Labor Force Telework Flexibility and Asset Prices: Evidence from the Covid-19 Pandemic

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胡震霆 2022/01/09

Introduction

Background:

During the Covid-19 pandemic, we've seen in many countries:

- a sizeable drop in the equity returns and operating and operating as well as financial performance on firms.
- a grow in the application of telework in some industries thus having more flexibilities in transforming working pattern and suffer less in the shock of pandemic.

Research introductions:

- we construct a measure LFTF that captures the industry-level labor force telework flexibility.
- We carried out some empirical experiment on the relationship between LFTF and stock return as well as firms' performance and extend it to the level of G7.
- We develop a dynamic model economy to investigate the driving force of previous empirical findings.

Researching Problems

Empirically:

- How to construct LFTF scores for every industry?
- What is the relationship between LFTF scores and stock returns?
- What is the relationship between LFTF scores and firms' performance?
- Out-of-sample exercise: from US sample to other G7 countries

Theoretically:

- Building a heterogeneous industry dynamic model to understand the driving forces for the empirical findings

Conclusions

Empirically:

- we utilize the industry-job composition and job-attributes information to construct a measure that captures the industry-level labor force telework flexibility.
- firms in high LFTF industries significantly outperform firms in low LFTF industries in stock returns and operating during the pandemic.
- the positive LFTF-return relation extends to G7 countries and is affected by the pandemic severity in individual countries.

Theoretically:

- Job task flexibility is the key driving force of firm value and firm policy fluctuations.

And other derived conclusions…

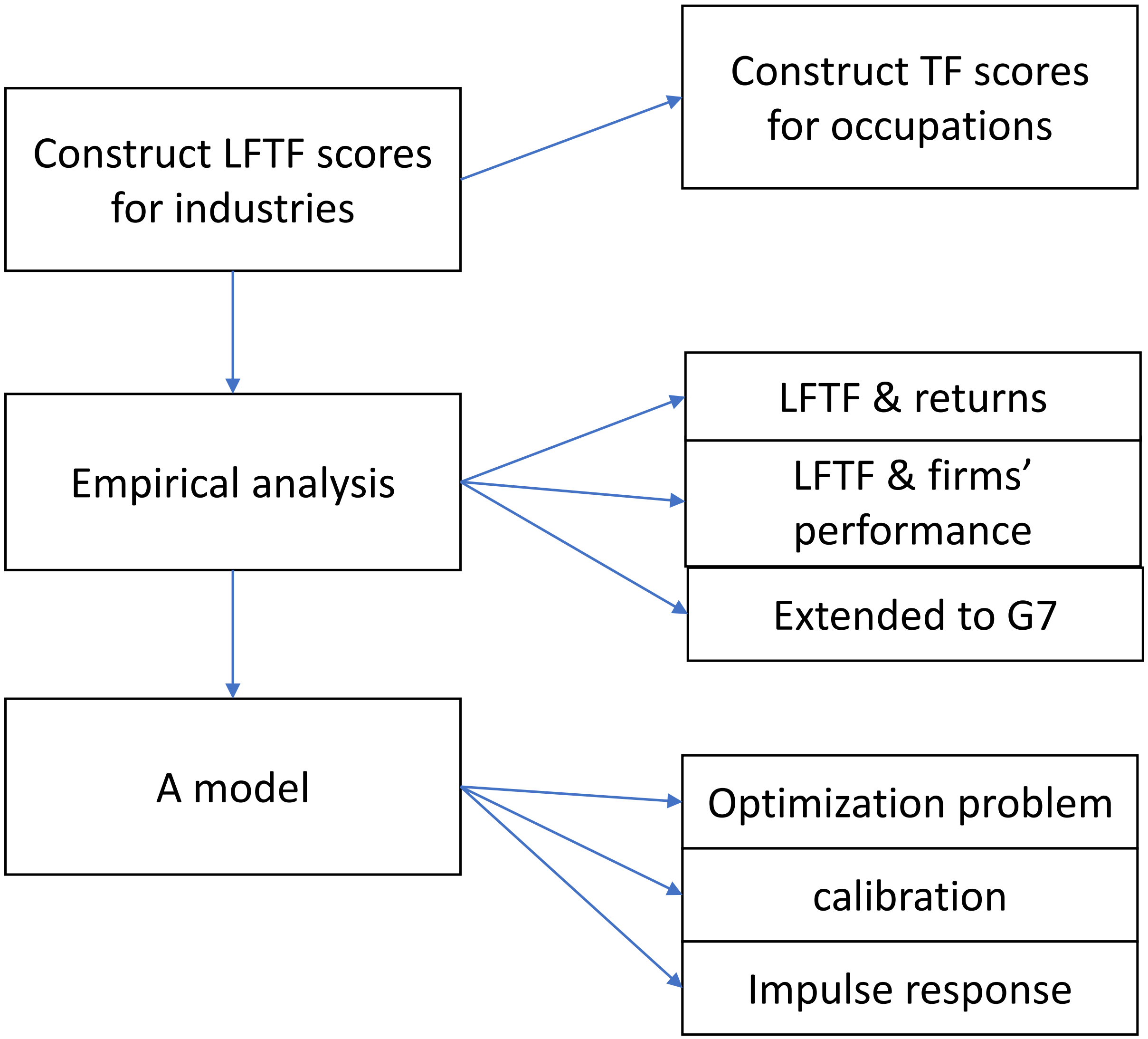
Contribution

- This paper contributes to the fast-growing body of work on the impact of the Covid-19 pandemic on the economy and financial markets.
- Chetty et al (2020) find that the drop of consumer spending in the pandemic is due to contraction in firms' ability to supply certain goods and services without health risks, rather thana reduction in consumer purchasing power, implying that the pandemic shock is more likely to be a firm supply shock than a consumer demand shock
- We can infer the ability and our model highlight a combined shock.
- Previous research focus on the negative impact on the financial market of the pandemic shock.
- Our findings indicate the heterogeneity of impact on different LFTF quintiles across industries and we provide a model to investigate it.

Contribution

- ◆ This study contributes to the literature that studies telework feasibility of US occupations and other aspects of telework.
- ➢ Our studies focus on the ICT characteristics of jobs while constructing LFTF measurement and even though we didn’t assess the labor productivity directly, our findings prove indirectly that industries with high LFTF scores perform with higher labor productivity.
- ◆ This study contributes to the literature that studies the link between labor market frictions and financial market.
- ➢ Our studies highlights the labor productivity difference across industries channeled through telework flexibility affect the work activity in traditional workplace and the returns and performance of firms soon afterwards.

Framework



Construct LFTF scores for industries
Construct TF scores for occupations
Empirical analysis
LFTF & returns
LFTF & firms' performance
Extended to G7
A model
Optimization problem
calibration
Impulse response

Measuring Labor Force Telework Flexibility(LFTF)

Definition:

the extent to which a firm can maintain its labor productivity through telework while minimizing virus infections among its employees in the wake of the pandemic.

Data sources:

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at the industry level: the Bureau of Labor Statistics' Occupational Employment Statistics (OES) program in 2019, which contains information about job composition of industries and the number of employees and their corresponding wages for each occupation for industries

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at the occupation level: US Department of Labor's Occupational Information Network (O*NET) , which contains information about the relevance and importance of a large set of job characteristics.

Measuring Labor Force Telework Flexibility(LFTF)

Measuring a Telework Flexibility score(TF) for each occupation:

Basis1:

The central component of telework is the infrastructure of information and communication technologies (ICT) that enable the work activities at alternative worksites. （信息通讯技术）So the TF scores should incorporate the ICT part as the main part, which we infer from 5 job characteristics from O*NET.

Part 1: 5 characters associated with information and communication technologies

(1) Interacting with Computers

(2) Getting Information

(3) Processing Information

(4) Analyzing Data or Information

(5) Documenting/Recording Information

Measuring Labor Force Telework Flexibility(LFTF)

Measuring a Telework Flexibility score(TF) for each occupation:

Basis2:

Workers in jobs that require having contact with others, requiring are at a higher risk of exposure to infections, and hence are more likely to be disrupted in the wake of a pandemic if the job tasks cannot be switched to telework.

We infer this part from 4 characteristics of job from O*NET as well

Part 2: 4 characters associated with person contact(negative effects)

(6) Face-to-Face Discussions

(7) Contact with Others

(8) Physical Proximity（物理上的接触程度）

(9) Indoor, Environmentally Controlled

Measuring Labor Force Telework Flexibility(LFTF)

Measuring a Telework Flexibility score(TF) for each occupation:

To construct the occupation-level TF score(which has been standardized), we sum over all nine standardized characteristic scores for each occupation and scale the resulting score to values between 0 and 10.

we list in Table 2 occupations with the highest and lowest TF scores, together with their corresponding scores.

Rank	Occupation Code	Occupation Title	TF
1	27-2031	Dancers	0.00
2	39-3011	Gaming Dealers	0.59
3	27-2011	Actors	0.71
4	39-5092	Manicurists and Pedicurists	0.78
5	39-5093	Shampooers	0.78
770	19-3011	Economists	8.76
771	19-2042	Geoscientists, Except Hydrologists and Geographers	8.86
772	15-2021	Mathematicians	8.97
773	15-2091	Mathematical Technicians	9.18
774	19-2011	Astronomers	10.00

Measuring Labor Force Telework Flexibility(LFTF)

Aggregate the occupation-level TF scores at the level of industries:

We merge the OES industry-occupation data with the O*NET occupation-level TF scores. Having the employment number for each industry-occupation and the corresponding TF score for each occupation, we construct LFTF measure for each industry i as following:

$$LFTF_i = \sum_j TF_j \times \frac{emp_{i,j}}{\sum_j emp_{i,j}}$$

TF_j : the TF score for occupation j.

emp_j : the employment in industry i for occupation j.

we list in Table 3 industries with the highest and lowest LFTF scores, together with their corresponding scores.

Measuring Labor Force Telework Flexibility(LFTF)

Rank	NAICS Code	Industry Title	LFTF
1	624400	Child Day Care Services	2.48
2	812100	Personal Care Services	2.57
3	713100	Amusement Parks and Arcades	2.68
4	447100	Gasoline Stations	2.94
5	722500	Restaurants and Other Eating Places	2.95
6	722300	Special Food Services	3.01
7	445300	Beer, Wine, and Liquor Stores	3.06
8	448200	Shoe Stores	3.22
9	713900	Other Amusement and Recreation Industries	3.23
10	448100	Clothing Stores	3.23
		⋮	
259	541300	Architectural, Engineering, and Related Services	6.08
260	524100	Insurance Carriers	6.09
261	518200	Data Processing, Hosting, and Related Services	6.18
262	541200	Accounting, Tax Preparation, Bookkeeping, and Payroll Services	6.18
263	511200	Software Publishers	6.23
264	525100	Insurance and Employee Benefit Funds	6.23
265	541600	Management, Scientific, and Technical Consulting Services	6.26
266	541500	Computer Systems Design and Related Services	6.31
267	521100	Monetary Authorities-Central Bank	6.41
268	541700	Scientific Research and Development Services	6.54

Empirical Result --- LFTF & equity returns

Portfolio Analysis:

- Calculate value-weighted average of returns for each industry and the cumulative returns from 2020.1.1-2020.3.31
- Sort the industries into quintiles based on the value of their LFTF scores in 2019
- Compare cumulative returns across LFTF quintiles.

Occupation → Industry → Sector

Panel A: Portfolio Formation across All Sectors						
	Low-LFTF	2	3	4	High-LFTF	High-Low
Average LFTF	3.881	4.719	5.092	5.325	5.891	2.010
Cum. Return	−16.31%***	−16.89%***	−13.04%***	−12.22%***	−3.31%	13.00%***
t-Ratio	(−4.26)	(−4.82)	(−3.53)	(−2.86)	(−1.31)	(2.81)
Panel B: Portfolio Formation within Sectors						
	Low-LFTF	2	3	4	High-LFTF	High-Low
Average LFTF	4.543	4.860	5.108	5.202	5.566	1.023
Cum. Return	−25.54%***	−13.33%***	−11.60%***	−8.02%**	−5.38%*	20.15%***
t-Ratio	(−8.09)	(−4.70)	(−3.56)	(−2.12)	(−1.79)	(4.63)

Empirical Result --- LFTF & equity returns

A Decomposition Analysis of LFTF-Return Relationship:

decompose the LFTF score into two components:

- ICT component: part 1 of TF score
- Person contact component: part 2 of TF score

$$CumRet_i = b_0 + b_1 \cdot LFTF_{ICT,i} + b_2 \cdot LFTF_{Contact,i} + f_s + \epsilon_i$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LFTF	0.049**	0.132***						
	(2.23)	(3.61)						
LFTF_{ICT}			0.057***	0.095***			0.055***	0.115***
			(2.94)	(2.85)			(2.77)	(3.49)
$\text{LFTF}_{Contact}$					-0.038	0.046	-0.016	0.108**
					(-0.91)	(0.82)	(-0.40)	(2.11)
Intercept	-0.370***	-0.781***	-0.456***	-0.675***	0.067	-0.359	-0.361	-1.335***
	(-3.24)	(-4.28)	(-4.03)	(-3.47)	(0.31)	(-1.25)	(-1.38)	(-3.56)
Sector FE	N	Y	N	Y	N	Y	N	Y
N	109	109	109	109	109	109	109	109
R-sq	0.043	0.340	0.072	0.311	0.011	0.244	0.074	0.340

Empirical Result --- LFTF & Firm performance

Impact of LFTF on Operating and Financial Performance:

We compare changes in the performance measures between 2019 forth fiscal quarter and the 2020 first fiscal quarter. We are not able to fully account for the impact of the pandemic on the firms' performance due to data availability.

Here is how the measurement of performance constructed:

- *Profitability* is defined as net income (NI) divided by total assets (AT).
- *Sales* is defined as sales (SALE) divided by total assets (AT).
- *log(Emp.)* is the natural logarithm of the number of total full-time employees in the industry, obtained from the Bureau of Labor Statistics Current Employment Statistics dataset.
- *log(Investment)* is defined as the natural logarithm of the sum of capital expenditure (CAPX) and cost of goods sold (COGS), aggregated at the industry level.
- *Financial Leverage* is defined as total liabilities (LT) divided by total assets (AT).
- *Cash holdings* is defined as cash and cash equivalent (CHE) divided by total assets (AT).

Empirical Result --- LFTF & Firm performance

Impact of LFTF on Operating and Financial Performance:

Similar to portfolio analysis, we group firms by their industry LFTF quintiles and calculate the mean change in each industry.

It's worth noting that on the financing side, there is a reverse pattern which means pandemic disruption poses more severe liquidity concerns for industries.

	Low-LFTF	2	3	4	High-LFTF	High-Low
ΔProfitability	−2.77%***	−1.02%***	−1.25%***	−0.72%***	−0.73%	2.03%**
	(−2.83)	(−3.69)	(−2.87)	(−2.69)	(−1.63)	(2.18)
ΔSales	−5.72%**	−2.72%***	−1.70%***	−1.48%***	−1.07%	4.65%**
	(−2.05)	(−4.17)	(−3.54)	(−4.95)	(−1.30)	(2.05)
Δlog(Emp.)	−45.25%***	−20.28%***	−12.79%***	−9.61%***	−4.26%***	40.99%***
	(−6.38)	(−6.80)	(−5.11)	(−4.67)	(−5.79)	(6.51)
Δlog(Investment)	−21.46%***	−8.53%***	−6.71%***	−9.13%***	−7.64%**	13.82%*
	(−2.59)	(−2.62)	(−3.21)	(−5.81)	(−2.42)	(1.89)
ΔFin. Leverage	3.18%***	1.79%***	2.31%***	1.69%***	1.46%***	−1.71%**
	(3.74)	(5.54)	(5.34)	(7.88)	(4.28)	(−2.23)
ΔCash	4.94%***	2.27%***	1.59%**	1.39%***	2.24%**	−2.70%*
	(4.99)	(6.69)	(2.32)	(3.83)	(2.26)	(−1.72)

Empirical Result --- LFTF & G7

International Evidence of LFTF-Return Relationship:

Variable processing:

We assume that the LFTF value for each industry is the same as its US counterpart. Then one piece of data have 2 dimensions including country and sector.

Typically, we carry out portfolio analysis at first:

	Low-LFTF	2	3	4	High-LFTF	High-Low
Panel A: Portfolio Formation Across All Country-Sectors						
Average LFTF	3.671	4.683	5.071	5.318	5.945	2.274
Cum. Return	−18.40%***	−14.36%***	−11.11%***	−14.46%***	−7.80%***	10.60%***
t-Ratio	(−9.78)	(−8.22)	(−4.58)	(−7.79)	(−3.35)	(3.54)
Panel B: Portfolio Formation Within Countries						
Average LFTF	3.689	4.717	5.048	5.324	5.910	2.221
Cum. Return	−17.48%***	−17.11%***	−11.35%***	−12.24%***	−7.94%***	9.54%***
t-Ratio	(−9.04)	(−9.64)	(−4.72)	(−6.61)	(−3.51)	(3.20)
Panel C: Portfolio Formation Within Country-Sectors						
Average LFTF	4.474	4.876	5.138	5.338	5.601	1.127
Cum. Return	−17.19%***	−13.16%***	−13.33%***	−8.81%***	−8.28%***	8.91%***
t-Ratio	(−8.57)	(−5.79)	(−6.4)	(−3.93)	(−3.31)	(2.77)

Empirical Result --- LFTF & G7

International Evidence of LFTF-Return Relationship:

Following analysis focus on regressing the industry cumulative returns on their LFTF, similar to previous research, the regression takes the form as follow, where f_x means fixed effects . (if included)

$$CumRet_{i,c} = b_0 + b_1 \cdot LFTF_i + f_c + f_s + f_{c,s} + \epsilon_i$$

We first report the result combining all countries:

Panel A: All Countries				
	(1)	(2)	(3)	(4)
LFTF	0.041***	0.047***	0.088***	0.084***
	(3.60)	(4.24)	(4.25)	(4.47)
Intercept	−0.333***	−0.365***	−0.569***	−0.545***
	(−6.03)	(−6.71)	(−5.58)	(−5.94)
FE	-	Country	Sector	Country-Sector
N	398	398	398	398
R-sq	0.030	0.080	0.167	0.430

Empirical Result --- LFTF & G7

International Evidence of LFTF-Return Relationship:

We then report the result regarding every country:

	Canada		Germany		France	
	(1)	(2)	(1)	(2)	(1)	(2)
LFTF	0.049	0.043	−0.004	0.050	0.075***	0.100
	(1.36)	(0.51)	(−0.09)	(1.09)	(3.21)	(1.58)
Intercept	−0.383**	−0.353	−0.088	−0.368	−0.551***	−0.673**
	(−2.16)	(−0.84)	(−0.37)	(−1.61)	(−4.78)	(−2.11)
FE	-	Sector	-	Sector	-	Sector
N	50	50	43	43	51	51
R-sq	0.019	0.542	0.000	0.495	0.135	0.389

United Kingdom		Italy		Japan	
(1)	(2)	(1)	(2)	(1)	(2)
0.049**	0.117**	0.128***	0.200*	0.038**	0.062***
(2.05)	(2.14)	(3.05)	(1.86)	(2.29)	(2.86)
−0.437***	−0.775***	−0.814***	−1.192**	−0.275***	−0.393***
(−3.70)	(−2.86)	(−3.93)	(−2.10)	(−3.52)	(−3.8)
-	Sector	-	Sector	-	Sector
66	66	31	31	157	157
0.039	0.340	0.204	0.542	0.054	0.205

Empirical Result --- LFTF & G7

International Evidence of LFTF-Return Relationship:

Interpretation of results above:

- Germany and Canada have the lower death rate among the western G7 countries, whereas France, UK and Italy have much higher death rate, which may explain the pattern of the significance heterogeneity.
- Even though Japan have a lower death rate, its firms with more foreign direct investment and exports suffer more on stock returns during the pandemic and therefore there is spill-over specifically for Japanese industries

Empirical Result --- LFTF & FF5*

Relationship between LFTF factor and FF5 factors:

We further investigate how the LFTF-returns relationship is affected by the severity of the pandemic. The regressions take as follows:

$$CumRet_{i,c} = b_0 + b_1 \cdot LFTF_i + f_c + f_s + f_{c,s} + \epsilon_i$$

$$b_{LFTF,c} = b_0 + b_1 \cdot Intensity_c + \epsilon_i$$

$Intensity_c$ has two measurement:

- The logarithm of the infection rate per 100000 population
- The logarithm of the death rate per 100000 population

	(1)	(2)	(3)	(4)
Intensity (Death)	0.009**	0.022**		
	(2.61)	(2.25)		
Intensity (Infection)			0.011**	0.031*
			(2.18)	(1.90)
Constant	0.146***	0.337**	0.139***	0.327**
	(3.60)	(2.58)	(3.07)	(2.18)
Within Sector	No	Yes	No	Yes
N	21	21	21	21

Empirical Result --- LFTF & FF5*

Relationship between LFTF factor and FF5 factors:

During the pandemic, many factor portfolios suffered, especially the value factor. Here we investigate to what extent can the factors in FF5 can be explained by the LFTF factor. The regression take as follow:

$$R_{FF,t} = b_0 + b_1 \times R_{LFTF,t} + b_2 \times (R_{Mkt,t} - R_{f,t}) + \epsilon_t$$

Where $R_{FF,t}$measures the FF5 factors except MKT, $R_{LFTF,t}$ measures the LFTF spread between highest and lowest portfolio. $R_{Mkt,t}$ measures the market factor.

We find that LFTF factor can explain a significant variation in HML and SMB factors while the explanatory power for other factors are much weaker.

The results suggest that the labor force in growth firms is more compatible with telework, and can better transform working pattern thus suffering less in the pandemic. And the labor force in big firms may be better equipped with ICT and can switch smoothly to telework condition thus suffering less in the pandemic

(the parameters b_1 are both significantly negative)

Model Analysis---constructing

Model points:

- We construct a model with 2 tasks for output of an industry: In-person task1 and Flexible task2, where task1 needs more labor while task 2 needs more capital.
- In addition, each industry faces models for motion, cost, demand and discount. Along with all those above, we can derive the optimal L&K input for the model and then deriving a series of economic variable, which forms an economy.
- The economy faces shocks from labor, demand and macro-uncertainty, which affect corresponded variable. Note that labor shock only affects task1.
- We can simulate the shock of pandemic with the shocks above.

Model Analysis---constructing

In-person task:

The form of task1 as follow:

$$Y_{1,t}^{j} = \left\{ (1-\mu_1) \left(S_t^{Agg} S_t^{j} L_{1,t}^{j} \right)^{\xi_1} + \mu_1 \left(K_{1,t}^{j} \right)^{\xi_1} \right\}^{\frac{1}{\xi_1}}, \qquad \begin{aligned} L_{1,t+1}^{j} &= (1-\delta_l)\, L_{1,t}^{j} + H_{1,t}^{j}, \\ K_{1,t+1}^{j} &= (1-\delta_k)\, K_{1,t}^{j} + I_{1,t}^{j}, \end{aligned}$$

$$G_{1,t}^{j} = \frac{c_{1,L}}{2} \left(\frac{H_{1,t}^{j}}{L_{1,t}^{j}} \right)^2 L_{1,t}^{j} + \frac{c_{1,K}}{2} \left(\frac{I_{1,t}^{j}}{K_{1,t}^{j}} \right)^2 K_{1,t}^{j},$$

Where notably:

ξ_1 determines the elasticity of substitution between capital and labor in task1, which takes the form: $1/(1-\xi_1)$

S_t^{Agg} *and* S_t^{j} measure the productivity of labor and follow 2-state Markov process which suffer the shock of labor

$G_{1,t}^{j}$ is the adjustment cost, which is regard as cost in the overall model.

Task 2 takes nearly the same form as task1, except that there is no S_t^{Agg} or S_t^{j} and thus won't be affected by labor shock.

Model Analysis---constructing

Revenue :

The form of revenue takes as follow:

$$Y_t^j = \left[(1-\varphi^j)\left(Y_{1,t}^j\right)^\rho + \varphi^j\left(Y_{2,t}^j\right)^\rho\right]^{\frac{1}{\rho}}, \qquad Y_t^j = B_t^{Agg} B_t^j \left(P_t^j\right)^{-\varepsilon},$$

$$E_t^j = \left(B_t^{Agg} B_t^j\right)^{1/\varepsilon}\left[(1-\varphi^j)\left(Y_{1,t}^j\right)^\rho + \varphi^j\left(Y_{2,t}^j\right)^\rho\right]^{\frac{1-1/\varepsilon}{\rho}}.$$

Where notably:

ρ determines the elasticity of substitution between two tasks, which takes the form:$1/(1-\rho)$

ε determines the elasticity of price elasticity.

B_t^{Agg} *and* B_t^j are the demand shifters on aggregate and industry-specific level, which follow the 2-state Markov process and are affected by demand shock.

$E_t^j = Y_t^j * P_t^j$ measures the income for the industry j.

Model Analysis---constructing

Aggregate uncertainty & Maximization:

The form of aggregate uncertainty takes as follow:

$$\sigma_t$$

And the form of discount model takes as follow:

$$M_{t,t+1} = \frac{1}{1+r_f} \frac{e^{-\gamma_s \Delta \log S_{t+1}^{Agg} - \gamma_\sigma \Delta \log \sigma_{t+1} - \gamma_B \Delta \log B_{t+1}}}{\mathbb{E}_t \left[e^{-\gamma_s \Delta \log S_{t+1}^{Agg} - \gamma_\sigma \Delta \log \sigma_{t+1} - \gamma_B \Delta \log B_{t+1}} \right]},$$

Where notably:

σ_t takes form of 2-state Markov process and measures the shock from aggregate uncertainty.

σ_t governs the recovery process for all shocks, in particular, when σ_t is high, the low state of S_t^{Agg} and S_t^j; B_t^{Agg} and B_t^j are more persistent.

$M_{t,t+1}$ is the discount rate of future value(cash flow).

$\gamma_s, \gamma_B, \gamma_\sigma$ are the price of risk for shocks, which are calibrated so as to all the shocks lead to a lower $M_{t,t+1}$

Model Analysis---constructing

Aggregate uncertainty & Maximization:

The form of Maximization takes as follow:

$$V_t^j = \max_{L^j_{1,t+1}, L^j_{2,t+1} K^j_{1,t+1}, K^j_{2,t+1}} \left[D_t^j + \mathbb{E}_t \left(M_{t,t+1} V^j_{t+1} \right) \right]$$

Where notably:

- We need to determine the solution to the L&K
- With L&K , we can derive other variables including V, H and I, which measures firms' value and performance in an industry.

To drive the solution:

- The functional forms are not available analytically, we solve for these functions numerically with value function iteration.(too hard to explain)
- Here we get an economy exposed to certain shocks.

Model Analysis--- Calibrations

Important parts of calibration:

While calibrating all the Markov process, we calibrate the value and transition probabilities of the time-series variable $\sigma_t, S_t^{Agg}, S_t^j, B_t^{Agg}, B_t^j$, some of the forms take as follows:

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \text{where } \Pr(\sigma_{t+1} = \sigma_i | \sigma_t = \sigma_k) = \pi_{k,i}^{\sigma}.$$

$$S_t^{Agg} \in \left\{S_L^{Agg}, S_H^{Agg}\right\}, \text{where } \Pr\left(S_{t+1}^{Agg} = S_i^{Agg} | S_t^{Agg} = S_k^{Agg}\right) = \pi_{k,i}^{S^{Agg}}(\sigma_t)$$
$$S_t^j \in \left\{S_L^j, S_H^j\right\}, \text{where } \Pr\left(S_{t+1}^j = S_i^j | S_t^j = S_k^j\right) = \pi_{k,i}^{S^j}(\sigma_t),$$

From which, we assume that part of the process of S_t is affected by the aggregate uncertainty σ_t, when $\sigma_t = \sigma_H$, $\pi_{L,H}^S$ is lower than that when $\sigma_t = \sigma_L$, which is the same for $\pi_{L,H}^B$.

However, the value of σ_t doesn't affect $\pi_{H,L}^{S/B}$, which means the emerge of the shocks of pandemic doesn't depend on the aggregate uncertainty.

Model Analysis--- Calibrations

Important parts of calibration:

While calibrating industries heterogeneity, we sort the model into 5 industries, which is consistent with the number of portfolios studied in the previous section.

We embody the heterogeneity through 3 sources:

(1) The fraction of output for task2 φ^j for each industry.

(2) The drop in S_t^j while facing the labor shock.

(3) The drop in B_t^j while facing the demand shock.

The highest φ^j correspond to the highest LFTF quintile which has on average highest fraction of telework compatible employees.

In addition, higher φ^j follows lower drop in S_t^j and B_t^j when facing shocks.

Model Analysis--- Calibrations

Some details of calibration

Table 10: Parameter values under baseline calibration

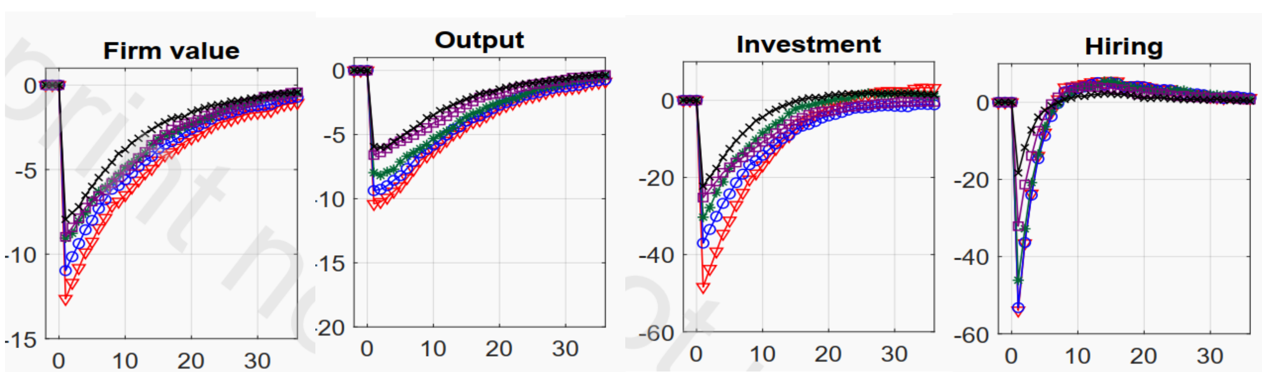
Description	Notation	Value	Justification
Technology			
Subjective discount factor	β	0.9999	Long-run average of real interest rate
Elasticity of price	ε	4	Price elasticity (Hall 1988) and (Bloom 2009)
Labor share in task 1	μ_1	0.7	Aggregate labor share of 60%
Labor share in task 2	μ_2	0.1	Aggregate labor share of 60%
Elasticity of substitution between capital and labor in task 1	ξ_1	-1	Capital and labor elasticity of 0.5 (Chrinko 2008)
Elasticity of substitution between capital and labor in task 2	ξ_2	-1	Capital and labor elasticity of 0.5 (Chrinko 2008)
Wage	W	1	Wage rate normalized to 1
Rate of depreciation for capital	δ	0.1/52	Capital depreciation rate assumed 10% per year
Rate of exit for labor	δ	0.36/52	Labor exit rate assumed 36% per year
Capital adjustment cost in task 1	$c_{1,K}$	20	Industry investment rate volatility
Capital adjustment cost in task 2	$c_{2,K}$	20	Industry investment rate volatility
Labor adjustment cost in task 1	$c_{1,L}$	10	Industry hiring rate volatility
Labor adjustment cost in task 2	$c_{2,L}$	10	Industry hiring rate volatility
Uncertainty shock (2 state Markov)			
Conditional volatility of productivity	σ_L	0.05	Baseline uncertainty (Low market volatility)
Conditional volatility in high uncertainty state	σ_H	0.20	High uncertainty (Peak market volatility in March 2020)
Transition probability low to high uncertainty	$\pi^{\sigma}_{L,H}$	2.60%	Uncertainty shocks following Bloom et al 2018
Transition probability remaining in high uncertainty	$\pi^{\sigma}_{H,H}$	94.3%	Probability of remaining in high uncertainty (Bloom et al 2018)
Aggregate labor shock (2 state Markov)			
High aggregate labor productivity	S^{Agg}_H	1	Labor supply normalized to 1
Low aggregate labor productivity	S^{Agg}_L	0.87	Aggregate labor supply dropped by 13% in March 2020
Aggregate demand shifter (2 state Markov)			
High aggregate demand	B^{Agg}_H	1	Demand normalized to 1
Low aggregate demand	B^{Agg}_L	0.99	Aggregate aggregate dropped by 1% in March 2020 (Brinca et al (2020))

Model Analysis--- Impulse response

Impulse of different kinds of shocks:

We run our model for 5 industries for a total of 300 periods and kick one or more shocks down/up to its low/high level in period 201 and let the model continue to run as before to simulate the constant impact of the pandemic. We do this for 1000 times and report the average response in charts. The results of Impulse responses are listed as follows:

Panel A: Shocks of the baseline model							
	(1) Data	(20 Labor shock	(3) Uncertainty	(4) Demand	(5) Combined	(6)	(7)
Return spread	−17.08	−10.79	−0.10	−1.00	−16.97		



Model Analysis--- Impulse response

Inspecting the mechanism:

We perform some changes to the baseline calibration to analyse the economic force driving the result, which including:

(1) The role of expected recovery length, which is reflected by the transition possibilities $\pi_{L,H}^{S/B}$, we raise/lower the value of $\pi_{L,H}^{S/B}$.

(2) The role of elasticity of substitution between tasks, which is reflected by $1/(1-\rho)$ in the model of aggregate output, we raise the value of it.

(3) The role of market price of risk for all shocks, which is reflected by: $\gamma_s, \gamma_B, \gamma_\sigma$ in the discount rate model $M_{t,t+1}$, we cut off the risk price of shocks.

(4) The role of price elasticity, which is reflected by: ε in the model of demand, we lower the price elasticity.

The results are as follows:

Panel B: Model comparison

	Data	Baseline	ShortRec	LongRec	HighEls	ZeroRP	LowPE
Return spread	−17.08	−16.97	−7.61	−19.58	−20.57	−9.02	−11.60