Do bankers matter for main street? The financial intermediary labor channel*

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Abstract

Financial intermediary (FI) stress, measured by leverage, is an important driver of asset prices and quantities. We identify a new and equally important FI channel driving risk and the real sector: FIs are stressed when FI labor share (FLS) is high. FLS negatively forecasts aggregate output, investment, and credit growth; it positively forecasts the cost of credit. High FLS banks lend less and are riskier. Firms connected to such banks borrow less, grow less, and pay more to borrow. A DSGE model where FIs endogenously use labor to increase screening in bad times explains these findings.

Keywords: Financial intermediaries, Labor market frictions

JEL classification: E43, G21, J11.

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1 Introduction

This paper studies how the labor needs and labor costs of the financial sector affect aggregate risk and the real economy. Financial intermediaries (FIs) have been shown to play a central role in driving aggregate fluctuations over the business cycle. However, existing studies mostly focus on the financial leverage channel of FIs in affecting risk; the effect of FI labor needs and labor costs on FI health and the real economy is usually overlooked. We show that the labor channel of FIs is an important driver of asset prices and quantities, not only of the financial sector but also of the real economy.

Empirically, a high FI labor share (FLS), defined as the compensation to value added ratio, appears to be associated with stress in financial sector, which spills over into the real economy. A high FLS is contemporaneously associated with low output growth, investment growth, and debt growth, but high credit spreads. A high FLS also predicts low future output growth, investment growth, and debt growth, but high credit spreads. Our estimates imply that when FLS is one standard deviation above its mean, the one year ahead borrowing cost is 70bp higher, and one year ahead debt, GDP, and investment are, respectively 3.5%, 0.5%, and 2% lower. In the cross-section, banks with a high labor share lend less and have higher credit risk. Firms connected to such banks borrow less, pay more to borrow, have higher credit risk, and lower earnings growth; they also invest less, especially if they are financially constrained.[1] Additionally, FI labor behaves quite differently from other sectors. While employment in most sectors is strongly pro-cyclical, falling drastically during recessions, FI employment is far less sensitive to the business cycle: in bad times, FI employment as a share of total employment and FLS both rise.

To explain these empirical facts, we build an otherwise standard DSGE model, but where FIs raise deposits and equity from households and lend to corporations. FIs are needed because on the firm side, trade-off theory makes it more profitable for firms to have at least some debt financing, while on the household side, households can invest in corporate equity, but are assumed to be unable to invest in corporate debt.

The key innovation in our model is that FIs must hire labor in order to intermediate capital. FI labor needs are proportional to the size of their balance sheet. Additionally, they can hire more labor to screen out unproductive firms and improve their return on investment. Endogenously, screening becomes relatively more worthwhile in bad times, when expected losses from investing in unproductive firms are greater. This attenuates some of the business cycle variation since unproductive firms are less likely to receive financing when screening is higher. Since screening is stronger in bad times, FI labor becomes less pro-cyclial than aggregate labor. We use the counter-cyclicality of FI employment share and of FLS in the data to discipline the importance of screening

[1] FLS is defined as compensation as a fraction of value added. As discussed in Section 3.4, the predictive power of FLS in the time-series and the cross sectional analysis is not simply driven by the variation in value added.

in the model. The relatively higher labor needs in bad times also increase credit spreads as FIs require higher revenues to compensate the extra labor. With these features, the model implies that as in the data, high FLS is related to low output, investment, and debt growth and to high credit spreads, both contemporaneously and predictively.[2] A similar model with screening shut off cannot replicate this because FI labor and FLS are both pro-cyclical.

We explore alternative channels that may allow a model to match the same empirical facts. We find that when screening is turned off, segmenting labor markets by introducing frictions of switching from FI to non-FI labor does not lead to counter-cyclical FI employment share or FLS. This is because when frictions lead to excess labor in the financial sector, financial sector wages fall, undoing much of the effect on compensation and therefore FLS. Similarly, when screening is turned off, introducing a wedge between financial sector and non-financial sector wages (for example through wage rigidity) does not lead to a counter-cyclical FI employment share or FLS. This is because when financial sector wages are relatively high, financial sector employment falls, undoing much of the effect on FLS.

One alternative to screening that does work is a shock to FI labor needs (FLN) – essentially an FI labor-specific productivity shock – that exogenously requires FIs to hire more labor per unit of intermediated capital. When FIs require more labor per unit of intermediated capital, they raise credit spreads to compensate themselves for the additional cost, leading to a contraction in lending and in real activity. Such shocks are analogous to the "financial shocks" in Jermann and Quadrini (2012) and Khan and Thomas (2013), but specific to the labor FIs need, as opposed to the collateral constraint shocks that they model. These shocks can be interpreted as either a reduced form way to proxy for the endogenous screening in our baseline model, or as truly exogenous shocks – for example due to regulation. In Appendix Section B.1, we provide evidence of such shocks affecting FI employment and lending.

Although our model is about aggregate quantities, the same intuition holds for individual FIs. If an individual FI suddenly faces a larger number of bad borrowers it will endogenously screen more, raising its labor share and credit spreads, while reducing lending. Alternatively, if an individual FI suddenly requires more labor to intermediate capital for an exogenous reason, the FI's labor share will rise and its lending will fall. If firms face switching costs when choosing their lenders, firms connected to the affected FI will also be adversely affected. As discussed above, we empirically test these relationships at the aggregate, bank, and firm level. Additionally, we find that a high FLS predicts higher stock return volatility and earnings volatility at the bank level, consistent with banks retaining more labor ahead of uncertain times.

Literature review This paper builds on five broad strands of literature. Primarily, our paper is part of a growing literature that provides empirical support for the importance of FI labor and shocks

[2] In principle, even if FIs hire more labor, FLS need not rise if wages were to fall sufficiently, but since FI wages are tied to aggregate wages through labor market clearing, wages do not fall by enough.

to FI labor productivity. Flanagan (2024) estimates that banks create 190bp of value added on their syndicated loans, most of which is paid to the bank's employees. He attributes most of this to the bank's screening and monitoring activities and shows that this value added was higher in more complex situations – consistent with our assumption that there are certain times or circumstances when banks require more labor to intermediate capital.[3] Sharpe and Sherlund (2016), Choi et al. (2022), and Ma (2023) all document the importance of labor capacity constraints for mortgage lenders; this implies that the amount of lending is tied to the number of loan officers, as in our model. These papers also document that when demand is high and lenders are at their capacity constraint, they switch toward borrowers who are easier to process, for example refinancing (as opposed to new originations) and high credit score borrowers - in effect, this makes loan officers more productive in good times. In addition, Fuster et al. (2022b) document that the price of intermediation fluctuates significantly, reflecting capacity constraints, and that in 2008-2014, the price of intermediation increased by about 30bp per year, reflecting higher mortgage servicing costs and an increased legal and regulatory burden. Finally, Fuster et al. (2022a) show that during the Covid-19 pandemic, there was a large and sustained increase in intermediation markups, due to pandemic related labor market frictions and operational bottlenecks.[4] We build the first model that seriously consideres the roles of FI labor and its effect on business cycle quantities; we also provide empirical evidence consistent with the model's predictions. Philippon and Reshef (2012) is the only other paper we are aware of that theoretically studies FI labor, however, they focus on the long term evolution of compensation in the financial sector and do not consider cyclical fluctuations.

Second, our paper is related to the FI asset pricing literature, which studies how constraints on FIs affect asset prices and risk premia. Studies including Danielsson et al. (2004), Gromb and Vayanos (2010), He and Krishnamurthy (2011), Adrian and Boyarchenko (2012), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Gromb and Vayanos (2018), and Krishnamurthy and Li (2022) have argued theoretically that FI financial leverage should matter for risk and asset prices because they are marginal investors when they are constrained. Empirical support for these theories has been found by, among others, He et al. (2017), Etula (2013), Adrian et al. (2014), Haddad and Muir (2018), and Ma (2018); for example FI financial leverage is a priced factor for the cross-section of asset returns. Jermann and Quadrini (2012) and Khan and Thomas (2013) both model an exogenous shock to capital constraints. While these papers primarily focus on the financial constraints of intermediaries – either equity- or debt-based, which leads to reduced lending

[3]Specifically, he shows that the value added is higher for firms that are smaller, younger, and without a credit rating. It was also higher for firms previously audited by Arthur Anderson after its exit from auditing following the Enron and Worldcom scandals.

[4]There is also a related literature on the busyness of agents impacting their financial decisions. Fich and Shivdasani (2006) show that when board members are busy, corporate governance is weaker. Kempf et al. (2016) show that firms whose shareholders are distracted are more likely to make bad decisions. Wang (2022) show that proxy advisors make worse recommendations when the proxy statement is more complex and when the advisors are especially busy.

to the real sector – our model introduces a novel perspective by focusing on how FIs use and pay for their labor. This innovation provides new insights into how FIs influence economic dynamics, distinct from traditional financing constraints channel. We support the model mechanism with direct evidence at both macro and micro levels showing that FI labor share predicts cost of debt, banks' risk, and real outcomes, even when controlling for FI financial leverage, corroborating the importance of FI labor.

Third, our paper relates to the macroeconomic literature studying the role of FIs in amplifying the shocks to business cycles.[5] Christiano et al. (2014) embed agency problems associated with financial intermediation as in Bernanke et al. (1999) into a monetary dynamic general equilibrium model; they find volatility shocks are important in driving the business cycle. Gertler and Kiyotaki (2015) study the macro implications of banking instability in a DSGE model with financial accelerator effects and bank runs. Begenau and Landvoigt (2021) study the macroeconomic impact of capital regulation in a model with both commercial banking and shadow banking sectors. Elenev et al. (2021) investigate the macro-prudential policy in a large scale quantitative model with financially constrained producers and intermediaries. Diamond et al. (2020), Bolton et al. (2022), and Li (2022) all build macro models of intermediaries with a focus on the liquidity of either assets or liabilities. We complement this literature by showing that the labor needs and labor costs of the financial sector matter for FI health, which directly affects the loan supply to the real sector; this in turn affects the real investment and asset prices. Unlike many of the papers in this literature, in our model, FIs dampen the business cycle because they are more likely to screen out unproductive firms in bad times.

Fourth, the paper is related to the empirical literature investigating the relationship between FIs and firms' real decisions.[6] Peek and Rosengren (1997) document that shocks to Japanese stock market causes the US branches of Japanese banks reduce their loans, with the effect being stronger for weaker banks. Ivashina and Scharfstein (2010) document large drops in lending of banks during the financial crisis. Iyer et al. (2013) show that the during the 2008 financial crisis, firms connected to more affected banks had larger credit disruptions; Chodorow-Reich (2014) shows such firms decreased employment by more. We show that banks with higher labor share cut lending more and hence affect the real investment of their borrowers.

Finally, this paper relates to the broad macroeconomic literature on wages and labor,[7] although only more recently has this literature begun to relate to financial economics.[8] On the other hand, financial economists have also recently begun exploring links between labor and asset prices both

[5] Classic papers on the amplification of the frictions of financial intermediaries to aggregate shocks include Bernanke and Gertler (1989), Carlstrom and Fuerst (1997), Bernanke et al. (1999), etc.

[6] A partial list of papers include Bernanke (1983), Slovin et al. (1993), Gan (2007), etc.

[7] Examples include Pissarides (1979), Calvo (1983), Taylor et al. (1983), Taylor (1999), Shimer (2005), Hall (2005), Gertler and Trigari (2009).

[8] See Hall (2016) who reviews the recent literature and shows that a higher discount rate is associated with higher unemployment.

in structural models,[9] and empirical analysis.[10]

In the remainder of this paper, Section 2 introduces the model incorporating the Financial Intermediary (FI) endogenous labor screening channel, which motivates the empirical analysis of the relationships between Financial Leverage Scores (FLS), quantities, and prices. This model also helps understand the underlying mechanisms. Section 3 discusses the aggregate and cross-sectional empirical results. Finally, Section 4 concludes the paper.

2 Model

We build a model of an economy with financial intermediaries who raise equity and deposits from households, lend corporate debt to firms, and require labor to manage their balance sheet and to screen out unproductive firms. Considering FIs' labor is a key innovation of our model.[11] There is an infinitely lived, representative household who can invest in three assets: risky corporate equity, risky FI equity, and riskless FI deposits. Firms can raise capital through a combination of equity and corporate debt. To pin down the debt-to-equity mix, we assume an optimal target leverage ratio, with additional costs when firms deviate from this optimal. Firms are of two types – productive or unproductive – with the types unknown at the time they raise capital. The two roles of FI labor is to manage FI balance sheets and to screen out unproductive firms. Both activities are costly and require hiring labor, which makes corporate debt relatively expensive compared to a model where FIs do not need labor. At the same time, screening by FIs increases the fraction of capital managed by productive firms and makes the overall economy more productive.

A version of our model where financial intermediaries are unnecessary is isomorphic to a standard model with infinitely lived firms and capital adjustment costs. However, for tractability, we set up the firm's problem in a non-standard way – firms have an OLG lifecycle where new firms are born each period and live until next period only. This allows us to solve the firm's problem

[9] Examples include Danthine and Donaldson (2002), Berk et al. (2010), Berk and Walden (2013), Petrosky-Nadeau et al. (2018), Belo et al. (2014), Donangelo (2014), Li and Palomino (2014), Palacios (2015), Favilukis and Lin (2015), Zhang et al. (2014), Blanco and Navarro (2016), Donangelo et al. (2010), and Favilukis et al. (2020).

[10] Many papers have linked asset returns or financing decisions to various measures of operating leverage, most related to labor. These include Ruback and Zimmerman (1984), Abowd (1989), Hirsch (1991), Chen et al. (2011), Lee and Mas (2012), Simintzi et al. (2014),Weber (2015), Favilukis and Lin (2016), Gorodnichenko and Weber (2016), Tuzel and Zhang (2017), D'Acunto et al. (2018), Donangelo et al. (2019), Donangelo (2018), Campello et al. (2017), and Qiu and Shen (2017). On the other hand Lettau et al. (2019) and Greenwald et al. (2023) show that the aggregate labor share is related to the cross-section of equity returns and to asset price movements; they attribute to it proxying for redistribution risk.

[11] The literature has taken various approaches to model the financial sector. For example, Jermann and Quadrini (2012) and Khan and Thomas (2013) do not directly model intermediaries but rather model shocks to borrowing constraints. Elenev et al. (2021) explicitly model FIs who lend and borrow but who do not require labor. Bernanke et al. (1999) model intermediaries who pay a monitoring cost that is increasing in the size of their balance sheet, but unrelated to labor. Chari et al. (1995) do model FIs which have labor needs increasing in the size of the balance sheet, but these FIs do not screen and the focus of the paper is to study various kinds of monetary aggregates, not FI labor specifically.

analytically as a function of the state, and makes it computationally tractable to solve the full model with intermediaries. In Appendix Section C.2, we set up and solve a model without financial intermediaries, but with 2-period firms and show that indeed, its solution is identical to the standard planner's problem.

Table 1 summarizes the model's parameters and Appendix Table A.27 summarizes the model's variables. Figure 1 summarizes the timeline of firm and FI actions in the model.

2.1 Households

Households have CRRA utility and supply an exogenously specified (not necessarily constant) amount of labor N_t. They buy $\theta_{c,t+1}$ shares of corporate equity at a price $V_{cn,t}$ (cn for corporate new) per firm, which is sold for $V_{co,t+1}$ (co for corporate old) at $t+1$. As will be discussed below, of this amount, Π_t goes to the entrepreneurs who own the uncapitalized firm, while the remaining $V_{cn,t} - \Pi_t$ is used to buy capital. Since there is a representative agent, entrepreneurs are also households and return Π_t to the common pot. Households also buy $\theta_{FI,t+1}$ shares of FI equity at a price of $V_{FI,n,t}$ (FI, n for FI new) per FI, which is sold for $V_{FI,o,t+1}$ (FI, o for FI old) at $t+1$. Finally, households invest in risk free FI deposits with face value $B_{d,t+1}$ at an interest rate $R_{d,t}$. We assume that FIs hold corporate debt while households do not. Let Ω_t be the household's financial net worth, $W_t N_t$ the wage multiplied by the labor supply (equivalently labor income), C_t its consumption. The household's problem is:

$$\begin{aligned} U(\Omega_t) = &\max_{C_t, B_{d,t+1}, \theta_{FI,t+1}, \theta_{c,t+1}} \frac{C_t^{1-\gamma}}{1-\gamma} + \beta E_t\left[U(\Omega_{t+1})\right] \quad \text{s.t.} \\ &\theta_{c,t+1} V_{cn,t} + \theta_{FI,t+1} V_{FI,n,t} + B_{d,t+1}/R_{d,t} = \Omega_t + W_t N_t + \Pi_t - C_t \\ &\Omega_{t+1} = \theta_{c,t+1} V_{co,t+1} + \theta_{FI,t+1} V_{FI,o,t+1} + B_{d,t+1} \end{aligned} \tag{1}$$

The household's stochastic discount factor is $M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}$. The returns on corporate equity and FI equity are, respectively, $R_{c,t+1} = \frac{V_{co,t+1}}{V_{cn,t}}$ and $R_{FI,t+1} = \frac{V_{FI,o,t+1}}{V_{FI,n,t}}$. The Euler equations for productive firm equity, FI equity, and deposits are:

$$1 = E_t[M_{t+1} R_{c,t+1}] = E_t[M_{t+1} R_{FI,t+1}] = E_t[M_{t+1} R_{d,t}] \tag{2}$$

2.2 Firms

At t, a measure one of new firms are born; they own zero capital. Firms live for just two periods: new firms at t become old firms at $t+1$ and then shut down. A fraction p of the firms are productive and the remaining $1-p$ are unproductive, although ex-ante, their types are unknown. Productive firms differ from unproductive firms in their productivity realized at $t+1$: $Z_{i,t+1} \in \{Z_{p,t+1}, Z_{u,t+1}\}$ where $Z_{p,t+1}$ and $Z_{u,t+1}$ are random variables. Specifically, if the aggregate state realized at $t+1$ is

good, then all firms have the same productivity: $Z_{p,g} = Z_{u,g} = 1$ where p and u differentiate between productive and unproductive firms, while g stands for good aggregate state. If the aggregate state is bad, then unproductive firms have lower productivity: $Z_{u,b} < Z_{p,b} = 1$ where b stands for bad aggregate state. In other words, in the good state, all firms have realized productivity 1 but in the bad state, a fraction $1-p$ of firms have lower productivity. Aggregate productivity follows a 2-state Markov process, staying in the current state with probability q and switching with $1-q$, its realization becomes publicly known at the start of a period.

New, uncapitalized firms are owned by entrepreneurs, who are part of the representative agent. Entrepreneurs sell new, uncapitalized firms to equity investors for Π_t. The equity investors then raise additional equity capital in amount $K_{e,t+1}Q_t + \Psi_t$ by selling shares, where Q_t is the price of capital, $K_{e,t+1}$ is the amount of capital firms can buy from issued equity proceeds, and Ψ_t is a reduced form trade-off theory style cost which penalizes firms whose capital structure is away from optimal.[12] Total equity issued by new corporations is $V_{cn,t} = \Pi_t + Q_t K_{e,t+1} + \Psi_t$.

After issuing equity, firms are imperfectly screened by FIs with screening intensity ζ_t. The FI is able to discover and screen out a fraction ζ_t of the $1-p$ unproductive firms – a total of $\zeta_t(1-p)$ firms – and it does not offer additional capital to these firms.[13] The remaining firms are 'screened-in', these are all p productive firms as well as $(1-p)(1-\zeta_t)$ unproductive firms. Screened-in firms issue additional debt in amount $B_{cd,t+1}/R_{cd,t}$ (cd for corporate debt), where $B_{cd,t+1}$ is the face value of corporate debt and $R_{cd,t}$ is its interest rate. The total capital raised by these firms is $K_{de,t+1} = K_{e,t+1} + K_{d,t+1}$ where $K_{d,t+1} = \frac{1}{Q_t} B_{cd,t+1}/R_{cd,t}$. After financing is complete, $\zeta_t(1-p)$ unproductive firms have capital $K_{e,t+1}$ with no debt, while $(1-\zeta_t)(1-p)$ unproductive firms and p productive firms have capital $K_{de,t+1}$ with debt face value $B_{cd,t+1}$.

Next, conditional on $K_{e,t+1}$, $K_{d,t+1}$ and $B_{cd,t+1}$ we solve the firm's problem backwards. We explain how $K_{e,t+1}$, $K_{d,t+1}$ and $B_{cd,t+1}$ are determined in Section 2.4. To generate a quantitatively important impact of FI screening on the aggregate economy, we assume that at the start of $t+1$, the aggregate shock is known, however neither firms nor investors know yet which of the screened-in firms are productive and which are unproductive. Therefore, all screened-in firms with capital $K_{de,t+1}$ hire identical labor, leading to misallocation of too much labor in unproductive firms.[14] We define a screened-in firm's average productivity as $\hat{Z}_{t+1} = \frac{pZ_{p,t+1} + (1-p)(1-\zeta_t)Z_{u,t+1}}{p + (1-p)(1-\zeta_t)}$; note that $\hat{Z}_{t+1}$

[12] We discuss the specification of Ψ_t in Section 2.6.

[13] In principle, the FI could offer additional financing at different terms to these firms. However, in our calibration, this would be suboptimal. This is because we have decreasing returns to scale ($\rho < 1$) and the number of unproductive firms $(1-p)$ is relatively small. As a result, the unproductive firm's optimum, profit maximizing capital demand is less than the equity capital $K_{e,t+1}$ they have already raised. We also assume they cannot sell this capital back to investors or to other firms.

[14] We have also solved a version of the model where firm type is known as of $t+1$. Our main results are qualitatively similar, however, the benefits of screening have a smaller impact on output. This is because when unproductive firms know their type, even if they have too much capital, they will hire appropriately little labor, leaving more labor for productive firms. Since labor share is around 2/3, misallocation of capital to unproductive firms (without misallocation to labor) lead to relatively small distortions to output.

is not a random variable as of $t+1$ because the aggregate state, and therefore the values of $Z_{p,t+1}$ and $Z_{u,t+1}$ are known.

At $t+1$, there are three different kinds of old firms: unproductive firms that are not financed by the FI (u) with capital $K_{e,t+1}$ and no debt, financed unprodutive firms (uf) with capital $K_{de,t+1}$ and debt $B_{cd,t+1}$, and financed productive firms (pf) with the same capital and debt as uf. Note that types uf and pf are indistinguishable to both outside investors and management at the time they are choosing labor. Old firms of type $i \in (u, uf, pf)$ produce output with a Cobb-Douglas production function using capital $K_{i,t+1}$ purchased at t and labor $N_{i,t+1}$ hired at $t+1$. They also choose how much new capital $S_{i,t+1}$ to create, pay adjustment costs associated with creation and installation of new capital, and sell their capital to new $t+1$ firms for $S_{i,t+1}Q_{t+1}$. After production, but before creating new capital, some of the firms experience an idiosyncratic depreciation shock destroying all of their existing capital, therefore the depreciation rate $\delta_{t+1} \in (\overline{\delta}, 1)$ is an idiosyncratic random variable – the purpose of this is to make debt risky.[15] Firms use the proceeds from selling their output and new capital to first pay employees, second pay back creditors, and third pay any remainder to their equity holders.

Firm type i's $t+1$ payout to shareholders, or equivalently its value $V_{i,co,t+1}$ is:

$$\begin{aligned} V_{i,co,t+1} &= Z_{i,t+1}K_{i,t+1}^{\alpha\rho}(A_{t+1}N_{i,t+1})^{1-\alpha} - N_{i,t+1}W_{t+1} \\ &\quad + K_{i,t+1}(1-\delta_{t+1}) - S_{i,t+1} - \nu_{k,0}\left(\frac{S_{i,t+1}}{K_{i,t+1}} - \nu_{k,1}\right)^2 K_{i,t+1} + Q_{t+1}S_{i,t+1} - B_{cd,i,t+1} \end{aligned} \tag{3}$$

Each firm's choice of investment $I_{i,t+1} = S_{i,t+1} - K_{i,t+1}(1-\delta_{t+1})$ is orthogonal to its production decision or its choice of labor $N_{i,t+1}$; its created capital $S_{i,t+1}$ is independent of the realized depreciation shock. The investment choice satisfies

$$Q_{t+1} = 1 + 2\nu_{k,0}\left(\frac{S_{i,t+1}}{K_{i,t+1}} - \nu_{k,1}\right) \tag{4}$$

In equilibrium, aggregate capital is $K_{t+2} = S_{t+1}$.[16]

The firms's choice of labor satisfies:

$$N_{i,t+1} = \begin{cases} \left((1-\alpha)Z_{u,t+1}A_{t+1}^{1-\alpha}K_{e,t+1}^{\alpha\rho}/W_{t+1}\right)^{1/\alpha} & \text{screened-out: } i = u \\ \left((1-\alpha)\hat{Z}_{t+1}A_{t+1}^{1-\alpha}K_{de,t+1}^{\alpha\rho}/W_{t+1}\right)^{1/\alpha} & \text{screened-in: } i \in (uf, pf) \end{cases} \tag{5}$$

[15] Unproductive firms have lower output than productive firms, but this alone is not enough to make debt risky because firms are one period firms, the typical equity to value ratio is around 60%, and the typical output to capital ratio is only around 33%, therefore variations in output alone are not enough to drive equity to zero for one-period firms.

[16] $S_{i,t+1}$ is independent of the depreciation shock because, for tractability, the adjustment cost depends on capital before the depreciation shock. Therefore, as in the frictionless model, aggregate capital at $t+2$ is linear in aggregate capital at $t+1$: $K_{t+2} = \sum p_i K_{i,t+2} = \sum p_i \left((1-\delta_{t+1})K_{i,t+1} + I_{i,t+1}\right) = \sum p_i S_{i,t+1} = S_{t+1} = \left(\nu_{k,1} + \frac{Q_{t+1}-1}{2\nu_{k,0}}\right)K_{t+1}$.

Note that screened-in firms choose labor to maximize profit based on their expected productivity $\hat{Z}_{t+1}$ because they don't know their type when choosing labor.[17]

We can rewrite the firm's value conditional on optimal labor and investment by plugging equations 4 and 5 into the equation 3:

$$V_{i,co,t+1} = max(0, X^0_{i,t+1}K^{\rho}_{i,t+1} + X^1_{i,t+1}K_{i,t+1} - B_{cd,i,t+1}) \tag{6}$$

where $K_{u,t+1} = K_{e,t+1}$; $K_{uf,t+1} = K_{pf,t+1} = K_{de,t+1}$; $B_{cd,u,t+1} = 0$; $B_{cd,uf,t+1} = B_{cd,pf,t+1} = B_{cd,t+1}$; and $X^0_{i,t+1}$ and $X^1_{i,t+1}$ are in Appendix equation C.4. Additionally, firms have limited liability, so that $V_{i,co,t+1} > 0$ and creditors take losses when equity falls to zero.

The value of the firm to the entrepreneur is the ex-ante, time t discounted average value of the possible realizations, minus the additional capital that investors must raise.

$$\Pi_t = E_t\left[M_{t+1}\left(\zeta_t(1-p)V_{u,co,t+1} + (1-\zeta_t)(1-p)V_{uf,co,t+1} + pV_{pf,co,t+1}\right)\right] - Q_tK_{e,t+1} - \Psi_t \tag{7}$$

2.3 Financial Intermediaries

At t, new competitive FIs are born who will live for one period. New FIs raise equity in amount $V_{FI,n,t}$ and deposits $B_{d,t+1}/R_{d,t}$, pay labor costs $N_{FI,t}W_t$, and lend all of their remaining capital to firms, with lending per screened-in firm being $B_{cd,t+1}/R_{cd,t}$. The $t+1$ face values of deposits and corporate debt are, respectively $B_{d,t+1}$ and $B_{cd,t+1}$. The contracted corporate interest rate at t, to be repaid at $t+1$ is $R_{cd,t}$ and the actual amount repaid, accounting for default, is $\hat{R}_{cd,t+1} \leq R_{cd,t}$. At $t+1$, FIs collect revenue from corporate lending, pay off depositors, pay the remainder of their capital to equity holders, and then shut down; at the same time, a new set of competitive FIs are born.[18]

FIs face a capital constraint κ, limiting the ratio of deposits to equity. We assume that FIs are always at this constraint.[19]

$$B_{d,t+1}/R_{d,t} = \kappa V_{FI,n,t} \tag{8}$$

The variable ζ_t summarizes the FI's screening intensity. A FI with screening intensity ζ_t is able to discover a fraction ζ_t of unproductive firms, implying a total of $(1-p)\zeta_t$ unproductive firms being screened-out. The remaining $p + (1-p)(1-\zeta_t)$ are screened-in; the FI does not know their type

[17] There is no need to discount or account for risk aversion because this choice happens within the period and the outcome is not correlated with any aggregate shock.

[18] The standard FI asset pricing channel works by having FIs suffer negative shocks, leading to low equity valuations, and causing them to contract balance sheets. This channel is dynamic. Because our FIs live for two periods, that channel is absent by construction. One could reintroduce it either by having time-varying equity issuance costs, leading to low FI equity in some periods, or by linking FIs intertemporaly, for example by having the new FI's equity issuance at $t+1$ be a function of the old FI's dividend payout at $t+1$.

[19] This would be easy to endogenize. For example, if there was a preference by households for liquidity, then deposit funding would be cheaper than equity funding, and FIs would choose to maximize deposit funding.

but knows the fraction of each type. As ζ_t rises to one, the FI can perfectly separate productive from unproductive firms. As discussed in Section 2.2, FIs do not lend to screened-out unproductive firms, therefore, total corporate lending is

$$B_{FI,a,t+1}/R_{cd,t} = (p + (1-p)(1-\zeta_t))B_{cd,t+1}/R_{cd,t} \tag{9}$$

where $B_{FI,a,t+1}$ (FI, a for FI assets) is the face value of total FI assets and $B_{cd,t+1}$ is the face value of corporate debt in each FI financed firm.

FIs need labor to operate; labor demand at t is:

$$N_{FI,t} = \eta_{FI,0} + \eta_{FI,1} A_t^{-\frac{1-\alpha}{1-\alpha\rho}} (B_{FI,a,t+1}/R_{cd,t}) + \eta_{FI,2} A_t^{-\frac{1-\alpha}{1-\alpha\rho}} (B_{FI,a,t+1}/R_{cd,t})\zeta_t^2 \tag{10}$$

where on the right, the first term indicates a fixed cost of operating, the second term indicates a variable cost of operating – labor needed is proportional to the size of the balance sheet, and the third term indicates the cost of screening.[20] Equation 10 can be thought of the FI's production function – the FI produces intermediation and screening services; this function gives labor needs per unit of such services.

Total FI lending is given by its equity plus deposits minus labor costs

$$V_{FI,n,t}(1+\kappa) - W_t N_{FI,t} = B_{FI,a,t+1}/R_{cd,t} = (p + (1-p)(1-\zeta_t))B_{cd,t+1}/R_{cd,t} \tag{11}$$

Let s_{t+1} be the probability that a firm's capital is destroyed by the depreciation shock. The FI's random payout at $t+1$ is:

$$\begin{aligned} V_{FI,o,t+1} &= (V_{FI,n,t}(1+\kappa) - W_t N_{FI,t})\hat{R}_{cd,t+1} - \kappa V_{FI,n,t} R_{d,t} \quad \text{where} \\ \hat{R}_{cd,t+1} &= (1-s_{t+1})R_{cd,t} + s_{t+1}\frac{\left(pV^{\delta}_{pf,co,t+1} + (1-p)(1-\zeta_t)V^{\delta}_{uf,co,t+1}\right)}{(p+(1-p)(1-\zeta_t))K_{d,t+1}Q_t} \end{aligned} \tag{12}$$

where the second term represents the recovery rate and $V^{\delta}_{i,co,t+1} = X^0_{i,t+1}K^{\rho}_{i,t+1} + X^{1,\delta=1}_{i,t+1}K_{i,t+1}$ represents the firm's value conditional on receiving a depreciation shock that wipes out its capital.[21] The FI's return on equity is defined as

$$R_{FI,t+1} = \frac{V_{FI,o,t+1}}{V_{FI,n,t}} \tag{13}$$

[20] Because the economy is growing and $B_{FI,a,t+1}$ is non-stationary, we need to detrend any variables scaled by it to make them stationary. The economy's balanced growth path follows $A_t^{\frac{1-\alpha}{1-\alpha\rho}}$ where $A_t = (1+g)^t$, we discuss this in Appendix Section C.3.

[21] The formula for $X^1_{i,t+1}$ as a function of δ_{t+1} is given by Appendix equation A.15. $X^{1,\delta=1}_{i,t+1}$ is its value when $\delta_{t+1} = 1$, that is when the firm's capital fully depreciates after production. When this happens the firm still has value because it already used labor and capital to produce. Even though our assumptions imply that FI screening intensity ζ_t cannot affect the probability of default s_{t+1}, screening affects the recovery rate by having a higher share of lending go to high productivity firms, therefore, screening can improve the FI's return on investment.

2.4 Choice of capital and financing method

Ex-ante, before the firms raise equity, the FI offers to all firms a contract with four attributes $(\zeta_t, K_{e,t+1}, K_{d,t+1}, R_{cd,t})$ in order to maximize its own profit. Recall that $K_{e,t+1}$ is the capital financed by the equity issuance and $K_{d,t+1}$ is the additional capital financed by debt. We choose this approach in order to avoid dealing with frictions unrelated to our mechanism, for example, risk shifting.[22]

According to the contract, first, after paying Π_t to the entrepreneur but prior to being screened by the FI, firms agree to raise equity from public markets in amount $Q_t K_{e,t+1} + \Psi_t$ at terms fair for an average firm, determined by the public market. Of this, $Q_t K_{e,t+1}$ will pay for new capital and Ψ_t will pay for capital structure related costs. Second, the FI screens firms with intensity ζ_t. Third, firms screened-out as unproductive receive no additional capital, while screened-in firms are offered to issue an additional $Q_t K_{d,t+1}$ of debt capital at an interest rate $R_{cd,t}$. The FI chooses this contract to maximize its own equity value $V_{FI,n,t} = E_t[M_{t+1} V_{FI,o,t+1}]$. The FI offers this contract subject to firms being ex-ante no worse off than simply raising money from the equity market, and subject to the FI market being competitive implying that the return on the FI's equity satisfies the household's Euler equation 2.[23,24]

This problem can be conveniently separated into two steps. First, the FI maximizes total surplus Σ_t by choosing $(\zeta_t, K_{e,t+1}, K_{d,t+1})$. Second, the FI chooses $R_{cd,t}$ so that the firm's participation constraint is satisfied[25] and so that other competitive FIs would not undercut this FI. Formally,

[22] For instance, if the FI were to offer firms an interest rate $R_{cd,t}$ and allow firms to choose any quantity of debt given that interest rate, the quantity they would choose would be socially suboptimal because firms would not internalize the effect of their capital choice on output in defaulted states. The FI could improve on this by offering a menu of price and quantity pairs, however modeling this full menu, including off-equilibrium offers, is more difficult than our approach.

[23] The above contract implies that the FI offers this contract to firms ex-ante, even before they raise equity, and that neither the FI nor the firm are able to change the terms of the contract ex-post. There are alternative – possibly more realistic – ways to model the FI's interaction with firms. For example, we could have instead assumed that the firms first choose how much equity $K_{e,t+1}$ to issue given their expectations about screening probability and interest rates. Then, conditional on the amount of equity issued, the FI chooses screening intensity ζ_t in order to maximize the surplus of only those firms which are not screened-out and to which it lends. We chose our particular contracting method because it leads to an equilibrium that is the same as one the social planner would choose if it faced the same costs as the FI. In other words, our contracting method is designed to avoid other possible frictions and isolate the role of FI labor needed for screening and creating debt securities.

[24] If there is no screening ($\zeta_t = 0$), the FI's optimal choices are identical to firms' optimal choices if they could raise debt and equity directly from households and if households faced the same balance sheet costs as the FI.

[25] The value of the firm computed in equation 7 should be at least as high as the value in a non-FI pooling equilibrium. To solve for this value, we recompute equation 7 but set debt financing to zero, shut down screening, and allow firms to pay for investment only through equity issuance from investors who do not know firm types.

the FI solves the following problem:

$$\begin{aligned}\Sigma_t = \max_{\zeta_t, K_{e,t+1}, K_{d,t+1}} \quad & E_t\left[M_{t+1}\left(X^0_{u,t+1}K^{\rho}_{e,t+1} + X^1_{u,t+1}K_{e,t+1}\right)\right](1-p)\zeta_t + \\ & E_t\left[M_{t+1}\left(X^0_{uf,t+1}K^{\rho}_{de,t+1} + X^1_{uf,t+1}K_{de,t+1}\right)\right](1-p)(1-\zeta_t) + \\ & E_t\left[M_{t+1}\left(X^0_{pf,t+1}K^{\rho}_{de,t+1} + X^1_{pf,t+1}K_{de,t+1}\right)\right]p \\ & -Q_tK_{e,t+1} - (p + (1-p)(1-\zeta_t))Q_tK_{d,t+1} - \Psi_t - W_tN_{FI,t}\end{aligned} \tag{14}$$

where the first three lines represent the enterprise values of the unproductive unfinanced, unproductive financed, and productive financed firms, respectively, and the fourth line includes the cost of buying capital, the penalty for deviating from optimal capital structure, and the cost of hiring FI labor.

In the second step we determine $R_{cd,t}$ by satisfying two conditions.[26] First, the FI market is competitive, therefore the household's Euler equation 2 must be satisfied – if the FI return $R_{FI,t}$ is too high, new FIs enter and undercut existing FIs by offering lower interest rates to firms, which leads to equilibrium $R_{cd,t}$ falling. Second, conditional on the FIs being able to earn a satisfactory rate of return, the ex-ante expected equity value of the firm defined in equation 7 using capital and debt that optimize the FI's problem in equation 14 must be no smaller than the maximal value of equation 7 if the firm cannot issue debt.

2.5 Equilibrium

By aggregating up the household's budget constraint in equation 1, we solve for the aggregate budget constraint

$$C_t = \left(\sum Z_{i,t}K^{\alpha\rho}_{i,t}(A_tN_{i,t})^{1-\alpha}\right) + K_t(1 - E_{t-1}[\delta_t]) - K_{t+1} - \nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)^2 K_t - \Psi_t \tag{15}$$

The problem's equilibrium is determined by solving the FI's problem in equation 14, subject to the Euler equations determining households' demand for FI equity and deposits holding (2, 12, 13); firms choosing optimal investment (4) and labor (5); the ratio of FI equity to deposits satisfying the FI's capital constraint (8); FIs' capital after labor costs equaling the supply of corporate lending by FIs and the demand for corporate debt by firms (11); the definition of labor demand by FIs (10); and the aggregate budget constraint (15), which can be used to compute the stochastic discount factor M_{t+1}. Additionally, the labor demand, aggregated across all firms and FIs $pN_{pf,t} + (1-p)(1-\zeta_t)N_{uf,t} + (1-p)\zeta_tN_{u,t} + N_{FI,t}$ should equal to the aggregate labor supply N_t which is a stochastic process described in Section 2.6.

We solve the problem by analytically computing the first order conditions of equation 14 and

[26] Note that $R_{cd,t}$ is not necessary to determine this problem's equilibrium, although it is necessary for determining how surplus is split between FIs and firms, and therefore computing firms' equity value and return.

then numerically solving a system of equations including the first order conditions, and the equations in the previous paragraph. Appendix Section C.4 provides additional details.

2.6 Calibration

The model is solved at an annual frequency. Here we discuss the choices of the model's parameters, which are also summarized in Table 1.

Preferences The time discount factor $\beta = 0.988$ is chosen to target the capital-to-output ratio of 3. Risk aversion $\gamma = 2$ which is a value consistent with microeconomic estimates of risk aversion.

Technology The capital share parameter $\alpha = 0.35$ to match aggregate labor share of 0.65. The return to scale parameter $\rho = 0.9$ so that profit share is around 0.1. The aggregate depreciation rate is $\overline{\delta} = 0.06$ per year, to match the investment-to-output ratio of 0.23. The growth rate of productivity is $g = 0.015$, a standard value in business cycle models; as shown in Appendix Section C.3, this implies that the balanced growth path grows at a rate of $-1 + (1+g)^{\frac{1-\alpha}{1-\alpha\rho}} = 0.014$. We set the capital adjustment cost parameters $\nu_{k,0} = 0.5$ and $\nu_{k,1} = (1+g)^{\frac{1-\alpha}{1-\alpha\rho}}$ to target a volatility of investment growth to volatility of output growth ratio of 3 and so that costs are zero in the deterministic steady state.

Capital structure For firms who are screened-in, we define the cost function as $\Psi_{f,t} = \nu_{d,0}\left(\frac{K_{d,t+1}-\nu_{d,1}\hat{\Pi}_t}{\hat{\Pi}_t}\right)^2 \hat{K}_{t+1}$ where $\hat{K}_{t+1}$ is aggregate capital and $\hat{\Pi}_t = E_t[M_{t+1}(pX^0_{pf,t+1} + (1-p)(1-\zeta_t)X^0_{uf,t+1}]K^{\rho}_{de,t+1}$ is expected future profit. This function is a reduced form way of modeling trade-off theory and implies that costs are minimized when the ratio of debt financed capital to expected future profit is equal to $\nu_{d,1}$.[27] We set $\nu_{d,0} = 0.005$ and $\nu_{d,1} = 4.1$ to target a debt-to-value ratio of 0.45 and a debt growth volatility of 0.037. We assume that unproductive firms who are screened-out face no costs $\Psi^u_t = 0$. This is because these firms, by assumption, are 100% equity, thus setting a quadratic cost would potentially lead to an unrealistically large penalty.

Financial sector We set the FI deposit to equity ratio $\kappa = 4$, in the data this quantity is 4.3.[28] In the baseline screening model, we set the fixed component of FI labor demand to $\eta_{FI,0} = 0$, the component proportional to the balance sheet to $\eta_{FI,1} = 0.01$ in order to target the average labor share of the financial sector of 0.6, and the screening component to $\eta_{FI,2} = 0.0208$ in order to target the correlation of FI employment growth with output growth of 0.4.

Productivity shocks The aggregate productivity state is either good or bad; the probability of switching is 0.1, calibrated to match the HP-filtered autocorrelation of aggregate output. Productive firms are normalized to have the same productivity in both states of the world – $Z_{p,g} = Z_{p,b} = 1$

[27] We experimented with alternative target ratios, for example $K_{d,t+1}/K_{de,t+1}$. While the model's key results were qualitatively similar to the ones we present, the volatility of debt growth was far too low. Using the debt capital to expected profit ratio lead to a more realistic debt growth process.

[28] In the Integrated Macro Accounts, the average of the financial sector's total liabilities divided by total liabilities and equity for 1960-2019 is 0.81, implying $\kappa = 4.2$.

– and they are a fraction $p = 0.884$ of all firms.[29] Unproductive firms have the same productivity as productive in the good state of the world, but lower in the bad state – $Z_{u,g} = 1, Z_{u,b} = 0.65$ – this value is chosen to match the volatility of private sector output.

Depreciation shocks The model has idiosyncratic, independent, identically distributed depreciation shocks in order to allow for corporate defaults. Any period may be a high or a low default period; the probability of each is 50% and independent of the productivity state or past default. If $t+1$ is a high default period, a fraction $s^h = 0.011$ of the firms experience a $\delta_{t+1} = 1$ depreciation shock, if $t+1$ is a low default period, the fraction is $s^l = 0.009$. The remaining firms have a depreciation of $\delta_{t+1} = \frac{\overline{\delta} - s_{t+1}}{1 - s_{t+1}}$, this ensures that aggregate depreciation is always $\overline{\delta}$, regardless of the default state. We choose s^h and s^l in order to match the volatility of financial sector value added. Note that even though high default states are not more likely in low output times, recovery rates are lower in such times, leading to pro-cyclical financial sector value added.[30]

Labor supply We assume that labor supply is perfectly correlated with output shocks, taking the value $N_t = 1$ when the aggregate state is good, and $N_t = 0.93$ when the aggregate state is bad. These numbers target the volatility of employment growth to volatility of output growth ratio in the data. We have also solved a model with constant labor. While the main results are similar, that model is unable to have both counter-cyclical $\frac{N_{FI}}{N}$ and pro-cyclical N_{FI}, as observed in the data.

2.7 Results in screening model

This section presents the model's quantitative results. We begin by reporting the unconditional moments implied by models with and without screening. Then we highlight the model's key prediction: FLS measures the stress of financial intermediaries and it predicts quantities and asset prices.

2.7.1 Model implied unconditional moments

Panel A of Table 2 compares the standard macroeconomic moments between model and data. The TFP shocks are chosen to approximately match the volatility of private output growth in the data, it is 0.033 in the model, compared to 0.034 in the data for 1949-2021. As in the data, consumption

[29] Our results of interest are not sensitive to p. However, setting p too low leads to relatively little screening by FIs. This is because when the productive firm's productivity is normalized to one, a larger fraction of unproductive firms requires a higher (closer to one) productivity of unproductive firms to match aggregate output volatility. When unproductive firms are more similar to productive firms, a FI's incentive to screen declines.

[30] We could have made these default states correlated with output, we chose not to because financial sector value added has a reasonable volatility and cyclicality even without such a correlation. Note that even though s^h and s^l are in the same range as default probabilities for public U.S. firms, these numbers need not exactly match the data. A key quantity of interest for our results is financial sector value added, which depends both on default probabilities and recovery rates. We do not need to match both default probability and recovery rate, as long as financial sector value added behaves similar to the data.

growth, employment growth, and wage growth are far less volatile than output growth, while investment growth is far more volatile. All but wage growth are highly correlated with output growth, though the correlations in the model are higher – this is often the case in models with just one aggregate shock.

Panel B of Table 2 shows moments specific to our model. Corporate debt growth is about as volatile as aggregate output growth in both model and data, though it is more pro-cyclical in the model. Employment in the financial sector is pro-cyclical, though it is less volatile in the model. Even though employment is pro-cyclical, financial sector employees as a share of all employees is strongly counter-cyclical. This pattern can also be seen in Figure 2. This moment is key for identifing the screening channel, we choose the screening cost to match the correlation of financial sector employment growth with output growth, which leads to a negative correlation of financial sector employment share with output growth. Another key moment is the labor share of the financial sector (FLS), which is counter-cyclical in both model and data. Finally, the financial sector's value added is volatile and pro-cyclical.

2.7.2 FLS as a measure financial stress

We next explore the model implied relationships between FLS, macro quantities and asset prices. We use the impulse response functions to a negative TFP shock in Figure 3 to highlight the model's main predictions. We also inspect the mechanism by contrasting these results to those in an identical model but where screening costs are infinite ($\eta_{FI,2} = \infty$ in equation 10) and FIs do not screen. We show that FLS measures the stress of financial intermediaries and the real economy, as screening during bad times raises their labor costs relative to revenue. This effect also spills over to the corporate sector.

Recall that in our model, productive firms always have a constant TFP of one; a negative productivity shock causes unproductive firms to switch from a TFP of one to a lower number, leading to lower aggregate TFP. Lower TFP by bad firms at $t = 0$ reduces recovery rates for lenders, which makes screening more attractive. Financial sector employment falls upon impact, but by far less than in a model without screening (Panel B). Screening at $t = 0$ implies relatively more lending to productive firms, leading to a higher share of capital belonging to productive firms at $t = 1$ (Panel H). The higher share of capital belonging to productive firms makes the economy more efficient, with the fall in output being less severe than in an economy with no screening (Panel C). The relatively higher output also leads to higher investment (Panel D) and consumption (Panel G), thus screening attenuates productivity shocks. Since FIs are able to screen out bad firms, they have less reason to cut lending, therefore the fall in debt is also less severe than in an economy without screening (Panel E). However, screening is expensive, the corporate spread rises significantly (Panel F). Both economies have the same default probabilities, therefore the rise is to compensate the financial sector for higher labor costs associated with screening.

The financial labor share (FLS), the fraction of financial sector output paid to labor, rises after negative aggregate productivity shocks (Panel A). Thus, as in the data, FLS is counter-cyclical. This happens because in the screening model, financial sector employment falls by less than financial sector profit, making financial sector labor costs relative to the output increase in bad times. Note that in a model without screening, FLS is pro-cyclical because financial sector employment falls by more than profits.

Panel C of Table 2 shows the relationship between FLS and several variables measuring macroeconomic and credit market stress. Contemporaneously, FLS is negatively associated with output growth, investment growth, and credit growth; it is positively associated with credit spreads. This is because FLS endogenously rises when FIs believe there is more risk in credit markets. Moreover, FLS also predicts these same variables going forward. Higher FLS forecasts lower growth in macroeconomic activities and higher risk in credit markets. This suggests that FLS measures economic stress persistently both in the real and financial sectors, which is a novel prediction implied by the model. Panel C of Table 2 shows that the same univariate relationships also hold in the data. In Section 3 we test these relationships more carefully, including a standard set of controls, extending the tests to alternative horizons, and carrying out the tests in the cross-section of FIs.

2.8 Alternative channels and extensions

In this section we explore alternative channels and extensions that may lead to similar empirical predictions. As we showed in Section 2.7, turning off screening makes FLS and $\frac{N_{FI}}{N}$ pro-cyclical, which is counter-factual. Therefore, in the absence of screening, the model requires a mechanism to make financial sector labor sufficiently less pro-cyclical. We consider mechanisms that make financial sector wages less correlated with corporate wages in 2.8.1, segmented markets leading to frictions in moving labor across sectors in 2.8.2, fixed costs in FI labor demand in 2.8.3, and shocks to FI productivity in 2.8.4. In Table 3 we prsent the results of various models for several select moments in order to highlight which mechanims can, and which cannot replicate the patterns in the data.

2.8.1 Less integrated FI and corporate wages

In our baseline model with screening, the labor markets in the financial and corporate sectors were perfectly integrated and all employees earned the same wage W_t. Here, we shut down screening ($\eta_{FI,2} = \infty$) and explore cases in which the financial sector pays a different, less pro-cyclical wage.[31]

First, we add wage rigidity in the financial sector. We do this by defining the financial sector

[31] For simplicity, we assume that the financial sector hires as many or as few employees as it wants – that is the number implied by equation 10 – at this wage, and the corporate wage then clears aggregate labor supply and demand. In Section 2.8.2 we explore a segmented labor market with specialized labor in each sector.

wage as $W_{FI,t} = 0.5\overline{W}(1+g)^{t\frac{1-\alpha}{1-\alpha\rho}} + 0.5W_{c,t}$ where $W_{c,t}$ is the market clearing wage in the corporate sector, and $\overline{W}(1+g)^{t\frac{1-\alpha}{1-\alpha\rho}}$ is the unconditional average wage, accounting for trend growth. Since compensation, in the numerator of FLS, is determined by wages and employment, rigid wages may allow FLS to become less pro-cyclical, but they cannot match the counter-cyclicality of FLS in the data. This is because wage rigidity causes wages to be relatively higher in bad times, which leads FIs to hire fewer employees in bad times. This counterfactually makes N_{FI} more volatile and more pro-cyclical (it is already too pro-cyclical in the model without screening). This dampens the effect of counter-cyclical wages on compensation and on FLS; in the end, FLS is still pro-cyclical, which is counterfactual.

Second, we add a shock to financial sector wages to make them less correlated with corporate wages. Specifically, we define $W_{FI,t} = W_t(1+\epsilon_t)$ where ϵ_t is uncorrelated with TFP shocks and calibrated to match $\frac{\sigma(W_{FI,t})}{\sigma(W_{c,t})} = 1.69$ in the data. As with rigid wages, FLS is still pro-cyclical, although slightly less so; furthermore, $N_{FI,t}$ becomes more volatile and more pro-cyclical.

2.8.2 Segmented labor markets

So far, we have assumed that labor markets are integrated. However, in the real world, financial sector labor may be more skilled, or special in other ways, and therefore it may be costly to adjust labor across sectors. To model this, we adjust the utility function in equation 1 to be

$$\frac{\left(C_t - \theta_0(N_{FI,t} - \overline{N}_{FI})^2\right)^{1-\gamma}}{1-\gamma} \tag{16}$$

One can interpret of $\overline{N}_{FI}$ as the number of employees who are naturally skilled to work in the financial sector. Having more or fewer employees work in the FI sector is costly where θ_0 represents the strength of these costs. These costs can be interpreted as retraining costs. This function implies that there are two labor markets – corporate and financial – and a separate wage to clear each market – $W_{c,t}$ and $W_{FI,t}$. The first order conditions imply that financial sector labor will satisfy $N_{FI,t} = \overline{N}_{FI} + \frac{W_{FI,t} - W_{c,t}}{2\theta_0}$. This expression is intuitive, employment in the financial sector will rise relative to its natural employment only if wages in the financial sector are above wages in the corporate sector. We calibrate $\overline{N}_{FI}$ so that there are no costs in the deterministic steady state, and we calibrate θ_0 in order to match the ratio of wage volatilities in the two sectors.[32]

With this extension, we first solve a model with segmented markets but without screening ($\eta_{FI,2} = \infty$). This model cannot match our moments of interest in the data. Financial sector employment ($N_{FI,t}$) does become less volatile and less pro-cyclical since segmented markets make it more costly to quickly vary employment; however it is still far too pro-cyclical relative to the

[32]The target is $\frac{\sigma(W_{FI,t})}{\sigma(W_{c,t})} = 1.69$. In the model without screening, $\overline{N}_{FI} = 0.0204$ and $\theta_0 = 5$. In the model with screening $\overline{N}_{FI} = 0.0215$ and $\theta_0 = 45$.

data. Consistent with the data, financial sector wages become more volatile and more pro-cyclical. However, a too pro-cyclical $N_{FI,t}$ leads to counterfactual implications: fianancial sector employment share ($\frac{N_{FI}}{N}$) is pro-cyclial and financial sector labor share (FLS) is pro-cyclical and no longer signals stress in credit markets.

We next return to the model with screening, but add market segmentation.[33] This model performs quantitatively similar to the baseline screening model for the original quantities of interest. Specifically, $N_{FI,t}$ is pro-cyclical while $N_{FI,t}/N_t$ and FLS are counter-cyclical; both contemporaneously and predictively, FLS is negatively associated with output, investment, and debt growth and positively with credit spreads. However, this model also matches the differential wage behavior between corporate and financial sectors observed in the data, whereas in the baseline screening model, the two sectors have identical wages. Thus, segmented markets do not, by themselves, explain why financial sector employment share is counter-cyclical and why FLS is associated with credit market stress, but they can (in conjunction with screening) help explain the behavior of financial sector wages.

2.8.3 Fixed costs in FI employment

The simplest way to make financial sector labor less pro-cyclical is to reduce its dependence on the size of the balance sheet in the FI's labor demand equation 10. To do this, we shut down screening ($\eta_{FI,2} = \infty$), reduce dependence on the balance sheet by changing $\eta_{FI,1}$ from 0.01 to 0.0025, and simultaneously, increase the fixed cost $\eta_{FI,0}$ from 0 to 0.015 in order to continue matching the level of labor share.

With this change, financial sector wage growth becomes less volatile, although it is still perfectly correlated with output growth, like the model without screening in Section 2.7. Note that actual correlation is around 0.4, which our screening model matches. Otherwise, this model delivers qualitatively similar results as the model with screening. Specifically, FLS and $\frac{N_{FI}}{N}$ are both counter-cyclical; FLS is negatively associated with output, investment, and debt growth, but positively with credit spreads.

One can think of the fixed component in FIs' labor demand as a reduced form way of making financial sector employment less pro-cyclical, whereas the model with screening microfounds this counter-cyclicality. Or, if the financial sector does have significant fixed labor needs unrelated to its size, one can think of this as an alternative channel to explain the data.

2.8.4 Shocks to FI productivity

Another way to make financial sector labor less pro-cyclical is to add shocks to the financial sector's productivity, we refer to these as financial labor need (FLN) shocks. To do this, we change the FI's

[33] When we solve this model, we recalibrate the parameters to match the target moments.

labor demand function in equation 10. We again shut down screening ($\eta_{FI,2} = \infty$), set $\eta_{FI,0} = 0$ to shut down the fixed component, and we replace the constant $\eta_{FI,1}$ by a time-varying shock to financial sector productivity $\eta_{FI,1,t}$. When $\eta_{FI,1,t}$ is high, FIs require more labor to intermediate a dollar of capital. We allow $\eta_{FI,1,t}$ to take on the values (0.0107,0.0100,0.0093) and choose the stochastic process such that its correlation with TFP is -0.80, that is, FIs are especially unproductive and require more labor when firms are also unproductive. These values were chosen to as well as possible fit the counter-cyclical behavior of FLS and $\frac{N_{FI}}{N}$.[34]

Like the fixed cost model in Section 2.8.3, this model delivers qualitatively similar results to the model with screening. Specifically, FLS and $\frac{N_{FI}}{N}$ are both counter-cyclical; FLS is negatively associated with output, investment, and debt growth, but positively with credit spreads. However, financial sector labor growth is far too volatile. Figure 4 presents impulse responses in this model to either TFP or FLN shocks. Responses to FLN shocks look qualitatively similar to the screening model: after labor needed per dollar of capital increases, FLS and corporate spreads rise, while output, investment, and debt issuance fall. In both models, financial labor employment relative to total employment rises. One difference is that in the screening model, financial sector employment falls but by less than total employment; here financial sector employment rises in response to FLN shocks. In the data, financial sector employment is pro-cyclical (but by less so than aggregate employment). To match this fact, the model needs a correlation between TFP shocks – which make financial sector employment pro-cyclical – and FLN shocks.

As with fixed costs, we can interpret FLN shocks in one of two ways. First, as a reduced form way of getting financial sector employment to be less pro-cyclical. The model with screening microfounds the reason for why FIs would require more labor per unit of capital in bad times – the risk of lending to unproducitive firms is greater and FIs endogenously choose to screen more. In order to avoid explicitly modeling screening, one can imagine that when the FLN shock is high, in the absence of additional labor, the FI's return on investment would be very low, therefore FIs must hire more labor per dollar of assets. Second, there could be actual shocks to financial sector productivity that are unrelated to screening. For example regulatory shocks, like Dodd-Frank or Sarbanes-Oxley, can require financial intermediaries to hire more people to deal with additional regulation. Another example is litigation risk, which may be higher during recessions, leading to higher demand for debt collection and legal services by intermediaries. We provide additional evidence for such shocks in Appendix Section B.1.

[34] We also solved a model where the financial productivity shocks were uncorrelated with TFP. In this case, while it was possible to make FLS and $\frac{N_{FI}}{N}$ less pro-cyclical, we were unable to make them counter-cyclical while also maintaining a pro-cyclical N_{FI}.

3 Empirical evidence

In this section we explore empirical relationships between labor share in the financial sector and the fluctuations in asset prices, credit, and quantities of the real sector. We do so first, using aggregate, time series analysis of U.S. data, and second, using a cross-sectional analysis of bank-firm-level data.

In the aggregate-level time series analysis, we document that a high financial intermediary labor share (FLS) is associated with stress credit markets and the real economy. Specifically, using aggregate data, FLS is negatively associated with both contemporaneous and future debt growth, investment growth, and output growth; it is positively associated with both the contemporaneous and future corporate borrowing costs. These empirical findings mirror the prediction of our model in Section 2, as shown in Panel C of Table 2.

Using bank-level data, a bank holding company's labor share positively predicts the bank's risk, measured as expected default frequency (EDF); it negatively predicts its loan growth. Furthermore, in the bank-firm pair analysis, using Dealscan loan origination data, we show that firms connected to a bank with a high labor share experience lower debt growth, have higher expected default risk, pay more to borrow, and see lower earnings growth. Their investment growth is negative but not statistically significant, however it is significant for a subset of firms who are financially constrained. These empirical findings mirror the aggregate empirical findings. While our model only speaks to aggregate quantities, the mechanism in our model should also work at the individual bank level, and would be consistent with these empirical findings.

3.1 Aggregate-level time series analysis

This section performs time series analysis using aggregate data. We show that when the labor share of the financial sector is high, current and future corporate debt growth, GDP growth, and investment growth tend to be low; current and future costs of corporate borrowing tend to be high. We first describe the data, then the empirical specifications and the results.

3.1.1 Data and variable definitions

Our dependent variables of interest are non-financial sector debt growth, Baa minus Fed Funds spread, aggregate GDP growth, and aggregate private investment growth. Our key independent variable is labor share in the financial sector (FLS), which is the ratio of compensation of employees to net value added of the financial business sector from Integrated Macroeconomic Accounts (IMA). The measure of compensation includes salaries, wages, pensions, and other benefits such as bonuses. Appendix Figure A.1 plots a time series of FLS.

As controls, we include aggregate labor share (LS), aggregate GDP growth, aggregate wage

growth (ΔW), credit spread (CS), term spread (TS), price-dividend ratio (PD), and financial sector value added growth (ΔFVA). We additionally control for FI leverage ratios constructed from Adrian et al. (2014) (hereafter "AEM") and He et al. (2017) (hereafter "HKM"). The final sample for aggregate time series regressions contains annual data from 1961 to 2019.[35] Appendix Section A contains more detailed definitions about these variables.

3.1.2 Descriptive statistics

Table 4 presents summary statistics for financial sector labor share (FLS), value added growth, and financial leverage ratios constructed from the literature ("HKM" and "AEM"). Other aggregate variables include GDP growth, non-financial corporate debt growth, investment growth, wage growth, consumption growth, and aggregate labor share. All the growth rates are calculated based on real quantities. The average FLS is 0.64, somewhat higher than the labor share for the aggregate economy, which is 0.55. The correlation of the two is just -0.02, suggesting that FLS contains different information than the aggregate labor share.[36] FLS is counter-cyclical, its correlation with real GDP growth is -0.30. FLS positively correlates with the financial sector leverage ratios but these correlations are 0.16 and 0.43, implying that FLS captures different information from financial leverage.

3.1.3 FLS and credit markets

We begin by exploring the impact of FLS on credit markets, specifically corporate debt growth and the cost of credit, measured by the spread between Baa bonds yields and the Federal Funds rate.

Table 5 shows that FLS is negatively associated with contemporaneous debt growth (Panel A) and negatively predicts future debt growth at 1-year, 3-year, and 5-year horizons (Panels B, C, D). The first column presents the results from a univariate regression – the t-statistics for contemporaneous, 1-year, 3-year, and 5-year horizons are respectively -2.83, -5.22, -5.88, and -3.87.[37] The univariate R^2's are 0.06, 0.24, 0.23, and 0.19. The strong statistical significance remains when we add controls. In Appendix Table A.2 we show that this is also true for financial sector credit growth.

Table 6 shows that FLS is positively associated with contemporaneous cost of credit (Panel A),

[35] We start in 1961 because that is the start of Integrated Macroeconomic Accounts (IMA) data and end in 2019 just before the Covid-19 pandemic. The time series of HKM (1970-2019) and AEM (1970-2012) are available for a shorter sample.

[36] Notably FLS does not display a downward trend in our sample, in contrast to the aggregate labor which has trended downward during the last 40 years. This implies that our econometric tests do not suffer the spurious tests issues due to non-stationarity raised in Granger and Newbold (1974).

[37] In all of our empirical results, we report t-statistics based on Newey and West (1987) standard errors with 13 lags. The optimal number of lags suggested by Stata function ivreg2 is between 8 and 17 depending on the specificatoin. In appendix Tables A.7-A.14, we also report results with 8 lags, and with the optimal number of lags.

and positively predicts future cost of credit at 1-year, 3-year, and 5-year horizons (Panels B, C, D). The univariate t-statistics are, respectively 3.72, 4.21, 2.42, and 1.78 with R^2's of 0.09, 0.14, 0.05, and 0.01. The strong statistical significance remains for the 1-year horizon when we add controls; for 3-year and 5-year horizons, all coefficients remain positive but some become insignificant with controls. The only exception is that the Baa - Fed Funds spread contemporaneous slope on FLS becomes negative and insignificant when controlling for term spread. This is because the two spreads are very strongly contemporaneously correlated.

These results are in line with our model, where in response to a worsening economy and higher lending risks to unproductive firms, FIs increase screening and FLS rises. Despite stronger screening, lending opportunities are overall worse and financial intermediaries contract their business activities and lend less. Additionally, in order to cover their relatively higher labor costs, financial intermediaries must charge higher interest rates. Firms are willing to pay higher interest because as lending is cut, they are further away from their optimal capital structure, thus the benefit of an extra dollar of debt, relative to equity capital increases.

3.1.4 FLS and real outcomes

Next, we study the impact of FLS on real quantities, specifically aggregate GDP growth and investment growth. The exercise is analogous to the ones in the previous subsection, but with two new dependent variables; these results are presented in Table 7 for GDP growth and Table 8 for investment growth.

FLS is negatively associated with contemporanoeus GDP growth (Panel A), and negatively predicts future GDP growth at 1-year, 3-year, and 5-year horizons (Panels B, C, D). The univariate t-statistics are, respectively -4.62, -2.23, -1.78, and -1.52.[38] Similarly, FLS is negatively contemporaneously associated with investment growth (Panel A) and negatively predicts investment growth (Panels B, C, D), with univariate t-statistics of -7.35, -2.64, -1.89, and -0.17 for 1-year, 3-year, and 5-year horizons respectively (Panels B, C, D). However, this predictability has a shorter horizon than for credit variables in the previous section as these results become statistically insignificant for some controls and for the 5-year horizon.

Like the credit results, these results are in line with our model, where FIs respond to a worsening economy by increasing screening. This implies that a higher FLS is associated with lower investment and output, both contemporaneously and in the future. Note that in the model, following bad times, output and investment are low, but are higher than they would be if FIs were unable to screen.

[38]The negative contemporaneous correlation between FLS and GDP growth may raise concerns that the shock originates from firms and propagates to the financial sector. To aleviate this concern, we confirm that GDP growth does not Granger cause FLS, while FLS does Granger cause GDP growth at 10% significance.

3.2 Bank-level analysis

In this section, analogous to the previous section, we explore the empirical relationships between bank level labor market fluctuatons and firm level fluctuations in credit, credit risk, and real outcomes. We do so through panel regressions. Bank-level regressions significantly expand sample size and allow us to include more granular variables and fixed effects to control for other factors and the credit demand effect. We show that banks with higher FLS tend to lend less and have higher risk, as measured by EDF.

3.2.1 Data and variables definitions

For bank-level regression analysis, we focus on bank holding companies and use balance sheet variables from FR Y-9C, available from Federal Reserve Bank of Chicago. Following the literature, we apply several filters to select bank holding companies.[39] The final sample for bank-level analysis is a panel consisting of 41,511 annual observations in total, including 4,307 unique bank holding companies from 1986 to 2019.[40]

Our key independent variable is bank i's labor share, which is defined as the ratio of labor expenses to the sum of earnings before interest and labor expenses: $FLS_{i,t} = \frac{XLR_{i,t}}{EBIT_{i,t}+XLR_{i,t}}$, where XLR is the labor expenses and EBIT is the earnings before interest. As with the aggregate results, this measure includes salaries, wages, pensions, and other benefits such as bonuses. The bank level dependent variables are the bank's average expected default frequency (EDF) over the next 3 years and the 3 year growth in total loans.[41] Bank holding company characteristics used as controls include bank size, return to assets, capital ratio, interest expense, earnings growth, and share of non-performing commercial and industrial (C&I) loans.[42] We also include bank holding company fixed effect α_i and its state-year fixed effect $\delta_{s,t}$, where s is for state and t is for year. The state-year fixed effect is used to control for local demand and other local shocks effect including changes in

[39] We drop observations with missing values or non-positive values for total assets; we keep bank holding companies (RSSD9331=28); we drop Grandfathered savings and loan holding company (RSSD9425=18); we drop lower-tier holding companies whose higher-tier also files Y-9C (BHCK9802=2); we keep holding company (RSSD9048=500), and exclude securities broker or dealer (RSSD9048=700), insurance broker or company (RSSD9048=550), utility company (RSSD9048=710), and other non-depository institution (RSSD9048=720) but keep Goldman Sachs, Morgan Stanley, Ally, and American Express. Finally, we drop observations with negative labor share.

[40] The number of bank holding companies by year is shown in Appendix Figure A.2.

[41] These are items BHCK2122+BHCK2123. We also consider sub-components like C&I loans (BHCK1766); C&I loans to firms in U.S. (BHCK1763), consumer loans (BHCK1975) and real estate loans (BHCK1410).

[42] Size is measured as log of total asset (BHCK2170), return to assets is measured as ratio of net income (BHCK4340) to total assets (BHCK2170), capital ratio is measured as ratio of total equity to total assets, interest expense is measured as the ratio of total interest expense (BHCK4073) to total deposits (BHDM6631+BHDM6636+BHFN6631+BHFN6636), while share of non-performing C&I loan is measured as ratio of total non-performing C&I loan (BHCK1606+BHCK1607+BHCK1608) to total loan. Note that capital ratio is a measure of financial leverage for banks, similar to the leverage ratios that we use in the aggregate analysis.

bank regulation. We estimate the following model:

$$y_{i,t+k} = \alpha_i + \delta_{s,t} + \beta FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}, \tag{17}$$

where $y_{i,t+k}$ is either bank i's 3 year loan growth or its 3 year credit risk.[43]

3.2.2 Bank FLS and bank loan growth

In this subsection, we examine the bank's loan growth over the next 3 years as the variable of interest $y_{i,t+k}$. Table 9 shows that a bank's labor share ($\text{FLS}_{i,t}$) negatively and significantly predicts total loan growth over the next 3 years (columns (1) to (4)), as well as C&I loan growth (columns (5) to (8)). The relationship is strong, with t-statistics ranging from -7.8 to -26.2, depending on the specification. The coefficient estimates in the first rows of column (4) and (8) imply that a one-standard-deviation increase in bank labor share reduces total loan growth and business loan growth rates by 25.3% and 36.2%.[44]

3.2.3 Bank FLS and bank risk

In this subsection, we examine the bank's risk, as measured by its average EDF, equity return volatility, and earnings growth volatility over the next 3 years as the variables of interest $y_{i,t+k}$.[45] The first four columns of Table 10 show that a bank's labor share ($\text{FLS}_{i,t}$) positively and significantly predicts the bank's future credit risk, with t-statistics between 4.8 and 7.3, depending on the specification. The coefficient estimate in the last column implies that a one-standard-deviation increase in labor share increases EDF by 42%.[46]

The remaining columns of Table 10 show that a bank's labor share ($\text{FLS}_{i,t}$) positively and significantly predicts the bank's future realized risk, as measured by equity return volatility or by earnings growth volatility, with t-statistics between 9.1 and 2.1, depending on the specification. This result is consistent with our screening model, where banks ex-ante increase labor demand when they expect borrowers to become more risky, leading to more volatility in their subsequent earnings and equity returns.[47]

[43] We define loan growth as $y_{i,t+k} = \Delta Loan_{i,t+k} = 2\frac{Avg(Loan_{i,t+1:t+k}) - Avg(Loan_{i,t-k+1:t})}{Avg(Loan_{i,t+1:t+k}) + Avg(Loan_{i,t-k+1:t})}$ and credit risk as $y_{i,t+k} = Avg(EDF_{i,t+1:t+k})$ where the forecast horizon is 3 years ($k = 3$).

[44] The standard deviation of FLS is 0.298, leading to 0.298*0.14=4.2% lower growth rates of total and business loans. The average 3 year growth rates are 16.6% and 11.6% respectively, therefore the reductions are 4.2/16.6=25.3% and 4.2/11.6=36.2%.

[45] Unlike the loan growth sample, this sample is from 1992 to 2011 due to data availability.

[46] The standard deviation of FLS is 0.273, leading to 0.273*1.39 = 0.38 higher EDF. The average EDF is 0.90, therefore the increase is 0.38/0.90 = 42%.

[47] EDF measures probability of default, which largely depends on the bank's leverage, and its volatility. In Appendix Table A.21, we show that FLS also positively predicts the level of book leverage, but is not significantly related to the change in leverage.

3.3 Bank-firm pair analysis

In the previous subsection, we analyze how loan lending at the bank holding company level is affected by its labor share. However, if firms were to simply substitute their borrowing from affected to unaffected banks, then any effects on firms would be limited. On the other hand, if firms are "locked-in", as proposed by Sharpe (1990) and Rajan (1992), and empirically tested by Chodorow-Reich (2014), then firms with relationships to affected banks would also be affected. Indeed, below we show that firms that are connected to affected banks by lending relationships issue less debt, pay higher prices for the debt they issue, have higher expected default probability, and have slower earnings growth. Although they do not invest significantly less on average, those firms that are financially constrained do invest significantly less.

3.3.1 Data and variables definitions

We study lender-borrower pairs at an annual frequency by using loan issuance data from Dealscan and combining it with firms' accounting data from Compustat.[48] We focus on syndicated loans, which are usually large loans with long maturities that are frequently issued by multiple lenders. For each syndicated loan, we only consider the lead lender's balance sheet and we use allocation information to determine lead lender's loan amount.[49]

Our key independent variable is the labor share of the lead lender i in year t ($FLS_{i,t}$). If the firm borrows multiple facilities from different lead lenders in a year, we use the weighted average (by loan amount) of lead lenders' labor share. We examine the effect of FLS on various firm level variables of interest $y_{i,j,t+k}$ where borrower j is borrowing from lender i in year t. We control for both lender and borrower's characteristics in the fixed effect regression specification:

$$y_{i,j,t+k} = \alpha_i + \delta_{s,t} + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k}, \tag{18}$$

where α_i is the bank fixed effect and $\delta_{s,t}$ is either the year or state-year or industry-year fixed effect. We include firm's state-year and 1-digit SIC-year fixed effects to address the concern that local economic conditions or industry conditions may affect firms' demand for loans.

The outcome variables $y_{i,j,t+k}$ we consider are firm j's growth in loan issuance over the next

[48] WRDS has updated the Dealscan dataset starting from the summer of 2021. The update is a reorganization of the entire dataset, combining all the information in a single table and changing loan identifiers. The analysis here is based on a vintage of Dealscan, which is now considered the "legacy" version on WRDS. In particular, we use data from the following tables: Facility-Legacy, Package-Legacy, Company-Legacy, Lenders-Legacy, Current Facility Pricing-Legacy and Dealscan-Compustat Linking Database.

[49] We apply the same filters to select bank holding companies as the ones used in the bank-level regression analysis, with additional details in Appendix Section A.5. The merged sample contains 47 unique bank holding companies compared to 4307 in the full sample. The bank companies in the merged sample are larger ($18 billion versus $13 billion average size) and have higher FLS (0.67 versus 0.63), but are relatively similar in their ROE, leverage, capital ratio, and cost of funding.

3 years, average borrowing cost over the next 3 years, average distance to default over the next 3 years, change in investment rate over the next 3 years, or earnings growth over the next 3 years.[50,51] Firm characteristics used as controls include firm size, Tobin's Q, cash, financial leverage, past sales growth, tangibility and credit rating. Details about variable construction are provided in Appendix Table A.1.

The final sample for this pair panel regression analysis contains 17,907 bank-firm pair observations with 47 banks and 2709 firms from 1986 to 2019.[52] For bank-firm credit spread, we further merge the data with the loan pricing dataset, shrinking the sample to 15,601 bank-firm pair observations with 47 banks and 2342 firms. Summary statistics for bank holding companies are presented in Appendix Table A.20.

3.3.2 Bank FLS and firm credit outcomes

In this subsection, we examine the relationship between a bank's labor share (FLS) and various credit outcomes for firms connected to this bank. We find that firms connected to banks with high FLS borrow less, pay more to borrow, and have higher expected default rates. These results are presented in Table 11.

In Panel A, we investigate the growth rate of firm j's total loan borrowing over a 3-year window as the variable of interest $y_{i,j,t+k}$. A bank's labor share negatively and significantly predicts the growth rate of loan issuance by firms that are connected to the bank through a lending relationship, with t-statistics ranging from -2.3 to -2.9, depending on the specification. The coefficient estimate of -0.51 in column (3) implies that a one-standard-deviation increase in a bank's labor share reduces new issuance of connected firms by 10.3%.[53]

[50] Loan issuance data from Dealscan is available at a quarterly frequency. We thus aggregate the amount of loan issuance every year for each bank-firm pair. We define issuance growth as $y_{i,j,t+k} = \Delta Loan\ Amount_{i,j,t+k} = 2\frac{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} - \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} + \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}$. We measure borrowing cost as as the weighted average (by loan amount) of loan spread "All-in-drawn" from Dealscan Loan Pricing dataset. We only consider facilities that use "LIBOR" as the base rate and drop facilities that have negative "All-in-drawn" or "All-in-drawn" over 1000 basis points. We drop facilities that have maturities shorter than one year. The borrowing cost is defined as $y_{i,j,t+k} = Avg(Loan\ Spread_{i,j,t+1:t+k})$. We follow Merton (1974) and Gilchrist and Zakrajšek (2012) to measure firm-level distance to default (D2D) and define $y_{i,j,t+k} = Avg(D2D_{t+1:t+k})$. Change in investment rate is defined as $y_{i,j,t+k} = \frac{Avg(CAPX_{t+1:t+k}) - Avg(CAPX_{t-k+1:t})}{PPENT_t}$. Earnings growth is defined as $y_{i,j,t+k} = 2\frac{Avg(IB_{t+1:t+k}) - Avg(IB_{t-k+1:t})}{Avg(IB_{t+1:t+k}) + Avg(IB_{t-k+1:t})}$ where IB is Income Before Extraordinary Items. In all cases, the forecast horizon is 3 years ($k = 3$).

[51] To create a panel that is similar to a credit registry, we follow Lin and Paravisini (2013) for a modified approach of Khwaja and Mian (2008), sum the total amount of lending for each firm over subsequent three-year periods and use these aggregated loan amounts to compute the loan growth. Thus, when a new loan is initiated, we can compare the amount borrowed that year (and the following two years) to the amount borrowed in the three years prior to the new loan. We follow an analogous strategy for other variables of interest.

[52] In our final sample, 95.6% of the firm-year observations have single lender, 4.3% of the firm-year observations have two lenders. We drop observations where firms have over three lenders in that period.

[53] The standard deviation of FLS is 0.156, leading to a 0.156*51% = 8.0% lower growth rate of loan borrowing. The average loan growth rate over 3 years is 78%, therefore this is a 8.0/78 = 10.3% reduction.

In Panel B, we investigate firm j's borrowing cost over the next 3 years as the variable of interest $y_{i,j,t+k}$. A bank's labor share positively predicts the borrowing cost for firms that are connected to the bank through a lending relationship, although the statistical significance is marginal. The coefficient estimate of 0.33 in column (3) implies that a one-standard-deviation increase in a bank's labor share increases borrowing costs of connected firms by 5.0 bp or 3.0%.[54]

In Panel C, we investigate firm j's credit risk (measured as distance to default) over the next 3 years as the variable of interest $y_{i,j,t+k}$. A bank's labor share positively and significantly predicts the credit risk (negatively predicts distance to default) of firms that are connected to the bank through a lending relationship, with t-statistics between -2.8 and -3.8. The coefficient estimate of -1.61 in column (3) implies that a one-standard-deviation increase in a bank's labor share decreases the distance to default of connected firms by 3.9%.[55]

3.3.3 Bank FLS and firm real outcomes

In this subsection, we examine the relationship between a bank's labor share (FLS) and investment rate or earnings growth for firms connected to this bank. We find that firms connected to banks with high FLS experience lower earnings growth. They do not, on average, experience significant investment rate reductions, although the most financially constrained firms do reduce investment rate. These results are presented in Table 12.

In Panel A, we investigate the change of firm j's investment rate over a 3-year window as the variable of interest $y_{i,j,t+k}$. A bank's labor share negatively but insignificantly predicts a lower investment rate for firms that are connected to the bank through a lending relationship, with t-statistics between -0.8 and -1.09. However, as we show in Appendix Table A.24, when we focus on financially constrained firms, defined as in the top tercile by their Whited and Wu (2006) financial constraint index, the t-statistics rise to between -1.6 and -2.3 for constrained firms, while the point estimates are near zero for unconstrained. Since firms have other margins of adjustment – like using internal funds, borrowing from alternative lenders, or raising equity – it makes sense that financially constrained firms would be most affected.

In Panel B, we investigate the growth rate of firm j's earnings over a 3-year window as the variable of interest $y_{i,j,t+k}$. A bank's labor share negatively and significantly predicts the growth rate of earnings by firms that are connected to the bank through a lending relationship, with t-statistics ranging from -2.1 to -2.4, depending on the specification. The coefficient estimate of -0.64 in column (3) implies that a one-standard-deviation increase in a bank's labor share reduces earnings

[54]The standard deviation of FLS is 0.153, leading to a 0.153*33 bp = 5.0 bp increase in the borrowing cost. The average borrowing cost is 169 basis points per year, and therefore, this is a 5.0/169 = 3.0% increase.

[55]The standard deviation of FLS is 0.156, leading to a -1.61*0.156 = -0.251 change in the distance to default. The average three-year distance to default is 6.46, and therefore, this is a -0.251/6.46 = 3.9% decrease in firm's credit risk.

growth of connected firms by 37.7%.[56] In Appendix Table A.24 we show that as with investment, the effect is much stronger for financially constrained firms, and near zero for unconstrained.

3.4 Robustness

In the aggregate results above, we focus on bivariate regressions, comparing FLS to other predictors one at a time. In Appendix Tables A.3 and A.4 we redo the results with multivariate regressions that include all predictors together. Although the danger of multicolinearity makes these results difficult to interpret, FLS remains significant in almost all specifications. The one exception is 1 year ahead borrowing cost predictability, which keeps the same sign, but becomes insignificant.

In all of our aggregate regressions, we have included aggregate labor share as a control, thus the results suggest that there is something unique to the labor share of financial intermediaries. As an additional placebo, we have constructed a labor share measure of high skilled workers, unfortunately, it is only available starting in 1997. In Appendix Table A.19, we show that high skilled labor share does not predict any of our variables of interest. On the other hand, despite the shorter sample, financial sector labor share retains most of its predictive power. We have also checked that non-financial, non-corporate sector labor share, non-financial, corporate sector labor share, and government labor share do not exhibit the same predictability as financial labor share.

Since FLS is a ratio, it may be interesting to know whether its predictability is due to the numerator (compensation) or the denominator (value added). Both the numerator and the denominator are non-stationary, therefore we cannot include both independently in the regression. In all aggregate regressions, we include the growth of value added (ΔFVA) as one of the controls, and in all bank level regressions, we include the growth rate of EBIT as one of the controls. This implies that it is not just movements in bank profits that are driving FLS. For our bank level results in Section 3.2, since the identification comes from the cross-section, we can include both the numerator and the denominator of FLS in the regression independently. Results in Appendix Table A.22 suggest that it is variation in compensation, rather than value added that is mostly responsible for the predictability.

In appendix Figure A.1 we plot the time series of FLS. It is notable that there is a spike in 2008, when financial sector value added fell by significantly more than compensation. We have confirmed that most of our results are not driven by this spike. Appendix Tables A.15-A.18 are analogous to Tables 5-8 but include only the FLS as an independent variable in the years 1961-2007.[57] The significance of all contemporaneous results is unaffected; the predictability of debt growth is also unaffected; credit spread and investment growth remain significantly predictable at a one year

[56] The standard deviation of FLS is 0.156, leading to a 0.64* 0.156 = 0.10 lower growth rate of earnings. The average earnings rate over three years is 26.5% and therefore, this is a 0.10/0.265 = 37.7% reduction.

[57] In unreported results, we have also tried simply excluding 2008 or setting the 2008 value of FLS to be the maximum of all previous years. The results are similar to the ones we present.

horizon, however, the predictive relationships between GDP and FLS, as well as the 3- and 5- year predictive relationship between FLS, credit spread and investment, become insignificant. Though we drop 2008 for the purpose of this robustness check, the 2008 spike in FLS aligns with our theoretical framework. In the data from that period, the real net value added of the financial sector decreased by 26.5%, whereas the real total compensation of the financial sector dropped only slightly, by 0.86%. This minimal decline in compensation was largely due to relatively stable employment levels within the sector. The high compensation relative to the low net value added resulted in a negative after-tax net operating income for the financial sector, significantly increasing its stress which also spilled over to the real economy. These observations are consistent with our model's prediction that a countercyclically high FLS, driven primarily by the employment channel, imposes stress on the financial sector and affects investment and output in the corporate sector as well.

4 Conclusion

We study the relationship between financial sector employment, credit markets, and real quantities. Empirically, we find that financial sector employment as a fraction of aggregate employment, as well as financial labor share (FLS) are counter-cyclical, rising when output is low. We show that adding screening or FI productivity shocks to a DSGE model allows it to capture this counter-cyclicality. In the model, both contemporaneously and predictively, FLS is negatively associated with output, investment, and corporate credit, and positively with corporate credit spreads. We confirm similar relationships in both aggregate and bank level data.

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Figure 1: Timeline of model

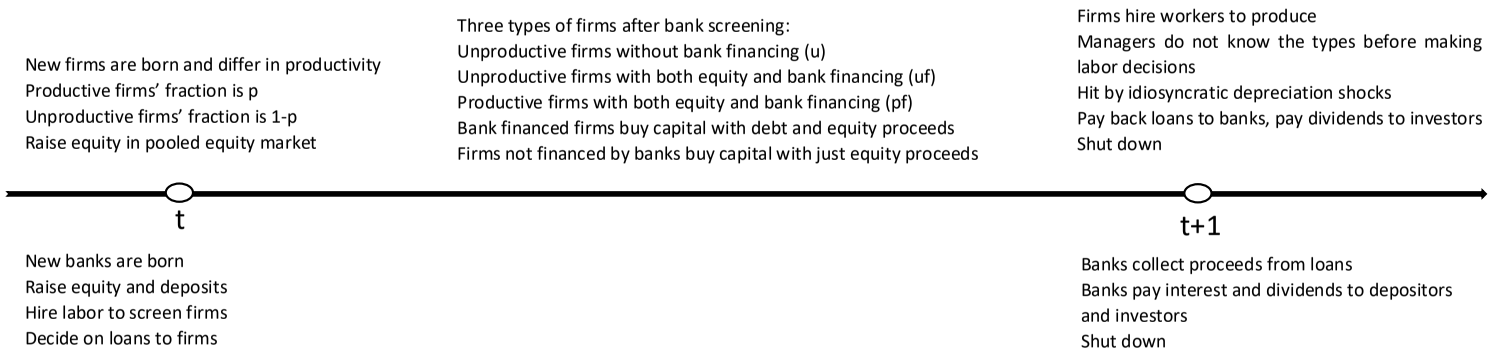


Figure 2: Financial sector employment share of total employment, time series

This figure plots the financial sector employment share of total employment over time, and compares it to GDP. The series are USFIRE, PAYEMS, and GDPC1 respectively in FRED. Since both series are non-stationary, the top panel plots HP-filtered values and the bottom growth rates.

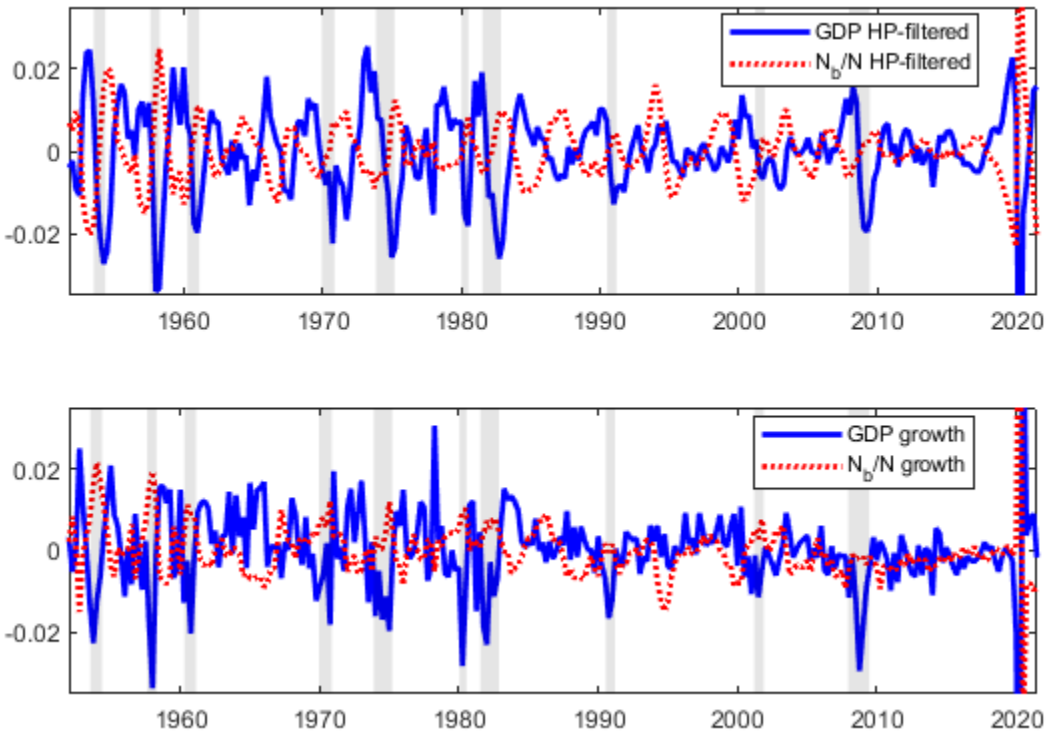


Figure 3: Impulse responses to a TFP shock, Screening versus No Screening models

This figure plots the impulse response functions to a TFP shock, where the aggregate productivity state switches from good at $t = -1$ to bad at $t = 0$. To produce the figure, we first compute a simulation over 10,000 periods, and then average across all paths in which the TFP state switches from good to bad, note that after $t = 0$ we are averaging over many random paths for TFP. The figure compares impulse responses in the model with screening versus the model without screening. The figure reports the financial sector labor share, labor in the financial sector, aggregate output, aggregate investment, aggregate corporate debt, the corporate spread between the interest on corporate bonds and deposits, aggregate consumption, and the share of capital belonging to good firms.

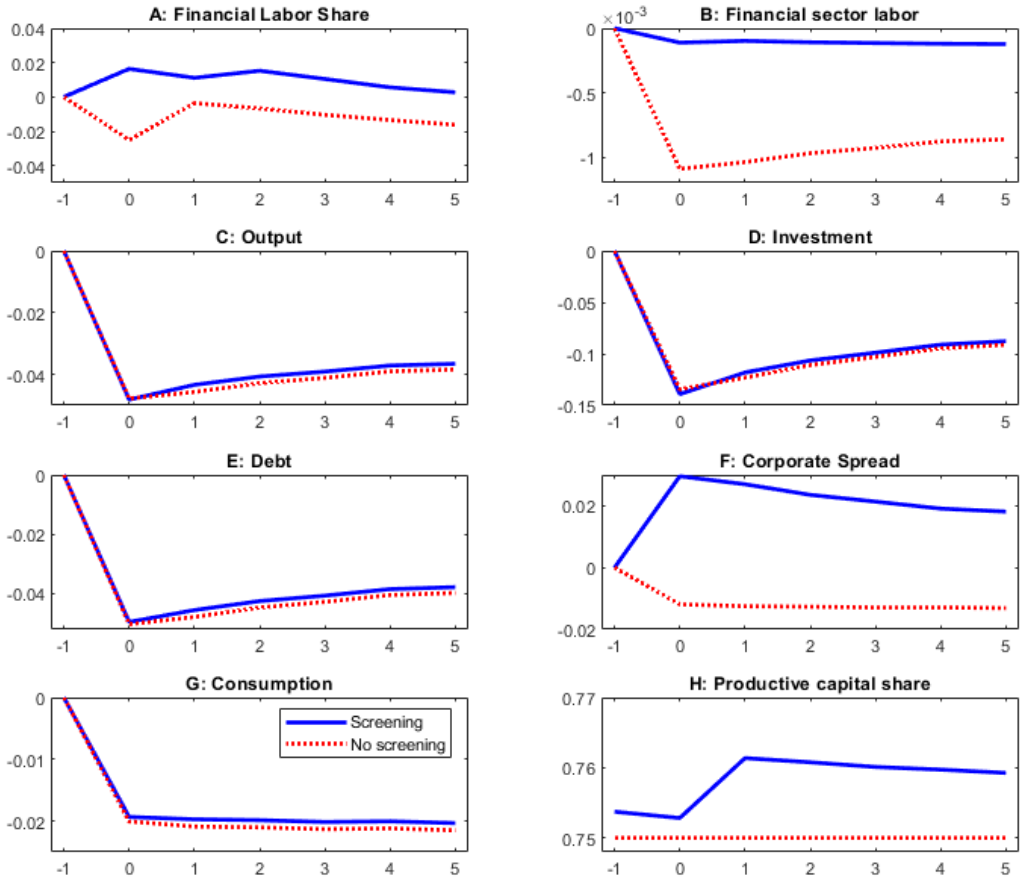


Figure 4: Impulse responses in FLN shock model, TFP versus FLN shock

This figure plots the impulse response functions to either a TFP shock or an FLN shock in the model described in Section 2.8.4, where FIs are subject to labor productivity (FLN) shocks. For the TFP shock, the aggregate productivity state switches from good at $t = -1$ to bad at $t = 0$. For the FLN shock, the labor needed per dollar of balance sheet assets $\eta_{FI,1,t}$ switches from median at $t = -1$ to high at $t = 0$. To produce the figure, we simulate the model for 100 periods calling the 100th period $t = 0$, we then switch the relevant shock (TFP or FLN) at period 101, then continue simulating. The calibrated stochastic process implies that the two shocks are correlated, however the impulse response aims to isolate the effect of just one shock. For this reason, for the purpose of computing impulse responses, we force the other shock (FLN if the impulse response is for TFP, TFP if the impulse response is for FLN) to be independent of the impulse response shock. We repeat this procedure 50 times and average over them to plot the fiture. The figure reports the financial sector labor share, labor in the financial sector, aggregate output, aggregate investment, aggregate corporate debt, the corporate spread between the interest on corporate bonds and deposits, aggregate consumption, and the share of capital belonging to good firms.

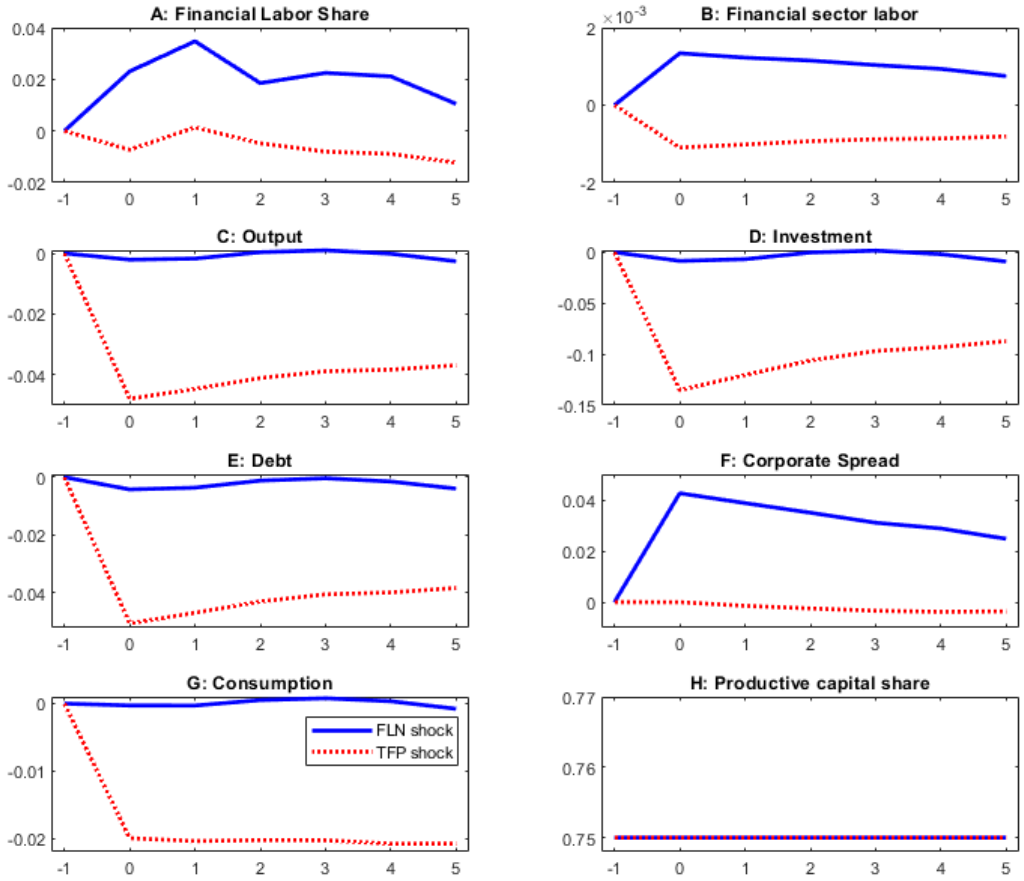


Table 1: Calibration

This table presents the values of the parameters used to solve the model.

Variable	Parameter	Description	Target Description	Target Moment
		Standard parameters		
β	0.988	Time discount factor	Capital/Output	3
γ	2.0	Risk aversion		
α	0.35	Capital share in production	Labor Share	0.65
ρ	0.90	Return to scale	Profit share	0.10
$\overline{\delta}$	0.06	Aggregate depreciation rate	Investment/Output	0.23
g	0.015	Growth rate		
$\nu_{k,0}$	0.50	Strength of capital adjustment cost	$\sigma(I)/\sigma(Y)$	3
$\nu_{k,1}$	$-(1+g)^{\frac{1-\alpha}{1-\alpha\rho}}$	Zero cost capital growth	Cost in steady state	0
		Financial sector		
κ	4.0	FI leverage ratio		
$\eta_{FI,0}$	0.0	Fixed component of labor demand		
$\eta_{FI,1}$	0.01	Balance sheet component of labor demand	FI labor share	0.6
$\eta_{FI,2}$	0.0208	Screening component of labor dmeand	FI employment and output growth correlation	0.4
		Capital structure		
$\nu_{d,0}$	0.005	Strength of capital structure cost	Debt/Value	0.45
$\nu_{d,1}$	4.1	Zero cost capital to profit ratio	Debt growth volatility	0.037
		Shocks		
p	0.884	Fraction of productive firms		
$(Z_{p,b}, Z_{p,g})$	(1,1)	Productivity of productive firms conditional on productivity state		
$(Z_{u,b}, Z_{u,g})$	(0.65,1)	Productivity of unproductive firms conditional on productivity state	Output volatility	3.4%
(N_b, N_g)	(0.93.1)	Labor supply conditional on productivity state	Employment growth volatility	2.2%
(s^h, s^l)	(0.011,0.009)	Fraction with default shock conditional on state	Fin sector value added volatility	6.9%

Table 2: Model moments

Panel A presents business cycle moments from the model and data, these include the standard devistions of output growth, employment growth, consumption growth, investment growth, and wage growth; and the correlations of these quantities with output growth. Panel B presents financial sector moments from the model and data, these include corporate debt growth, financial sector employment growth, financial sector employment share growth, value added growth, and financial sector labor share (FLS); and the correlations of these quantities with output growth. Panel C presents coefficients from regressing various quantities of interest on FLS both contemporaneously and one year ahead, for both model and data. GDP is defined as Real Private GDP which subtracts Government spending from GDP in BEA Table 1.1.6. Employment (N) is total non-farm employment (PAYEMS) from FRED. Consumption (C) is Personal Consumption Expenditures from BEA Table 1.1.3. Investment (INV) is Fixed Investment from BEA Table 1.1.3. Wage is compensation from BEA Table 2.1, discounted by CPI, and divided by employment. Financial sector employment (N_{FI}) is USFIRE from FRED. Debt is non-financial debt securities and loans (BCNSDODNS) from FRED. Value added is the financial sector's net value added from the BEA integrated macro accounts Table S.6.q. Financial labor share (FLS) is financial business total compensation of employeees from the BEA integrated macro accounts Table S.6.q, divided by Value added. All quantities in Panels A and B are computed for 1947-2021, except Value added and FLS, which are available starting in 1960.

	Panel A: Business cycle moments			
	Data		Model	
x	$\sigma(x)$	$\rho(x, \Delta GDP)$	$\sigma(x)$	$\rho(x, \Delta GDP)$
ΔGDP	0.034	1.000	0.033	1.000
ΔN	0.022	0.724	0.024	0.996
ΔC	0.020	0.836	0.014	0.980
ΔINV	0.095	0.890	0.104	0.992
ΔWAGE	0.018	0.116	0.010	0.965
	Panel B: Financial moments			
	Data		Model	
x	$\sigma(x)$	$\rho(x, \Delta GDP)$	$\sigma(x)$	$\rho(x, \Delta GDP)$
ΔDEBT	0.037	0.305	0.035	0.999
ΔN_{FI}	0.019	0.418	0.004	0.385
$\Delta \frac{N_{FI}}{N}$	0.018	-0.436	0.022	-0.973
ΔValueAdded	0.069	0.174	0.065	0.311
FLS	0.055	-0.168	0.038	-0.190
	Panel C: FLS regressions			
	Contemporaneous: $Y_t = a + bFLS_t$		Predictive: $Y_{t+1} = a + bFLS_t$	
	Data	Model	Data	Model
ΔGDP	-0.13	-0.16	-0.11	-0.036
	(4.62)		(2.23)	
ΔINV	-0.40	-0.44	-0.40	-0.023
	(7.35)		(2.64)	
ΔDEBT	-0.37	-0.17	-0.69	-0.036
	(2.83)		(5.22)	
$R^{BAA} - R^{FF}$	0.11	0.004	0.14	0.004
	(3.72)		(4.21)	

Table 3: Alternative models, selected moments

This table presents selected moments from the data, the screening model, and several alternative models. The four moments are the correlation of GDP growth with financial sector employment growth, the correlation of GDP growth with the growth of financial sector employment relative to total employment, the correlation of GDP growth with financial labor share (FLS), and the ratio of the volatilities of financial sector wage growth to total wage growth. The first row presents moments from the data. The rows labeled 'Screening' and 'No screening' present the baseline model with screening and the same model with screening turned off, both discussed in Section 2.7. The rows labeled 'Wage rigid' and 'Wage shock' presents models with no screening and either rigid wages or an independent shock to wages, both discussed in Section 2.8.1. The rows labeled 'Segm. Mkt' and 'Segm. Mkt + Screen' present models with segmented models without and with screening, both discussed in Section 2.8.2. The row labeled 'Fixed cost' present a model with a fixed component of labor demand, discussed in Section 2.8.3. Finally, the row labeled 'FLN shocks' presents a model with shocks to financial sector labor productivity, discussed in Section 2.8.4.

	$\rho(\Delta N_{FI}, \Delta GDP)$	$\rho(\Delta \frac{N_{FI}}{N}, \Delta GDP)$	$\rho(FLS, \Delta GDP)$	$\frac{\sigma(\Delta W_{FI})}{\sigma(\Delta W)}$
Data	0.42	-0.44	-0.17	1.69
Screening	0.41	-0.97	-0.16	1.00
No screening	1.00	0.99	0.09	1.00
Wage rigid	1.00	0.99	0.10	0.50
Wage shock	1.00	0.99	0.09	1.69
Segm. Mkt	1.00	0.99	0.09	1.69
Segm. Mkt + Screen	0.35	-0.97	-0.19	1.69
Fixed cost	1.00	-0.99	-0.11	1.00
FLN shocks	0.33	-0.27	-0.09	1.00

Table 4: Summary statistics

This table reports the summary statistics of key variables. Key variables include financial sector labor share (FLS), growth rate of net value added (ΔNVA_Fin), and leverage ratio of financial intermediaries constructed as in HKM and AEM. It also includes aggregate GDP growth (ΔGDP), debt growth of non-financial corporate sector (ΔDebt_NCOR), investment growth (ΔINV), aggregate wage growth (ΔWage), consumption growth (ΔCons), and aggregate labor share (Agg_LS). The sample consists of annual observations from 1961 to 2019. All the variables are real.

x	Mean	StDev	AC	Corr(FLS,x)
Panel A: Financial Sector				
FLS	0.64	0.05	0.54	1.00
ΔNVA_Fin	0.04	0.07	-0.13	-0.57
HKM	18.15	6.09	0.83	0.16
AEM	17.95	11.30	0.78	0.43
Panel B: Aggregate economy				
ΔGDP	0.03	0.02	0.37	-0.30
ΔDebt	0.03	0.07	0.47	-0.27
ΔINV	0.03	0.13	0.38	-0.33
ΔWage	0.03	0.02	0.48	-0.26
ΔCon	0.01	0.01	0.48	-0.16
LS_Agg	0.55	0.01	0.92	-0.02

Table 5: Aggregate FLS and debt growth

This table reports the results of aggregate-level regressions of debt growth in the non-financial corporate sector at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Debt growth at $t+k$ is defined as $\frac{Debt_{t+k}}{Debt_t}$ when $k>0$ and $\frac{Debt_t}{Debt_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.37***	-0.16	-0.13	-0.30**	-0.27	-0.16	-0.36***	-0.54***	-0.26*	-0.32**
t	-2.83	-0.83	-0.79	-2.44	-1.22	-1.20	-2.70	-2.61	-1.68	-2.20
Control		2.58***	1.82***	1.56***	-0.07*	-0.03*	0.00	-0.24	0.00***	0.00
t		2.96	5.63	7.15	-1.84	-1.92	-0.54	-0.93	-3.24	-0.68
R2	0.06	0.26	0.35	0.14	0.18	0.20	0.04	0.07	0.15	0.04
Panel B: 1-year ahead										
FLS	-0.69***	-0.65***	-0.50***	-0.60***	-0.64***	-0.74***	-0.69***	-0.65**	-0.58***	-0.60***
t	-5.22	-7.13	-6.16	-5.85	-7.66	-10.97	-5.49	-2.29	-6.55	-4.71
Control		0.44	1.44***	2.01***	-3.79	0.67	0.01	0.05	-0.29***	-0.08
t		0.51	4.05	3.08	-1.09	0.51	0.17	0.19	-4.62	-1.59
R2	0.24	0.23	0.42	0.39	0.27	0.23	0.23	0.23	0.34	0.24
Panel C: 3-years ahead										
FLS	-1.56***	-1.64***	-1.38***	-1.44***	-1.55***	-1.84***	-1.53***	-1.52***	-1.35***	-1.16**
t	-5.88	-6.69	-5.89	-6.78	-6.26	-7.70	-5.38	-3.55	-5.64	-2.81
Control		-1.05	1.28	258.18	-0.33	4.10**	-0.17	3.99	-0.52**	-0.35*
t		-0.45	1.39	1.86	-0.04	2.47	-1.52	0.13	-2.51	-1.90
R2	0.23	0.22	0.24	0.27	0.21	0.27	0.24	0.21	0.28	0.27
Panel D: 5-years ahead										
FLS	-1.99**	-2.09**	-1.89**	-1.91**	-1.98**	-2.28***	-1.92**	-2.27**	-1.70**	-1.19
t	-3.87	-3.53	-3.41	-4.11	-3.74	-4.91	-3.97	-3.49	-2.84	-1.27
Control		-1.27	0.64	1.64	-0.76	3.87	-0.32**	-0.35	-0.69	-0.75**
t		-0.41	0.41	0.62	-0.06	1.26	-2.34	-1.10	-1.26	-1.99
R2	0.19	0.18	0.18	0.19	0.17	0.20	0.23	0.18	0.24	0.30

Table 6: Aggregate FLS and Baa - Fed Funds spread

This table reports the results of aggregate-level regressions of the Baa - Fed Funds spread at $t+k$ on the finacnial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	0.11***	0.05*	0.11**	0.13***	0.10**	-0.01	0.10***	0.17***	0.10***	0.09***
t	3.72	2.28	2.57	4.31	2.39	-0.40	3.74	3.24	3.47	4.14
Control		-0.73***	0.24	0.30	1.28	1.73***	0.02**	7.26*	-0.04	0.03
t		-7.80	0.01	1.23	1.65	14.23	2.18	1.72	-0.77	1.45
R2	0.09	0.34	0.07	0.13	0.15	0.90	0.13	0.12	0.06	0.08
Panel B: 1-year ahead										
FLS	0.14***	0.08***	0.10***	0.14***	0.12***	0.07**	0.13***	0.14***	0.12***	0.10***
t	4.21	3.97	2.90	4.50	4.35	2.01	4.88	2.85	3.28	4.32
Control		-0.68	-30.29***	-5.55	1.76***	0.97***	0.03***	-0.27	0.00	0.04***
t		-0.19	-6.34	-0.24	3.42	8.94	3.15	-0.07	-0.11	4.03
R2	0.14	0.36	0.26	0.13	0.26	0.39	0.19	0.13	0.10	0.17
Panel C: 3-years ahead										
FLS	0.09**	0.08**	0.06	0.08**	0.08**	0.12***	0.09***	0.09	0.08*	0.03
t	2.42	2.52	1.46	2.13	2.36	2.89	3.60	1.54	1.81	0.49
Control		-0.12	-0.23***	-21.30*	0.85*	-0.32	0.05***	-0.30	-0.01	0.05*
t		-0.77	-3.29	-1.68	1.88	-1.25	2.97	-0.08	-0.13	1.93
R2	0.05	0.04	0.11	0.06	0.06	0.06	0.18	0.03	0.01	0.07
Panel D: 5-years ahead										
FLS	0.07*	0.05*	0.06**	0.07**	0.06**	0.06**	0.06**	0.09**	0.03	-0.01
t	1.78	1.65	2.02	2.28	1.96	2.02	2.23	2.19	1.04	-0.24
Control		-0.22	-0.05	6.17	0.49	0.08	0.03***	3.67**	-0.05*	0.06*
t		-1.38	-0.59	0.28	0.79	0.29	2.74	2.25	-1.69	1.81
R2	0.01	0.02	0.00	0.00	0.01	0.00	0.09	0.01	0.00	0.04

Table 7: Aggregate FLS and GDP growth

This table reports the results of aggregate-level regressions of GDP growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. GDP growth at $t+k$ is defined as $\frac{GDP_{t+k}}{GDP_t}$ when $k>0$ and $\frac{GDP_t}{GDP_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.13***	-0.07**		-0.09***	-0.09***	-0.14***	-0.13***	-0.07	-0.08***	-0.09***
t	-4.62	-2.19		-3.60	-3.31	-5.05	-5.33	-0.93	-3.36	-3.75
Control		0.77***		0.91***	-0.03***	0.00	0.00	0.08	0.00***	0.00
t		6.68		6.55	-4.39	0.39	0.68	0.87	-7.95	-1.23
R2	0.07	0.26		0.40	0.29	0.07	0.06	0.10	0.30	0.08
Panel B: 1-year ahead										
FLS	-0.11**	-0.13***	-0.06	-0.07**	-0.10***	-0.17***	-0.11**	-0.02	-0.07**	-0.06
t	-2.23	-3.68	-1.70	-2.12	-2.66	-4.87	-2.30	-0.26	-2.13	-1.61
Control		-0.32	0.32***	0.79***	-0.42	0.98*	-0.01	0.12**	-0.10***	-0.04*
t		-1.26	5.39	3.93	-0.54	1.83	-0.43	2.12	-4.57	-1.85
R2	0.04	0.06	0.13	0.29	0.03	0.20	0.03	0.11	0.15	0.06
Panel C: 3-years ahead										
FLS	-0.19*	-0.24***	-0.17**	-0.14*	-0.19**	-0.26***	-0.18	-0.17	-0.10	-0.02
t	-1.78	-3.06	-2.29	-1.95	-2.24	-3.31	-1.61	-1.08	-1.61	-0.17
Control		-0.65	0.14	1.02**	0.01	1.02	-0.05	0.03	-0.23***	-0.15
t		-0.80	0.44	1.98	0.01	1.53	-1.20	0.33	-2.80	-1.96
R2	0.02	0.03	0.01	0.09	0.00	0.04	0.03	0.00	0.15	0.10
Panel D: 5-years ahead										
FLS	-0.24	-0.26*	-0.22**	-0.20*	-0.23*	-0.25	-0.23	-0.25	-0.11	0.02
t	-1.52	-1.73	-1.98	-1.71	-1.72	-1.63	-1.44	-1.13	-0.95	0.12
Control		-0.23	0.15	1.00	-1.44	0.10	-0.08	-0.01	-0.32**	-0.25**
t		-0.29	0.31	0.31	-0.36	0.19	-1.29	-0.09	-2.02	-2.13
R2	0.02	0.00	0.00	0.05	0.01	0.00	0.04	0.00	0.17	0.16

Table 8: Aggregate FLS and Investment growth

This table reports the results of aggregate-level regressions of investment growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Investment growth at $t+k$ is defined as $\frac{INV_{t+k}}{INV_t}$ when $k>0$ and $\frac{INV_t}{INV_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.40***	-0.20**	-0.13*	-0.34***	-0.30***	-0.43***	-0.42***	-0.31*	-0.34***	-0.43***
t	-7.35	-2.54	-1.87	-4.24	-2.65	-4.49	-6.50	-1.73	-3.57	-5.91
Control		2.48***	2.12***	1.37***	-0.08***	0.00	0.04	0.12	0.00***	0.00
t		6.63	10.30	3.69	-5.25	0.35	1.48	0.48	-4.28	0.25
R2	0.11	0.39	0.70	0.21	0.35	0.10	0.11	0.11	0.18	0.09
Panel B: 1-year ahead										
FLS	-0.40***	-0.44***	-0.29**	-0.33**	-0.37***	-0.63***	-0.40***	-0.15	-0.36***	-0.34***
t	-2.64	-3.34	-2.10	-2.23	-2.86	-5.48	-2.70	-0.88	-2.62	-4.19
Control		-0.53	0.83***	1.61***	-1.81	3.40***	0.00	0.32**	-0.21*	-0.11
t		-1.12	5.23	3.63	-1.14	3.86	-0.06	2.13	-1.77	-1.05
R2	0.11	0.10	0.18	0.24	0.10	0.39	0.09	0.18	0.13	0.12
Panel C: 3-years ahead										
FLS	-0.43*	-0.62***	-0.51**	-0.39*	-0.45*	-0.84***	-0.41*	-0.16	-0.33	-0.10
t	-1.89	-3.39	-2.06	-1.75	-1.78	-4.93	-1.83	-0.54	-1.28	-0.32
Control		-2.35*	-0.55	0.92	2.07	5.94***	-0.14	0.34*	0.02	-0.33
t		-1.92	-1.11	0.81	0.43	4.67	-1.28	1.73	0.06	-1.14
R2	0.01	0.05	0.00	0.00	0.00	0.18	0.02	0.01	-0.03	0.02
Panel D: 5-years ahead										
FLS	-0.06	-0.14	-0.20	-0.06	-0.03	-0.28	-0.02	0.23	0.15	0.69
t	-0.17	-0.40	-0.55	-0.19	-0.09	-0.78	-0.07	0.51	0.35	1.28
Control		-0.92	-0.92	0.00	-2.62	2.92	-0.20	0.37	0.27	-0.37
t		-1.01	-1.37	0.00	-0.42	1.32	-1.26	1.44	0.55	-0.82
R2	-0.02	-0.03	-0.02	-0.04	-0.03	0.00	0.00	-0.02	-0.03	0.03

Table 9: Bank level FLS and bank loan growth

This table reports the results of predicting loan growth in the U.S at $t+k$ by bank holding companies' labor share (FLS) at t using panel bank holding company data from FR Y-9C. This table presents both the univariate and multivariate regression results with bank holding company and year or state-year fixed effect. The coefficient estimates are obtained from the following regression:

$$\Delta Loan_{i,t+k} = \alpha_i + \delta_{s,t} + \beta_1 FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}$$

where $\Delta Loan_{i,t+k} = 2\frac{Avg(Loan_{i,t+1:t+k}) - Avg(Loan_{i,t-k+1:t})}{Avg(Loan_{i,t+1:t+k}) + Avg(Loan_{i,t-k+1:t})}$ is the loan growth of bank i over a 3-year window ($k = 3$). Column (1) to (4) present the predictability results with dependent variable being growth rate of total loan and column (5) to (8) present the predictability results with dependent variable being growth rate of commercial and industrial (C&I) loan. The control variables include size, ROA, capital ratio, non-performing C&I loan share, interest expense and earning growth. The Appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks. The final sample is from 1986 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Total loan growth			Commercial&Industrial loan growth			
FLS	-0.17***	-0.14***	-0.16***	-0.14***	-0.18***	-0.15***	-0.15***	-0.14***
	(-26.17)	(-22.19)	(-14.19)	(-13.35)	(-17.14)	(-14.66)	(-8.43)	(-7.76)
BHC Size			-0.08***	-0.08***			-0.08***	-0.07***
			(-9.08)	(-9.21)			(-5.86)	(-5.36)
BHC ROA			0.78	-0.20			0.42	-0.51
			(1.08)	(-0.27)			(0.37)	(-0.44)
BHC Capital Ratio			-0.26*	-0.10			0.28	0.54**
			(-1.84)	(-0.71)			(1.21)	(2.31)
BHC NPL Share			-4.44***	-3.62***			-10.45***	-9.24***
			(-12.33)	(-9.99)			(-17.00)	(-14.99)
BHC Interest Expense			-4.71***	-3.94***			-3.06***	-2.33***
			(-9.69)	(-8.35)			(-4.46)	(-3.38)
BHC ΔEBIT			0.01***	0.01***			0.01***	0.01***
			(9.06)	(8.25)			(6.47)	(5.65)
N	36969	36857	32555	32430	36949	36837	32516	32391
adj. R^2	0.501	0.546	0.542	0.577	0.401	0.428	0.436	0.459
BHC FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No	Yes	No
State_Year FEs	No	Yes	No	Yes	No	Yes	No	Yes

Table 10: Bank level FLS and bank risk

This table reports the results of predicting of bank holding company's risk by bank holding companies' labor share (FLS) at t using panel bank data from FR Y-9C. The risk is measured as the expected default frequency (EDF) from $t+1$ to $t+3$, or the average annual stock return volatility from $t+1$ to $t+3$ or the volatility of bank earning growth from $t+1$ to $t+3$. This panel presents both the univariate and multivariate regression results with bank holding company and state-year fixed effect. The coefficient estimates are obtained from the following regression:

$$y_{i,t+1:t+3} = \alpha_i + \delta_{s,t} + \beta_1 FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+3}.$$

The control variables include size, ROA, capital ratio, non-performing C&I loan share, and interest expense. The Appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks. The final sample is from 1992 to 2011.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Expected default frequency (EDF)				Stock return volatility				Earning growth volatility			
FLS	1.39***	1.24***	1.52***	1.38***	2.50***	2.38***	2.01***	1.85***	1.51***	1.21***	0.95**	0.92**
	(7.27)	(6.44)	(5.42)	(4.83)	(9.09)	(8.80)	(5.02)	(4.46)	(5.02)	(4.12)	(2.12)	(2.14)
Size			0.65***	0.48***			0.53**	0.27			0.30	0.18
			(4.77)	(3.43)			(2.13)	(0.97)			(1.26)	(0.69)
ROA			15.61	13.21			-25.75	-30.06			-41.56**	-20.30
			(1.13)	(0.90)			(-1.15)	(-1.27)			(-1.97)	(-0.93)
Cap. Rat.			-10.79***	-9.37***			-14.98***	-13.24***			5.15	3.64
			(-3.79)	(-3.39)			(-3.39)	(-3.12)			(1.31)	(0.82)
Int. Exp.			9.17*	7.61			26.63***	34.65***			2.52	-0.16
			(1.91)	(1.46)			(2.83)	(3.28)			(0.34)	(-0.02)
NPL Share			11.36	7.67			-18.40	-31.84*			50.76**	61.57***
			(1.19)	(0.76)			(-0.99)	(-1.71)			(2.54)	(3.08)
ΔEBIT			-0.08***	-0.08***			-0.06*	-0.06*				
			(-3.59)	(-3.28)			(-1.77)	(-1.66)				
N	6621	6483	6383	6242	6808	6661	6573	6423	5857	5688	5851	5680
adj. R^2	0.556	0.626	0.575	0.637	0.604	0.647	0.616	0.657	0.381	0.407	0.385	0.410
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
State_Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 11: Bank level FLS and firm credit

This table reports the results of predicting borrowing quantity, price of bank loans, or distance to default for non-financial U.S firms over a 3-year window by bank holding companies' labor share (FLS) at t using panel data with bank-firm lending relationship. The coefficient estimates are obtained from the following regression:

$$y_{i,j,t+k} = \alpha_i + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k},$$

where $y_{i,j,t+k} = \Delta Loan\ Amount_{i,j,t+k} = 2\frac{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} - \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}{\sum_{m=t+1}^{m=t+k} Loan\ Amount_{i,j,m} + \sum_{m=t-k+1}^{m=t} Loan\ Amount_{i,j,m}}$ is the growth rate of loan borrowing in Panel A, $y_{i,j,t+k} = Avg(Loan\ Spread_{i,j,t+1:t+k})$ the average loan spreads measured as"All-in-drawn" from Dealscan Loan Pricing in Panel B, and $y_{i,j,t+k} = Avg(D2D_{t+1:t+k})$ is default risk in Panel C ($k = 3$). The control variables include bank characteristics (bank size, ROA, capital ratio, non-performing C&I loan ratio, interest expense and earning growth) and firm characteristics (firm size, Tobin's Q, cash, financial leverage, past sales growth, excess return and credit rating). The regressions are estimated under different fixed effect specifications. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks and firms. The final data sample is from 1986 to 2019.

	(1)	(2)	(3)
	Panel A: Loan borrowing growth		
FLS	-0.49***	-0.46**	-0.51***
	(-2.83)	(-2.26)	(-2.92)
N	15277	14916	15262
adj. R^2	0.121	0.123	0.123
	Panel B: Credit spread		
FLS	0.36*	0.29*	0.33*
	(1.88)	(1.70)	(1.87)
N	15008	14659	15000
adj. R^2	0.461	0.469	0.470
	Panel C: Distance to default		
FLS	-1.84***	-1.66***	-1.61***
	(-3.75)	(-2.79)	(-3.14)
N	14353	13994	14337
adj. R^2	0.499	0.507	0.514
BHC FEs	Yes	Yes	Yes
Year FEs	Yes	No	No
Firm State_Year FEs	No	Yes	No
1-digit SIC_Year FEs	No	No	Yes

Table 12: Bank level FLS and firm real outcomes

This table reports the results of predicting non-financial U.S firms' changes in investment rate or earnings growth over a 3-year window by bank holding companies' labor share (FLS) at t using panel data with bank-firm lending relationship. The coefficient estimates are obtained from the following regression:

$$y_{i,j,t+k} = \alpha_i + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k},$$

where $y_{i,j,t+k} = \frac{Avg(CAPX_{t+1:t+k}) - Avg(CAPX_{t-k+1:t})}{PPENT_t}$ for investment rate changes in Panel A and $y_{i,j,t+k} = 2\frac{Avg(IB_{t+1:t+k}) - Avg(IB_{t-k+1:t})}{Avg(IB_{t+1:t+k}) + Avg(IB_{t-k+1:t})}$ for earnings growth in Panel B ($k = 3$). The control variables include bank characteristics (bank size, ROA, capital ratio, non-performing C&I loan ratio and interest expense) and firm characteristics (firm size, Tobin's Q, cash, financial leverage, past sales growth, excess return, tangibility and credit rating). The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks and firm. The final data sample is from 1986 to 2019.

	(1)	(2)	(3)
	Panel A: Investment rate change		
FLS	-0.03	-0.04	-0.04
	(-0.80)	(-0.96)	(-1.09)
N	14701	14337	14684
adj. R^2	0.267	0.270	0.285
	Panel B: Earnings growth		
FLS	-0.68**	-0.73**	-0.64**
	(-2.07)	(-2.42)	(-2.06)
N	14799	14427	14782
adj. R^2	0.005	0.004	0.008
Bank FEs	Yes	Yes	Yes
Year FEs	Yes	No	No
State_Year FEs	No	Yes	No
1-digit SIC_Year FEs	No	No	Yes

Appendix

A Details on Data and Sample Construction

Below are details of how we construct aggregate and firm-level variables, how we identify lead lenders for each loan origination, and the filters we apply to obtain our final sample.

A.1 Aggregate Variables Construction

The aggregate sample for aggregate time series regressions contains annual data from 1961 to 2019. Financial sector labor share is the ratio of compensation of employees to net value added of the financial business sector from Integrated Macroeconomic Accounts (IMA); while aggregate labor share is the ratio of aggregate compensation of employees to GDP. We apply the Hamilton (2017) filter[58] to remove the trend of the aggregate labor share. Wage growth is the growth rate in the real wages and salaries per full-time equivalent employee from NIPA Table 6.6, deflated by the Consumer Price Index for All Urban Consumers from FRED. Market return and risk-free rate are from Kenneth French's data library. Debt growth is the growth rate of credit market instrument liabilities (sum of real debt and loans) for non-financial business sector from the Flow of Funds Table L.103. Non-financial business sector leverage is defined as the ratio of its liabilities to corporate equity. Similarly, we obtain debt growth and leverage ratio for financial business sector using debt, loans and equity data from IMA. Aggregate investment growth is the growth rate of fixed investment from NIPA Table 1.1.5. Value added growth is the growth rate of the real net value added for non-financial corporate sector from IMA. The credit spread is the Moody's Baa corporate bond yield in excess of Aaa corporate bond yield from the Federal Reserve. Term Spread is 10-year Treasury rate minus 1-year Treasury rate. The 3-month T-bill rate, corporate bond yield and Treasury rate are from St. Louis Fed. The price-dividend (PD) ratio is obtained from Shiller's webpage. We get the leverage ratio of AEM and HKM directly from Asaf Manela's website. We then take the simple average to obtain the annual observations.

Table A.1 below describes the definition and sources of the main variables.

[58] We regress the aggregate labor share on a constant and four lagged values of aggregate labor share as of date $t-k$ where we try $k = 2, 3, ..., 10$. We estimate the cyclical component of aggregate labor share with rolling-window using data from 1948 to 2019 and drop the first 10 observations.cyclical $\text{LS}_t = \text{LS}_t - \hat{\beta}_0 - \hat{\beta}_1 \text{LS}_{t-k} - \hat{\beta}_2 \text{LS}_{t-k-1} - \hat{\beta}_3\ \text{LS}_{t-k-2} - \hat{\beta}_4 \text{LS}_{t-k-3}$. We use $k = 2$ for the benchmark results. The results are robust for k varies from 2 to 10.

A.2 Labor Skill Measure

Our benchmark analysis uses the Specific Vocational Preparation (SVP) data from the 1991 Dictionary of Occupational Titles (DOT)[59], available from the Department of Labor, and employee data from the Bureau of Labor Statistics (BLS), Occupational Employment Statistics (OES) program. For each occupation defined in the DOT, it provides information about the Specific Vocational Preparation (SVP) level of the occupation. The SVP measures the amount of time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. SVP takes value from 1 to 9, where SVP = 1 corresponds to the lowest level of preparation and SVP = 9 corresponds to the highest level of preparation. We define high skill occupations to be those that have are associated with a SVP equal to or greater than 7 (over 2 years of preparation).[60] The total wage payment of high skill workers are computed as the product of total employment and average annual wage rate. The labor share of high skill workers ("HSLS") is defined as the ratio of total wage payment of high skill workers to GDP for the aggregate economy. The labor share of high skill workers in the finance industry ("HSFLS") is defined as the total wage payment of high skill workers to the net value added of finance industry. The aggregate high skill workers labor share has a mean of 0.2 and a standard deviation of 0.03. The high skill workers labor share in the finance industry has a mean of 0.142 and a standard deviation of 0.015. The correlation between HSFLS and FLS is around 0.62 and the correlation between HSFLS and HSLS is around 0.08.

[59] Dictionary of Occupational Titles (DOT): Revised Fourth Edition, 1991 from U.S. Department of Labor. The data for 1991 DOT are obtained from the Inter-university Consortium for Political and Social Research (ICPSR) Study No 6100 v.1 (DOI:10.3886).

[60] The following is the detailed explanation of SVP index: 1. Short demonstration only; 2. Anything beyond short demonstration up to and including 1 month; 3. 1 month $<$ preparation time $\leq$ 3 months; 4. 3 month $<$ preparation time $\leq$ 6 months; 5. 6 month $<$ preparation time $\leq$ 1 year; 6. 1 year $<$ preparation time $\leq$ 2 year; 7. 2 year $<$ preparation time $\leq$ 4 year; 8. 4 year $<$ preparation time $\leq$ 10 year; 9. over 10 years.

Table A.1: Variable Definitions

Variable Definitions		
Definition		Data sources
Bank Characteristics		
Labor share	Labor expense over sum of labor expense and earning FLS = $\frac{\text{XLR}}{\text{XLR+EBITDA}}$	FR Y-9C
Size	Log of total book assets (BHCK2170)	FR Y-9C
ROA	Net income (BHCK4340) divided by total assets (BHCK2170)	FR Y-9C
Interest Expense	Total interest expense (BHCK4073) divided by total deposits (sum of BHDM6631, BHDM6636, BHFN6631, and BHFN6636)	FR Y-9C
Capital ratio	Total equity (BHCK3210) divided by total assets (BHCK2170)	FR Y-9C
Non-performing Loan	Sum of BHCK5525, BHCK5524, BHCK5526 and BHCK4635, divided by total loan	FR Y-9C
Loan growth	$\Delta \text{Loan}_t = \frac{\text{Loan}_t - \text{Loan}_{t-1}}{0.5(\text{Loan}_t + \text{Loan}_{t-1})}$	FR Y-9C
Earnings growth	$\Delta Earning_t = \frac{EBIT_t - EBIT_{t-1}}{0.5*(EBIT_t + EBIT_{t-1})}$	FR Y-9C
Total Loan	Sum of BHCK2122 and BHCK2123	FR Y-9C
Business Loan	BHCK1766 (Commercial & Industrial Loan)	FR Y-9C
Business Loan (U.S)	BHCK1763	FR Y-9C
Real Estate Loan	BHCK1410	FR Y-9C
Consumer Loan	BHCK1975	FR Y-9C
Data Processing Fees	BHCKC017	FR Y-9C
Legal expense	BHCK4141	FR Y-9C
Firm Characteristics		
Investment rate	Capital expenditure (CAPX) over lagged PPENT	Compustat
Earnings growth	$\Delta \text{Earnings}_t = \frac{\text{IB}_t - \text{IB}_{t-1}}{0.5(\text{IB}_t + \text{IB}_{t-1})}$	Compustat
Firm size	Log of total assets (AT)	Compustat
Financial leverage	Sum of short-term and long-term debt (DLC + DLTT), divided by total assets	Compustat
Cash	Cash and short-term investment (CHE), divided by total assets	Compustat
Tobin's Q	$\frac{\text{AT+CSHOxPRCC}_F - \text{CEQ}}{\text{AT}}$	Compustat
Credit rating	S&P long-term SPLTICRM	Compustat
Sales growth	$\Delta \text{Sales}_t = \frac{\text{Sales}_t - \text{Sales}_{t-1}}{0.5(\text{Sales}_t + \text{Sales}_{t-1})}$	Compustat
Tangibility	$(0.715 \times \text{RECT} + 0.547 \times \text{INVT} + 0.535 \times \text{PPENT})/\text{AT}$	Compustat
Excess return	RET − risk-free rate	CRSP
Whited-Wu index	WW Index = 0.65 - 0.091 CF - 0.062DIVPOS + 0.021TLTD - 0.044LNTA + 0.102ISG - 0.035SG.	Hennessy and Whited (2007)
Aggregate variables		
Financial sector labor share	Compensation of employees divided by net value added	IMA/NIPA
Aggregate labor share	Compensation of employees divided by GDP	NIPA
Wage growth	Growth rate of the real wages and salaries per full-time equivalent employee	NIPA
CPI	Consumer Price Index for All Urban Consumers	FRED
Debt growth	Growth rate of credit market instrument liabilities (sum of real debt and loans) for non-financial business sector	Flow of Funds
	Growth rate of credit market instrument liabilities (sum of real debt and loans) for financial business sector	IMA
Investment growth	Growth rate of nonresidential fixed investment	NIPA
GDP growth	Growth rate of real GDP	NIPA
Value added growth	Growth rate of real net value added	IMA
Credit spread	Moody's Baa corporate bond yield in excess of Fed Funds rate	St. Louis Fed
Term spread	10-year Treasury rate minus 1-year Treasury rate	St. Louis Fed
PD	price-dividend (PD) ratio	Shiller's webpage
Financial leverage	FI financial leverage (AEM and HKM)	Asaf Manela's website
Market excess return	Market return and risk-free rate	Kenneth French

A.3 Distance to Default (D2D)

Following Merton (1974) and Gilchrist and Zakrajšek (2012), the distance to default is defined as

$$D2D = \frac{log(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V}, \tag{A.1}$$

where V is the total value of firm, μ_V is the annual expected return on V, σ_V is the annual volatility of the firm's value, and D is firm's debt. Firm value V is estimated following an iterative procedure,

1. Set an initial value for the firm value equal to the sum of firm debt and equity: $V = E + D$, where $E = \text{PRC} \times \text{SHROUT}$ (daily stock price times the number of shares outstanding from CRSP).

2. Estimate μ_V and σ_V over a 250-day moving window. The return on firm value is defined as the daily log return on assets, $\Delta logV$.

3. Get a new estimate of V for every day of the 250-day moving window based on the Black-Scholes-Merton option-pricing framework

$$E = V\Phi(\delta_1) - e^{-rT}D\Phi(\delta_2), \tag{A.2}$$

   where $\delta_1 = \frac{log(V/D)+(r+0.5\sigma_V^2)T}{\sigma_V^2\sqrt{T}}$ and $\delta_2 = \delta_1 - \sigma_V\sqrt{T}$ where r is the daily one-year constant maturity Treasury-yield from St. Louis Fed.

4. Iterate on steps 2 and 3 until convergence.

A.4 Identifying Lead Lenders

We use Dealscan, which contains origination information on both sole-lender loans and syndicated loans, to determine relationships between firms and banks. There are two variables in Dealscan that are useful in determining the lead agent: a text variable "LenderRole" that defines the lender role and a Yes/No lead arranger credit variable "LeadArrangerCredit". In the case of syndicated loans with multiple lenders, we follow lender's ranking hierarchy proposed by Chakraborty, Goldstein and MacKinlay (2018) to identify the lead lender for each loan:

1. LenderRole == "Admin Agent"
2. LenderRole == "Lead Bank"
3. LenderRole == "Lead Arranger"
4. LenderRole == "Mandated Lead Arranger"
5. LenderRole == "Mandated Arranger"
6. LenderRole == "Arranger" or "Agent" and LeadArrangerCredit == "Yes"
7. LenderRole == "Arranger" or "Agent" and LeadArrangerCredit == "No"
8. LenderRole is defined as other than those previously listed ("Participant" and "Secondary investor" are also excluded) and LeadArrangerCredit == "Yes"
9. LenderRole is defined as other than those previously listed ("Participant" and "Secondary investor" are also excluded) and LeadArrangerCredit == "No"
10. LenderRole == "Participant" or "Secondary investor"

For a given loan package, the lender with the highest title (following our ten-part hierarchy) is considered as the lead agent. About 81% of the matched facility in our sample has only one lead lender. About 76% of the matched facilities in our sample have a single lead lender that fall under one of the first six categories. Any loan where a single lead agent cannot be determined is excluded from the sample. To determine each lender's loan amount, we do the following: for those loans which have allocation information, we use the provided data (FacilityAmt $\times$ BankAllocation) . For those loans without allocation data, we estimate the average allotment given the lender's position in the syndicate and the syndicate size. Specifically, we estimate the missing values for "BankAllocation" in a Tobit regression where we include number of lenders, number of lead agents, lenders' ranking, loan amount and an indicator for lead agent.

A.5 Sample Selection

Compustat We apply the following filters to our Compustat firms sample:

- We drop firms in finance, insurance, and real estate sectors (SIC $\in$ [6000, 6799]), utilities (SIC $\in$ [4900, 4999]) and public administration (SIC $\in$ [9000, 9999]).
- We drop firms with negative or missing sales or assets, and negative cash.

FR Y-9C We apply the following filters to our bank holding company (BHC) sample:

- We drop observations with missing or negative total assets (BHCK2170)
- We keep bank holding companies (RSSD9331==28)
- We drop lower-tier holding companies whose higher-tier also files Y-9C (BHCK9802==2)
- We keep holding company (RSSD9048 ==500) and exclude securities broker or dealer (RSSD9048 ==700), insurance broker or company (RSSD9048 ==550), utility company (RSSD9048 ==710), and other non-depository institution (RSSD9048 ==720) but keep Goldman Sachs, Morgan Stanley, Ally and American Express.
- We drop observations with negative labor share and interest expense.

Dealscan We apply the following filters to our Dealscan sample:

- We keep facilities measured in U.S Dollars. (Currency==“United States Dollars”)
- We keep facilities with borrowers and lenders in USA. (Country==“USA”)
- We keep facilities with borrowers that are corporations. (InstitutionType==“Corporation”)
- We keep facilities with lenders that are U.S banks. (InstitutionType ==“US Bank”)
- We keep facilities that are either sole-lender loans or syndicated loans. (DistributionMethod ==“Syndication” or DistributionMethod ==“Sole Lender”)
- We keep facilities with single lead agent belongs to the first six categories listed above.
- We only keep holding companies that have issued at least 50 facilities in our merged sample.
- We keep firms that have at least three observations in the sample.

Loan pricing We apply the following filters to our loan pricing sample:

- We drop facilities with negative loan spread (“All-in-Drawn”) or facilities with loan spread over 1000 basis points.
- We drop facilities with maturity less than one year.

B Additional Empirical Results

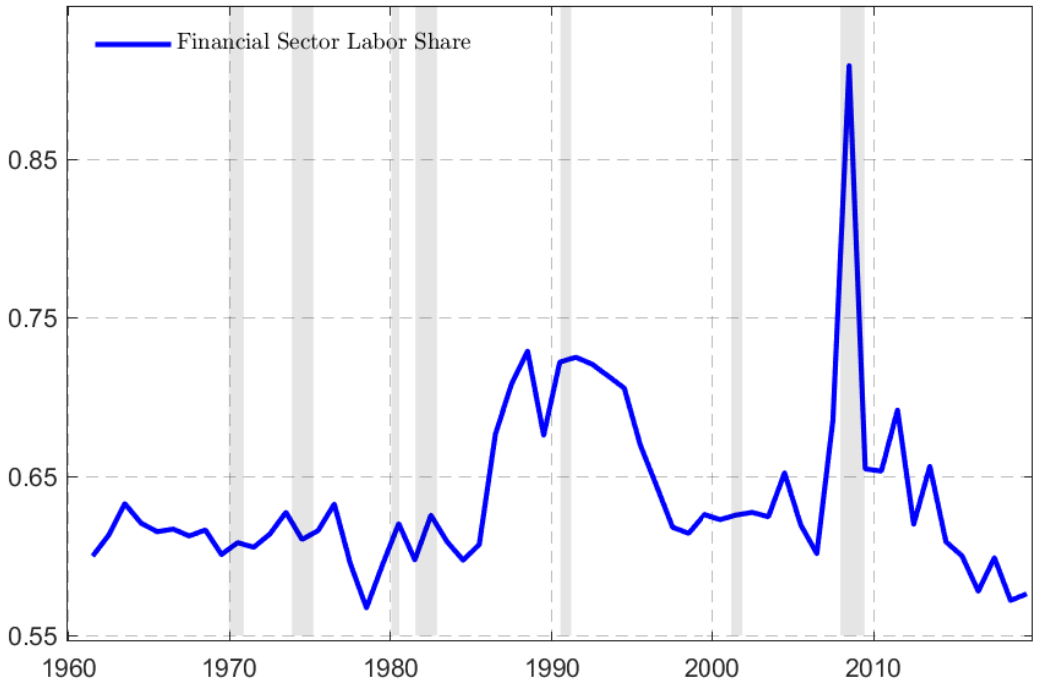
This section provides additional empirical results, we summarize them here, although most are mentioned in the main text. Figure A.1 shows a time series plot of FLS. Table A.2 shows the relationship between FLS and debt growth in the financial sector, it is analogous to Table 5 which does this for aggregate debt growth. Tables A.3 and A.4 provide multivariate results relating FLS and various controls to aggregate equity returns, debt growth, cost of credit, GDP growth, and investment growth; they are analogous to Tables 5-8. Tables A.5 and A.6 show that FLS also forecasts corporate equity return positively, suggesting it is also linked to stress outside of credit markets. Tables A.7-A.14 recompute the main results (Tables 5-8) with alternative lags for Newey-West standard errors. Tables A.15-A.18 recompute the main results but change the sample to 1961-2007. Table A.19 recomputes the main aggregate results with the labor share of high skilled workers as a control; it is analogous to Tables 5-8 and A.5.

Table A.20 provides summary statistics for the firm level results. Table A.21 shows the relationship between a bank's FLS and its leverage. Table A.22 separates the numerator (compensation) and the denominator (value added) in the firm level results. Table A.23 relates bank level FLS to bank level loan growth and is similar to Table 9, but it breaks down loans by type. Table A.24 relates bank level FLS to real firm level outcomes and is similar to Table 12 but it separates firms into constrained and unconstrained. Figure A.3 uses a scatterplot to highlight the negative relationship between output and the financial sector employment as a share of total employment; Table A.25 compares the cyclicality of labor in the financial sector to other industries.

Table A.26 and Figure A.4 provide direct evidence for one specific source of FLN shocks. For example, a higher regulation burden raises the FIs' legal and data processing expenses. FIs that have increasing legal and data processing expenses also have a higher FLS, a lower growth rate of loan lending, and a higher interest rate charged from its borrowers.

Figure A.1: Financial sector labor share (FLS), time series

This figure plots the financial sector labor share (FLS) over time. FLS is computed as the ratio of compensation of employees to net value added of the financial business sector from Integrated Macroeconomic Accounts (IMA).



B.1 Evidence of FLN shocks

In this section, we discuss evidence for direct shocks to the FI's labor productivity, we refer to these as financial labor need (FLN) shocks. The model in Section 2.8.4 relies on such shocks to match the patterns observed in the data. These shocks might arise from various sources.

One likely source of such shocks is regulatory. For example Dodd-Frank or Sarbanes-Oxley, may lead financial intermeidaries to hire more people to deal with additional regulation.[61,62] The Covid-19 pandemic provides an alternative example. Banks were extremely busy with PPP loans, as they needed to verify various information about borrowers in a short period of time and therefore required more labor to intermediate capital. Another example is that default and litigation risk may be higher during recessions, leading to higher demand for debt collection and legal services by financial intermediaries.[63]

Below, we provide direct evidence showing that individual banks' increased regulatory compliance burden is associated with an increase in labor share, and in turn, less future lending and higher rates. We also show that aggregate regulatory shocks affect the compliance burden and labor share. To do so, we create two proxies of compliance burden and show that FLS is positively related to these proxies. These results are in Table A.26.

The first measure defines the regulatory compliance burden of bank i in year t as its legal and data processing expenses, scaled by total assets; this measure uses the same bank data as in Section 3.2. Analogous to an instrumental variables approach, in the first stage, we ask how much of the change in FLS can be explained by the change in regulatory burden – the relationship is significant, this is in Column (1) of Panel A. In the second stage, we show that the predicted change in FLS negatively and significantly predicts the loan growth over the next three years, and positively and

[61] For example, the Wall Street Journal writes: "A labor-market squeeze and evolving regulatory pressures are driving demand for compliance officers ... sectors such as financial services beefed up their compliance departments following the financial crisis of 2008 and the enactment of new regulatory regimes like the 2010 Dodd-Frank Act... Cryptocurrency is one area that has heated up for compliance jobs" (Sun (2022)). Similarly, the New York Times writes "New regulation has long been one of Washington's unofficial job creation tools. After the enactment of the Foreign Corrupt Practices Act in the late 1970s, hundreds of lawyers and accountants were hired by companies to strengthen their internal controls. The Sarbanes-Oxley Act of 2002 became a boon for the Big Four accounting firms as public corporations were forced to tighten compliance in the wake of the Enron and WorldCom scandals. Now, the Dodd-Frank Act is quickly becoming such a gold mine that even Wall Street bankers, never ones to undercharge, are complaining that the costs are running amok" (Dash (2011)).

[62] A survey of banks by S&P Global (S&P Global Market Intelligence (2017)) provides additional evidence for the importance of FLN shocks in the context of Dodd-Frank. 49% of responders said compliance costs were up at least 20%, 59% said compliance costs now account for at least 10% of their annual expenses. "Operating in the current regulatory environment significantly drives up our overhead costs," said a Texas community banker; "We just pass the lost revenue or cost onto the end consumer," said a community banker from Iowa; "It isn't profitable to make loans under $1 million" said a Florida community banker; "in 20 years I doubt we will be left with anything else besides megabanks... This will have a dramatic, chilling effect on small business creation and economic growth" said a credit union respondent.

[63] For example the debt collection industry boomed in the aftermath of the 2007 financial crisis (Blumberg (2010) and Bassett (2008)), as did debt related lawsuits (Martin (2010)). This implies that the labor needs of debt holders increased.

significantly predicts the loan spreads on the bank's lending over the next three years. In Panel B, we carry out the same exercise but our measure of regulatory compliance burden is defined at the aggregate level (time-series variation only) using banking regulation documents.[64] Again, this proxy negatively and significantly predicts loan growth and positively and significantly predicts loan spreads. If changes in either of these two regulatory burden measures are exogenous to an individual bank, these proxies can be interpreted as instrumental variables.

In column (4) of Panel B we also show that the change in legal and processing expenses (the first measure) is itself positively and significantly related to the aggregate increase in regulatory burdens (the second measure). This is also consistent with survey evidence. For example, 49% of the respondents in an S&P Global Market Intelligence survey said compliance costs were up 20% or more since Dodd-Frank was implemented, and 59% said compliance costs now account for at least 10% of their annual expenses.

[64]To construct this measure, we follow Hogan and Burns (2019), who measure regulation burdens using the text of banks and banking regulation documents. More specifically, we use the number of regulatory restrictions, which captures the text of the Code of Federal Regulations Title 12 for language that restricts activities such as "shall" or "shall not" and "must" or "must not."

Figure A.2: Number of Bank Holding Companies

This figure plots the number of bank holding companies from FR Y-9C in our sample every year from 1986 to 2019. The number of bank holding companies increase from 1,321 in year 1986 to 2,204 in year 2005. The number of bank holding companies drops dramatically after 2005 to 304 in year 2019.

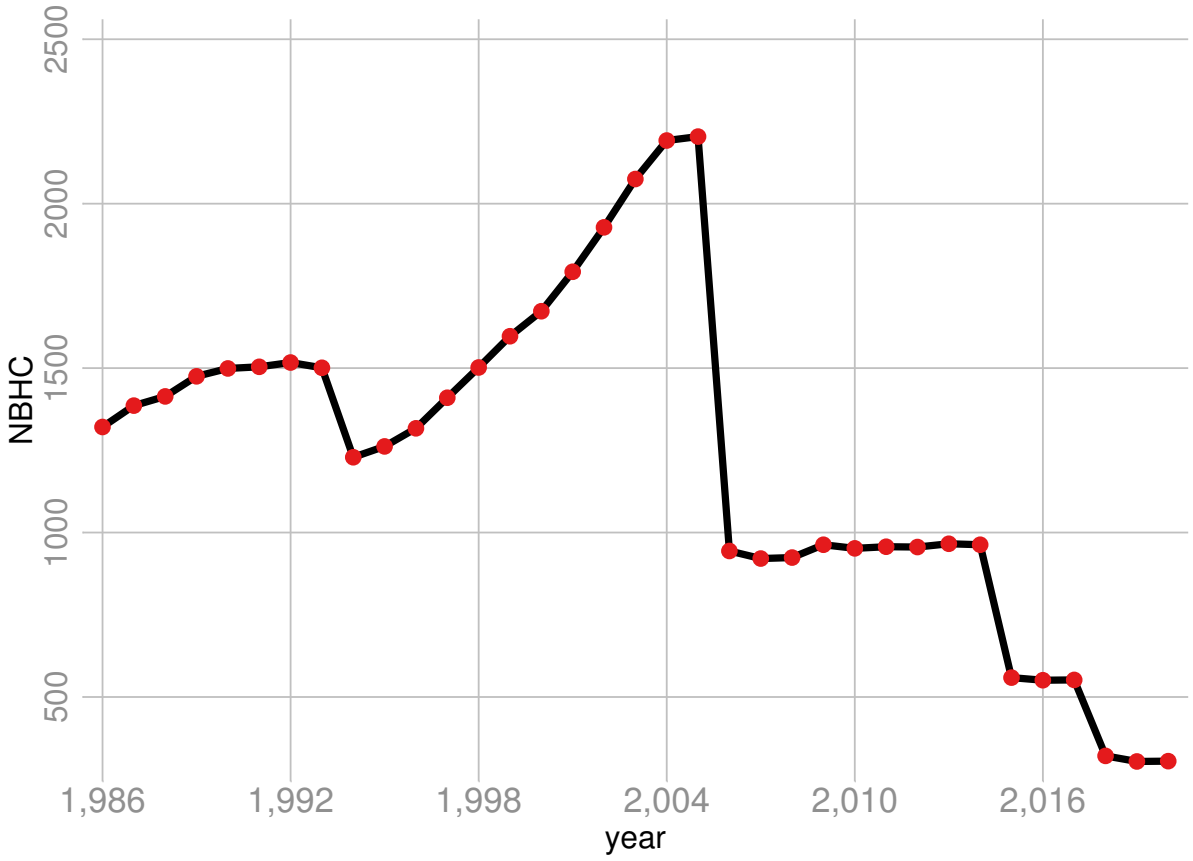


Table A.2: Aggregate FLS and financial sector debt growth

This table reports the results of aggregate-level annual time-series contemporaneous (t), 1-year ahead ($t+1$), 3-year ahead ($t+3$), and 5-year ahead ($t+5$) predictability of financial sector debt growth by financial sector labor share at t (FLS). The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls							
		LS	ΔGDP	ΔWage	CS	TS	PD	ΔFVA	HKM	AEM
Panel A: Contemporaneous effect on debt growth, financial sector										
FLS	-0.27*	-0.27	-0.05	-0.21	-0.20	-0.08	-0.26*	-0.33	-0.15	-0.24**
t	-1.93	-0.48	-0.37	-1.45	-1.51	-0.50	-1.89	-1.21	-0.92	-2.25
Control		2.45**	1.66***	1.22***	-0.05	-0.03*	0.00	-0.08	0.00*	0.00
t		2.51	3.81	3.46	-1.45	-1.78	-0.45	-0.40	-1.93	-0.24
R2	0.02	0.22	0.28	0.07	0.09	0.15	0.01	0.01	0.13	0.01
Panel B: Predicting debt growth, financial sector, 1-year ahead										
FLS	-0.50***	-0.42***	-0.30*	-0.42**	-0.48***	-0.49**	-0.49***	-0.40	-0.40**	-0.43***
t	-2.76	-2.66	-1.85	-2.25	-2.99	-2.53	-2.72	-1.55	-2.20	-3.50
Control		0.98	1.52***	1.85***	-1.70	-0.15	-0.06	0.14	-0.26**	-0.07
t		1.07	3.94	3.42	-0.58	-0.08	-1.29	0.78	-1.98	-0.97
R2	0.13	0.15	0.34	0.26	0.12	0.11	0.14	0.12	0.21	0.12
Panel C: Predicting debt growth, financial sector, 3-year ahead										
FLS	-1.47***	-1.31***	-1.17***	-1.36***	-1.45***	-1.36***	-1.41***	-1.42**	-1.23**	-0.95***
t	-3.59	-2.96	-2.58	-3.26	-3.39	-2.81	-4.47	-2.11	-2.53	-3.61
Control		1.96	2.18*	2.46**	-1.91	-1.62	-0.45*	0.07	-0.61	-0.47**
t		0.56	1.73	2.45	-0.18	-0.38	-1.95	0.14	-1.38	-2.23
R2	0.14	0.14	0.19	0.16	0.13	0.13	0.26	0.13	0.19	0.19
Panel D: Predicting debt growth, financial sector, 5-year ahead										
FLS	-2.48***	-2.10***	-2.16***	-2.38***	-2.47***	-1.92***	-2.30***	-2.57**	-2.12**	-1.05*
t	-3.24	-2.67	-2.61	-3.21	-3.04	-2.96	-4.78	-1.99	-2.37	-1.78
Control		4.49	2.16	2.16	-1.23	-7.45	-0.89**	-0.11	-0.87	-1.34***
t		0.83	0.86	0.78	-0.06	-1.44	-2.52	-0.13	-0.97	-3.81
R2	0.14	0.16	0.15	0.14	0.13	0.18	0.32	0.13	0.18	0.33

Table A.3: FLS and credit markets, multivariate

This table reports the results of aggregate-level annual time-series regressions predicting debt growth or borrowing cost (measured by the Baa-FedFunds spread) at $t+k$ by financial sector labor share at t (FLS). The forecast horizon is k=1, 3, or 5 years. The regressions are multivariate. The first column presents the coefficient on FLS and the remaining columns the coefficients on the controls: real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	FLS	LS	ΔGDP	ΔWage	CS	TS	PD	ΔFVA	HKM	R^2
Panel A: Debt growth										
$k=1$	-0.66***	-1.14*	1.21**	1.01	-0.01	0.00	-0.04	-0.18	0.00	0.42
t	-3.85	-1.93	2.18	1.09	-0.20	-0.16	-1.29	-1.46	-0.59	
$k=3$	-1.84***	-0.19	0.13	-0.68	0.10	0.07***	-0.38***	-0.28	-0.01***	0.45
t	-5.94	-0.08	0.14	-0.47	1.01	2.68	-6.47	-0.97	-5.49	
$k=5$	-2.62***	-0.24	-0.99	-2.49*	0.11	0.09*	-0.64***	-0.63*	-0.02***	0.45
t	-4.04	-0.06	-0.82	-1.90	1.04	1.69	-4.40	-1.95	-11.06	
Panel B: Borrowing cost										
$k=1$	0.01	-0.08	-0.25	0.03	0.01	0.01***	0.02***	-0.02	0.00	0.56
t	0.40	-0.71	-1.44	0.13	1.78	7.18	4.08	-0.93	-0.29	
$k=3$	0.14***	-0.06	0.04	-0.17	0.01*	-0.01***	0.08***	0.06***	0.00	0.39
t	3.05	-0.30	0.71	-1.52	1.68	-3.43	6.79	2.75	1.13	
$k=5$	0.06	-0.30	0.09	0.40	-0.01	-0.01***	0.05***	0.02	0.00***	0.20
t	1.60	-1.59	0.62	1.64	-0.92	-2.95	5.40	0.80	4.72	

Table A.4: FLS and real quantities, multivariate

This table reports the results of aggregate-level annual time-series regressions predicting GDP growth and Investment growth at $t + k$ by financial sector labor share at t (FLS). The forecast horizon is k=1, 3, or 5 years. The regressions are multivariate. The first column presents the coefficient on FLS and the remaining columns the coefficients on the controls: real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	FLS	ΔWage	ΔGDP	LS	TS	PD	ΔFVA	CS	HKM	R^2
Panel A: GDP growth										
$k = 1$	-0.09*	-0.25	0.04	0.35	0.01	0.01***	-0.04***	0.03	0.00***	0.46
t	-1.94	-0.79	0.29	1.40	0.83	3.10	-3.07	0.88	-3.36	
$k = 3$	-0.27**	-0.35	-0.55**	0.22	0.03	0.02**	-0.15***	-0.07	-0.01***	0.43
t	-2.56	-0.34	-2.20	0.53	0.84	2.11	-4.25	-0.66	-3.93	
$k = 5$	-0.23	-0.30	-0.75	0.02	0.03	0.01	-0.19***	-0.05	-0.01***	0.33
t	-1.28	-0.19	-1.62	0.03	0.63	0.87	-2.97	-0.38	-4.91	
Panel B: Investment growth										
$k = 1$	-0.45***	0.15	0.06	0.77	-0.02	0.04***	-0.09***	0.09	0.00	0.47
t	-3.19	0.27	0.17	1.08	-0.61	4.64	-2.60	0.86	-0.80	
$k = 3$	-0.85***	1.38	-2.62***	-0.72	0.04	0.09***	-0.40***	0.13	-0.01***	0.41
t	-3.32	0.58	-5.07	-0.60	0.52	3.74	-4.61	0.56	-3.89	
$k = 5$	-0.11	2.15	-3.60**	-1.73	0.01	0.08***	-0.47***	0.39	-0.01***	0.26
t	-0.29	0.79	-2.37	-1.00	0.09	2.92	-3.53	1.73	-4.68	

Table A.5: Aggregate FLS and excess equity return

This table reports the results of aggregate-level regressions of stock market excess return at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.59	-0.98*	-0.62	-0.50	-0.61	-0.98**	-0.60	0.04	-0.59	-0.29
t	-1.17	-1.85	-1.15	-1.02	-1.16	-2.21	-1.20	0.09	-1.08	-0.76
Control		-4.74***	-0.19	1.98*	0.01	0.05***	0.00	0.85***	0.00	0.00**
t		-3.95	-0.29	1.95	0.22	2.43	0.22	2.58	-0.01	-2.40
R2	0.02	0.13	0.00	0.03	0.00	0.10	0.00	0.08	0.00	0.03
Panel B: 1-year ahead										
FLS	0.36**	0.16	0.20	0.26	0.28	0.17	0.42***	0.67*	0.18	0.49*
t	1.96	0.70	0.85	1.60	1.39	1.00	2.78	1.83	1.13	1.86
Control		-2.38	-1.21	-2.18*	5.70	2.75**	-0.23***	0.42	0.45***	-0.11
t		-1.41	-1.15	-1.80	1.41	2.01	-3.87	1.57	2.71	-0.83
R2	-0.01	0.01	0.00	0.01	-0.01	0.00	0.03	0.00	0.03	-0.02
Panel C: 3-years ahead										
FLS	1.93***	1.40***	1.70**	1.67***	1.90***	1.35**	1.99***	2.59***	1.61**	2.56***
t	2.94	2.79	2.45	2.94	2.61	2.07	3.14	3.71	2.37	3.80
Control		-6.63***	-1.66	-5.70**	2.97	8.30*	-0.39*	0.84***	0.84**	-0.56*
t		-2.94	-1.19	-2.25	0.42	1.85	-1.67	3.08	2.35	-1.78
R2	0.09	0.16	0.09	0.15	0.08	0.15	0.11	0.10	0.13	0.11
Panel D: 5-years ahead										
FLS	5.17***	5.42***	4.19***	4.60***	4.83***	4.26***	5.35***	6.58***	4.20***	5.80***
t	3.25	2.80	2.70	3.54	2.66	3.22	3.83	4.28	2.86	3.83
Control		-11.62***	-3.80	-12.63***	28.59***	12.11**	-0.90***	1.76**	2.35***	-0.59
t		-3.39	-1.61	-4.18	2.66	2.00	-3.51	2.07	3.74	-1.17
R2	0.26	0.34	0.27	0.38	0.30	0.30	0.33	0.28	0.40	0.26

Table A.6: FLS and excess equity return, multivariate

This table reports the results of aggregate-level annual time-series regressions predicting stock market excess return at $t + k$ by financial sector labor share at t (FLS). The forecast horizon is k=1, 3, or 5 years. The regressions are multivariate. The first column presents the coefficient on FLS and the remaining columns the coefficients on the controls: real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	FLS	ΔWage	ΔGDP	LS	TS	PD	ΔFVA	CS	HKM	R^2
$k = 1$	0.28	-0.22	-0.95	-1.58	-0.04	0.04	-0.24***	0.41	0.00	0.00
t	0.77	-0.08	-0.84	-0.63	-0.40	1.41	-3.22	1.43	0.17	0
$k = 3$	1.13*	-6.49	0.68	-7.15**	-0.29**	0.09	-0.47**	0.42	0.00	0.30
t	1.79	-1.25	0.28	-2.23	-2.36	1.48	-2.09	0.94	0.72	0
$k = 5$	4.95***	-6.72	3.71*	-16.23***	-0.08	0.12***	-0.59***	1.78**	0.01	0.55
t	6.31	-1.31	1.83	-4.73	-0.60	3.18	-2.58	2.46	0.93	0

Table A.7: Aggregate FLS and debt growth, 8 lags

This table reports the results of aggregate-level regressions of debt growth in the non-financial corporate sector at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Debt growth at $t+k$ is defined as $\frac{Debt_{t+k}}{Debt_t}$ when $k>0$ and $\frac{Debt_t}{Debt_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter[65]), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 8. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.37***	-0.16	-0.13	-0.30**	-0.27	-0.16	-0.36**	-0.54**	-0.26	-0.32*
t	-2.68	-0.85	-0.75	-2.30	-1.27	-1.17	-2.54	-2.27	-1.66	-1.86
control	0.00	2.58***	1.82***	1.56***	-0.07*	-0.03*	-0.02	-0.24	-0.00***	-0.00
t	0.00	2.92	5.95	5.67	-1.91	-1.95	-0.48	-0.83	-3.10	-0.56
R2	0.06	0.26	0.35	0.14	0.18	0.20	0.04	0.07	0.15	0.04
Panel B: 1-year ahead										
FLS	-0.69***	-0.65***	-0.50***	-0.60***	-0.64***	-0.74***	-0.69***	-0.65**	-0.58***	-0.60***
t	-4.97	-6.38	-5.67	-5.48	-6.67	-9.14	-5.06	-2.28	-5.96	-3.83
Control	0.00	0.44	1.44***	2.01***	-0.04	0.01	0.01	0.05	-0.00***	-0.00
t	0.00	0.48	3.43	3.34	-1.13	0.54	0.15	0.19	-3.24	-1.24
R2	0.24	0.23	0.42	0.39	0.27	0.23	0.23	0.23	0.34	0.24
Panel C: 3-years ahead										
FLS	-1.56***	-1.64***	-1.38***	-1.44***	-1.55***	-1.84***	-1.53***	-1.52***	-1.35***	-1.16***
t	-4.96	-5.77	-5.08	-5.70	-5.12	-6.56	-4.59	-3.15	-4.82	-2.42
Control	0.00	-1.05	1.28	2.58*	-0.00	0.04**	-0.17	0.04	-0.01**	-0.00*
t	0.00	-0.43	1.42	1.88	-0.04	2.09	-1.27	0.13	-2.01	-1.73
R2	0.23	0.22	0.24	0.27	0.21	0.27	0.24	0.21	0.28	0.27
Panel D: 5-years ahead										
FLS	-1.99***	-2.09***	-1.89***	-1.91***	-1.98***	-2.28***	-1.92***	-2.27***	-1.70***	-1.19
t	-3.35	-3.19	-3.04	-3.52	-3.20	-4.11	-3.27	-2.85	-2.61	-1.20
Control	0.00	-1.27	0.64	1.64	-0.01	0.04	-0.32*	-0.35	-0.01	-0.01**
t	0.00	-0.40	0.42	0.64	-0.06	1.25	-1.90	-0.93	-1.24	-1.97
R2	0.19	0.18	0.18	0.19	0.17	0.20	0.23	0.18	0.24	0.30

Table A.8: Aggregate FLS and Baa - Fed Funds spread, 8 lags

This table reports the results of aggregate-level regressions of the Baa - Fed Funds spread at $t+k$ on the finacnial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 8. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls							
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	0.11***	0.05**	0.11***	0.13***	0.10**	-0.01	0.10***	0.17***	0.10**	0.08***
t	3.54	2.12	2.58	4.11	2.30	-0.37	3.45	2.80	2.21	2.75
control	0.00	-0.73***	0.00	0.30	0.01	0.02***	0.02**	0.07	0.00	0.00
t	0.00	-7.84	0.01	1.27	1.57	15.82	2.10	1.52	0.77	1.25
R2	0.09	0.34	0.07	0.13	0.15	0.90	0.13	0.12	0.10	0.10
Panel B: 1-year ahead										
FLS	0.14***	0.08***	0.10**	0.14***	0.12***	0.07*	0.13***	0.14**	0.12**	0.09**
t	3.71	2.83	2.32	3.57	3.36	1.83	4.09	2.34	2.50	2.48
Control	0.00	-0.68***	-0.30	-0.06	0.02***	0.01***	0.03***	-0.00	0.00	0.00**
t	0.00	-5.92	-1.60	-0.24	3.31	7.77	2.87	-0.06	1.39	2.29
R2	0.14	0.36	0.26	0.13	0.26	0.39	0.19	0.13	0.19	0.19
Panel C: 3-years ahead										
FLS	0.09***	0.08***	0.06	0.08**	0.08**	0.12***	0.09***	0.09*	0.08*	0.03
t	2.61	2.59	1.58	2.27	2.49	3.00	3.36	1.65	1.84	0.54
Control	0.00	-0.12	-0.23**	-0.21	0.01	-0.00	0.05***	-0.00	0.00	0.00***
t	0.00	-0.62	-2.46	-1.54	1.44	-1.13	2.96	-0.08	1.38	2.71
R2	0.05	0.04	0.11	0.06	0.06	0.06	0.18	0.03	0.08	0.15
Panel D: 5-years ahead										
FLS	0.07*	0.05	0.06	0.07*	0.06*	0.06*	0.06*	0.09*	0.05	-0.02
t	1.66	1.30	1.57	1.89	1.73	1.75	1.66	1.87	1.30	-0.30
Control	0.00	-0.22	-0.05	0.06	0.00	0.00	0.03**	0.04	0.00	0.00***
t	0.00	-1.25	-0.44	0.24	0.77	0.29	2.35	1.47	1.62	2.95
R2	0.01	0.02	-0.00	-0.00	0.01	-0.00	0.09	0.01	0.05	0.19

Table A.9: Aggregate FLS and GDP growth, 8 lags

This table reports the results of aggregate-level regressions of GDP growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. GDP growth at $t+k$ is defined as $\frac{GDP_{t+k}}{GDP_t}$ when $k>0$ and $\frac{GDP_t}{GDP_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 8. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.13***	-0.07*		-0.09***	-0.09***	-0.14***	-0.13***	-0.07	-0.08***	-0.09***
t	-4.02	-1.87		-2.94	-3.28	-4.66	-4.51	-0.88	-2.63	-3.38
control	0.00	0.77***		0.91***	-0.0***3	0.00	0.01	0.08	-0.00***	-0.00
t	0.00	6.05		7.15	-4.22	0.41	0.66	0.88	-6.97	-1.19
R2	0.07	0.26		0.40	0.29	0.07	0.06	0.10	0.30	0.08
Panel B: 1-year ahead										
FLS	-0.11**	-0.13***	-0.06	-0.07**	-0.10**	-0.17***	-0.11**	-0.02	-0.07*	-0.06
t	-2.12	-3.45	-1.52	-1.92	-2.30	-4.79	-2.19	-0.25	-1.81	-1.28
Control	0.00	-0.32	0.32***	0.79***	-0.00	0.01**	-0.01	0.12**	-0.00***	-0.00
t	0.00	-1.30	4.42	4.21	-0.49	1.97	-0.41	2.18	-3.05	-1.52
R2	0.04	0.06	0.13	0.29	0.03	0.20	0.03	0.11	0.15	0.06
Panel C: 3-years ahead										
FLS	-0.19	-0.24**	-0.17	-0.14	-0.19*	-0.26**	-0.18	-0.17	-0.10	-0.02
t	-1.54	-2.56	-1.57	-1.50	-1.75	-2.83	-1.43	-0.93	-1.12	-0.14
Control	0.00	-0.65	0.14	1.02*	0.00	0.01	-0.05	0.03	-0.00**	-0.00*
t	0.00	-0.83	0.36	1.68	0.01	1.49	-1.16	0.29	-2.27	-1.82
R2	0.02	0.03	0.01	0.09	0.00	0.04	0.03	0.00	0.15	0.10
Panel D: 5-years ahead										
FLS	-0.24	-0.26	-0.22	-0.20	-0.23	-0.25	-0.23	-0.25	-0.11	0.02
t	-1.34	-1.51	-1.53	-1.36	-1.37	-1.42	-1.26	-1.03	-0.74	0.10
Control	0.00	-0.23	0.15	1.00	-0.01	0.00	-0.08	-0.01	-0.00*	-0.00**
t	0.00	-0.30	0.32	1.22	-0.36	0.19	-1.22	-0.08	-1.87	-2.08
R2	0.02	0.00	0.00	0.05	0.01	-0.00	0.04	-0.00	0.17	0.16

Table A.10: Aggregate FLS and Investment growth, 8 lags

This table reports the results of aggregate-level regressions of investment growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Investment growth at $t+k$ is defined as $\frac{INV_{t+k}}{INV_t}$ when $k>0$ and $\frac{INV_t}{INV_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 8. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.40***	-0.20**	-0.13**	-0.34***	-0.30***	-0.43***	-0.42***	-0.31	-0.33***	-0.38***
t	-5.98	-2.20	-2.00	-3.79	-2.87	-4.65	-5.84	-1.51	-3.72	-4.73
control	0.00	2.48***	2.12***	1.37***	-0.08***	0.00	0.04	0.12	-0.00***	-0.00
t	0.00	5.67	9.54	3.67	-4.74	0.38	1.34	0.45	-3.46	-0.33
R2	0.11	0.39	0.70	0.21	0.35	0.10	0.11	0.11	0.17	0.09
Panel B: 1-year ahead										
FLS	-0.40**	-0.44***	-0.29*	-0.33**	-0.37**	-0.63***	-0.40**	-0.15	-0.35**	-0.30***
t	-2.42	-3.05	-1.89	-2.05	-2.49	-4.81	-2.46	-0.82	-2.09	-2.62
Control	0.00	-0.53	0.83***	1.61***	-0.02	0.03***	-0.00	0.32**	-0.00**	-0.00
t	0.00	-1.13	4.17	4.07	-1.05	3.80	-0.05	2.17	-1.96	-1.24
R2	0.11	0.10	0.18	0.24	0.10	0.39	0.09	0.18	0.12	0.11
Panel C: 3-years ahead										
FLS	-0.43	-0.62**	-0.51	-0.39	-0.45	-0.84***	-0.41	-0.16	-0.34	-0.06
t	-1.48	-2.58	-1.46	-1.32	-1.42	-4.00	-1.40	-0.39	-1.17	-0.14
Control	0.00	-2.35*	-0.55	0.92	0.02	0.06***	-0.14	0.34	-0.00	-0.00
t	0.00	-1.76	-0.69	0.71	0.40	3.92	-1.27	1.34	-1.21	-1.45
R2	0.01	0.05	-0.00	0.00	-0.00	0.18	0.02	0.01	0.01	0.06
Panel D: 5-years ahead										
FLS	-0.06	-0.14	-0.20	-0.06	-0.03	-0.28	-0.02	0.23	0.09	0.52
t	-0.15	-0.35	-0.43	-0.15	-0.08	-0.71	-0.06	0.42	0.21	0.90
Control	0.00	-0.92	-0.92	0.00	-0.03	0.03	-0.20	0.37	-0.00	-0.01*
t	0.00	-0.80	-1.25	0.00	-0.41	1.24	-1.23	1.22	-1.40	-1.87
R2	-0.02	-0.03	-0.02	-0.04	-0.03	-0.00	0.00	-0.02	0.00	0.10

Table A.11: Aggregate FLS and debt growth, optimal lags

This table reports the results of aggregate-level regressions of debt growth in the non-financial corporate sector at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Debt growth at $t+k$ is defined as $\frac{Debt_{t+k}}{Debt_t}$ when $k>0$ and $\frac{Debt_t}{Debt_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter[66]), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 17. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.37***	-0.16	-0.13	-0.30***	-0.27	-0.16	-0.36***	-0.54***	-0.26*	-0.32**
t	-3.33	-0.86	-0.88	-2.72	-1.29	-1.24	-3.10	-2.93	-1.79	-2.29
control	0.00	2.58***	1.82***	1.56***	-0.07*	-0.03*	-0.02	-0.24	-0.00***	-0.00
t	0.00	2.97	5.46	8.25	-1.83	-1.95	-0.58	-0.99	-3.33	-0.68
R2	0.06	0.26	0.35	0.14	0.18	0.20	0.04	0.07	0.15	0.04
Panel B: 1-year ahead										
FLS	-0.69***	-0.65***	-0.50***	-0.60***	-0.64***	-0.74***	-0.69***	-0.65**	-0.58***	-0.60***
t	-5.71	-8.12	-6.87	-6.40	-9.30	-13.89	-5.99	-2.37	-7.26	-4.98
Control	0.00	0.44	1.44***	2.01***	-0.04	0.01	0.01	0.05	-0.00***	-0.00*
t	0.00	0.53	4.23	2.92	-1.08	0.50	0.18	0.19	-5.21	-1.71
R2	0.24	0.23	0.42	0.39	0.27	0.23	0.23	0.23	0.34	0.24
Panel C: 3-years ahead										
FLS	-1.56***	-1.64***	-1.38***	-1.44***	-1.55***	-1.84***	-1.53***	-1.52***	-1.35***	-1.16***
t	-7.80	-7.83	-7.36	-9.58	-8.62	-9.32	-6.94	-4.27	-7.15	-3.08
Control	0.00	-1.05	1.28	2.58*	-0.00	0.04**	-0.17	0.04	-0.01**	-0.00**
t	0.00	-0.46	1.41	1.72	-0.04	2.47	-1.60	0.14	-2.46	-1.99
R2	0.23	0.22	0.24	0.27	0.21	0.27	0.24	0.21	0.28	0.27
Panel D: 5-years ahead										
FLS	-1.99***	-2.09***	-1.89***	-1.91***	-1.98***	-2.28***	-1.92***	-2.27***	-1.70***	-1.19
t	-4.47	-3.76	-3.85	-4.88	-4.39	-5.66	-4.76	-4.41	-3.19	-1.28
Control	0.00	-1.27	0.64	1.64	-0.01	0.04	-0.32**	-0.35	-0.01	-0.01*
t	0.00	-0.42	0.43	0.59	-0.06	1.19	-2.38	-1.33	-1.28	-1.92
R2	0.19	0.18	0.18	0.19	0.17	0.20	0.23	0.18	0.24	0.30

Table A.12: Aggregate FLS and Baa - Fed Funds spread, optimal lags

This table reports the results of aggregate-level regressions of the Baa - Fed Funds spread at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 14, 13, 12 and 8 for contemporaneous, 1-year, 3-year, and 5-year ahead predictability, respectively. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls							
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	0.11***	0.05**	0.11**	0.13***	0.10**	-0.01	0.10***	0.17***	0.10**	0.08***
t	3.67	2.20	2.54	4.25	2.35	-0.41	3.70	3.25	2.36	4.10
control	0.00	-0.73***	0.00	0.30	0.01*	0.02***	0.02**	0.07*	0.00	0.00
t	0.00	-7.74	0.01	1.24	1.65	14.01	2.17	1.75	0.81	1.18
R2	0.09	0.34	0.07	0.13	0.15	0.90	0.13	0.12	0.10	0.10
Panel B: 1-year ahead										
FLS	0.14***	0.08***	0.10***	0.14***	0.12***	0.07**	0.13***	0.14***	0.12***	0.09***
t	4.21	3.97	2.90	4.50	4.35	2.01	4.88	2.85	3.12	4.04
Control	0.00	-0.68***	-0.30*	-0.06	0.02***	0.01***	0.03***	-0.00	0.00	0.00***
t	0.00	-6.34	-1.70	-0.24	3.42	8.94	3.15	-0.07	1.45	2.45
R2	0.14	0.36	0.26	0.13	0.26	0.39	0.19	0.13	0.19	0.19
Panel C: 3-years ahead										
FLS	0.09**	0.08***	0.06	0.08**	0.08**	0.12***	0.09***	0.09	0.08*	0.03
t	2.49	2.59	1.48	2.18	2.42	2.93	3.72	1.57	1.83	0.56
Control	0.00	-0.12	-0.23***	-0.21	0.01*	-0.00	0.05***	-0.00	0.00	0.00***
t	0.00	-0.74	-3.13	-1.62	1.78	-1.23	2.97	-0.08	1.43	3.00
R2	0.05	0.04	0.11	0.06	0.06	0.06	0.18	0.03	0.08	0.15
Panel D: 5-years ahead										
FLS	0.07*	0.05	0.06	0.07*	0.06*	0.06*	0.06*	0.09*	0.05	-0.02
t	1.66	1.30	1.57	1.89	1.73	1.75	1.66	1.87	1.30	-0.30
Control	0.00	-0.22	-0.05	0.06	0.00	0.00	0.03**	0.04	0.00	0.00***
t	0.00	-1.25	-0.44	0.24	0.77	0.29	2.35	1.47	1.62	2.95
R2	0.01	0.02	-0.00	-0.00	0.01	-0.00	0.09	0.01	0.05	0.19

Table A.13: Aggregate FLS and GDP growth, optimal lags

This table reports the results of aggregate-level regressions of GDP growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. GDP growth at $t+k$ is defined as $\frac{GDP_{t+k}}{GDP_t}$ when $k>0$ and $\frac{GDP_t}{GDP_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 17. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.13***	-0.07*		-0.09***	-0.09***	-0.14***	-0.13***	-0.07	-0.08***	-0.09***
t	-4.02	-1.87		-2.94	-3.28	-4.66	-4.51	-0.88	-2.63	-3.38
control	0.00	0.77***		0.91***	-0.03***	0.00	0.01	0.08	-0.00***	-0.00
t	0.00	6.05		7.15	-4.22	0.41	0.66	0.88	-6.97	-1.19
R2	0.07	0.26		0.40	0.29	0.07	0.06	0.10	0.30	0.08
Panel B: 1-year ahead										
FLS	-0.11**	-0.13***	-0.06	-0.07*	-0.10**	-0.17***	-0.11**	-0.02	-0.07*	-0.06
t	-2.12	-3.45	-1.52	-1.92	-2.30	-4.79	-2.19	-0.25	-1.81	-1.28
Control	0.00	-0.32	0.32***	0.79***	-0.00	0.01**	-0.01	0.12**	-0.00***	-0.00
t	0.00	-1.30	4.42	4.21	-0.49	1.97	-0.41	2.18	-3.05	-1.52
R2	0.04	0.06	0.13	0.29	0.03	0.20	0.03	0.11	0.15	0.06
Panel C: 3-years ahead										
FLS	-0.19	-0.24**	-0.17	-0.14	-0.19*	-0.26***	-0.18	-0.17	-0.10	-0.02
t	-1.54	-2.56	-1.57	-1.50	-1.75	-2.83	-1.43	-0.93	-1.12	-0.14
Control	0.00	-0.65	0.14	1.02*	0.00	0.01	-0.05	0.03	-0.00**	-0.00*
t	0.00	-0.83	0.36	1.68	0.01	1.49	-1.16	0.29	-2.27	-1.82
R2	0.02	0.03	0.01	0.09	0.00	0.04	0.03	0.00	0.15	0.10
Panel D: 5-years ahead										
FLS	-0.24	-0.26	-0.22	-0.20	-0.23	-0.25	-0.23	-0.25	-0.11	0.02
t	-1.34	-1.51	-1.53	-1.36	-1.37	-1.42	-1.26	-1.03	-0.74	0.10
Control	0.00	-0.23	0.15	1.00	-0.01	0.00	-0.08	-0.01	-0.00*	-0.00**
t	0.00	-0.30	0.32	1.22	-0.36	0.19	-1.22	-0.08	-1.87	-2.08
R2	0.02	0.00	0.00	0.05	0.01	-0.00	0.04	-0.00	0.17	0.16

Table A.14: Aggregate FLS and Investment growth, optimal lags

This table reports the results of aggregate-level regressions of investment growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k = 0$), 1-year ($k = 1$), 3-year ($k = 3$), and 5-year ($k = 5$) ahead. Investment growth at $t+k$ is defined as $\frac{INV_{t+k}}{INV_t}$ when $k > 0$ and $\frac{INV_t}{INV_{t-1}}$ when $k = 0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 17. The sample consists of annual observations from 1961 to 2019. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.40***	-0.20***	-0.13*	-0.34***	-0.30**	-0.43***	-0.42***	-0.31**	-0.33***	-0.38***
t	-8.67	-2.84	-1.89	-4.83	-2.51	-4.34	-7.15	-1.98	-4.48	-4.78
control	0.00	2.48***	2.12***	1.37***	-0.08***	0.00	0.04	0.12	-0.00***	-0.00
t	0.00	7.34	10.61	3.84	-5.45	0.35	1.51	0.50	-3.82	-0.36
R2	0.11	0.39	0.70	0.21	0.35	0.10	0.11	0.11	0.17	0.09
Panel B: 1-year ahead										
LS	-0.40***	-0.44***	-0.29**	-0.33***	-0.37***	-0.63***	-0.40***	-0.15	-0.35**	-0.30***
t	-2.97	-3.82	-2.39	-2.58	-3.33	-6.10	-3.07	-0.92	-2.55	-4.96
Control	0.00	-0.53	0.83***	1.61***	-0.02	0.03***	-0.00	0.32**	-0.00**	-0.00
t	0.00	-1.11	6.08	3.49	-1.17	3.83	-0.06	2.10	-2.39	-1.48
R2	0.11	0.10	0.18	0.24	0.10	0.39	0.09	0.18	0.12	0.11
Panel C: 3-years ahead										
LS	-0.43**	-0.62***	-0.51**	-0.39*	-0.45*	-0.84***	-0.41**	-0.16	-0.34*	-0.06
t	-2.16	-3.38	-2.26	-1.91	-1.97	-5.86	-2.11	-0.52	-1.69	-0.19
Control	0.00	-2.35**	-0.55	0.92	0.02	0.06***	-0.14	0.34	-0.00	-0.00*
t	0.00	-1.99	-1.33	0.89	0.48	4.86	-1.32	1.53	-1.35	-1.67
R2	0.01	0.05	-0.00	0.00	-0.00	0.18	0.02	0.01	0.01	0.06
Panel D: 5-years ahead										
LS	-0.06	-0.14	-0.20	-0.06	-0.03	-0.28	-0.02	0.23	0.09	0.52
t	-0.19	-0.41	-0.59	-0.20	-0.10	-0.89	-0.08	0.47	0.28	1.17
Control	0.00	-0.92	-0.92	0.00	-0.03	0.03	-0.20	0.37	-0.00	-0.01*
t	0.00	-1.16	-1.34	0.00	-0.47	1.34	-1.26	1.27	-1.36	-1.95
R2	-0.02	-0.03	-0.02	-0.04	-0.03	-0.00	0.00	-0.02	0.00	0.10

Table A.15: Aggregate FLS and debt growth, 1961-2007

This table reports the results of aggregate-level regressions of debt growth in the non-financial corporate sector at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Debt growth at $t+k$ is defined as $\frac{Debt_{t+k}}{Debt_t}$ when $k>0$ and $\frac{Debt_t}{Debt_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter[67]), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations on FLS from 1961 to 2007 and the associated dependent variables. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.51***	-0.26	-0.26*	-0.43***	-0.45**	-0.21	-0.50***	-0.60***	-0.39***	-0.44***
t	-3.62	-1.26	-1.72	-4.14	-2.44	-1.32	-3.52	-2.69	-2.96	-3.03
control	0.00	2.53***	1.79***	1.58***	-0.07**	-0.03*	-0.02	-0.14	-0.00***	-0.00
t	0.00	3.10	6.47	6.70	-2.08	-1.88	-0.49	-0.75	-3.43	-1.03
R2	0.07	0.27	0.37	0.16	0.21	0.20	0.06	0.07	0.16	0.06
Panel B: 1-year ahead										
FLS	-0.55**	-0.60***	-0.40**	-0.50***	-0.56**	-0.73***	-0.55**	-0.35	-0.47***	-0.53**
t	-2.52	-2.90	-2.43	-3.84	-2.53	-4.26	-2.57	-1.28	-3.13	-2.45
Control	0.00	-0.60	1.30***	2.25***	-0.01	0.02	-0.00	0.49***	-0.00***	-0.00
t	0.00	-0.95	4.20	3.93	-0.51	1.54	-0.03	4.16	-3.95	-0.60
R2	0.10	0.09	0.30	0.39	0.08	0.14	0.08	0.19	0.19	0.08
Panel C: 3-years ahead										
FLS	-1.53***	-1.78***	-1.41***	-1.46***	-1.51***	-2.26***	-1.50***	-1.22**	-1.36***	-1.35**
t	-2.97	-4.13	-3.10	-3.31	-2.75	-4.18	-2.65	-2.38	-3.20	-2.46
Control	0.00	-3.10*	1.09	2.94**	0.02	0.07***	-0.18*	0.75**	-0.01**	-0.00*
t	0.00	-1.79	1.28	2.21	0.29	3.99	-1.70	2.48	-2.23	-1.89
R2	0.12	0.15	0.12	0.18	0.10	0.25	0.13	0.14	0.18	0.17
Panel D: 5-years ahead										
FLS	-2.25***	-2.50***	-2.20**	-2.21**	-2.24**	-2.84***	-2.19***	-2.19**	-2.02**	-1.89**
t	-2.59	-3.08	-2.54	-2.57	-2.51	-3.53	-2.64	-2.51	-2.18	-2.09
Control	0.00	-3.13	0.46	1.99	0.02	0.06	-0.37***	0.15	-0.01	-0.01**
t	0.00	-1.02	0.29	0.75	0.11	1.38	-2.63	0.34	-1.24	-2.23
R2	0.13	0.14	0.11	0.13	0.11	0.16	0.18	0.11	0.19	0.26

Table A.16: Aggregate FLS and Baa - Fed Funds spread, 1961-2007

This table reports the results of aggregate-level regressions of the Baa - Fed Funds spread at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations on FLS from 1961 to 2007 and the associated dependent variables. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	0.14***	0.07***	0.14**	0.16***	0.13***	-0.04**	0.13***	0.17***	0.13**	0.11***
t	2.91	2.65	2.57	3.35	2.94	-2.25	3.10	2.62	2.31	3.36
control	0.00	-0.73***	-0.01	0.28	0.01*	0.02***	0.02**	0.04	0.00	0.00
t	0.00	-8.49	-0.07	1.16	1.81	14.93	2.26	1.15	0.87	1.51
R2	0.09	0.34	0.07	0.12	0.16	0.91	0.12	0.09	0.10	0.11
Panel B: 1-year ahead										
FLS	0.14***	0.09***	0.11***	0.14***	0.15***	0.05	0.14***	0.11***	0.13***	0.11***
t	3.17	3.30	2.64	3.28	3.77	1.23	3.56	2.61	2.77	4.48
Control	0.00	-0.67***	-0.25	-0.06	0.02***	0.01***	0.02*	-0.08	0.00	0.00***
t	0.00	-6.02	-1.49	-0.31	3.94	7.86	1.73	-1.03	1.22	4.58
R2	0.08	0.27	0.17	0.06	0.21	0.24	0.10	0.09	0.09	0.18
Panel C: 3-years ahead										
FLS	0.08	0.08	0.06	0.08	0.09	0.16*	0.07*	0.06	0.07	0.05
t	1.38	1.41	0.91	1.22	1.53	2.29	1.79	0.99	1.13	1.06
Control	0.00	-0.02	-0.21***	-0.21	0.01	-0.01***	0.04***	-0.05	0.00	0.00***
t	0.00	-0.09	-3.05	-1.63	1.36	-4.26	2.73	-1.50	1.12	2.97
R2	0.01	-0.02	0.05	0.01	0.01	0.11	0.12	-0.00	0.01	0.12
Panel D: 5-years ahead										
FLS	0.05	0.04	0.05	0.05	0.05	0.05	0.04	0.07	0.04	0.01
t	0.89	0.74	0.98	1.01	0.89	0.91	0.99	1.40	0.67	0.28
Control	0.00	-0.16	-0.02	0.06	0.00	-0.00	0.03***	0.04	0.00	0.00***
t	0.00	-0.86	-0.24	0.28	0.37	-0.04	2.66	1.15	1.36	3.18
R2	-0.01	-0.02	-0.03	-0.03	-0.03	-0.03	0.06	-0.03	0.01	0.18

Table A.17: Aggregate FLS and GDP growth, 1961-2007

This table reports the results of aggregate-level regressions of GDP growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. GDP growth at $t+k$ is defined as $\frac{GDP_{t+k}}{GDP_t}$ when $k>0$ and $\frac{GDP_t}{GDP_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations on FLS from 1961 to 2007 and the associated dependent variables. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.14***	-0.06		-0.09**	-0.11***	-0.15***	-0.14***	-0.07	-0.08**	-0.09***
t	-2.79	-1.39		-2.06	-3.36	-3.46	-3.00	-1.15	-2.07	-2.97
control	0.00	0.80***		0.93***	-0.03***	0.00	0.01	0.09	-0.00***	-0.00*
t	0.00	7.09		7.09	-4.72	0.35	0.67	1.31	-7.91	-1.80
R2	0.04	0.24		0.39	0.29	0.03	0.03	0.10	0.29	0.07
Panel B: 1-year ahead										
FLS	-0.08	-0.12*	-0.04	-0.06	-0.08	-0.24***	-0.08	0.01	-0.05	-0.06
t	-1.03	-1.74	-0.67	-1.39	-1.02	-3.82	-1.02	0.09	-1.20	-0.84
Control	0.00	-0.52**	0.33***	0.84***	-0.00	0.02***	-0.01	0.21***	-0.00***	-0.00
t	0.00	-2.43	5.38	4.47	-0.28	2.86	-0.33	3.38	-4.34	-1.49
R2	-0.01	0.04	0.08	0.28	-0.03	0.30	-0.03	0.12	0.10	0.01
Panel C: 3-years ahead										
FLS	-0.14	-0.24	-0.13	-0.12	-0.14	-0.33*	-0.13	-0.11	-0.07	-0.07
t	-0.72	-1.43	-0.78	-0.82	-0.63	-1.84	-0.62	-0.50	-0.59	-0.31
Control	0.00	-1.19	0.08	1.11**	0.01	0.02***	-0.05	0.09	-0.00***	-0.00*
t	0.00	-1.63	0.24	2.10	0.20	3.82	-1.12	0.85	-2.66	-1.96
R2	-0.01	0.04	-0.03	0.07	-0.03	0.06	-0.01	-0.03	0.11	0.09
Panel D: 5-years ahead										
FLS	-0.19	-0.23	-0.18	-0.16	-0.19	-0.23	-0.17	-0.17	-0.08	-0.06
t	-0.72	-0.92	-0.80	-0.73	-0.71	-0.76	-0.64	-0.62	-0.42	-0.25
Control	0.00	-0.59	0.09	1.03	-0.01	0.00	-0.08	0.05	-0.00*	-0.00**
t	0.00	-0.69	0.18	1.24	-0.22	0.54	-1.26	0.40	-1.93	-2.03
R2	-0.01	-0.02	-0.03	0.02	-0.03	-0.03	0.00	-0.03	0.14	0.15

Table A.18: Aggregate FLS and Investment growth, 1961-2007

This table reports the results of aggregate-level regressions of investment growth at $t+k$ on the financial labor share at t. The regressions are annual and include contemporaneous ($k=0$), 1-year ($k=1$), 3-year ($k=3$), and 5-year ($k=5$) ahead. Investment growth at $t+k$ is defined as $\frac{INV_{t+k}}{INV_t}$ when $k>0$ and $\frac{INV_t}{INV_{t-1}}$ when $k=0$. The table presents univariate regressions in the first column, and bivariate regressions in the remaining columns. The first column presents the univariate predictability result while the rest of the columns present the bivariate predictability results with additional control variables including aggregate labor share (LS) (with Hamilton (2017) filter), real GDP growth (ΔGDP), aggregate wage growth (ΔWage), credit spread (CS), term spread (TS), price dividend ratio (PD), financial sector value added growth (ΔFVA), and the leverage ratios from AEM and HKM. The Appendix provides additional details on variable construction. The coefficient estimates are in percentage terms. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations on FLS from 1961 to 2007 and the associated dependent variables. All the variables are real.

	Univariate	Bivariate controls								
		LS	ΔGDP	ΔWage	CS	TS	P/D	ΔFVA	HKM	AEM
Panel A: Contemporaneous										
FLS	-0.46***	-0.21*	-0.17*	-0.39**	-0.39***	-0.49***	-0.48***	-0.34**	-0.37***	-0.40***
t	-3.62	-1.73	-1.73	-2.53	-3.21	-3.23	-3.36	-2.03	-2.65	-4.06
control	0.00	2.54***	2.14***	1.43***	-0.08***	0.00	0.04	0.18	-0.00***	-0.00
t	0.00	6.50	10.22	4.18	-5.18	0.35	1.51	0.93	-3.36	-0.97
R2	0.08	0.38	0.70	0.19	0.36	0.07	0.08	0.10	0.15	0.08
Panel B: 1-year ahead										
FLS	-0.21*	-0.28**	-0.11	-0.16	-0.21**	-0.64***	-0.20*	0.03	-0.16	-0.18*
t	-1.89	-2.55	-1.03	-1.19	-2.00	-3.92	-1.86	0.31	-1.58	-1.67
Control	0.00	-0.88**	0.89***	1.79***	-0.01	0.04***	-0.02	0.58***	-0.00***	-0.00
t	0.00	-2.31	5.26	5.97	-0.50	3.64	-0.52	5.69	-2.75	-0.80
R2	-0.00	0.01	0.10	0.21	-0.02	0.39	-0.02	0.16	0.03	-0.01
Panel C: 3-years ahead										
FLS	-0.23	-0.44	-0.28	-0.20	-0.21	-0.91***	-0.20	-0.07	-0.13	-0.06
t	-0.62	-1.33	-0.75	-0.56	-0.52	-2.78	-0.55	-0.18	-0.37	-0.16
Control	0.00	-2.62	-0.42	1.09	0.03	0.07***	-0.18	0.37	-0.00*	-0.00
t	0.00	-1.67	-0.72	0.97	0.44	5.62	-1.62	1.16	-1.95	-1.55
R2	-0.02	0.01	-0.04	-0.03	-0.04	0.14	0.01	-0.03	-0.00	0.05
Panel D: 5-years ahead										
FLS	0.23	0.24	0.15	0.23	0.20	0.13	0.27	0.30	0.39	0.50
t	0.36	0.39	0.26	0.38	0.33	0.22	0.51	0.43	0.61	0.88
Control	0.00	0.13	-0.67	0.03	-0.04	0.01	-0.26	0.16	-0.01*	-0.01*
t	0.00	0.07	-0.97	0.02	-0.50	0.53	-1.61	0.46	-1.94	-1.89
R2	-0.02	-0.04	-0.03	-0.04	-0.03	-0.04	0.03	-0.04	0.04	0.12

Table A.19: High skilled labor share as a placebo

This table reports the results of aggregate-level annual time-series 1-year ahead $(t+1)$ predictability of various variables of interest by high skilled labor share (HSLS) or by financial sector labor share (FLS) at t. The variables of interest are the market premium $(R^m - R^f)$, debt growth (ΔDebt), Baa minus Fed Funds credit spread (CrSpr), investment growth (ΔInv) and GDP growth (ΔGDP) in columns 1-5. The top panel presents univariate results with just HSLS, the bottom panel presents bivariate results with HSLS and FLS. The t-statistics reported below each coefficient estimate are obtained using Newey-West standard error with number of lags equal to 13. The sample consists of annual observations from 1997 to 2019. All the variables are real.

	$R^m - R^f$	ΔDebt	CrSpr	ΔInv	ΔGDP
Panel A: Univariate					
HSLS	-0.21	-0.55	25.95	-1.69	-0.17
t	-0.10	-0.31	0.61	-0.98	-0.53
R^2	-0.05	-0.04	-0.01	-0.02	-0.03
Panel B: Bivariate					
HSLS	-1.44	1.87*	-26.66	1.76**	0.42***
t	-0.61	1.89	-0.92	2.17	4.99
FLS	0.004	-0.008***	0.17***	-0.011***	-0.002***
t	1.40	-4.93	4.34	-8.50	-12.33
R^2	-0.09	0.36	0.28	0.20	0.39

Table A.20: Summary statistics, bank holding company

This table reports the summary statistics of bank holding companies and Compustat firms from our merged sample. The sample consists of annual observations from 1986 to 2019.

	Mean	SD	p25	p50	p75	Count
Size	19.96	1.38	18.95	20.27	21.30	17907
Capital ratio	0.08	0.02	0.07	0.08	0.10	17907
ROA	0.01	0.00	0.01	0.01	0.01	17907
NPL share	0.01	0.00	0.00	0.00	0.01	17907
Labor share	0.66	0.16	0.56	0.61	0.69	17907
Business Loan (Billion)	84.62	64.85	27.61	66.63	130.35	17907
Total Loan (Billion)	396.71	337.64	86.28	251.47	726.92	17907
Business Loan (to U.S firms) (Billion)	62.38	51.30	19.45	41.35	98.00	17907

Table A.21: Bank level FLS and bank leverage

This table reports the results of predicting of bank holding company's average annual stock return volatility from $t+1$ to $t+3$ by bank holding companies' labor share (FLS) at t using panel bank data from FR Y-9C. This panel presents both the univariate and multivariate regression results with bank holding company and state-year fixed effect. The coefficient estimates are obtained from the following regression:

$$y_{i,t+1:t+3} = \alpha_i + \delta_{s,t} + \beta_1 FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+3}.$$

where y is bank leverage or the changes in bank leverage. The control variables include size, ROA, non-performing C&I loan share, interest expense and earning growth. The Appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks. The final sample is from 1992 to 2011.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bank Leverage				ΔBank Leverage			
FLS	0.01***	0.01***	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(4.08)	(3.68)	(0.26)	(-0.20)	(-0.50)	(-1.04)	(-0.09)	(-0.54)
BHC Size			-0.00*	-0.00			0.00	0.00
			(-1.65)	(-1.13)			(1.01)	(0.48)
BHC ROA			-0.54***	-0.60***			-0.07	-0.06
			(-3.70)	(-4.05)			(-0.45)	(-0.35)
BHC Interest Expense			0.23***	0.24***			-0.28***	-0.33***
			(3.88)	(3.64)			(-4.21)	(-4.40)
BHC NPL Share			-0.24**	-0.17			-0.16	-0.13
			(-2.34)	(-1.54)			(-1.55)	(-1.12)
BHC ΔEBIT			-0.00	-0.00			-0.00	-0.00
			(-0.46)	(-0.80)			(-0.32)	(-0.10)
N	6390	6228	6177	6010	6390	6228	6177	6010
adj. R^2	0.659	0.680	0.664	0.684	0.313	0.348	0.323	0.357
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
State_Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A.22: Predicting U.S bank loan growth: separating numerator and denominator

This table reports the results of predicting total loan growth in the U.S at $t+k$ by bank holding companies' labor share (FLS) at t using panel bank holding company data from FR Y-9C. The coefficient estimates are obtained from the following regression:

$$\Delta Loan_{i,t+k} = \alpha_i + \delta_{s,t} + \beta_1 FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}$$

where $\Delta Loan_{i,t+k} = 2\frac{Avg(Loan_{i,t+1:t+k}) - Avg(Loan_{i,t-k+1:t})}{Avg(Loan_{i,t:t+k}) + Avg(Loan_{i,t-k+1:t})}$ is the loan growth of bank i over a 3-year window ($k=3$). Columns (1) and (2) are identical to columns (3) and (4) in Table 9 for easier comparison. The remaining columns include the same fixed effects as in column (2), i.e., bank holding company fixed effects and state-year fixed effects. The control variables include size, ROA, capital ratio, non-performing C&I loan share, interest expense and earning growth. The Appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using standard errors clustered by banks. The final sample is from 1986 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FLS	-0.157***	-0.144***							
	(-14.19)	(-13.35)							
ln(FLS)			-0.219***						
			(-12.05)						
ln(XLR)				-0.119***		-0.188***			
				(-7.51)		(-11.06)			
ln(XLR+EBIT)					-0.003	0.103***			
					(-0.24)	(8.21)			
XLR/TA							-6.200***		-6.206***
							(-6.88)		(-6.88)
EBIT/TA								-3.075	-3.277
								(-1.19)	(-1.27)
size	-0.075***	-0.079***	-0.085***	0.028*	-0.072***	-0.007	-0.085***	-0.074***	-0.086***
	(-9.08)	(-9.21)	(-9.73)	(1.79)	(-5.27)	(-0.42)	(-9.52)	(-8.63)	(-9.55)
roe	0.781	-0.201	-4.046***	6.068***	6.452***	0.736	6.095***	8.050***	7.946***
	(1.08)	(-0.27)	(-3.89)	(12.93)	(8.13)	(0.87)	(12.92)	(5.23)	(5.16)
cap ratio	-0.262*	-0.100	-0.088	-0.031	-0.168	-0.028	-0.049	-0.168	-0.047
	(-1.85)	(-0.71)	(-0.63)	(-0.21)	(-1.18)	(-0.20)	(-0.34)	(-1.19)	(-0.324)
int exp	-4.711***	-3.940***	-4.078***	-4.094***	-3.931***	-4.120***	-4.045***	-3.921***	-4.037***
	(-9.69)	(-8.35)	(-8.60)	(-8.65)	(-8.18)	(-8.74)	(-8.51)	(-8.15)	(-8.49)
ciNPL loan	-4.442***	-3.623***	-3.583***	-3.825***	-3.960***	-3.681***	-3.829***	-3.999***	-3.874***
	(-12.33)	(-9.99)	(-9.87)	(-10.40)	(-10.75)	(-10.08)	(-10.44)	(-10.85)	(-10.56)
ebitgr	0.009***	0.008***	0.006***	0.005***	0.004***	0.006***	0.005***	0.005***	0.005***
	(9.06)	(8.25)	(6.97)	(5.29)	(4.79)	(6.94)	(5.28)	(5.14)	(5.33)
N	32555	32430	32430	32430	32430	32430	32430	32430	32430
adj. R^2	0.542	0.577	0.578	0.576	0.570	0.579	0.574	0.570	0.574

Table A.23: Predicting U.S bank loan growth: other types of loans

This table reports the results of predicting loan growth in the U.S at $t+k$ by bank holding companies' labor share (FLS) or labor expenses (XLR) or value added (XLR+EBIT) at t using panel bank holding company data from FR Y-9C. All regressions include bank holding company and state-year fixed effect. The coefficient estimates are obtained from the following regression:

$$\Delta Loan_{i,t+k} = \alpha_i + \delta_{s,t} + \beta FLS_{i,t} + \Gamma' Controls_{i,t} + \epsilon_{i,t+k}$$

where $\Delta Loan_{i,t+k} = 2\frac{Avg(Loan_{i,t+1:t+k}) - Avg(Loan_{i,t-k+1:t})}{Avg(Loan_{i,t+1:t+k}) + Avg(Loan_{i,t-k+1:t})}$ is the loan growth of bank i over a 3-year window ($k=3$). Columns (1) and (2) are identical to columns (3) and (4) of Table 9 in the main text. The subsequent columns change the key forecasting variable to ln(FLS) in (3), ln(XLR) in (4), ln(EBIT+XLR) in (5), ln(XLR) and ln(EBIT+XLR) in (6), XLR/TA in (7). EBIT/TA in (8), and XLR/TA and EBIT/TA in (9). The control variables include size, ROA, capital ratio, non-performing C&I loan share, interest expense and earning growth. The Appendix provides additional details on variable construction. The t-statistics reported in the parentheses below each coefficient estimate are obtained using errors cluster over banks. The final sample is from 1986 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	C& I (to U.S firms) loan growth				Real estate loan growth				Consumer loan growth			
FLS	-0.18***	-0.15***	-0.14***	-0.13***	-0.17***	-0.13***	-0.17***	-0.15***	-0.14***	-0.12***	-0.17***	-0.15***
	(-17.22)	(-14.68)	(-8.19)	(-7.53)	(-23.66)	(-19.51)	(-13.46)	(-13.07)	(-11.68)	(-9.73)	(-8.36)	(-6.91)
BHC Size			-0.08***	-0.07***			-0.08***	-0.09***			-0.10***	-0.09***
			(-5.87)	(-5.58)			(-8.33)	(-8.98)			(-6.22)	(-5.90)
BHC ROA			0.72	-0.15			0.21	-1.13			-2.28	-1.65
			(0.64)	(-0.13)			(0.25)	(-1.39)			(-1.62)	(-1.16)
BHC Capital ratio			0.34	0.57**			-0.28*	-0.14			-0.43	-0.14
			(1.49)	(2.47)			(-1.68)	(-0.89)			(-1.51)	(-0.48)
BHC NPL Share			-10.53***	-9.31***			-2.83***	-1.75***			-3.64***	-2.74***
			(-17.03)	(-14.92)			(-6.38)	(-3.92)			(-4.92)	(-3.63)
BHC Interest Expense			-2.93***	-2.18***			-5.30***	-4.45***			-3.77***	-2.73***
			(-4.32)	(-3.17)			(-9.11)	(-7.79)			(-4.11)	(-2.94)
BHC ΔEBIT			0.01***	0.01***			0.01***	0.01***			0.01***	0.00***
			(5.99)	(5.24)			(8.27)	(7.77)			(4.06)	(2.71)
N	36690	36567	32264	32128	36949	36837	32510	32385	36951	36839	32520	32395
adj. R^2	0.402	0.428	0.436	0.459	0.450	0.500	0.487	0.529	0.363	0.397	0.384	0.413
BHC FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
State_Year FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table A.24: Bank level FLS and firm real outcomes, constrained subsample

This table reports the results of predictability of non-financial U.S firms' changes in investment rate, earnings growth and default risk over a 3-year window by bank holding companies' labor share (FLS) at t using panel data with bank-firm lending relationship. Firms are split into financially constrained and unconstrained, where constrained firms are defined to be in the top 33% of the sample by the Whited-Wu index. The coefficient estimates are obtained from the following regression:

$$y_{i,j,t+k} = \alpha_i + \beta FLS_{i,t} + \Gamma' Bank\ Controls_{i,t} + \Theta' Firm\ Controls_{j,t} + \epsilon_{i,j,t+k},$$

where $y_{i,j,t+k} = \frac{Avg(CAPX_{t+1:t+k}) - Avg(CAPX_{t-k+1:t})}{PPENT_t}$ for investment rate changes in Panel A and $y_{i,j,t+k} = 2\frac{Avg(IB_{t+1:t+k}) - Avg(IB_{t-k+1:t})}{Avg(IB_{t+1:t+k}) + Avg(IB_{t-k+1:t})}$ for earnings growth in Panel B ($k = 3$). The control variables include bank characteristics (bank size, ROA, capital ratio, non-performing C&I loan ratio and interest expense) and firm characteristics (firm size, Tobin's Q, cash, financial leverage, past sales growth, excess return, tangibility and credit rating). The t-statistics reported in the parentheses below each coefficient estimate are obtained using errors cluster over bank and firm. The final data sample is from 1986 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
	Constrained firms			Unconstrained firms		
	Top 33% of WW index			Bottom 33% of WW index		
	Panel A: Investment rate change					
FLS	-0.14	-0.33**	-0.17*	-0.01	-0.01	-0.02
	(-1.55)	(-2.34)	(-1.73)	(-0.42)	(-0.47)	(-0.64)
N	4672	4385	4656	5138	4772	5115
adj. R^2	0.284	0.283	0.299	0.198	0.224	0.233
	Panel B: Earnings growth					
FLS	-2.60*	-2.59*	-2.50*	-0.08	0.08	0.57
	(-1.75)	(-2.01)	(-1.76)	(-0.15)	(0.08)	(1.01)
N	4695	4404	4679	5186	4822	5164
adj. R^2	0.009	0.003	0.016	0.005	-0.011	0.007
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	Yes	No	No
State_Year FEs	No	Yes	No	No	Yes	No
1-digit SIC_Year FEs	No	No	Yes	No	No	Yes

Table A.25: Cyclicality of labor relative to aggregate labor for selected industries

This table computes the cyclicality of an industry's employment share of total employment for selected industries likely to have high human capital. The first column presents the correlation of HP-filtered N_i/N with HP-filtered real GDP, while the second column presents the correlation of growth rates. All variables are from FRED. Real GDP is defined as GDPC1, financial employment is USFIRE, while the other variables can be found in Table B-1, Employees on nonfarm payrolls by industry sector.

	HP filter	Growth
	Broad categories, 1952-2019	
Finance	-0.668	-0.469
Information	0.171	0.132
Professional Services	-0.156	-0.096
Education and Health	-0.690	-0.542
	Finer categories, 1990-2019	
Finance	-0.297	-0.081
Computer and electronic manufacturing	0.054	0.054
Computing Infrastruct., Data Processing, Web Hosting	-0.034	0.085
Telecommunication	-0.108	0.142
Professional, Scientific, And Technical Services	0.010	0.106
Legal Services	-0.448	-0.285
Accounting services	-0.069	0.072
Architectural and Engineering	0.205	0.254
Computer system design	0.162	0.230
Management and technical consulting	-0.110	0.067
Healthcare and Social Assistance	-0.652	-0.560
Non-Fin, Non-Healthcare average	-0.038	0.081

Figure A.3: Financial sector employment share of total employment, scatter plot

This figure plots a scatter plot of the financial sector employment share of total employment compared to GDP. The series are USFIRE, PAYEMS, and GDPC1 respectively in FRED. Since both series are non-stationary, the left panel plots HP-filtered values and the right growth rates.

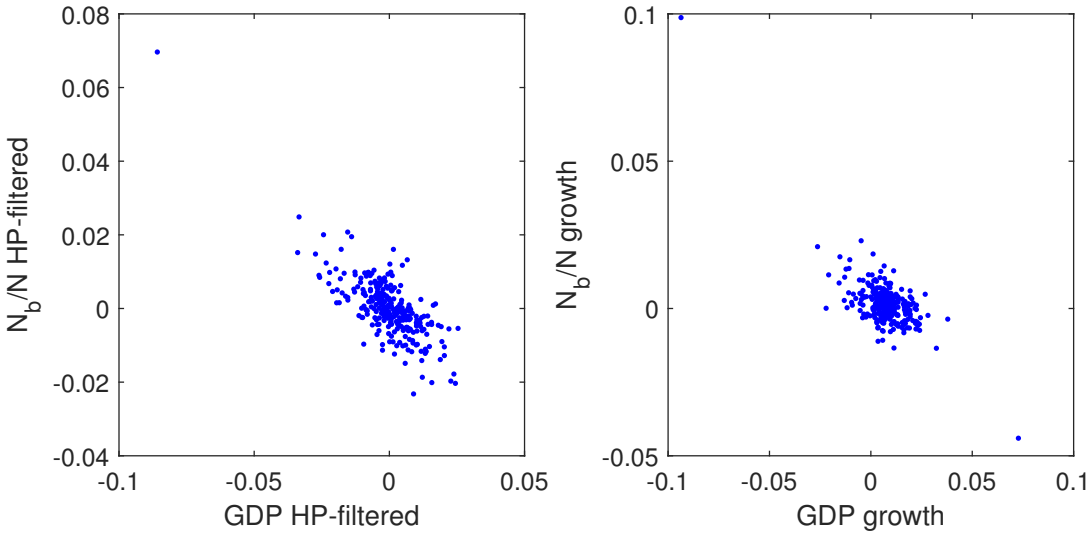


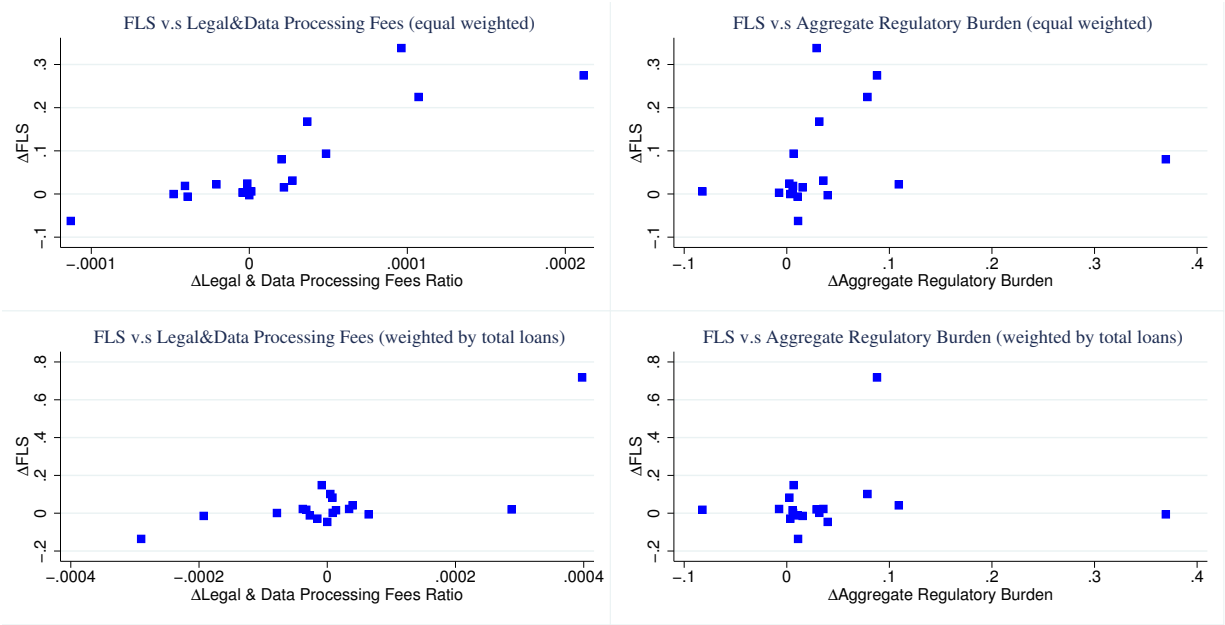
Table A.26: Shock to bank labor expenses

In Panel A, we use the change in a bank's legal and processing fees scaled by total assets (defined for each bank i and year t) to measure banks' regulation compliance burden. Analogous to an instrumental variable approach, column (1) reports results from the first stage of regressing the change in a bank's FLS on the contemporaneous change in its legal and data processing fees, the unit of observation is bank-year. We define $\Delta\widehat{FLS}_{t,i}$=0.062 + 79.9*($\Delta$ Legal and data processing fees / TA)$_{t,i}$. Column (2) reports results from regressing the a bank's three-year loan growth from [t-2:t] to [t+1:t+3] on $\Delta\widehat{FLS}$. Column (3) reports results from regressing the average loan spreads (measured as "All-indrawn" from Dealscan Loan Pricing) for the loans that the bank issues from t+1 to t+3 on $\Delta\widehat{FLS}$. The unit of observation is bank-year and we aggregate the loan-level measures to the bank-year level for all loans available in Dealscan issued by a particular bank, weighted by the individual loan amount. Therefore, the number of observation in column (3) is substantially smaller as the number of banks in Dealscan is very small. Panel B is similar but we capture the compliance burden component for FLS with an aggregate measure of regulatory burden where $\Delta\widehat{FLS}_{t,i}$=0.045 + 0.259*($\Delta$ Regulatory Burden)$_t$. Column (4) of Panel B shows that the change in the legal and data processing fees (the instrument in Panel A) is also related to aggregate regulatory burden.

	(1) FLS	(2) Loans	(3) Spread	(4) Legal and data processing fees x 1000 / Total Assets
Panel A: Legal and processing fees				
Legal and data processing fees / TA	79.907***			
	(6.57)			
$\widehat{FLS}$		-0.251***	1.622**	
		(-6.95)	(2.16)	
Bank controls	-	Yes	Yes	
Firm and Loan controls	-	-	Yes	
N	15487	13021	316	
adj. R^2	0.007	0.581	0.611	
FEs	-	Bank and year	Bank	
Panel B: Aggregate regulatory burden				
Regulatory Burden	0.259***			0.193***
	(4.14)			(3.83)
$\widehat{FLS}$		-0.985***	1.690**	
		(-14.42)	(2.15)	
Bank controls	-	Yes	Yes	Yes
Firm and Loan controls	-	-	Yes	-
N	17426	14920	351	15218
adj. R^2	0.002	0.472	0.575	-0.033
FEs	-	Bank	Bank	Bank

Figure A.4: Shock to bank labor expenses

This figure plots the aggregation of bank-level labor share (FLS) against their regulation cost (legal and data processing fees) induced by the aggregate regulatory burden from 2002 to 2019. The labor share and regulation cost in the top panel are produced by equal weighted aggergation, and in the bottom panel by taking a weighted average by the dollar value of total loans



C Model

C.1 Frictionless planner's problem

Let Z_t and N_t be exogenously specified and random variables determining TFP and labor supply; let A_t be a determenistic trend growing at rate g. The planner maximizes the sum of expected future utility over consumption C_t subject to the budget constraint setting output $Z_t K_t^{\alpha\rho}(A_t N_t)^{1-\alpha}$ equal to investment I_t plus adjustment costs plus consumption.

$$\begin{aligned} J_t &= \max_{I_t} \tfrac{C_t^{1-\gamma}}{1-\gamma} + \beta E_t[J_{t+1}] \quad \text{s.t.} \\ C_t &= Z_t K_t^{\alpha\rho}(A_t N_t)^{1-\alpha} - I_t - \nu_{k,0}\left(\tfrac{S_t}{K_t} - \nu_{k,1}\right)^2 K_t \\ K_{t+1} &= S_t = (1-\delta)K_t + I_t \\ A_{t+1} &= A_t(1+g) \end{aligned} \tag{A.3}$$

The first order and envelope conditions are

$$\begin{aligned} &C_t^{-\gamma}\left(1 + 2\nu_{k,0}\left(\tfrac{S_t}{K_t} - \nu_{k,1}\right)\right) = \beta E_t[\tfrac{\partial J_{t+1}}{\partial K_{t+1}}] \\ &\tfrac{\partial J_t}{\partial K_t} = C_t^{-\gamma}\left(\alpha\rho Z_t K_t^{\alpha\rho-1}(A_t N_t)^{1-\alpha} + 1 - \delta + 2\nu_{k,0}\nu_{k,1}\left(\tfrac{S_t}{K_t} - \nu_{k,1}\right) + \nu_{k,0}\left(\tfrac{S_t}{K_t} - \nu_{k,1}\right)^2\right) \end{aligned} \tag{A.4}$$

Combining, the solution to the planner's problem can be characterized by two stochastic functional equations (the Euler equation and the budget constraint) and two unknown functions $I(K_t, Z_t)$ and $C(K_t, Z_t)$.

$$\begin{aligned} &1 = E_t\left[\beta\left(\tfrac{C_{t+1}}{C_t}\right)^{-\gamma} \tfrac{\alpha\rho Z_{t+1}K_{t+1}^{\alpha\rho-1}(A_{t+1}N_{t+1})^{1-\alpha} + 1 - \delta + 2\nu_{k,0}\nu_{k,1}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right) + \nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2}{1 + 2\nu_{k,0}\left(\frac{S_t}{K_t} - \nu_{k,1}\right)}\right] \\ &C_t = Z_t K_t^{\alpha\rho}(A_t N_t)^{1-\alpha} - I_t - \nu_{k,0}\left(\tfrac{S_t}{K_t} - \nu_{k,1}\right)^2 K_t \end{aligned} \tag{A.5}$$

where $S_t = (1-\delta)K_t + I_t$.

C.2 Frictionless decentralized problem

In this section we write down a version of our model without FIs or debt; the full model in Section 2 is an extension of this frictionless problem. We take this step because for tractability, we set up the firm's problem in a non-standard way and believe it is helpful for the reader to understand the simpler problem first. Typically in models with capital adjustment costs firms are infinitely lived, which requires the firms' problem to be solved numerically. In our model new firms are born each period and live until next period only, which allows us to solve the firm's problem analytically as a function of the state, and makes it computationally tractable to solve the full model. We also show

that the decentralized frictionless problem with 2-period firms in this section is isomorphic to the planner's problem, and also, according to the first welfare theorem, to the standard decentralized economy with infinitely lived firms.

C.2.1 Households

Households have CRRA utility and supply an exogenously specified (not necessarily constant) amount of labor N_t. Households buy new uncapitalized firms from entreprenuers for Π_t and spend an additional $K_{t+1}Q_t$ to buy capital for the firms for a total of $V_{cn,t+1} = \Pi_t + K_{t+1}Q_t$ per firm. Since there is a representative agent, entrepreneurs are also households and return Π_t to the common pot. Let Ω_t be the household's financial net worth, W_tN_t the wage multiplied by the labor supply (equivalently labor income), C_t its consumption, θ_{t+1} the shares of equity it buys at t ($\theta_t = 1$ in equilibrium), $V_{cn,t}$ (cn is for corporate new) the t equity value of a firm born at t after it has raised capital, and $V_{co,t+1}$ (co is for corporate old) the $t+1$ equity value of a firm born at t, which pays out its profit at $t+1$ and then shuts down. For brevity, we do not include a risk free asset in this problem, though it is available in the full problem. The household's problem is:

$$\begin{aligned} U(\Omega_t) &= \max_{C_t} \frac{C_t^{1-\gamma}}{1-\gamma} + \beta E_t\left[U(\Omega_{t+1})\right] \quad \text{s.t.} \\ \theta_{t+1}V_{cn,t} &= \Omega_t + W_tN_t + \Pi_t - C_t \\ \Omega_{t+1} &= \theta_{t+1}V_{co,t+1} \end{aligned} \tag{A.6}$$

Combining the household's first order and envelope conditions, we can solve for the standard Euler equation for equity returns:

$$1 = E_t[M_{t+1}R_{t+1}] \text{ where } M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} \text{and } R_{t+1} = \frac{V_{co,t+1}}{V_{cn,t}} \tag{A.7}$$

C.2.2 Firms

New, uncapitalized firms are owned by entrepreneurs, who are part of the representative agent with the rest of the households. Entrepreneurs sell new, uncapitalized firms to equity investors for Π_t. The equity investors then decide how much capital K_{t+1} to buy for a price Q_t per unit. To do this, firms raise an additional Q_tK_{t+1} by selling shares, implying a total equity value $V_{cn,t} = \Pi_t + Q_tK_{t+1}$.[68]

The value of a new firm at t is equal to the present discounted value of $t+1$ cash flows. At $t+1$, old firms produce output with a Cobb-Douglas production function using capital K_{t+1} purchased at t, labor N_{t+1} hired at $t+1$, a stochastic TFP process Z_{t+1}, and a deterministicly growing, labor

[68] When returns to scale are constant ($\rho = 1$), the firm's value is linear in capital and the value of a new firm without capital is $\Pi_t = 0$, however with decreasing return to scale ($\rho < 1$), even a firm no capital has value $\Pi_t > 0$.

augmenting productivity component A_{t+1}. They also choose how much new capital S_{t+1} to create, pay adjustment costs associated with creation and installation of new capital, and sell their capital to new $t+1$ firms for $S_{t+1}Q_{t+1}$. Firms use the proceeds from selling their output and new capital to pay wages to employees and the rest to equity holders. In equilibrium the aggregate capital sold by old firms to new firms at $t+1$ is equal to the aggregate capital at $t+2$: $S_{t+1} = K_{t+2}$. The firms' $t+1$ payout to shareholders, or equivalently its value $V_{co,t+1}$, is

$$\begin{aligned} V_{co,t+1} &= Z_{t+1}K_{t+1}^{\alpha\rho}(A_{t+1}N_{t+1})^{1-\alpha} - W_{t+1}N_{t+1} + \\ &\quad K_{t+1}(1-\delta) - S_{t+1} - \nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2 K_{t+1} + Q_{t+1}S_{t+1}. \end{aligned} \tag{A.8}$$

In the above equation, investment is $I_t = S_{t+1} - K_{t+1}(1-\delta)$.[69]

The firm's choice of labor satisfies $W_t = (1-\alpha)Z_t A_t^{1-\alpha}\left(\frac{K_t^\rho}{N_t}\right)^\alpha$. The firm's choice of investment is orthogonal to the labor decision and satisfies $Q_t = 1 + 2\nu_{k,0}\left(\frac{K_{t+1}}{K_t} - \nu_{k,1}\right)$. Plugging these back into equation A.8

$$V_{co,t+1} = X_{t+1}^0 K_{t+1}^\rho + X_{t+1}^1 K_{t+1} \tag{A.9}$$

where we define $X_t^0 = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}} W_t^{\frac{\alpha-1}{\alpha}} Z_t^{\frac{1}{\alpha}} A_{t+1}^{\frac{1-\alpha}{\alpha}}$ and $X_{t+1}^1 = 1-\delta+\nu_{k,1}\left(Q_{t+1}-1\right)+\frac{1}{4\nu_{k,0}}\left(Q_{t+1}-1\right)^2$.

At t, after buying the firm, its new owners must decide how much capital to buy, equivalently, how much additional equity to issue. To do so, they solve the following problem:

$$\Pi_t = \max_{K_{t+1}} E_t[M_{t+1}V_{co,t+1}] - Q_t K_{t+1} \tag{A.10}$$

First, since $V_{cn,t} = \Pi_t + Q_t K_{t+1}$, the household's Euler equation A.7 will automatically be satisfied. Second, taking the first order conditions of equation A.10 leads to:

$$1 = E_t\left[M_{t+1}\frac{\rho X_{t+1}^0 K_{t+1}^{\rho-1} + 1 - \delta + \nu_{k,1}(Q_{t+1}-1) + \frac{1}{4\nu_{k,0}}(Q_{t+1}-1)^2}{Q_t}\right] \tag{A.11}$$

Finally, to close this problem, we must solve for the aggregate budget constraint. To do so, start with the household's budget constraint in equation A.6, then plug in $\theta_t = 1$, $V_{cn,t} = \Pi_t + Q_t K_{t+1}$, $V_{co,t}$ from equation A.8, and $S_t = K_{t+1}$ to get

$$C_t = Z_{t+1}K_{t+1}^{\alpha\rho}(A_{t+1}N_{t+1})^{1-\alpha} - I_t - \nu_{k,0}\left(\frac{S_t}{K_t} - \nu_{k,1}\right)^2 K_t \tag{A.12}$$

By plugging in the definitions of W_t, X_t^0, and S_t, one can confirm that equations A.11 and A.12

[69] If there were no adjustment costs ($\nu_{k,0}$=0), then $Q_t = 1$ and the value of the old firm at $t+1$ is simply the value of output plus undepreciated capital: $V_{co,t+1} = Z_{t+1}K_{t+1}^{\alpha\rho}(A_{t+1}N_{t+1})^{1-\alpha} - W_{t+1}N_{t+1} + K_{t+1}(1-\delta)$. With adjustment costs, firms who sell S_{t+1} units of new capital lose the capital itself, plus disassembly costs $\nu_{k,0}\left(\frac{S_{t+1}}{K_{t+1}} - \nu_{k,1}\right)^2$.

are identical to the ones that solve the planner's problem in Appendix C.1.

C.3 Detrending

The above problem is not stationary but can be detrended. Since the planner's problem and the decentralized problem are identical, we focus on the planner's problem. All variables except N_t and J_t have trend $X_t = A_t^{\frac{1-\alpha}{1-\alpha\rho}} = A_t^{\chi}$ and can be rewritten using lower case: $c_t = C_t/X_t$, $k_t = K_t/X_t$, etc. There is no need to detrend N_t and the trend in J_t is $X_t^{1-\gamma}$. Therefore, the whole problem can be rewritten as:

$$\begin{aligned} j_t &= \max_{i_t} \tfrac{c_t^{1-\gamma}}{1-\gamma} + \widehat{\beta} E_t[j_{t+1}] \quad \text{s.t.} \\ c_t &= Z_t k_t^{\alpha\rho} N_t^{1-\alpha} - i_t - \nu_{k,0}\left(\tfrac{s_t}{k_t} - \nu_{k,1}\right)^2 k_t \\ k_{t+1} &= s_t(1+g)^{-\frac{1-\alpha}{1-\alpha\rho}} = \left((1-\delta)k_t + i_t\right)(1+g)^{-\frac{1-\alpha}{1-\alpha\rho}} \end{aligned} \tag{A.13}$$

where $\widehat{\beta} = \beta(1+g)^{\frac{(1-\gamma)(1-\alpha)}{1-\alpha\rho}} = \beta(1+g)^{(1-\gamma)\chi}$.

The solution of this problem can be characterized by two functional equations: the Euler equation and the budget constraint:

$$\begin{aligned} 1 &= E_t\left[\widehat{\beta}(1+g)^{-\chi}\left(\tfrac{c_{t+1}}{c_t}\right)^{-\gamma}\left(\frac{\alpha\rho Z_{t+1}k_{t+1}^{\alpha\rho-1} + 1 - \delta + 2\nu_{k,0}\nu_{k,1}\left(\frac{s_{t+1}}{k_{t+1}} - \nu_{k,1}\right) + \nu_{k,0}\left(\frac{s_{t+1}}{k_{t+1}} - \nu_{k,1}\right)^2}{1 + 2\nu_{k,0}\left(\frac{s_t}{k_t} - \nu_{k,1}\right)}\right)\right] \\ c_t &= Z_t k_t^{\alpha\rho} N_t^{1-\alpha} - i_t - \nu_{k,0}\left(\tfrac{s_t}{k_t} - \nu_{k,1}\right)^2 k_t \end{aligned} \tag{A.14}$$

where the state is (Z_t, k_t) and the unknown functions are $c(Z_t, k_t)$ and $i(k_t, s_t)$. The full model in Section 2 can be detrended in the same way.

C.4 Solution algorithm

After detrending all of the equations in the full model, we then solve the model numerically. Note that because firms and FIs in our model live for only two periods, we can solve their problems analytically as a function of the aggregate state. Furthermore, because of the overlapping generation set up, we do not need to keep track of and approximate the cross-sectional distribution of capital and productivity across firms. Therefore, our state space is the true state space, rather than an approximation of the true state space, as is often the case in models with heterogenous firms or agents. The state space includes four variables: the TFP shock z_t, the aggreggate default shock d_t, the capital per firm of those firms who do not receive FI financing $k_{t+1,e}$, the capital per firm of those firms who do receive FI financing $k_{t,de}$, and the intensity of screening from the previous period ζ_{t-1}. The TFP shock z_t is an exogenously specified 2-state Markov shock with transition probabilities described in Section 2.6 – it defines whether the aggregate productivity state is good

or bad. The default shock d_t is an exogenously specified independent, identically distributed 2-state shock described in Section 2.6 – it defines whether the number of firms suffering a default shock is high or low. The endogenous state variables $k_{t+1,de}$, $k_{t+1,e}$, and ζ_{t-1} are discretized on grids of sizes 36, 28, and 9, respectively. We define $\Gamma_t = (z_t, d_t, k_{t,de}, k_{t,e}, \zeta_{t-1})$ as the aggregate state.

We begin by specifying a set of beliefs for $k_{t+1,de}$ (FI financed firms' capital next period), $k_{t+1,e}$ (FI unfinanced firms' capital next period), c_t (consumption), $v_{cn,t}$ (new firm equity value), $v_{FI,n,t}$ (new bank equity value), w_t (wage), ζ_t (FIs' screening choice), $R_{cd,t}$ (interest rate on corporate debt), $R_{d,t}$ (interest rate on deposits), and Q_t (price of capital) all as a function of the aggregate state Γ_t. Even though $k_{t+1,de}$ and $k_{t+1,e}$ are part of the $t+1$ state Γ_{t+1}, they are both determined at t and are functions of Γ_t. Note that since $\Gamma_{t+1} = (z_{t+1}, d_{t+1}, k_{t+1,de}, k_{t+1,e}, \zeta_t)$, and since z_{t+1} and d_{t+1} are exogenous random shocks with known probability distributions, the specified beliefs also provide us with a belief about the evolution of the aggregate state Γ_{t+1}. We use the term beliefs because in partial equilibrium, we can solve the firm's, FI's, and household's problems for any set of beliefs. However, since we are solving for a rational expectations equilibrium, in equilibrium the beliefs will be consistent with the actual behavior of these variables.

At every point in the discretized state space, using the specified beliefs, we numerically solve the FI's problem in equation 14 for optimal capital for each firm $(k_{t+1,e}, k_{t+1,de})$ and for screening intensity ζ_t. We then use these to update the beliefs. Specifically, $k_{t+1,de}$, $k_{t+1,e}$, and ζ_t are updated directly from the FI's optimal choices. We use the aggregate budget constraint in equation 15 to update c_t. We use labor demand by FIs from equation 10 and by firms from equation 5 to compute aggregate labor demand and compare it to the exogenously specified labor supply described in Section 2.6 to update the wage w_t. To update the price of capital Q_t we compare the aggregate capital demand by firms, determined from solving the FI's problem $(p + (1-p)(1-\zeta_t)k_{t+1,de} + (1-p)\zeta_t k_{t+1,e}$ to the aggregate capital supply computed from firms' optimal investment policies in equation 4. To update the value of new firms $v_{cn,t}$ we first compute the realized return on corporate equity using $v_{i,co,t+1}$ in equation 6; for this we need to compute the intermediate quantities $X^0_{i,t+1}$ and $X^1_{i,t+1}$ in equations A.15 below. We then compute the Euler equation error in equation 2 that is implied by this return and use it to update $v_{cn,t}$. To update the value of new FIs $v_{FI,n,t}$ we use equation 11 relating FI equity value to its balance sheet and labor expenses. To update the corporate interest rate $R_{cd,t}$ we first compute the FI's realized return on equity using equations 12, 13, and the definition of $v_{FI,n,t}$. We then use the FI's Euler equation error from equation 2 to update $R_{cd,t}$. Finally, to update the deposit rate $R_{d,t}$ we simply use the deposit Euler equation 2. In order to have a smooth convergence towards the rational expectations equilibrium, we update slowly by putting putting a large weight on the previous beliefs. Once the problem is converged, we check that none of the beliefs are changing and that all Euler equation errors are zero at every point in the state space.

$$X^1_{i,t+1} = 1 - \delta_{t+1} + \nu_{k,1}(Q_{t+1} - 1) + \frac{1}{4\nu_{k,0}}(Q_{t+1} - 1)^2 \quad \forall \quad i$$
$$X^0_{i,t+1} = \begin{cases} Z^{1/\alpha}_{u,t+1} A^{\frac{1-\alpha}{\alpha}}_{t+1} W^{(\alpha-1)/\alpha}_{t+1} \alpha(1-\alpha)^{(1-\alpha)/\alpha} & \text{if} \quad i = u \\ \hat{Z}^{1/\alpha}_{t+1} A^{\frac{1-\alpha}{\alpha}}_{t+1} W^{(\alpha-1)/\alpha}_{t+1} (1-\alpha)^{1/\alpha} \left(\frac{Z_{i,t+1}}{\hat{Z}_{t+1}} (1-\alpha)^{-1} - 1 \right) & \text{if} \quad i \in (uf, pf) \end{cases} \tag{A.15}$$

C.5 TFP versus FLN shocks

For the 'FLN shocks' model discussed in Section 2.8.4, we compare the effects of TFP versus FLN shocks. To do so, we carry out an exercise similar to Jermann and Quadrini (2012) where, for the period 1948-2019, we extract from the data time series of TFP and FLN shocks, feed them into the model, and report the time-series correlations between model and data moments. For TFP shocks, we use annual TFP level from John Fernald's website, and HP-filter the series with filtering parameter 100. For FLN shocks we HP-filter the data series for financial sector labor as a fraction of all employment $\frac{N_{FI}}{N}$ and then standardize it by subtracting mean and dividing by standard deviation. We also standardize the Baa spread over the Fed Funds rate. We then average the two series; since Baa spread over the Fed Funds is only available starting in 1955, pre-1955 we simply use $\frac{N_{FI}}{N}$. We then report the correlations of HP-filtered output, investment, debt, $\frac{N_{FI}}{N}$, as well as unfiltered $R_{cd} - R_f$ between model and data.

Table A.28 reports the results from this exercise for HP-filtered output, investment, debt, financial sector employment as a share of total employment $\frac{N_{FI}}{N}$, as well as unfiltered credit spread $R_{cd} - R_f$. We first do this for the Screening and No screening models in Section 2.7, these models do not have FLN shocks, therefore the only exogenous shock is TFP. The correlations of output, investment, and debt between the Screening model and data are, respectively 0.53, 0.47, and 0.31; the correlations in the No screening model are similar. On the other hand, for $\frac{N_{FI}}{N}$ and $R_{cd} - R_f$, the Screening model does much better; the correlations are 0.23 and 0.31 in the Screening model compare to -0.23 and -0.26 in the No screening model.

We then do this for the 'FLN shocks' model discussed in Section 2.8.4. We compare a case with just TFP shocks (where FLN shocks are set to their median value) to a case with both shocks. Again, both cases perform similarly for output, investment, and debt, with correlations of 0.53, 0.47, and 0.31 respectively. On the other hand, for $\frac{N_{FI}}{N}$ and $R_{cd} - R_f$, FLN shocks make a significant difference, with correlations rising to 0.29 and 0.43 from -0.23 and 0.04 when FLN shocks are added.

Table A.27: Summary of variables in model

Variable	Description
Π_t	Value of uncapitalized firm = Entrepreneur's profit
W_t	Wage
N_t	Aggregate labor supply (specified exogenously)
$N_{FI,t}$	FI labor demand
$\theta_{FI,t+1}$	Household demand for FI shares (1 in equilibrium)
$\theta_{c,t+1}$	Household demand for corporate shares (1 in equilibrium)
Ω_t	Household wealth
$R_{d,t}$	Rate of return on deposits
$R_{cd,t}$	Promised rate of return on corporate debt (cd)
$\hat{R}_{cd,t+1}$	Realized reate of return on corporate debt
$B_{d,t+1}$	Face value of deposits (d)
$B_{cd,t+1}$	Face value of corporate debt, conditional on being screened-in
$B_{cd,pf,t+1} = B_{cd,uf,t+1} = B_{cd,t+1}; B_{cd,u,t+1} = 0$	Face value of corporate debt for each firm type u unproductive unfinanced, uf unproductive financed, pf productive financed
$B_{FI,a,t+1} = (p + (1-p)(1-\zeta_t))B_{cd,t+1}$	Face value of FI assets
$V_{cn,t}$	Value of average new corporate firm
$V_{i,co,t+1} = X^0_{i,t+1}K^{\rho}_{i,t+1} + X^1_{i,t+1}K_{i,t+1} - B_{cd,i,t+1}$	Value of type $i \in (u, uf, pf)$ old corporate firm
$V^{\delta}_{i,co,t+1}$	Value of old corporate firm conditional on depreciation shock
$V_{co,t+1} = pV_{pf,co,t+1} + (1-p)(1-\zeta_t)V_{uf,co,t+1} + (1-p)\zeta_t V_{u,co,t+1}$	Average value of old corporate firm, across all types
$V_{FI,n,t}$	Value of new FI
$V_{FI,o,t+1}$	Value of old FI
p	Fraction of productive firms
q	Probability aggregate state stays at current level
$s_{t+1} \in (s^h, s^l)$	probability of idiosyncratic depreciation shock
$Z_{p,t+1} \in (Z_{p,b}, Z_{p,g})$	Productivity of productive firm in bad or good aggregate state
$Z_{u,t+1} \in (Z_{u,b}, Z_{u,g})$	Productivity of unproductive firm in bad or good aggregate state
$\hat{Z}_{t+1} = \frac{pZ_{p,t+1} + (1-p)(1-\zeta_t)Z_{u,t+1}}{p + (1-p)(1-\zeta_t)}$	Average productivity of screened-in firms
Q_t	Price of capital
$K_{e,t+1} = K_{u,t+1}$	Capital raised from equity issues = Capital of (screend-out) firms not financed by FI
$K_{d,t+1} = \frac{1}{Q_t}B_{cd,t+1}$	Capital raised from debt issues
$K_{de,t+1} = K_{e,t+1} + K_{d,t+1} = K_{pf,t+1} = K_{uf,t+1}$	Capital of productive and unproductive (screened-in) firms financed by FI
$S_{u,t+1} = S_{uf,t+1} = S_{pf,t+1}$	New capital created by all firms
Ψ_t	Trade-off theory costs
ζ_t	Screening intensity

Table A.28: Alternative models, correlations with data

This table reports the correlations of several model quantities of interest with the data for 1948-2019. To create this table, we simulate the model for 73 years using TFP or FLN shocks extracted from the data. For TFP shocks, we use annual TFP level from John Fernald's website, and HP-filter the series with filtering parameter 100. For FLN shocks we HP-filter the data series for financial sector labor as a fraction of all employment $\frac{N_{FI}}{N}$ and then standardize it by subtracting mean and dividing by standard deviation. We also standardize the Baa spread over the Fed Funds rate. We then average the two series; since Baa spread over the Fed Funds is only available starting in 1955, pre-1955 we simply use $\frac{N_{FI}}{N}$. We then report the correlations of HP-filtered output, investment, debt, $\frac{N_{FI}}{N}$, as well as unfiltered $R_{cd} - R_f$ between model and data. We do this for the Screening and No screening models, both discussed in Section 2.7 and for the 'FLN shocks' model discussed in Section 2.8.4. For the 'FLN shocks' model, we do this for just TFP shocks (setting FLN shocks to their median value) or both shocks.

Model	Shock	GDP	INV	Debt	$\frac{N_{FI}}{N}$	$R_{cd} - R_f$
No screening	TFP only	0.53	0.46	0.30	-0.23	-0.26
Screening	TFP only	0.53	0.47	0.31	0.23	0.31
FLN shocks	TFP only	0.53	0.47	0.30	-0.23	0.04
FLN shocks	TFP and FLN	0.53	0.47	0.31	0.29	0.43