal of Economics*, 127, 57–95.

Strebulaev, Ilya A and Toni M Whited (2012), "Dynamic Models and Structural Estimation in Corporate Finance." *Foundations and Trends in Finance*, 6, 1–163.

Tauchen, George (1986), "Finite state markov-chain approximations to univariate and vector autoregressions." *Economics letters*, 20, 177–181.

Terry, Stephen J (2017a), "Alternative methods for solving heterogeneous firm models." *Journal of Money, Credit and Banking*, 49, 1081–1111.

Terry, Stephen J. (2017b), "The macro impact of short-termism." Working paper.

Winberry, Thomas (2017), "Lumpy investment, business cycles, and stimulus policy."

Woodford, Michael (2003), "Imperfect common knowledge and the effects of monetary policy." In *Knowledge, Information, and Expectations in Modern Macroeconomics* (Philippe Aghion, Roman Frydman, Joseph Stiglitz, and Michael Woodford, eds.), Princeton University Press.

Young, Eric R (2010), "Solving the Incomplete Markets Model with Aggregate Uncertainty Using the Krusell–Smith Algorithm and Non-Stochastic Simulations." *Journal of Economic Dynamics and Control*, 34, 36–41.

Appendices

A Model

A.1 Solving the Model

The computational algorithm involves iteration on an outer loop (related to debt pricing) and an inner loop (related to firm policies). Before solving the model, we discretize the state space $(s, k, b) = (z, \eta_z, A, \eta_A, k, b)$ into $n_z \times n_z \times n_A \times n_A \times n_k \times n_b$ grid points. We then discretize the rational and perceived diagnostic transitions of the exogenous states according to Tauchen (1986). The computational algorithm - following Strebulaev and Whited (2012) - proceeds as follows:

Start outer loop.

1. Guess a default policy $df^{\theta}(s, k, b)$, and compute the implied debt prices $q^{\theta}(s, k, b)$ according to the lenders diagnostic zero-profit condition Equation (17).

   Start inner loop.

   (a) Given the debt prices $q^{\theta}(s, k, b)$ and default policy $df^{\theta}(s, k, b)$, solve the diagnostic firm's Bellman Equations (14), (15), and (16) for $V^{\theta}(s, k, b)$, $V^{\theta}_{ND}(s, k, b)$, and $V^{\theta}_{D}(s)$ as well as the implied optimal policies for investment and debt issuance $k'^{\theta}(s, k, b)$, $b'^{\theta}(s, k, b)$. Use standard discrete-state, discrete-policy dynamic programming policy iteration to do so.

2. Compute updated default policies $df^{\theta}(s, k, b)$ according to the default choice defining V^{θ} in Equation (14), i.e., $V^{\theta}_{ND}(s, k, b) < V^{\theta}_{D}(s)$.

3. Compute the ergodic distribution $\mu(s, k, b)$ implied by the firm policies for default, capital, and debt $df^{\theta}(s, k, b)$, $k'^{\theta}(s, k, b)$, and $b'^{\theta}(s, k, b)$.

4. Compute the mass of states in which the guessed default policy differs from the updated default policy. If this set of states has mass lower than some tolerance, exit. If not, then go to top and restart with the updated set of default states as your new guess.

We implement this computationally intensive algorithm in heavily parallelized Fortran on a 2017 iMac Pro, with runtimes around 250 seconds. Table A1 reports the value of several dimensions used for the baseline solution of the model.

Table A1: Computational Choices

Quantity	Description	Value
T^{sim}	Simulated periods	250
T^{erg}	Initially discarded periods	25
N^{firm}	Number of firms	1250
N^{IRF}	Number of IRF economies	10000
T^{IRF}	Length of IRF economies	75
T^{decomp}	Length of historical decomposition	2
n_z	Micro productivity grid size	5
n_A	Macro productivity grid size	5
n_k	Capital grid size	30
n_b	Debt grid size	30

Notes: The table reports various computational values used in discretizing and solving the model.

A.2 Simulating the Model

After the model is solved, we unconditionally simulate the model by drawing exogenous uniform random shocks and combining this information with the transition matrix for macro TFP to simulate the macro process for A_t for some periods $t = 1, ..., T^{sim} + T^{erg}$. At the micro level, we simulate the model "non-stochastically" according to the method of Young (2010), i.e., we store the dynamics of the weight of the cross-sectional distribution at each discretized point in the state space (s, k, b) rather than simulating a large number of firms. Note that when simulating the model, all macro shocks and distributional dynamics are determined according to the *rational* or true representations of the driving process, even though debt pricing and firm polices may involve diagnostic expectations.

With the simulated distribution in hand for each period, macro series of interest are simply weighted sums of micro-level outcomes across this distribution, discarding the first T^{erg} periods to remove the influence of initial conditions. Note that we do in fact simulate a number of individual firms N^{firm} for the purpose of computing moments within our SMM estimation algorithm, but this is not a step required for the purpose of solving the model or simulating within-period business cycle aggregates.

A.3 Computing Impulse Responses

Our approach to impulse response calculation in this nonlinear context follows Koop et al. (1996), i.e., we compute nonlinear generalized impulse responses. To understand the impact of a given sequence of shocks, we perform the following:

1. For a large number N^{irf} of economies of length T^{irf}, simulate two different versions of the simulation, the "shock" and "no shock" versions. For each economy and each version, we simulate the macro TFP process by first drawing T^{irf} uniform shocks for comparison with the macro TFP transition matrix. Then, simulate both versions unconditionally using identical macro TFP shocks until period $T^{shock} < T^{irf}$.

2. From period T^{shock} and continuing as long as the desired sequence of exogenous innovations you wish to impose lasts, impose a number of periods of certain pre-determined innovations in productivity for the "shock" case, while continuing to simulate the "no shock" economy unconditionally.

3. After the imposed shocks sequence is complete, simulate macro TFP in both economies as normal.

4. After the macro TFP process is determined for each pair of economies, compute the business cycle aggregates of interest in each economy, period, and version by using the simulation approach outlined above.

5. If business cycle aggregate $X_{i,t}^{shock}$ is series X in economy i in period t in the shock case, and $X_{i,t}^{noshock}$ is series X in economy i in period t in the no shock case, then define the impulse response to the predetermined sequence of innovations as

$$IRF_t^X = \frac{1}{N^{irf}} \sum_{i=1}^{N^{irf}} \frac{X_{i,t}^{shock} - X_{i,t}^{noshock}}{X_{i,t}^{noshock}}.$$

The main text's set of impulse response figures reports the series IRF^X for the indicated macro-financial aggregates. Note, however, that the impulse responses presented in the text are scaled to equal an exact shock size, while the productivity grid in the model varies discretely. We achieve this by imposing movements up or down by a single grid point, imposing Step 2 above only with a certain probability chosen in each period to deliver the desired average shock size.

A.4 Performing the Spread Matching Exercise

In a classic linear setting, performing historical decompositions such as the one used in Section 6 is typically a trivial matter of inverting a data path using simple linear algebra. However, our nonlinear model with heterogeneity and a discretized productivity process poses some additional computational challenges. Given the empirical path across two period $t = 1, 2$ for macro credit spreads to match $(S_1, S_2, ..., S_T^{decomp})$, we proceed as follows.

First, we pick an initial period drawn from a representative location in the unconditional simulation of the model, fixing the associated simulated cross-sectional distribution of firm-level states μ_0 drawn from the simulation of the model. Call this period $t = 0$, and note that at the end of period 0 a cross-sectional distribution μ_1 is pre-determined. Then for each period $t = 1, ..., T^{decomp}$, do the following:

1. Guess a value for macro TFP A_t, and find the bracketing interval $[A_{i-1}, A_i]$ together with linear interpolation weights $\omega(A_t, i) = \frac{A_t - A_{i-1}}{A_i - A_{i-1}}$ for the guessed value of productivity.

2. Compute the implied policies of all firms in the cross-sectional distribution μ_t given a macro TFP level equal to A_i, together with the implied macro spread level $S(A_i)$. Repeat the process for macro TFP equal to A_{i-1} to obtain $S(A_{i-1})$.

3. Assume that firms play a "mixed strategy" over the two macro TFP grid points, in which case the resulting macro spread level is $(1 - \omega(A_t, i))S(A_{i-1}) + \omega(A_t, i)S(A_i)$.

4. If the implied macro spread level is not equal to the desired spread value S_t to within some tolerance, then update your guess for macro TFP A_t and return to Step 1. Otherwise proceed.

5. Given a productivity guess which delivers exactly the correct interpolated value of macro productivity in period t, compute the beginning-of-period distribution μ_{t+1} of firm-level states by pushing forward a fraction $\omega(A_t, i)$ of the distribution μ_t using firm policies associated with A_i and a fraction $1 - \omega(A_t, i)$ of the distribution μ_t using firm policies associated with A_{i-1}.

At the end of this process, you have determined a smooth value of productivity A_t which gives you an implied macro spread series exactly consistent with the target value in period t, and you have updated the cross-sectional distribution in an internally consistent fashion given the smooth value of productivity between grid points. Repeating this process for each period $t = 1, ..., T^{decomp}$ yields a productivity path A_t, as well as a set of cross-sectional distributions μ_t, which exactly match the target data path for spread. All other macro aggregates of interest can then be computed from the distributional and macro TFP path. Note that for the spread matching exercise for the Great Recession and financial crisis in Section 6, we set $T^{decomp} = 2$, with $t = 0$ being the "Pre-Crisis" period and $t = 2$ being the "Crisis" period.

A.5 General Equilibrium Solution Algorithm

We follow an outer loop/inner loop approach to solving the model with endogenous wages.

1. Guess a mapping from a truncated history of macro states

$$(A_{t-K}, A_{t-K+1}, ..., A_{t-1}, A_t) \to W_t.$$

2. Solve the model conditional upon this tractable truncated history, where $(A_t, A_{t-1}, ..., A_{t-K})$ enters the firm's state vector and hence the Bellman equations determining investment, default, and debt issuance policies.

3. Simulate the model for a large number of periods $t = 1, ..., T$, clearing markets with W_t in each period t by numerically solving the nonlinear equation

$$\left(\frac{W_t}{\omega}\right)^{\lambda} = \int n(s, k, b|W_t) d\mu_t(s, k, b)$$

   for each period t in the simulation. Note that this is a well behaved nonlinear equation in one variable. The static labor policies $n(s, k, b|W_t)$ are strictly declining in W_t on the RHS and the function on the LHS is strictly increasing in W_t. In practice, markets can be cleared robustly using bisection or another similar algorithm.

4. Based on the simulated wage data, update your wage prediction mapping from Step 1. If the mapping has converged to within some tolerance, exit. If not update the mapping and return to Step 1.

A few practical comments are in order. First, given the discretized macro TFP state space, we store the wage mapping nonparametrically as a matrix of mean wages conditional upon each combination of truncated macro TFP histories. After simulation, the wage mapping update step simply involves repeated calculations of mean wages within the appropriate subsamples of the simulated data. Second, because the macro state is replaced with macro TFP shock histories rather than with an augmented endogenous macro moment, there is no need to create an approximate anticipated default rule used to price debt. Lenders simply price debt according to the usual no-arbitrage condition in Equation (17), conditional upon firm default policies which now have as explicit inputs the macro TFP shock histories. Third, because no endogenous moments are forecasted in our solution method, there is no Den Haan (2010)-style distinction between static and dynamic forecasts of the wage. In other words, there is no room for forecast errors about endogenous macro moments to accumulate over time, since only exogenous shock histories are used for forecasts. So, unlike in typical adaptations of the Krusell and Smith (1998) method, the R^2 of the implicit wage forecast rule is in this case an appropriate metric of accuracy. With this in mind, Figure A1 plots the estimated R^2 of regressions of the log wage on fully populated sets of dummies for macro TFP histories of up to a given lag length. Once a single lag is taken into account, incorporating information from yesterdays' TFP level about the current distribution of capital and hence labor demand in the cross section, the R^2 measures stabilize. Our baseline case, which uses a single lag with $K = 1$ in the wage prediction rule, is therefore a parsimonious but apparently accurate choice.

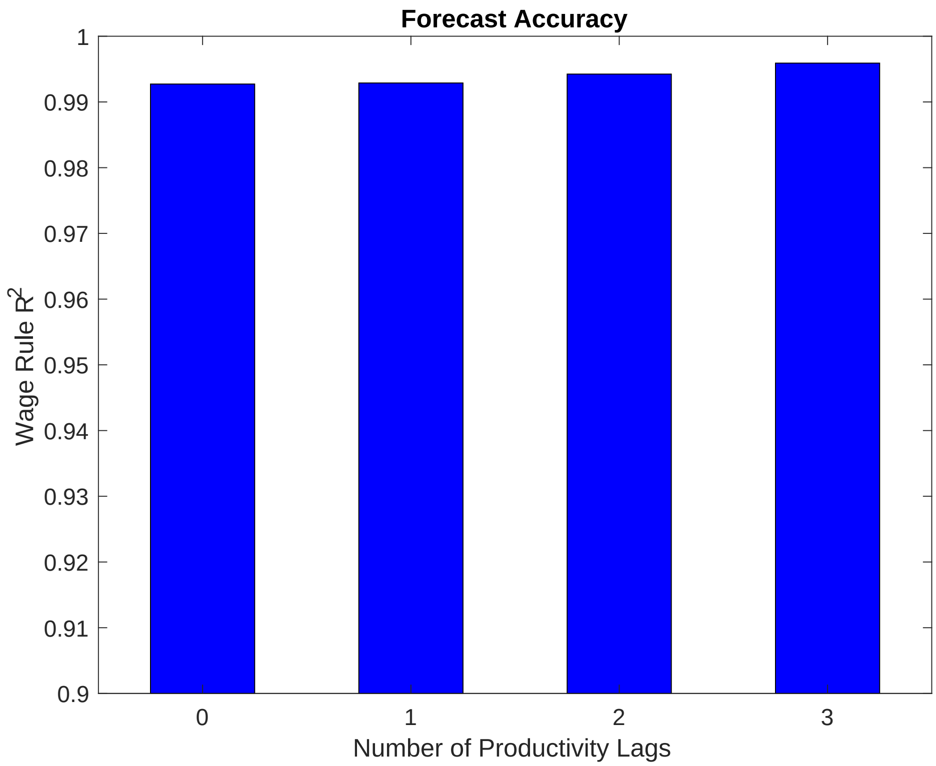


Figure A1: Wage Predictions and TFP Lags

Notes: The figure plots the R^2 of nonparametric regressions of log wages on discrete histories of macro TFP of increasing length.

B Data

B.1 Microdata on Firm Beliefs from Compustat and IBES-Guidance

In our analysis of firm financial and profit forecasts we use a combination of the Compustat Fundamentals Annual and IBES manager guidance databases. The combined sample for the Compustat-IBES data spans 1999-2017 for 8620 firm-fiscal years spanning 1320 firms. To construct our sample, we discard utilities and financials as well as any firm-years with negative values for assets, capital, employment or sales. Descriptive statistics for each variable from this sample used in our analysis, as well as firm revenues and capital, are reported in Table B1. Robustness checks for the forecast error reversion regressions in Section 2 in the main text also follow below.

Table B1: Sample Descriptive Statistics

Quantity	Mean	Standard Deviation
Sales	6732.4	23268.8
Capital	1499.4	6286.3
Profit	0.448	1.062
Investment	0.321	0.238
Debt Issuance	-0.404	3.883
Forecast Error	-0.267	0.804
Forecast	0.823	0.933

Notes: The table reports descriptive statistics for the sample of 1320 firms from 1999-2017 in the combined Compustat-IBES database. The first two rows represent revenues and the book value of the capital stock, in $ millions. The remaining rows reflect the ratio of realized earnings to the book value of the capital stock, the capital expenditures investment rate, the ratio of end of period total liabilities to the capital stock, the next-period forecast error defined as realized future profits minus manager guidance scaled by firm capital, and the next period forecast defined as manager profit guidance scaled by firm capital. The sample was winsorized before computing the descriptive statistics above.

The variable definitions are given as follows, with both empirical and model information attached:

- **Earnings or profits** are equal to GAAP net income, Compustat `ib`. The model equivalent is $\pi = (1-\tau)(y - Wn - AC(i,k) - \phi) + \tau(Rb + \delta k) - \delta k$.

- **Capital** k is equal to the book value of plants, property, and equipment, Compustat `ppent`. The model equivalent is the state variable k.

- **Investment** i is equal to the total value of capital expenditures, Compustat `capxv`. The model equivalent is the policy variable $i = k' - (1-\delta)k$.

- **Debt** b is equal to the total net value of liabilities, Compustat `dltt` + `dlc` − `che`. The model equivalent is the state variable b.

- **Forecast error** fe is equal to the realized value of earnings π minus the forecast level of earnings π^f made from the previous fiscal year, where realized earnings are Compustat `ib` and forecast earnings are equal to manager guidance from the IBES database. The model equivalent is the earnings value π above, minus the forecast level implied by firm-level diagnostic expectations, the definition of π, and firm policies predetermined in the previous period.

We also use the merged Compustat-IBES guidance sample to run various robustness checks to the firm forecast error predictability regressions reported in the main text. Table B2 shows similar forecast error predictability maintains after the Great Recession. Table B3 shows that forecast error predictability is robust in a sample of firms present for five or more years in the data. Table B4 shows that forecast error predictability remains present after discarding all firms with high-yield debt as classified by Moody's ratings. Table B5 shows that forecast error predictability is robust in a specification with all variables in first differences.

B.2 Microdata on Bonds from FISD-TRACE

We use the WRDS US Corporate Bond Return database, which merges the Mergent FISD and FINRA TRACE datasets with issuance and secondary market information on corporate bond issues, respectively. We consider only unsecured, unconvertible debentures and convert secondary market yields to spreads based on comparable Treasury rates, with a resulting dataset of around 80,000 issues from mid-2002 to late 2019. We link the bond return database to Compustat firm financials through the WRDS CRSP link, and we aggregate from the issue to firm level by computing average yields and bond returns for a firm in Q4 of a given year. The resulting dataset spans around 1,500 large US public firms. Linking this panel to the IBES-manager guidance data yields the sample used in Table 2 in the main text. Table B6 replicates Table 2 but does not include current profit controls for the investment regressions nor lagged spread controls for the spread regressions. Table B7 replicates Table 2 conditioning only on investment grade bonds.

B.3 Macro Data

At the macro level, we use a combination of information from the NIPA accounts, the BIS, Moody's. The following variables are relevant, all at annual frequency or converted to annual frequency by averaging.

- **Output** Y is real GDP from the NIPA accounts.
- **Debt** B is real total nonfinancial corporate credit in the US from the BIS.
- **Investment** I is real nonresidential private investment from the NIPA accounts in the data.

- **Spreads** are the Moody's BAA spread relative to 10-year Treasury bonds, at an annualized rate.
- **TFP** is the annualized value of the series `dtfp` from John Fernald's website.
- **Profit Fcst** is the sum of earnings guidance across firms in a given year from our Compustat-IBES merged database.

In the empirical business cycle moments in Table 8, we reports moments from the HP-filtered values of output, investment, and debt, together with unadjusted spread levels. In the spread matching/Great Recession exercise in Figure 4, we report the average spread and the average growth of credit, output, investment, and profit forecasts in each subperiod.

B.4 SMM Estimation

Our SMM estimation exercise in Section 5 involves three steps: 1) moment and covariance matrix calculations, 2) model estimation, and 3) standard error calculation. We detail each of these steps in turn.

B.4.1 Moment and Covariance Matrix Calculation

Table 4 reports a set of 18 target moments at the micro and macro levels for our SMM estimation exercise. The micro moments are a covariance matrix of the vector

$$X_{it} = (\text{Forecast Error}_{it+1}, \text{Profit}_{it}, \text{Investment}_{it}, \text{Debt}_{it}, \text{Spread}_{it})'$$

for firm i in fiscal year t from our merged Compustat-IBES-FISD-TRACE sample. The merged sample with each of those variables available for all firms spans 387 firms and 2919 total observations. To compute the micro moments, we use the following procedure:

- Demean X_{it} by firm and year to obtain $\hat{X}_{it}$
- Compute the covariance matrix as the mean of $\hat{X}_{it}\hat{X}'_{it}$.
- Apply the standard formula for the clustered covariance of a mean vector to obtain the moment covariance matrix Ω_{Micro}, clustering across firms.

With the estimated micro moments and the estimated moment covariance matrix for the micro moments in hand, we then turn to the calculation of the macro moments and their covariance matrix. Note that the macro moments are the mean default rate, the mean spread, and the standard deviation of real GDP growth. We compute the mean default and spread series from our merged FISD-TRACE data on corporate debt, and we compute real GDP growth from the NIPA data. The point estimates of these macro moments are trivial to compute. We then compute an estimate of the covariance matrix of these macro moments Ω_{Macro} using a stationary block bootstrap.

Note that for our later inference based on clustering at the firm level, we will rely upon asymptotics in the number of firms, together with an assumption that the macro sample length T and the number of firms N behave proportionally with $T/N \to \gamma$ for some constant γ as $N \to \infty$. This allows us to rely on asymptotics of the basic form

$$\sqrt{N}(\hat{\mu} - \mu) \to_{d,N\to\infty} N(0, \Omega), \tag{18}$$

where $\hat{\mu}$ is the estimated moment vector (with micro and macro moments) and Ω is the joint moment covariance adjusted for γ.

$$\Omega = \begin{bmatrix} \Omega_{Micro} & 0 \\ 0 & \frac{1}{\gamma}\Omega_{Macro} \end{bmatrix}.$$

Table 4 reports $\hat{\mu}$ and standard errors based on the approximating variance from (18).

B.4.2 Point Estimation Calculation

We compute the point estimates $\hat{\beta}$ for the vector of estimated parameters β in Tables 5 and 6 by solving the following standard SMM optimization problem

$$\min_{\beta}(\mu^S(\beta) - \hat{\mu})'\hat{\Omega}^{-1}(\mu^S(\beta) - \hat{\mu})$$

where $\mu^S(\beta)$ is the model value of the moments given β computed from simulated data, $\hat{\Omega}^{-1}$ is the asymptotically efficient weighting matrix given by the inverse of the estimated moment covariance matrix, and $\hat{\mu}$ is the empirical moment vector. We employ particle swarm optimization to solve this optimization problem, a stochastic global optimization routine that bears substantial similarity to simulated annealing and genetic algorithms.

B.4.3 Standard Error Calculation

Given the ratio between the number of firms N^{sim} in the model simulation used to compute $\mu^S(\beta)$ and the empirical number of firms N, the SMM estimators asymptotic covariance matrix Σ follows

$$\sqrt{N}(\hat{\beta} - \beta) \to_{d,N\to\infty} N(0, \Sigma) \tag{19}$$

where

$$\Sigma = \left(1 + \frac{N^{sim}}{N}\right)\left(\frac{\partial \mu^S(\beta)}{\partial \beta'}\Omega^{-1}\frac{\partial \mu^S(\beta)}{\partial \beta}\right)^{-1}. \tag{20}$$

Equation (20) yields a feasible formula for Σ after substitution of the estimated covariance matrix $\hat{\Omega}$ and numerical calculation of the moment Jacobian matrix $\frac{\partial \mu^S(\beta)}{\partial \beta'}$ within the model using forward differentiation from the point estimates $\hat{\beta}$. With these elements in hand, Tables 5 and 6 report standard errors based on the approximating variance from (19).

B.5 Robustness Tables

Table B2: Predictable Forecast Errors: Post-Great Recession

	(1)	(2)	(3)	(4)
	Fcst. $Error_{t+1}$	Fcst. $Error_{t+1}$	Fcst. $Error_{t+1}$	Fcst. $Error_{t+1}$
$Forecast_t$	-0.320***			
	(0.052)			
$Profits_t$		-0.133***		
		(0.030)		
$Investment_t$			-0.398***	
			(0.107)	
Debt $Issuance_t$				-0.051***
				(0.013)
Firm Effect	X	X	X	X
Time Effects	X	X	X	X
Years	2010-18	2010-18	2010-18	2010-18
Firm-Years	3880	3880	3880	3880

Notes: The table reports estimates of specifications on the merged Compustat - IBES Guidance sample at the firm-fiscal year level, restricting to the post-Great Recession period. Forecasts are earnings guidance, profits are earnings, investment is tangible capital expenditures, debt issuance is end-of-period net debt, and forecast errors are actual earnings minus manager guidance at a 1-year horizon. All series are relative to firm tangible capital stocks at the beginning of the year. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of future forecast errors is 0.781, the standard deviation of forecasts is 0.914, the standard deviation of profits is 1.008, the standard deviation of investment is 0.216, and the standard deviation of debt issuance is 3.719. For all series, 0.01=1% relative to a firm's tangible capital stock.

Table B3: Predictable Forecast Errors: Forecasts for 5 or More Years

	(1)	(2)	(3)	(4)
	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$
Forecast$_t$	-0.243***			
	(0.030)			
Profits$_t$		-0.036*		
		(0.021)		
Investment$_t$			-0.451***	
			(0.066)	
Debt Issuance$_t$				-0.040***
				(0.007)
Firm Effect	X	X	X	X
Time Effects	X	X	X	X
Years	1999-18	1999-18	1999-18	1999-18
Firm-Years	9564	9564	9564	9564

Notes: The table reports estimates of specifications on the merged Compustat - IBES Guidance sample at the firm-fiscal year level, restricting to firms with at least 5 years of forecasts. Forecasts are earnings guidance, profits are earnings, investment is tangible capital expenditures, debt issuance is end-of-period net debt, and forecast errors are actual earnings minus manager guidance at a 1-year horizon. All series are relative to firm tangible capital stocks at the beginning of the year. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of future forecast errors is 0.777, the standard deviation of forecasts is 0.921, the standard deviation of profits is 1.012, the standard deviation of investment is 0.232, and the standard deviation of debt issuance is 3.760. For all series, 0.01=1% relative to a firm's tangible capital stock.

Table B4: Predictable Forecast Errors: Investment Grade Debt

	(1)	(2)	(3)	(4)
	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$
Forecast$_t$	-0.229***			
	(0.031)			
Profits$_t$		-0.050**		
		(0.022)		
Investment$_t$			-0.445***	
			(0.068)	
Debt Issuance$_t$				-0.036***
				(0.007)
Firm Effect	X	X	X	X
Time Effects	X	X	X	X
Years	1999-18	1999-18	1999-18	1999-18
Firm-Years	8620	8620	8620	8620

Notes: The table reports estimates of specifications on the merged Compustat - IBES Guidance sample at the firm-fiscal year level, restricting to firms with Moody's rated investment grade debt. Forecasts are earnings guidance, profits are earnings, investment is tangible capital expenditures, debt issuance is end-of-period net debt, and forecast errors are actual earnings minus manager guidance at a 1-year horizon. All series are relative to firm tangible capital stocks at the beginning of the year. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of future forecast errors is 0.804, the standard deviation of forecasts is 0.933, the standard deviation of profits is 1.062, the standard deviation of investment is 0.238, and the standard deviation of debt issuance is 3.883. For all series, 0.01=1% relative to a firm's tangible capital stock.

Table B5: Predictable Forecast Errors: First Differences

	(1)	(2)	(3)	(4)
	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$	Fcst. Error$_{t+1}$
Forecast$_t$	-0.385***			
	(0.047)			
Profits$_t$		-0.304***		
		(0.021)		
Investment$_t$			-0.286***	
			(0.073)	
Debt Issuance$_t$				-0.035***
				(0.012)
Firm Effect	X	X	X	X
Time Effects	X	X	X	X
Years	2000-18	2000-18	2000-18	2000-18
Firm-Years	7125	7125	7125	7125

Notes: The table reports estimates of specifications on the merged Compustat - IBES Guidance sample at the firm-fiscal year level. Forecasts are earnings guidance, profits are earnings, investment is tangible capital expenditures, debt issuance is end-of-period net debt, and forecast errors are actual earnings minus manager guidance at a 1-year horizon. All series are relative to firm tangible capital stocks at the beginning of the year. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of future forecast errors is 0.652, the standard deviation of forecasts is 0.383, the standard deviation of profits is 0.780, the standard deviation of investment is 0.178, and the standard deviation of debt issuance is 1.713. For all series, 0.01=1% relative to a firm's tangible capital stock. All series are in first differences.

Table B6: Linking Forecast Errors and Credit Spreads: No Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$Return_t$	$Return_t$	Δ $Spread_t$	Δ $Spread_t$	Δ $Investment_t$	Δ $Investment_t$
Estimation	OLS	IV	OLS	IV	OLS	IV
Fcst. $Error_t$	0.001	0.007*	-0.003***	-0.007**	0.008	0.453***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.007)	(0.096)
First Stage		Fcst. $Error_t$		Fcst. $Error_t$		Fcst. $Error_t$
$Investment_{t-1}$		-0.562***		-0.562***		-0.562***
		(0.105)		(0.105)		(0.105)
Years	2003-18	2003-18	2003-18	2003-18	2003-18	2003-18
Firm-Years	2852	2852	2852	2852	2852	2852
Time Effects	X	X	X	X	X	X
First Stage F		28.94		28.94		28.94

Notes: The table reports estimates of specifications on the merged Compustat - IBES - FISD/TRACE sample at the firm-fiscal year level. The top panel plots OLS and IV second-stage estimates. The bottom panel, where relevant, reports IV first-stage estimates. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of the bond return is 0.014, the standard deviation of spread growth is 0.024, the standard deviation of investment growth is 0.090, the standard deviation of the forecast error is 0.438, and the standard deviation of lagged investment is 0.133. For all series, 0.01=1% relative to a firm's tangible capital stock.

Table B7: Linking Forecast Errors and Credit Spreads: Investment Grade Debt

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$Return_t$	$Return_t$	Δ $Spread_t$	Δ $Spread_t$	Δ $Investment_t$	Δ $Investment_t$
Estimation	OLS	IV	OLS	IV	OLS	IV
Fcst. $Error_t$	0.00004	0.007*	-0.001**	-0.007***	0.020**	0.409***
	(0.0005)	(0.003)	(0.0004)	(0.003)	(0.009)	(0.074)
First Stage		Fcst. $Error_t$		Fcst. $Error_t$		Fcst. $Error_t$
$Investment_{t-1}$		-0.568***		-0.568***		-0.568***
		(0.118)		(0.118)		(0.118)
Years	2003-18	2003-18	2003-18	2003-18	2003-18	2003-18
Firm-Years	1984	1984	1984	1984	1984	1984
Time Effects	X	X	X	X	X	X
First Stage F		23.27		23.27		23.27

Notes: The table reports estimates of specifications on the merged Compustat - IBES - FISD/TRACE sample at the firm-fiscal year level, restricting to firms with Moody's rated investment grade debt. The top panel plots OLS and IV second-stage estimates. The bottom panel, where relevant, reports IV first-stage estimates. Columns (3)-(4) control for lagged spreads, and columns (5)-(6) control for current profits in the second stage. Standard errors are clustered at the firm level. * = 10% level, ** = 5% level, and ***=1% level. The standard deviation of the bond return is 0.014, the standard deviation of spread growth is 0.024, the standard deviation of investment growth is 0.090, the standard deviation of the forecast error is 0.438, and the standard deviation of lagged investment is 0.133. For all series, 0.01=1% relative to a firm's tangible capital stock.