Investor Composition, Bond Liquidity, and Labor Market*

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Abstract

We study how liquidity risk in corporate bond markets affects employment and how investor composition shapes this transmission. Using panel data on U.S. firms and their corporate bondholder base, we show that increases in bond liquidity premia predict slower employment growth, with economically large effects. The relationship is substantially stronger for firms whose bonds are more heavily held by mutual funds. Instrumental-variable estimates exploiting maturity cutoffs and fund-flow-driven shifts in ownership support a causal interpretation. To interpret these findings, we develop a heterogeneous-firm model with defaultable debt and investor heterogeneity. In the model, liquidity shocks raise the effective cost of bond financing through prices and issuance wedges, and the real effects are amplified when debt is held by investors with liquidity-sensitive funding. A deep-learning-based global solution quantifies the implied labor market effects.

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1 Introduction

Corporate bond markets play a central role in financing real economic activities. For many firms, bond issuance finances not only long-term investment but also working capital needs that support ongoing production and employment. Over the past two decades, the investor base of U.S. corporate bonds has undergone a pronounced shift. Traditional buy-and-hold investors such as insurance companies and pension funds now account for a smaller share of outstanding corporate debt, while open-ended mutual funds have become increasingly important holders (Bretscher et al., 2025). Unlike traditional institutions, mutual funds issue redeemable liabilities and may face liquidity pressure when investors withdraw capital. These structural changes have coincided with repeated episodes of stress in corporate bond markets, raising a fundamental question: to what extent does liquidity risk in corporate bond markets affect real economic activity, and in particular labor market outcomes?

This paper studies how liquidity risk in corporate bond markets relates to employment and other real firm outcomes, and how this relationship varies with the composition of a firm's bondholders. Our central finding is that liquidity shocks propagate to the real economy not only through aggregate financial conditions, but also through the fragility of the investor base. When bonds are predominantly held by investors subject to redemption pressure—such as mutual funds—liquidity shocks trigger outflows, depress bond prices, and tighten firms' effective financing conditions. Firms respond by cutting back on hiring, investment, and debt issuance. By contrast, when bonds are held by long-horizon investors with stable funding, liquidity shocks are absorbed with limited real consequences.

Our empirical analysis begins by documenting a strong negative relationship between liquidity premium and labor market dynamics. We measure liquidity premium as bond spread in excess of credit default swap (CDS) spread, following Longstaff et al. (2005). At the aggregate level, we find that a higher bond-CDS spread differential significantly predicts lower employment growth and higher unemployment. The same pattern appears in firm-level data: increases in the liquidity premium are associated with sizable declines in employment growth. This effect is substantially stronger among financially constrained firms and during periods of elevated aggregate liquidity risk. Crucially, we identify mutual fund bond ownership as a key amplifier of this transmission. Firms with high mutual fund ownership exhibit significantly higher sensitivity to liquidity shocks; specifically, firms with bond ownership one standard deviation above the average are nearly twice as sensitive to liquidity risk as those with zero ownership.

To establish a causal link between mutual fund ownership and employment outcomes, we employ two instrumental variable strategies: one exploiting the exogenous variation in bond demand around the 10-year maturity cutoff due to fund mandates, and a second using a shift-share instrument based on fund flows. Both strategies confirm that the amplification effect is causal. We further unpack the mechanisms driving this fragility, finding that the effect is transmitted through fund flows, rollover risk, and cash buffers. Consistent with the view that mutual fund fragility stems from liquidity mismatch, we show that fund outflows and high rollover risk exacerbate the negative impact of liquidity shocks on employment, while substantial cash buffers mitigate it. These effects are not limited to employment but extend to other corporate decisions, including debt issuance and capital investment.

Finally, we validate that this transmission mechanism is specific to the run-prone nature of mutual funds. By repeating our analysis using insurance companies—traditional long-term investors with stable liability structures—we find no such amplification effect on firm-level outcomes, supporting the hypothesis that the results are driven by the financial fragility inherent to open-ended funds. Our findings are robust to alternative specifications, including the use of high-frequency quarterly job posting data, which confirms that firms with higher mutual fund bond ownership significantly reduce labor demand in response to rising liquidity premiums.

To understand the mechanisms behind these empirical findings and study their quantitative implications, we develop a dynamic model with heterogeneous firms, defaultable corporate debt, and labor market frictions. Firms face both aggregate and idiosyncratic productivity shocks and choose investment, hiring, and financing subject to convex adjustment costs, wage rigidity, and limited liability. Production exhibits decreasing returns to scale, wages respond sluggishly to aggregate conditions, and default arises endogenously when continuation values fall sufficiently low. The model is designed to capture the joint determination of firms' financing conditions and real decisions in the presence of financial frictions.

A central feature of the model is heterogeneity in the investor base of corporate bonds. Corporate debt is held by financial intermediaries with different funding structures, which differ in the elasticity of their demand for bonds to aggregate liquidity conditions. We capture this heterogeneity through a liquidity wedge in firms' bond issuance proceeds: when aggregate liquidity deteriorates, bonds held by investors with more fragile funding—such as mutual funds subject to redemption pressure—experience lower debt issuance and larger price dislocations, while bonds held by long-horizon investors provide more stable financing. As a result, firms face different effective financing conditions depending on bondholder composition. When a negative liquidity shock hits, firms whose bonds are primarily held by mutual funds experience a sharper decline in bond prices and a larger increase in external financing costs. These firms respond by cutting back leverage, investment, and hiring, leading to a stronger contraction in real activity, such as employment, relative to firms financed by more stable investors.[1]

Numerically solving this model is challenging because it features a high-dimensional state space with endogenous default decisions and endogenous pricing of defaultable corporate debt. Standard numerical approaches typically rely on nested fixed-point iterations over value functions and bond prices, which quickly become infeasible in this environment. We address these challenges with two methodological innovations. First, we adopt a taste-shock formulation of default, borrowed from the sovereign and consumer default literature, which smooths the discrete default decision and yields differentiable policy functions. Second, we employ a deep-learning-based global solution method that directly approximates value and policy functions and enforces equilibrium conditions without iterating on a separate bond pricing fixed point. We calibrate the model at a monthly frequency using standard parameter values from the literature and discipline key remaining parameters to match salient firm-level and aggregate moments in the data.

[1] In the current draft, heterogeneity in bondholder funding structure affects bond financing conditions through a reduced-form liquidity wedge in the firm's budget constraint. We are developing a microfoundation based on an over-the-counter trading framework with heterogeneous investors in the spirit of Duffie et al. (2005), which endogenizes this wedge through equilibrium trading frictions in corporate bond markets.

The first set of quantitative results characterizes the model's value and policy functions. The solved continuation value and decision rules exhibit economically intuitive and nonlinear relationships across state variables. Firm value is increasing in capital and decreasing in debt, reflecting the interaction of productive capacity, collateral, and financing constraints. Its dependence on employment is non-monotone, rising at low employment levels and declining at high levels due to diminishing returns, wage rigidity, and convex labor adjustment costs. Default emerges endogenously for firms with low productivity, low capital, or high leverage.

The second set of results studies the dynamic effects of aggregate liquidity shocks under heterogeneous investor bases. A negative liquidity shock raises firms' effective cost of bond financing and leads to declines in investment and hiring. Crucially, the contraction in employment is substantially larger for firms whose bonds are held by investors with more elastic funding, such as mutual funds. Higher demand elasticity amplifies bond price declines following liquidity shocks, tightening financing conditions and strengthening the transmission from financial markets to real activity. In contrast, firms financed by long-horizon investors experience more muted responses.

Taken together, the model highlights how heterogeneity in bondholder composition shapes the propagation of financial shocks to the labor market. These mechanisms suggest that the real effects of financial market disruptions depend not only on firm balance sheets, but also on who holds corporate debt—an insight with important implications for financial regulation and the design of policies aimed at stabilizing employment during periods of market stress.

Related literature. Our paper builds on four broad strands of the literature. First, it is closely related to work on liquidity risk and trading frictions in over-the-counter (OTC) markets. Duffie et al. (2005) show that search frictions alone are sufficient to depress prices and generate spreads. However, for corporate bonds, these frictions are not independent of credit risk. He and Milbradt (2014) model the mutual reinforcement of liquidity and default, demonstrating that low secondary market liquidity increases the cost of equity issuance and debt rollover, thereby precipitating earlier default. Structural estimation of this channel by Chen et al. (2018) confirms that this amplification mechanism accounts for a substantial portion of observed credit spreads. Furthermore, this literature connects micro-level frictions to systemic risk; Brunnermeier and Pedersen (2009) demonstrate that when market liquidity is tied to the funding liquidity of intermediaries, small shocks can lead to a destabilizing spiral and sudden market dry-ups, a dynamic for which Acharya and Pedersen (2005) find evidence of a systematic risk premium.

Second, the empirical literature on corporate bond pricing has long established that yield spreads are not driven solely by default risk but contain a significant non-default component, widely attributed to illiquidity. In their seminal work, Longstaff et al. (2005) use the credit default swap (CDS) market to decompose corporate yield spreads, finding that a substantial portion of the spread is due to liquidity rather than credit risk alone. This "liquidity premium" is further formalized by Bao et al. (2011), who document the substantial illiquidity of corporate bonds and show that this illiquidity is priced in the cross-section of returns, particularly during periods of market stress. Subsequent research reinforces these findings; for instance, Friewald et al. (2012) and Dick-Nielsen et al. (2012) demonstrate that liquidity frictions widen spreads significantly during financial crises, effectively decoupling bond prices from their fundamental default probabilities. Crucially, this liquidity component is not merely a financial friction but has predictive power for the real economy. Gilchrist and Zakrajšek (2012) show that the "excess bond premium"–the component of spreads not explained by expected default–is a robust predictor of economic activity, suggesting that shocks to the supply of credit, often driven by the financial intermediary sector, have tangible consequences for aggregate output and employment.

Third, our paper relates to the macro-finance literature on the relationship between financial frictions and real outcomes. Gilchrist and Zakrajšek (2012) provides aggregate evidence that credit spreads—summarized by the "excess bond premium"—have strong predictive power for business-cycle fluctuations. Unlike the credit-supply shocks emphasized by Jermann and Quadrini (2012) and Khan and Thomas (2013), we focus on aggregate shocks to the debt-issuance wedge and study their implications for bond-market liquidity risk premia and employment. The financial frictions in our model are in the spirit of Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke et al. (1999), among others. A key distinction is that disruptions in the financial sector are the source of business-cycle fluctuations in our framework (as in Jermann and Quadrini (2012) and Khan and Thomas (2013)), rather than serving primarily to amplify shocks originating elsewhere in the economy. Finally, whereas Favilukis et al. (2020) study how labor market frictions shape credit risk and debt issuance, we examine how bond-market liquidity risk premia affect real activity through heterogeneous bond investors' sensitivity to liquidity shocks.

Lastly, recent literature moves beyond aggregate liquidity measures to investigate how bondholder composition and heterogeneous demand elasticities determine asset prices. To isolate demand-side effects from fundamental credit risk, Bretscher et al. (2023) exploits exogenous demand shocks generated by index maturity mandates, establishing that passive fund demand causally alters yield spreads and issuance behavior. The elasticity of this demand varies significantly across investor types. Li and Yu (2023) and Fang (2023) identify open-ended mutual funds as a source of fragility, linking their high turnover and flow-performance sensitivity to excess volatility in spreads. Conversely, Coppola (2025) identifies the stabilizing role of insurance companies, showing that their long horizons and distinct regulatory constraints effectively flatten the demand curves for the bonds they hold. Zhou (2024) extends this framework to the open economy, showing that domestic financial stability depends on the relative dominance of these "fickle" versus "stable" investors in the sovereign and corporate bond markets.

2 Data

We obtain data for aggregate variables from FRED and the Bureau of Labor Statistics (BLS), firm characteristics from Compustat, and stock returns from CRSP. Data for bond spread is constructed from TRACE Enhanced merged with Mergent FISD, and data for bond credit default swaps (CDS) spread is downloaded from Markit. Finally, we obtain data for bond holding of funds from the eMaxx database of Thomson Reuters, and fund flow data from the CRSP Mutual Fund database. Variable definitions are detailed in Table A.1.

We obtain from FRED two sets of aggregate variables: labor market variables and macroeconomic variables. Labor market variables include unemployment level and rate, job vacancies, and unemployed persons per job opening ratio (from the BLS Job Openings and Labor Turnover Survey (JOLTS)). Macroeconomic variables include VIX and industry production. All variables are at a monthly frequency from July 2002 to December 2023.

We obtain firm characteristics from Compustat Annual, and construct our main variables of interests, including employment growth, investment rate, and debt issuance. We use stock returns data from CRSP to construct firm-level idiosyncratic volatility.

Bond Spread and CDS Spread. We first merge TRACE Enhanced with Mergent FISD data, then clean and filter the merged data following Dickerson et al. (2023). The sample period is from July 2002 to September 2023. We construct bond spread as the difference between bond yield and 3-month treasury yield.

We obtain CDS spread data from the Markit database. We follow the conventional rule in the literature to focus on the documentation clause type of 'modified restructuring', and tenor of 5 years, as in Bai and Collin-Dufresne (2019), Blanco et al. (2005), and Li (2025). Tenor refers to the duration of a CDS contract, and Bai and Collin-Dufresne (2019) and Blanco et al. (2005) document that CDS contracts with 5-year tenor are the most liquid in the derivative market. We also use the sample of 10-year CDS contracts as a robustness check as the 2021 CDS Indices Primer states: "[$\cdots$] other tenors, such as the 10 year, are becoming more common."

Bond Holding and Ownership. We obtain bond holding data from Lipper eMaxx database of Thomson Reuters. This database contains the corporate bond CUSIP-level holdings data for different types of investors including mutual funds, insurance companies, pension funds, and others. We construct the bond ownership measure by

$$\text{Bond Ownership}_{i,t} = \frac{\sum_j \text{Amount Held}_{j,i,t}}{\text{Amount Outstanding}_{i,t}}, \tag{1}$$

where Amount $\text{Held}_{j,i,t}$ is mutual fund j's holdings of firm i's bonds at the end of year t and Amount $\text{Outstanding}_{i,t}$ is firm i's bonds outstanding.

Fund Flows. We construct mutual fund flow shock following Dou et al. (2022), the data is obtained from CRSP Mutual Fund database. Specifically, we define flows at the fund level as

$$\text{flow}_{i,t} = \frac{Q_{i,t} - Q_{i,t-1} \times (1 + R_{i,t})}{Q_{i,t-1}}, \tag{2}$$

where $Q_{i,t}$ and $R_{i,t}$ are, respectively, the total net assets (TNA) and the net return for fund i in month t. We require the lagged TNA to be higher than \$15 million as in Elton et al. (2001), otherwise, the flow observation is dropped for fund i in month t.

In order to construct the unpredictable component in fund flows, we control for lagged fund flows because fund flows are persistent. We also control for lagged fund performance to account for flow-performance sensitivity. Furthermore, Berk and Tonks (2007) document that the empirical measure, $\text{flow}_{i,t}$ defined by equation (2), is an imperfect proxy for fund-flow shocks owing to intermediate, contemporaneous flows and returns within month t. To mitigate this concern, we also control for contemporaneous fund performance by running a pooled panel regression

$$\text{flow}_{i,t} = b_0 + \sum_{k=1}^{2} b_k \times ER_{i,t-k+1} + b_3 \times \text{flow}_{i,t-1} + \theta_t + \varepsilon_{i,t}, \tag{3}$$

where $ER_{i,t}$ is the fund excess return relative to the market return, R_t^{mkt}, over month t, $\text{flow}_{i,t-1}$ represents the lagged fund flows, and θ_t represents the month fixed effects. We then define the fund-flow shock after controlling for the flow-performance sensitivity at the fund level as

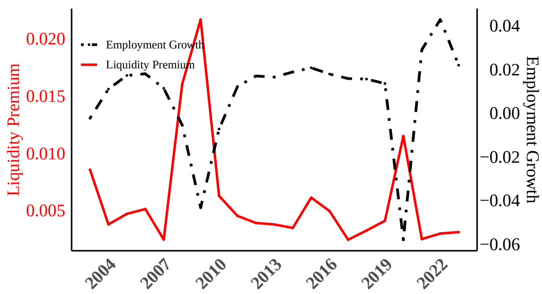
$$\text{flow shock}_{i,t} = \theta_t + \varepsilon_{i,t}. \tag{4}$$

3 Empirical Results

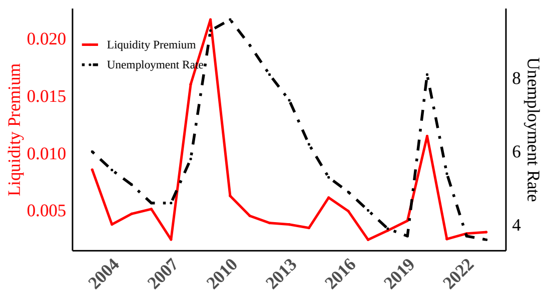
3.1 Aggregate-Level Results

We start by showing the correlation between liquidity premium and labor market dynamics at the aggregate level. Our main liquidity premium measure is the bond-

CDS spread differential. Figure 1 plots the annual bond-CDS spread differential aggregated from firm-level, along with employment growth (panel (a)) and unemployment rate (panel (b)). Panel (a) shows a strong negative correlation between liquidity premium and employment growth, suggesting in periods with high liquidity risk, employment growth is typically low; the correlation is -0.78. Panel (b) shows a positive correlation between liquidity premium and unemployment rate, the correlation is 0.49.



(a) Employment Growth



(b) Unemployment Rate

Figure 1: Liquidity Premium and Labor Market Dynamics

We then run the following predictive time series regression to show the effect of liquidity risk on labor market dynamics,

$$LaborMarket_t = \alpha + \beta \times LiquidityPremium_{t-1} + \varepsilon_t, \tag{5}$$

where *LaborMarket* is the labor market variable, including employment growth, unemployment rate, labor market tightness, and unemployed persons per job opening ratio, *LiquidityPremium* is the proxy for liquidity. We adopt two proxies for liquidity premium: the aggregate differential of bond-CDS spread and the bid-ask spread. The regression is at the monthly level, and we control for industry production growth and VIX change. Table 1 presents the results. Panel A shows the results of the aggregate differential of bond-CDS spread, and Panel B shows the results of bid-ask spread. Both of the liquidity premium measurements negatively predict labor market tightness and employment growth, and positively predict unemployment rate and the unemployed persons per job opening ratio. Altogether, the results reveal that the liquidity premium has a significant effect on labor market dynamics at the aggregate level.

[Table 1 here.]

3.2 Firm-Level Analysis

In this section we start by examining the effect of liquidity risk on employment at the firm level, followed by the amplification of this effect across two dimensions: across firms for financially constrained firms, and across time in periods of high aggregate liquidity risk. We then investigate the causal effect of mutual fund bond ownership on firm-level employment by interacting liquidity risk and mutual fund bond ownership and using two instrumental variable strategies. We also show that the effect of liquidity risk and mutual fund bond ownership is not concentrated on employment, but extends to other financial and real outcomes. We further inspect three potential mechanisms–fund flows, rollover risk, and cash buffer–through which mutual fund bond ownership effect may have on firms. Finally, we explore the heterogeneity in bond ownership among funds by testing the bond ownership of insurance funds, and find that the significant impact on firm-level financial and real outcomes does not show up in insurance fund bond ownership.

3.2.1 Liquidity Risk and Employment

Table 2 examines the effect of liquidity risk on employment. Our main variable of interest is the liquidity premium proxied by firm-level bond-CDS spread differential. Columns 1 to 3 present the univariate regression results of employment growth on liquidity premium, varying specifications and samples. Our main result, presented in Column 2, shows a significant coefficient of -0.3142 with t-statistics of -2.25. This represents a decline of $\frac{0.1344\times|-0.3142|}{0.0097}$=35% of employment growth per year, relative to its unconditional mean, following a one-standard-deviation increase in liquidity premium, the effect is both statistically and economically significant. Column 3 shows that the effect is larger among financially constrained firms, the coefficient is -0.4298 with t-statistics of -2.52.

In Columns 4 and 5, we examine the amplification effect across firms and across time by including an interaction term with financial constraint (Column 4) and an additional triple interaction term with aggregate liquidity shock (Column 5). Column 4 shows that financially constrained firms, relative to unconstrained firms, experience a more pronounced decline in employment growth of 18% on average. Column 5 confirms the amplification effect of financial constraint, and shows that the effect is further amplified in periods when aggregate liquidity risk is high.

[Table 2 here.]

3.2.2 Effect of Mutual Fund Bond Ownership on Employment

Table 3 examines the effect of mutual fund bond ownership on employment. Column 1 presents our baseline OLS regression results. Our main variables of interest are liquidity premium and the interaction between liquidity premium and bond ownership. The interaction coefficient is -0.8342 with t-statistics of -1.97, indicates that for firms with average mutual fund bond ownership (0.165), their employment growth has around $\frac{-0.2495+(-0.8342\times0.165)}{-0.2495} - 1$=55% higher sensitivity to those firms with no bond held by mutual fund, and for firms with one-standard-deviation bond ownership above average, their sensitivity is nearly twice $((-0.2495 + (-0.8342 \times (0.165 + 0.105)))/-0.2495)$ as high as firms with zero bond ownership.

Instrumental Variable Strategy. We then exploit two instrumental variable strategies to establish the causal effect of mutual fund bond ownership on employment. The first instrument exploits an exogenous discontinuous change in investor composition when bonds cross the 10-year maturity threshold, which stems from the investment mandates of mutual funds (see, for example, Bai et al. (2023), Bretscher et al. (2023), Li and Yu (2023), Li (2025)). Bai et al. (2023) and Li and Yu (2023) document that a large fraction of of corporate bond funds are intermediate-term, and only invest in bonds whose maturity is less than 10 years due to their investment mandates. Therefore, bonds with time-to-maturity less than 10 years face larger demand from mutual funds, and hence the larger mutual fund bond ownership. Specifically, we estimate the following two-stage regression

$$\text{Ownership} = \alpha + \gamma \mathbb{1}_{\text{maturity}_{it} > c} + \Theta \mathbf{X}_{it} + \varepsilon_{it}, \tag{6}$$

$$\begin{aligned} y_{it} = & \alpha_t + \beta \text{Liquidity} \times \widehat{\text{Ownership}} + \delta \text{Liquidity} \\ & + \rho \widehat{\text{Ownership}} + \Theta \mathbf{X}_{it} + \varepsilon_{it}. \end{aligned} \tag{7}$$

The first-stage regression estimates the effect of the maturity cutoff on mutual fund bond ownership. In the second stage, we regress the firm outcome on the instrumented bond ownership and its interaction with liquidity premium.

The second instrument is a shift-share instrument on bond ownership, following Fang (2023). The idea is that firms whose initial mutual fund bond holders have experienced larger inflows over time should experience increase in bond ownership, while firms whose initial mutual fund bond holders have shrunk over time need to seek for other investors to sustain funding, and these funds might not be mutual funds. Therefore, we construct the shift-share instrument as

$$z_{i,t} = \frac{\sum_j \text{Amount Held}_{j,i,t_0} \text{Fund Flow}_{j,t_0,t}}{\text{Amount Outstanding}_{i,t}}, \tag{8}$$

where t_0 is the beginning of sample period. Amount Held_{j,i,t_0} is mutual fund j's bond ownership of firm i's bonds at t_0, Fund $\text{Flow}_{j,t_0,t}$ is the cumulative net flows to bond fund i from t_0 to t, and Amount $\text{Outstanding}_{i,t}$ is firm i's total bonds outstanding at t.

Column 2 in Table 3 presents the regression results using our first instrument, and Column 3 presents the results for the second instrument. In both regressions, the interaction term of liquidity premium and bond ownership, which is our main variable of interest, remain negatively significant. And their magnitudes are both larger than the coefficient obtained from the OLS regression, suggesting that there is indeed endogeneity concern regarding the bond ownership. The F-statistics in both instrumental variable regressions are above the conventional threshold of 10.

[Table 3 here.]

3.2.3 Effect of Mutual Fund Bond Ownership on Financial and Real Outcomes

We explore whether the effect of mutual fund bond ownership extend to other firm decisions. Table 4 presents the results for the effect of mutual fund bond ownership on debt issuance and investment. Columns 1, 2, 4 and 5 repeat our liquidity risk analysis for employment, and show that liquidity premium negatively significantly affect firms' debt issuance and investment, with financially constrained firms experience more pronounced effects. Columns 3 and 6 examine whether mutual fund bond ownership amplifies the negative effect of liquidity premium on debt issuance and investment, respectively. The debt issuance and investment of firms with one-standard-deviation mutual fund bond ownership is almost twice and 2.5 times as sensitive as to those with zero mutual fund bond ownership, respectively.

Taken together, Table 4 that the effect of mutual fund bond ownership is not concentrated on firms' employment decisions, but extend to other important firm activities such as financing and investment decisions.

[Table 4 here.]

3.2.4 Inspecting Mechanisms of Bond Ownership

We further examine potential mechanisms through which bond ownership affect firm employment and other financial and real outcomes. We focus on three channels: mutual fund flows, rollover risk, and cash buffer.

Mutual Fund Flows. We investigate whether the pressure of fund redemptions amplifies the effect of bond ownership. The fragility of mutual funds stems largely from the liquidity mismatch between their open-ended liabilities and illiquid assets. When funds experience significant outflows, they may be forced to engage in fire sales to meet redemption requests, depressing bond prices and raising borrowing costs for firms (Coval and Stafford, 2007). As a result, firms whose bondholders face larger outflows will experience a more severe contraction in employment and other activities.

Rollover Risk. We examine whether the firm's debt maturity structure amplifies the impact of mutual fund bond ownership. Firms with a large fraction of debt maturing in the short term—high rollover risk—are more dependent on the stability of their investor base. If a firm relies heavily on mutual funds for financing and simultaneously faces immediate refinancing needs, any fragility or retrenchment by those funds becomes binding.

Cash Buffer. We explore whether internal liquidity can shield firms from the negative effects of mutual fund bond ownership. While high mutual fund ownership exposes firms to capital supply shocks, firms with substantial internal resources—cash buffers—are less reliant on external capital markets to fund their operations. A strong cash position allows firms to decouple their employment and other decisions from the volatility of their bondholders.

Table 5 examines the three channels that we discuss above. As mentioned earlier, we follow Dou et al. (2022) to construct the fund flow shock, so the fund flow shock measures the fund inflow rather than outflow. Note that our baseline result–interaction between liquidity premium and mutual fund bond ownership–remain negatively significant across all specifications, confirming our baseline findings. Another variable of interest in these regressions is the interaction between each channel with mutual fund bond ownership. Across all specifications, we can see that each of the three channels significantly transmits the effect of mutual fund bond ownership. Column 1 shows that mutual fund inflow (outflow) substantially mitigates (amplifies) the negative effect of mutual fund bond ownership on employment growth, firms held by mutual funds with a one-standard-deviation increase in fund inflow (outflow) will have $0.0187 \times 0.17 \times 0.57 = 0.18\%$ higher (lower) employment growth, relative to the average employment growth 0.85%, this is more than a one-fifth decline. Columns 2 and 3 present the results for rollover risk and cash buffer channels, and show that rollover risk significantly amplifies the effect of mutual fund bond ownership, whereas cash buffer reduces it, consistent with our expectation.

Table 6 examines the three channels with respect to firms' financing and investment decisions, specifically debt issuance and capital investment. The interaction effect between liquidity premium and mutual fund bond ownership again remain negatively significant across all regressions, lending further support to our previous findings. Columns 1 and 4 examine the fund flow channel of mutual fund bond ownership and the effect on debt issuance and investment, respectively. The coefficient in column 1 is 0.9359 with t-statistics of 0.83, and in column 4 is 0.6692 with t-statistics of 1.72, suggest that mutual fund inflow (outflow) significantly mitigates (amplifies) the effect of mutual fund bond ownership on investment. Columns 2 and 5, and 3 and 6 examine the rollover risk channel and the cash buffer channel of bond ownership. The results show that mutual fund bond ownership affect firm's debt issuance through both rollover risk and cash buffer channels, while remaining silent for investment. Collectively, these findings confirm that mutual fund bond ownership plays a pivotal role in shaping firms' financial and real outcomes, with its impact significantly amplified or mitigated through specific transmission channels. This heterogeneity is economically reasonable, suggesting that real investment activities are more responsive to fund flow shocks, whereas debt issuance decisions are tied more closely to internal liquidity management via rollover risk and cash holdings.

[Table 5 here.]

[Table 6 here.]

3.2.5 Heterogeneity in Bond Ownership

We have shown that mutual fund bond ownership significantly affects firm employment and other financial and real outcomes, and this effect can be exerted through three channels including mutual fund flows, rollover risk, and cash buffer. In this section, we ask whether this effect also exists in the bond ownership of other types of funds, and we focus on the bond ownership of insurance funds, which is a typical type of traditional and large corporate bond investors (e.g., Li (2025)).

Table 7 examines the effect of insurance fund bond ownership. Column 1 runs our baseline bond ownership regression, and columns 2 to 4 investigate different mechanisms for the effect of bond ownership. Across all regressions, insurance fund bond ownership does not have significant effect on firm employment, and none of the mechanisms appear to mediate its effect.

[Table 7 here.]

3.3 Robustness Checks

We conduct three sets of robustness checks. As our main results are at annual frequency, we test whether these results, especially the effect of liquidity premium and bond ownership, exist also in quarterly data. In Table B.1, we use job postings data from Revelio Labs as a proxy for employment growth at quarterly frequency, and examine whether our main results carry through. We additionally control for job category fixed effect, removing time-invariant unobserved heterogeneity across jobs, and quarter fixed effects, removing common time-specific shocks and seasonality. Column 1 examines the effect of liquidity premium, and column 2 examines the effect of mutual fund bond ownership. The job postings of firms with one-standard-deviation higher mutual fund bond ownership above average is more than twice $((-0.2452 \times 0.112 - 0.0228)/-0.0228 = 2.2)$ as sensitive to liquidity premium as average firms, validating our main results at quarterly frequency.

In the second robustness check, we employ the sample of 10-year tenor CDS contracts. Table B.2 shows that the results remain qualitatively and quantitatively similar to our main findings using 5-year CDS contracts sample. We conduct a third set of robustness check by excluding crisis periods, including financial crisis and Covid periods. Table B.3 shows that our main results of liquidity premium and mutual fund bond ownership carry through.

[Table B.1 here.]

[Table B.2 here.]

[Table B.3 here.]

4 Model

We develop a discrete-time partial equilibrium model with a continuum of heterogeneous firms. Firms choose investment, hiring, and financing optimally under both aggregate and idiosyncratic risk. Corporate debt is defaultable and traded in financial markets. A key feature of the model is heterogeneity in the investor base for corporate bonds: debt is held by intermediaries with different funding structures. As a result, the sensitivity of firms' bond financing conditions to aggregate liquidity depends on the ownership composition—debt held by mutual funds is more exposed to liquidity shocks, whereas debt held by long-horizon institutions provides more stable funding. This mechanism governs how aggregate liquidity shocks transmit to firms' financing costs and, ultimately, to their real decisions. We capture this channel with a reduced-form wedge in debt issuance whose exposure to aggregate liquidity shocks varies with investor composition.

4.1 Firm's Problem

The firm, indexed by $i \in I$, uses capital inputs K_{it} and labor inputs N_{it} to produce output Y_{it}, according to the following Cobb-Douglas production technology:

$$Y_{it} = Z_{it} \left(K_{it}^{\alpha} N_{it}^{1-\alpha} \right)^{\theta}, \tag{9}$$

where $0 < \theta < 1$ controls returns to scale. The aggregate productivity X_t follows a log-AR(1) process

$$x_{t+1} = \rho_x x_t + \sigma_x \varepsilon_{t+1}^{x}, \quad \varepsilon_{t+1}^{x} \sim \mathcal{N}(0,1), \tag{10}$$

where $x_{t+1} = \log\left(X_{t+1}\right)$.

Firms are also exposed to idiosyncratic productivity shocks, which follow the log-AR(1) process

$$z_{i,t+1} = (1-\rho_z)\bar{z} + \rho_z z_{i,t} + \sigma_z \varepsilon_{i,t+1}^{z}, \qquad \varepsilon_{i,t+1}^{z} \sim \mathcal{N}(0,1), \tag{11}$$

with $z_{i,t} = \log Z_{i,t}$ and $\varepsilon_{i,t+1}^{z}$ independent across firms and from ε_{t+1}^{x}.

Physical capital accumulation is given by

$$K_{i,t+1} = (1-\delta)K_{it} + I_{it}, \tag{12}$$

where I_{it} represents investment by firms at time t and $0 < \delta < 1$ denotes the capital depreciation rate.

Investment and labor adjustment are subject to convex adjustment costs

$$\Phi_{i,t} = \frac{c_k}{2}\left(\frac{I_{i,t}}{K_{i,t}}\right)^2 K_{i,t} + \frac{c_n}{2}\left(\frac{N_{i,t} - (1-\delta_n)N_{i,t-1}}{N_{i,t-1}}\right)^2 N_{i,t-1}, \tag{13}$$

where $c_k, c_n > 0$. The convex cost component captures the fact that the adjustment costs may be related to the rate of adjustment because of higher costs for more rapid changes.

Wage Equation We introduce wage rigidity following Belo et al. (2014):

$$W_t = \tau_1 \exp(\tau_2 x_t), \tag{14}$$

where the scaling factor $\tau_1 > 0$, and $0 < \tau_2 < 1$ allows us to capture the empirical fact that the aggregate real wage rate is less volatile than aggregate output as well as the procyclicality of the real wage rate.

Debt contract and default choice with taste shock Firms can issue one-period defaultable debt $B_{i,t+1}$ at price $P_{i,t}$, with coupon rate c. At each date t, equity holders decide whether to continue operating the firm or default. In default, the firm is liquidated, and creditors recover liquidation value

$$L_{i,t} = \varphi(1-\delta)K_{i,t}, \tag{15}$$

where $0 < \varphi < 1$ denotes the recovery ratio.

We model default using a taste shock formulation.[2] Let $V^r_{i,t}$ denote the continuation value of operating the firm and $V^d_{i,t}$ the value in default. Equity holders observe idiosyncratic shocks $\epsilon^r_{i,t}$ and $\epsilon^d_{i,t}$, i.i.d. type-I extreme value with scale pa-

[2]Rather than modeling default as a deterministic discrete choice, we introduce idiosyncratic type-I extreme value shocks to continuation and default values. This yields a smooth default probability that converges to the standard limited-liability default rule as the scale parameter $\xi_d \to 0$. This approach is now standard in quantitative sovereign and consumer default models and greatly facilitates global solution methods without altering the underlying economic mechanism (Dvorkin et al., 2021; Chatterjee et al., 2023; Mihalache, 2025).

rameter ξ_d, independent of productivity shocks. The ex-ante firm value is

$$V_{i,t} = \mathbb{E}_\epsilon \max\{V^r_{i,t} + \epsilon^r_{i,t}, V^d_{i,t} + \epsilon^d_{i,t}\} = \xi_d \log\left[\exp\Big(\frac{V^r_{i,t}}{\xi_d}\Big) + \exp\Big(\frac{V^d_{i,t}}{\xi_d}\Big)\right]. \tag{16}$$

The implied *ex-ante default probability* is

$$\mathcal{D}_{i,t} = \frac{\exp\big(V^d_{i,t}/\xi_d\big)}{\exp\big(V^r_{i,t}/\xi_d\big) + \exp\big(V^d_{i,t}/\xi_d\big)}. \tag{17}$$

The proof of Equations (16) (17) is in Appendix C.1. We normalize $V^d_{i,t} = 0$, so we have

$$V_{i,t} = \xi_d \log\left[1 + \exp\Big(\frac{V^r_{i,t}}{\xi_d}\Big)\right], \tag{18}$$

$$\mathcal{D}_{i,t} = \frac{1}{1 + \exp\big(V^r_{i,t}/\xi_d\big)}. \tag{19}$$

As $\xi_d \to 0$, default becomes deterministic: the firm defaults if and only if $V^r_{i,t} < 0$. Conditional on continuation, the firm chooses investment, labor, and next-period debt to maximize equity value:

$$V^r_{i,t} = \max_{I_{i,t}, N_{i,t+1}, B_{i,t+1}} \Big\{D_{i,t} + \mathbb{E}_t[M_{t,t+1}V_{i,t+1}]\Big\}. \tag{20}$$

where $M_{t,t+1}$ is the stochastic discount factor specified later in Equation (26).

Given default risk, the price of debt satisfies

$$P_{i,t} = \mathbb{E}_t\left[M_{t,t+1}\left((1+c)(1-\mathcal{D}_{i,t+1}) + \frac{L_{i,t+1}}{B_{i,t+1}}\mathcal{D}_{i,t+1}\right)\right]. \tag{21}$$

Liquidity wedge and payout Taxable corporate profits are equal to output minus fixed operating cost, capital depreciation, wages, and coupon payments $Y_{i,t} - W_t N_{i,t} - \delta K_{i,t} - cB_{i,t} - f$. The firm's equity payout before issuance costs satisfies

$$E_{i,t} = (1-\tau)(Y_{i,t} - W_t N_{i,t} - f) + \tau\delta K_{i,t} - I_{i,t} - \Phi_{i,t} - (1+(1-\tau)c)B_{i,t} + P_{i,t}B_{i,t+1}e^{\gamma l_t}, \tag{22}$$

where τ is the corporate tax rate, $\tau\delta K_t$ is the depreciation tax shield.

The term $e^{\gamma l_t}$ is a liquidity wedge that scales bond issuance proceeds. The aggregate l_t follows an AR(1) process as

$$l_{t+1} = \rho_l l_t + \sigma_l \varepsilon^l_{t+1}, \quad \varepsilon^l_{t+1} \sim \mathcal{N}(0,1). \tag{23}$$

A lower aggregate state l_t reduces effective bond financing, increasing the cost of external funds. The parameter γ governs the sensitivity of bond financing to aggregate liquidity conditions and captures heterogeneity in investor funding stability: higher γ corresponds to bondholders subject to stronger redemption-driven liquidity shocks, while lower γ corresponds to stable long-horizon investors.

When the sum of investment and the capital and debt adjustment costs exceeds the sum of after-tax operating profits and the net debt financing, firms can take external funds by means of seasoned equity offerings. The external equity issuance is $\max\{-E_{it}, 0\}$, and we follow Hennessy and Whited (2007) to model equity issuance costs as:

$$\Psi(E_{it}) = (\eta_0 - \eta_1 E_{it}) \mathbf{1}_{\{E_{it}<0\}}, \tag{24}$$

with $\eta_0, \eta_1 > 0$. Finally, firms do not incur costs when paying dividends or repurchasing shares. The cash flow distributed to shareholders is

$$D_{it} = E_{it} - \Psi(E_{it}). \tag{25}$$

Stochastic discount factor Given the focus on the production side of the economy, we follow Berk et al. (1999) and Zhang (2005), and directly specify the stochastic discount factor (SDF) as

$$M_{t,t+1} = \beta \frac{\exp(\gamma_{x,t}(x_t - x_{t+1}) + \gamma_{l,t}(l_t - l_{t+1}))}{\mathbb{E}_t[\exp(\gamma_{x,t}(x_t - x_{t+1}) + \gamma_{l,t}(l_t - l_{t+1}))]} \tag{26}$$

$$\text{where } \gamma_{x,t} = \gamma_{x,0} + \gamma_{x,1}\big(x_t - \mathbb{E}[x]\big), \tag{27}$$

$$\gamma_{l,t} = \gamma_{l,0} + \gamma_{l,1}\big(l_t - \mathbb{E}[l]\big). \tag{28}$$

4.2 Recursive Equilibrium

For tractability, we assume the aggregate liquidity-wedge state and aggregate productivity are perfectly correlated, capturing the idea that periods with high liquidity premia coincide with sharp declines in productivity. We now write the firm's problem in recursive form. We drop the firm index i. The state vector is

$$S_t := (K_t, N_t, B_t, X_t, Z_t). \tag{29}$$

A recursive equilibrium is a set of value functions $\{V(S), V^r(S)\}$ and policy functions $\{\mathcal{D}(S), I(S), N'(S), B'(S), P(S)\}$ satisfying

1. The Bellman equation

$$V^r(S_t) = \max_{I_t, N_{t+1}, B_{t+1}} \Big\{ D_t + \mathbb{E}_t[M_{t,t+1} V(S_{t+1})] \Big\}. \tag{30}$$

   where the ex-ante firm value satisfies

$$V(S_t) = \xi_d \log\left[1 + \exp\Big(\frac{V^r(S_t)}{\xi_d}\Big)\right], \tag{31}$$

   and dividends satisfy

$$D_t = (1-\tau)(Y_t - W_t N_t - f) + \tau\delta K_t - I_t - \Phi_t - (1+(1-\tau)c)B_t + P_t B_{t+1} e^{\gamma x_t} - \Psi(E_t), \tag{32}$$

   with Y_t, W_t, Φ_t, E_t, and $\Psi(\cdot)$ are defined earlier.

2. The default rule

$$\mathcal{D}(S_t) = \frac{1}{1 + \exp\big(V^r(S_t)/\xi_d\big)}. \tag{33}$$

3. The bond pricing equation

$$P_t(S_t) = \mathbb{E}_t\left[M_{t,t+1}\left((1+c)(1-\mathcal{D}(S_{t+1})) + \frac{L_{t+1}}{B_{t+1}}\mathcal{D}(S_{t+1})\right)\right]. \tag{34}$$

   with the SDF $M_{t,t+1}$ defined in Equation (26).

4. The state transition $S_{t+1} = (K_{t+1}, N_{t+1}, B_{t+1}, X_{t+1}, Z_{t+1})$, where $K_{t+1} =$

$(1-\delta)K_t + I_t$, and (X_t, Z_t) follow the stochastic processes specified earlier.

5 Model Solution and Quantitative Results

5.1 Deep Learning Based Solution Method

The model features a five-dimensional state space and endogenous defaultable bond pricing. Solving such heterogeneous-firm models with equilibrium bond prices typically requires nested fixed-point iterations over value and price functions, as in Kuehn and Schmid (2014). We instead adopt a deep-learning-based global solution method, following recent advances in Azinovic et al. (2022); Maliar et al. (2021); Han et al. (2021); Duarte et al. (2024).

The key idea is to approximate equilibrium value and policy functions by flexible function approximators and directly optimize over their parameters so that equilibrium conditions hold. In particular, we parameterize the continuation value and the firm's policy rules for next-period capital, labor, and debt using neural networks. Once these objects are parameterized, all remaining equilibrium objects, such as default probabilities and bond prices, are implied by the model's equilibrium equations. The solution is obtained by adjusting neural network parameters to minimize the sum of residuals of the Bellman equation and the firm's optimality conditions.[3]

Formally, we approximate

$$V_r(S_t) \approx \widehat{V}_r(S_t; \Theta_V), \tag{35}$$

$$K_{t+1}(S_t) \approx \widehat{K}(S_t; \Theta_K), \quad N_{t+1}(S_t) \approx \widehat{N}(S_t; \Theta_N), \quad B_{t+1}(S_t) \approx \widehat{B}(S_t; \Theta_B), \tag{36}$$

where $\Theta_V, \Theta_K, \Theta_N, \Theta_B$ denote neural network parameters.

The training objective aggregates equilibrium residuals across the entire state space; its explicit form is reported in Appendix D. The solution algorithm is summarized in Algorithm 1. After training, all equilibrium conditions are satisfied to

[3]The taste-shock formulation of default yields smooth default probabilities, and the bond pricing equation is differentiable in policy arguments. These features make gradient-based training of neural network approximations particularly well suited for solving the model.

high numerical precision, with residuals on the order of 10^{-7}–10^{-6} across the state space.

5.2 Calibration

Each period t corresponds to a month. Table 8 reports the baseline parameterization. Parameters are chosen either from existing literature, such as Belo et al. (2025), or to match key firm-level and aggregate moments reported in Table 9. In particular, adjustment cost, fixed operating cost, and liquidity sensitivity parameters are set to discipline investment volatility, employment dynamics, leverage, and default frequencies.

[Table 8 here.]

[Table 9 here.]

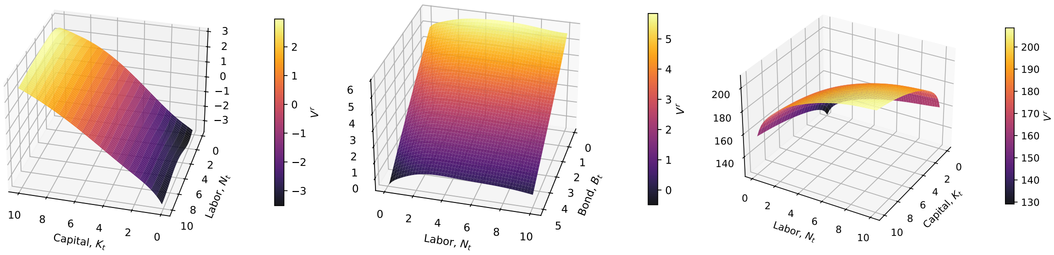
Table 9 compares selected data moments with their model-implied counterparts. The model matches the average default probability (2.6% in the model versus 1.7% in the data) and average leverage closely. It also reproduces realistic credit spreads and a Sharpe ratio of 0.68, comparable to its empirical counterpart. At the firm level, the model generates volatile and persistent debt and employment dynamics of the same order of magnitude as in the data.

5.3 Results

5.3.1 Value and Policy Functions

Figures 2–5 illustrate the solved continuation value and policy functions. All functions are five-dimensional in $(K_t, N_t, B_t, x_t, z_t)$. For visualization, we fix selected state variables and plot the remaining dimensions. Unless otherwise stated, we set $x_t = 0$ and consider two firm-level productivity states: low productivity $z_L = -4.279$ and high productivity $z_H = 0.759$.

Figure 2 plots the continuation value V^r along three two-dimensional slices of the state space. Panels (a) and (c) show V^r as a function of (K_t, N_t) at a fixed intermediate level of debt for low and high productivity, respectively, while panel



(a) $V^r(K, N, z_L)$ (b) $V^r(N, B, z_H)$ (c) $V^r(K, N, z_L)$

Figure 2: Value function of (K, N, B) at middle B or K, low z_L or high z_H

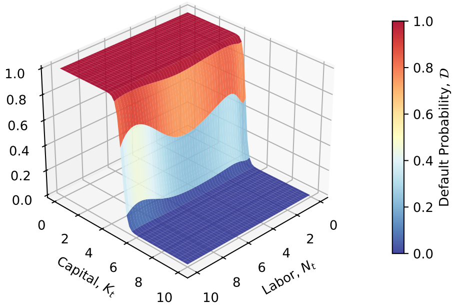
(b) plots V^r as a function of (N_t, B_t) at a fixed intermediate level of capital. Across all panels, firm value is increasing in capital and decreasing in debt. Higher capital raises productive capacity, whereas higher outstanding debt tightens financing constraints and increases default risk, lowering continuation value.

The dependence of firm value on employment is nonlinear and non-monotone. In Figure 2(b), at low employment levels, increases in N_t raise firm value by expanding production. At higher employment levels, however, continuation value declines, reflecting diminishing returns to labor with wage rigidity and convex labor adjustment costs that make large payrolls costly to sustain. As a result, firm value is maximized at interior employment levels rather than at corner solutions.

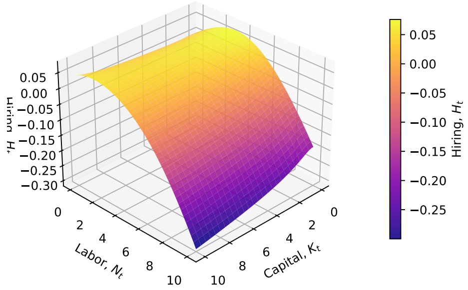
Productivity shifts the entire value surface. When productivity is high, V^r remains strictly positive over the state space, implying zero default risk. When productivity is low, V^r becomes negative for firms with low capital or high debt, generating an endogenous default region. These patterns are directly mirrored in the default probability plots discussed below.

Figures 3 and 4 report the policy functions for default probability $\mathcal{D}$, hiring $H = N_{t+1} - (1 - \delta_n)N_t$, investment $I = K_{t+1} - (1 - \delta)K_t$, and next-period debt B', plotted as functions of (K_t, N_t) at fixed intermediate levels of B_t and x_t. At low productivity (Figure 3), firms with low capital optimally default, while surviving firms reduce hiring and investment. Higher current capital and employment imply lower hiring and lower investment, reflecting decreasing marginal returns.

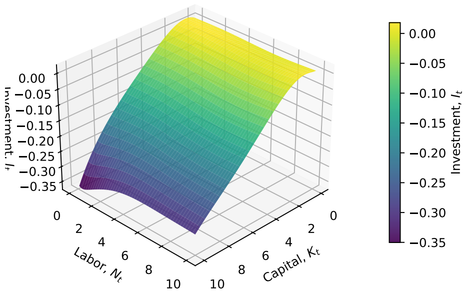
At high productivity (Figure 4), default disappears. Hiring exhibits a hump shape in current employment: firms with very low or very high employment adjust



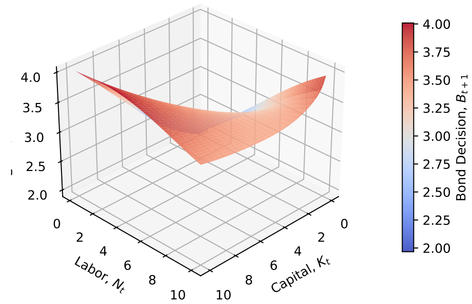
(a) Default $\mathcal{D}$



(b) Hiring H



(c) Investment I



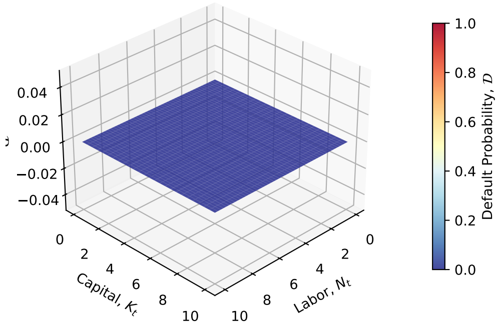
(d) Debt B'

Figure 3: Policy as functions of (K, N) at middle B, x, low z

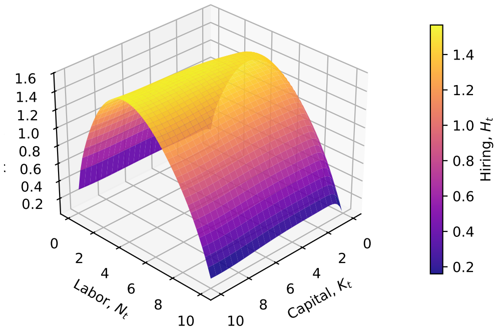
less, while intermediate firms expand hiring most aggressively. Investment displays a similar hump shape in capital, consistent with convex capital adjustment costs. Debt issuance shows a U-shaped dependence on capital and labor, reflecting the joint role of financing investment and smoothing internal funds.

Figure 5 presents an additional slice of the policy functions at fixed intermediate level of capital, low aggregate productivity, and low firm-level productivity, plotted as functions of (N_t, B_t). Default probability increases sharply with debt, consistent with the value function in Figure 2(b). Default risk is highest for firms with very high debt and either very low or very high employment, mirroring regions where continuation value is lowest. Hiring is decreasing in current employment and increasing in debt, reflecting both labor adjustment costs and financing needs. Investment is increasing in employment, while debt issuance exhibits a hump-shaped dependence on employment, peaking at intermediate labor levels.

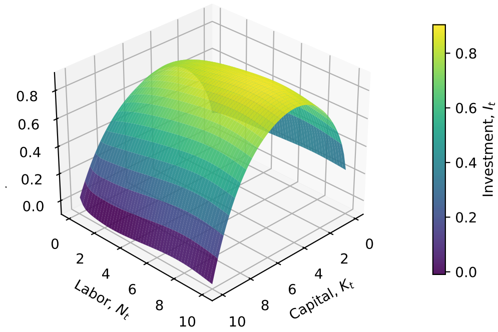
Overall, the shapes of the value and policy functions are economically intuitive



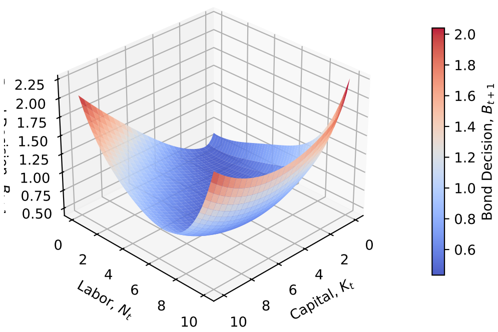
(a) Default $\mathcal{D}$



(b) Hiring H



(c) Investment I



(d) Debt B'

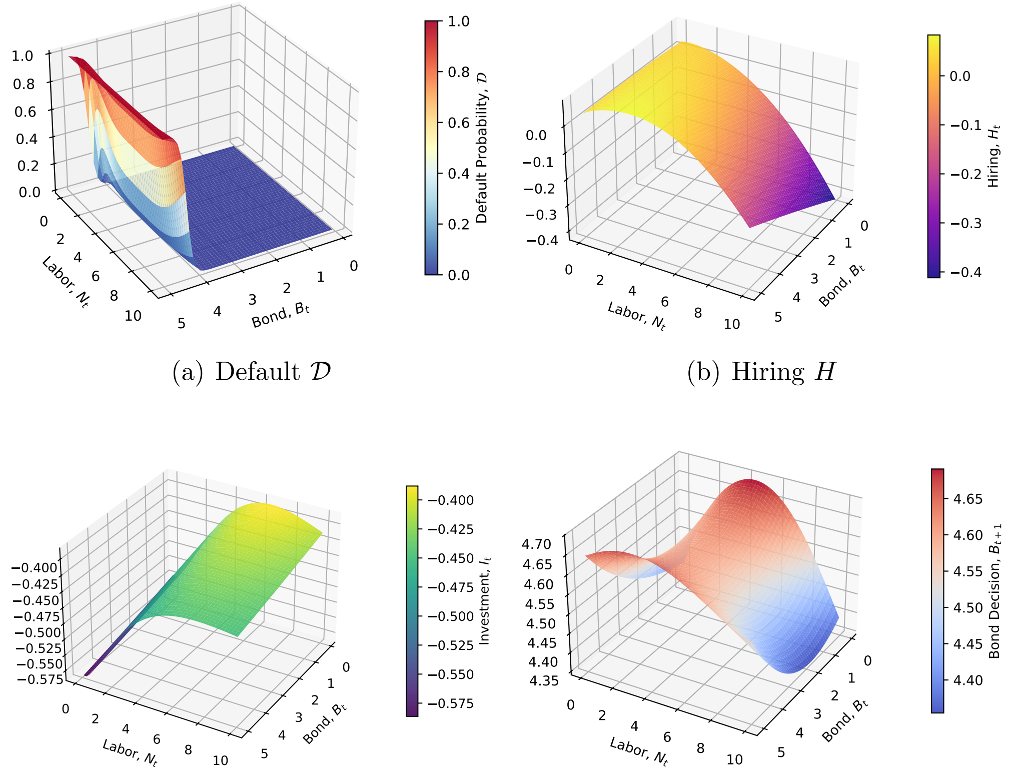
Figure 4: Policy as functions of (K, N) at middle B, x, high z

and internally consistent across state-space slices. They confirm that the deep-learning-based solution captures rich nonlinear interactions between employment, investment, leverage, and default in a high-dimensional environment.

5.3.2 IRF to Liquidity Shock: The Role of Heterogeneous Investor

We now study the dynamic response of aggregate employment and bond issuance to a negative aggregate liquidity shock, and how this response depends on the composition of corporate bond investors. Figure 6 reports generalized impulse responses (GIRFs) of aggregate employment N_t following a one-period adverse liquidity shock.

Because the model is nonlinear and features endogenous default and bond pricing, impulse responses are computed using the GIRF framework of Koop et al.



(a) Default $\mathcal{D}$

(b) Hiring H

(c) Investment I

(d) Debt B'

Figure 5: Policy as functions of (N, B) at middle K, low x, z

(1996). Let $\mathcal{I}_{t-1}$ denote the information set at time $t-1$, and let S_t denote the vector of aggregate state variables, including aggregate productivity and liquidity conditions. For any outcome Y_{t+h}, the GIRF at horizon h is defined as

$$\mathrm{GIRF}_Y(h) = \mathbb{E}[Y_{t+h} \mid S_t = \underline{S}, \mathcal{I}_{t-1}] - \mathbb{E}[Y_{t+h} \mid S_t = S_t^*, \mathcal{I}_{t-1}], \tag{37}$$

where S_t^* denotes the realized aggregate state along an unshocked path, while $\underline{S}$ replaces the aggregate liquidity state in period t with its lowest realization, holding fixed all other state variables.

Both expectations are taken conditional on the same information set $\mathcal{I}_{t-1}$ and are computed using identical sequences of idiosyncratic shocks. Future aggregate innovations are also held fixed across the two paths; however, because aggregate states evolve persistently, the different realization of the aggregate shock at time t implies that future aggregate states generally differ across the shocked and unshocked paths. GIRFs are computed by averaging the difference in outcomes across many simulated paths. All responses are reported as percentage deviations from the ergodic mean of the corresponding variable.

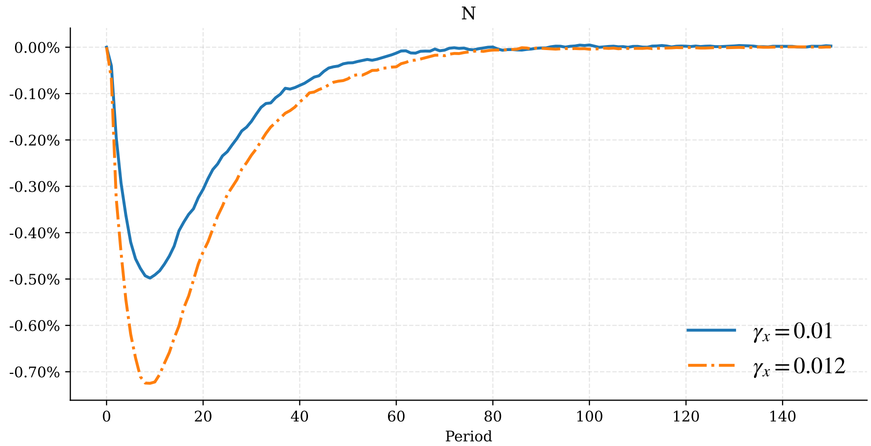


Figure 6: Employment dynamics to a liquidity shock with heterogeneous investor elasticity

We conduct this experiment under two values of the liquidity sensitivity parameter γ, which governs how strongly bond financing conditions respond to aggregate liquidity through investor composition. A higher γ corresponds to a larger share of corporate bonds held by investors with elastic funding, such as mutual funds, while a lower γ reflects a more stable investor base.

Figure 6 shows that aggregate employment declines following the liquidity shock in both economies, with a larger contraction when investor demand is more elastic. When $\gamma = 0.01$, employment falls by about 0.5 percent at its trough, while increasing γ to 0.012 deepens the decline to roughly 0.65 percent. The response of employment is highly persistent, reflecting the strong persistence of the underlying aggregate shock, calibrated with $\rho_x = 0.95$, which sustains tight financing conditions and delays the recovery of labor demand. The amplification mechanism operates through bondholder fragility. When corporate debt is held by investors with more elastic funding, adverse liquidity shocks generate larger price dislocations in bond markets, tightening firms' effective financing conditions and inducing sharper employment cuts.

6 Conclusion

This paper shows that liquidity risk in corporate bond markets has economically meaningful real effects and that these effects depend critically on who holds firms' debt. Using panel data on U.S. firms, corporate bond liquidity premia, and bondholder composition, we document that increases in the bond–CDS spread differential predict weaker labor market outcomes both in aggregate (lower employment growth and higher unemployment) and at the firm level (slower employment growth). Importantly, this relationship is strongly heterogeneous: firms whose bonds are more heavily held by open-ended mutual funds—investors with redeemable liabilities and flow-driven funding pressure—exhibit substantially greater sensitivity of employment, issuance, and investment to liquidity premia.

To move beyond correlation, we use two complementary instrumental-variable strategies—variation around maturity cutoffs tied to fund mandates and shift-share variation from fund flows—to isolate plausibly exogenous changes in mutual fund ownership. Both approaches support a causal interpretation: mutual fund ownership amplifies the transmission of liquidity shocks to firm outcomes. Additional evidence on mechanisms is consistent with a liquidity-mismatch channel: the amplification is stronger when fund flows are adverse and when firms face greater rollover needs, and it is weaker when firms have larger cash buffers. By contrast, we do not find comparable amplification for insurance-company ownership, consistent with the view that stable long-horizon liabilities dampen rather than propagate liquidity stress.

To interpret these findings and assess their quantitative implications, we develop a partial-equilibrium model of heterogeneous firms with defaultable debt, labor adjustment frictions, and investor-dependent bond financing conditions. Liquidity shocks operate by tightening effective bond financing through prices and issuance proceeds, and the resulting contraction in investment and hiring is stronger when the investor base is more "elastic" to liquidity conditions. The model reproduces key empirical patterns and provides a disciplined mapping from changes in liquidity conditions and ownership composition to labor market outcomes.

The results highlight a broader implication: the real effects of market disruptions depend not only on firm balance sheets, but also on the structure of creditor demand. From a policy perspective, interventions that affect the resilience of key bond market investors—such as liquidity management tools, redemption design, and dealer/intermediary capacity—may influence employment dynamics during periods of market stress. More generally, our findings suggest that monitoring investor composition can improve early-warning signals for the real consequences of bond-market liquidity deterioration.

Table 1: Liquidity Risk and Labor Market Dynamics

Dependent Variable	Labor Market Tightness (1)	Unemployed Persons/ Job Opening (2)	Unemployment Rate (3)	Employment Growth (4)
Panel A: aggregate bond-CDS spread differential				
Liquidity Premium	-38.2147**	102.1171**	95.7323*	-0.2819***
	(-2.04)	(2.39)	(1.73)	(-2.73)
Panel B: bid-ask spread				
Liquidity Premium	-0.8935*	2.9728***	2.9661**	-0.0037*
	(-1.83)	(2.91)	(2.26)	(-1.68)
Control Variables	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are the t-statistics. Standard errors are Newey-West standard errors with lag equals $floor[4 \times (sample\ size/100)^{2/9}]$ as in Newey and West (1994). Control variables include industry production growth and change in VIX. Unemployed Persons/Job Opening is Unemployed Persons Per Job Opening Ratio. *Return to main text.*

Table 2: Liquidity Risk and Employment Growth

Dependent Variable	ΔEmployment				
	(1)	(2)	(3)	(4)	(5)
Liquidity Premium	-0.2802**	-0.3142**	-0.4298**	-0.5135***	-0.5171***
	(-2.13)	(-2.25)	(-2.52)	(-3.25)	(-3.48)
Liquidity Premium × Financial Constraint				-0.0944***	-0.1641***
				(-3.28)	(-5.63)
Liquidity Premium × Financial Constraint × Aggregate Liquidity Shock					-0.2167***
					(-4.12)
Specification	w/o Ctrl. Variables	w/ Ctrl. Variables	Constrained Firms	All Firms	All Firms
No. of Observations	5,706	5,630	2,016	5,577	5,577
No. of Firms	548	539	321	534	534
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm

Note: The numbers in parentheses are the t-statistics. Standard errors are clustered at the firm level. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Variables with Δ is calculated by $\frac{x_t - x_{t-1}}{0.5\times(x_t + x_{t-1})}$. *Return to main text.*

Table 3: Bond Ownership and Employment Growth

Dependent Variable		ΔEmployment	
	(1)	(2)	(3)
Liquidity Premium	-0.2495*	-0.5136	-0.0370
	(-1.67)	(-0.16)	(-0.18)
Bond Ownership	0.0113	-0.0229	0.0340
	(0.74)	(-0.03)	(0.70)
Liquidity Premium			
× Bond Ownership	-0.8342**	-3.9948*	-2.3386*
	(-1.97)	(-1.75)	(-1.73)
Regression	OLS	IV	IV
Instrument		Maturity Cutoff	Shift-share
F-stat		15.8	28.8
No. of Observations	5,488	3,578	5,243
No. of Firms	537	338	527
Firm Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Control Variables	Yes	Yes	Yes

Note: The numbers in parentheses are the t-statistics. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Variables with Δ is calculated by $\frac{x_t - x_{t-1}}{0.5 \times (x_t + x_{t-1})}$. *Return to main text.*

Table 4: Liquidity Risk and Financial and Real Outcomes

Dependent Variable	Investment			Debt Issuance		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity Premium	-0.1468*	-0.1741*	-0.0334	-0.2455*	-0.2818*	-0.1268
	(-1.79)	(-1.86)	(-0.46)	(-1.78)	(-1.67)	(-0.90)
Liquidity Premium						
× Financial Constraint		-0.0108			-0.0672*	
		(-0.32)			(-1.69)	
Liquidity Premium						
× Bond Ownership			-0.4983**			-1.0818**
			(-1.98)			(-2.06)
No. of Observations	5,677	5,626	5,562	5,691	5,629	5,635
No. of Firms	548	541	546	548	541	546
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: The numbers in parentheses are the t-statistics. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Variables with Δ is calculated by $\frac{x_t - x_{t-1}}{0.5\times(x_t + x_{t-1})}$. *Return to main text.*

Table 5: Mechanisms of Mutual Fund Bond Ownership Effect on Employment

Dependent Variable	ΔEmployment		
	(1)	(2)	(3)
Liquidity Premium	-0.2357	-0.2281	-0.2007
	(-1.34)	(-1.00)	(-1.05)
Bond Ownership	-0.0051	0.0279	-0.0072
	(-0.32)	(1.47)	(-0.39)
Liquidity Premium × Bond Ownership	-0.9505**	-0.9118**	-0.8465**
	(-1.98)	(-2.04)	(-1.98)
Fund Flow Shock × Bond Ownership	0.0187*		
	(1.66)		
Rollover × Bond Ownership		-0.0729*	
		(-1.67)	
Cash × Bond Ownership			0.1696*
			(1.91)
Fund Flow Shock	-0.0012		
	(-0.83)		
Rollover		-0.0049	
		(-0.36)	
Cash			0.0316
			(0.90)
Liquidity Premium × Fund Flow Shock	-0.0027		
	(-0.02)		
Liquidity Premium × Rollover		-0.0225	
		(-0.06)	
Liquidity Premium × Cash			-0.4836
			(-0.35)
No. of Observations	5,166	5,112	5,488
No. of Firms	528	524	537
Firm Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Clustering	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes

Note: The numbers in parentheses are the t-statistics. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Variables with Δ are calculated by $\frac{x_t - x_{t-1}}{0.5\times(x_t + x_{t-1})}$. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. *Return to main text.*

Table 6: Mechanisms of Mutual Fund Bond Ownership Effect on Financial and Real Outcomes

Dependent Variable	Investment			Debt Issuance		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity Premium	-0.0286	-0.0691	-0.0677	-0.0186	-0.3130*	-0.0500
	(-1.48)	(-0.50)	(-0.66)	(-0.12)	(-1.72)	(-0.25)
Bond Ownership	-0.0057	-0.0423***	-0.0245**	-0.0685***	-0.0350	-0.0762***
	(-1.29)	(-2.72)	(-2.09)	(-3.93)	(-1.55)	(-4.34)
Liquidity Premium × Bond Ownership	-0.2488**	-0.5427**	-0.5298*	-1.4349***	-1.2229**	-0.9909*
	(-1.98)	(-2.04)	(-1.88)	(-3.05)	(-2.28)	(-1.66)
Fund Flow Shock × Bond Ownership	0.6692*			0.9359		
	(1.72)			(0.83)		
Rollover × Bond Ownership		0.0548			-0.1176*	
		(1.54)			(-1.78)	
Cash × Bond Ownership			0.0317			0.1326**
			(0.68)			(2.22)
Fund Flow Shock	-0.1806			0.7252		
	(-1.48)			(1.46)		
Rollover		-0.0061			-0.0107	
		(-0.73)			(-0.47)	
Cash			0.0277*			-0.0003
			(1.81)			(-0.02)
Liquidity Premium × Fund Flow Shock	1.9381*			-5.3786		
	(1.69)			(-1.17)		
Liquidity Premium × Rollover		0.1370			0.8051**	
		(0.59)			(2.09)	
Liquidity Premium × Cash			0.2963			-0.8072
			(0.29)			(-0.54)
No. of Observations	5,300	5,227	5,477	5,304	5,237	5,549
No. of Firms	537	529	538	537	531	546
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Mechanisms of Mutual Fund Bond Ownership Effect on Financial and Real Outcomes (Continued)

Dependent Variable	Investment			Debt Issuance		
	(1)	(2)	(3)	(4)	(5)	(6)

Note: The numbers in parentheses are the t-statistics. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Variables with Δ are calculated by $\frac{x_t - x_{t-1}}{0.5\times(x_t + x_{t-1})}$. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. *Return to main text.*

Table 7: Heterogeneity in Bond Ownership: Insurance Fund

Dependent Variable	ΔEmployment			
	(1)	(2)	(3)	(4)
Liquidity Premium	-0.3060**	-0.3039*	-0.3154	-0.2773
	(-2.13)	(-1.85)	(-1.49)	(-1.53)
Bond Ownership	-0.0025	-0.0021	0.0110	-0.0015
	(-0.37)	(-0.30)	(1.33)	(-0.22)
Liquidity Premium × Bond Ownership	-0.3156	-0.3297	-0.3347	-0.1839
	(-0.52)	(-0.38)	(-0.51)	(-0.30)
Fund Flow Shock × Bond Ownership		-0.0004		
		(-0.11)		
Rollover × Bond Ownership			-0.0271	
			(-1.33)	
Cash × Bond Ownership				0.0542
				(1.59)
Fund Flow Shock		-0.0002		
		(-0.17)		
Rollover			-0.0192	
			(-0.84)	
Cash				0.0215
				(0.56)
Liquidity Premium × Fund Flow Shock		0.0375		
		(0.29)		
Liquidity Premium × Rollover			0.1359	
			(0.37)	
Liquidity Premium × Cash				-0.3628
				(-0.26)
No. of Observations	5,576	5,167	5,113	5,489
No. of Firms	537	528	523	537
Firm Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Clustering	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes

Note: The numbers in parentheses are the t-statistics. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Variables with Δ are calculated by $\frac{x_t - x_{t-1}}{0.5\times(x_t+x_{t-1})}$. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. *Return to main text.*

Table 8: Baseline calibration

Parameter	Interpretation	Value	Target / Source
β	Discount factor	0.99585	Monthly real rate 5% annualized
τ	Corporate tax rate	0.30	Statutory U.S. corporate tax
φ	Recovery rate	0.60	Belo et al. (2025)
θ	Returns to scale	0.82	Belo et al. (2025)
α	Capital share	0.2805	Belo et al. (2025)
δ	Capital depreciation	0.01	Belo et al. (2025)
δ_n	Labor exit rate	0.0214	Belo et al. (2025)
c_k	Capital adjustment cost	10.0	Average investment
c_n	Labor adjustment cost	7.5	Employment growth
f	Fixed operating cost	1.3	Average default rate
η_0	Equity issuance fixed cost	0.5	Hennessy and Whited (2007)
η_1	Equity issuance slope	0.0	Hennessy and Whited (2007)
τ_1	Wage scale	0.025	Belo et al. (2025)
τ_2	Wage elasticity to X_t	1.0	Belo et al. (2025)
ρ_x	Aggregate TFP persistence	0.95	
σ_x	Aggregate TFP volatility	0.10	Output volatility
$\bar{z}$	Average log firm productivity	-2.6	
ρ_z	Idiosyncratic persistence	0.97	Firm-level TFP persistence
σ_z	Idiosyncratic volatility	0.50	Firm-level dispersion
ξ_d	Taste-shock scale	0.10	Smooth default approximation
γ	Liquidity sensitivity	0.001	MF vs insurer ownership effects
γ_0	SDF risk aversion level	5.0	
γ_1	Time-varying risk price slope	0.0	

Return to main text.

Table 9: Data Moments and Model Moments

Moment	Data (1)	Model (2)
	Panel A: Firm-level moments	
ΔDebt	0.0382	0.0040
SD(ΔDebt)	0.2130	0.1202
AR1(ΔDebt)	-0.1260	0.8671
ΔEmployment	0.0097	0.0046
SD(ΔEmployment)	0.1340	0.0626
AR1(ΔEmployment)	-0.0110	0.9738
Investment Rate	0.1940	0.1702
SD(Investment Rate)	0.1150	0.3959
AR1(Investment Rate)	0.3070	0.9819
	Panel B: Aggregate moments	
Leverage Ratio	0.3280	0.4850
Default Probability	0.0173	0.0128
Credit Spread	0.0105	0.0170
Stock Return	0.0889	0.1199
Stock Return Volatility	0.1557	0.1424
Sharpe Ratio	0.5814	0.4827

Return to main text.

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Appendix

A Data Details and Sample Construction

A.1 Aggregate Variables

The sample for aggregate variables contain monthly data from July 2002 to December 2023. Labor market tightness is calculated as the ratio of job vacancies over unemployment level divided by 1000[4]. Unemployed persons per job opening ratio is obtained from Bureau of Labor Statistics. Unemployment rate is obtained from FRED. Employment growth is the growth of employment level from FRED.

We use two proxies for aggregate-level liquidity premium, the first is aggregate bond-CDS spread differential, which is aggregated from bond-level bond spread minus CDS spread. The second is bid-ask spread obtained from WRDS Bond Returns database, and aggregated to monthly frequency. Table A.1 describes the definition and sources of our main variables.

A.2 Liquidity Premium

Our liquidity premium measure is bond spread in excess of CDS spread. Longstaff et al. (2005) decompose bond credit spread into a default and a non-default component, using CDS spread, and argue that the CDS spread mainly summarizes the information of the bond default risk, and the difference between bond credit spread and CDS spread, i.e., bond-CDS spread differential, should reflect the non-default component. Following their argument, we use bond-CDS spread differential as our liquidity premium measure. Bond spread is calculated based on data from TRACE and Mergent, and CDS spread is obtained from Markit database. We first obtain and calculate bond returns from TRACE Enhanced and Mergent FISD. We follow Dick-Nielsen (2014) and Dickerson et al. (2023) to clean and filter the data. The monthly corporate bond return at time t for each bond i in the sample is calculated as

$$R_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1 \tag{38}$$

[4]This calculation follows from `https://fredblog.stlouisfed.org/2015/08/labor-market-tightness/`.

where $P_{i,t}$ is the clean bond price for bond i at time t, $AI_{i,t}$ is the accrued interest for bond i at time t, and $C_{i,t}$ is the coupon (if any) for bond i at time t. We then compute bond spread as bond returns in excess of duration-matched US T-Bond interpolated yields, where the interpolated yields are calculated following Dickerson et al. (2023).

CDS spread is obtained from Markit database. We exclude data with duration of CDS contracts less than one year because their aggregate time series show very different trend compared to those with duration of CDS contracts equal or more than one year. Figure A.1 shows the time series of CDS spread of 5-year tenor and 10-year tenor of CDS contracts, because 5-year CDS contracts constitute the most liquid segment of the CDS market, while 10-year CDS contracts are becoming more common in recent years. We also restrict our sample to the documentation clause type as 'Modified Restructuring' following the conventional rule[5].

A.3 Sample Selection

A.3.1 Compustat

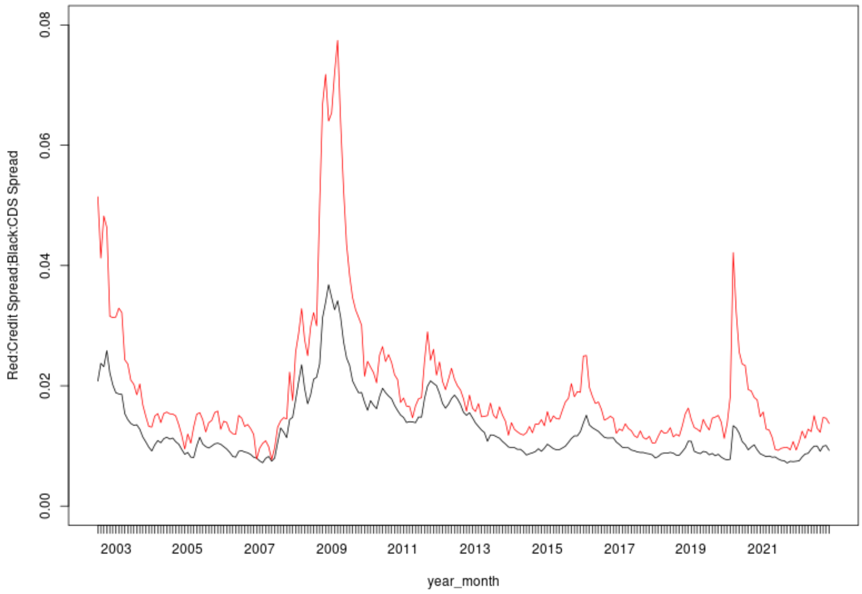
The sample period is from 2002 to 2023. Financial, utilities, and public sector firms are excluded from the main sample. All the variables are at annual frequency. Our main dependent variable in the empirical tests is employment growth, which is measured as $\frac{EMP_t - EMP_{t-1}}{\frac{1}{2}(EMP_t + EMP_{t-1})}$. We define debt issuance as change in assets minus change in book equity, scaled by lagged asset, following Greenwood and Hanson (2013), and measure investment as $\frac{CAPX_t}{PPENT_{t-1}}$. All our empirical specifications include both firm and time fixed effects.

[5] See, for example, Bai and Collin-Dufresne (2019).

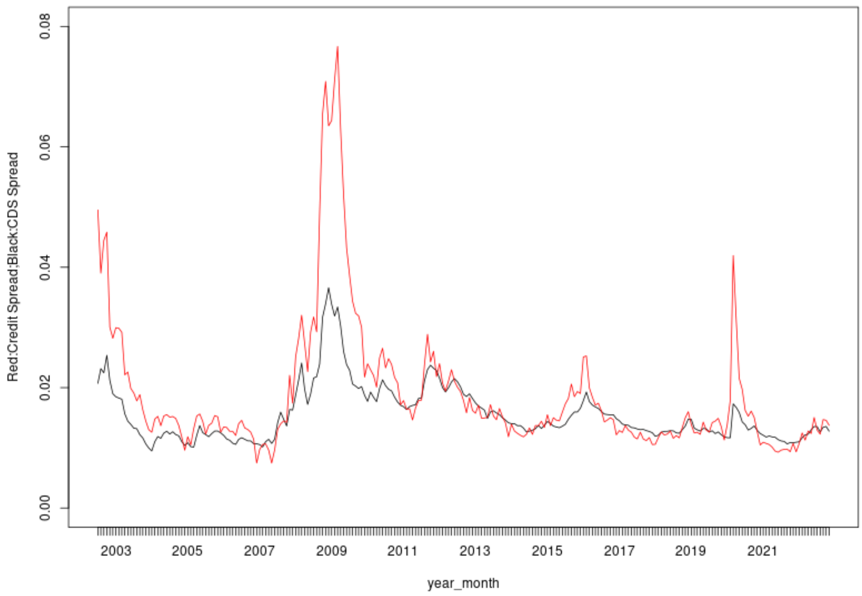
Table A.1: Variable Definition

Variable	Definition	Source
Labor Market		
Unemployment Rate	UNRATE	FRED
Unemployment Level	UNEMPLOY	FRED
Job Vacancies	LMJVTTUVUSM647S	FRED
Employment	CE16OV	FRED
Unemployed Persons Per Job Opening Ratio	NA	BLS JOLTS
Macroeconomic		
VIX	VIXCLS	FRED
Industry Production	INDPRO	FRED
Liquidity		
Bid-Ask Spread	NA	WRDS Bond Returns
Bond spread	NA	TRACE
CDS spread	NA	Markit
Firm Characteristics		
ΔEmployment	$(\text{EMP}_t - \text{EMP}_{t-1})/[0.5 \times (\text{EMP}_t + \text{EMP}_{t-1})]$	Compustat
Investment Rate	$\text{CAPX}_t/\text{PPENT}_{t-1}$	Compustat
Debt	DLC+DLTT	Compustat
Tangibility	$\text{PPENT}_t/\text{AT}_{t-1}$	Compustat
Book Leverage	Debt/(Debt+CEQ)	Compustat
Return on Assets	$\text{EBITDA}_t/\text{AT}_{t-1}$	Compustat
Idiosyncratic Volatility	Annualized standard deviation of firms' cum-dividend daily stock returns	CRSP
Tobin's q	Market value of asset/(0.9×AT+0.1×Market value of asset)	Compustat
Firm Size	log(AT)	Compustat

Figure A.1: CDS Spread and Bond Spread: 5-Year- and 10-Year-Duration of Contracts



(a) 5 Year



(b) 10 Year

B Additional Empirical Results

This section provides additional empirical results.

B.1 Job Postings from Revelio Labs

Table B.1: Liquidity Risk, Bond Ownership, and Job Postings

Dependent Variable	Number of Job Postings	
	(1)	(2)
Liquidity Premium	-0.0300**	-0.0228**
	(-2.17)	(-2.13)
Bond Ownership		-0.0013
		(-0.41)
Liquidity Premium		
$\times$ Bond Ownership		-0.2452*
		(-1.70)
No. of Observations	32,232	23,091
Job Category Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Quarter Fixed Effect	Yes	Yes
Clustering	Firm	Firm
Control Variables	Yes	Yes

Note: The numbers in parentheses are the t-statistics. Standard errors are clustered at the firm level. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Number of job postings is scaled by annual employment of firms. *Return to main text.*

B.2 Results with CDS Contracts of 10Y Tenor

Table B.2: Robustness Check with 10Y Tenor

Dependent Variable	ΔEmployment					
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity Premium	-0.3651**	-0.4808***	-0.2813*	-0.3942**	-0.5801	-0.1283
	(-2.36)	(-2.88)	(-1.68)	(-2.45)	(-0.20)	(-0.55)
Bond Ownership			0.0100	-0.0029	-0.0364	0.0204
			(0.65)	(-0.46)	(-1.07)	(0.44)
Liquidity Premium × Financial Constraint		-0.0972*				
		(-1.81)				
Liquidity Premium × Bond Ownership			-0.6890*	-0.1200	-3.6743*	-2.0282
			(-1.68)	(-0.22)	(-1.92)	(-1.62)
No. of Observations	5,478	5,428	5,428	5,429	3,517	5,133
Regression	OLS	OLS	OLS	OLS	IV	IV
Funds	Mutual Funds	Mutual Funds	Mutual Funds	Insurance Funds	Mutual Funds	Mutual Funds
Instrument					Maturity Cutoff	Shift-share
F-stat					23.1	15.6
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: The numbers in parentheses are the t-statistics. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Variables with Δ is calculated by $\frac{x_t - x_{t-1}}{0.5\times(x_t + x_{t-1})}$. *Return to main text.*

B.3 Excluding Crisis Periods

Table B.3: Liquidity Risk, Bond Ownership, and Employment: Excluding Crisis Periods

Dependent Variable	ΔEmployment	
	(1)	(2)
Liquidity Premium	-0.3919**	-0.2195
	(-2.38)	(-1.39)
Bond Ownership		0.0294*
		(1.77)
Liquidity Premium		
× Bond Ownership		-1.3765**
		(-2.31)
No. of Observations	4,454	4,349
No. of Firms	524	518
Firm Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Clustering	Firm	Firm
Control Variables	Yes	Yes

Note: The numbers in parentheses are the t-statistics. Standard errors are clustered at the firm level. Control variables include tangibility, book leverage, return of assets, change in idiosyncratic volatility, Tobin's q, firm size, and stock return. Crisis periods include financial crisis and Covid periods. *Return to main text.*

C Model Appendix

C.1 Derivation with Taste Shocks

We derive Equations (16) (17) following the sovereign default literature with taste shocks (Dvorkin et al., 2021; Mihalache, 2025). Fix t and suppress the firm index

i to simplify notation. Let the two alternatives be "continue" (r) and "default" (d), with deterministic components V_t^r and V_t^d. Assume $(\epsilon_t^r, \epsilon_t^d)$ are i.i.d. across alternatives and distributed type-I extreme value (Gumbel) with common scale $\xi_d > 0$.[6] Define realized payoffs

$$U_t^r = V_t^r + \epsilon_t^r, \qquad U_t^d = V_t^d + \epsilon_t^d,$$

and the ex-ante value

$$V_t := \mathbb{E}_\epsilon\big[\max\{U_t^r, U_t^d\}\big].$$

Step 1: Default probability (logit). The firm defaults if and only if $U_t^d \geq U_t^r$, i.e. $\epsilon_t^r - \epsilon_t^d \leq V_t^d - V_t^r$. Under the i.i.d. type-I extreme value assumption with common scale ξ_d, the difference $\epsilon_t^r - \epsilon_t^d$ has the logistic distribution with scale ξ_d, i.e. with CDF

$$F_{\Delta\epsilon}(x) = \frac{1}{1 + \exp(-x/\xi_d)}.$$

Hence the default probability equals

$$\begin{aligned}\mathcal{D}_t &:= \Pr\big(U_t^d \geq U_t^r\big) = \Pr\big(\epsilon_t^r - \epsilon_t^d \leq V_t^d - V_t^r\big) = F_{\Delta\epsilon}(V_t^d - V_t^r) \\ &= \frac{1}{1 + \exp\big(-(V_t^d - V_t^r)/\xi_d\big)} = \frac{\exp(V_t^d/\xi_d)}{\exp(V_t^r/\xi_d) + \exp(V_t^d/\xi_d)}.\end{aligned} \tag{39}$$

This proves (17).

Step 2: Expected max (log-sum-exp). A standard property of the i.i.d. type-I extreme value model is that the expected maximum equals a "log-sum-exp" term plus a constant. To see this, define for any $u \in \mathbb{R}$ the CDF of a type-I extreme value with scale ξ_d and location m:

$$F(\epsilon) = \exp\left(-\exp\left(-\frac{\epsilon - m}{\xi_d}\right)\right).$$

[6] A convenient normalization is to choose the location parameter so that $\mathbb{E}[\epsilon_t^a] = 0$ for $a \in \{r, d\}$, e.g. $\epsilon_t^a \sim \text{Gumbel}(-\xi_d\mu, \xi_d)$ where μ is the Euler–Mascheroni constant. This location affects levels but not choice probabilities. The results below depend only on the i.i.d. type-I extreme value assumption and the common scale ξ_d.

Using independence, for any $y \in \mathbb{R}$,

$$\begin{aligned}
\Pr\bigl(\max\{U_t^r, U_t^d\} \le y\bigr) &= \Pr\bigl(\epsilon_t^r \le y - V_t^r,\ \epsilon_t^d \le y - V_t^d\bigr) \\
&= F(y - V_t^r)\, F(y - V_t^d) \\
&= \exp\Bigl(-\exp\Bigl(-\tfrac{y-(V_t^r+m)}{\xi_d}\Bigr) - \exp\Bigl(-\tfrac{y-(V_t^d+m)}{\xi_d}\Bigr)\Bigr) \\
&= \exp\Bigl(-\exp\Bigl(-\tfrac{y-(m+\xi_d \log(\exp(V_t^r/\xi_d)+\exp(V_t^d/\xi_d)))}{\xi_d}\Bigr)\Bigr).
\end{aligned}$$

Thus $\max\{U_t^r, U_t^d\}$ is itself type-I extreme value with the same scale ξ_d and location

$$m^\star = m + \xi_d \log\bigl(\exp(V_t^r/\xi_d) + \exp(V_t^d/\xi_d)\bigr).$$

Taking expectations and using $\mathbb{E}[\text{Gumbel}(m, \xi_d)] = m + \xi_d \mu$,

$$\mathbb{E}\bigl[\max\{U_t^r, U_t^d\}\bigr] = m^\star + \xi_d \mu = m + \xi_d \mu + \xi_d \log\bigl(\exp(V_t^r/\xi_d) + \exp(V_t^d/\xi_d)\bigr).$$

With the mean-zero normalization $m = -\xi_d \mu$, the constant term vanishes and we obtain

$$V_t = \xi_d \log\left[\exp\Bigl(\frac{V_t^r}{\xi_d}\Bigr) + \exp\Bigl(\frac{V_t^d}{\xi_d}\Bigr)\right], \tag{40}$$

which proves (16).

Remark: Deterministic default as $\xi_d \to 0$. Let $\Delta := V_t^r - V_t^d$. From (39),

$$\mathcal{D}_t = \frac{1}{1+\exp(\Delta/\xi_d)} \longrightarrow \begin{cases} 1, & \Delta < 0\ (V_t^r < V_t^d), \\ 1/2, & \Delta = 0, \\ 0, & \Delta > 0\ (V_t^r > V_t^d), \end{cases} \qquad \text{as } \xi_d \to 0,$$

so the choice converges to the usual deterministic rule except at the knife-edge $\Delta = 0$.

C.2 First Order Conditions (FOCs)

Taking the FOCs with respect to the control variables $x \in \{K_{t+1}, N_{t+1}, B_{t+1}\}$ in Equation (30):

$$\begin{aligned}
&\frac{\partial}{\partial x}\left[D_t + \mathbb{E}_t M_{t,t+1} V(S_{t+1})\right] \\
=&\frac{\partial}{\partial x} D_t + \mathbb{E}_t M_{t,t+1} \frac{\partial}{\partial x} V(S_{t+1}) \\
=&\Lambda_t \frac{\partial E_t}{\partial x} + \mathbb{E}_t M_{t,t+1}(1-\mathcal{D}(S_{t+1})) \frac{\partial V_r(S_{t+1})}{\partial x} \\
=&\Lambda_t \frac{\partial}{\partial x}\left[(1-\tau)\left(Y_t - W_t N_t - f\right) + \tau\delta K_t - K_{t+1} + (1-\delta)K_t - \Phi_t - \left(1+(1-\tau)c\right) B_t + P_t B_{t+1}\right] \\
&+ \mathbb{E}_t M_{t,t+1}(1-\mathcal{D}(S_{t+1})) \frac{\partial V_r(S_{t+1})}{\partial x} \\
=&\Lambda_t \frac{\partial}{\partial x}\Bigg[(1-\tau)\left(Z_t K_t^{\alpha}(X_t N_t)^{(1-\alpha)\theta} - W_t N_t - f\right) + \tau\delta K_t - K_{t+1} + (1-\delta)K_t \\
&- \frac{c_k}{2}\left(\frac{I_t^+}{K_t}\right)^2 K_t - \frac{c_n}{2}\left(\frac{N_{t+1}-N_t}{N_t}\right)^2 N_t - \frac{c_b}{2}\left(\frac{B_{t+1}-B_t}{B_t}\right)^2 P_t B_t \\
&- \left(1+(1-\tau)c\right) B_t \\
&+ \underbrace{\mathbb{E}_t\left(M_{t,t+1}\left((1+c)(1-\mathcal{D}(S_{t+1})) + \frac{L_{t+1}}{B_{t+1}}\mathcal{D}(S_{t+1})\right)\right)}_{P_t} B_{t+1}\exp(\gamma x_t)\Bigg] \\
&+ \mathbb{E}_t M_{t,t+1}(1-\mathcal{D}(S_{t+1})) \frac{\partial V_r(S_{t+1})}{\partial x}
\end{aligned}$$

where we use $\Lambda_t := 1 + \eta_1 \mathbb{I}_{\{H_t>0\}} = 1 + \eta_1 \mathbb{I}_{\{E_t<0\}}$, ignoring the case $\Lambda_t \in [1, 1+\eta_1]$ being a subgradient when $E_t = 0$. For state variables $x \in \{K_t, N_t, B_t\}$, derivatives are similar but without the last 2 terms.

The differentiability argument in the presence of discrete choices follows Druedahl and Jørgensen (2017) as in their Proposition C.1. for interior and Corollary C.1. for constrained areas.

We also use

$$
\begin{aligned}
\frac{\partial V(S_{t+1})}{\partial x} =& \xi_d \frac{1}{\exp(V_r(S_{t+1})/\xi_d)+1} \exp(V_r(S_{t+1})/\xi_d) \frac{1}{\xi_d} \frac{\partial V_r(S_{t+1})}{\partial x} \\
=& \frac{\exp(V_r(S_{t+1})/\xi_d)}{\exp(V_r(S_{t+1})/\xi_d)+1} \frac{\partial V_r(S_{t+1})}{\partial x} \\
=& (1-\mathcal{D}(S_{t+1})) \frac{\partial V_r(S_{t+1})}{\partial x}.
\end{aligned}
$$

The following is useful by taking FOC of Equation (34):[7]

$$
\begin{aligned}
\frac{\partial P_t}{\partial K_{t+1}} =& \mathbb{E}_t \left[M_{t,t+1} \left(\left(\frac{L_{t+1}}{B_{t+1}} - (1+c) \right) \frac{\partial \mathcal{D}\left(S_{t+1}\right)}{\partial K_{t+1}} + \frac{\mathcal{D}\left(S_{t+1}\right)}{B_{t+1}} \frac{\partial L_{t+1}}{\partial K_{t+1}} \right) \right], \\
\frac{\partial P_t}{\partial N_{t+1}} =& \mathbb{E}_t \left[M_{t,t+1} \left(\frac{L_{t+1}}{B_{t+1}} - (1+c) \right) \frac{\partial \mathcal{D}\left(S_{t+1}\right)}{\partial N_{t+1}} \right], \\
\frac{\partial P_t}{\partial B_{t+1}} =& \mathbb{E}_t \left[M_{t,t+1} \left(\left(\frac{L_{t+1}}{B_{t+1}} - (1+c) \right) \frac{\partial \mathcal{D}\left(S_{t+1}\right)}{\partial B_{t+1}} - \frac{L_{t+1}}{B_{t+1}^2} \mathcal{D}(S_{t+1}) \right) \right],
\end{aligned}
$$

where

$$
\frac{\partial \mathcal{D}\left(S_{t+1}\right)}{\partial x} = -\frac{1}{\xi_d} \mathcal{D}\left(S_{t+1}\right) \left(1-\mathcal{D}\left(S_{t+1}\right)\right) \frac{\partial V_r\left(S_{t+1}\right)}{\partial x} \text{ for } x \in \{K_{t+1}, N_{t+1}, B_{t+1}\}
$$

and

$$
\frac{\partial L_{t+1}}{\partial K_{t+1}} = \varphi(1-\tau)(1-\delta)
$$

The envelope conditions for $V_r(S_t)$ are

$$
\frac{\partial V_r(S_t)}{\partial K_t} = \Lambda_t \left((1-\tau) \frac{\partial Y_t}{\partial K_t} + \tau\delta + 1 - \delta - \frac{\partial \Phi_t}{\partial K_t} \right), \tag{41}
$$

$$
\frac{\partial V_r(S_t)}{\partial N_t} = \Lambda_t \left((1-\tau) \left(\frac{\partial Y_t}{\partial N_t} - W_t \right) - \frac{\partial \Phi_t}{\partial N_t} \right), \tag{42}
$$

[7] Note

$$
\frac{\partial L_{t+1}}{\partial N_t} = 0 \text{ (since } N_t \text{ is lagged labor in } S_{t+1}, L_{t+1} \text{ depends on } N_{t+1}\text{)}, \frac{\partial L_{t+1}}{\partial B_{t+1}} = 0.
$$

$$\frac{\partial V_r(S_t)}{\partial B_t} = \Lambda_t(-(1+(1-\tau)c)), \tag{43}$$

where

$$\frac{\partial Y_t}{\partial K_t} = \alpha\theta \frac{Y_t}{K_t} \tag{44}$$

$$\frac{\partial \Phi_t}{\partial K_t} = -c_{00}(1-\delta)\left(\frac{I_t^+}{K_t}\right)^{t_m-1} + \frac{c_{00}(1-t_m)}{t_m}\left(\frac{I_t^+}{K_t}\right)^{t_m} \tag{45}$$

$$+ c_{01}(1-\delta)\left(\frac{-I_t^-}{K_t}\right)^{t_m-1} + \frac{c_{01}(1-t_m)}{t_m}\left(\frac{-I_t^-}{K_t}\right)^{t_m}, \tag{46}$$

$$\frac{\partial \Phi_t}{\partial N_t} = -c_{10}\left(\frac{(N_{t+1}-N_t)^+}{N_t}\right)^{t_n-1} + \frac{c_{10}(1-t_n)}{t_n}\left(\frac{(N_{t+1}-N_t)^+}{N_t}\right)^{t_n} \tag{47}$$

$$+ c_{11}\left(\frac{-(N_{t+1}-N_t)^-}{N_t}\right)^{t_n-1} + \frac{c_{11}(1-t_n)}{t_n}\left(\frac{-(N_{t+1}-N_t)^-}{N_t}\right)^{t_n}. \tag{48}$$

Λ in (41),(42), (43) will cause discontinuity in the partial derivatives of V_r.

FOC w.r.t. K_{t+1}

$$\Lambda_t\left(-1 - \frac{\partial \Phi_t}{\partial K_{t+1}} + B_{t+1}\frac{\partial P_t}{\partial K_{t+1}}\exp(\gamma x_t)\right) + \mathbb{E}_t\left[M_{t,t+1}(1-\mathcal{D}(S_{t+1}))\frac{\partial V_r(S_{t+1})}{\partial K_{t+1}}\right] \leq 0 \tag{49}$$

with the equality holding if $I_t > 0$, and

$$\frac{\partial \Phi_t}{\partial K_{t+1}} = c_{00}\left(\frac{I_t}{K_t}\right)^{t_m-1}\mathbf{1}_{I_t>0} - c_{01}\left(\frac{-I_t}{K_t}\right)^{t_m-1}\mathbf{1}_{I_t<0}.$$

FOC w.r.t. N_{t+1}

$$\Lambda_t\left[-\frac{\partial \Phi_t}{\partial N_{t+1}} + B_{t+1}\frac{\partial P_t}{\partial N_{t+1}}\exp(\gamma x_t)\right] + \mathbb{E}_t\left[M_{t,t+1}(1-\mathcal{D}(S_{t+1}))\frac{\partial V_r(S_{t+1})}{\partial N_{t+1}}\right] = 0, \tag{50}$$

where

$$\frac{\partial \Phi_t}{\partial N_{t+1}} = c_{10}\left(\frac{N_{t+1}-N_t}{N_t}\right)^{t_n-1}\mathbf{1}_{N_{t+1}>N_t} - c_{11}\left(\frac{-(N_{t+1}-N_t)}{N_t}\right)^{t_n-1}\mathbf{1}_{N_{t+1}<N_t}.$$

FOC w.r.t. B_{t+1}

$$\Lambda_t \left(P_t + B_{t+1} \frac{\partial P_t}{\partial B_{t+1}} \exp(\gamma x_t) \right) + \mathbb{E}_t \left[M_{t,t+1}(1 - \mathcal{D}(S_{t+1})) \frac{\partial V_r(S_{t+1})}{\partial B_{t+1}} \right] = 0. \quad (51)$$

Note that since V_r is finite, $\mathcal{D}$ will never be exactly 1. So analytically FOC should hold in the entire interior of the state space. Numerically, $\mathcal{D}$ can be indistinguishable from 1 for computers, but (49), (50)and (51) still give the optimal (interior) policies since expectation terms representing future impacts are automatically eliminated from the equations and firms just want to maximize the current period D_t.

D Numerical Appendix

The deep learning algorithm solves the firm's dynamic problem by enforcing the equilibrium conditions pointwise over the state space.

Objective function. The loss function aggregates residuals from the Bellman equation (30) and the firm's first-order conditions with respect to next-period capital, labor, and debt (49), (50), (51).

Let $S_t = (K_t, N_t, B_t, X_t, Z_t)$ denote the state vector. Ignoring time subscripts for notational convenience, rewrite the first-order conditions (49)–(51) by moving expectation terms to the right-hand side. Define

$$LHS_K, LHS_N, LHS_B \quad \text{and} \quad RHS_K, RHS_N, RHS_B$$

as the left- and right-hand sides of the first-order conditions with respect to K_{t+1}, N_{t+1}, and B_{t+1}, respectively. Expectations are taken over (X_{t+1}, Z_{t+1}) conditional on S_t.

The loss function evaluated at state S_t is

$$\begin{aligned}\mathcal{L}(S_t) = &\left(LHS_K(S_t) - RHS_K(S_t)\right)^2 \\ &+ \left(LHS_N(S_t) - RHS_N(S_t)\right)^2 \\ &+ \left(LHS_B(S_t) - RHS_B(S_t)\right)^2 \\ &+ \Big(V^r(S_t) - D_t - \mathbb{E}_t[M_{t,t+1}V(S_{t+1})]\Big)^2.\end{aligned} \tag{52}$$

The last term enforces the Bellman equation for the continuation value. The equilibrium corresponds to $\mathcal{L}(S_t) = 0$ for all S_t.

Function approximation. We approximate the continuation value and policy functions by neural networks:

$$V_r(S_t) \approx \widehat{V}_r(S_t; \Theta_V), \qquad K_{t+1}(S_t) \approx \widehat{K}(S_t; \Theta_K), \tag{53}$$

$$N_{t+1}(S_t) \approx \widehat{N}(S_t; \Theta_N), \qquad B_{t+1}(S_t) \approx \widehat{B}(S_t; \Theta_B), \tag{54}$$

and $\mathbf{\Theta} = (\Theta_V, \Theta_K, \Theta_N, \Theta_B)$ collects all network parameters. Given these approximations, default probabilities, bond prices, and their functional derivatives entering the first-order conditions are computed using the model's equilibrium equations.

Training algorithm. The parameters $\mathbf{\Theta}$ are chosen to minimize the expected loss over the state space. The numerical procedure is summarized in Algorithm 1.

Convergence performance. Figure A.2 plots the aggregate loss over training epochs, while Figure A.3 reports the individual components corresponding to the Bellman equation and the three first-order conditions. Transient oscillations reflect the cosine-annealing learning-rate schedule with warm restarts. At convergence, all residuals fall to the order of 10^{-7}–10^{-6}, indicating that the equilibrium conditions are satisfied with high numerical precision.

Algorithm 1: Deep-learning-based solution algorithm

1. Parameterize $V_r(S_t)$, $K_{t+1}(S_t)$, $N_{t+1}(S_t)$, and $B_{t+1}(S_t)$ by neural networks with parameters $\mathbf{\Theta}$.

2. Initialize parameters $\mathbf{\Theta}^0$.

3. For iterations $n = 0, 1, 2, \dots$:

   (a) Draw a batch of K state points

   $$Q^n = \{S_k\}_{k=1}^K = \{(K_k, N_k, B_k, X_k, Z_k)\}_{k=1}^K.$$

   (b) Evaluate $\widehat{V}_r(S_k)$, $\widehat{K}(S_k)$, $\widehat{N}(S_k)$, and $\widehat{B}(S_k)$ for all k.

   (c) Using the Markov transition of (X_t, Z_t), compute default probabilities, bond prices, and all derivatives required to form equilibrium residuals.

   (d) Compute the average loss

   $$L(\mathbf{\Theta}^n, Q^n) = \frac{1}{K}\sum_{k=1}^{K} \mathcal{L}(S_k). \tag{55}$$

   (e) Update parameters using a gradient-based method, for example

   $$\mathbf{\Theta}^{n+1} = \mathbf{\Theta}^n - \zeta^n \nabla_{\mathbf{\Theta}} L(\mathbf{\Theta}^n, Q^n), \tag{56}$$

   with step size $\zeta^n > 0$.

   (f) Iterate until $L(\mathbf{\Theta}^n, Q^n) \leq \varepsilon$.

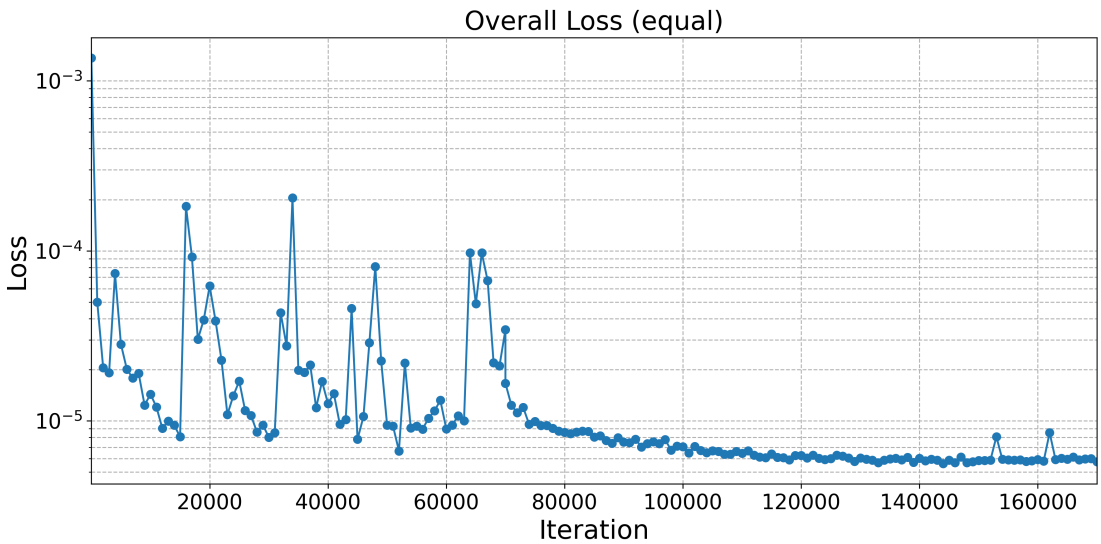


Figure A.2: Loss along the training epochs

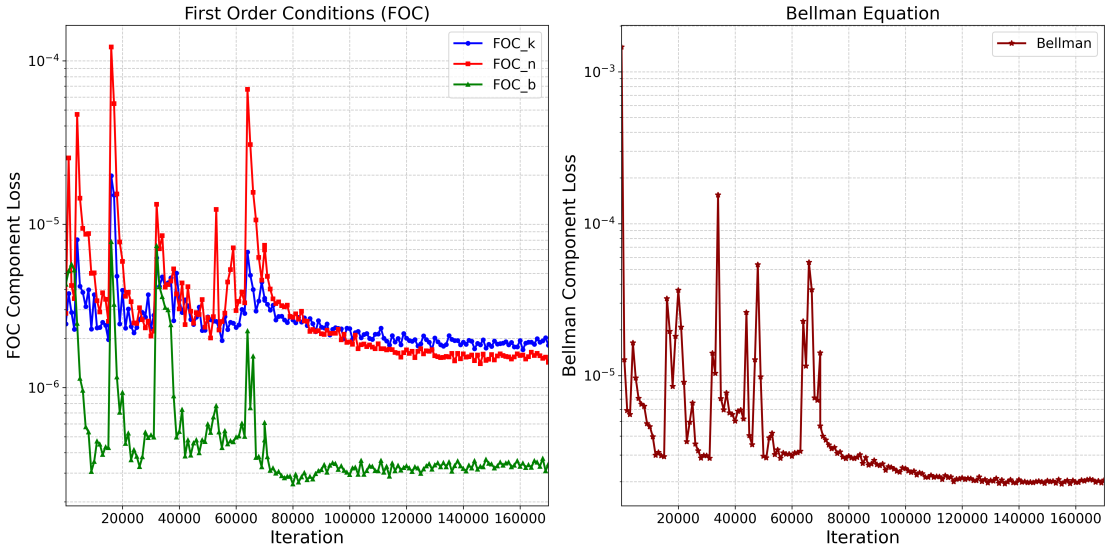


Figure A.3: Each loss component along the training epochs