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 layoffs increase with heightened uncertainty 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. This evidence diverges from the typical real option channel embedded in standard search models, which predict a suspension of layoffs due to increased option value of waiting during periods of high uncertainty. This discrepancy motivates me to construct a new search model by incorporating financial and labor contracting frictions. They together generate a default risk channel: each worker means a wage commitment, which firms are less willing to maintain when heightened uncertainty raises their bankruptcy risks. This mechanism replicates layoff behaviors consistent with the data and accounts for over 70% of the impact of uncertainty on unemployment, greatly improving the model's ability to capture unemployment dynamics during recessions.

My empirical analysis estimates how layoffs respond to uncertainty shocks, conditional on firms' financial conditions. Leveraging U.S. Census employer-employee matched data (LEHD), I distinguish layoffs from hiring at a micro level. This data is merged with Compustat-CRSP firm-level data, where I measure firm-level uncertainty as the annualized standard deviation of daily stock returns. To mitigate endogeneity concerns, I adopt Alfaro, Bloom, and Lin's (2024) methodology, using Bartik-type instruments based on firms' exposure to exchange rate volatility and policy uncertainty, along with first-moment controls to isolate the role of second-moment shocks. Firm financial constraints are defined by the mode of three indicators: absence of an S&P rating, a high Whited and Wu (2006) index, and a high Size & Age index (Hadlock, 2010).[1]

I find that for financially constrained firms, a one standard deviation increase in un-

[1] Since the financial constraint indicator is not randomly assigned—a common challenge in empirical corporate finance—I interpret my empirical results as correlations rather than causal estimates.

certainty shocks is associated with a 0.5 percentage point higher likelihood of layoffs—a pattern not observed in financially unconstrained firms. This result is not driven by first-moment shocks, as they are controlled for, nor by contemporaneous reverse effects of layoffs, since both uncertainty shocks and financial constraint indicators are lagged. And it is not attributed to aggregations of reallocation across firms or restructuring within firms, as the analysis is conducted at the job level, with worker, firm, and time fixed effects included. This evidence challenges the reliance solely on search frictions for a complete understanding of uncertainty's impacts on labor market dynamics. The baseline search framework's lack of firm financial heterogeneity prevents it from generating the observed heterogeneous responses to uncertainty shocks, and its inherent irreversible hiring costs will predict a freeze in layoffs, counteracting the observed pattern.

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. As in 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. Default leads to 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 provide empirical supporting evidence for this friction using Census data and a micro-foundation by assuming that 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

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

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 framework.

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 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: increasing unemployment benefits for workers versus

[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.

providing wage subsidies to firms. First, the policy of raising unemployment benefits was implemented by the U.S. during the Covid recession. The model reveals that while this policy aims to support unemployed workers, it drives up wages, making hiring riskier for firms and ultimately exacerbating unemployment. Second, I investigate the policy of subsidizing firms to pay wages, similar to strategies implemented by Germany during the Great Recession and the Covid recession. According to my model, wage subsidies insure firms against idiosyncratic shocks, mitigating the negative impact of high uncertainty, so this approach outperforms the policy of raising unemployment benefits. However, wage subsidies encourage labor hoarding and hinder efficient worker reallocation. The losses from misallocation outweigh the gains from providing insurance, ultimately decreasing overall efficiency.

Related Literature. My paper contributes to four strands of literature. First, it differentiates mechanisms through which uncertainty shocks affect business cycles. One of the most well-known hypotheses is the real option channel, studied by Schaal (2017) and others, including Bernanke (1983), Bloom et al. (2018*b*), Dixit, Dixit and Pindyck (1994), Leduc and Liu (2016), and McDonald and Siegel (1986). This theory emphasizes the irreversible costs of employment and investment, leading firms to suspend decisions during periods of heightened uncertainty. However, it predicts a freeze in layoffs, whereas my empirical findings suggest otherwise. This discrepancy led me to explore another prominent mechanism—the default risk channel (Arellano, Bai and Kehoe, 2019; Gilchrist, Sim and Zakrajšek, 2014): higher uncertainty raises default risk, forcing firms to cut employment and wages. While both channels imply reduced investment and hiring, only the default risk channel aligns with the observed increase in layoffs. Motivated by this, I develop a search model that incorporates firm default risk and show its critical role in shaping unemployment fluctuations.[4]

Second, my model contributes to a growing literature that brings firm financial frictions into search models. Monacelli, Quadrini and Trigari (2023), 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 bar-

[4] Other mechanisms could also explain the increase in layoffs, such as the risk premium channel driven by fluctuations in the stochastic discount factor (Borovicka and Borovicková, 2018; Freund, Lee and Rendahl, 2023; Hall, 2017; Kehoe et al., 2023; Martellini, Menzio and Visschers, 2021). However, as my empirical results reveal the role of firm financial conditions, I adopt the default risk channel to generate financial heterogeneity directly.

gaining positions, but I examine firm financing for wage payments. Christiano, Trabandt and Walentin (2011), Chugh (2013), Garin (2015), Liu, Miao and Zha (2016), 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 default risk channel of uncertainty shocks.[5] 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.[6]

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.[7] 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 default risk 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 pre-determined wages under asymmetric information, and adapt this idea to a dynamic

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

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

[7] 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).

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 evidence motivating the modeling of uncertainty shocks. Section 2.1 describes the data and defines the variables. Section 2.2 explains the construction of instrument variables. Sections 2.3 and 2.4 present empirical results 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.[8] LEHD is sourced from the UI wage records, recording any job with positive annual earnings across all four quarters. The data starts from 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 offers four advantages. First, it distinguishes between layoffs and hiring, a distinction often unavailable in firm-level data like Compustat. Second, while aggregate layoff data (e.g., from JOLTS) is publicly available, aggregation can capture labor reallocation across firms, making layoffs mechanically rise with realized volatility. Third, LEHD provides individual worker observations, enabling control for worker heterogeneity through fixed effects. Fourth, it includes firm identifiers, facilitating linkage with other firm-level datasets.

[8] 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.

I then merge the LEHD dataset with firm-level data from the CRSP/Compustat Merged - Fundamentals Annual (Compustat) using 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. They are first constructed at the quarterly frequency, and then I annualize them to be consistent with the annual data on uncertainty shocks.

The LEHD dataset provides quarterly worker earnings data. 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 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 calculate workers' annualized earnings, I first adjust for inflation using the Consumer Price Index (CPI) from the BLS.[9] 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

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

neither of the first two conditions are met.

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. I follow Davis and Haltiwanger (1992) and Alfaro, Bloom and Lin (2024) to define the growth rate of variable y at quarter t 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 constructed as 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 challenge in measuring firms' financial constraints—I follow Alfaro, Bloom and Lin (2024) and lag it by five years to better reflect firms' ex-ante financial conditions. To further address concerns about unobserved heterogeneity, I include a range of control variables and fixed effects.[10]

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.

[10] Compustat provides a long quarterly panel of firms with detailed balance sheet information, but it only includes publicly held firms, which are generally less financially constrained. Thus, the empirical findings may underestimate the impact of uncertainty shocks and should be viewed as conservative estimates.

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, σ_{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.

2.2 Instrument Variables

When using firm-level stock price volatility to estimate responses to uncertainty shocks, three endogeneity concerns arise. First, a positive second-moment shock may coincide with a first-moment shock, causing omitted variable bias if the latter is not controlled for. Second, unobserved factors, such as agency frictions within firms, may also lead to omitted variable bias. Third, reverse causality may occur if job outcomes influence the firm's stock price volatility.

To mitigate these endogeneity concerns, I run two-stage least squares (2SLS) regressions using instrumental variables from Alfaro, Bloom and Lin (2024). They constructed a set of Bartik-type instruments by exploiting firms' differential exposures to the fluctuations in nine aggregate commodity prices. I select seven of these instruments, excluding two weaker ones to enhance relevance. The chosen instruments correspond to seven commodities: economic policy uncertainty as developed by Baker, Bloom and Davis (2016), and the exchange rates of six currencies—Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona. This results in over-identification, with seven instruments for the single endogenous variable of firm-level uncertainty shocks.

In 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 on four factors from an asset pricing model, which removes systematic fluctuations due to common risk factors (Carhart, 1997). On the right-hand side, α_s is the industry fixed effect, and r_t^c represents the growth rate of commodity c's price.

Eq. (1) is estimated using 5-year rolling windows. The coefficients $\beta_{s,\tau}^c$ capture industry-level sensitivities to commodity prices, where τ denotes the timing of the rolling estimation windows. These sensitivities are lagged by two years and then multiplied by commodity volatilities to serve as instrumental variables:

$$\left|\beta_{s,t-2}^c\right| \cdot \Delta\sigma_t^c, \forall c. \tag{2}$$

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

$$\beta_{s,t-2}^c \cdot r_t^c, \forall c. \tag{3}$$

The instrumental variables are used to mitigate endogeneity concerns. First, all regressions include first-moment controls to isolate the role of the second moment. Second, the Bartik-type instruments, constructed from aggregate uncertainty shocks and industry-level exposure, are less likely to be affected by firm-level unobservables. Third, since job-level dependent variables within firms are also less likely to influence industry-level instruments, this approach helps alleviate concerns about reverse causality. Additionally, I conduct weak-instrument robust inference to assess the relevance condition and Hansen-Sargan over-identification J tests to evaluate the exclusion restriction.

However, the instrumental variable approach does not fully eliminate potential endogeneity concerns. First, the financial constraint indicator may not be exogenous, even when lagged by five years. Second, stock returns and commodity prices can fluctuate for reasons beyond exogenous productivity shocks. Third, even if sensitivities to stock returns are lagged, they may still be correlated with firm employment decisions for other unobserved factors. Given these limitations, I interpret the 2SLS regressions with caution and do not claim causality. Instead, they serve as complementary tests alongside OLS regressions to examine how layoffs relate to heightened uncertainty.

2.3 Motivating Empirical Evidence for the Firm Financial Friction

To examine the channels of uncertainty shocks, I use the following regression to estimate the responses of layoffs to uncertainty shocks:

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

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 financial constraint indicator, $\mathbb{1}_{jt-5}^{\text{fin-constraint}}$. The interaction's coefficient, β_{2h}, estimates the increase in layoffs associated with a one standard deviation increase in uncertainty shocks in ex-ante financially constrained firms. Both the uncertainty shock and its interaction are instrumented in the 2SLS regression.

The regression also includes a vector of firm-side control variables, Z_{jt}, following Alfaro, Bloom and Lin (2024). This set of controls includes six lagged firm-level financial variables: Tobin's Q, annualized stock returns, tangibility, book leverage, returns on assets, and firm sizes measured by sales. 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 (γ_j), firm fixed effect (δ_j), and year fixed effects (ϕ_t) to account for unobserved heterogeneity. The error term is denoted by ϵ_{ijt}. The standard errors are clustered at the 2-digit SIC industry level, in line with the variability of the instruments.

Table 2 presents the OLS and 2SLS estimates for β_1 and β_2. The first three columns project layoffs on uncertainty shocks, with the estimated β_1 showing no significance. The next three columns introduce an interaction between uncertainty shocks and firms' financial conditions. The estimated coefficient of the interaction term, β_2, is significantly positive in both OLS (Columns 4 and 5) and 2SLS (Column 6). The baseline 2SLS estimate in Column (6) is 0.005, suggesting that a one standard deviation increase in uncertainty shocks is associated with a 0.5 percentage point higher layoff probability in financially constrained

Table 2: Responses of Worker Layoffs to Uncertainty Shocks

	OLS		2SLS	OLS		2SLS
$\mathbb{1}^{\text{layoff}}_{ijt}$	(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)
$\Delta\sigma_{jt-1} \cdot \mathbb{1}^{\text{fin-constraint}}_{jt-5}$				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, $\mathbb{1}^{\text{layoff}}_{ijt}$, on lagged firm-level uncertainty, $\Delta\sigma_{jt-1}$, and their interaction with firms' 5-year lagged financial constraint indicators, $\mathbb{1}^{\text{fin-constraint}}_{jt-5}$ (where i is workers, j firms, and t time). Uncertainty, σ_{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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

firms relative to unconstrained firms. This estimate is robust to weak instruments, with a conditional likelihood ratio (CLR) test p-value of 0.039. Additionally, the Sargan-Hansen J test of over-identification validates the exclusion restriction, with a p-value of 0.351.

The increase in layoffs with uncertainty suggest that an additional mechanism is needed beyond the real option channel, which instead predicts a freeze in layoffs under high uncertainty. The empirical results also highlight the role of firm financial conditions in shaping responses to uncertainty shocks, emphasizing the need to model financial heterogeneity. Together, these findings motivate the inclusion of firm financial frictions in the model.

2.4 Motivating Empirical Evidence for the Labor Contracting Friction

In my search 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 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. 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 the firm financial friction 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. 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.[11] Consistent with their findings, my model also 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 correlation with 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—comprising OLS

[11] Note that these cited findings pertain to *transitory* idiosyncratic shocks. They do not conflict with studies showing that wage pass-through can result from large and persistent firm shocks (e.g., Baker (2018)). Nor do they contradict the literature on the firm size wage premium, which links larger firms with higher wages (Bloom et al., 2018*a*; Brown and Medoff, 1989; Lallemand, Plasman and Rycx, 2007; Oi and Idson, 1999), as much of the firm size heterogeneity observed in the data is permanent.

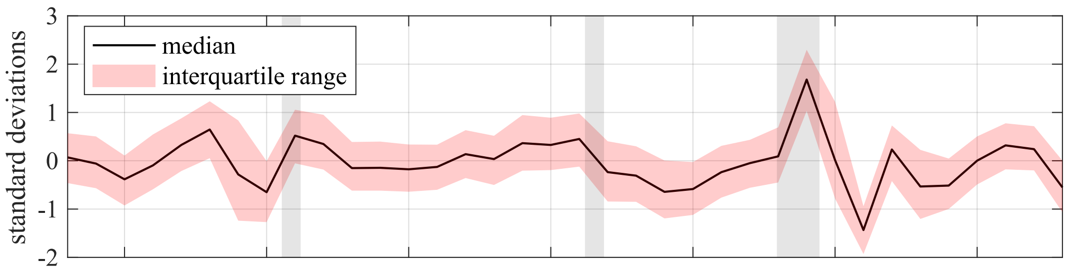
Table 3: Responses of Worker Earnings to Uncertainty Shocks

	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, σ_{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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(Columns 1 and 2) and 2SLS (Column 3) regressions—show no significant correlation between uncertainty shocks and worker earnings. The next three columns examine how worker earnings vary with uncertainty shocks under different firm financial conditions. The unconditional coefficients of uncertainty shocks, β_1, remain insignificant, suggesting little association between earnings and uncertainty shocks in unconstrained firms. For financially constrained firms, the OLS regressions in Columns (4) and (5) still display

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.

insignificant coefficients, β_2, for the interaction term. The only exception is the 2SLS regression in Column (6), which estimates a significantly negative coefficient of -0.009 for β_2. This implies that in financially constrained firms, a one standard deviation increase in uncertainty shocks is associated with worker earnings growth lower by 0.9 percentage points.[12]

As shown in Figure 1, during the Great Recession, uncertainty shocks increased by about two standard deviations, leading to a wage decline of only 1.8 percentage points in financially constrained firms. This small magnitude is unlikely to have a significant economic impact. Besides this back-of-the-envelope calculation, I also conduct a robustness test in Section 5.1 by incorporating this wage pass-through into the quantitative model. The findings confirm that the quantitative results remain robust to this small 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 default risk 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).

[12] Di Maggio et al. (2022) also finds a similar pass-through from uncertainty to workers' income using proprietary data from a credit bureau.

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.

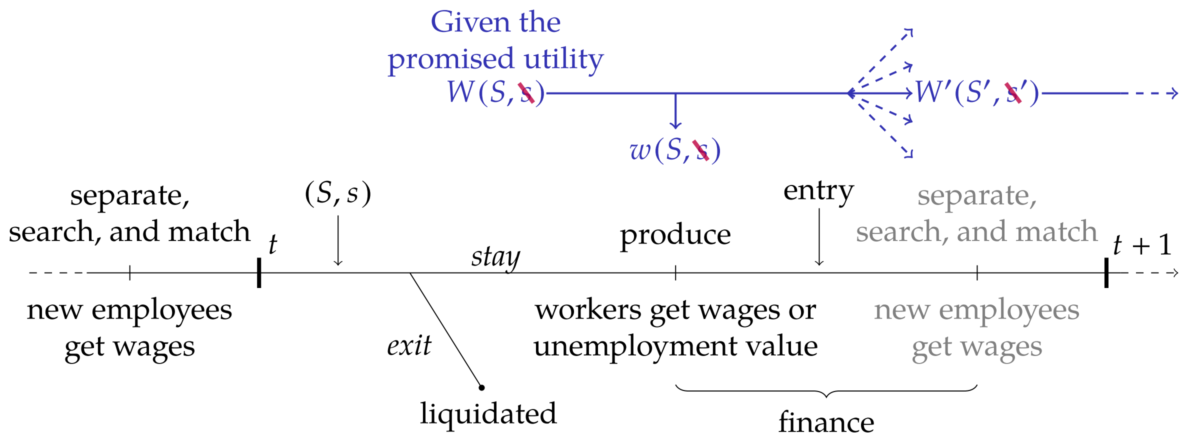
Shocks. Firms are subject to idiosyncratic productivity shocks governed by the Markov process $\pi_z(z'|z,\sigma)$, where σ represents the time-varying uncertainty in firm-level productivity. A higher σ increases the dispersion of future shocks, raising the probability of drawing lower productivity. 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 ϵ, which follows a normal distribution $\Phi_\epsilon \equiv \mathcal{N}(\mu_\epsilon, \sigma_\epsilon^2)$. 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, θ, 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, μ_u denotes unemployed workers, μ_e stands for employed workers, and λ 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 θ 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, τ 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,

Figure 2: Timing



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

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 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 λ. 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 π_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 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 utilities to its employees $\{W(S, s; i)\}_{i\in[0,n]}$, with i indexing incumbent employees.

Firms choose current equity payout Δ, 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:

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

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

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

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

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

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

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

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

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

where $F_m(S,z) = \left[\frac{\bar{w}_m+(1-\psi)\frac{\beta}{1-\beta}\bar{w}_m}{(1-\Phi(A\xi\,\mathbb{E}[A'z'n'^{\alpha}-\int_0^{n'} w(i')di'-\bar{w}_m-\epsilon'])\zeta\,\mathbb{E}\,z'}\right]^{\frac{1}{\alpha}}\bar{u}$, 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.[13] Equity payouts, Δ, equal output Azn^{α} minus incumbent employees' wages $\int_0^n w(i)di$, minus the manager's wage $\bar{w}_m$, minus the stochastic operating cost ϵ, 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 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

[13] 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.

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 constraint requires firms to maintain sufficient leverage by including borrowings, Qb', on the left-hand side. It is influenced by two parameters: the agency friction, ζ, and auditing quality, ξ. The intuition is to prevent the manager from diverting funds for personal use. Such a constraint is essential for matching firm leverage observed in the data, avoiding scenarios where firms save a large cash buffer and outgrow the financial friction. Appendix B provides the formal microfoundation. The concept of agency costs from large free cash flows was first introduced by Jensen (1986) and later empirically validated by Lang, Stulz and Walkling (1991), Richardson (2006), and Harford, Mansi and Maxwell (2008).[14]

[14] Agency friction is not the only reason firms borrow in the data; financing growth is another important factor. Incorporating firm life-cycle dynamics and investment-driven borrowing would improve the model's realism. However, such an extension requires substantial computational complexity. For tractability, I leave this for future research.

3.4 Debt Pricing

I assume that the economy's financial market is small compared to the global market, leading to an exogenous risk-free interest rate $r = 1/\beta - 1$.[15] Risk-neutral international financial intermediaries lend to firms through one-period bonds competitively.

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 later. This enterprise value, detailed 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, the firm's employment level, n_0, is reset 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 reveals a high correlation coefficient of 0.96 between π' 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 η denotes the recovery rate, and ι 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.

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 status depends on a continuum of historically-dependent labor contracts. To address this, Proposition 1 provides an approach to uniquely pin down wages when the model does not include on-the-job search.

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

[15] With a constant risk-free rate, my model isolates the effects of uncertainty from potential general equilibrium feedback through interest rate fluctuations. Allowing the risk-free rate to respond endogenously in the capital market is an important topic (Khan and Thomas, 2008; Koby and Wolf, 2020; Winberry, 2021). However, this would break the model's block recursivity and make it computationally infeasible. Since my paper focuses on labor rather than investment, I leave this extension for future research.

in the model without on-the-job search (i.e., $\lambda = 0$).

Proof The proof can be found in Appendix C. □

Here, the promise-keeping constraint binds as always, while the binding participation constraint results 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, the participation constraint binds.

Proposition 1 applies in the model without on-the-job search ($\lambda = 0$). Introducing on-the-job search complicates the problem, as firms have an incentive to reduce turnover. If this effect is stronger than the financial friction, the participation constraint may not bind. However, on-the-job search is not central to my analysis. As shown in Schaal (2017), job-to-job transitions play a limited role in separations, with most occurring through layoffs. Given this, I leave the interaction between on-the-job search and firm financial frictions for future research. Nevertheless, to maintain comparability with Schaal (2017), I retain on-the-job search in the quantitative solution and assume Proposition 1 still holds in this case.

Given Proposition 1, wages are determined straightforwardly. 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.

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 τ.

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 wages (19) and (20), I rewrite the firm's problem (7) using cash on hand X as a state variable:

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

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

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

$$X' = A'z'n'^{\alpha} - n'[\bar{u} + (1-\lambda)\mu(S')] - \bar{w}_m - \epsilon' - b', \tag{25}$$

$$\bar{\epsilon}(S', z', b', n') = A'z'n'^{\alpha} - n'[\bar{u} + (1-\lambda)\mu(S')] - b' + M(S', z', n') - \bar{w}_m, \tag{26}$$

When a firm's cash on hand is sufficiently high, it avoids the financial friction and operates under a set of policies 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:*

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

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

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:

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

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

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

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 θ 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 $\{x(S, s, \boldsymbol{C}), \boldsymbol{W}(S, s, \boldsymbol{C})\}$; 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.[16]

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 Functional Forms and Parameters

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

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

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

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

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

where σ_t is the time-varying uncertainty affecting the standard deviation of the innovation. Lastly, the i.i.d. operating cost shock ϵ 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

[16] 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	β	0.988	5% annual interest rate
Decreasing returns to scale coefficient	α	0.66	Labor share
Persistence of productivity	ρ_z	0.95	Schaal (2017)
Panel B: Parameters from Moment Matching			
Aggregate shocks			
Persistence of aggregate productivity	ρ_A	0.920	Autocorrelation of output
SD of aggregate productivity	σ_A	0.024	SD of output
Mean of uncertainty	$\bar{\sigma}$	0.248	Mean of IQR
Persistence of uncertainty	ρ_σ	0.880	Autocorrelation of IQR
SD of uncertainty	σ_σ	0.092	SD of IQR
Correlation between ϵ_t^A and ϵ_t^σ	$\rho_{A\sigma}$	−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	λ	0.100	EE rate
Matching function elasticity	γ	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	σ_ϵ	0.080	Mean credit spread
Agency friction	$\tilde{\zeta}$	2.400	Median leverage
Auditing quality	ξ	1.780	Correlation (output, spreads)
Recovery	$\tilde{\eta}$	2.410	Correlation (IQR, spreads)
Exogenous exit rate	π_d	0.021	Annual exit rate

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

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, β, is set at 0.988, implying an annual risk-free interest rate of 5%, as used by Schaal (2017). The labor coefficient, α, is fixed at 0.66, reflecting the labor share. The persistence of idiosyncratic productivity, ρ_z, is set to 0.95, following Schaal (2017).[17]

[17] I conduct a comparative-statics exercise in Appendix F by setting $\rho_z = 0.90$, which results in similar unemployment dynamics during recessions.

Table 5: Matched Moments

Moments	Data	Benchmark Model			No Contracting Frictions	
		$A+\sigma$	$A+\sigma$ (Δ^w)	A only	$A+\sigma$	A only
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+σ' 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 only' means the model only has aggregate productivity shocks.

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, (ρ_A, σ_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 Arellano, Bai and Kehoe (2019) and Bloom et al. (2018*b*). The sales data, sourced from Compustat, is 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 $(\mu_\sigma, \rho_\sigma, \sigma_\sigma)$. Additionally, the correlation between output and the IQR determines the correlation ($\rho_{A\sigma}$) between aggregate productivity shocks and uncertainty shocks.[18]

Second, for labor market dynamics, I calibrate the unemployment utility ($\bar{u}$), vacancy posting cost (c), and relative on-the-job search efficiency (λ) 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 γ 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, $\mu_\epsilon + \bar{\omega}_m$, 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, σ_ϵ, 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, $\tilde{\zeta} \equiv \zeta/(\bar{\omega}_m + (1-\lambda)\frac{\beta}{1-\beta}\bar{\omega}_m)$, 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 ξ, and the correlation between the interquartile range and credit spreads sets the recovery rate η. Finally, the exogenous exit rate π_d is calibrated using the annual exit rate from Business Dynamics Statistics, capturing firm exits beyond defaults.

4.2 External Validation

This section presents decision rules and validates the model against empirical evidence.

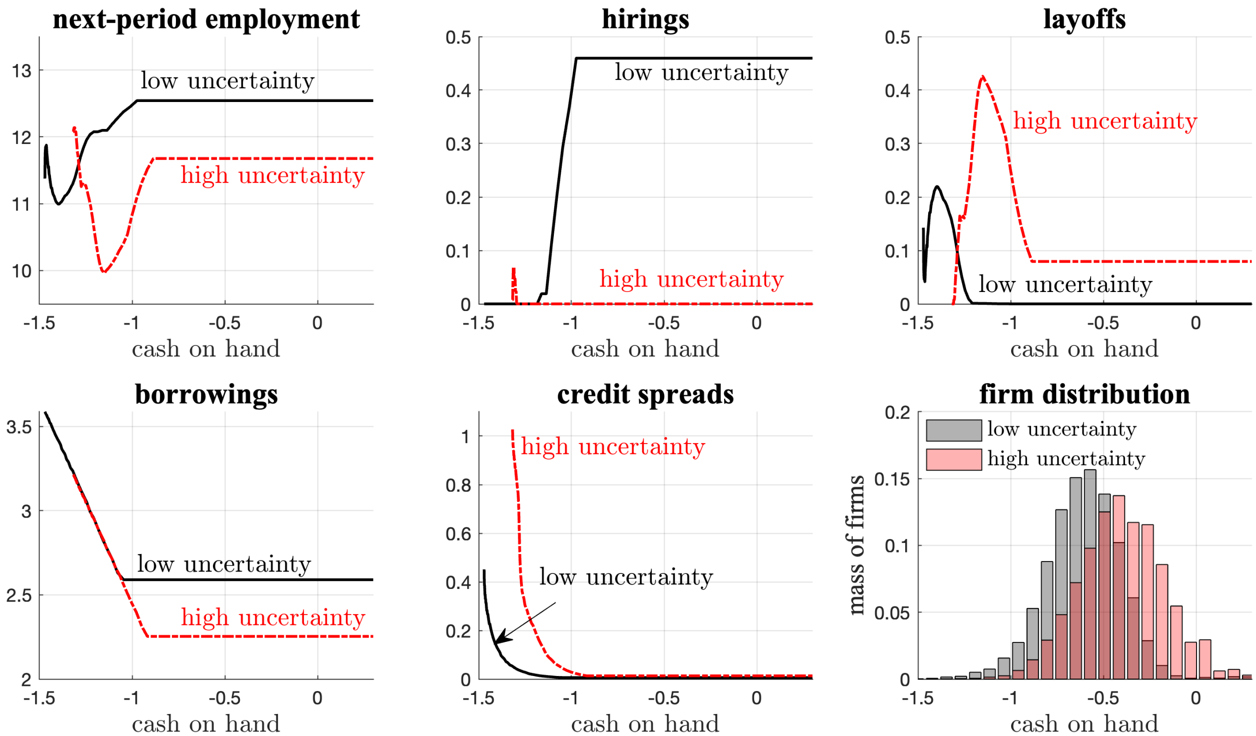
4.2.1 Firm-Level Decisions

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

[18] I follow Arellano, Bai and Kehoe (2019) in using the IQR of sales growth to indirectly infer uncertainty shocks. This approach aligns with the paper's mechanism, where low sales directly lead to default risk. Using TFP estimates from other models can misstate sales volatility, leading to counterfactual default and credit spreads (see Appendix E for more detailed discussion).

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 compares 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.

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 affects firms' decisions by increasing the likelihood of drawing low idiosyncratic productivity, as reflected in the wider dispersion of firms' output shown in Figure G.1. Heightened uncertainty increases the risk of defaults, discouraging firms from borrowing. Figure 3 depicts that higher uncertainty results in larger credit spreads and reduced borrowing. This precautionary motive also appears in firms' cash holdings: the last panel shows a rightward shift in the distribution of firms' cash on hand under high uncertainty. Furthermore, since 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.

4.2.2 Validation Against Empirical Evidence

To validate the model, I re-estimate the empirical regression (4) using a simulated panel of 5,000 workers and 3,000 firms over 1,000 periods. Panel A of Table 6 presents the 2SLS results of projecting job-level layoff indicators against changes of firms' stock return volatility and their interaction with financial constraint indicators. These regressions include controls for first-moment shocks, firm-level variables, and fixed effects. In the model, stock returns are calculated as changes in firm value, $\boldsymbol{J}_{jt}$, with volatility measured as the standard deviation of cross-sectional returns, as the model is not daily. The change in stock return volatility is instrumented by the uncertainty shock, $\Delta\sigma_t$, consistent with the empirical 2SLS approach. A firm's financial constraint indicator is set to one if its cash on hand is below the period's median, as cash on hand sufficiently reflects a firm's financial condition in the model.

Column (1) in Panel A copies the empirical 2SLS regression result from Table 2, showing a 0.51% increased layoff probability in financially constrained firms when uncertainty rises by one standard deviation. Model-simulated regressions in Columns (2), (3), and (4) yield coefficients ranging from 0.2% to 0.3%, with and without time fixed effects. These results suggest that the model captures roughly half of the layoff increase observed in the data. Although the model's coefficient size is smaller, it also highlights the role of financial heterogeneity in shaping the labor market's response to uncertainty shocks.

Panel B contrasts the results with the standard search model's predictions, estimating unconditional responses to uncertainty shocks without considering firm financial conditions. In Column (1), the empirical regression from Table 2 shows an insignificant but positive responses of layoffs to uncertainty. My model's results in Columns (2) and (3) similarly show positive coefficients. In contrast, Schaal's (2017) search framework predicts a negative response of layoffs to uncertainty shocks, driven by the option value of waiting due to irreversible search costs.[19] This discrepancy highlights the need to enrich the search framework to evaluate uncertainty shocks' impact on the labor market.

[19] 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.

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)
$\Delta\sigma_{jt-1}$	-0.00038		0.00024	-0.00016
	(0.00162)		(0.00013)	(0.00014)
$\Delta\sigma_{jt-1} \cdot \mathbb{1}\{\text{lagged fin-constraint}_{jt}\}$	0.00514**	0.00199	0.00281	0.00331
	(0.00249)	(0.00018)	(0.00018)	(0.00019)
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	0.00201	0.00107	-0.00242	-0.00238
	(0.00157)	(0.00009)	(0.00009)	(0.00030)	(0.00029)
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. The regressions project job-level layoff indicators, $\mathbb{1}_{ijt}^{\text{layoff}}$, against changes of firms' stock return volatility, $\Delta\sigma_{jt-1}$, with and without the interaction with firms' lagged financial constraint indicators, $\mathbb{1}\{\text{lagged fin-constraint}_{jt}\}$, where i indexes workers, j firms, and t time. Panel A displays regressions conditional on heterogeneous financial conditions, while Panel B presents unconditional regressions. The first column shows the empirical 2SLS regression result from Table 2, while subsequent columns are model simulations for 5,000 workers and 3,000 firms over 1,000 periods. Stock returns are calculated as the change in firm value $\boldsymbol{J}_{jt}$, with each period's volatility measured as the standard deviation of cross-sectional returns, given the models are not daily. The change in stock return volatility is instrumented by the change in uncertainty shock, $\Delta\sigma_t$, mirroring the empirical 2SLS setup. My model and Schaal (2017) differ in shock timing but define uncertainty shocks uniformly as those directly influencing layoffs. The financial constraint indicator is set to one if the firm's cash on hand is below that period's median in the model. Firm-level controls, where available, include the first-moment control (ΔA_{t-1}), lagged stock returns, leverage, sales-based firm sizes, their interactions with lagged financial constraint indicators, and the lagged financial constraint indicator itself. Regressions standardize stock return volatility changes and incorporate both worker and firm-fixed effects, omitting time fixed effects in some cases to estimate uncertainty shock coefficients, with 2-period lagged uncertainty and aggregate productivity growth ($\Delta\sigma_{t-2}$ and ΔA_{t-2}) included as aggregate controls. Significance stars are only reported for data regressions: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

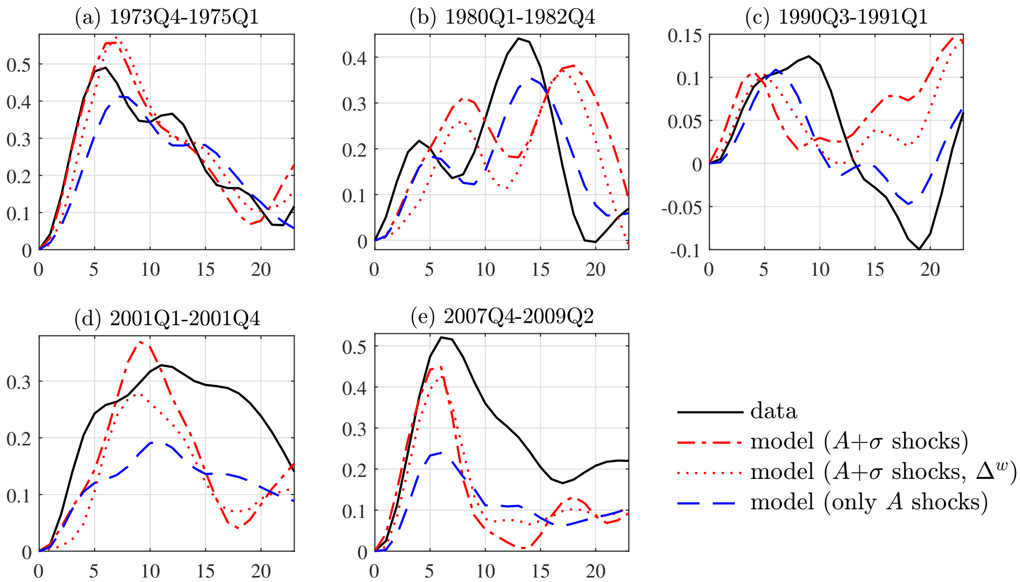
The state variables $\boldsymbol{X}_t$ are combinations of aggregate productivity, uncertainty, and credit spreads.[20] The observables $\boldsymbol{Y}_t$ include aggregate output and the interquartile range (IQR) of firm sales growth. The mapping function $g(\cdot)$ is derived by projecting simulated 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

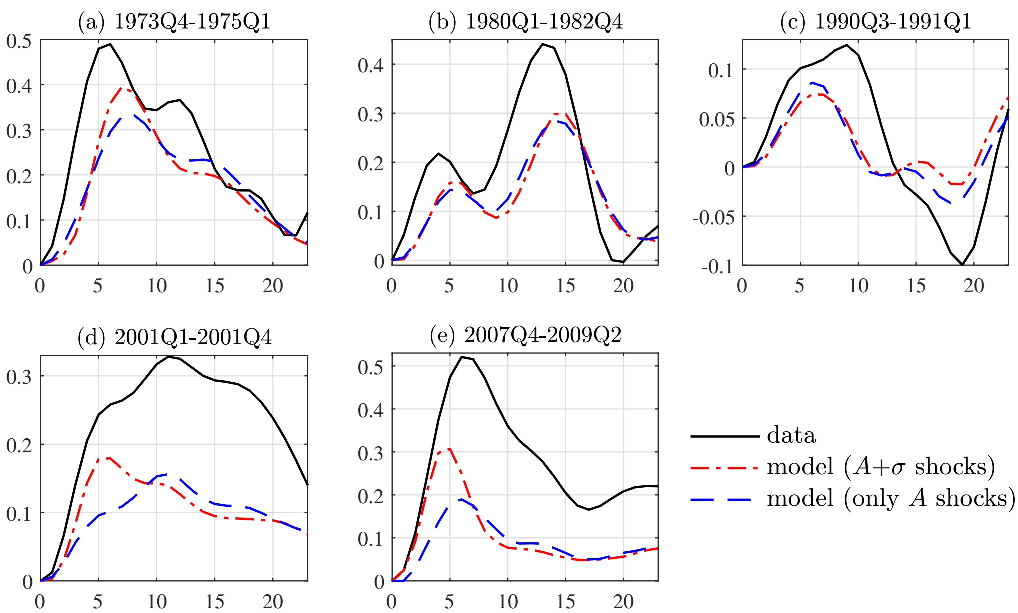
[20] There are five groups of state variables in $\boldsymbol{X}_t$: (i) a constant; (ii) $\{\log A_{t-p}, \log \sigma_{t-p}\}_{p=0}^5$; (iii) $\{\log A_{t-p} \cdot \log \sigma_{t-p}, \{\log A_{t-p} \cdot \log \sigma_{t-q}, \log A_{t-q} \cdot \log \sigma_{t-p}\}_{q=p+1}^3\}_{p=0}^2$; (iv) $\{(\Delta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

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 the benchmark models, and Panel B uses 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 as in 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 'Δ^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'). 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 σ shocks	0.557	0.382	0.107	0.370	0.449
$\Rightarrow$ Data explained by adding σ shocks	29.5%	5.9%	-1.7%	53.9%	40.2%
	25.6% on average				
Both A and σ shocks (Δ^w)	0.574	0.371	0.141	0.280	0.429
$\Rightarrow$ Data explained by adding σ shocks	32.8%	3.6%	-4.8%	26.3%	36.3%
	18.9% on average				
Models without contracting frictions					
Only A shocks	0.333	0.285	0.086	0.156	0.190
Both A and σ shocks	0.395	0.298	0.074	0.179	0.307
$\Rightarrow$ Data explained by adding σ 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. Models are recalibrated. 'Only A Shocks' means models with only aggregate productivity shocks. 'Both A and σ Shocks' refers to models with both aggregate productivity shocks and uncertainty shocks, where 'Δ^w' means the model allowing heterogeneous pass-through from uncertainty shocks to wages as estimated in Table 3, Column (6).

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 G.3 plots the estimated shocks, and Figure G.5 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.[21] This comparison reveals a significant deterioration in the model's explanatory power without considering uncertainty shocks, particularly during

[21] All reference models have been recalibrated, with their parameter values in Table G.1 and matched moments in Table 5. Figure 4 focuses on recession periods, starting from the pre-recession peak. The full unemployment series from 1972Q2 to 2018Q3 is shown in Figure G.4.

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 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.

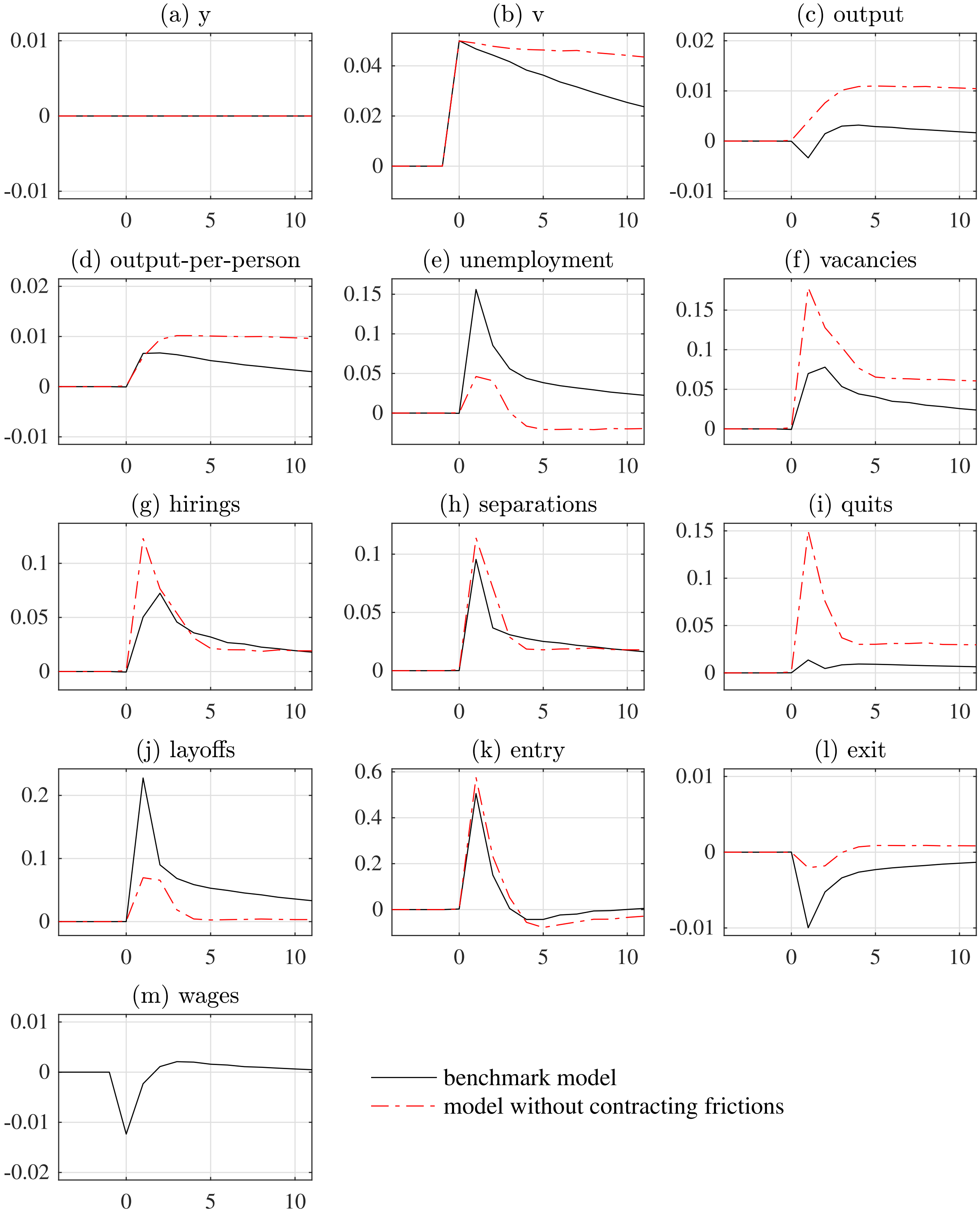
Figure 5 plots aggregate impulse responses to elevated uncertainty. Without contracting frictions, a positive uncertainty shock leads to an output boom. In contrast, the benchmark model with contracting frictions reveals a clear recession in output and a rise in unemployment. Figure 6 decomposes these responses into two groups: financially constrained and financially unconstrained firms, categorized by the median cash on hand. The figure demonstrates that elevated uncertainty is expansionary for financially unconstrained firms, with the recession entirely driven by the contraction of financially constrained firms.

Additionally, Panel B of Figure 4 shows that the model without contracting frictions performs worse in explaining spikes in unemployment during recessions. 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 G.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.

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. While the pass-through is small, I formally test the robustness of the labor contracting friction by incorporating this conditional wage pass-through, Δ^w, into the model:

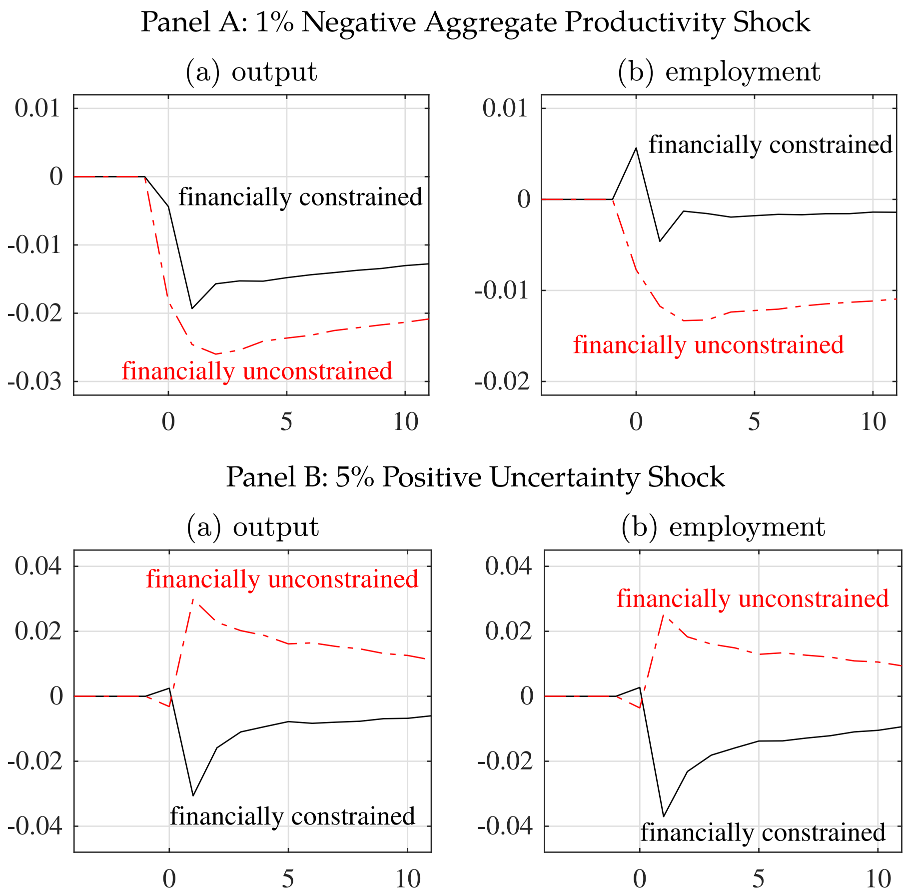
$$\Delta^w(\Delta\sigma, z) = -0.949\% \frac{\Delta\sigma}{\text{SD}(\Delta\sigma)}, \text{ if } z < \text{median}(z), \tag{41}$$

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



Notes: The panels are impulse responses to a 5% transitory 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. Models are recalibrated. I use Schaal's (2017) code when plotting this figure.

Figure 6: Decomposition of Aggregate Impulse Responses



Notes: The panels decompose the impulse responses of aggregate output and unemployment into two groups: financially constrained firms (solid black lines) and financially unconstrained firms (dash-dot red lines). Firms are classified as financially constrained if their cash on hand is below that period's median; otherwise, they are financially unconstrained. Panel A shows the responses to 1% transitory negative aggregate productivity shock, and Panel B displays the results of a 5% positive uncertainty shock. 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.

where $\mathrm{SD}(\Delta\sigma)$ equals $\sqrt{2(1-\rho_\sigma)}\sigma_\sigma$[22], and $\mathrm{median}(z)$ represents the average median idiosyncratic productivity. Using idiosyncratic productivity as a criterion, instead of endogenous variables like cash on hand, maintains the model's computational tractability (i.e., block recursivity) while still capturing the firms' financial conditions. With this pass-through, compensation to incumbent workers becomes $[1+\Delta^w(\Delta\sigma, z)]w(S)$. For

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

simplicity, I assume that the wage decline does not cause workers to exit the firm, offering a conservative estimate of uncertainty's negative effects.

Panel A of Figure 4 illustrates that including wage pass-through, denoted by "(Δ^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 (compare Figure G.6 and Figure 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 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.

Challenges in Generating Slow Recovery. While Figure 4 shows that incorporating uncertainty shocks effectively captures the rise in unemployment during economic downturns, it does not fully replicate the slow recovery of unemployment following the 2001 recession and the Great Recession. This limitation arises for two reasons. First, the Oi-Hartman-Abel effect remains present. Although this expansionary effect is largely weakened by the default risk channel, it still leads to a mild expansion after elevated uncertainty (Figure 5). Second, adverse shocks dissipate quickly (Figure G.3). The model's tight linkage between shocks and economic performance results in a relatively rapid recovery.

Several extensions could address this limitation. For example, Kozlowski, Veldkamp and Venkateswaran (2020) show that slow adjustments in beliefs about shocks can lead to prolonged recessions. Salgado, Guvenen and Bloom (2019) find that skewness shocks can cause persistent downturns in a model with risk-averse entrepreneurs. Ilut, Kehrig and Schneider (2018) highlight that asymmetric responses to good and bad shocks can generate slow hiring. However, to preserve the model's tractability and maintain the focus of this paper, I leave these extensions as important directions for future research.

5.2 Policy Implications

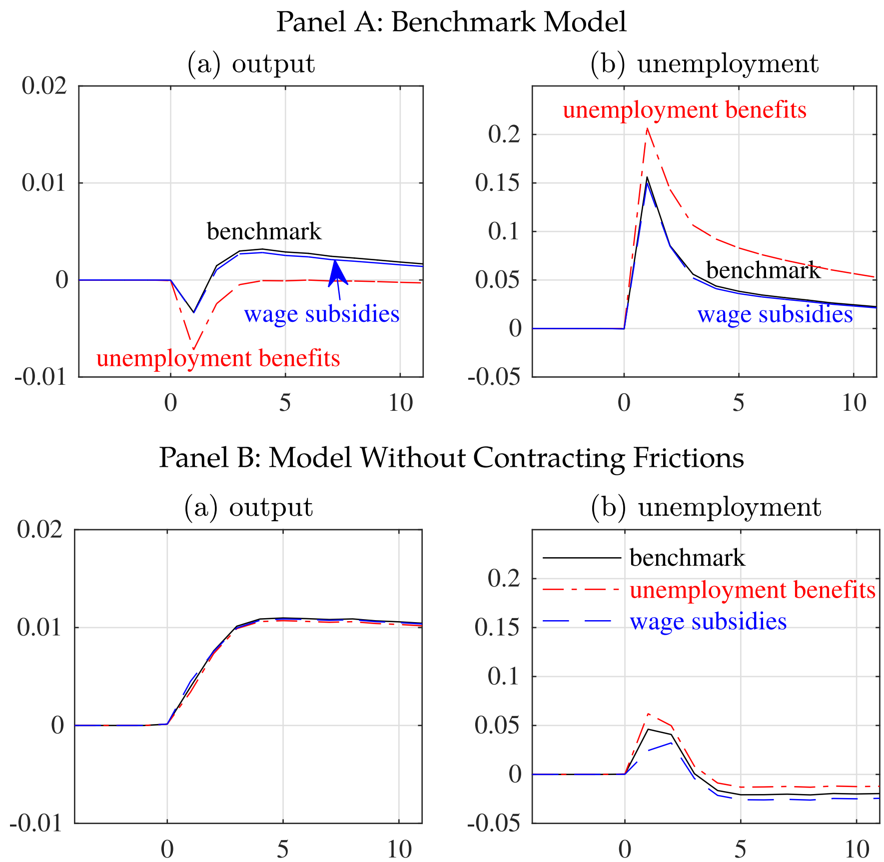
Given my model's insights into uncertainty and unemployment, I use it to evaluate two labor market stabilization policies that have become topical during recent recessions: increasing unemployment benefits and subsidizing wage payments.

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 7, 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 G.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

Figure 7: 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.

idle workers' wages. This subsidy rate matches the expenditure ratio of the UI policy experiment, also costing 4.86 basis points of output.

Figure 7, Panel A, shows the impulse responses of wage subsidies with dash-dot blue 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 G.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 7, 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 G.3 quantifies these differences: efficiency loss from the UI policy drops dramatically from 4.3 to 7×10^{-5} basis points, and for wage subsidies, the loss decreases from 2.6 to 4×10^{-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 default risk channel of uncertainty shocks using employer-employee matched 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.

While this paper focuses on first- and second-moment shocks, an important direction for future research is to explore the role of higher-order moments in the labor market. Recent evidence by Salgado, Guvenen and Bloom (2019) shows that skewness shocks often precede significant declines in macroeconomic activity, even after accounting for first- and second-moment effects. Furthermore, they find that adverse skewness shocks can lead to persistent downturns in a model with risk-averse entrepreneurs. Such an extension could improve the model's ability to explain the slow recoveries post recessions.

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Online Appendices

A Micro-Foundations for the Labor Contracting Friction

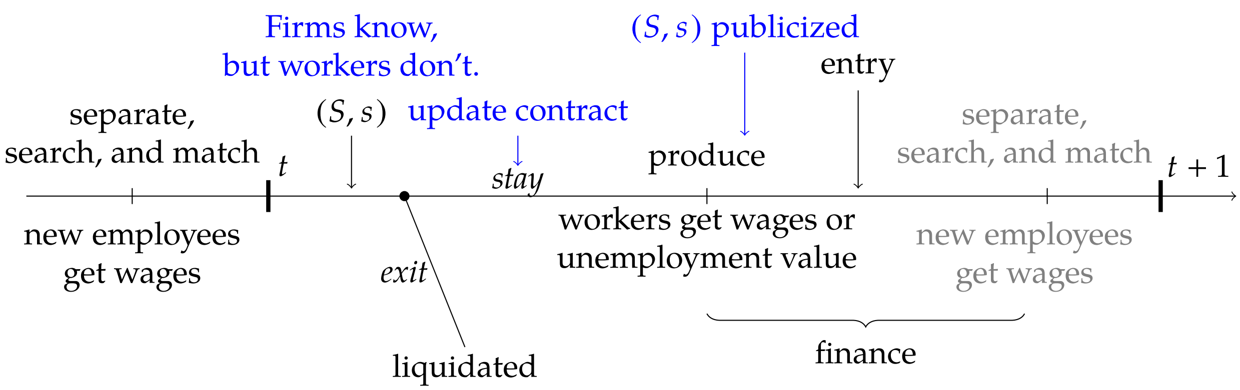
In this section, I micro-found the labor contracting friction in eq. (12), using the asymmetric information between firms and their employees. The logic follows Hall and Lazear (1984), who demonstrates the optimality of predetermined wages in a two-period model under asymmetric information. My model 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:

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

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:

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

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

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

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

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

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

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 ζ 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, ξA, is based on a measure of auditing quality, ξ, 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 ψ of becoming self-employed (else returning to the manager market). Therefore, the firm adheres to the following incentive-compatible condition to prevent potential deviations:

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

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

C Additional Proofs

Proposition 1 *Both the participation constraint* (13) *and the promise-keeping constraint* (14) *bind in the model without on-the-job search (i.e.,* $\lambda = 0$*).*

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 ϵ^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 δ to denote $\bar{W}(i')$ from now on.

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

3. Pay an additional bonus $\tilde{w}$ to the worker today, 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. From the firm's perspective, its labor expense today increases by $\epsilon^m \tilde{w}$.

4. Increase the debt b' by $\epsilon^m (1 - \tau(i))\delta$, 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. 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:

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

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. Construct an alternative policy, similar to Case 1, that frontloads wages and increases borrowing. Then, the firm's equity payouts increase.

Additionally, the agency friction constraint (15) still 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. □

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, σ. The number of grids for firm-level idiosyncratic productivity, z, equals 13. The grids of z depend on the last-period uncertainty, σ_{-1}. Therefore, both σ and σ_{-1} are firms' state variables in the numerical implementation. I use Tauchen's method to discretize A, σ, 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 θ 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^{old} and M^{new} is less than 10^{-7} and that between Q^{old} and Q^{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 $[X_{\min}, X_{\max}]$. The lower bound, $X_{\min}$, equals $-M(A, \sigma, \sigma_{-1}, z, n)$. The upper bound, $X_{\max}$, 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 ϵ', 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,σ):

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

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_{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 α, 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*b*). In contrast, I follow both Bloom et al. (2018*b*) 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 data. Such heightened sales volatility raises firm default risks and leads to excessively high credit spreads.[1] 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 ϵ_t^{σ}. Figure G.2 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 G.2 demonstrates that the business cycle statistics of my model without contracting frictions closely resemble those in Schaal (2017).

[1] 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 Results with $\rho_z = 0.90$

This section presents results with the persistence of idiosyncratic productivity, ρ_z, reduced from 0.95 to 0.90. The parameter values in Table G.1 remain unchanged, treating this as a comparative-statics exercise to assess the role of ρ_z.

Figure F.1 plots unemployment dynamics during the five recessions, which closely resemble the results for $\rho_z = 0.95$ shown in Figure 4. Table F.1 summarizes that the average contribution of uncertainty shocks to the peak-to-trough increase in unemployment increases under $\rho_z = 0.90$, as idiosyncratic productivity becomes less predictable.

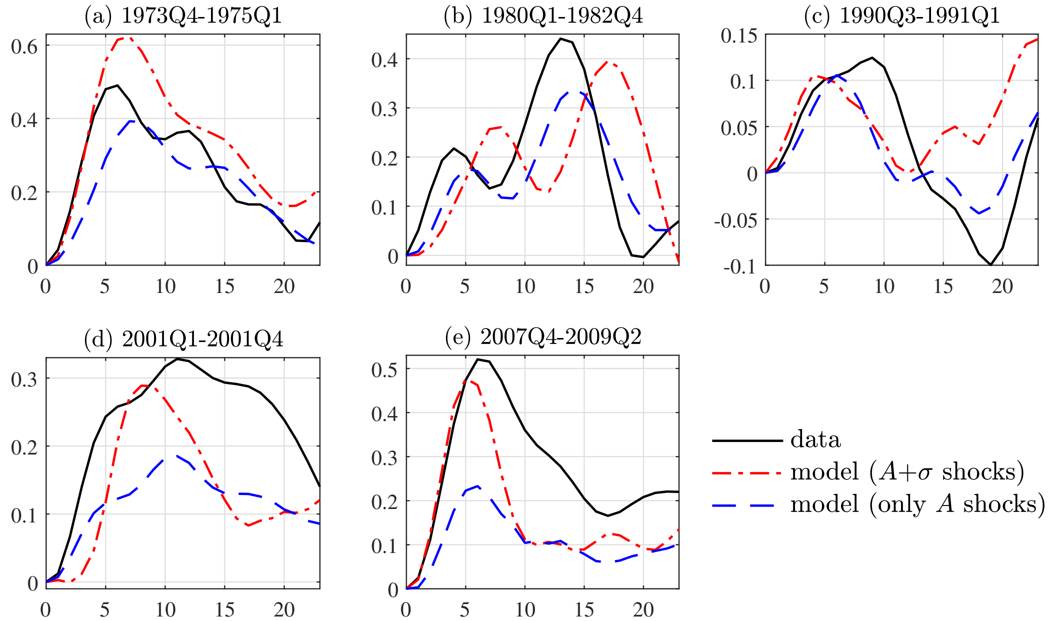
Table F.1: Peak-To-Trough Changes of Unemployment During Recessions ($\rho_z = 0.90$)

	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	0.392	0.340	0.106	0.185	0.233
Both A and σ shocks	0.623	0.395	0.106	0.289	0.477
$\Rightarrow$ Data explained by adding σ shocks	47.0%	12.6%	0.1%	31.6%	46.9%
	27.6% on average				
Models without contracting frictions					
Only A shocks	0.330	0.279	0.086	0.154	0.188
Both A and σ shocks	0.432	0.297	0.070	0.222	0.364
$\Rightarrow$ Data explained by adding σ shocks	21.0%	4.1%	-12.4%	20.8%	33.8%
	13.4% on average				

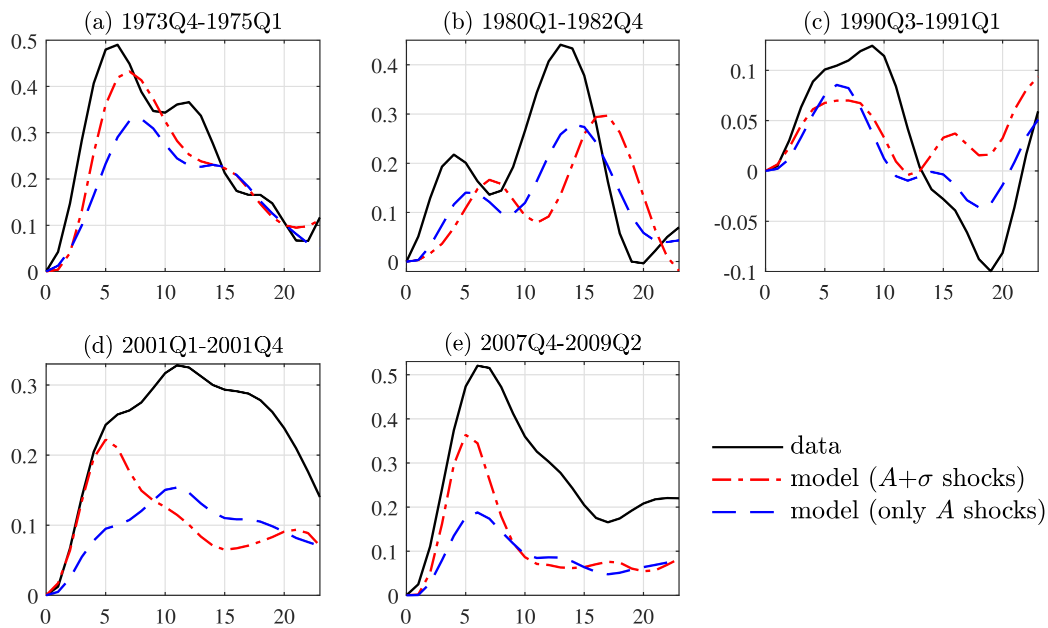
Note: The table compares peak-to-trough unemployment changes during recessions across data, benchmark models, and models without contracting frictions, with $\rho_z = 0.90$. Model parameters are from Table G.1. 'Only A Shocks' means models with only aggregate productivity shocks. 'Both A and σ Shocks' refers to models with both aggregate productivity shocks and uncertainty shocks.

Figure F.1: Unemployment Series with and Without Modeling Contracting Frictions ($\rho_z = 0.90$)

Panel A: Benchmark Models



Panel B: Models Without Contracting Frictions



Notes: The panels display model predictions for unemployment during recessions with $\rho_z = 0.90$: Panel A uses the benchmark models, and Panel B uses models without contracting frictions. Model parameters are from Table G.1, 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 and 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.

G Additional Tables and Figures

Table G.1: Parameters of Reference Models

Parameters	Notations	Benchmark Model $A+\sigma$	Benchmark Model $A+\sigma(\Delta^w)$	Benchmark Model A only	No Contracting Frictions $A+\sigma$	No Contracting Frictions A only
Aggregate shocks						
Persistence of aggregate productivity	ρ_A	0.920	0.920	0.920	0.912	0.912
SD of aggregate productivity	σ_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	ρ_σ	0.880	0.875	-	0.926	-
SD of uncertainty	σ_σ	0.092	0.092	-	0.186	-
Correlation between ϵ_t^A and ϵ_t^σ	$\rho_{A\sigma}$	-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	λ	0.100	0.100	0.100	0.120	0.120
Matching function elasticity	γ	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	σ_ϵ	0.080	0.080	0.071	0.080	0.080
Agency friction	$\tilde{\zeta}$	2.400	2.400	2.400	-	-
Auditing quality	ξ	1.780	1.780	1.780	-	-
Recovery rate	η	2.410	2.410	2.410	-	-
Exogenous exit rate	π_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 only' means the model only has aggregate productivity shocks. The corresponding matched moments are shown in Table 5.

Table G.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 σ 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 σ Shocks (Δ^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 σ 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	-

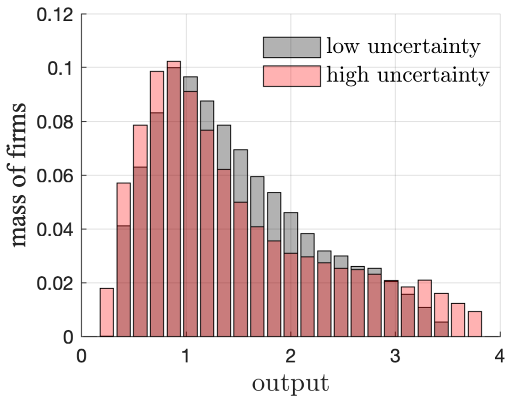
Notes: Panel A shows the business cycle moments observed in the data. Panels B and C present moments from 3,000-quarter simulations of the benchmark model and the model without contracting frictions, both including and excluding uncertainty shocks. 'Both A and σ Shocks' indicates the model incorporates both aggregate productivity shocks and uncertainty shocks, 'Δ^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 G.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

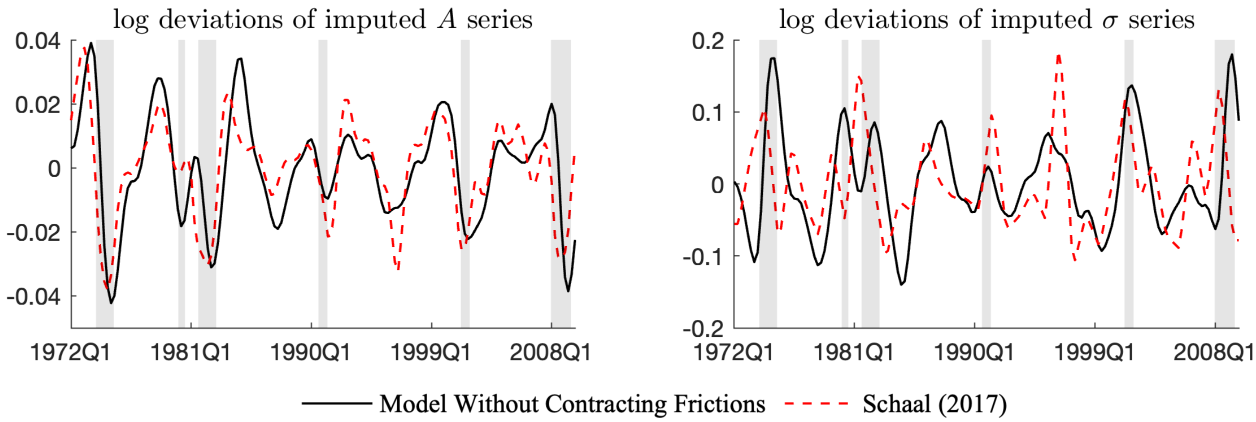
Notes: The table compares model-simulated moments with and without labor market policies. Panel A specifies the policies, and Panel B displays moments from 3,000-quarter simulations of the benchmark model and the model without contracting frictions. Policies are implemented when uncertainty exceeds its 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 G.1: Distribution of Firms' Output



Notes: The figure compares the stochastic stationary distributions of firms' output under low (black) and high (red) uncertainty. 'High' and 'low' states are defined as one unconditional standard deviation above or below the mean.

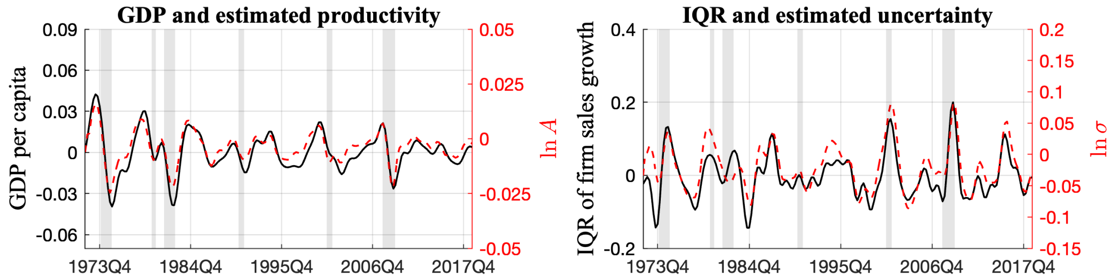
Figure G.2: Comparison of Estimated Shocks with Schaal (2017)



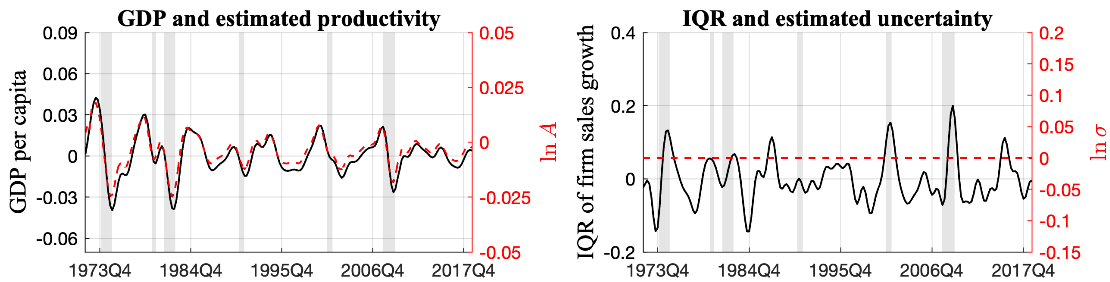
Notes: This figure compares the shocks estimated by my model (without contracting frictions) with those estimated by Schaal (2017). The black lines show the estimated log deviations of aggregate productivity, A, and uncertainty, σ, from my model. The red dashed lines depict the shocks as estimated by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

Figure G.3: Estimated Aggregate Productivity and Uncertainty

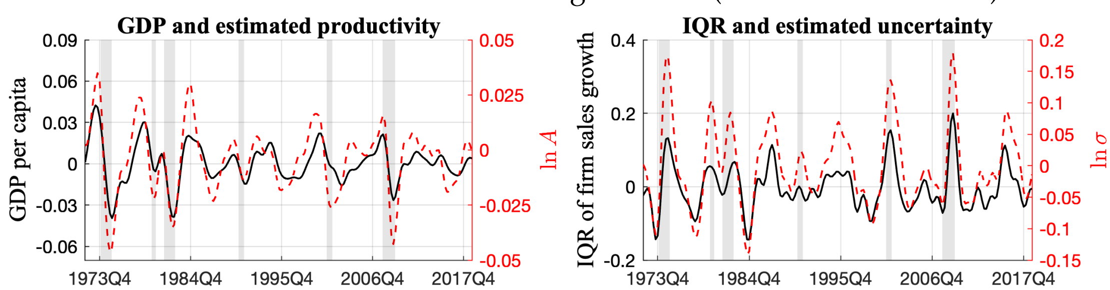
Panel A: Benchmark Model (Both A and σ Shocks)



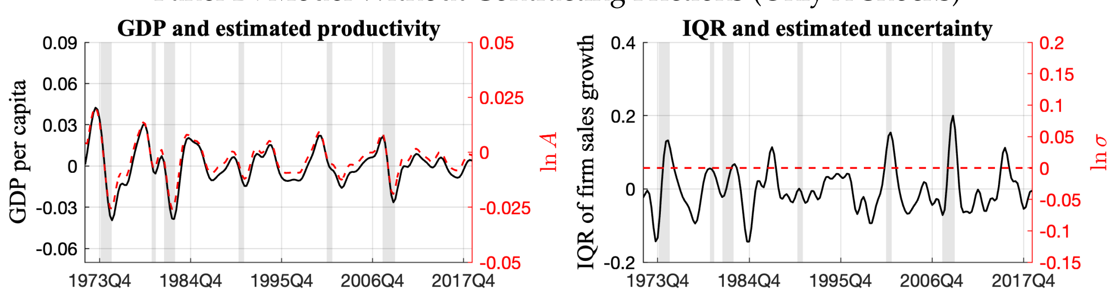
Panel B: Benchmark Model (Only A Shocks)



Panel C: Model Without Contracting Frictions (Both A and σ Shocks)



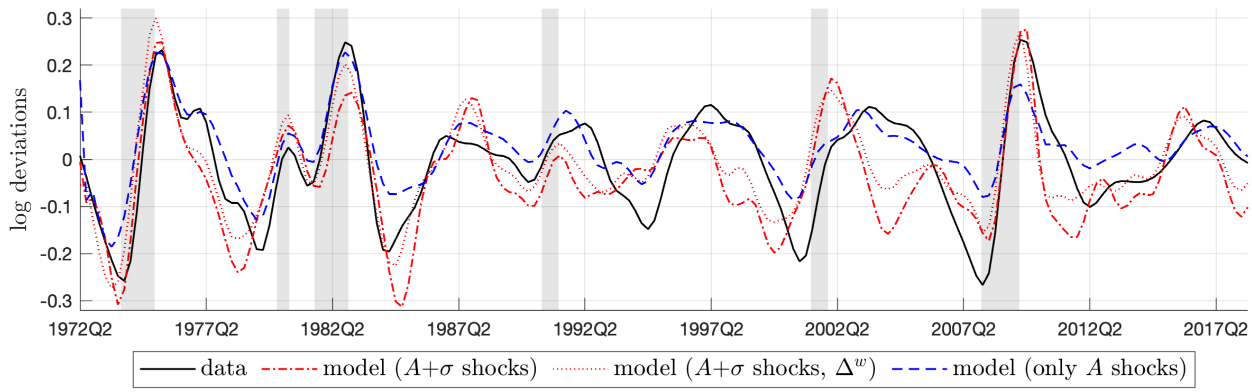
Panel D: Model Without Contracting Frictions (Only A Shocks)



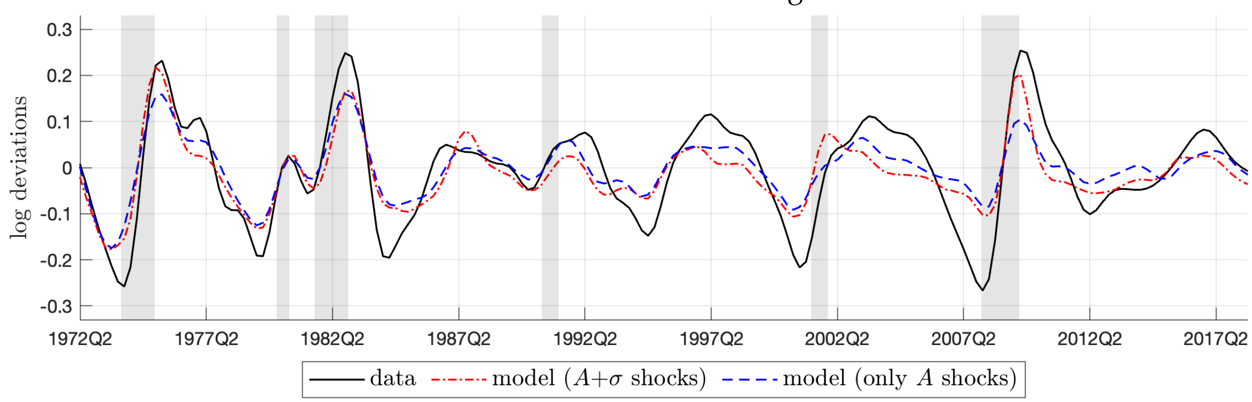
Notes: This figure shows the estimated aggregate productivity and uncertainty of four models. Using the particle filter, I estimate aggregate productivity, A, and uncertainty, σ, from GDP per capita and the interquartile range (IQR) of firm sales growth data series. These series are detrended with a 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 G.4: Entire Unemployment Series with and Without Modeling Contracting Frictions

Panel A: Benchmark Models



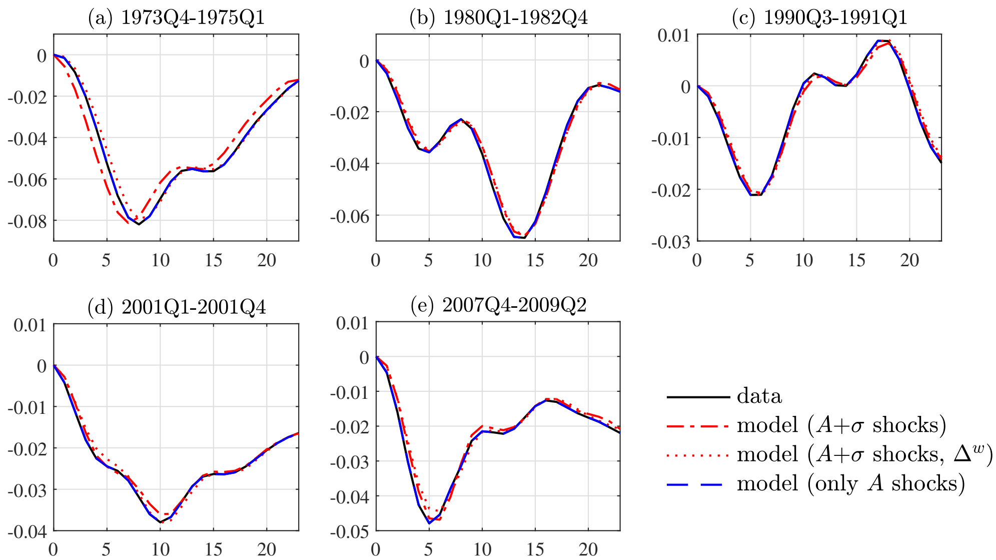
Panel B: Model Without Contracting Frictions



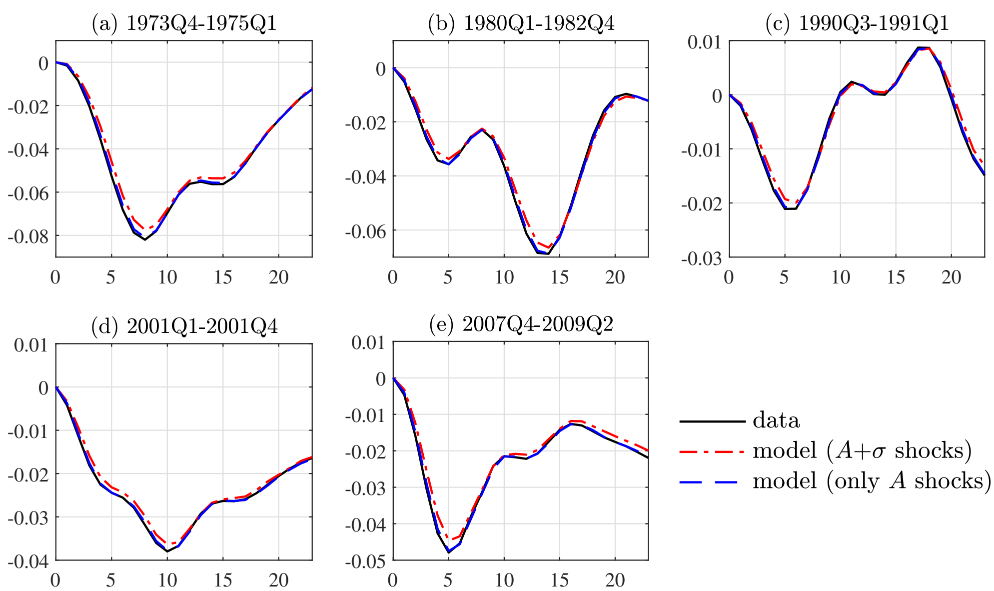
Notes: The panels display model predictions for unemployment from 1972Q2 to 2018Q3: Panel A uses the benchmark models, and Panel B uses models without contracting frictions. Models are recalibrated, with aggregate productivity and uncertainty shocks estimated using a particle filter on output data and firms' sales growth IQR, detrended for 6 to 32 quarter fluctuations as in 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 'Δ^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'). Series are depicted as log deviations from pre-recession peaks. I use Schaal's (2017) code when plotting this figure.

Figure G.5: Output Series with and Without Modeling Contracting Frictions

Panel A: Benchmark Models

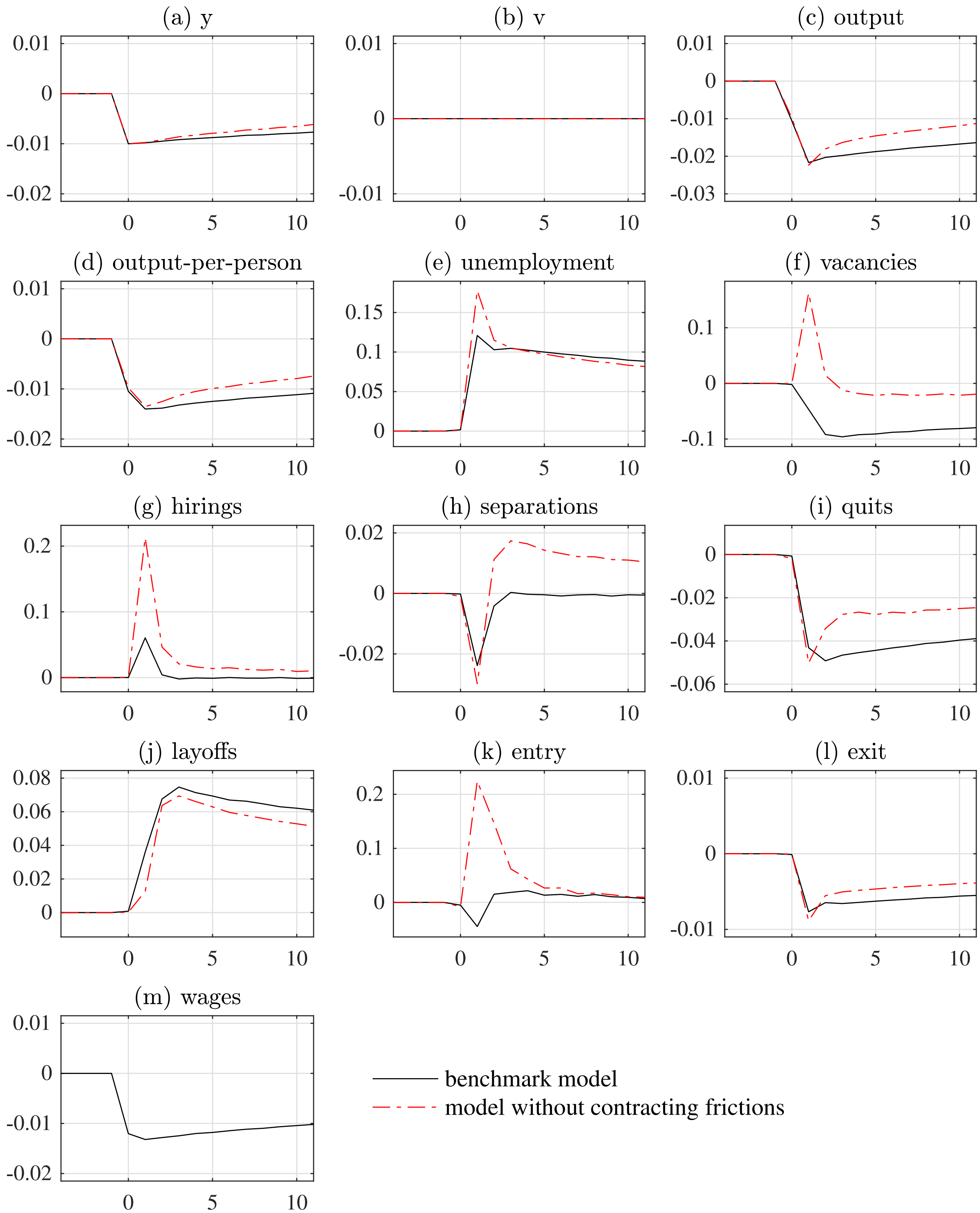


Panel B: Models Without Contracting Frictions



Notes: The panels display the model's predictions for output during recessions: Panel A uses the benchmark models, and Panel B uses 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 as in 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 'Δ^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'). Series are depicted as log deviations from pre-recession peaks. I use Schaal's (2017) code when plotting this figure.

Figure G.6: 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. Models are recalibrated. I use Schaal's (2017) code when plotting this figure.