# Uncertainty and Unemployment Revisited: The Consequences of Financial and Labor Contracting Frictions*

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**Abstract**

This paper revisits how uncertainty affects unemployment. Using Census employer-employee data, it finds that elevated uncertainty increases layoffs in financially constrained firms, an observation not predicted by standard search models where uncertainty freezes layoffs via irreversible search costs. A newly constructed search model can replicate the empirical evidence by incorporating financial and labor contracting frictions, so wage bills act as debt-like commitments, which firms are averse to taking on when uncertainty raises firm default risks. The model captures the increases in unemployment observed during U.S. past recessions, attributing over 70% of uncertainty's impact on unemployment to the two contracting frictions.

**Keywords**: Search and matching, financial frictions, incomplete labor contracts, uncertainty, volatility, firm heterogeneity, business cycles, labor market policies.

**JEL Codes**: E24, E32, E44, D53, D83, J08.

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# 1 Introduction

Unemployment increases a lot during recessions, as does the uncertainty faced by firms. To what extent does the elevated uncertainty of firm-level idiosyncratic productivity account for the observed increase in unemployment? Existing research shows that the power of uncertainty shocks to explain unemployment is limited within the canonical search framework (Schaal, 2017). In this paper, I revisit the impact of uncertainty on unemployment and find that, when financial and labor contracting are frictional, uncertainty shocks are crucial in accounting for the observed increase in unemployment during recessions.

My argument is developed in two steps. First, using U.S. Census employer-employee matched data, I discover that financially constrained firms are more likely to lay off workers when uncertainty increases. Second, I construct a new search model that can replicate this empirical evidence by incorporating financial and labor contracting frictions. They together generate a risk premium channel: each worker means a wage commitment, which firms are less willing to maintain when heightened uncertainty raises their bankruptcy risks. This mechanism accounts for over 70% of the impact of uncertainty on unemployment, greatly improving the model's ability to capture unemployment dynamics during recessions.

The key insight of my empirical work is to identify the mechanisms through which uncertainty shocks generate downturns. There are two influential theories in this field. First, the *real option* channel, investigated by Schaal (2017) and others, including Bernanke (1983), Bloom et al. (2018), Dixit and Pindyck (1994), Leduc and Liu (2016), and McDonald and Siegel (1986), emphasizes the irreversible costs of hiring and investment, causing firms to suspend those decisions under elevated uncertainty. Second, the *risk premium* channel, as studied by Arellano, Bai and Kehoe (2019), Christiano, Motto and Rostagno (2014), and Gilchrist, Sim and Zakrajšek (2014), focuses on financial frictions, suggesting that higher uncertainty increases default risks and compels firms to reduce costs by downsizing.

Although both theories explain how uncertainty can lead to recessions, distinguishing between them is challenging: they similarly predict reductions in investment, employment, and hiring. However, I propose that layoffs serve as the identifying moment: the real-option channel implies *fewer* firings, whereas the risk premium channel predicts *more*. Thus, by observing more layoffs under uncertainty, we can reject the absence of the risk premium channel. To empirically test this hypothesis, the first step is to obtain layoffs data at the job level. Neither aggregate nor firm-level data is sufficient, as volatility-driven reallocation across firms or restructuring within firms can also lead to more layoffs.

Therefore, I leverage U.S. Census employer-employee matched data (LEHD). This restricted micro-level data ensures granularity and avoids any bias from aggregation. It also allows me to distinguish layoffs from other employment margins such as hirings, which is often unavailable in most firm-level data that only provide information on overall employment. I then merge LEHD with Compustat-CRSP firm-level data, where I measure firm-level uncertainty as the annualized standard deviation of daily stock returns. To estimate the causal effect of uncertainty shocks, I adopt Alfaro, Bloom, and Lin's (2024) methodology, using Bartik-type instruments based on firms' exposure to exchange rates and policy uncertainty, along with various first-moment controls.

I use the merged dataset to estimate the effect of uncertainty shocks on layoffs, conditional on firms' financial constraints, calculated as the mode of three indicators: the absence of an S&P rating, a high Whited and Wu (2006) index, and a high Size & Age index (Hadlock, 2010). I find that for financially constrained firms, a one standard deviation increase in uncertainty shock raises the likelihood of worker layoffs by 0.5 percentage points, a response not observed for unconstrained firms. This evidence challenges the reliance solely on the real-option channel for a complete understanding of uncertainty's impacts. The baseline search framework, with its inherent irreversible hiring costs, would predict a freeze in layoffs, counteracting the observed pattern. Additionally, its lack of firm financial heterogeneity prevents it from generating the observed heterogeneous responses to uncertainty shocks.

Motivated by the empirical findings, I construct a new search model, building upon Schaal (2017) who extends the directed search framework in Menzio and Shi (2010) to include multi-worker firms and decreasing returns to scale production technology. This enhancement enables endogenous hirings and separations within firms. Like Schaal (2017), my model features two aggregate shocks: aggregate productivity shocks and uncertainty shocks. Then, I extend his model by introducing a labor contracting friction, along with a more standard firm financing friction. The latter assumes firms can only borrow through state-uncontingent debt with limited enforcement, leading to endogenous default.[1] Default results in costly liquidation. The labor contracting friction, a new feature of my model, implies wages are insensitive to transitory firm-level idiosyncratic shocks within the intertemporal firm-worker labor contracts.[2] I empirically validate this friction using Census data. And I theoretically micro-found it by assuming firms have private information about their shocks.

In my model, the incomplete financial and labor contracts suggest that wage bills are isomorphic to state-uncontingent debt, so firms are averse to taking on these debt-like wage commitments when idiosyncratic risk rises. This leads to less hiring and more layoffs in times of high uncertainty, so unemployment increases. A condition for this mechanism is the model's timing of employment decisions. Like typical search models, I assume that firms make hiring or firing decisions before shocks are realized. Thus, even if a firm decides to lay off workers, it must still pay the current period's wages. So, even with endogenous separations, wage bills remain a valid financial concern.

Note that the mechanism requires both financial and labor contracting frictions; neither is effective in isolation. Essentially, financial and labor contracts are substitutes when they are both intertemporal and dynamic. If labor contracts are complete, firms can borrow through workers rather than through state-uncontingent debt. Conversely, if the financial market is complete, how wages are paid within labor contracts becomes irrelevant, as it is the present value of wages that influences the decisions to hire or fire.

The model is highly non-linear, centering around a frictional labor market, a discrete default choice, occasionally binding financial constraints, and second-moment shocks. To accurately capture these non-linearities, I solve it using a global method with parallel programming. The model is calibrated to match the business cycle moments of GDP and the interquartile range (IQR) of firm sales growth rates, alongside standard labor market flows and financial market moments. For an external validation, model-simulated regressions show that workers in financially constrained firms are indeed more likely to be laid off when uncertainty is high, a pattern consistent with the empirical evidence but absent in the canonical search model.

I then use the model for two quantitative analyses. First, I quantify the role of uncertainty shocks in driving up unemployment during past U.S. recessions. I apply a particle filter to

[1] I choose endogenous default over discount factor shocks, as increased default risks can generate firm deleveraging in recessions, whereas higher discount rates generally encourage firms to borrow more.

[2] This does not require sticky wages: they can adjust fully in response to workers' outside opportunities.

estimate the historical series of aggregate productivity and uncertainty shocks.[3] Then, I input the estimated structural shocks into the model to predict unemployment. I find that the average peak-to-trough increase in unemployment during recessions implied by my model is about the same as that in the data. Counterfactual exercises further show that the model's performance along this dimension diminishes markedly if I eliminate any of three elements: uncertainty shocks, the financial friction, or the labor contracting friction. Notably, uncertainty shocks account for an average of 26% of unemployment increases in the past five recessions, from the 70s to the Great Recession. The number falls to only 7% in a counterfactual model without labor and financial contracting frictions. That is, the two contracting frictions contribute to over 70% of uncertainty's impact on unemployment.

In my second quantitative exercise, I evaluate two labor market stabilization policies during periods of high uncertainty. First, I examine the policy of increasing unemployment benefits, which the U.S. implemented during the Covid recession. The model shows that while this policy aims to support unemployed workers, it drives up wages, making hiring riskier for firms and, in the end, leading to higher unemployment. Second, I investigate the policy of subsidizing firms to pay wages, as seen in Germany's social security system and the U.S.'s Paycheck Protection Program (PPP). Wage subsidies can insure firms against idiosyncratic shocks, mitigating the negative impact of uncertainty. Therefore, the model suggests that this strategy outperforms the policy of raising unemployment benefits. However, wage subsidies also promote labor hoarding and hinder worker reallocation. The losses from misallocation outweigh the gains from providing insurance, still reducing overall efficiency.

***Related Literature.*** My paper contributes to four strands of literature. Primarily, it extends studies on how uncertainty shocks affect business cycles. As mentioned earlier, this area is mainly influenced by two theories: the real-option channel and the risk-premium channel. Empirically, I use their divergent predictions regarding layoffs to reveal the need to include the risk-premium channel in studies of uncertainty shocks. Quantitatively, I construct a tractable new search model that addresses both channels and examine their relative importance.

Second, my model contributes to a growing literature that brings firm financial fric-

[3] A particle filter is a Monte Carlo Bayesian estimator for the posterior distribution of structural shocks. It is similar to a Kalman filter but can be applied to non-linear models.

tions into search models. Monacelli, Quadrini and Trigari (2022), Mumtaz and Zanetti (2016), Petrosky-Nadeau (2014), Petrosky-Nadeau and Wasmer (2013), and Wasmer and Weil (2004) focus on financing needs for capital acquisitions, vacancy posting, or bargaining positions, but I examine firm financing for wage payments. Christiano, Trabandt and Walentin (2011), Chugh (2013), Garin (2015), Sepahsalari (2016), and Zanetti (2019), consider intra-period financial frictions like working capital requirements and collateral constraints. In contrast, I model inter-period financial contracts to generate endogenous firm default risk, so I can capture the intertemporal risk premium channel of uncertainty shocks.[4] While Blanco and Navarro (2016) include firm default in a search framework, their model treats wages as pure internal transfers. My model, however, introduces a labor contracting friction so that wage payments within contracts do affect allocations.[5]

Third, my labor contracting friction offers a fresh perspective to the literature on wage stickiness and unemployment fluctuations. Prominent studies like Gertler and Trigari (2009), Hall (2005), Hall and Milgrom (2008), Menzio and Moen (2010), and Shimer (2004) link unemployment volatility to the stickiness of wages for newly hired workers. My model, however, focuses on within-match contracting friction, without distorting the present value for newly hired workers.[6] Some recent research also considers incumbent worker wages, yet still focuses on wage stickiness in response to aggregate shocks (Bils, Chang and Kim, 2022; Blanco et al., 2022; Fukui, 2020; Schoefer, 2021). I propose an alternative mechanism of wage insensitivity to transitory idiosyncratic firm shocks, shifting away from the conventional focus on wage stickiness to aggregate shocks. In fact, aggregate wage stickiness alone is ineffective here; if it replaces wage insensitivity to idiosyncratic shocks, the risk premium channel of micro-level uncertainty will vanish.

Fourth, my labor contracting friction is informed by literature exploring asymmetric information's impact on labor market outcomes. Acemoglu (1995), Azariadis (1983), Chari (1983), Green and Kahn (1983), Hart (1983) demonstrate how asymmetric information can affect wage variability and lead to inefficient employment. I particularly draw from Hall and Lazear's (1984) two-period model, which shows the constrained optimality of

[4] I model firms' default risk following Arellano, Bai and Kehoe (2019), Khan and Thomas (2013), and Ottonello and Winberry (2020).

[5] Favilukis, Lin and Zhao (2020) and Schoefer (2021) document empirical evidence for the interaction between labor costs and firm financing.

[6] Although it is beyond the scope of this paper, new hire wage stickiness is an ongoing debate (Bils, Kudlyak and Lins, 2022; Gertler, Huckfeldt and Trigari, 2020; Grigsby, Hurst and Yildirmaz, 2021; Hazell and Taska, 2020; Kudlyak, 2014; Pissarides, 2009; Rudanko, 2009).

pre-determined wages under asymmetric information, and adapt this idea to a dynamic directed search framework. Recent advancements by Menzio (2005) and Kennan (2010) apply asymmetric information to generate endogenous new hire wage stickiness. In contrast, my mechanism operates through incumbent wage insensitivity and its interaction with the firm financial friction.

***Layout.*** The paper proceeds as follows. Section 2 explains the data and presents the empirical findings. Section 3 sets up the model. Section 4 parameterizes and validates the model against data. Section 5 conducts quantitative analyses. Section 6 concludes.

# 2 Empirical Motivation

In this section, I provide empirical motivation for including the risk premium channel in the analysis of how uncertainty shocks affect the labor market. Section 2.1 describes the data and defines the variables. Section 2.2 explains the identification strategy. Sections 2.3 and 2.4 present empirical evidence for the firm financial friction and labor contracting friction, respectively.

## 2.1 Data Description

My sample is an annual employer-employee matched panel that includes job-level information on layoffs and earnings, along with firm-level uncertainty and financial conditions.

***Data Sources.*** I draw a 10% random sample of workers from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Snapshot 2021, which offers data for each employer-employee pair.[7] LEHD is sourced from the UI wage records, recording any job with positive annual earnings across all four quarters. The data starts in the 1990s for most states, with Maryland data dating back to 1985, and extends up to the first quarter of 2022. Using employer-employee matched data has three advantages. First, it allows for distinguishing between layoffs and hiring, a distinction often not available in firm-level employment data. Second, it provides granular observations and helps avoid bias from the compositional changes of workers within firms. Third, it includes firm identifiers, facilitating merging with datasets on the firm side.

I then merge the LEHD dataset with firm-level data from the CRSP/Compustat Merged

[7] This paper has access to 24 states of LEHD: Arizona, California, Colorado, Connecticut, Delaware, Indiana, Kansas, Maine, Maryland, Massachusetts, Missouri, Nevada, New Jersey, New Mexico, New York, North Dakota, Ohio, Oklahoma, Pennsylvania, South Dakota, Tennessee, Utah, Virginia, and Wisconsin.

- Fundamentals Annual (Compustat) through the Longitudinal Business Database (LBD) and the Compustat-SSEL Bridge (CSB). Additionally, I merge the sample with Alfaro, Bloom and Lin's (2022) dataset on uncertainty shocks, which is also constructed from CRSP/Compustat. Their dataset includes measures of firm-level uncertainty shocks, the Bartik-type instruments for these shocks, and indicators of firm-level financial constraints, spanning from 1993 to 2019.

***Variables.*** In my analysis, the key dependent variables are job-level layoffs and earnings growth. I first construct them at the quarterly frequency and then annualize them to be consistent with the annual data on uncertainty shocks.

Using quarterly worker earnings data from the LEHD dataset, I follow Abowd, Lengermann and McKinney (2003) and Sorkin (2018) to focus on the worker's dominant employer—the one offering the highest total earnings over the current and previous quarters. A worker is considered laid off if two conditions are met: the employee does not remain in their dominant job in the subsequent quarter, and the employee records no earnings in any U.S. state. The latter information is sourced from the LEHD's Employment History Files, which detail the number of states where the employee has any positive earnings. Although the LEHD does not explicitly separate layoffs from voluntary quits, Hyatt et al. (2014) show that patterns of separation to non-employment closely align with layoffs from the Job Openings and Labor Turnover Survey (JOLTS), validating this layoff measure. I annualize the layoff indicator, marking it as one if a layoff occurs in any quarter during the year, and zero otherwise.

To annualize worker earnings, I first adjust them for inflation using the Consumer Price Index (CPI) from the BLS.[8] To address biases from varied employment start dates within a quarter, I follow Abowd, Lengermann and McKinney (2003) and categorize employment into three types: "full-quarter" (earnings positive in the current and both adjacent quarters), "continuous" (earnings positive in the current and one adjacent quarter), and "discontinuous" (cases not meeting the other criteria). Annual earnings are then calculated as follows: four times the average for "full-quarter" earnings if any are present, eight times the average for "continuous" earnings if "full-quarter" earnings are absent but "continuous" quarters exist, and twelve times the average of "discontinuous" quarters if neither of the first two conditions are met.

[8] I use the CPI for All Urban Consumers, normalizing the 2011 Q4 price to 1.

Table 1: Summary Statistics

| Variables | N (observations) | Mean | St. Dev. |
|---|---|---|---|
| $\Delta\sigma_{jt}$ | 15,160,000 | -0.015 | 0.987 |
| $\mathbb{1}_{jt}^{\text{fin-constraint}}$ | 15,160,000 | 0.101 | 0.302 |
| $\mathbb{1}_{ijt}^{\text{layoff}}$ | 15,160,000 | 0.055 | 0.229 |
| $\Delta\text{Earnings}_{ijt}$ | 13,340,000 | 0.016 | 0.308 |

*Note:* This table shows the summary statistics of the variables used in regressions. The variable $\Delta\sigma_{jt}$ represents the change in firm-level uncertainty, $\mathbb{1}_{jt}^{\text{fin-constraint}}$ denotes firm financial constraint indicators , $\mathbb{1}_{ijt}^{\text{layoff}}$ means the job-level layoff indicator, and $\Delta\text{Earnings}ijt$ refers to the growth in job-level earnings (where $i$ is workers, $j$ firms, and $t$ time). Uncertainty, $\sigma_{jt}$, is the annualized standard deviations of firm $j$'s daily stock returns within year $t$. The firm-level financial constraint indicator is the mode of three indicators: absence of an S&P rating, a Whited and Wu (2006) index higher than the cross-sectional median, and a Size & Age index proposed by Hadlock (2010) exceeding the cross-sectional median. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2652. (CBDRB-FY22-P2652-R9856) The numbers are rounded according to the Census Bureau's disclosure avoidance requirements.

The primary explanatory variables in my analysis are firm-level uncertainty shocks and financial constraint indicators, both obtained from Alfaro, Bloom and Lin's (2022) dataset based on CRSP/Compustat. Uncertainty shocks are measured as the growth rates of the annualized standard deviations of firms' stock returns, yielding a firm-level annual panel. The growth rate of variable $y$ at time $t$ is defined as $\frac{y_t - y_{t-1}}{(y_t + y_{t-1})/2}$, which is mathematically bounded between $-2$ and 2. This definition of growth rates is applied throughout the paper.

The firm-level financial constraint indicator is the mode of three measures: the absence of an S&P rating, a Whited and Wu (2006) index above the cross-sectional median, and a Size & Age index by Hadlock (2010) exceeding the cross-sectional median. Recognizing that this indicator is not randomly assigned—a key limitation—I lag it five years to focus on firms' ex-ante financial conditions. Additionally, I incorporate a range of control variables and fixed effects to reduce the influence of unobserved heterogeneity.

***Sample Selection.*** On the worker side, I focus on individuals aged 22 to 55 to avoid issues related to early working age and retirement, following Graham et al. (2019). Observations with annual earnings below \$3,250 in 2011Q4 dollars are excluded, as in Card, Heining and Kline (2013) and Sorkin (2018). Additionally, only jobs with a maximum duration of at least 3 years are included, thereby excluding part-time and temporary employment. On the firm side, a firm needs to be matched with a minimum of 10 employees to be considered. I also adopt the same criteria as Alfaro, Bloom and Lin (2024), requiring firms to have at least 200 daily stock returns in a given year, and focusing on ordinary common shares listed on major exchanges such as NYSE, AMEX, or Nasdaq. Firm-level variables are winsorized at the 0.5 and 99.5 percentiles.

Table 1 presents the summary statistics. The regression samples consist of around 15 million observations, involving 3,800 unique firms and 2 million unique workers.

## 2.2 Identification Strategy

When using firm-level stock price volatility to estimate the effects of uncertainty shocks on job outcomes, three endogeneity concerns emerge. First, a positive second-moment shock may coincide with a first-moment shock, leading to omitted variable bias. Second, unobserved variables such as agency frictions within firms might contribute to additional omitted variable bias by influencing both stock price volatility and job outcomes simultaneously. Third, there is a possibility of reverse causality, where layoffs or changes in earnings could themselves impact the firm's stock price volatility.

To address these endogeneity concerns, I use a two-stage least squares (2SLS) regression approach, using instruments for firm-level uncertainty shocks from Alfaro, Bloom and Lin (2024). They constructed a set of Bartik-type instruments by exploiting firms' differential exposures to the fluctuations of nine aggregate commodity prices. For my analysis, I select seven of these instruments, excluding two relatively weaker ones to ensure a strong relevance with firm-level uncertainty shocks. The selected instruments are based on seven commodities: economic policy uncertainty as developed by Baker, Bloom and Davis (2016), and the exchange rates of six currencies—the Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona. This approach means an over-identification, with seven instrumental variables being used for the one endogenous variable of firm-level uncertainty shocks.

In their approach to constructing instrumental variables, Alfaro, Bloom and Lin (2024) first estimate firms' exposures to aggregate commodity price fluctuations at the 2-digit SIC industry level, using the following regression:

$$r_{j,t}^{\text{risk-adj}} = \alpha_s + \sum_c \beta_s^c \cdot r_t^c + \epsilon_{j,t}, \tag{1}$$

where $j$ indicates the firm, $t$ the day, $s$ the 2-digit SIC industry sector, and $c$ the commodity. The dependent variable $r_{j,t}^{\text{risk-adj}}$ is the risk-adjusted stock return of firm $j$ on day $t$, defined as the residuals from regressing the firm's excess stock returns against four factors from an asset pricing model, in order to remove systematic fluctuations due to common risk factors (Carhart, 1997). On the right-hand side, $\alpha_s$ is the industry fixed effect, and $r_t^c$ represents the growth rate of commodity $c$'s price. The coefficients $\beta_s^c$ then capture industry-level sensitivities to commodity prices. These sensitivities are then multiplied by the volatilities of the commodities to formulate the instrumental variables:

$$|\beta_s^c| \cdot \Delta\sigma_t^c, \forall c. \tag{2}$$

Furthermore, they construct a set of corresponding first-moment controls as the products of the exposures and the commodities' growth rates:

$$\beta_s^c \cdot r_t^c, \forall c. \tag{3}$$

I use their methodology to address endogeneity and establish the causality effect of uncertainty shocks. First, first-moment controls are included in all my regressions to isolate the effects of the second moment. Second, the Bartik-type instruments, based on aggregate uncertainty shocks and industry-level exposure, are unlikely to be influenced by firm-level unobservables like internal agency frictions. Third, this approach reduces the risk of reverse causality bias, with job-level dependent variables within firms unlikely to impact the industry-level instruments. Additionally, for my over-identification 2SLS regressions, I conduct conditional likelihood ratio (CLR) tests for weak-instrument robust inference, and I also implement Hansen-Sargan over-identification $J$ tests to validate the exclusion condition.

## 2.3 Empirical Evidence for the Firm Financial Friction

To identify the risk premium channel from the real option channel of uncertainty shocks, I use the following regression to estimate the effect of uncertainty shocks on job-level layoffs, conditional on firms' financial conditions:

$$\mathbb{1}_{ijt}^{\text{layoff}} = \beta_1 \Delta\sigma_{jt-1} + \beta_2 \Delta\sigma_{jt-1} \cdot \mathbb{1}_{jt-5}^{\text{fin-constraint}} + \Gamma' Z_{jt} + \gamma_i + \delta_j + \phi_t + \varepsilon_{ijt}, \tag{4}$$

where $\mathbb{1}_{ijt}^{\text{layoff}}$, the dependent variable, equals one if worker $i$ from firm $j$ is laid off in year $t$. The firm's uncertainty shock, $\Delta\sigma_{jt-1}$, is standardized and interacts with a five-year lagged

Table 2: Responses of Worker Layoffs to Uncertainty Shocks

| | OLS | | 2SLS | OLS | | 2SLS |
|---|---|---|---|---|---|---|
| $\mathbb{1}_{ijt}^{\text{layoff}}$ | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta\sigma_{jt-1}$ | -0.00114 | -0.00112 | 0.00013 | -0.00142 | -0.00144 | -0.00038 |
| | (0.00081) | (0.00079) | (0.00157) | (0.00089) | (0.00089) | (0.00162) |
| $\Delta\sigma_{jt-1} \cdot \mathbb{1}_{jt-5}^{\text{fin-constraint}}$ | | | | 0.00252** | 0.00290** | 0.00514** |
| | | | | (0.00112) | (0.00120) | (0.00249) |
| 1st-stage $F$ | | | 58.61 | | | 34.37 |
| CLR test $p$-val | | | 0.003 | | | 0.039 |
| Sargan-Hansen $J$ test $p$-val | | | 0.598 | | | 0.351 |
| Number of firms | 3,800 | 3,800 | 3,800 | 3,800 | 3,800 | 3,800 |
| Number of workers | 2,324,000 | 2,324,000 | 2,324,000 | 2,324,000 | 2,324,000 | 2,324,000 |
| Number of observations | 15,160,000 | 15,160,000 | 15,160,000 | 15,160,000 | 15,160,000 | 15,160,000 |
| IVs' 1st-moment controls | × | ✓ | ✓ | × | ✓ | ✓ |
| Firm controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Firm, worker, time FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:* This table presents OLS and 2SLS regressions results, projecting job-level layoff indicators, $\mathbb{1}_{ijt}^{\text{layoff}}$, on lagged firm-level uncertainty, $\Delta\sigma_{jt-1}$, and their interaction with firms' 5-year lagged financial constraint indicators, $\mathbb{1}_{jt-5}^{\text{fin-constraint}}$ (where $i$ is workers, $j$ firms, and $t$ time). Uncertainty, $\sigma_{jt}$, is the annualized standard deviations of firm $j$'s daily stock returns within year $t$. The firm-level financial constraint indicator is the mode of three indicators: absence of an S&P rating, a Whited and Wu (2006) index above the cross-sectional median, and a Size & Age index by Hadlock (2010) exceeding the cross-sectional median. Seven instrumental variables for uncertainty shocks are based on firms' exposure to seven commodity price fluctuations and sourced from Alfaro, Bloom and Lin (2024). The 1st-stage $F$ statistic are the robust Kleibergen-Paap $F$ statistic. CLR (Conditional Likelihood Ratio) tests yield $p$-values for weak instrument robust inferences. Hansen $J$ test $p$-values assess over-identification. IVs' 1st-moment controls correspond to the 2nd-moment instruments for uncertainty shocks. Firm-level controls include six lagged firm financial variables: Tobin's Q, stock returns, tangibility, book leverage, returns on assets, and sales-based firm sizes. Firm-level controls also include the lagged firm's financial constraint indicator and its interactions with both IVs' 1st-moment controls and the six firm financial controls. Regressions standardize uncertainty changes and include worker, firm, and time-fixed effects. Standard errors (in parentheses) are clustered at the 2-digit SIC industry level. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2652. (CBDRB-FY22-P2652-R9856) The numbers are rounded according to the Census Bureau's disclosure avoidance requirements. Statistical significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

financial constraint indicator, $\mathbb{1}_{jt-5}^{\text{fin-constraint}}$, which reflects the ex-ante financial conditions of the firm. The interaction's coefficient, $\beta_2$, estimates the additional increase in layoffs in financially constrained firms resulting from an uncertainty shock. Both the uncertainty shock and its interaction are instrumented in the 2SLS regressions.

The regression also includes a vector of firm-side control variables, $Z_{jt}$, following Alfaro, Bloom and Lin (2024). It consists of six lagged firm-level financial variables: Tobin's Q, annualized stock returns, tangibility, book leverage, returns on assets, and firm sizes measured by sales, with Tobin's Q and stock returns serving as first-moment controls. Additional controls include the lagged firm's financial constraint indicator, along with its interactions with the seven first-moment controls in eq. (3) and the six firm-level financial variables. The regression also includes worker fixed effect ($\gamma_j$), firm fixed effect ($\delta_j$), and year fixed effects ($\phi_t$) to account for unobserved heterogeneity. The error term is denoted by $\epsilon_{ijt}$. The standard errors are clustered at the 2-digit SIC industry level, aligning with the variability of the instruments.

Table 2 presents the OLS and 2SLS regression estimates for $\beta_1$ and $\beta_2$. The first three columns project layoffs on uncertainty shocks, with the estimated $\beta_1$ showing no significant average effect.[9] However, the next three columns examine the interaction between uncertainty shocks and firms' financial conditions. The estimated coefficient of the interaction, $\beta_2$, is significantly positive in both OLS regressions (Columns 4 and 5) and the 2SLS regression (Column 6). Specifically, the baseline 2SLS result in Column (6) reports a coefficient of 0.005, indicating that a one standard deviation increase in uncertainty shock raises the layoff probability in financially constrained firms by 0.5 percentage points more than in unconstrained firms. This result is weak-instrument robust, with a conditional likelihood ratio (CLR) test $p$-value of 0.039. Furthermore, the Sargan-Hansen $J$ test of over-identification confirms the exclusion restriction with a $p$-value of 0.351.

This evidence reveals the significant role of firm financial conditions in shaping the impact of uncertainty shocks. It supports the risk premium channel, which predicts increased job layoffs in financially constrained firms under high uncertainty. In contrast, the real option channel, suggesting a freeze in both layoffs and hiring under high uncertainty, does not account for financial heterogeneity and lacks the mechanism to explain the observed pattern. Thus, the empirical evidence of increased layoffs underscores the necessity of including firm financial frictions in models of uncertainty shocks.

## 2.4 Empirical Evidence for the Labor Contracting Friction

In my model, the labor contracting friction is another key component, working together with the firm financial friction. Alone, the financial friction is inconsequential in the context of long-term, intertemporal employment relationships within search models. When

[9] While my analysis reveals no significant average impact of uncertainty shocks on layoffs, Di Maggio et al. (2022) find a strong positive effect using a different set of proprietary data provided by credit bureaus.

labor contracts are complete, they serve as perfect financial instruments, allowing firms to borrow through firm-worker relationships rather than relying on incomplete financial assets. This eliminates idiosyncratic firm risk and the risk premium channel. To generate the layoff patterns observed in the data, I introduce a labor contracting friction where wages are insensitive to transitory firm-specific idiosyncratic shocks. This friction limits the use of labor contracts as a tool for hedging against idiosyncratic risk, bringing financial risk to the forefront.

***Existing Evidence on Transitory Idiosyncratic Shocks.*** Existing research provides empirical evidence supporting this labor contracting friction. Guiso, Pistaferri and Schivardi (2005) use matched employer-employee data from Italy to estimate an AR(1) process for firms' value-added, finding an insignificant pass-through of *transitory* firm-level idiosyncratic shocks to worker earnings. Consistently, Rute Cardoso and Portela (2009) observe a similar result for firms' sales shocks, using data from Portugal. Both studies suggest a negligible wage response to short-term firm-specific fluctuations.

While some studies document significant impacts of firm characteristics on workers' wages, they often do not distinguish between transitory and *permanent* shocks. Therefore, the findings of the aforementioned studies do not conflict with the literature. In line with their estimation, my model focuses on the uncertainty that expands the dispersion of transitory shocks, filtering out firms' permanent components when calibrating the model.

***My Evidence on Uncertainty Shocks.*** In addition to existing evidence, I use my sample to further document that uncertainty shocks have little impact on workers' earnings. Using the same empirical approach as for layoffs, I adapt the specification (4), substituting the dependent variable with worker earnings growth, $\Delta\text{Earnings}_{ijt}$.

Table 3 presents the regression results. The first three columns uniformly show an insignificant average effect of uncertainty shocks on worker earnings. The next three columns add an interaction between uncertainty shocks and firms' financial constraint indicators. Here, the estimated $\beta_1$ remains insignificant, suggesting little response of earnings in unconstrained firms. For financially constrained firms, the OLS regressions in Columns 4 and 5 also report an insignificant coefficient $\beta_2$.

The only exception is the 2SLS regression in Column (6), which displays a significantly negative coefficient for $\beta_2$ at $-0.009$. This suggests that, in financially constrained firms, a one standard deviation increase in uncertainty shock reduces worker earnings growth

Table 3: Responses of Worker Earnings to Uncertainty Shocks

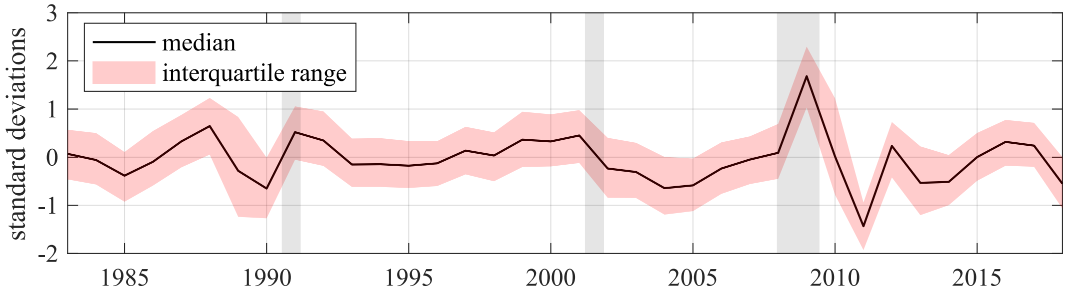
| | OLS | | 2SLS | OLS | | 2SLS |
|---|---|---|---|---|---|---|
| $\Delta\text{Earnings}_{ijt}$ | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta\sigma_{jt-1}$ | -0.00058 | -0.00066 | 0.00016 | -0.00029 | -0.00042 | 0.00102 |
| | (0.00118) | (0.00119) | (0.00403) | (0.00130) | (0.00131) | (0.00407) |
| $\Delta\sigma_{jt-1} \cdot \mathbb{1}_{jt-5}^{\text{fin-constraint}}$ | | | | -0.00261 | -0.00226 | -0.00949*** |
| | | | | (0.00183) | (0.00167) | (0.00354) |
| 1st-stage $F$ | | | 60.01 | | | 34.79 |
| CLR test $p$-val | | | 0.182 | | | 0.064 |
| Sargan-Hansen $J$ test $p$-val | | | 0.367 | | | 0.373 |
| Number of firms | 3,700 | 3,700 | 3,700 | 3,700 | 3,700 | 3,700 |
| Number of workers | 2,328,000 | 2,328,000 | 2,328,000 | 2,328,000 | 2,328,000 | 2,328,000 |
| Number of observations | 13,340,000 | 13,340,000 | 13,340,000 | 13,340,000 | 13,340,000 | 13,340,000 |
| IVs' 1st-moment controls | × | ✓ | ✓ | × | ✓ | ✓ |
| Firm controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Firm, worker, time FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:* This table presents OLS and 2SLS regressions results, projecting worker earnings growth, $\Delta\text{Earnings}_{ijt}$, on lagged firm-level uncertainty, $\Delta\sigma_{jt-1}$, and their interaction with firms' 5-year lagged financial constraint indicators, $\mathbb{1}_{jt-5}^{\text{fin-constraint}}$ (where $i$ is workers, $j$ firms, and $t$ time). Uncertainty, $\sigma_{jt}$, is the annualized standard deviations of firm $j$'s daily stock returns within year $t$. The firm-level financial constraint indicator is the mode of three indicators: absence of an S&P rating, a Whited and Wu (2006) index above the cross-sectional median, and a Size & Age index by Hadlock (2010) exceeding the cross-sectional median. Seven instrumental variables for uncertainty shocks are based on firms' exposure to seven commodity price fluctuations and sourced from Alfaro, Bloom and Lin (2024). The 1st-stage $F$ statistic are the robust Kleibergen-Paap $F$ statistic. CLR (Conditional Likelihood Ratio) tests yield $p$-values for weak instrument robust inferences. Hansen $J$ test $p$-values assess over-identification. IVs' 1st-moment controls correspond to the 2nd-moment instruments for uncertainty shocks. Firm-level controls include six lagged firm financial variables: Tobin's Q, stock returns, tangibility, book leverage, returns on assets, and sales-based firm sizes. Firm-level controls also include the lagged firm's financial constraint indicator and its interactions with both IVs' 1st-moment controls and the six firm financial controls. Regressions standardize uncertainty changes and include worker, firm, and time-fixed effects. Standard errors (in parentheses) are clustered at the 2-digit SIC industry level. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2652. (CBDRB-FY22-P2652-R9856) The numbers are rounded according to the Census Bureau's disclosure avoidance requirements. Statistical significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

by 0.9 percentage points. As shown in Figure 1, during the Great Recession, uncertainty shocks increased by about two standard deviations, which implies a wage decline of only 1.8 percentage points in constrained firms. This magnitude appears too small to have a significant economic impact.

To formally assess its magnitude, I conduct a robustness test in Section 5.1 by incorporating this wage pass-through into the model. The results confirm that uncertainty shocks

Figure 1: Uncertainty Shocks




*Notes:* This figure shows the median and interquartile range of firm-level uncertainty shocks, as derived from firm-level stock returns.

still drive sizable increases in unemployment. Therefore, I focus on the benchmark model that abstracts from this wage pass-through.

# 3 Model

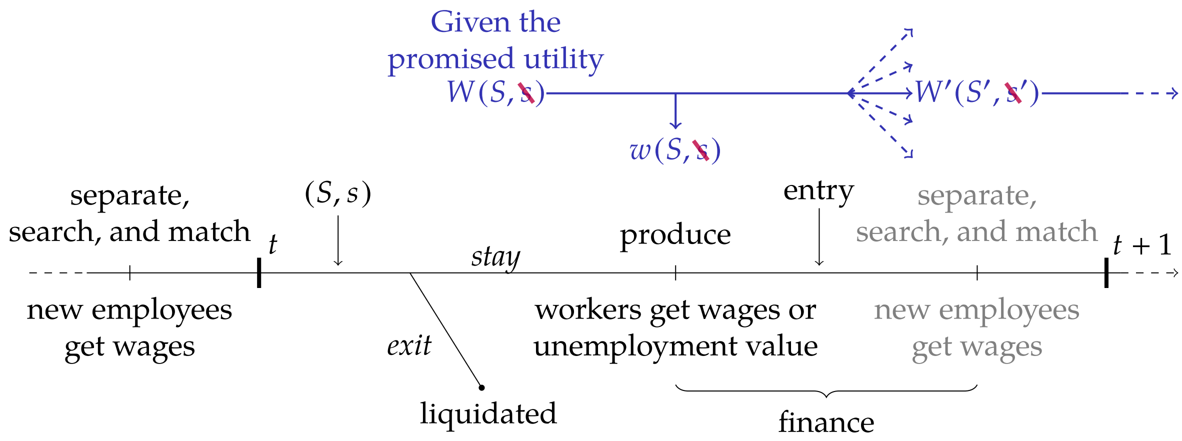
I now build a search model consistent with the empirical findings to study the impact of uncertainty shocks on unemployment. To integrate the risk premium channel, this model adopts the financial friction following Arellano, Bai and Kehoe (2019), and introduces a labor contracting friction. For computational tractability, it also features directed search and block recursive equilibrium, drawing on approaches from Menzio and Shi (2010, 2011), Kaas and Kircher (2015), and Schaal (2017).

## 3.1 Environment and Timing

There are four types of agents in the economy: workers, firms, managers, and international financial intermediaries. All of them are risk neutral. Workers are infinitely lived with the same productivity, and their total population is normalized to one unit. Firms hire workers and managers to produce homogeneous goods, financing by borrowing from international financial intermediaries.

***Shocks.*** Firms are subject to idiosyncratic productivity shocks governed by the Markov process $\pi_z(z'|z,\sigma)$, where $\sigma$ represents the time-varying uncertainty in firm-level productivity. A higher $\sigma$ increases the dispersion of future shocks, raising the probability of drawing lower productivity. Firms also face an aggregate productivity shock $A$. The two aggregate shocks are represented as $S = (A, \sigma)$. Additionally, firms also experience an i.i.d. operating cost shock $\epsilon$, which follows a normal distribution $\Phi_\epsilon \equiv \mathcal{N}(\mu_\epsilon, \sigma_\epsilon^2)$.

Figure 2: Timing




*Notes:* This figure depicts the timing of the economy (black axis) and the evolution of promised utilities (blue axis).

Firm-specific idiosyncratic shocks are denoted as $s = (z, \epsilon)$.

***Labor market.*** I assume directed search. Each labor submarket is indexed by a promised utility $x$, representing the lifetime utility that firms offer to workers recruited from that submarket. The tightness of each submarket, $\theta$, is the ratio of vacancies to job-seeking workers. Formally, $\theta = \frac{v}{\mu_u + \lambda \mu_e}$, where $v$ is the number of vacancies, $\mu_u$ denotes unemployed workers, $\mu_e$ stands for employed workers, and $\lambda$ represents the efficiency of on-the-job search. I use $p(\theta)$ to indicate the job-finding rate for workers and $q(\theta)$ for the vacancy-filling rate for firms. The equilibrium relationship between $x$ and $\theta$ will be governed by the free entry condition.

My model assumes one-sided limited commitment, where workers can leave if they have a better outside option, while firms adhere to labor contracts due to reputational concerns. The recursive-form labor contract is represented as $C = \{w, \tau, W'(S', s'), d(S', s')\}$, where $w$ is the current wage, $\tau$ is the layoff probability, $W'(S', s')$ is the next-period employment value as promised by the firm, and $d(S', s')$ indicates the firm's decision to exit.

***Timing.*** The model's key timing assumption is the sequence of employment decisions and the realization of shocks, as depicted in Figure 2. In line with typical search models, I assume firms hire or fire workers before shocks $(S, s)$ are realized, so employment is like risky investment due to its uncertain returns. If a firm decides to lay off workers, it must still pay the current period's wages. Thus, wage bills remain a valid financial concern, even with endogenous separations.

Next, firms decide to stay or exit. Exiting firms default on all debts, including labor contracts, resulting in the liquidation of their operations. On the other hand, continuing firms produce goods and pay workers wages. At the same time, unemployed workers receive unemployment benefits. Next, new firms may enter the market by paying an entry cost, after which all firms re-engage in the labor market. Throughout the process, firms finance their expenditures by borrowing from international financial intermediaries.

## 3.2 Worker's Problem

There are two types of workers in the economy: unemployed and employed. For simplicity, the model abstracts from individuals not participating in the labor force.

***Unemployed Worker's Problem.*** An unemployed worker, upon receiving unemployment benefits $\bar{u}$, selects a submarket $x_u$ to search for jobs, aiming to maximize their lifetime utility. The matching probability $p(\theta(S, x_u))$ depends on the aggregate shocks and the promised utility of the chosen submarket. The value of being unemployed is thus defined as:

$$\boldsymbol{U}(S) = \max_{x_u} \bar{u} + p(\theta(S, x_u))x_u + (1 - p(\theta(S, x_u)))\beta\,\mathbb{E}\,\boldsymbol{U}(S'). \tag{5}$$

***Employed Worker's Problem.*** The value of employment is contingent on the labor contract $C = \{w,\ \tau,\ W'(S', s'),\ d(S', s')\}$. An employed worker earns a wage $w$ and engages in on-the-job searching by selecting a submarket $x$. If a new job is secured, the worker earns $x$ as lifetime utility. The job-finding rate for on-the-job search is discounted by the relative efficiency $\lambda$. In the event of a layoff or firm exit, the worker transitions to unemployment, receiving the unemployment value $\boldsymbol{U}(S')$. If not laid off, the worker continues with the firm, receiving the promised utility $W'(S', s')$. Workers can leave voluntarily if the promised utility falls below the unemployment value. The value of employment is expressed as:

$$\begin{aligned}\boldsymbol{W}(S, s, \boldsymbol{C}) = \max_{x}\ & w + \lambda p(\theta(S, x))x \\ & + (1 - \lambda p(\theta(S, x)))\beta\,\mathbb{E}\Big\{[\tau + (1 - \tau)(\pi_d + (1 - \pi_d)d(S', s'))]\boldsymbol{U}(S') \\ & + (1 - \tau)(1 - \pi_d)(1 - d(S', s'))\max\{W'(S', s'), \boldsymbol{U}(S')\}\Big\},\end{aligned} \tag{6}$$

where $\pi_d$ denotes the exogenous exit rate of firms.

### 3.3 Firm's Problem

Firms aim to maximize their present value, defined as the discounted sum of equity payouts. A firm's state variables include aggregate shocks $S \in \boldsymbol{S}$, firm-specific shocks $s \in \boldsymbol{s}$, the number of employees $n$, and the set of promised utilities to its employees $\{W(S,s;i)\}_{i\in[0,n]}$, with $i$ indexing incumbent employees.

Firms choose current equity payout $\Delta$, next-period debt $b'$, next-period employment $n'$, hiring numbers $n_h$, search submarket $x_h$, and next-period exit decisions $d(S',s')$. Each firm posts vacancies in only one submarket per period. Firms also decide current-period wages $w(i)$ for incumbent workers, layoff probabilities $\tau(i)$, wages $w_h(i')$ for new hires, and the set of next-period lifetime utilities $\{W(S',s';i')\}_{S'\in\boldsymbol{S}',s'\in\boldsymbol{s}';i'\in[0,n']}$, subject to participation and promise-keeping constraints. Each firm employs one manager at a fixed wage, $\bar{w}_m$.

Equations (7) to (15) detail the firm's problem starting from the production stage, with explanations following:

$$\begin{aligned}\boldsymbol{J}(S,s,b,n,\{W(S,s;i)\}_{i\in[0,n]}) = &\max_{\substack{\Delta,b',n',n_h,x_h,d(S',s'),\\ \{w(i),\tau(i)\}_{i\in[0,n]},\\ \{w_h(i')\}_{i'\in(n'-n_h,n']},\\ \{W'(S',s';i'),\bar{W}(i')\}_{S'\in\boldsymbol{S}',s'\in\boldsymbol{s}';i'\in[0,n']}}} \Delta \\ &+ \beta(1-\pi_d)\,\mathbb{E}_{S',s'|S,s}\left\{(1-d(S',s'))\boldsymbol{J}(S',s',b',n',\{W(S',s';i')\}_{S'\in\boldsymbol{S}',s'\in\boldsymbol{s}';i'\in[0,n']})\right\}\end{aligned} \tag{7}$$

$$\text{s.t. } \Delta = Azn^{\alpha} - \int_0^n w(i)di - \bar{w}_m - \epsilon - b - c\frac{n_h}{q(\theta(S,x_h))} - \int_{n'-n_h}^{n'} w_h(i')di' + Q(S,z,b',n')b' \geq 0, \tag{8}$$

$$n' = \int_0^n (1-\tau(i))(1-\lambda p(\theta(S,x^*(S;i))))di + n_h, \tag{9}$$

$$i'(i) = \int_0^i (1-\tau(j))(1-\lambda p(\theta(S,x^*(S))))dj, \forall i \in [0,n], \tag{10}$$

$$\begin{aligned}x^*(S;i) = \arg\max_x p(\theta(S,x))\Big\{x - \beta\,\mathbb{E}\left\{[\tau + (1-\tau)(\pi_d + (1-\pi_d)d(S',s'))]\boldsymbol{U}(S')\right.\\ \left. + (1-\tau)(1-\pi_d)(1-d(S',s'))\max\{W'(S',s';i'),\boldsymbol{U}(S')\}\right\}\Big\},\end{aligned} \tag{11}$$

$$W'(S',s';i') = \boldsymbol{U}(S') + \bar{W}(i'), \tag{12}$$

$$\bar{W}(i')\geq 0, \tag{13}$$

$$\boldsymbol{W}(S,s,\boldsymbol{C})\geq \begin{cases} W(S,s;i) & \text{for } i\in[0,n], \\ x_h & \text{for newly hired employees,} \end{cases} \tag{14}$$

$$Q(S,z,b',n')b' - n_h \frac{c}{q(\theta(S,x_h))} - \int_{n'-n_h}^{n'} w_h(i')di' \geq M(S,z,n) - F_m(S,z), \tag{15}$$

where $F_m(S,z) = \left[\frac{\bar{w}_m + (1-\gamma)\frac{\beta}{1-\beta}\bar{w}_m}{(1-\Phi(A\xi\,\mathbb{E}[A'z'n'^{\alpha} - \int_0^{n'} w(i')di' - \bar{w}_m - \epsilon']))\zeta\,\mathbb{E}\,z'}\right]^{\frac{1}{\alpha}} \bar{u}$, and $M(S,z,n)$ denotes the maximum possible borrowing net of hiring costs:

$$M(S,z,n) = \max_{\substack{b',n',n_h,x_h,d(S',s'),\\ \{\tau(i)\}_{i\in[0,n]},\{w_h(i')\}_{i'\in(n'-n_h,n']},\\ \{W'(S',s';i'),\bar{W}(i')\}_{S'\in\boldsymbol{S}',s'\in\boldsymbol{s}';i'\in[0,n']}}} Q(S,z,b',n')b' - n_h\frac{c}{q(\theta(S,x_h))} - \int_{n'-n_h}^{n'} w_h(i')di' \tag{16}$$

$$\text{s.t. (9), (12), (13), and (14).} \tag{17}$$

***Financial friction.*** The model features the financial friction via a non-negative equity payout constraint (eq. (8)), preventing firms from accessing unlimited equity issuance.[10] Equity payouts, $\Delta$, equal output $Azn^{\alpha}$ minus incumbent employees' wages $\int_0^n w(i)di$, minus the manager's wage $\bar{w}_m$, minus the stochastic operating cost $\epsilon$, minus debt $b$, minus vacancy posting costs $c\frac{n_h}{q(\theta(S,x_h))}$, minus wages for newly hired workers $\int_{n'-n_h}^{n'} w_h(i')di'$, and plus borrowings $Q(S,z,b',n')b'$. The production function, characterized by decreasing returns to scale ($\alpha < 1$), allows within-firm layoffs and hirings. The cost of hiring $n_h$ new workers equals $c\frac{n_h}{q(\theta(S,x_h))}$, where $q$ is the vacancy-filling rate and $c$ is the posting cost per vacancy. The bond price $Q$ is determined such that the international financial intermediaries break even, which will be defined later.

***Employment dynamics.*** Eq. (9) describes the law of motion for employment, with eq. (10) detailing how an employee's index transitions from $i$ to $i'$. The firm's next-period employment is remaining employees plus new hires. Separations can be due to on-the-job search or layoffs. Eq. (11) shows that each employee $i$ chooses the optimal on-the-job

[10] The model could include costly equity issuance, but recalibration for sizable issuance costs is needed to match credit spread data. Due to its computational costs, this extension is deferred to future research.

search market, $x^*(S;i)$, to maximize their expected lifetime utility. The probability for a worker transitioning to another firm is then $\lambda p(\theta(S, x^*(S;i)))$. If the worker does not find a new job, they face a layoff probability $\tau(i)$.

***Labor contracting friction.*** The labor contracting friction is defined in eq. (12), which assumes a particular form for next-period promised utilities. These utilities consist of two components: the outside option of unemployment, $\boldsymbol{U}(S')$, and a utility markup, $\bar{W}(i')$, determined by the firm. The unemployment option allows labor contracts to adjust to changes in workers' outside options. In contrast, the utility markup $\bar{W}(i')$ is not contingent on future shocks $(S', s')$—a key element of labor contracting friction. If firms could condition future promises on upcoming shocks, labor contracts would replace state-uncontingent bonds as better financial instruments.

In Appendix A, I micro-found this labor contracting friction based on information frictions, following Hall and Lazear (1984) and Lemieux, MacLeod and Parent (2012). I assume that firms observe shocks, but workers do not, and there are no penalties for firms that misrepresent their statuses. Under these conditions, contracts tie to firm-specific shocks are impractical. For aggregate shocks, workers can infer them through outside options and accept wage cuts. However, for firm-specific idiosyncratic shocks, the lack of credible information makes workers skeptical of firms' claims about their financial health, particularly since firms have an incentive to understate their condition to reduce labor costs. Therefore, incentive-compatible labor contracts do not depend on firm-level idiosyncratic shocks.

***Limited commitment.*** One-sided limited commitment is reflected in eqs. (13) and (14). In my model, firms are committed to labor contracts, whereas workers are not. The participation constraint (13) requires that firms offer a non-negative utility markup to retain their workers; otherwise, workers would prefer unemployment. The promise-keeping constraint (14) requires firms to ensure the employment value meets or exceeds the promised lifetime utility. For an incumbent worker $i \in [0, n]$, the promised utility is $W(S, s; i)$, which is one of the firm's state variables. For a newly hired worker, the promised utility is $x_h$, determined by the firm's choice of hiring submarket.

***Agency friction.*** As in other models with financial frictions, firms in my model have a strong incentive to save. To address this, Constraint (15) incorporates an agency friction, following Arellano, Bai and Kehoe (2019). This inequality requires firms to maintain sufficient leverage by placing the firm's borrowings, $Qb'$, on its left-hand side. It is influenced by two parameters: agency friction, $\zeta$, and auditing quality, $\xi$. The micro-foundation is detailed in Appendix B. The intuition is to prevent the manager from diverting funds for personal use. Such a constraint is necessary for matching firm leverage observed in the data, avoiding scenarios where firms save a large cash buffer and outgrow the financial friction. The agency friction is inspired by Jensen (1986). For other ways to generate borrowing under financial frictions, Quadrini (2011) provides one summary.

## 3.4 Debt Pricing

I assume the economy's financial market is small compared to the global market, resulting in an exogenous risk-free interest rate $r = 1/\beta - 1$. Risk-neutral international financial intermediaries competitively lend to firms through one-period bonds. This setup ensures the block recursivity of the model.

The debt price schedule $Q(S, z, b', n')$ reflects firm-specific default risks. If a firm defaults, creditors can recover a portion of the firm's enterprise value $\hat{\boldsymbol{V}}(S', z', X' + b', n_0)$ by collecting current-period profits and selling the firm. This enterprise value, defined in eq. (27) below, represents the firm's worth without the non-negative equity payout constraint, with any negative equity payout treated as the creditors' loss. After the final production cycle[11], the firm's employment level, $n_0$, resets to zero as all workers are dismissed.

To simplify the computation, I approximate the firm's enterprise value for recovery using a linear function of its profits $\pi' = A'z'n'^{\alpha} - \int_0^{n'} w(i')di' - \bar{w}_m - \mu_\epsilon$. Model simulation shows a high correlation coefficient of 0.96 between $\pi'$ and $\hat{\boldsymbol{V}}(S', z', \pi', n_0)$, confirming a strong linear relationship and validating the approximation.

The break-even bond price $Q(S, z, b', n')$ is calculated as follows:

$$Q(S, s, b', n') = \beta\, \mathbb{E}_{S', s'|S, s} \left\{(1-\pi_d)(1-d(S', s')) + [1-(1-\pi_d)(1-d(S', s'))] \min\{\eta \frac{\iota \pi'}{b'}, 1\}\right\}, \tag{18}$$

where $\eta$ denotes the recovery rate, and $\iota$ is the the coefficient used to approximate the enterprise value from profits. Their product $\tilde{\eta} = \eta\iota$ is what affects decisions, so my calibration focuses on $\tilde{\eta}$ and refers to it as recovery.

[11] To avoid unemployment fluctuations being mechanically driven by varying default rates, I assume that firms continue production in the default period, contributing to GDP and employment (see Appendix D).

### 3.5 Wages Within Labor Contracts

Modeling the interaction between dynamic labor contracts and firms' financial conditions is challenging. A key difficulty, known as the 'dimensionality curse,' occurs when a firm's financial condition depends on a continuum of historically-dependent labor contracts. To address this, Proposition 1 provides an approach to uniquely pin down wages.

**Proposition 1** *The participation constraint* (13) *and the promise-keeping constraint* (14) *bind.*

**Proof** The proof can be found in Appendix C. □

The binding participation constraint (13) implies that promised utilities exactly compensate workers' outside options. From the worker's problem (5) and (6), with the binding promise-keeping constraint (14), an incumbent worker's wage is determined as the net utility of unemployment minus potential gains from on-the-job search:

$$\begin{aligned} w(S) &= \boldsymbol{U}(S) - \lambda \max_x p(\theta(S,x))[x - \beta\,\mathbb{E}\,\boldsymbol{U}(S')] - \beta\,\mathbb{E}\,\boldsymbol{U}(S') \\ &= \bar{u} + (1-\lambda)\max_x p(\theta(S,x))[x - \beta\,\mathbb{E}\,\boldsymbol{U}(S')]. \end{aligned} \tag{19}$$

Similarly, a newly hired worker's wage is:

$$w_h(S) = x_h - \beta\,\mathbb{E}\,\boldsymbol{U}(S'). \tag{20}$$

Given these wage expressions, the infinite-dimensional distribution of promised utilities becomes redundant as a state variable. As a result, the firm's problem can be simplified by removing the implicit contract constraints (12), (13), and (14). This resolves the dimensionality problem and allows numerical solutions.

The uniqueness of wages stems from three assumptions: asymmetric information, secured creditors, and limited commitment. First, asymmetric information prevents labor contracts from indexing wages on future idiosyncratic firm shocks, restricting the allocation of wage payments *across states*. Second, the model assumes secured creditors have priority in firm bankruptcy recoveries, in line with US bankruptcy law. This seniority structure discourages firms from deferring wages, as such backloading is like borrowing from workers at higher interest rates than collateralized bonds. Lastly, because workers are not committed to labor contracts, firms cannot frontload wages arbitrarily; employees may leave if their job's value falls below outside options. The latter two assumptions limit the allocation of wages *across time*. Therefore, wages are uniquely determined in my model.

Notice that my model does not require wages to be sticky to *aggregate* shocks; instead, it allows wages to respond flexibly to any aggregate shock that affects workers' outside opportunities. In my model, wages are not contingent on *idiosyncratic* firm shocks. This distinction in wage responsiveness aligns with empirical findings. Carlsson, Messina and Skans (2016) use matched employer-employee data from Sweden to show that the response of worker earnings to sector-level productivity shocks is three times that of firm-level productivity shocks. Souchier (2022) document consistent findings from French matched employer-employee data.

## 3.6 Cash on Hand

In this section, I simplify the firm's problem. First, given that workers are homogeneous, the distribution of layoff probabilities within firms becomes irrelevant. Therefore, I adopt a symmetric decision rule, where all employees face the same layoff probability $\tau$.

Second, if a firm exits, its value drops to zero. Thus, a firm defaults if and only if it cannot satisfy the non-negative equity payout constraint (8). As a result, default occurs if the operating cost exceeds the threshold $\bar{\epsilon}(S,z,b,n)$, defined as:

$$\bar{\epsilon}(S,z,b,n) \equiv Azn^{\alpha} - \int_0^n w(i)di - b + M(S,z,n) - \bar{w}_m, \tag{21}$$

where $M(S,z,n)$ is the maximum net borrowing defined in eq. (16).

Plugging in the default cutoff (21) and the newly hired worker's wage (20), I rewrite the firm's problem (7) using cash on hand $X$ as a state variable:

$$\boldsymbol{V}(S,z,X,n) = \max_{\substack{\Delta,b',n',\\ \tau,n_h,x_h}} \Delta + \beta(1-\pi_d)\,\mathbb{E}_{S',z'|S,z}\int_{-\infty}^{\bar{\epsilon}(S',z',b',n')} \boldsymbol{V}(S',z',X',n')d\Phi_{\epsilon}(\epsilon') \tag{22}$$

$$\text{s.t. } (9),(11),(15),(19) \tag{23}$$

$$\Delta = X + Q(S,z,b',n')b' - n_h\frac{c}{q(\theta(S,x_h))} - n_h[x_h - \beta\,\mathbb{E}\,\boldsymbol{U}(S')] \geq 0, \tag{24}$$

$$X' = A'z'n'^{\alpha} - n'w(S') - \bar{w}_m - \epsilon' - b', \tag{25}$$

$$\bar{\epsilon}(S',z',b',n') = A'z'n'^{\alpha} - n'w(S') - b' + M(S',z',n') - \bar{w}_m, \tag{26}$$

When a firm's cash on hand is sufficiently high, it avoids the financial friction, and its policies become independent of the cash on hand, denoted as $\hat{b}(S,z,n)$, $\hat{n}(S,z,n)$, $\hat{\tau}(S,z,n)$, $\hat{n}_h(S,z,n)$, and $\hat{x}_h(S,z,n)$. Lemma 3.1 characterizes firms' decisions and provides a partitioning method to solve the firm's problem, following Khan and Thomas (2013), Arellano, Bai and Kehoe (2019), and Ottonello and Winberry (2020).

**Lemma 3.1** *(Decision Cutoffs): If $X < -M(S,z,n)$, the firm cannot satisfy the nonnegative external equity payout condition and has to default. If $X \geq \hat{X}(S,z,n) \equiv -\{Q(S,z,\hat{b},\hat{n})\hat{b} - \hat{n}_h \frac{c}{q(\theta(S,\hat{x}_h))} - \hat{n}_h[\hat{x}_h - \beta\,\mathbb{E}\,\boldsymbol{U}(S')]\}$, the firm solves following relaxed problem (27), and the level of cash on hand does not affect the optimal decisions:*

$$\begin{aligned}\hat{\boldsymbol{V}}(S,z,X,n) = \max_{\substack{b',n',\\ \tau,n_h,x_h}} \; & X + Q(S,z,b',n')b' - n_h \frac{c}{q(\theta(S,x_h))} - n_h[x_h - \beta\,\mathbb{E}\,\boldsymbol{U}(S')] \\ & + \beta(1-\pi_d)\,\mathbb{E}_{S',z'|S,z} \int_{-\infty}^{\bar{\epsilon}(S',z',b',n')} \boldsymbol{V}(S',z',X',n')\,d\Phi_\epsilon(\epsilon')\end{aligned} \tag{27}$$

$$\text{s.t. (9), (11), (15), (19), (25), and (26).} \tag{28}$$

**Proof** The proof can be found in Appendix C. □

## 3.7 Firm Entry and Equilibrium

New firms enter the market by paying a fixed entry cost, $k_e$. Their productivity is drawn from the stationary distribution of idiosyncratic productivity $g_z(\cdot)$. New entrants do not produce in the entry period but can hire workers, similar to incumbent firms. Entrants start with zero debt and no labor, solving the following optimization problem:

$$\boldsymbol{J}_e(S,z) = \max_{n_h,x_h} -n_h \frac{c}{q(\theta(S,x_h))} - n_h[x_h - \beta\,\mathbb{E}\,\boldsymbol{U}(S')] \tag{29}$$

$$+ \beta(1-\pi_d)\,\mathbb{E}_{S',z'|S,z} \int_{-\infty}^{\bar{\epsilon}(S',z',b_0,n_h)} \boldsymbol{V}(S',z',X',n_h)\,d\Phi_\epsilon(\epsilon'), \tag{30}$$

$$\text{s.t.} \;\; b_0 = 0, \;\; \text{(25), and (26).} \tag{31}$$

I denote the new entrant's optimal decisions with $n_e$, $x_e$, and $d_e$.

Firms only post vacancies in markets with the lowest hiring cost, which is defined as:

$$\kappa(S) \equiv \min_{x_h}[x_h + \frac{c}{q(\theta(S,x_h))}]. \tag{32}$$

In equilibrium, only submarkets that offer the lowest hiring costs are active. For a given $\kappa(S)$, the relationship between a market's promised utility $x$ and market intensity $\theta$ is given by:

$$\theta(S,x) = \begin{cases} q^{-1}\left(\frac{c}{\kappa(S)-x}\right), & \text{if } x \leq \kappa(S) - c, \\ 0, & \text{if } x \geq \kappa(S) - c. \end{cases} \tag{33}$$

Markets where the promised utility $x$ exceeds $\kappa - c$ are inactive because the vacancy filling rate cannot exceed one.

The value of $\kappa(S)$ is determined by the free entry condition, which requires that the entry cost equals the expected entry value for all aggregate states $S$:

$$k_e = \sum_z \boldsymbol{J}_e(S,z) g_z(z), \forall S. \tag{34}$$

The model's equilibrium is then defined as follows:

**Definition 3.1** *Let $s^f$ summarize the firm's state variables $(S, z, X, n)$. The block recursive equilibrium consists of the policy and value functions of unemployed workers $\{x_u(S), \boldsymbol{U}(S)\}$; of employed workers $\{x(S,s,C), \boldsymbol{W}(S,s,C)\}$; of incumbent firms $\{\Delta(s^f)$, $b'(s^f)$, $n'(s^f)$, $\tau(s^f)$, $n_h(s^f)$, $x_h(s^f)$, $w(S)$, $w_h(S)\}$; of new firms $\{n_e(S)$, $x_e(S)$, $\boldsymbol{J}_e(S)\}$; the hiring cost per worker $\kappa(S)$; the labor market tightness $\theta(S,x;\kappa(S))$; and bond price schedules $Q(S,z,b',n')$ such that*

1. *Given the bond price schedules, the hiring cost, and the labor market tightness, the policy and value functions of unemployed workers, employed workers, incumbent firms, and entering firms solve their respective problems (5), (6), (19), (20), (22), and (29).*

2. *The bond price schedule satisfies (18).*

3. *The hiring cost per worker and the labor market tightness function satisfy (32) and (33).*

4. *The free entry condition (34) holds.*

Let $\Upsilon(z, X, n)$ denote the mass of firms with states $(z, X, n)$. Its law of motion is:

$$\begin{aligned} &\Upsilon'(z', X', n') \\ &= \sum_{z,X,n,\epsilon'} (1-\pi_d)(1-d(S',s';S,z,X,n))\mathbb{1}\{X'(S',s';S,z,X,n) = X'\}\phi_\epsilon(\epsilon')\pi_z(z'|z,\sigma)\mathbb{1}\{n'(S,z,X,n) = n'\}\Upsilon(z,X,n) \\ &\quad + m_e(S,\Upsilon)\sum_{z,\epsilon'}(1-\pi_d)(1-d_e(S',s';S,z))\mathbb{1}\{X'_e(S',s';S,z) = X'\}\phi_\epsilon(\epsilon')\pi_z(z'|z,\sigma)\mathbb{1}\{n_e(S) = n'\}g_z(z), \end{aligned} \tag{35}$$

where the mass of entrants $m_e(S, \Upsilon)$ ensures the number of jobs created by firms matches those found by workers.[12]

# 4 Parameterization

Section 4.1 calibrates the model. Section 4.2 validates the model against micro-level evidence. Appendix D details the computational algorithm of global grid search.

## 4.1 Calibration

***Functional Forms.*** The model features four shocks: aggregate productivity $A$, uncertainty $\sigma$, firm-level idiosyncratic productivity $z$, and operating cost $\epsilon$. Both aggregate productivity and uncertainty follow log AR(1) processes:

$$\log A_{t+1} = \rho_A \log A_t + \sigma_A \sqrt{1-\rho_A^2}\epsilon_t^A, \epsilon_t^A \sim \mathcal{N}(0,1), \tag{36}$$

$$\log \sigma_{t+1} = (1-\rho_\sigma)\log\bar{\sigma} + \rho_\sigma \log \sigma_t + \sigma_\sigma \sqrt{1-\rho_\sigma^2}\epsilon_t^\sigma, \epsilon_t^\sigma \sim \mathcal{N}(0,1). \tag{37}$$

I allow for correlation between $\epsilon_t^A$ and $\epsilon_t^\sigma$, denoted by the correlation coefficient $\rho_{A\sigma}$. Firm-level idiosyncratic productivity also follows a log AR(1) process:

$$\log z_{jt+1} = \rho_z \log z_{jt} + \sigma_t \sqrt{1-\rho_z^2}\epsilon_{jt}^z, \epsilon_{jt}^z \sim \mathcal{N}(0,1). \tag{38}$$

where $\sigma_t$ is the time-varying uncertainty affecting the standard deviation of innovation. Lastly, the i.i.d. operating cost shock $\epsilon$ follows a normal distribution $\mathcal{N}(\mu_\epsilon, \sigma_\epsilon^2)$.

The model uses Menzio and Shi's (2010) and Schaal's (2017) job finding probability function, whcih maintains transition rates within the range of zero to one:

$$p(\theta) = \theta(1+\theta^\gamma)^{-1/\gamma}. \tag{39}$$

The vacancy-filling rate $q(\theta) = \frac{p(\theta)}{\theta}$.

***Assigned Parameters.*** Table 4 lists the parameter values. Parameters in Panel A are set exogenously, following standard practices in the literature. The quarterly discount factor, $\beta$, is set at 0.988, implying an annual risk-free interest rate of 5%, as used by Schaal (2017). The labor coefficient, $\alpha$, is fixed at 0.66, reflecting the labor share. The persistence

[12] In simulations, jobs created by incumbent firms may occasionally exceed those found by workers, leading to the issue of undefined negative entry. To address this, I add population growth, detailed in Appendix D.

Table 4: Parameter Values

| Parameters | Notations | Values | Sources/Matched Moments |
|---|---|---|---|
| **Panel A: Assigned Parameters** | | | |
| Discount factor | $\beta$ | 0.988 | 5% annual interest rate |
| Decreasing returns to scale coefficient | $\alpha$ | 0.66 | Labor share |
| Persistence of productivity | $\rho_z$ | 0.95 | Schaal (2017) |
| **Panel B: Parameters from Moment Matching** | | | |
| **Aggregate shocks** | | | |
| Persistence of aggregate productivity | $\rho_A$ | 0.920 | Autocorrelation of output |
| SD of aggregate productivity | $\sigma_A$ | 0.024 | SD of output |
| Mean of uncertainty | $\bar{\sigma}$ | 0.248 | Mean of IQR |
| Persistence of uncertainty | $\rho_\sigma$ | 0.880 | Autocorrelation of IQR |
| SD of uncertainty | $\sigma_\sigma$ | 0.092 | SD of IQR |
| Correlation between $\epsilon_t^A$ and $\epsilon_t^\sigma$ | $\rho_{A\sigma}$ | −0.020 | Correlation (output, IQR) |
| **Labor market** | | | |
| Unemployment benefits | $\bar{u}$ | 0.142 | EU rate |
| Vacancy posting cost | $c$ | 0.001 | UE rate |
| Relative on-the-job search efficiency | $\lambda$ | 0.100 | EE rate |
| Matching function elasticity | $\gamma$ | 1.600 | $\epsilon_{UE/\theta}$ |
| Entry cost | $k_e$ | 15.21 | Entry/Total job creation |
| Mean operating cost | $\bar{w}_m + \mu_\epsilon$ | 0.001 | Average establishment size |
| **Financial market** | | | |
| SD of production costs | $\sigma_\epsilon$ | 0.080 | Mean credit spread |
| Agency friction | $\tilde{\zeta}$ | 2.400 | Median leverage |
| Auditing quality | $\xi$ | 1.780 | Correlation (output, spreads) |
| Recovery | $\tilde{\eta}$ | 2.410 | Correlation (IQR, spreads) |
| Exogenous exit rate | $\pi_d$ | 0.021 | Annual exit rate |

*Note:* Panel A shows parameters exogenously assigned. Panel B shows parameters endogenously calibrated.

of idiosyncratic productivity, $\rho_z$, is set at 0.95, following Schaal (2017).

***Fitted Parameters.*** Panel B of Table 4 displays parameters calibrated jointly, with matched moments in Table 5. The first set of parameters controls the AR(1) processes of aggregate shocks. Aggregate productivity parameters, $(\rho_A, \sigma_A)$, target the autocorrelation and standard deviation of output, using real GDP data from BEA, detrended by an HP-filter with a parameter of 1,600, as processed by Schaal (2017). Uncertainty is calibrated by the interquartile range (IQR) of residual sales growth rates across firms, as in Bloom et al. (2018). The sales data, sourced from Compustat, is adjusted for inflation using CPI and residualized by applying firm and industry-quarter fixed effects. This process accounts for permanent firm heterogeneity and industry-specific fluctuations. The resulting sales growth residuals form the IQR, after detrending, pins down the uncertainty parameters

Table 5: Matched Moments

| Moments | Data | Benchmark Model $A+\sigma$ | Benchmark Model $A+\sigma\ (\Delta^w)$ | Benchmark Model $A$ | No Contracting Frictions $A+\sigma$ | No Contracting Frictions $A$ |
|---|---|---|---|---|---|---|
| **Aggregate shocks** | | | | | | |
| Autocorrelation of output | 0.839 | 0.868 | 0.869 | 0.877 | 0.838 | 0.867 |
| SD of output | 0.016 | 0.015 | 0.014 | 0.015 | 0.019 | 0.017 |
| Mean of IQR | 0.171 | 0.169 | 0.168 | 0.160 | 0.161 | 0.169 |
| Autocorrelation of IQR | 0.647 | 0.611 | 0.667 | - | 0.623 | - |
| SD of IQR | 0.013 | 0.011 | 0.012 | - | 0.010 | - |
| Correlation (output, IQR) | -0.351 | -0.305 | -0.329 | - | -0.314 | - |
| **Labor market** | | | | | | |
| UE rate | 0.834 | 0.814 | 0.818 | 0.817 | 0.840 | 0.832 |
| EU rate | 0.076 | 0.083 | 0.083 | 0.080 | 0.063 | 0.070 |
| EE rate | 0.085 | 0.081 | 0.082 | 0.082 | 0.044 | 0.044 |
| $\epsilon_{UE/\theta}$ | 0.720 | 0.717 | 0.710 | 0.707 | 0.711 | 0.705 |
| Average establishment size | 15.6 | 15.4 | 15.4 | 15.3 | 15.5 | 15.6 |
| Entry/Total job creation | 0.21 | 0.18 | 0.18 | 0.18 | 0.27 | 0.25 |
| **Financial market** | | | | | | |
| Mean credit spread (%) | 1.09 | 0.96 | 0.97 | 0.97 | - | - |
| Median leverage (%) | 26 | 21 | 21 | 21 | - | - |
| Correlation (output, spreads) | -0.549 | -0.503 | -0.583 | - | - | - |
| Correlation (IQR, spreads) | 0.462 | 0.448 | 0.427 | - | - | - |
| Annual exit rate (%) | 8.9 | 9.0 | 9.0 | 9.2 | 9.0 | 9.0 |

*Note:* This table shows the moments matched by the benchmark model and the model without contracting frictions. '$A$+$\sigma$' means the model has both aggregate productivity shocks and uncertainty shocks, '$A$+$\sigma(\Delta^w)$' refers to the model allowing heterogeneous pass-through from uncertainty shocks to wages as estimated in Table 3, Column (6), and '$A$' means the model only has aggregate productivity shocks.

$(\mu_\sigma, \rho_\sigma, \sigma_\sigma)$. Additionally, the correlation between output and the IQR determines the correlation $(\rho_{A\sigma})$ between aggregate productivity shocks and uncertainty shocks.

Second, for labor market dynamics, I calibrate the unemployment utility $(\bar{u})$, vacancy posting cost $(c)$, and relative on-the-job search efficiency $(\lambda)$ using transitions from employment to unemployment (EU), unemployment to employment (UE), and employment to employment (EE). The data moments are the quarterly equivalents of monthly rates in Schaal (2017), initially from Shimer (2005) for EU and UE rates and Nagypál (2007) for the EE rate. The calibrated $\bar{u}$ is about 62% of average labor productivity, similar to the 63% estimated by Schaal (2017) and 71% by Hall and Milgrom (2008). The matching function elasticity $\gamma$ is calibrated by the elasticity of the UE rates to labor market tightness from Shimer (2005). The entry cost $k_e$ matches the share of jobs created by entrants from Schaal (2017) using Business Employment Dynamics. The mean operating cost, $\mu_\epsilon + \bar{w}_m$, matches the average establishment size reported by Schaal (2017) using the 2002 Economic Census.

The last set of parameters deals with the financial market. The standard deviation of operating costs, $\sigma_\epsilon$, is determined by the average credit spread between Baa and Aaa corporate bonds from Moody's. This credit spread is modeled as the annualized difference between borrowing costs and the risk-free interest rate: $\frac{1}{Q(S,z,b',n')} - \frac{1}{\beta}$. The agency friction parameter, $\tilde{\zeta} \equiv \zeta/(\bar{w}_m + (1-\lambda)\frac{\beta}{1-\beta}\bar{w}_m)$, encouraging firms to borrow, is calibrated using median leverage data from Moody's in Arellano, Bai and Kehoe (2019). The correlation between output and credit spreads informs the auditing technology parameter $\xi$, and the correlation between the interquartile range and credit spreads sets the recovery rate $\eta$. Finally, the exogenous exit rate $\pi_d$ is calibrated using the annual exit rate from Business Dynamics Statistics, capturing firm exits beyond defaults.

## 4.2 External Validation

In this section, I illustrate the decision rules of firms and validate the model using empirical evidence.

### 4.2.1 Firm-Level Decisions

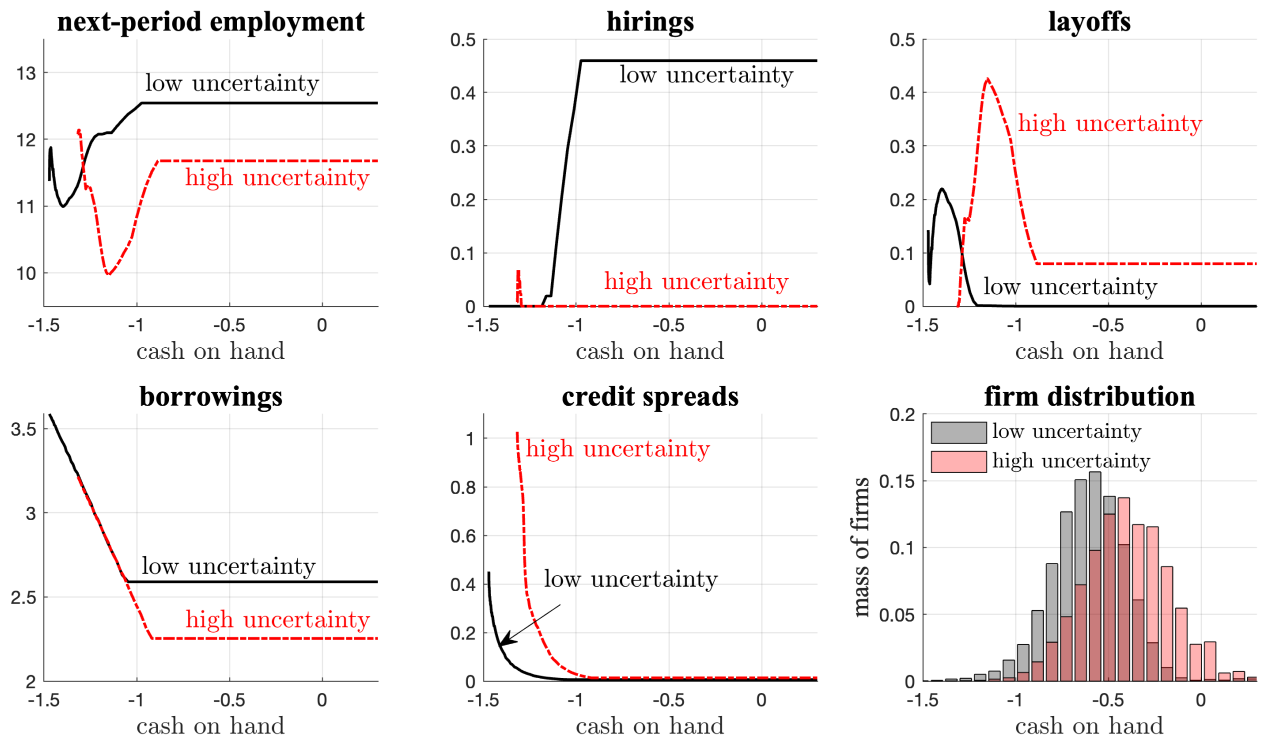
Figure 3 shows how median firms' decisions depend on cash on hand and uncertainty levels, with aggregate productivity held constant.

***Cash on Hand.*** As cash on hand decreases, firms borrow more to meet the non-negative equity payout constraint, resulting in higher credit spreads. Increased default risks let firms to cut employment by hiring less and firing more. Note that at very low cash levels where the default rate spikes, some firms take the risk and hire more, aiming for higher productivity conditional on survival. However, this strategy is limited to a small subset of firms, as shown in the distribution graph in the last panel.

***Uncertainty.*** Uncertainty markedly affects firms' decisions, as demonstrated in the graph where higher uncertainty leads to larger credit spreads and less borrowing. This is driven by the greater risk of low productivity and potential defaults, making firms reluctant to borrow. Such risk aversion also shows up on firms' cash on hand; the last panel displays that firms hold more cash under higher uncertainty, opting for safer portfolios.

Moreover, when wages are insensitive to firm-specific shocks, wage bills are similar to debt-like obligations. As such, retaining employees is isomorphic to borrowing more, compelling firms to reduce hiring and increase layoffs when uncertainty is high.

Figure 3: Firm's Decisions Rules and Distribution




*Notes:* The first five panels show the median firm's decision rules for cash on hand, with the firm's productivity and employment held at median values, and aggregate productivity set high. Solid black lines represent low uncertainty states, and dash-dot red lines denote high uncertainty. The last panel contrasts the stochastic stationary distributions of firms' cash on hand under low (black) and high (red) uncertainty. "High" and "low" states are defined as one unconditional standard deviation above or below the mean.

### 4.2.2 Validation Against Empirical Evidence

As an external validation, I re-estimate the empirical regression (4) using a model-simulated panel of 3,000 workers and 5,000 firms across 1,000 periods.[13] Panel A of Table 6 presents the results, projecting layoff indicators against uncertainty shocks and the interaction with firms' financial constraint indicators. In the model, a firm is considered financially constrained if its cash on hand is below that period's median. This criterion is used because cash on hand effectively reflects a firm's financial condition in the model.

In Panel A, Column (1) displays the baseline 2SLS empirical result from Table 2, showing a 0.51% increased layoff probability in financially constrained firms when uncertainty

[13] As workers are homogeneous in the model and to maintain computational efficiency, I limit the number of simulated workers.

Table 6: Responses of layoffs to Uncertainty Shocks: Model versus Data

Panel A. Heterogenous Responses Conditional on Firm Financial Conditions

| | Data | Model | | |
|---|---|---|---|---|
| $\mathbb{1}_{ijt}^{\text{layoff}}$ | (1) | (2) | (3) | (4) |
| $\Delta\sigma_{t-1}$ | -0.00038 | | 0.00067 | 0.00075 |
| | (0.00162) | | (0.00018) | (0.00018) |
| $\Delta\sigma_{t-1} \cdot \mathbb{1}\{\text{lagged fin-constraint}_{jt}\}$ | 0.00514** | 0.00543 | 0.00557 | 0.00557 |
| | (0.00249) | (0.00025) | (0.00025) | (0.00025) |
| Firm controls | ✓ | ✓ | ✓ | ✓ |
| Firm, worker FEs | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | × | × |
| Aggregate controls | × | × | × | ✓ |

Panel B. Unconditional Responses

| | Data | Model | | Schaal (2017) | |
|---|---|---|---|---|---|
| $\mathbb{1}_{ijt}^{\text{layoff}}$ | (1) | (2) | (3) | (4) | (5) |
| $\Delta\sigma_{jt-1}$ | 0.00013 | 0.00317 | 0.00327 | -0.00017 | -0.00018 |
| | (0.00157) | (0.00012) | (0.00012) | (0.00007) | (0.00007) |
| Firm controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Firm, worker FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | × | × | × | × |
| Aggregate controls | × | × | ✓ | × | ✓ |

*Note:* This table compares the empirical evidence from Table 2 with simulations from my benchmark model and Schaal's (2017) model. Panel A shows firms' layoff responses conditional on heterogeneous financial conditions, while Panel B presents unconditional responses to uncertainty shocks. The first column in each panel is the 2SLS regression result from Table 2. Subsequent columns employ regressions using model simulations for 3,000 workers and 5,000 firms over 1,000 periods. The regressions project job-level layoff indicators, $\mathbb{1}_{ijt}^{\text{layoff}}$, against 1-year lagged changes of uncertainty, $\Delta\sigma_{t-1}$, with and without the interaction with firms' lagged financial constraint indicators, $\mathbb{1}\{\text{lagged fin-constraint}_{jt}\}$, where $i$ denotes workers, $j$ represents firms, and $t$ stands for time. My model and Schaal's (2017) model differ slightly in the timing of shock realization; hence, $\sigma_{t-1}$ is uniformly defined as the uncertainty shock realized right before and directly influencing layoffs at time $t$ in both models. Each regression standardizes changes in uncertainty and incorporates both worker and firm-fixed effects. Model regressions consistently contain firm-side controls, in line with the data methodology. These include $\Delta A_{t-1}$ and $\Delta z_{jt-1}$ as the first-moment controls, lagged firm sales as the gauge for firm size, their interactions with the lagged firm's financial constraint indicator, and the lagged financial constraint indicator itself. In model regressions, the financial constraint indicator is set to one if the firm's cash on hand is below that period's median. Time fixed effects are omitted in certain columns to estimate the coefficient of $\Delta\sigma_{t-1}$, compensated by including 2-period lagged uncertainty and aggregate productivity growth ($\Delta\sigma_{t-2}$ and $\Delta A_{t-2}$) as aggregate controls, given $\sigma$ and $A$ are the sole aggregate shocks in the model. Significance stars are only reported for data regressions: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

rises by one standard deviation. The following Columns (2), (3), and (4) from model simulations report similar coefficients of around 0.55%. This consistency suggests that the parameterized model successfully captures the role of financial heterogeneity on the impact of uncertainty shocks.

Panel B compares my model with the standard search model by examining unconditional responses to uncertainty shocks. Column (1) repeats the 2SLS empirical regression result from Table 2, which shows an insignificantly positive effect of uncertainty on layoffs. Columns (2) and (3) of my model also display positive estimated coefficients. In contrast, Columns (4) and (5) show that Schaal's (2017) search framework predicts a clear negative impact of uncertainty on layoffs, attributed to irreversible search costs and the increased option value of waiting.[14] This difference highlights the importance of incorporating financial heterogeneity into the search model to more accurately evaluate the effects of uncertainty shocks.

# 5 Quantitative Analyses

I then use the model for two quantitative analyses. Section 5.1 applies the model to study U.S. recessions, and Section 5.2 evaluates labor market stabilization policies.

## 5.1 Event Study for U.S. Recessions

This section uses the model to analyze five past U.S. recessions, from the 1970s to the Great Recession. Using a particle filter approach similar to Bocola and Dovis (2019), I estimate historical aggregate productivity and uncertainty shocks, and then compare the model-predicted unemployment with actual data.

***Model-Predicted Unemployment.*** A particle filter is a Monte Carlo Bayesian estimator, used to estimate the posterior distribution of structural shocks in non-linear systems like mine. To use it, the first step is to simplify the infinite-dimensional firm distribution within my model into the following auxiliary finite-state state-space system:

$$\begin{aligned} \boldsymbol{Y}_t &= g(\boldsymbol{X}_t) + \epsilon_t^Y, \\ \boldsymbol{X}_t &= f(\boldsymbol{X}_{t-1}, \epsilon_t^X), \end{aligned} \tag{40}$$

where $\boldsymbol{Y}_t$ is a vector of observables, and $\boldsymbol{X}_t$ is a finite-dimensional state vector. Function $g$

[14] Appendix E details three differences in my calibration from Schaal (2017), each necessary for integrating the financial friction. But none of these differences cause the distinct layoff responses.

maps the states to observations, and $f$ describes the transition of states. Both state shocks $\epsilon_t^X$ and measurement errors $\epsilon_t^Y$ are modeled as serially uncorrelated Gaussian variables.

The state variables $\boldsymbol{X}_t$ are combinations of aggregate productivity, uncertainty, and credit spreads.[15] The observables $\boldsymbol{Y}_t$ include aggregate output and the interquartile range (IQR) of firm sales growth. The mapping function $g(\cdot)$ is derived by projecting simulated output and IQR on the state variables, with $R^2$ of 0.999998 and 0.9997 confirming the mapping's accuracy. The state transition function $f(\cdot)$ governs the transitions of aggregate productivity and uncertainty, as defined in eqs. (36) and (37).

Given the state-space system (40), I apply a particle filter to estimate historical aggregate shocks. The observables are GDP per capita from BEA and the interquartile range (IQR) of firm sales growth from Compustat. Both series are detrended by a band-pass filter to focus on business cycle fluctuations within 6 to 32 quarters, consistent with Schaal (2017). To simulate the states, I generate 10,000 particles that evolve and refine based on their likelihoods to accurately predict the observables. Figure F.2 plots the estimated shocks, and Figure F.3 confirms the observables are accurately matched.

Next, I feed the estimated aggregate shocks into the model to predict unemployment. Panel A of Figure 4 displays the results: the actual unemployment data (black lines) closely align with the benchmark model's predictions (dash-dotted red lines), indicating the model's effectiveness in capturing unemployment spikes. Additionally, to isolate the role of uncertainty shocks, the dashed blue lines show the predictions from the model with only aggregate productivity shocks.[16] This comparison reveals a significant deterioration in the model's explanatory power without considering uncertainty shocks, particularly during the 2001 Recession and the Great Recession—periods characterized by large increases in uncertainty but only modest decreases in aggregate TFP.

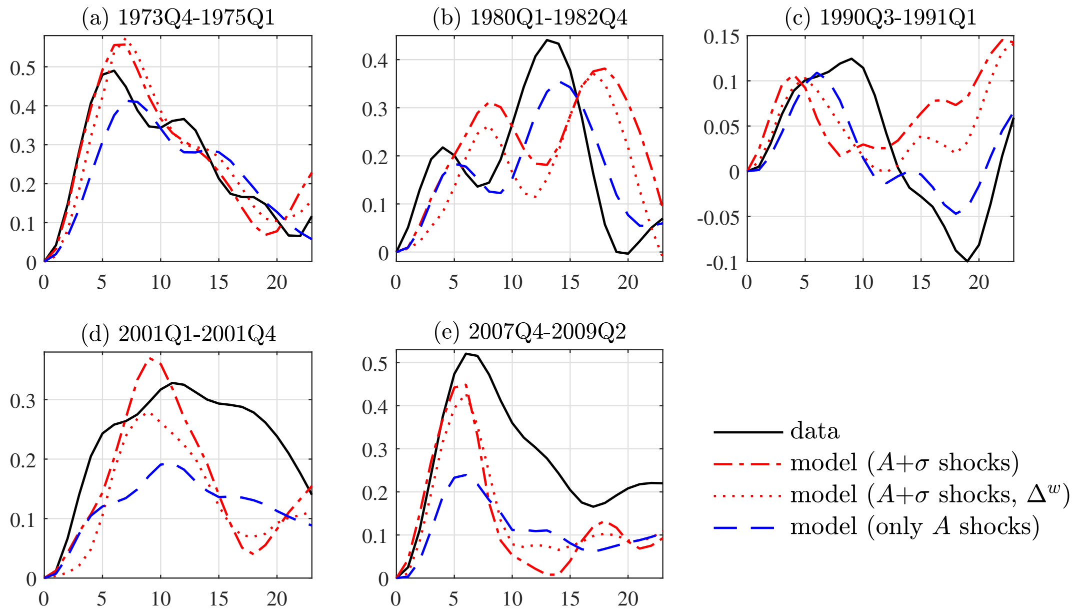
***The Role of Contracting Frictions.*** The key to this result is the interaction between financial and labor contracting frictions. Without either of them, the model collapses to the one without contracting frictions at all. If labor contracts are complete, firms

[15] There are five groups of state variables in $\boldsymbol{X}_t$: $(i)$ a constant; $(ii)$ $\{\log A_{t-p}, \log \sigma_{t-p}\}_{p=0}^5$; $(iii)$ $\{\log A_{t-p} \cdot \log \sigma_{t-p}, \{\log A_{t-p} \cdot \log \sigma_{t-q}, \log A_{t-q} \cdot \log \sigma_{t-p}\}_{q=p+1}^3\}_{p=0}^2$; $(iv)$ $\{(\Delta \log A_{t-p})^2, (\Delta \log \sigma_{t-p})^2, (\Delta \log A_{t-p})^2 \cdot \log \sigma_{t-1}, (\Delta \log \sigma_{t-p})^2 \cdot \log A_{t-1}\}_{p=0}^3$; $(v)$ $\{\log \text{spr}_{t-1} \cdot \log A_t, \log \text{spr}_{t-1} \cdot \log \sigma_t, \{\log \text{spr}_{t-p}, \log \text{spr}_{t-p} \cdot \log A_{t-1}, \log \text{spr}_{t-p} \cdot \log \sigma_{t-1}, \{\log \text{spr}_{t-p} \cdot (\Delta \log A_{t-q})^2, \log \text{spr}_{t-p} \cdot (\Delta \log \sigma_{t-q})^2\}_{q=0}^2\}_{p=1}^5\}$.

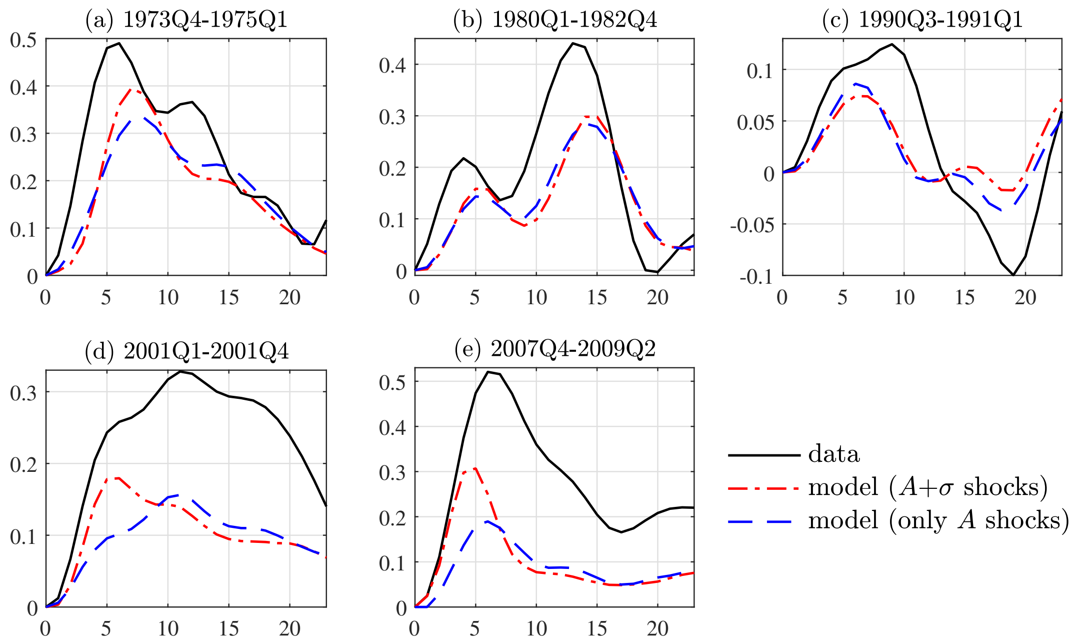
[16] All reference models have been recalibrated, with their parameter values in Table F.1 and matched moments in Table 5.

Figure 4: Unemployment Series With and Without Modeling Contracting Frictions

Panel A: Benchmark Models




Panel B: Models Without Contracting Frictions




*Notes:* The panels display model predictions for unemployment during recessions: Panel A uses benchmark models; Panel B, models without contracting frictions. Models are recalibrated, with aggregate productivity and uncertainty shocks estimated using a particle filter on output data and firms' sales growth IQR, detrended for 6 to 32 quarter fluctuations per Schaal (2017). Each panel compares actual data (solid black lines) against model-predicted unemployment (dash-dotted red lines for $A + \sigma$ shocks, dotted red lines for both shocks and wage pass-through as estimated in Table 3, Column (6), dashed blue lines for only $A$ shocks). Series are depicted as log deviations from pre-recession peaks. I use Schaal's (2017) code when plotting this figure.

Table 7: Peak-To-Trough Changes of Unemployment During Recessions

| | 1973-1975 | 1980-1982 | 1990-1991 | 2001 | 2007-2009 |
|---|---|---|---|---|---|
| **Data** | 0.490 | 0.441 | 0.124 | 0.328 | 0.521 |
| **Benchmark models** | | | | | |
| Only $A$ shocks | 0.413 | 0.355 | 0.109 | 0.193 | 0.239 |
| Both $A$ and $\sigma$ shocks | 0.557 | 0.382 | 0.107 | 0.370 | 0.449 |
| $\Rightarrow$ Data explained by adding $\sigma$ shocks | 29.5% | 5.9% | -1.7% | 53.9% | 40.2% |
| | 25.6% on average | | | | |
| Both $A$ and $\sigma$ shocks ($\Delta^w$) | 0.574 | 0.371 | 0.141 | 0.280 | 0.429 |
| $\Rightarrow$ Data explained by adding $\sigma$ shocks | 32.8% | 3.6% | -4.8% | 26.3% | 36.3% |
| | 18.9% on average | | | | |
| **Models without contracting frictions** | | | | | |
| Both $A$ and $\sigma$ shocks | 0.395 | 0.298 | 0.074 | 0.179 | 0.307 |
| Only $A$ shocks | 0.333 | 0.285 | 0.086 | 0.156 | 0.190 |
| $\Rightarrow$ Data explained by adding $\sigma$ shocks | 12.6% | 3.0% | -9.6% | 7.1% | 22.6% |
| | 7.1% on average | | | | |

*Note:* The table compares peak-to-trough unemployment changes during recessions across data, benchmark models, and models without contracting frictions. 'Both $A$ and $\sigma$ Shocks' refers to models with both aggregate productivity shocks and uncertainty shocks, where '$\Delta^w$' means the model allowing heterogeneous pass-through from uncertainty shocks to wages as estimated in Table 3, Column (6). 'Only $A$ Shocks' means models with only aggregate productivity shocks. Models are recalibrated.

can borrow directly from workers, eliminating the need for state-uncontingent bonds. Conversely, if the financial market is complete, the within-match labor contracting friction becomes irrelevant because only the present value of wages influences decisions.

Panel B of Figure 4 shows that the model without contracting frictions performs worse in explaining spikes in unemployment. Table 7 reports that, in my benchmark model, uncertainty shocks account for 26% of unemployment increases, compared to just 7% in the model without contracting frictions—indicating that over 70% of uncertainty's impact is driven by these frictions. Business cycle statistics in Table F.2 confirm that this conclusion holds beyond recessions. The finding echoes Schaal (2017), who discovers the inadequacy of the canonical search framework in capturing unemployment dynamics during the Great Recession. My research builds on his by incorporating the contracting frictions to reevaluate the effects of uncertainty shocks.

***Robustness of the Labor Contracting Friction.*** In my benchmark model, the labor contracting friction implies that wage are insensitive to idiosyncratic conditions. Yet, the

2SLS regression in Table 3, Column (6), shows a wage pass-through of $-0.949\%$ following a one standard deviation uncertainty shock for financially constrained firms. To test the robustness of the labor contracting friction, I introduce this conditional wage pass-through, $\Delta^w$, into the model:

$$\Delta^w(\Delta\sigma, z) = -0.949\% \frac{\Delta\sigma}{\mathrm{SD}(\Delta\sigma)}, \text{ if } z < \mathrm{median}(z), \tag{41}$$

where $\mathrm{SD}(\Delta\sigma)$ equals $\sqrt{2(1-\rho_\sigma)}\sigma_\sigma$[17], and $\mathrm{median}(z)$ represents the average median idiosyncratic productivity.[18] With this pass-through, compensation to incumbent workers becomes $[1 + \Delta^w(\Delta\sigma, z)]w(S)$. For simplicity, I assume that a negative pass-through does not cause workers to exit the firm, offering a conservative estimate of uncertainty's effects under wage pass-through.

Panel A of Figure 4 illustrates that including wage pass-through, denoted by "($\Delta^w$)", generates unemployment patterns similar to those predicted by the benchmark model. Table 7 further shows that uncertainty shocks still account for 18.9% of the increases in unemployment with this partial wage insensitivity. Given their similar predictions, I focus on the benchmark model that abstracts from this wage pass-through.

***Specialness of Uncertainty Shocks.*** Figure 4 and Table 7 also reveal that contracting frictions amplify the effects of uncertainty shocks more than aggregate productivity shocks. The key is their different equilibrium wage responses. As observed by Shimer (2005), the free entry condition in search models leads to wage declines that greatly absorb the negative impact of aggregate productivity shocks. In my model, wages also decrease a lot to contractionary aggregate TFP shocks.

However, for uncertainty shocks, this offsetting effect is much weaker, as shown by the smaller wage declines in the impulse response functions (Figures F.4 and F.5). The reason is that uncertainty shocks are dispersion shocks, spreading the distribution of firm-level productivity. This wider spread, in turn, leads to higher expected profits for firms, particularly for high-productivity firms—an impact known as the Oi-Hartman-Abel effect (Oi (1961), Hartman (1972), Abel (1983)). This expectation of higher profits limits the need

[17] According to eq. (37), $\mathrm{SD}(\Delta\sigma) = \mathrm{SD}(\log\sigma_{t+1} - \log\sigma_t) = \mathrm{SD}[-(1-\rho_\sigma)\log\sigma_t + \sigma_\sigma\sqrt{1-\rho_\sigma^2}\epsilon_t^\sigma] = \sqrt{(1-\rho_\sigma)^2\mathrm{Var}(\log\sigma_t) + \sigma_\sigma^2(1-\rho_\sigma^2)} = \sqrt{(1-\rho_\sigma)^2\sigma_\sigma^2 + \sigma_\sigma^2(1-\rho_\sigma^2)} = \sqrt{2(1-\rho_\sigma)}\sigma_\sigma$

[18] Using exogenous idiosyncratic productivity as a criterion, instead of endogenous variables like cash on hand, maintains the model's computational tractability while still capturing the firms' financial conditions.

for substantial wage reductions to satisfy the free entry condition. Since equilibrium wages do not decrease enough to cancel out the risk of drawing low idiosyncratic productivity, uncertainty shocks result in higher unemployment.

## 5.2 Policy Implications

Given my model's insights into uncertainty and unemployment, I use it to evaluate two labor market stabilization policies that have become topical during recent recessions: increasing unemployment benefits and subsidizing wage payments.

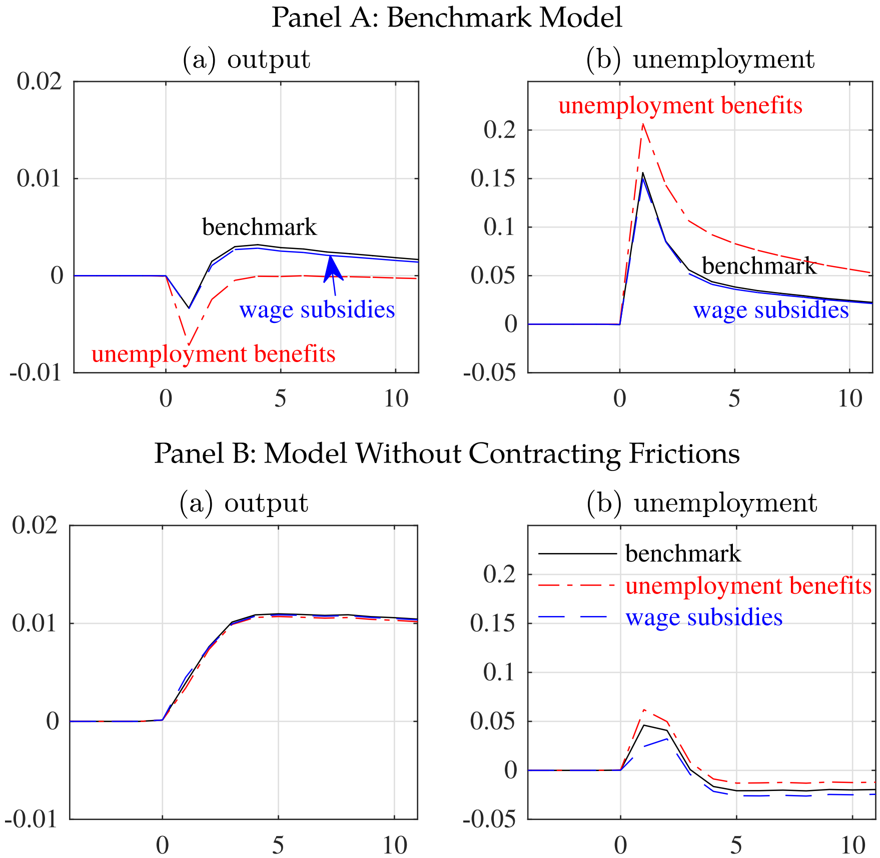
***Increasing Unemployment Benefits.*** During the 2020 Covid-19 pandemic, uncertainty increased dramatically (Altig et al., 2020). In response, the U.S. government implemented the Federal Pandemic Unemployment Compensation (FPUC) program, which added $600 to weekly unemployment benefits. To examine the impacts of this policy, my model simulates a 1% increase in unemployment benefits during high uncertainty periods, financed through a lump-sum tax costing 4.81 basis points of output. I assume the policy is fully anticipated by agents in the economy.

Figure 5, Panel A, plots the impulse responses to a 5% positive uncertainty shock. The solid black lines represent the benchmark model without policy interventions, and the dashed red lines depict the effects of increasing unemployment benefits. It is clear that this policy deepens the recession by reducing output and increasing unemployment. Table F.3 summarizes the policy's effects on model-simulated moments, indicating a 4.3 basis point reduction in the total surplus for workers and firms. The losses are attributed to labor market distortions caused by the higher unemployment benefits, which lead to higher wages, increased production costs, and greater financial burdens for firms.

***Subsidizing Wage Payments.*** On the other hand, Germany's social insurance program, Kurzarbeit, enables firms to reduce workers' hours, with the government compensating for part of the employees' lost earnings, thereby helping firms to retain staff during economic downturns. Similarly, the U.S. introduced the Paycheck Protection Program (PPP) during the Covid-19 recession. To model this policy, I give firms the option to idle part of their workforce when uncertainty is high, with the government subsidizing 84.4% of these idle workers' wages. This subsidy rate matches the expenditure ratio of the UI policy experiment, also costing 4.86 basis points of output.

Figure 5, Panel A, shows the impulse responses of wage subsidies with dash-dot blue

Figure 5: Aggregate Responses to a 5% Uncertainty Shock Under Policy Intervention




*Notes:* The panels depict impulse responses of aggregate output and unemployment to a 5% positive uncertainty shock at quarter 0. Panel A shows the benchmark model's results, and Panel B displays the results of the reference model without contracting frictions. Solid black lines are the results without policy intervention, labeled 'benchmark'. Dash-dot red lines correspond to the model with enhanced unemployment benefits policy, and dashed blue lines to the model with wage subsidies. Policies are activated when uncertainty exceeds its average. These impulse responses are averaged over 4,000 simulated paths and displayed as log deviations from the mean. I use Schaal's (2017) code when plotting this figure.

lines, revealing a slight decrease in output and a milder increase in unemployment. The policy's small overall impact is due to its conflicting effects. On the one hand, wage subsidies serve as state-contingent insurance for firms, aiding wage payments and enhancing employee retention. On the other hand, they encourage labor hoarding, leading to inefficient allocation of labor towards low-productivity firms that might otherwise downsize. According to Table F.3, this policy results in a reduction of 2.6 basis points in total surplus.

***The Role of Contracting Frictions.*** Financial and labor contracting frictions are crucial for accurate policy evaluation. Figure 5, Panel B, displays results from the counterfactual model without these frictions. In this model, the UI policy (dashed red lines) causes a much smaller output decline and rise in unemployment. Similarly, wage subsidies (dash-dot blue lines) show a stronger stabilization effect by reducing unemployment. Table F.3 quantifies these differences: efficiency loss from the UI policy drops dramatically from 4.3 to $7 \times 10^{-5}$ basis points, and for wage subsidies, the loss decreases from 2.6 to $4 \times 10^{-3}$ basis points. These results indicate that excluding contracting frictions from the model greatly underestimates the distortions caused by policies, and misleadingly suggests that the UI policy performs better than wage subsidies, as the relevance of within-match wages diminishes.

# 6 Conclusion

Prior research finds that uncertainty shocks have a limited impact on unemployment rates within the canonical search framework (Schaal, 2017). Building on this, I first empirically identify the additional risk premium channel of uncertainty shocks using micro-level data of layoffs. I then construct a novel search model that can replicate the empirical evidence by incorporating financial and labor contracting frictions. Given the two frictions, I find that uncertainty shocks have a large impact on unemployment rates. This is primarily because firms, with limited ability to hedge against idiosyncratic risks, are averse to committing to employment during periods of high uncertainty. Furthermore, my model offers new insights into evaluating labor market stabilization policies.

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# Online Appendices

## A Micro-Foundations for the Labor Contracting Friction

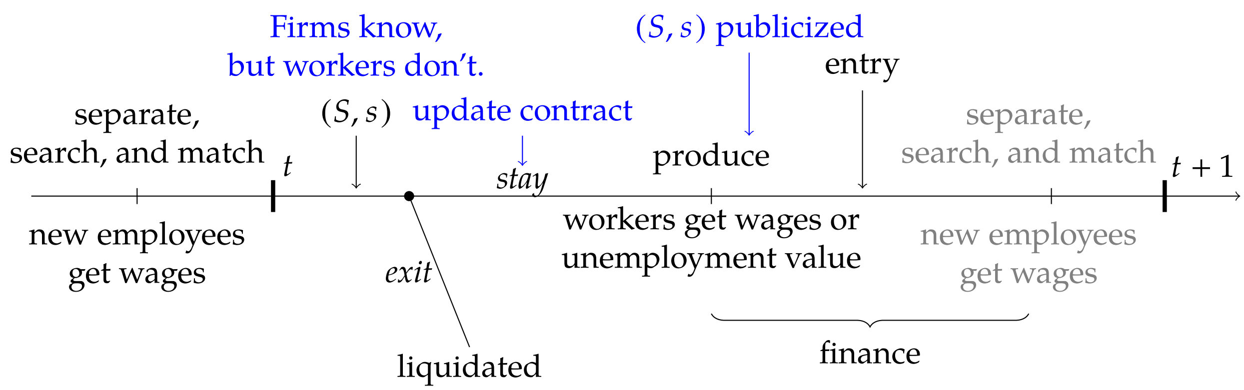
In this section, I micro-found the labor contracting friction in eq. (12), using the asymmetric information between firms and their employees. The logic follows Hall and Lazear (1984), who demonstrates the optimality of predetermined wages in a two-period model under asymmetric information. My model builds on this by allowing intertemporal labor contracts, operating under two main assumptions: firms immediately recognize realized shocks while employees become aware later during the production stage; additionally, firms are not penalized for misrepresenting information. Given the two assumptions, the only incentive-compatible promises are state-uncontingent. This section first establishes a model with asymmetric information, then demonstrates the optimality of state-uncontingent promises.

***Timing.*** Figure A.1 adds the timing for asymmetric information on top of Figure 2. When shocks $(S, s)$ realize at the beginning of each period, firms know the shocks, but workers do not. If a worker leaves the firm now, he is unemployed and obtains the unemployment value in the current period. Given the shocks, firms choose to exit or stay. Staying firms declare their current shocks are $\tilde{S}$ and $\tilde{s}$ and update contracts. Notice that the declaration can differ from the true state since workers do not observe the information now. I allow the declarations to differ across the firm's employees. Given that the labor contract has been updated, the worker gets nothing in the current period if he leaves the firm now. At the production stage, workers receive wage payments according to the labor contract, based on the firm's declaration of the state $(\tilde{S}, \tilde{s})$. After that, shocks $(S, s)$ become public information. At the end of the period, firms separate, search, and match.

The labor contract $C$ includes elements $\left\{w, \tau, \bar{W}(S', s'), d(S', s')\right\}$. Notice I assume that the contact directly specifics the markup $\bar{W}(S', s')$ between the lifetime promised utility $W'(S', s')$ and the outside value of unemployment $\boldsymbol{U}(S')$. This assumption of contracting only the utility markup, rather than the entire lifetime utility, allows for a realistic variation of the promised lifetime utility in response to changes in aggregate states.

***Employed worker's problem.*** The unemployment worker's problem does not change,

Figure A.1: Timing With Asymmetric Information




while the employed worker's problem becomes:

$$\begin{aligned} \boldsymbol{W}(S,s,C) = \max_x\ & w + \lambda p(\theta(S,x))x + (1-\lambda p(\theta(S,x)))\tau\beta\,\mathbb{E}_{S'|S}\,\boldsymbol{U}(S') \\ & + (1-\lambda p(\theta(S,x)))(1-\tau)\beta \max\Big\{ \underbrace{\mathbb{E}_{S'|S}\,\boldsymbol{U}(S')}_{\text{leave before the contract is updated}},\ \mathbb{E}_{S',s'|S,s}\,\{(\pi_d + (1-\pi_d)d(S',s'))\boldsymbol{U}(S') \\ & + (1-\pi_d)(1-d(S',s'))\max\{\boldsymbol{U}(S') + \bar{W}(\tilde{S}'^{*},\tilde{s}'^{*}), \underbrace{0 + \beta\,\mathbb{E}_{S''|S'}\,\boldsymbol{U}(S'')}_{\text{leave after the contract is updated}}\}\}\Big\}. \end{aligned} \tag{42}$$

As before, the worker receives the wage $w$ at the production stage. The worker can conduct on-the-job search and leave the firm. If the worker stays but gets laid off, he will be unemployed in the next period and receive the unemployment value $\boldsymbol{U}(S')$.

If the worker is not laid off, he can still leave the firm when the outside value is high enough. But the outside value depends on the timing of leaving the firm. If the worker leaves the firm before the contract is renewed, he is counted as unemployed and receives the unemployment value just like a laid-off worker. However, if he leaves the firm after the contract is renewed, he receives zero and gets the unemployment value one period later. This setup can be understood as the worker being ineligible to receive unemployment benefits after the labor relation renews, and drawing up contracts is time-consuming, so he does not have time to produce at home in the same period. Hence, the utility is zero in that period. This assumption implies that workers have no incentive to quit when they find the firm lies (Proposition 2(i)).

If the labor relation persists, the worker will receive the lifetime utility $\boldsymbol{U}(S')+\bar{W}(\tilde{S}'^{*},\tilde{s}'^{*})$. Notice that because of asymmetric information, the promised utility markup $\bar{W}$ to the worker depends on the firm's declaration of states $(\tilde{S}'^{*},\tilde{s}'^{*})$. To clarify, $\{\bar{W}(S',s')\}$ in the labor contract is the set of utility markups for the next period. However, how much the worker can get in the next period depends on the firm's declaration of states $(\tilde{S}'^{*},\tilde{s}'^{*})$.

***Firm's problem.*** A firm's states include realized aggregate shocks $S\in\boldsymbol{S}$, realized firm-specific shocks $s\in\boldsymbol{s}$, the number of employees $n$, and the set of promised utility markups to its employees $\{\bar{W}(S,s;i)\}_{S\in\boldsymbol{S},s\in\boldsymbol{s};i\in[0,n]}$, where $i$ is the index of incumbent employees within the firm. In a slight abuse of notation, $S$ and $s$ inside $\bar{W}(\cdot,\cdot;i)$ refer to the possible shocks instead of the realized shocks.

Besides the choice variables in the original firm's problem (7), the firm now also chooses to declare the current shocks, $\tilde{S}(i)$ and $\tilde{s}(i)$, to each employee $i$. The following equations (43) to (48) summarize the firm's problem:

$$\begin{aligned}\boldsymbol{J}(S,s,b,n,\{\bar{W}(S,s;i)\}_{S\in\boldsymbol{S},s\in\boldsymbol{s};i\in[0,n]}) = & \max_{\substack{\Delta,b',n',n_h,x_h,d(S',s')\\ \{\tilde{S}(i),\tilde{s}(i),w(i),\tau(i)\}_{i\in[0,n]},\\ \{w_h(i')\}_{i'\in(n'-n_h,n']},\\ \{\bar{W}(S',s';i')\}_{S'\in\boldsymbol{S}',s'\in\boldsymbol{s}';i'\in[0,n']}}} \Delta \\ & + \beta(1-\pi_d)\,\mathbb{E}_{S',s'|S,s}\left\{(1-d(S',s'))\boldsymbol{J}(S',s',b',n',\{\bar{W}(S',s';i')\}_{S'\in\boldsymbol{S}',s'\in\boldsymbol{s}';i'\in[0,n']})\right\}\end{aligned} \tag{43}$$

$$\text{s.t. } (8), (9), (10), (11), (15), \tag{44}$$

$$\begin{aligned}\boldsymbol{W}^E(i') \equiv \mathbb{E}_{S',s'|S,s}\{&(\pi_d+(1-\pi_d)d(S',s'))\boldsymbol{U}(S')\\ &+(1-\pi_d)(1-d(S',s'))\max\{\boldsymbol{U}(S')+\bar{W}(\tilde{S}'^{*},\tilde{s}'^{*};i'),0+\beta\,\mathbb{E}_{S''|S'}\boldsymbol{U}(S'')\}\},\end{aligned} \tag{45}$$

$$\boldsymbol{W}^E(i')\geq \mathbb{E}_{S'|S}\,\boldsymbol{U}(S'), \forall i'\in[0,n'], \tag{46}$$

$$\begin{aligned}\max_x\, & w(i)+\lambda p(\theta(S,x))x+(1-\lambda p(\theta(S,x)))\tau(i)\beta\,\mathbb{E}_{S'|S}\,\boldsymbol{U}(S')\\ &+(1-\lambda p(\theta(S,x)))(1-\tau(i))\beta\boldsymbol{W}^E(i')\geq\boldsymbol{U}(S)+\bar{W}(\tilde{S},\tilde{s};i),\ \ \text{for } i'\in[0,n'-n_h],\end{aligned} \tag{47}$$

$$w_h(i')+\beta\boldsymbol{W}^E(i')\geq x_h,\ \ \text{for } i'\in(n'-n_h,n']. \tag{48}$$

Equations (45) to (48) describe the new implicit contract constraints in the presence of asymmetric information. First, eq. (45) uses $W^E$ to denote the worker's expected lifetime utility if he stays with the firm. $W^E$ is also the last part of the employment value (42).

Constraint (46) is the new participation constraint, meaning that the worker's expected utility is at least the expected unemployment value so that he will stay. Eq. (47) is the new promise-keeping constraint for incumbent workers. This constraint requires the firm to commit to paying the employee at least the promised lifetime utility. The left-hand side is the incumbent worker's employment value, i.e., eq. (42). The right-hand side is the promised lifetime utility, comprised of two parts—the unemployment value $\boldsymbol{U}(S)$ and the promised utility markup $\bar{W}(\tilde{S}, \tilde{s}; i)$. Notice that $\tilde{S}(i)$ and $\tilde{s}(i)$ are the firm's declarations of shocks, two of the firm's choice variables. They can be different from the true shocks because of asymmetric information. Eq. (48) is the new promise-keeping constraint for newly hired workers. Its left-hand side is the newly hired worker's employment value. On the right-hand side, $x_h$ is the submarket where the firm employs new workers, and $x_h$ is also the promised lifetime utility of the vacancies posted in that submarket. Thus, firms can guarantee that newly hired workers receive at least the lifetime utility promised by the offer.

The following Proposition 2 demonstrates that the promised utility markup $\bar{W}$ is state-uncontingent.

**Proposition 2** *The labor relation between the firm and its employees has the following properties:*

*(i) Workers do not leave the firm even if they find the firm lied.*

*(ii) The promised utility markup $\bar{W}$ is state-uncontingent.*

**Proof** As for point (i), recall that employees discover whether the firm lied about shocks in the production stage, i.e. after the contract is updated. If they leave the firm now, they get nothing today and start receiving the unemployment value in the next period. So, even if the firm gives the worker zero wages and fires them right after the production stage, the worker is willing to stay with the firm.

As for point (ii), because employees will not leave the firm regardless, according to point (i), lying about the shocks has no consequences for the firm. Thus, firms always declare the lowest employment surplus in $\{\bar{W}(S, s; i)\}_{S \in \boldsymbol{S}, s \in \boldsymbol{s}}$ to each employee $i$. Therefore, the incentive-compatible labor contract requires the promised utility markup $\bar{W}$ to be state-uncontingent. □

## B Micro-Foundations for the Agency Friction

The micro-foundation of the agency friction in eq. (15), following Arellano, Bai and Kehoe (2019), is as follows. I assume there is a pool of potential managers, each firm employing one to operate its business. The total mass of managers is much smaller than of workers, so I abstract from managers when calculating unemployment. Managers have the option of self-employment, producing $\bar{w}_m$ units of goods. The market for managers is competitive, so a manager's wage is also $\bar{w}_m$.

Each period consists of a day and night. During the day, managers are monitored by the firm's shareholders, so managers conduct the firm's optimal policies: the manager uses borrowing $Q(S,z,b',n')b'$ and sales to pay dividends, wages of incumbent workers, his own wage, the operating cost, and debt. Search happens overnight, and the manager is supposed to use the remaining resources to pay vacancy posting costs and the wages of new workers. However, what happens during the night cannot be observed by shareholders until the next day. Therefore, the manager can propose an alternative production plan to the financial intermediary to borrow as much as possible. To convince the financial intermediary of the new plan $(\bar{b}', \bar{n}')$, the manager should prove by posting vacancies to have $\bar{n}'$ workers in the next period. That is, the manager needs to pay vacancy posting costs and wages for newly hired workers for this alternative proposal. In sum, to maximize available funds, the manager will come up with a proposal to achieve maximum possible borrowing net of hiring costs $M(S,z,n)$ defined in eq. (16).

Given the maximum net borrowing $M(S,z,n)$, the remaining credit available for the manager is the maximum net borrowing minus the previous borrowing plus the originally planned but unused money for search, i.e., the numerator of eq. (49). The manager uses the remaining credit to hire workers to produce for his own project. Because the manager only needs to hire workers for the next-period production, the outside value of unemployment benefits $\bar{u}$ is the lowest wage for the manager to retain workers to produce. The manager then uses the remaining credit to hire as many workers $n_s$ as possible:

$$n_s = \frac{M(S,z,n) - Q(S,z,b',n')b' + n_h \frac{c}{q(\theta(S,x_h))} + \int_{n'-n_h}^{n'} w_h(i')di'}{\bar{u}}. \tag{49}$$

The manager takes advantage of the firm's productivity for his sided project, so the output is

$$\zeta z' n_s^{\alpha}, \tag{50}$$

where $\zeta$ indicates the profitability of the manager's own project.

I allow an auditing technology to detect a manager's intention to deviate at night. The effectiveness of the auditing technology, $\xi A$, is based on a measure of auditing quality, $\xi$, proportional to aggregate productivity. The incentive and available resources to use the auditing technology are approximated by the firm's expected income $\mathbb{E}[A'z'n'^{\alpha} - \int_0^{n'} w(i')di' - \bar{w}_m - \epsilon']$. The more the firm expects to earn, the more it can and should pay for the auditing technology. I assume that the probability of the manager being caught is Gaussian and determined by the amount of auditing:

$$\Phi\Big(\xi A\, \mathbb{E}[A'z'n'^{\alpha} - \int_0^{n'} w(i')di' - \bar{w}_m - \epsilon]\Big). \tag{51}$$

I model the auditing technology to match the negative correlation between credit spreads and aggregate output. Without this auditing technology, a positive aggregate productivity shock would counterfactually raise credit spreads, as firms, experiencing higher income, would borrow more to avoid managerial deviations. In contrast, the auditing technology reduces the need for borrowing during periods of high aggregate productivity, thereby leading to a decrease in credit spreads, consistent with the data.

To deter managerial deviations, firms must ensure that their credit use does not leave substantial excess funds. If a manager deviates from the firm's optimal policies, shareholders will detect and fire him the next day. The deviating manager faces a probability $\gamma$ of becoming self-employed (else returning to the manager market). Therefore, the firm adheres to the following incentive-compatible condition to prevent potential deviations:

$$\Big(1-\Phi\Big(\xi A\, \mathbb{E}[A'z'n'^{\alpha}-\int_0^{n'} w(i')di'-\bar{w}_m-\epsilon]\Big)\Big)\, \mathbb{E}_t\, \beta\zeta A_{t+1} z_{t+1} n_s^{\alpha} + \gamma\, \mathbb{E}_t \sum_{j=2}^{\infty} \beta^j \bar{w}_m \leq \mathbb{E}_t \sum_{j=1}^{\infty} \beta^j \bar{w}_m. \tag{52}$$

This equation delivers the agency friction constraint (15) by plugging in eq. (49).

# C Additional Proofs

**Proposition** 1 *The participation constraint* (13) *and the promise-keeping constraint* (14) *bind.*

**Proof** First, the promise-keeping constraint (14) always binds. Otherwise, firms could lower wages and earn more. Then, I prove that the participation constraint (13) binds by contradiction. Imagine a scenario under the firm's optimal policy where a worker, designated as $i'$ for the next period, has a positive $\bar{W}(i') > 0$ in the contract. I can propose an alternative policy that sets $\bar{W}(i') = 0$ and delivers a higher firm's value. This analysis is first applied to incumbent employees, followed by the case of newly hired workers.

**Case 1.** Suppose $i'$ refers to an incumbent worker. Use $i$ to denote the worker's index in the current period and $\epsilon^m$ to denote the worker's mass of the firm's entire labor force.

I construct an alternative policy by making the following four changes to the original policy. The idea is to frontload wages and borrow more simultaneously:

1. Decrease the promised utility markup $\bar{W}(i')$ to zero, which just satisfies the participation constraint (13). To simply the notation, I use $\delta$ to denote $\bar{W}(i')$ from now on.

2. Decrease the worker's next-period wage $w(i')$ by exactly $\delta$. Since the wage decreases as much as the promised utility, the next-period promise-keeping constraint (14) still holds.

3. Promise to pay a bonus $\tilde{w}$ to the worker today conditional on not leaving the firm by on-the-job search, where $\tilde{w}$ equals $\beta\,\mathbb{E}[(1-\tau(i))(1-\pi_d)(1-d(S',s'))]\delta$. This additional payment guarantees that the worker has the same lifetime promised utility today, so today's promise-keeping constraint (14) is unaffected. Importantly, the worker's on-the-job search decision is not affected because the payment is given to the worker conditional on not transiting to another firm. From the firm's perspective, its labor expense today increases by $\epsilon^m(1-\lambda p(\theta(S, x^*(S;i))))\tilde{w}$.[1]

4. Increase the debt $b'$ by $\epsilon^m(1-\tau(i))(1-\lambda p(\theta(S, x^*(S;i))))\delta$, which equals the decrease in the firm's wage bills in the next-period. So, the next-period cash on hand of the firm does not change.

Given these four changes, I next show the firm's value increases. First, because the next-period cash on hand is the same, the next-period default decisions are unchanged.

[1] Notice that this additional payment is conditional on the worker does not leave the firm by on-the-job search. To simplify the wage expression derivation, I do not consider the conditional wage payments in the main paper. This simplification does not diminish the model's general applicability; it only changes the timing of wage payment within a given period without affecting the firm's total wage bills, $\int w(i)di$. The assumption can be relaxed by adding an additional first-order condition to the firm's problem. This change would not impact the uniqueness of wages within labor contracts as the job-finding function is strictly concave, although it would add a layer of complexity. An alternative simplification could be omitting on-the-job search altogether. I leave these to future research.

Also, the next-period employment $n'$ does not change, so neither is the expected value of the firm in the next period.

Second, the borrowing increases more than the increase in today's wage payments, so today's equity payouts increase:

$$
\begin{aligned}
&\Delta^{\text{new}} - \Delta = Q(S,s,b'^{\text{new}},n)b'^{\text{new}} - Q(S,s,b',n)b' - \epsilon^m(1-\lambda p(\theta(S,x^*(S;i))))\tilde{w} \\
&= \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}b'^{\text{new}} + \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\frac{\pi'^{\text{new}}}{b'^{\text{new}}},1\}\right\}b'^{\text{new}} \\
&\quad - \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}b' - \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\frac{\pi'}{b'},1\}\right\}b' \\
&\quad - \epsilon^m(1-\lambda p(\theta(S,x^*(S;i))))\tilde{w} \\
&= \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}b'^{\text{new}} - \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}b' \\
&\quad + \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi'^{\text{new}},b'^{\text{new}}\}\right\} \\
&\quad - \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi',b'\}\right\} - \epsilon^m(1-\lambda p(\theta(S,x^*(S;i))))\tilde{w} \\
&= \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}(b'^{\text{new}} - b') - \epsilon^m(1-\lambda p(\theta(S,x^*(S;i))))\tilde{w} \\
&\quad + \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi'^{\text{new}},b'^{\text{new}}\}\right\} \\
&\quad - \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi',b'\}\right\} \\
&= \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}\epsilon^m(1-\tau(i))(1-\lambda p(\theta(S,x^*(S;i))))\delta \\
&\quad - \epsilon^m(1-\lambda p(\theta(S,x^*(S;i))))\beta\,\mathbb{E}[(1-\tau(i))(1-\pi_d)(1-d(S',s'))]\delta \\
&\quad + \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi'^{\text{new}},b'^{\text{new}}\}\right\} \\
&\quad - \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi',b'\}\right\} \\
&= \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi'^{\text{new}},b'^{\text{new}}\}\right\} \\
&\quad - \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi',b'\}\right\}.
\end{aligned}
$$

Notice that $b'^{\text{new}} \geq b'$ by construction and $\pi'^{\text{new}} \geq \pi'$ because the next-period wage bills decrease. Therefore, $\min\{\eta\pi'^{\text{new}}, b'^{\text{new}}\} \geq \min\{\eta\pi', b'\}$. So,

$$
\begin{aligned}
\Delta^{\text{new}} - \Delta \geq &\beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi',b'\}\right\} \\
&- \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi',b'\}\right\} \\
=&0.
\end{aligned} \tag{53}
$$

Lastly, the agency friction constraint (15) holds under this constructed policy. The constraint's left-hand side increases as the borrowing increases, and its right-hand side decreases because of lower next-period wage bills.

**Case 2.** Suppose $i'$ is a newly hired worker in the current period. Similarly, construct an alternative policy by making the following four changes to the original policy:

1. Decrease the promised utility markup $\bar{W}(i')$ to zero, just satisfying the participation constraint. I use $\delta$ to denote $\bar{W}(i')$.

2. Decrease the worker's next-period wage $w(i')$ by $\delta$, so the next-period promise-keeping constraint still holds.

3. Increase the newly hired workers' wage $w_h(i')$ by $\beta\,\mathbb{E}[(1-\pi_d)(1-d(S',s'))]\delta$, guaranteeing that the worker still has the same lifetime promised utility $x_h$, so today's promise-keeping constraint still holds. On the firm-side, today's labor expense increases by $\epsilon^m\tilde{w}$, where $\epsilon^m$ denotes the worker's mass.

4. Increase the debt $b'$ by $\epsilon^m\delta$, which equals the decrease in the firm's wage bills in the next-period. Thus, the next-period cash on hand does not change.

Given these four changes, the firm's value increases for the following reasons. First, the firm's value in the next period is unaffected because the cash on hand and labor force are unchanged.

Second, the borrowing increases more than the increase in wage payments, so the equity payouts increase. Formally,

$$\begin{aligned}
\Delta^{\text{new}} - \Delta &= Q(S,s,b'^{\text{new}},n)b'^{\text{new}} - Q(S,s,b',n)b' - \epsilon^m\tilde{w} \\
&= \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}(b'^{\text{new}} - b') - \epsilon^m\tilde{w} \\
&\quad + \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi'^{\text{new}}, b'^{\text{new}}\}\right\} \\
&\quad - \beta\,\mathbb{E}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi', b'\}\right\} \\
&= \beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}\epsilon^m\delta - \epsilon^m\beta\,\mathbb{E}\left\{(1-\pi_d)(1-d(S',s'))\right\}\delta \\
&\quad + \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi'^{\text{new}}, b'^{\text{new}}\}\right\} \\
&\quad - \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi', b'\}\right\} \\
&= \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi'^{\text{new}}, b'^{\text{new}}\}\right\} \\
&\quad - \beta\,\mathbb{E}_{S',s'|S,s}\left\{[1-(1-\pi_d)(1-d(S',s'))]\min\{\eta\pi', b'\}\right\} \\
&\geq 0,
\end{aligned}$$

where the last inequality is due to $b'^{\text{new}} \geq b'$ and $\pi'^{\text{new}} \geq \pi'$.

Lastly, the agency friction constraint (15) holds. The constraint's left-hand side increases as the borrowing increases more than the increase in newly hired workers' wages, and its right-hand side decreases as next-period wage bills decrease.

In sum, I construct a feasible and better alternative policy, which contradicts the optimality of the original policy with a loose participation constraint. Therefore, the participation constraint always binds in the equilibrium. □

**Lemma** 3.1 *(Decision Cutoffs): If $X < -M(S, z, n)$, the firm cannot satisfy the nonnegative external equity payout condition and has to default. If $X \geq \hat{X}(S, z, n) \equiv -\{Q(S, z, \hat{b}, \hat{n})\hat{b} - \hat{n}_h \frac{c}{q(\theta(S,\hat{x}_h))} - \hat{n}_h[\hat{x}_h - \beta\, \mathbb{E}\, \boldsymbol{U}(S')]\}$, the firm solves the relaxed problem (27), and the level of cash on hand does not affect the optimal decisions.*

**Proof** If the firm's cash on hand $X$ is less than $-M(S, z, n)$, even though the firm borrows as much as possible, it cannot make nonnegative external equity payouts. So, the firm defaults and exits. If the firm's cash on hand $X$ is more than $\hat{X}(S, z, n)$, then $(\hat{b}, \hat{n}, \hat{\tau}, \hat{n}_h, \hat{x}_h)$ is also the solution to the firm's problem (22), as the non-negative equity payout constraint (24) holds automatically. In this case, cash on hand does not affect any constraints, and the optimal decisions do not depend on cash on hand. □

# D Computational Algorithm

This section explains the computational algorithm for solving and simulating the model. I use Fortran as the programming language and parallelize to run the code with 20 cores.

***Value Function Iteration.*** First, I define $h(A, \sigma)$ as the vacancy posting cost plus a newly hired worker's wage:

$$h(A, \sigma) \equiv \min_{x_h} \left[ \frac{c}{q(\theta(A, \sigma, x_h))} + w_h(A, \sigma, x_h) \right] \tag{54}$$

$$= \min_{x_h} \left[ \frac{c}{q(\theta(A, \sigma, x_h))} + x_h - \beta\, \mathbb{E}\, \boldsymbol{U}(A', \sigma') \right] \tag{55}$$

$$= \kappa(A, \sigma) - \beta\, \mathbb{E}\, \boldsymbol{U}(A', \sigma'). \tag{56}$$

$h(A, \sigma)$ represents the costs paid in the current period to hire a new worker, which is the key price I use to solve the labor market equilibrium.

Second, I discretize the state space. Aggregate productivity, $A$, is discretized into two points, i.e., high and low, the same for uncertainty, $\sigma$. The number of grids for firm-level idiosyncratic productivity, $z$, equals 13. The grids of $z$ depend on the last-period uncertainty, $\sigma_{-1}$. Therefore, both $\sigma$ and $\sigma_{-1}$ are firms' state variables in the numerical implementation. I use Tauchen's method to discretize $A$, $\sigma$, and $z$. Cash on hand, $X$, has 64 grids. Debt, $b$, has 301 grids. Employment, $n$, has 260 grids.

Then I use the following steps to solve the problem:

1. Initialize the iteration counter $k = 0$. Make the initial guess for the current-period hiring cost $h^{(0)}(A, \sigma)$.

2. Given $h^{(k)}(A, \sigma)$, solve the unemployment value $\boldsymbol{U}^{(k)}(A, \sigma)$ by the value function iteration, along with the first-order condition with respect to $x_u$:

$$\boldsymbol{U}^{(k)}(A, \sigma) = \max_{x_u} \bar{u} + p(\theta^{(k)}(A, \sigma, x_u))x_u + (1 - p(\theta^{(k)}(A, \sigma, x_u)))\beta\,\mathbb{E}\,\boldsymbol{U}^{(k)}(A', \sigma') \tag{57}$$

$$= \bar{u} + \max_{x_u} p(\theta^{(k)}(A, \sigma, x_u))[x_u - \beta\,\mathbb{E}\,\boldsymbol{U}^{(k)}(A', \sigma')] + \beta\,\mathbb{E}\,\boldsymbol{U}^{(k)}(A', \sigma') \tag{58}$$

Given the following mapping from eq. (32):

$$x(A, \sigma, \theta) = \kappa(A, \sigma) - \frac{c}{q(\theta)}, \tag{59}$$

derive the first-order condition with respect to $x_u$ that indicates the optimal choice of the labor market to search:

$$\theta_u^*(A, \sigma) = \left\{ \left[ \frac{c}{\max\{\kappa(A, \sigma) - \beta\,\mathbb{E}\,\boldsymbol{U}(A', \sigma'), c\}} \right]^{-\frac{\gamma}{1+\gamma}} - 1 \right\}^{\frac{1}{\gamma}} \tag{60}$$

$$= \left\{ \left[ \frac{c}{\max\{h(A, \sigma), c\}} \right]^{-\frac{\gamma}{1+\gamma}} - 1 \right\}^{\frac{1}{\gamma}} \tag{61}$$

When $h(A, \sigma) < c$, workers choose $\theta_u^* = 0$ to stay unemployed because the value of working offered in every submarket is less than the value of unemployment. On the other hand, as long as $h(A, \sigma) \geq c$, there always exists a market with $\theta$ close to 0 such that the value of employment is higher than unemployment, so workers want to search for jobs.

Plug the search decision $\theta_u^*(A, \sigma)$ into eq. (58) and get the updated $\boldsymbol{U}(A, \sigma)$. Repeat this process until $\boldsymbol{U}(A, \sigma)$ converges.

3. Given $h^{(k)}(A, \sigma)$, solve the bond pricing schedule $Q^{(k)}(A, \sigma, \sigma_{-1}, z, b', n')$ using the following iteration.

First, guess the bond pricing schedule $Q^{\text{old}}(A, \sigma, \sigma_{-1}, z, b', n') = \beta$ and the maximum net borrowing $M^{\text{old}}(A, \sigma, \sigma_{-1}, z, n) = \beta * b_{\max}$, where $b_{\max}$ denotes the upper-bound of the grids of debt.

Next, update $Q$ and $M$. Then repeat until the relative difference between $M^{\text{old}}$ and $M^{\text{new}}$ is less than $10^{-7}$ and that between $Q^{\text{old}}$ and $Q^{\text{new}}$ is less than $10^{-10}$.

(a) Update $Q(A, \sigma, \sigma_{-1}, z, b', n')$ according to the following equation:

$$Q^{\text{new}}(A, \sigma, \sigma_{-1}, z, b', n') = \beta \mathbb{E} \Big\{ (1 - \pi_d) \Phi_\epsilon(\bar{\epsilon}(A', \sigma', \sigma, z', b', n')) \\ + [1 - (1 - \pi_d)\Phi_\epsilon(\bar{\epsilon}(A', \sigma', \sigma, z', b', n'))] \min\{\tilde{\eta} \frac{A'z'n'^{\alpha} - n'w(A', \sigma') - \bar{w}_m - \mu_\epsilon}{b'}, 1\} \Big\}, \tag{62}$$

where the default cutoff, $\bar{\epsilon}(A', \sigma', \sigma, z', b', n')$, is calculated as follows

$$\bar{\epsilon}(A', \sigma', \sigma, z', b', n') \equiv A'z'n'^{\alpha} - n'w(A', \sigma') - b' + M^{\text{old}}(A', \sigma', \sigma, z', n') - \bar{w}_m, \tag{63}$$

and the incumbent worker's wage, $w(A', \sigma')$, is computed according to eq. (19).

(b) Update $M(A, \sigma, \sigma_{-1}, z, n)$:

$$M^{\text{new}}(A, \sigma, \sigma_{-1}, z, n) \equiv \max_{b', n', n_h, x_h} Q^{\text{new}}(A, \sigma, \sigma_{-1}, z, b', n')b' - n_h \frac{c}{q(\theta(A, \sigma, x_h))} - n_h w_h(A, \sigma, x_h) \tag{64}$$

$$= \max_{b', n', n_h} Q^{\text{new}}(A, \sigma, \sigma_{-1}, z, b', n')b' - n_h h^{(k)}(A, \sigma) \tag{65}$$

$$= \max_{b', n'} Q^{\text{new}}(A, \sigma, \sigma_{-1}, z, b', n')b' - H^{(k)}(A, \sigma, n, n') \tag{66}$$

where $H(A, \sigma, n, n')$ denotes the matrix of hiring costs

$$H^{(k)}(A, \sigma, n, n') \equiv \begin{cases} [n' - (1 - \lambda p(\theta^*(A, \sigma)))n] h^{(k)}(A, \sigma), & \text{if } n' > (1 - \lambda p(\theta^*(A, \sigma)))n, \\ 0, & \text{if } n' \leq (1 - \lambda p(\theta^*(A, \sigma)))n, \end{cases} \tag{67}$$

where the optimal on-the-job search market, $\theta^*(A, \sigma)$, is the same as the choice of unemployed workers, $\theta_u^*(A, \sigma)$.

4. Given $h^{(k)}(A, \sigma)$ and $Q^{(k)}(A, \sigma, \sigma_{-1}, z, b', n')$, solve the firm's problem by value function iteration as follows.

(a) Guess the firm's value function $\boldsymbol{V}^{\text{old}}(A, \sigma, \sigma_{-1}, z, X, n)$.

(b) Compute the expected future value:

$$G(A,\sigma,\sigma_{-1},z,b',n') \equiv \mathbb{E}\int_{-\infty}^{\bar{\epsilon}(A',\sigma',\sigma,z',b',n')} \boldsymbol{V}^{\text{old}}(A',\sigma',\sigma,z',X',n')d\Phi_\epsilon(\epsilon'), \tag{68}$$

where the default cutoff, $\bar{\epsilon}(A',\sigma',\sigma,z',b',n')$, is from eq. (63) and tomorrow's cash on hand is determined by

$$X' = A'z'n'^\alpha - n'w(A',\sigma') - \bar{w}_m - \epsilon' - b', \tag{69}$$

Then the firm's problem can be simplified into

$$\boldsymbol{V}^{\text{new}}(A,\sigma,\sigma_{-1},z,X,n) = \max_{\Delta,b',n'} \Delta + \beta(1-\pi_d)G(A,\sigma,\sigma_{-1},z,b',n')$$

$$\text{s.t. } \Delta = X + Q(A,\sigma,\sigma_{-1},z,b',n')b' - H(A,\sigma,n,n') \geq 0,$$

$$Q(A,\sigma,\sigma_{-1},z,b',n')b' - H(A,\sigma,n,n') \geq M(A,\sigma,\sigma_{-1},z,n) - F_m(A,\sigma,\sigma_{-1},z).$$

(c) Before solving $\boldsymbol{V}^{\text{new}}$, solve the relaxed problem first:

The relaxed problem is

$$\hat{\boldsymbol{V}}(A,\sigma,\sigma_{-1},z,n) = \max_{b',n'} Q(A,\sigma,\sigma_{-1},z,b',n')b' - H(A,\sigma,n,n') + \beta(1-\pi_d)G(A,\sigma,\sigma_{-1},z,b',n')$$

$$\text{s.t. } Q(A,\sigma,\sigma_{-1},z,b',n')b' - H(A,\sigma,n,n') \geq M(A,\sigma,\sigma_{-1},z,n) - F_m(A,\sigma,\sigma_{-1},z).$$

Let $\hat{b}(A,\sigma,\sigma_{-1},z,n)$ and $\hat{n}(A,\sigma,\sigma_{-1},z,n)$ denote the optimal policies of the relaxed problem.

(d) Given $\hat{b}(A,\sigma,\sigma_{-1},z,n)$ and $\hat{n}(A,\sigma,\sigma_{-1},z,n)$, update the grids of cash on hand. The grids of cash on hand $X$ are equidistantly distributed on $[X_{\text{min}}, X_{\text{max}}]$. The lower bound, $X_{\text{min}}$, equals $-M(A,\sigma,\sigma_{-1},z,n)$. The upper bound, $X_{\text{max}}$, equals the maximum of $\hat{X}(A,\sigma,\sigma_{-1},z,n) = -[Q(A,\sigma,\sigma_{-1},z,\hat{b},\hat{n})\hat{b} - H(A,\sigma,\sigma_{-1},n,\hat{n})]$.

(e) Update the firm's value function, $\boldsymbol{V}(A,\sigma,\sigma_{-1},z,X,n)$, by grid search. For each state $(A,\sigma,\sigma_{-1},z,X,n)$ of $\boldsymbol{V}(\cdot)$, I go though the combinations of choices $(b',n')$ to find the maximum objective value to update $\boldsymbol{V}^{\text{new}}(A,\sigma,\sigma_{-1},z,X,n)$, where $(b',n')$ should satisfy the non-negative equity payout constraint and the agency friction constraint. The grid search for optimal $b'$ and $n'$ in value function iterations is around the frictionless optimal levels of $b'$ and $n'$.

(e) Given $\boldsymbol{V}^{\text{new}}(A,\sigma,\sigma_{-1},z,X,n)$, update the expected future value, $G(A,\sigma,\sigma_{-1},z,b',n')$. For each state $(A,\sigma,\sigma_{-1},b',n')$ of $G(\cdot)$, I use Gauss-Legendre method to compute the integration with respect to $\epsilon'$, with the linear interpolation of $\boldsymbol{V}^{\text{new}}(A',\sigma',\sigma,z',X',n')$ with respect to $X'$. Denote the updated expected future value as $G^{\text{new}}(A,\sigma,\sigma_{-1},z,b',n')$.

5. Renew the current-period hiring cost, $h^{(k+1)}(A,\sigma)$, such that the free entry condition holds for each aggregate state $(A,\sigma)$:

$$k_e = \sum_z \boldsymbol{J}_e(A,\sigma,z) g_z(z), \forall (A,\sigma), \tag{70}$$

where the new entrant's value is solved by

$$\boldsymbol{J}_e(A,\sigma,z) = \max_{n_h,x_h} -n_h \frac{c}{q(\theta(A,\sigma,x_h))} - n_h w_h(A,\sigma,x_h) + \beta(1-\pi_d) G^{\text{new}}(A,\sigma,\sigma_{-1},z,b_0,n_h) \tag{71}$$

$$= \max_{n_h} -n_h h^{(k+1)}(A,\sigma) + \beta(1-\pi_d) G^{\text{new}}(A,\sigma,\sigma_{-1},z,b_0,n_h), \tag{72}$$

where the initial debt, $b_0$, equals zero.

6. The iteration stops when the expected future value converges, i.e., $\text{dist}(G^{\text{new}}, G^{\text{old}}) < 10^{-6}$, where I follow Judd (1998) and define the distance function as $\text{dist}(f^{(k+1)}, f^{(k)}) = \frac{(\sum_x (f^{(k+1)}(x) - f^{(k)}(x))^2)^{\frac{1}{2}}}{1 + (\sum_x f^{(k)}(x)^2)^{\frac{1}{2}}}$. If the problem does not converge, assign $k$ with $k+1$ and start from Step 2 again.

***New Entrants.*** In simulations, the mass of entrants $m_e(S,\Upsilon)$ is determined such that total jobs found by workers equals the total jobs created by incumbent firms and new entrants:

$$JF_{\text{workers}}(S,\Upsilon) = JC_{\text{incumbents}}(S,\Upsilon) + m_e(S,\Upsilon) JC_{\text{entrants}}(S,\Upsilon), \tag{73}$$

where

$$JF_{\text{workers}}(S,\Upsilon) = p(\theta(S,x_u^*(S)))\Big(1 - \sum_{z,X,n} n\Upsilon(z,X,n)\Big) + \sum_{z,X,n} \lambda p(\theta(S,x^*(S))) n\Upsilon(z,X,n), \tag{74}$$

$$JC_{\text{incumebents}}(S,\Upsilon) = \sum_{z,X,n} n_h(S,z,X,n)\Upsilon(z,X,n), \tag{75}$$

$$JC_{\text{entrants}}(S,\Upsilon) = \sum_z g_z(z) n_e(S,z). \tag{76}$$

In simulated business cycles, there can be instances where jobs created by incumbent firms, $JC_{\text{incumbents}}$, surpass those found by workers, $JF_{\text{workers}}$. When the total worker population is capped at one, this can result in undefined negative entry. To address this, I assume zero entry under such conditions and allow the worker population to expand to satisfy eq. (73). The expanded population is then normalized back to one unit. Simulation shows an average annual population growth rate below 0.5%, implying a small impact from the potential issue of negative entry. Another solution is to assign different entry costs for different aggregate states. See Kaas and Kircher (2015) for this treatment.

***Firm Defaults.*** To avoid unemployment fluctuations being mechanically driven by varying default rates, I assume that firms continue production in the default period, contributing to GDP and employment, although their firm values drop to zero upon defaulting. In the current period, these firms' employees are not included in unemployment statistics. They are laid off post-production, become eligible for unemployment benefits, and can immediately seek new employment. The distribution of producing firms, denoted by $\Upsilon^p(z,n)$, is defined as follows:

$$\begin{aligned}\Upsilon^p(z',n') = &\sum_{z,X,n,\epsilon'}(1-\pi_d)\pi_z(z'|z,\sigma)\mathbb{1}\{n'(S,z,X,n)=n'\}\Upsilon(z,X,n)\\ &+ m_e(S,\Upsilon)\sum_{z,\epsilon'}(1-\pi_d)\pi_z(z'|z,\sigma)\mathbb{1}\{n_e(S)=n'\}g_z(z).\end{aligned} \tag{77}$$

Aggregate output is the sum of all firms' output:

$$Y = \sum_{z,n} Azn^{\alpha}\Upsilon^p(z,n), \tag{78}$$

and the unemployment rate $u$ is the share of workers who do not produce:

$$u = 1 - \sum_{z,n} n\Upsilon^p(z,n). \tag{79}$$

# E Differences from the Calibration of Schaal (2017)

In my parametrization, I largely adhere to Schaal's (2017) methodology for estimating parameters related to shocks and the labor market, with three differences to incorporate financial friction.

First, while Schaal (2017) employs a monthly frequency, my model is quarterly, aligning better with financial data, particularly leverage and spreads. Firm leverage is typically defined as a firm's debt relative to annualized sales. In a quarterly model, annualized sales are four times the quarterly sales, whereas a monthly model requires multiplying monthly sales by 12. When targeting the same leverage ratio, the monthly model would require counterfactually high firm debt compared to per-period sales, leading to unrealistically high default risks. And incorporating multi-period debt in a monthly model would add unnecessary complexity. Thus, following finance literature, I choose a quarterly frequency.

Second, Schaal (2017) uses 0.85 as the decreasing returns to scale coefficient $\alpha$, and I use 0.66. Neither of our models explicitly incorporates capital; Schaal's (2017) choice of 0.85 aims to approximate total decreasing returns. He also points out that his results remain unaffected when adopting a labor share target of 0.66. My model focuses on wage payments, so I align with this labor share target of 0.66. Choosing 0.85 for the decreasing returns to scale coefficient would result in higher wage commitments, increasing risks for firms and potentially leading to counterfactually high credit spreads.

Third, in calibrating the uncertainty shock process, Schaal (2017) uses the interquartile range (IQR) of innovations to idiosyncratic productivity, as calculated by Bloom et al. (2018). In contrast, I follow both Bloom et al. (2018) and Arellano, Bai and Kehoe (2019) in using the IQR of firms' sales growth rates. This is because targeting the IQR of idiosyncratic productivity innovations results in sales volatility more than five times higher than what is observed in real data. Such heightened sales volatility raises firm default risks and leads to excessively high credit spreads.[2] To ensure more realistic financial behaviors, I adopt the IQR of firms' sales growth rates. The main difference between these two approaches is in the level of uncertainty $\bar{\sigma}$, but they exhibit similar business cycle behaviors in terms of uncertainty shocks $\epsilon_t^{\sigma}$. Figure F.1 illustrates this similarity, comparing the estimated aggregate productivity and uncertainty shocks in my model (without contracting frictions) with those in Schaal (2017).

Despite the three outlined differences, they do not affect the model's core mechanism. For example, Figure 4, which displays changes in unemployment during recessions, shows that my model (without contracting frictions) yields patterns similar to those in Schaal (2017). Additionally, Table F.2 demonstrates that the business cycle statistics of my model without contracting frictions closely resemble those in Schaal (2017).

[2] Another concern about the idiosyncratic productivity measure is its basis in revenue total factor productivity (TFPR), which may reflect firm pricing power rather than productivity (Bils, Klenow and Ruane, 2021; Hsieh and Klenow, 2009).

# F Additional Tables and Figures

Table F.1: Parameters of Reference Models

| | | Benchmark Model | | | No Contracting Frictions | |
|---|---|---|---|---|---|---|
| **Parameters** | **Notations** | $A+\sigma$ | $A+\sigma(\Delta^w)$ | $A$ only | $A+\sigma$ | $A$ only |
| **Aggregate shocks** | | | | | | |
| Persistence of aggregate productivity | $\rho_A$ | 0.920 | 0.920 | 0.920 | 0.912 | 0.912 |
| SD of aggregate productivity | $\sigma_A$ | 0.024 | 0.024 | 0.028 | 0.042 | 0.035 |
| Mean of uncertainty | $\bar{\sigma}$ | 0.248 | 0.248 | 0.250 | 0.300 | 0.280 |
| Persistence of uncertainty | $\rho_\sigma$ | 0.880 | 0.875 | - | 0.926 | - |
| SD of uncertainty | $\sigma_\sigma$ | 0.092 | 0.092 | - | 0.186 | - |
| Correlation between $\epsilon_t^A$ and $\epsilon_t^\sigma$ | $\rho_{A\sigma}$ | $-0.020$ | $-0.020$ | - | $-0.920$ | - |
| **Labor market** | | | | | | |
| Unemployment benefits | $\bar{u}$ | 0.142 | 0.142 | 0.142 | 0.150 | 0.155 |
| Vacancy posting cost | $c$ | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 |
| Relative on-the-job search efficiency | $\lambda$ | 0.100 | 0.100 | 0.100 | 0.120 | 0.120 |
| Matching function elasticity | $\gamma$ | 1.600 | 1.600 | 1.600 | 1.600 | 1.600 |
| Entry cost | $k_e$ | 15.21 | 15.21 | 14.87 | 14.70 | 15.21 |
| Mean operating cost | $\bar{w}_m + \mu_\epsilon$ | 0.001 | 0.001 | 0.001 | 0.100 | 0.100 |
| **Financial market** | | | | | | |
| SD of production costs | $\sigma_\epsilon$ | 0.080 | 0.080 | 0.071 | 0.080 | 0.080 |
| Agency friction | $\tilde{\zeta}$ | 2.400 | 2.400 | 2.400 | - | - |
| Auditing quality | $\xi$ | 1.780 | 1.780 | 1.780 | - | - |
| Recovery rate | $\eta$ | 2.410 | 2.410 | 2.410 | - | - |
| Exogenous exit rate | $\pi_d$ | 0.021 | 0.021 | 0.022 | 0.022 | 0.022 |

*Notes:* This table reports the calibrated parameters of the benchmark model and the model without contracting frictions. '$A+\sigma$' means the model has both aggregate productivity shocks and uncertainty shocks, '$A+\sigma(\Delta^w)$' refers to the model allowing heterogeneous pass-through from uncertainty shocks to wages as estimated in Table 3, Column (6), and '$A$' means the model only has aggregate productivity shocks. The corresponding matched moments are shown in Table 5.

Table F.2: Business Cycle Statistics

| | $Y$ | $Y/L$ | $U$ | $V$ | Hirings | Quits | Layoffs | Wages |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Data** | | | | | | | | |
| Std Dev. | 0.016 | 0.012 | 0.121 | 0.138 | 0.058 | 0.102 | 0.059 | 0.008 |
| cor($Y$,$x$) | 1 | 0.590 | -0.859 | 0.702 | 0.677 | 0.720 | -0.462 | 0.555 |
| **Panel B: Benchamark Model** | | | | | | | | |
| ***Both $A$ and $\sigma$ Shocks*** | | | | | | | | |
| Std Dev. | 0.015 | 0.013 | 0.106 | 0.097 | 0.048 | 0.029 | 0.111 | 0.011 |
| cor($Y$,$x$) | 1 | 0.910 | -0.500 | 0.774 | 0.140 | 0.884 | -0.202 | 0.876 |
| ***Both $A$ and $\sigma$ Shocks*** ($\Delta^w$) | | | | | | | | |
| Std Dev. | 0.014 | 0.012 | 0.111 | 0.092 | 0.048 | 0.027 | 0.117 | 0.012 |
| cor($Y$,$x$) | 1 | 0.886 | -0.500 | 0.747 | 0.067 | 0.896 | -0.244 | 0.808 |
| ***Only $A$ Shocks*** | | | | | | | | |
| Std Dev. | 0.015 | 0.011 | 0.079 | 0.081 | 0.019 | 0.028 | 0.053 | 0.010 |
| cor($Y$,$x$) | 1 | 0.988 | -0.901 | 0.904 | 0.010 | 0.964 | -0.853 | 0.980 |
| **Panel C: Model Without Contracting Frictions** | | | | | | | | |
| ***Both $A$ and $\sigma$ Shocks*** | | | | | | | | |
| Std Dev. | 0.019 | 0.016 | 0.090 | 0.085 | 0.060 | 0.079 | 0.068 | - |
| cor($Y$,$x$) | 1 | 0.990 | -0.797 | 0.485 | -0.101 | 0.401 | -0.602 | - |
| ***Only $A$ Shocks*** | | | | | | | | |
| Std Dev. | 0.017 | 0.014 | 0.076 | 0.061 | 0.041 | 0.057 | 0.053 | - |
| cor($Y$,$x$) | 1 | 0.994 | -0.882 | 0.658 | -0.158 | 0.610 | -0.813 | - |

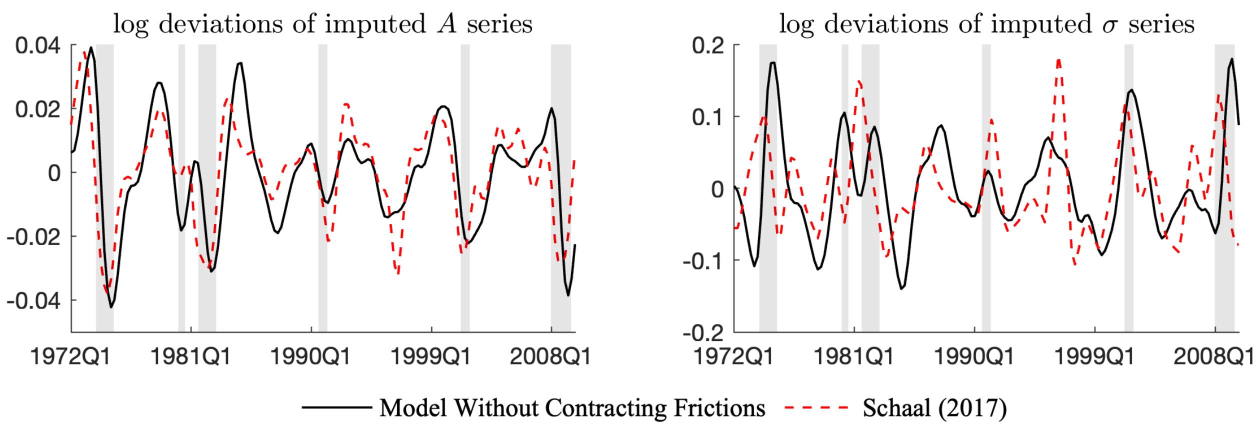
*Notes:* Panel A shows the business cycle moments observed in the data. Panels B and C present moments from 3,000-quarter simulations of the benchmark model and the model without contracting frictions, both including and excluding uncertainty shocks. 'Both $A$ and $\sigma$ Shocks' indicates the model incorporates both aggregate productivity shocks and uncertainty shocks, '$\Delta^w$' refers to the model allowing heterogeneous pass-through from uncertainty shocks to wages as estimated in Table 3, Column (6), and 'Only $A$ Shocks' denotes the model having only aggregate shocks. Both the data and the model simulations are log-detrended using the Hodrick-Prescott (HP) filter with smoothing parameter 1600. For consistency with the notations in Schaal (2017), $Y$ denotes output, $Y/L$ is output per worker, $U$ represents unemployment, and $V$ is vacancies.

Table F.3: The Aggregate Outcomes of Labor Market Policies

| | No Policy | UI Policy | Wage Policy |
|---|---|---|---|
| **Panel A: Policies** | | | |
| Increase in unemployment benefits | - | 1% | - |
| The replacement rate of wage subsidies | - | - | 84.4% |
| **Panel B: Aggregate Outcomes** | | | |
| ***Benchmark Model*** | | | |
| Mean of output | 100 | 99.593 | 99.938 |
| SD of output | 0.015 | 0.015 | 0.015 |
| Mean of unemployment (%) | 5.823 | 6.210 | 5.804 |
| SD of unemployment | 0.106 | 0.123 | 0.104 |
| Mean of average wages | 100 | 100.061 | 100.014 |
| SD of average wages | 0.011 | 0.011 | 0.011 |
| UE rate | 0.814 | 0.799 | 0.814 |
| EU rate | 0.083 | 0.085 | 0.083 |
| EE rate | 0.081 | 0.080 | 0.081 |
| Mean credit spread (%) | 0.96 | 0.96 | 0.97 |
| Median leverage (%) | 21 | 21 | 21 |
| Annual exit rate (%) | 9.0 | 9.0 | 9.0 |
| Fiscal cost share of output (basis points) | - | 4.809 | 4.862 |
| Total surplus | 100 | 99.957 | 99.974 |
| ***Model Without Contracting Frictions*** | | | |
| Mean of output | 100 | 99.963 | 99.992 |
| SD of output | 0.019 | 0.019 | 0.019 |
| Mean of unemployment (%) | 4.306 | 4.334 | 4.275 |
| SD of unemployment | 0.090 | 0.091 | 0.089 |
| Mean of average wages | - | - | - |
| SD of average wages | - | - | - |
| UE rate | 0.840 | 0.839 | 0.840 |
| EU rate | 0.063 | 0.064 | 0.063 |
| EE rate | 0.044 | 0.044 | 0.044 |
| Mean credit spread (%) | - | - | - |
| Median leverage (%) | - | - | - |
| Annual exit rate (%) | 9.0 | 9.0 | 9.0 |
| Fiscal cost share of output (basis points) | - | 3.274 | 0.000 |
| Total surplus | 100 | 99.99993 | 99.996 |

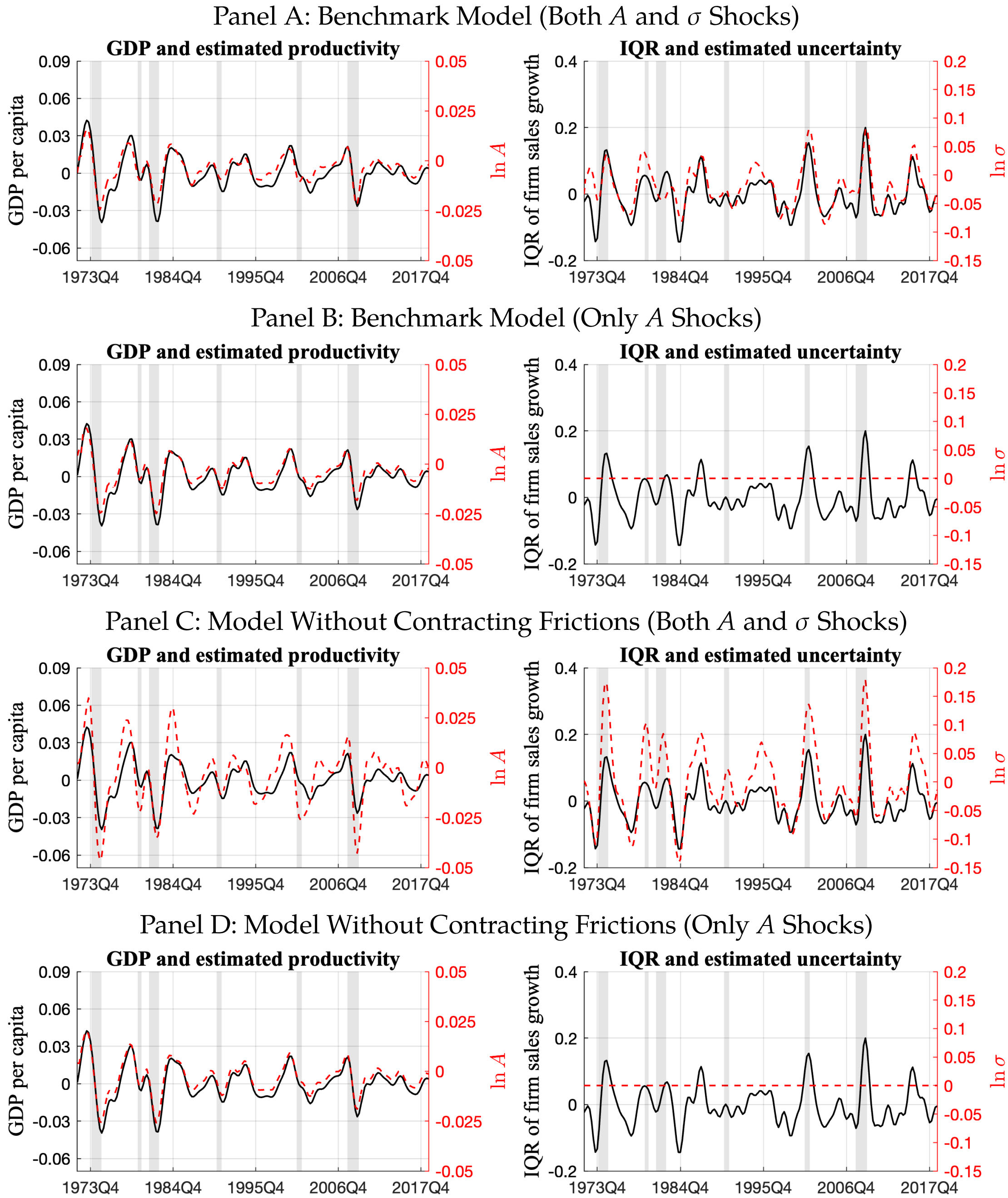
*Notes:* The table compares model-simulated moments with and without labor market policies. Panel A specifies the policies, and Panel B displays moments from 3,000-quarter simulations of the benchmark model and the model without contracting frictions. Policies are implemented when uncertainty exceeds its average level. For each policy, the model is re-solved, with the policies anticipated by economic agents. In the models without policy, the output, average wages, and total surplus are normalized to 100 for comparison. The standard deviations of output, unemployment, and average wages are calculated using log deviations, as determined by the Hodrick-Prescott (HP) filter with a smoothing parameter of 1,600.

Figure F.1: Comparison of Estimated Shocks with Schaal (2017)




*Notes:* This figure compares the shocks estimated by my model (without contracting frictions) with those estimated by Schaal (2017). The black lines show the estimated log deviations of aggregate productivity, $A$, and uncertainty, $\sigma$, from my model. The red dashed lines depict the shocks as estimated by Schaal (2017). Both series end at 2009Q4, the last period studied in Schaal (2017).

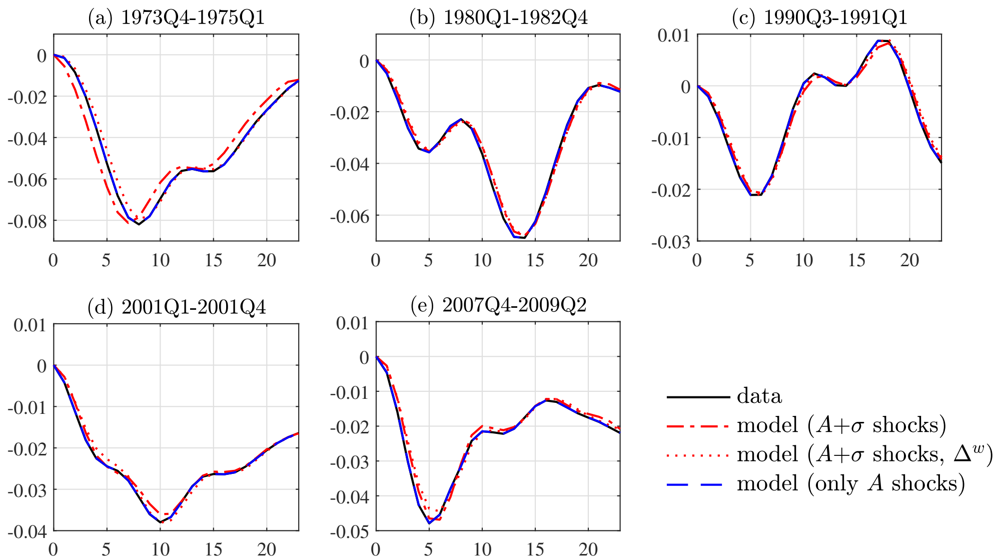
Figure F.2: Estimated Aggregate Productivity and Uncertainty



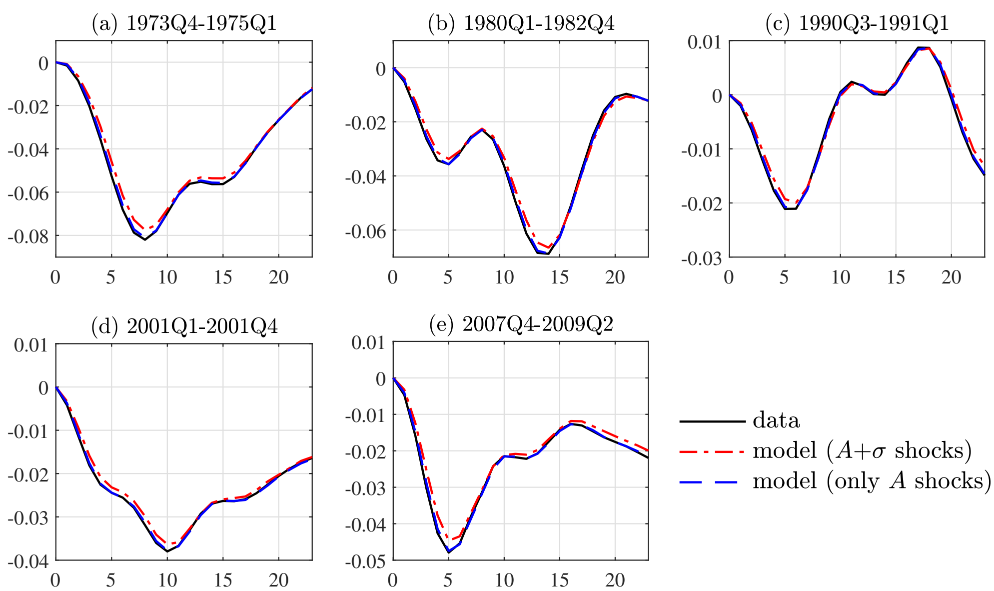

*Notes:* This figure shows the estimated aggregate productivity and uncertainty of four models. Using the particle filter, I estimate aggregate productivity, $A$, and uncertainty, $\sigma$, from GDP per capita and the interquartile range (IQR) of firm sales growth data series. These series are detrended with a band-pass filter to focus on fluctuations between 6 and 32 quarters, following Schaal (2017). The left-hand side panels show the log deviations of GDP (solid black lines) alongside the estimated demeaned logged aggregate productivity (dashed red lines). On the right-hand side, the panels present the log deviations of the IQR of firm sales growth (solid black lines) and the estimated demeaned logged uncertainty (dashed red lines). The log uncertainty is demeaned to facilitate comparison of its fluctuations across the models.

Figure F.3: Output Series With and Without Modeling Contracting Frictions

Panel A: Benchmark Models

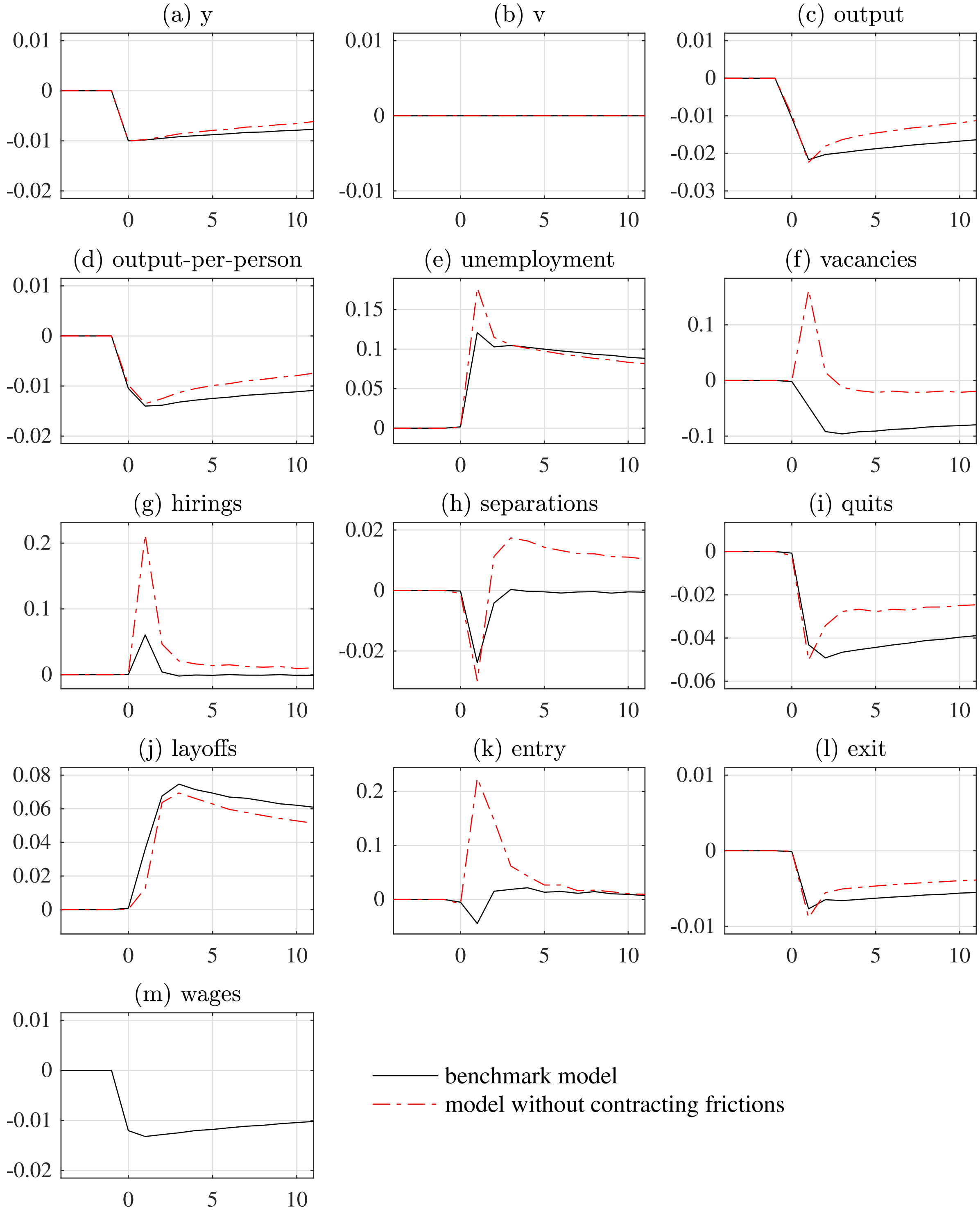



Panel B: Models Without Contracting Frictions



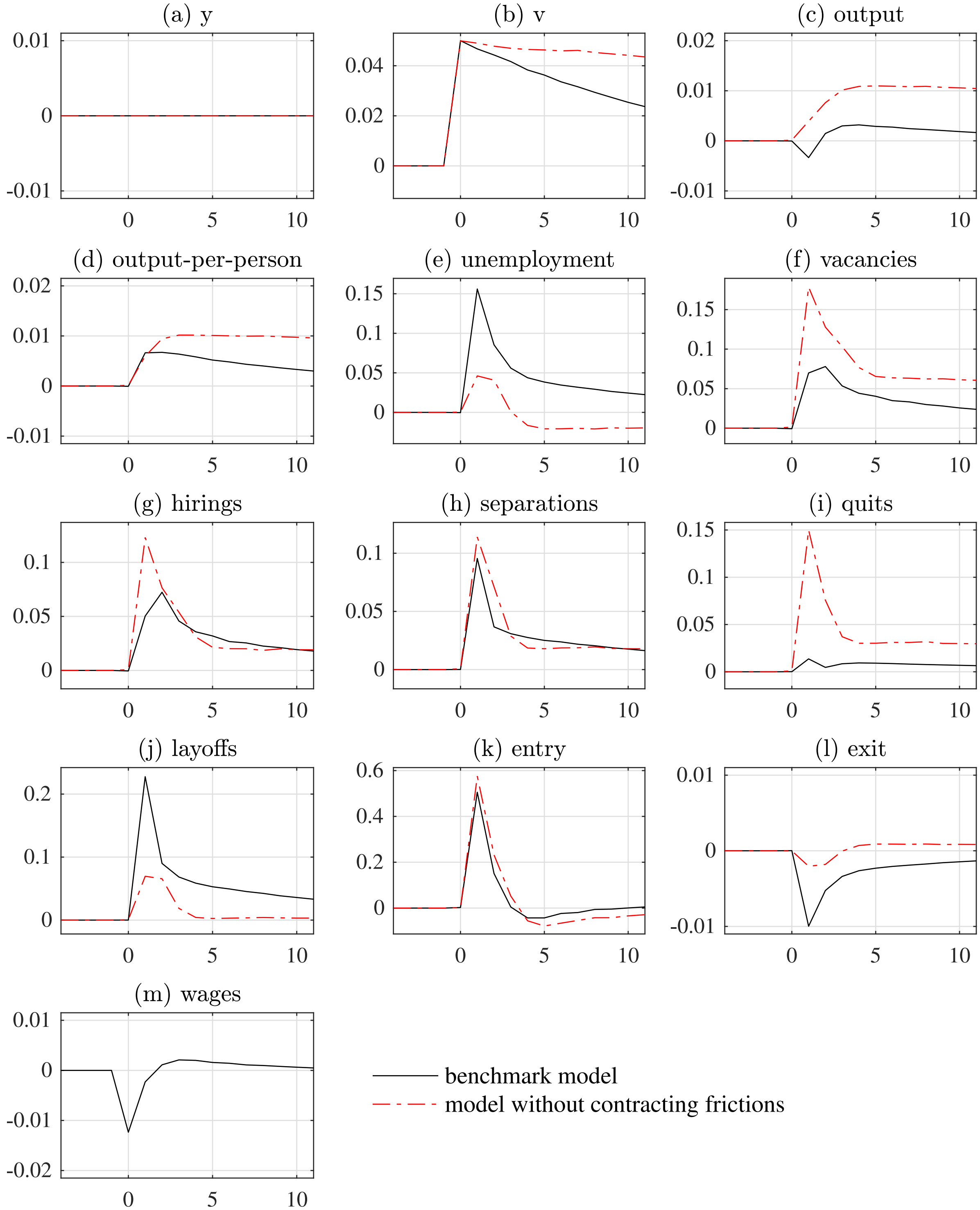

*Notes:* The panels display the model's predictions for output during recessions. Panel A presents the benchmark models, and Panel B shows the models with contracting frictions. Employing the particle filter, the aggregate productivity and uncertainty shocks are jointly estimated by matching output and the IQR of firm sales growth in the data. These data are detrended with a band-pass filter to highlight fluctuations between 6 and 32 quarters, following Schaal (2017). The actual output data are depicted by solid black lines. Models incorporating both aggregate productivity and uncertainty shocks are represented with dash-dotted or dotted red lines (labeled as '$A + \sigma$ shocks'), with '$\Delta^w$' referring to the model allowing heterogeneous pass-through from uncertainty shocks to wages as estimated in Table 3, Column (6). Models excluding uncertainty shocks are indicated by dashed blue lines (labeled as 'only $A$ shocks'). All series represent log deviations from the peak prior to each recession. I use Schaal's (2017) code when plotting this figure.

Figure F.4: Aggregate Impulse Responses to a 1% Negative Aggregate Productivity Shock




*Notes:* The panels are impulse responses to a 1% transitory negative aggregate productivity shock at quarter 0. The impulse responses are the average of 4,000 simulated paths, presented as log deviations from the mean. Solid black lines are the benchmark results. Dash-dot red lines are for the model without contracting frictions. I use Schaal's (2017) code when plotting this figure.

Figure F.5: Aggregate Impulse Responses to a 5% Positive Uncertainty Shock




*Notes:* The panels are impulse responses to a 5% positive uncertainty shock at quarter 0. The impulse responses are the average of 4,000 simulated paths, presented as log deviations from the mean. Solid black lines are the benchmark results. Dash-dot red lines are for the model without contracting frictions. I use Schaal's (2017) code when plotting this figure.