Covid and Productivity in Europe: A Responsiveness Perspective*

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Abstract

This paper studies the effects of Covid-19 on manufacturing output, employment and productivity across a set of European countries. Using a quantitative firm dynamics model with endogenous entry and exit, key parameters of adjustment costs and market power are estimated to match country-specific responsiveness of firms to exogenous shocks. The estimated model is used to simulate the effects of the Covid-19 shock, with and without policy measures. As seen through counterfactual exercises, the main impact of the policy interventions, treated here as work-sharing schemes targeted to low profitability firms and "no-firing" obligations, was to mitigate the drop in aggregate employment by keeping firms in business. Depending on the country, we calculate that the aggregate drop in employment would have been between 1.0 and 1.9 percentage points higher without policy support. We do not find evidence of adverse productivity effects from these interventions. From these counterfactuals, we establish the importance of targeted subsidies and the sensitivity of employment responses to firm beliefs.

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1 Introduction

In this paper we ask how firms' responsiveness to unanticipated variations in profitability matters for the economy-wide response to aggregate shocks. Specifically, we study the effects of the Covid-19 economic crisis on manufacturing output, employment and productivity across a set of European countries. The aggregate effects of the shock on output and employment are well documented: a sharp decline in economic activity followed by a relatively quick recovery.[1]

Instead of focusing on aggregates, this paper highlights country-specific responses of firms and resulting differences in aggregate outcomes. We first document pre-existing differences in how firms respond to unanticipated variations in their profitability across Europe. We then argue that this heterogeneity in responsiveness is crucial to understanding: (i) how individual firms responded to the Covid-19 shock in terms of employment and entry/exit decisions and (ii) how the labor market stabilization policies enacted by the various governments influenced these decisions.

Our analysis is built around a partial equilibrium firm dynamic labor demand model with rich adjustment costs and endogenous entry and exit decisions. We bring the model to the data through a simulated method of moments approach using harmonized annual firm-level data for manufacturing firms from ORBIS. We limit our attention to France, Germany, Italy and Spain given their prominence within Europe. In the estimation procedure we choose moments that capture the responsiveness of firms to variations in their profitability. Specifically, this requires the estimation of firm-level revenue functions to extract idiosyncratic shocks to demand and productivity that comprise profitability. With this measure, the extensive and intensive margin response of employment growth to these shocks can be estimated.

These measures of responsiveness are a key part of the analysis. First, they are of interest in their own right, providing a basis for comparison across countries.[2] Second, they are used as moments in the estimation to identify the costs of labor adjustment which are fundamental to the nature of firms' responses to the Covid-19 shock.

From the estimated model we find that the response of employment growth to profitability is increasing and convex in all countries. This means that the marginal response increases with the magnitude of the shock.[3] Furthermore, the adjustment costs for all countries are substantial, leading to large regions of inaction. This inaction, along with time-to-build in the employment adjustment, is key for understanding the productivity implications of the Covid-19 shock and the related policy support. Across countries, the heterogeneity in firm responsiveness at the micro-level reflects, *inter alia*, differences in labor adjustment costs.

The second part of the paper evaluates the effects of the Covid-19 shock and the consequent policy interventions on employment, output and productivity dynamics. To do so, we enrich our

[1] Europe experienced negative growth of real GDP of around 12% in the second quarter of 2020 and a sharp rebound after (Data from Eurostat's Quarterly National Accounts for Euro Area 19 countries).

[2] This parallels the comparison across decades in Decker, Haltiwanger, Jarmin, and Miranda (2020).

[3] This contrasts with the concavity of hiring reported in Ilut, Kehrig, and Schneider (2018) for US data.

baseline model by introducing an aggregate profitability shock that mimics the effects of Covid-19. We first show how the aggregate dynamics of employment and output can be rationalized by differences in responsiveness across European firms. We then quantify the economic costs in terms of employment and productivity if governments had not intervened.

For each country, we calibrate the size of the aggregate shock to match the country-specific drop in manufacturing employment with the respective country's policy support in place. In terms of policy support, we study the role of short-time work schemes and the effect of "no-firing" obligations. We then use the calibrated model to quantify (i) the impact of the shock absent the policies, (ii) the consequences of the aggregate shock and the policy support on firms' productivity and factor misallocation, (iii) the effect of the shock and policies on investment, (iv) the impact of interventions if policies were not targeted to the less profitable firms, and (v) the role of firms' beliefs in shaping the response of employment to the shock and associated policies.

The short-time work schemes, designed to reduce layoffs during the crisis, are shown to have had a major impact. Across all four countries, we calculate that the aggregate drop in employment would have been between 1.0 and 1.9 percentage points higher without the policy support designed to reduce layoffs.[4]

One of our main findings concerns the role of exit. While continuing firms did indeed reduce employment in response to the aggregate profitability decline, the biggest effect on employment arose from exit. This is the case across all four countries and reflects the large adjustment costs that limit the employment response of continuing firms. An important effect of the policy support was to offset the incentive to exit in the face of the large Covid-19 shock.

Despite our focus on labor instead of capital demand, we also discuss the implications of the Covid-19 shock and policies for capital investment across firms in our model. In our model capital demand is a function of employment and profitability. Hence, a firm's labor adjustment costs also impact its capital investment decisions. We find that the profitability drop associated with the Covid-19 shock decreases average capital investment across firms. However, the policy support does little to restore investment in response to the shock.

In additional exercises, we show that the efficacy of policy interventions depends crucially on the government's ability to target its assistance to low-profitability firms that would otherwise have likely exited or reduced employment solely because of the Covid-19 shock. We, furthermore, discuss the role of firms' beliefs in shaping the aggregate response to the Covid-19 shock. To that end, we run a counterfactual exercise in which we introduce dispersion in firms' beliefs about the evolution of the aggregate shock while keeping the average belief in the economy to its baseline value. We find that our model is highly non-linear in firm's expectations and that having a positive mass of pessimistic firms, who think the shock is very persistent, implies a more severe drop in employment and output.

The remainder of the paper is structured as follows. Next, we discuss the related literature and

[4]Importantly, for Italy this is a combination of the short-term work scheme and a no-firing restriction.

how we contribute to the debate on the effect of Covid-19 on firm dynamics. Section 2 introduces the data used for the structural estimation of our model. Section 3 and 4 outline the baseline model and the estimation procedure, respectively. Section 5 discusses cross-country differences in responsiveness. Section 6 is devoted to the study of the Covid-19 shock and the related policies. Together, the counterfactuals presented in Sections 6 and 7 enable us to evaluate the impact of the interventions as well as the importance of both the targeting of subsidies and firms' beliefs. Section 8 concludes.

Related Literature

Our paper relates to two strands of the literature. First, we contribute to the literature studying how firm responsiveness matters for macroeconomic outcomes. Decker, Haltiwanger, Jarmin, and Miranda (2020) show that the secular decline in firm responsiveness is one of the leading reasons behind the recent decline in business dynamism in the US. In this paper, we take a different perspective and document that cross-country heterogeneity in how firms respond to changes in profitability is crucial to understand how economies react to aggregate shocks. We also address the role that recessions have on factor reallocation. Foster, Grim, and Haltiwanger (2016), for instance, document that factor reallocation during the Great recession in the US was less productivity enhancing than in previous episodes. Bartelsman, Lopez-Garcia, and Presidente (2019) find similar results for Europe. Here we use the Covid-19 induced recession as a laboratory to study how cross-country differences in firm responsiveness and policy support across European countries matter for the effect of large shocks on aggregate productivity and factor reallocation.

Second, we contribute to the rapidly expanding literature that studies the effect of the Covid-19 shock and rescue policies on firms. Buera, Fattal-Jaef, Hopenhayn, Neumeyer, and Shin (2021) study the effect of the Covid-19 shock and support policies in a model with labor market frictions and heterogeneous firms facing financial constraints. They find that the persistent negative effects of the shock on aggregate employment and output can be contained by more flexible labor market policies, such as recall unemployment, or government support in the form of employment subsidies. Di Nola, Kaas, and Wang (2023) use a similar framework but focus on small businesses and the role of government grants to small businesses. The papers closest to ours, with a European focus, are: Albert, Caggese, and González (2020), Kozeniauskas, Moreira, and Santos (2022) and Harasztosi, Maurin, Pál, Revoltella, and Van Der Wielen (2022). The first use Spanish survey data and find that the large productivity decline following the Covid-19 pandemic will have a negative impact on firm entry decisions, in turn impacting the pace of job creation. Kozeniauskas, Moreira, and Santos (2022) combine survey and administrative firm-level data for Portugal to provide evidence for the offsetting effect of government policy support on productivity gains through reallocation in the Covid-19 recession. Finally, using balance sheet and extensive survey data of European firms, Harasztosi, Maurin, Pál, Revoltella, and Van Der Wielen (2022) study the distribution of policy support across firms and its effectiveness in supporting firm-level investment during the Covid-19 crisis. Contrary to Kozeniauskas, Moreira, and Santos (2022) their findings do not support the view that unconditional policy support to firms during a recession harms future growth prospects.

We contribute to this literature by focusing on the role of firm responsiveness to unanticipated changes in profitability. We compare the effectiveness of different policy measures across countries and provide counterfactuals in terms of employment and aggregate productivity had the government adopted different policies.

2 Data Facts

In this section we introduce the data used to estimate revenue-based total factor productivity (TFPR) and firm's responsiveness to these idiosyncratic profitability shocks. These moments are of direct interest and are used for the subsequent estimation of the structural model.

We use firm-level balance sheet and income statement data from Bureau van Dijk's (BvD) ORBIS database. The ORBIS database covers both private and publicly listed firms and is collected by BvD from a variety of sources, including national business registries. The complete ORBIS database covers more than 200 countries and over 200 million privately and publicly held corporations across all economics sectors. The panel dimension as well as the representativeness of ORBIS data varies from country to country according to which companies are required to file reports with business registries.[5]

For our analysis, we focus on firms in the manufacturing sector (NACE Rev. 2) in four core-European countries: France, Germany, Italy and Spain. We use a sample from 2014-2018 for two main reasons. First, the sample excludes the financial crisis and second, coverage for most recent years is still low due to reporting lags. We closely follow the procedures in Kalemli-Özcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas (2015) to obtain nationally representative samples of firms in each country.

The ORBIS firm-level data has several advantages that make it suitable for our analysis. First, it provides balance sheet and income statement information for both private and public firms of all sizes, allowing us to study the effects of the Covid-19 shock and policies on large as well as small- and medium-sized enterprises which were likely more severely affected. And second, the balance sheet information is harmonized across countries allowing for comparisons across countries. The disadvantage of the ORBIS data is that the balance sheet and income statement data is recorded only at an annual frequency. Moreover, the ORBIS panel is unbalanced but does not allow for a reliable identification of firm exit. The fact that firm exit from the ORBIS panel is unpredictable, i.e. unrelated to firm fundamentals, has two implications for our analysis. First, we do not attempt to estimate the exit decision from these data. Rather, we take employment-weighted exit rates from Eurostat as explained below. Second, since exit is effectively random, we can rely on an unbalanced

[5] For extensive discussions on the coverage and representativeness of the ORBIS dataset, see, e.g., Kalemli-Özcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas (2015), Bajgar, Berlingieri, Calligaris, Criscuolo, and Timmis (2020) or Gal (2013).

panel of firms in our estimation, obtaining the same estimates as on a balanced panel.

2.1 Summary Moments

Table 1 summarizes our data for the four countries and presents some basic data moments, a subset of which are used for the estimation. Median firm size, denoted μ_e, ranges from 6 in Spain to 35 workers in Germany.

The next 5 columns provide information on the employment growth distribution. Job growth, size-weighted, in the interval of $[-2.5\%, +2.5\%]$ is termed inaction. The measure JC+5 (JD+5) reports the size-weighted fraction of observations with job creation (destruction) rates over 5%. While JC+10 (JD+10) is the size-weighted fraction of observations with job creation (destruction) rates above 10%.

With regards to the employment growth distribution, between 27.7% and 35.0% of observations entail very small employment growth. These episodes of inaction are complemented with substantial evidence of job creation and destruction in excess of 10%, reaching nearly 23.7% in Spain. This mixture of inaction and large adjustment is often a consequence of non-convex adjustment costs.

Table 1: Data Moments

		Job Growth					Revenue Function			Responsiveness Regressions				Size-weighted
	μ_e	inaction	JC10+	JD10+	JC+5	JD+5	$\tilde{\alpha}$	$\tilde{\rho}$	$\tilde{\sigma}$	β_1^{int}	β_2^{int}	β_1^{ext}	β_2^{ext}	Exit Rate
France	17	0.329	0.132	0.047	0.255	0.125	1.040	0.920	0.301	0.343	0.255	-0.005	0.191	0.698
Germany	35	0.331	0.081	0.032	0.232	0.069	1.012	0.926	0.299	0.168	0.053	0.021	0.190	0.210
Italy	9	0.350	0.175	0.084	0.293	0.154	1.042	0.870	0.365	0.242	0.022	0.002	0.109	0.882
Spain	6	0.277	0.237	0.071	0.416	0.132	1.091	0.885	0.352	0.300	0.054	0.019	0.174	1.442

Notes — All moments are calculated from ORBIS data using an unbalanced panel of firms between 2014-2018. The exit rate is employment weighted and refers to the average of the "Employment share of enterprise deaths" from Eurostat's Business Dynamism Statistics (BDS) over the period 2014-2018. The exit rate is reported as a percentage. The estimation of the parameters pertaining to the revenue function is described in section 2.2.

The other moments come from revenue function and responsiveness regressions. These are explained in turn.

2.2 Revenue Function Estimation

To derive the key data moments measuring firms' responsiveness, we need to obtain a measure of firms' profitability innovations. We proceed in two steps. First, we estimate firms' revenue functions via ordinary least squares (OLS) and extract the firm's profitability shock as the residual from that regression. Following a large literature, we then assume that the profitability shock evolves as an AR(1) process. All estimations are performed separately for each country on the 1-digit NACE 2 Rev. manufacturing level. We purge the profitability shocks from aggregate components by including time dummies in the revenue function regression. This also removes mean effects from aggregate productivity. The estimating equation for the revenue function is given by

$$r_{i,t} = \alpha e_{i,t} + \sum_{t=2014}^{2018} \zeta_t \mathbb{D}_t + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the log of revenue and $\mathbb{D}_t$ is a time dummy. The profitability shock is given by the residual from (1) and follows an AR(1) process as in (2)

$$\varepsilon_{i,t} = \rho \varepsilon_{i,t-1} + \eta_{i,t}, \quad \eta_{i,t} \sim \mathcal{N}(0, \sigma_\eta^2). \tag{2}$$

It is worthwhile to emphasize that the revenue function is estimated using OLS and is, thus, subject to omitted variable bias. We, therefore, do not give a direct structural interpretation to the curvature of the revenue function α, estimated from equation (1), or to the persistence and standard deviation, (ρ, σ_η), inferred from the residual in (2). Instead, we rely on an indirect inference approach and use these estimated parameters as moments to match in a simulated method of moments estimation from which we then obtain the corresponding structural parameters.

Note, furthermore, that firm revenue depends only on labor as other inputs, particularly capital, are optimally chosen given profitability and the labor input. The emphasis here is on dynamic labor demand given the focus of policy interventions on labor market outcomes.[6]

The estimates from the revenue function estimation exercise for the four countries are shown in the block "Revenue Function" in Table 1. The OLS estimates of the curvature, $\tilde{\alpha}$, exceed one and range from 1.01 in Germany to a little over 1.09 in Spain. The estimated serial correlation of the profitability shocks, $\tilde{\rho}$, is around 0.90 in all countries and the standard deviation of the innovation, $\tilde{\sigma}$, is around 0.30.

2.3 Responsiveness Regressions

Another key input to our analysis are the coefficient estimates from the responsiveness regressions. We study responsiveness at both the extensive and intensive margins of employment adjustment.

Specifically, let $\mathbb{I}_{adj} = 0$ iff $g_{i,t}^{emp} \in [-2.5\%, +2.5\%]$. In this case, firm employment growth, $g_{i,t}^{emp}$ is sufficiently close to zero that we term this inaction.[7] To understand the determinants of inaction, consider:

$$\mathbb{I}_{it}^{adj} = \beta_0 + \beta_1^{ext} \eta_{i,t-1} + \beta_2^{ext} \eta_{i,t-1}^2 + \gamma^{ext} e_{i,t-1} + \nu_{i,t} \tag{3}$$

where $\mathbb{I}_{it}^{adj} = 1$ indicates employment adjustment by firm i in period t, $e_{i,t-1}$ is the log of lagged employment, and $\eta_{i,t-1}$ is the lagged profitability innovation, as described above. These coefficients indicate the responsiveness of the likelihood of employment adjustment to the current level of profitability and lagged employment. The quadratic term is important here since adjustment is

[6]As in the body of Decker, Haltiwanger, Jarmin, and Miranda (2020), the estimation looks at the response of employment to shocks. They have some evidence on investment responsiveness in their Appendix.

[7]The firm-level employment growth rate is measured as $g_{i,t}^{emp} = \frac{e_{i,t} - e_{i,t-1}}{.5*(e_{i,t} + e_{i,t-1})}$.

more likely for either extremely large or small shocks, i.e. the adjustment rate in theory is increasing in the absolute size of the deviation of the shock from its mean, all else the same.

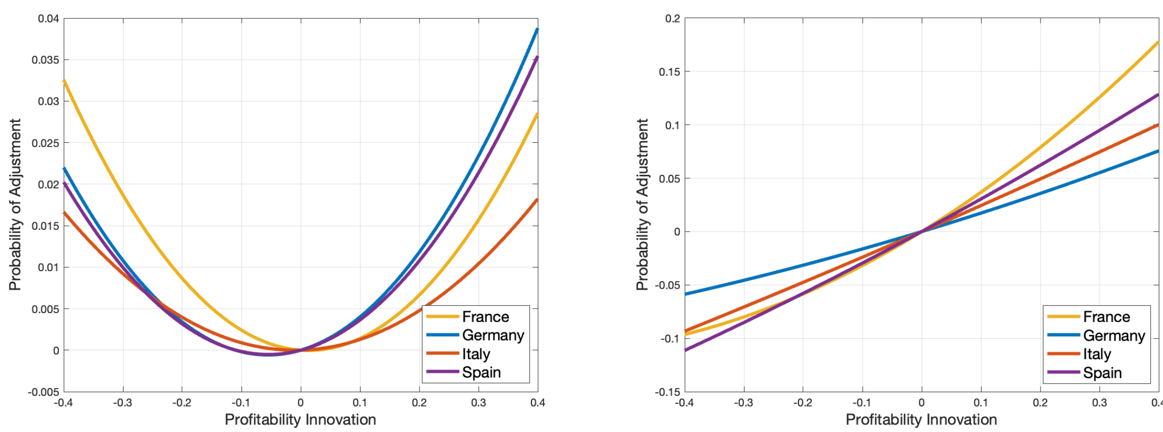
If there is employment adjustment, i.e. $\mathbb{I}_{it}^{adj} = 1$, then consider

$$g_{i,t}^{emp} = \beta_0 + \beta_1^{int}\eta_{i,t-1} + \beta_2^{int}\eta_{i,t-1}^2 + \gamma^{int}e_{i,t-1} + \zeta_{i,t}. \tag{4}$$

Here job growth depends on the innovation to lagged profitability as well as lagged employment. The response of current employment growth to the lagged profitability innovation is consistent with the timing of our model.

These estimates are shown for the four countries in the "Responsiveness Regression" block of Table 1. On the intensive margin, job growth is increasing in profitability at an increasing rate.

To illustrate these responsiveness regressions, Figure 1 shows (3) and (4) using the estimated parameters on the extensive and intensive margins for the four countries.[8] For extreme versions of the shock adjustment is more likely. For Italy this extensive margin response is muted compared to, say, Germany. Given adjustment, employment growth is increasing and slightly convex in the shock. The curvature is more pronounced in France given the large coefficient estimate on the quadratic term in (4).[9]



(a) Adjustment Probability (b) Employment Growth

Figure 1: Responsiveness: Extensive and Intensive Margins

Notes — The figure shows the responsiveness regression results for the probability of labor adjustment and employment growth from (3) and (4).

2.4 Exit

The estimated model also matches employment-weighted exit rates. These are taken from Eurostat. The exit rates are shown in the last column of Table 1 as well and range from 0.2% in Germany to

[8]The mean effects are removed to highlight the dependence on the profitability shock.

[9]Still, the predicted employment growth is not that much larger in France even for the large innovations.

1.4% in Spain. Job loss due to exit, on average, is relatively small in these countries.

3 Model

The analysis is built around a partial equilibrium model of dynamic labor demand at the firm level. The model specifies labor adjustment costs beyond those stemming from search and matching frictions such that firing is costly. The focus on labor facilitates a discussion of direct labor market interventions in our analysis of the Covid-19 period. In this framework, capital is freely flexible to enhance tractability.

The dynamic optimization problem contains two components. The first is the choice to continue operation or exit, given by:

$$V(A,e) = max(V^c(A,e), 0) \quad \forall (A,e) \tag{5}$$

where A is the current profitability (defined below) of the firm and e the stock of workers from the previous period. Here a firm that exits avoids all liabilities to existing workers.[10]

3.1 Continuers

The value of continuation is

$$V^c(A,e) = \max_{e'} R(A,e) - \omega e - C(e',e) - \Gamma + \beta E_{A'|A} V(A',e') \qquad \forall (A,e) \tag{6}$$

In this expression, $R(A,e)$ is the flow of revenue to the firm when its idiosyncratic profitability is A and it has e workers.[11] The revenue function, of course, combines the output of the firm with its price, which may also depend on the output of the firm. It is not possible to decompose revenue into these components since we measure revenue not output in the data. Accordingly, A incorporates both a demand and a technology shock, hence it is termed a profitability shock. Other flexible factors of production are assumed to be chosen optimally given the state and those choices are embedded in the revenue function: $R(A,e) = Ae^{\alpha}$.[12]

The function $C(e',e)$ represents the costs of adjusting the stock of workers. It is central to the discussion of responsiveness in general and the impact of Covid-19 in particular. The empirical analysis contains a rich specification of this cost function, allowing us to match inaction in employment adjustment as well as firm responsiveness to variations in profitability.

[10] It would be of interest to include changes in the liabilities of existing firms. But we are unaware of such policies.

[11] Aggregate shocks are introduced below. Capital is assumed to be flexible, allowing us to focus on labor dynamics and the associated policy interventions. There are no conceptual challenges in treating capital as a quasi-fixed factor of production. The difficulty is the estimation and simulation of the models with a large number of state variables. An interesting and open issue is understanding the interaction of dynamic factor demand with inferred markups and responsiveness moments.

[12] This follows the Cooper and Haltiwanger (2006) derivation of a revenue function.

The adjustment cost function, $C(e', e)$, is given by

$$\begin{aligned} C\left(e', e\right) &= \frac{\nu}{2}\left(\frac{e'-e}{e}\right)^2 e + [\gamma_p\left(e'-e\right) + F_p] I(e'-e > 0) \\ &- [\gamma_m\left(e'-e\right) - F_m] I(e'-e < 0) \end{aligned} \tag{7}$$

for $e' \neq e$. There are no adjustment costs when there is no net change in the number of workers.

Notice the timing of the model. The labor input is predetermined from past decisions so that there is a one period time to build in the model. This reflects rigidities in the labor markets of the countries we study.[13]

For this optimization problem, the firm takes the wage ω as given. In the estimation, the wage helps pin down the median size of plants. It also impacts the entry and exit margin.

The labor adjustment cost function includes multiple costs. One is the traditional quadratic adjustment cost, parameterized by ν. The next two are linear adjustment costs. Here γ_p is a linear hiring cost and γ_m is a linear firing cost. These may be thought of as recruiting and severance costs respectively. Finally, there are fixed adjustment costs, (F_p, F_m) which also depend on whether the plant is hiring or firing. In the estimation, we will distinguish the two cases of piece-wise linear and fixed costs.

The outcome of the firm optimization are two functions: $Z_\Theta(A, e) \in \{0, 1\}$ and $e' = \phi_\Theta(A, e)$ where Θ is a vector of parameters. Here $Z_\Theta(\cdot)$ is the exit decision where $Z_\Theta(A, e) = 1$ means exit and $Z_\Theta(A, e) = 0$ denotes the continuation of the firm. In the event of continuation, $e' = \phi_\Theta(A, e)$ represents the state contingent choice over employees.

The policy function that result from this optimization problem fit neatly into our analysis of responsiveness. On the extensive margin, $Z_\Theta(A, e) \in \{0, 1\}$ summarizes the state contingent choice. This choice is represented by the regression (4). As we shall see, the estimated model predicts a U-shaped adjustment hazard.

The empirical counterpart to the intensive choice of employment adjustment given $Z_\Theta(A, e) = 1$ is given by (3). Again this is a nonlinear approximation of the decision rule.

Note that these policy functions depend on the underlying structural processes and parameters of the revenue, compensation and adjustment cost functions as well as the discount factor. All of these influences are captured by the vector of parameters, denoted Θ. The fact that these policy functions are indexed by Θ indicates that these choices depend on this vector of parameters. Our goal is to estimate Θ through a simulated methods of moments approach for different sample periods to determine which elements of this vector are responsible for differential responses across countries to the Covid-19 shock.

[13] We considered a version of the model with no time to build but this baseline specification fits the moments better. The time-to-build structure adds an additional friction beyond the estimated adjustment costs. It is consistent with the inclusion of the lagged profitability innovation in the responsiveness regressions.

3.1.1 Entrants

The model includes entry. Entry occurs with a one period lag. Potential entrants receive a signal about their prospective profitability in the following period. The signal follows the same stochastic process as the idiosyncratic productivity. A potential entrant with a signal s enters if (and only if)

$$E_{A|s}V(A, \underline{e}) \geq 0 \tag{8}$$

where $\underline{e}$ is the lowest level of employment. Hence, given a signal s about its future profitability, a firm enters if its expected value of operating is weakly positive. After entry, the new firm behaves exactly as incumbent firms and incurs costs to adjust employment.

3.2 Stationary Equilibrium

In the absence of aggregate shocks, there is a steady state distribution of firms over (A, e). In a steady state equilibrium, firms are choosing to continue or not as per (5) and those who continue, make employment choices according to (6). For every firm that exits there is a new potential entrant endowed with a given signal s. However, only firms with a signal above some threshold level, denoted s^*, such that their expected value of entering is positive, will enter.

4 Estimation

The first step in the quantitative exercise is to estimate the parameters of the firm-level optimization problem. As discussed, the estimation is conducted for each individual country separately. This section describes our estimation approach and results. The quantitative analysis in the next sections build upon these estimates.

The estimation procedure is based on a steady state equilibrium of the model economy. Thus, there are no aggregate shocks in the model or in the moments matched. When solving and estimating the model we restrict parameter values such that a stationary distribution of firms over (A, e) exists. Once we found the stationary distribution of the model we simulate the economy for five years and select a balanced panel of surviving firms. Using this subset of firms we compute the desired moments. The only exception is the weighted exit rate, which is computed from the steady state equilibrium.[14]

4.1 Approach

The estimation relies on a simulated method of moments approach. The model parameters, collected in vector Θ, are selected so as to minimize the distance between model and data moments

[14] As discussed above, since exit from the Orbis panel is random, i.e. not forecastable with firm fundamentals, matching the moment from the simulated data of the balanced simulated panel with the data moments from an unbalanced panel seems appropriate. Put differently, if we randomly selected firms to exit from the simulated panel, the moments would not change.

according to:

$$£ \equiv min_{\Theta}((M^d - M^s(\Theta))/M^d)W((M^d - M^s(\Theta))/M^d)'. \tag{9}$$

Here, the dependence of the simulated moments on the parameter vector is given by $M^s(\Theta)$. The dependence of the simulated moments on Θ is the key to identification. The data moments are given by M^d. W is a conforming identity matrix.

4.1.1 Moments

The moments are given by vector $M^s(\Theta) \equiv (\tilde{\alpha}, \tilde{\rho}, \tilde{\sigma}_\eta, \beta_1^{int}, \beta_2^{int}, \beta_1^{ext}, \xi)$. They are chosen with two criteria in mind. First, they should be responsive to variations in the parameters, as identified through model simulation. Second, all else the same, they ought to be salient for the economic analysis, such as the parameters characterizing the responsiveness regressions. The selected moments are a subset of those presented in Table 1 with the addition of a size-weighted exit rate, ξ.[15] These moments are calculated in the actual and simulated data in exactly the same way.

As discussed above, note that $M^s(\Theta)$ includes estimates of coefficients from the OLS revenue function regressions. These are treated as moments to match, partly to help identify the underlying structural parameters of the revenue function curvature and the stochastic process for the profitability shocks.

Table 2: Moments

		Revenue Function			Responsiveness			Exit	£
		$\tilde{\alpha}$	$\tilde{\rho}$	$\tilde{\sigma}_\eta$	β_1^{int}	β_2^{int}	β_1^{ext}	ξ	
France	Data	1.040	0.920	0.301	0.343	0.255	-0.005	0.698	
	Model	0.896	0.895	0.173	0.222	0.032	-0.005	0.476	1.189
Germany	Data	1.012	0.926	0.299	0.168	0.053	0.021	0.210	
	Model	0.808	0.928	0.144	0.209	0.047	0.019	0.386	1.089
Italy	Data	1.042	0.870	0.365	0.242	0.022	0.002	0.882	
	Model	0.815	0.902	0.182	0.258	0.022	0.002	0.563	0.437
Spain	Data	1.091	0.885	0.352	0.300	0.054	0.019	1.442	
	Model	0.828	0.880	0.149	0.302	0.056	0.019	0.875	0.546

Notes — The moments here are: $\tilde{\alpha}$ = curvature of revenue function estimated via OLS, $\tilde{\rho}$ = persistence of idiosyncratic profitability shock obtained from the OLS revenue function estimation and assuming that idiosyncratic profitability shocks evolve according to an AR(1), $\tilde{\sigma}_\eta$ = standard deviation of profitability innovations η, $(\beta_1^{int}, \beta_2^{int}, \beta_1^{ext})$ = responsiveness regression coefficients, ξ = employment-weighted exit rate. "£" refers to the minimized distance between data and simulated moments achieved in the estimation.

[15] The subset was chosen so that the model parameters were just identified. The lagged employment in the responsiveness regression might have been informative about the adjustment cost parameters. But, from Table 5, the moments used in the estimation are very responsive to those paramters.

4.1.2 Parameters

There are three parameters that directly relate to the revenue function. First, there is the curvature of the revenue, α. Aside from the structural curvature, there are the two parameters that characterize the stochastic process for the profitability shock, (ρ, σ_η). To be clear, these three structural parameters are certainly informed by the moments $(\tilde{\alpha}, \tilde{\rho}, \tilde{\sigma}_\eta)$ but, due to omitted variable bias, are not the same. Further, movements in the structural parameters, (ρ, σ_η), will impact the responsiveness moments as well.[16]

The other parameters determine the adjustment costs. The analysis focuses on the case of a quadratic adjustment cost, ν, along with fixed costs of hiring and firing, (F_p, F_m) respectively. This choice of this specification reflects extensive experimentation with other models of adjustment costs. The fixed cost case fit the moments best. Thus, in (7), γ_p and γ_m are both set to zero. A final parameter, related to the exit moment, is the overhead cost of operation, Γ. There are seven moments and seven parameters so that the model is just identified, consistent with using the identify matrix to weight the moments.

4.2 Estimation Results

The moments, both data and simulated, as well as parameter estimates are shown in Tables 2 and 3, respectively. Overall the model does a fairly good job at matching moments. The fit is closest in Italy and relatively worse for France.[17]

Looking at the responsiveness moments, the estimated models match the signs and relative magnitudes from the data on the intensive margin, with the exception of France. The curvature in the French response is well below that in the data, and in line with other countries. In particular, the response of employment growth to profitability is increasing and convex so that profitability and employment are positively correlated in both the actual and simulated data. On the extensive margin of adjustment, for all countries except France, the probability of adjustment is increasing in the profitability shock.[18] This response is very closely matched in the estimation.

The estimated models generates the OLS estimates of the curvature of the revenue function quite well below that of the data.[19] The serial correlation is high in both the actual and simulated data. The model does not generate as much variability in profitability, as measured by the residual from the OLS regression.

[16] As pointed out to us by a referee, while the exit from Orbis may be unpredictable, that is not the case in the simulated data where exit decisions are impacted by fundamentals. Appendix sub-section A.3 describes an alternative estimation exercise with exogenous and endogenous exit and argues that our results are not sensitive to this form of selection bias.

[17] For France the estimate of β_2^{int} is much larger than other coefficients from the responsiveness regressions, and is tightly estimated. We are unable to match that moment. But, from Figure 1b, the intensive response of France is not that much different from the other countries.

[18] Though not matched, from Table 1 one can see that the quadratic term is positive in all countries so that, in principle, the shape shown in Figure 1a holds in the estimated model for large enough shocks.

[19] As discussed later, this reflects the identify weighting matrix.

As for the parameters reported in Table 3, first note that while there are differences across countries, these variations appear to be relatively minor.[20]

The estimated curvature of the revenue function is between 0.50 and 0.55. In a CRS production function with a labor share of 0.65, a curvature of 0.51 is a markup of about 60%. This is a large markup and we return to this point later in an exploration of the effects of different parameterizations for the counterfactuals. The profitability shocks are highly serially correlated. This is important for the responsiveness of employment to current shocks, given the one period time to build assumption of the model. The estimated standard deviations are about the same magnitude as those reported in Cooper and Haltiwanger (2006) for US plants.[21]

The adjustment costs feature a relatively large quadratic adjustment cost as well as fixed costs of hiring and firing workers. Interestingly, the hiring costs are an order of magnitude larger than the firing costs in all countries. Overall, there are no stark differences in adjustment costs across countries. This accords with the OECD assessments of dismissal costs where, despite differences across countries in specific components of firing costs, overall the four countries we study were rated very closely to one another.[22] However, as we shall see, there are substantial differences in outcomes, both in terms of realized adjustment costs and in responses to the Covid-19 shock.

Table 3: Parameters

Country	Parameters						
	ν	F_p	F_m	α	ρ	σ	Γ
France	4.794	0.122	0.019	0.518	0.959	0.594	0.238
	(0.175)	(0.004)	(0.002)	(0.003)	(0.005)	(0.020)	(0.013)”
Germany	5.250	0.220	0.019	0.519	0.961	0.506	0.216
	(0.206)	(0.005)	(0.002)	(0.024)	(0.002)	(0.009)	(0.010)
Italy	5.008	0.300	0.028	0.500	0.950	0.570	0.260
	(0.170)	(0.003)	(0.000)	(0.005)	(0.002)	(0.010)	(0.003)
Spain	4.391	0.159	0.024	0.542	0.965	0.559	0.335
	(0.105)	(0.004)	(0.000)	(0.011)	(0.001)	(0.008)	(0.002)

Notes — The parameters here are: ν = quadratic adjustment cost, (F_p, F_m) = fixed hiring and firing costs, (α, ρ, σ) = curvature of revenue functions, serial correlation of profitability shocks and the standard deviation of the innovation to profitability shocks. Γ denotes the fixed operating costs.

To put the estimated adjustment cost parameters into perspective, Table 4 reports the fixed hiring (firing) costs paid as fractions of the average revenues of firms that actually hire (fire).[23] Studying the adjustment costs incurred brings together the estimated adjustment cost parameters and the decision rules that regulate choices on both the extensive and intensive margins. In all countries, the firing costs paid as a fraction of revenue are substantially higher than the hiring

[20] This is not the consequence of starting the estimation at the same initial guess of parameters and looking locally.
[21] We are unaware of comparable estimates for these European countries.
[22] This comes from Table 3.3 of the 2020 OECD Employment Outlook, https://doi.org/10.1787/19991266.
[23] For comparison, Cooper, Haltiwanger, and Willis (2015) estimate a single fixed cost parameter, with no quadratic adjustment costs, at about 9% of average profit, not revenue, for US plants.

costs. This is in contrast to the estimated values and is indicative for firing occurring in states of low realized revenue. From this table, differences in realized adjustment costs are made clear, with the costs in Italy and Germany exceeding those in the other two countries.

Table 4: Fixed Adjustment Costs Incurred Relative to Revenue

Country	Fixed costs	
	Fixed hiring costs (F_m)	Fixed firing costs (F_p)
France	0.823%	5.248%
Germany	1.090%	12.360%
Italy	1.481%	15.982%
Spain	1.076%	7.166%

Notes — This table reports fixed costs (computed as F_m and F_p times average revenues) as fraction of average revenues of firms that actually hire or fire.

4.3 Identification and Robustness

There are a number of issues related to the parameterization of the model. The first is identification, seen by the sensitivity of moments to parameters and in the standard errors. The second has to do with the robustness of our findings, particularly the use of an identify matrix.

4.3.1 Response of Moments to Parameters

The mapping from parameters to moments is complex. Table 5 presents elasticities of the moments with respect to parameters, based on the parameter estimates for Germany.

These elasticities make clear which moments are central to the identification of a particular parameter. Looking, for example, at the quadratic cost of adjustment, we see that small variations have a relatively large impact on the responsiveness moments, with a much smaller effect on the estimated OLS curvature of the revenue function. Further, for the fixed cost of hiring, note too that the responsiveness moments are sensitive to this parameter. All of the moments seem very sensitive to ρ. Interestingly, variations in σ impact the OLS estimate of the innovation's standard deviation as well as two of the responsiveness coefficients.

From the perspective of the moments, the OLS estimate, $\tilde{\alpha}$, is largely determined by the structural curvature, α and the serial correlation of the profitability shock, ρ. The latter is relevant as it impacts the omitted variable bias through its effects on the correlation between period-t profitability and employment. Interestingly, increases in both of these parameters reduce the OLS estimate, $\tilde{\alpha}$. Thus the estimated model could increase these enough to match this moment. But that would be costly in terms of matching other moments, such as the responsiveness coefficients, which are very sensitive to these parameters as well.

Table 5: Elasticities of Moments with respect to Parameters

Parameter	Moments						
	$\tilde{\alpha}$	$\tilde{\rho}$	$\tilde{\sigma}_\eta$	β^{int}	β_2^{int}	β^{ext}	ξ
ν	0.376	-0.049	0.089	0.212	-39.575	-4.743	-0.332
F_m	0.428	-0.068	0.093	-1.133	-58.219	-15.492	-2.235
F_p	-0.086	0.013	-0.002	-0.261	-9.696	-2.618	0.215
α	-0.975	-0.229	-0.084	-4.679	-149.770	178.833	14.118
ρ	0.162	0.770	-11.705	5.769	-20.104	-161.353	0.900
σ	-0.999	-0.148	1.089	-4.834	-108.175	157.516	14.702
Γ	-1.494	-0.138	-0.116	-4.918	-124.912	201.343	15.030

Notes — This table computes the elasticities of moments to changes in parameters for Germany. The elasticity is computed as the percentage change in the moment over the percentage change in the parameter value. Elasticities are computed by changing one parameter at a time, holding the other fixed at the optimal solution. We here consider changes of 1% in the parameter values.

4.3.2 Standard Errors

Table 3 reports standard errors of the estimated parameters. Specifically, we created 1000 data sets with 10000 firms and 5 periods. The datasets differed because the shocks across firms and time are independently drawn for each of them. For each, we calculated the moments and then computed the variance covariance matrix of the moments across these simulated data sets. This matrix, along with the derivatives of the moments with respect to parameters, are inputs into the standard errors.[24]

4.3.3 Alternative Parameterizations

We consider two alternative parameterizations of the model.[25] One comes from re-estimation using a weighting matrix and the other through a calibration. For both, we present estimates and then trace the importance of these alternative parameterizations for the counterfactuals.

Weighting Matrix Appendix sub-section A.1 presents estimates using a weighting matrix. The weighting matrix was obtained through an iterative simulation process.[26]

Given the weights on the moments, the parameter estimates differ from the baseline. As seen from comparing Tables 3 and A.1, one difference is in the nature of adjustment costs. For all countries, the estimated quadratic adjustment cost is lower and the fixed costs considerably higher for all of the countries. For France, the estimated curvature of the revenue function is higher in the

[24]See Adda and Cooper (2003) for further discussion.

[25]This section was motivated by the suggestions of a referee.

[26]Starting from the baseline estimates, we simulated 1000 data sets with 10000 firms and 5 periods, as in the calculation of the standard errors. From these data sets, we calculated a variance covariance matrix of the moments. This was inverted and used as a weighting matrix for the next iteration. This process continued for 4 iterations when the difference in parameter vectors was near zero.

estimated model with a weighting matrix. It is lower in all other countries.

In terms of the moments, the model now fits the data generated OLS estimates of the curvature of the revenue function and the standard deviation of the inferred innovation much more closely. The responsiveness moments are also more closely fit, particularly those in France. The fit is considerably worse for the exit moment.[27]

Curvature of the Revenue Function Despite its centrality in numerous quantitative exercises, convincingly estimating the curvature of revenue (production) functions remains elusive. The issue is dealing with omitted variable bias. Our approach through SMM is to include that bias in both the estimates from the actual and simulated data. The resulting estimates of the curvature map into fairly large markups.

As an alternative, we can calibrate the curvature of the revenue function to match estimates of markups in Europe. To do so, we need both a markup and an estimate of the labor share. We obtain the average markup of manufacturing firms for all four countries from the 9^{th} vintage of the CompNet database's productivity module. Markups are calculated from a production function estimation procedure for a Cobb-Douglas production function.[28] We collect the labor share in the manufacturing sector in 2018 from EU Klems. Table 6 reports the respective values.

Table 6: Markups and Labor Shares

	Markup	Labor share
Germany	1.248	0.661
France	1.613	0.659
Italy	1.132	0.643
Spain	1.169	0.570

Notes — Markups are obtained from 9^{th} vintage of the CompNet database's productivity module. The labor share comes from EU Klems.

The estimates using the calibrated values for α are shown in Appendix sub-section A.2. Compared to the baseline estimates, the calibrated values of α are higher for all of the countries except France where the value matches the baseline estimation. All else the same, the higher values of α increase the responsiveness of employment to the profitability shock. Except for the fixed operating cost, the parameters from this experiment and the baseline are very similar. The fixed operating costs are estimated to be much lower to match the exit rate since the higher value of α reduced the profit of being an active firm.

[27]Looking at the weighting matrix for Germany, for example, the weight is lowest on the exit moment. Accordingly, the estimation does poorly in matching this moment.

[28]See https://www.comp-net.org/data/9th-vintage/ for details.

5 Responsiveness Across Countries

The estimates provide insights into observed differences in moments across countries. The point is to understand which of the parameters of one country differentiate it from another in terms of the responsiveness to shocks. Though the parameter estimates seem close, there do appear to be important differences in adjustment costs.

To shed light on this question, we select two of the four countries, Germany and Italy, for comparison. These countries will also be highlighted in the discussion of the impact of the Covid-19 and related policies so that differences in parameter estimates between them is a useful starting point for the discussion to follow. Taking these two countries, we systematically replace the estimated parameters for Germany with those of Italy. We do so by groups of parameters pertaining to different elements of the firm's optimization problem while keeping the parameters of the respective other groups at their estimated values: (i) adjustment costs, (ii) curvature of the revenue function, and (iii) the stochastic process of idiosyncratic profitability.[29]

The results are shown in Table 7. The curvature column reports simulated moments where the estimated curvature parameter from Germany, 0.519, is replaced by the curvature estimate for Italy, 0.500. Though these parameters seem close, the substitution leads to a reduction in the fit by a factor of nearly 6. Performing the same exercise for the parameters related to the adjustment costs and stochastic process for firm-level profitability, however, we see stark differences between the two countries, reflected in the strong deterioration of the model fit for Germany under the Italian parameters. With the Italian adjustment costs, the intensive margin responsiveness changes from a convex function, as in the data, to a concave one. Furthermore, the extensive choice of whether to adjust employment becomes much more sensitive to current profitability. This seems to reflect the lower quadratic and hiring cost in Italy. Estimated shocks in Italy are slightly more persistent and more volatile. Mixing this process with the German parameters, also leads to a sizeable deterioration in model fit. The differences are similar to those in the adjustment cost experiment: a concave job growth relationship and an increased responsiveness at the extensive margin.

Table 7: Replacement of German with Italian Parameters

	Baseline (Germany)	Curvature (α)	Adj. costs (ν, F_m, F_p)	Stoch. process (ρ, σ)
Responsiveness coefficient adjusters (β^{int})	0.209	0.202	0.213	0.183
Responsiveness coefficient adjusters (β_2^{int})	0.047	0.041	-0.046	-0.005
Responsiveness coefficient extensive margin (β^{ext})	0.019	-0.028	0.076	0.014
Size-weighted exit rate (ξ)	0.386	0.276	0.457	0.398
Curvature revenue function ($\tilde{\alpha}$)	0.808	0.861	0.765	0.863
Autoregressive coefficient ($\tilde{\rho}$)	0.928	0.930	0.930	0.912
Standard deviation innovation ($\tilde{\sigma}$)	0.144	0.145	0.144	0.182
Stat. Value	1.089	5.942	12.068	2.277

Notes — This table shows the moments from replacing German with Italian parameters with each change studied independently, not cumulatively.

[29] See Cooper, Haltiwanger, and Willis (2021) for a similar exercise across decades of the US.

A parallel exercise replacing the parameters of Germany with those of France and Spain are reported in Appendix section B. For Spain, as with Italy, the biggest difference in parameters comes from the replacement of German adjustment costs with those estimated for Spain. Compared to France adjustment costs are less important. Instead, replacing German with the stochastic process estimated for France implies a larger deterioration in the fit. The big changes appear in the extensive margins of employment adjustment and exit.

These exercises help to understand differences in responsiveness across countries. They are the foundation for the economic response to the Covid-19 shock. Country specific differences in parameters will generate country specific responses, both with and without policy interventions. So, as discussed, replacement of German adjustment cost parameters with those of Italy leads to very different responses to shocks. These differences across countries, all else the same, will contribute to differences in their response to the Covid-19 shock.

6 The Effects of Covid-19

In this section, we use the estimated model to study how firms and the economy respond to the Covid-19-induced recession and related policy support measures in terms of output, employment, productivity and factor misallocation. Importantly, we do not simply substitute the Covid-19 shock directly into the estimated responsiveness regressions. Doing so would miss a number of important elements including: (i) the abnormal size of the shock, (ii) the policy interventions that went along with the productivity decline, (iiii) the role of beliefs about the persistence of the shock. All of these are important features of this experience and require a model for their analysis.

For these exercises, we extend the above firm's problem to allow for an aggregate disaster state that mimics the effects of the pandemic and introduce two types of policy interventions that have been prominent in the countries under analysis during the Covid-19 pandemic: short-time work schemes and "no-firing" obligations. We furthermore make an assumption about the timing of the model, which reduces the importance of time to build. In particular, we assume that firms receive "news" about the realized state in period t one period in advance. With time to build, this effectively allows firms to respond contemporaneously to the shock. This assumption seems appropriate when studying the response to Covid-19 since the impact of the shock was at a frequency higher than the model decision period.

For the quantitative analysis, we start from a baseline model that includes the support policies and is calibrated to match country-specific drops in manufacturing employment with the policy measures in place. Our main exercise is then to evaluate the effect of the Covid-19 shock on aggregate employment and productivity, with and without the policy interventions. Note that, for these exercises, the policy interventions are strictly linked to the aggregate state of the economy, i.e. they are removed as soon as the economy recovers to the normal state.

Importantly, the simulations include both the exit and entry margin given by (5) and (8). The choice to exit will be impacted directly by the Covid-19 shock and related policies, since the outside option remains unchanged. The entry decision will also be affected, since the critical value of signal s^* at which firms decide to enter will be impacted by both the shock and the policies. The Covid-19 shock has two effects via the entry margin. On one hand, there will be less firm entry during the shock period. On the other hand, however, firms that enter will on average be more productive.[30]

In the following sections we describe in detail how we model and calibrate the Covid-19 shock as well as the policy support measures. We then study their effects on employment, output and productivity.

6.1 Covid-19 shock

We model the Covid-19 shock as the "disaster" realization of an aggregate state $\mathcal{S} = \{\text{normal}, \text{disaster}\}$ that follows a two-state Markov process:

$$Q(S'|S) = \begin{bmatrix} \pi_{nn} & \pi_{nd} \\ \pi_{dn} & \pi_{dd} \end{bmatrix}. \tag{10}$$

Here d denotes the "disaster" state and n denotes the non-disaster state or "normal" times. π_{jk} is the probability of transition from state j to k.[31] The probability that the economy enters the disaster state, π_{nd}, is set to 1%, which is consistent with the low probability of a disaster state, such as the outbreak of the pandemic. We initially set π_{dd} to the structural estimate of the serial correlation of the idiosyncratic profitability shock.[32]

In the presence of aggregate risk, the firm's state vector, hence, becomes (A, e, S), where S captures the aggregate state of the economy. In the disaster state, each firm's profitability is scaled down by a factor λ. The factor λ captures two effects related to Covid-19. First, at the firm level, the shock induces a fall in demand and thus profitability. Second, during the crisis period, some workers were unavailable for employment, reflecting illness and various distancing policies. This essentially acts as a worker-specific productivity shock that reduces the labor input and further harms profitability.

6.2 Policy support

At the outbreak of the pandemic, all four countries quickly introduced different policy measures to stabilize output and preserve employment. Firms were given different forms of wage subsidies to pay the salary to their workers, while working relatively little. We term this a short-term work

[30] The distribution over signals does not change with the aggregate state.

[31] Of course, $\sum_k \pi_{jk} = 1$ for all j.

[32] Absent independent country-specific information about beliefs, we imagine that a firm treats, say, a drop in demand during the crisis to have the same persistence as usual. We present experiments below that highlight the importance of beliefs for the response of firms to the shock and the policy.

(STW) policy.[33] Some countries, like Italy, also introduced an obligation not to fire workers.

In the firm optimization problem, we capture the STW policy via the parameter τ. The STW policy allows firms to reduce their wage bill since part of the hours worked are paid by the government, but at the same time directly impacts their revenues since workers on STW work less hours. This directly influences firms' hiring/firing decisions as well as whether to stay in the market or exit. The "no-firing" obligation is captured through the fixed costs of firing F_m as part of the labor adjustment costs and is modelled as a large enough increase in F_m such that no firm optimally decides to fire.[34]

Combining the policy support and the Covid-19 shock, the revised optimization problem of the firm, therefore, reads:

$$V(A, e, \mathcal{S}) = max(V^c(A, e, \mathcal{S}), 0)$$

$$V^c(A, (1-\tau)e, \mathcal{S}) = \max_{e'} \; R(A, (1-\tau)e, \mathcal{S}) - \omega(e)(1-\tau) - C(e', e) - \Gamma + \beta E_{A', \mathcal{S}'|A, \mathcal{S}} V(A', e', \mathcal{S}') \quad \forall (A, e, \mathcal{S}).$$

Here $\mathcal{S}$ again represents the aggregate state. The dependence of revenues on $\mathcal{S}$ is through the profitability shifter, λ.

6.3 Calibration of the Covid-19 Shock and Policy Support

A key component of the analysis of the Covid-19 shock and the related policy support is the magnitude of the revenue reduction. As discussed above, the revenue shifter, λ, is country specific and is calibrated to match the employment drop in each country's manufacturing sector.[35] Since we are calibrating λ to match the observed employment drop in the data, the model must include the country-specific policy measures that were in place at the time of the shock.

The parameters governing the policy interventions are shown in the first two columns of Table 8. The first column indicates the fraction of the workforce receiving the benefits of the policy. That fraction is lower in France and Germany and much higher in Italy.[36] The second column indicates the average reduction in hours across manufacturing firms. The average reduction in hours was considerably less in Italy compared to France and Germany.

[33] As we have no data on hours worked, we are unable to explicitly study work sharing. Instead we capture two features of the policy: (i) the reduction in the labor input and (ii) the reduction in the cost of employment.

[34] This restriction applies to all workers as the model does not include a distinction between permanent and temporary workers. For Italy, it appears that the no firing obligation did not preclude firms from ending temporary contracts at their date of termination. From https://data.oecd.org/chart/6Wbr, about 15% of Italian workers were on temporary contract between 2018 and 2021.

[35] An earlier exercise matched annual output reductions. But, due to time aggregation, this reduces the impact of the shock on output within a 'period' of the model, defined as the time in which the Covid-19 shock has hit. Focusing on employment, which did not recover as quickly, provides a better guide on the magnitude of the shock. That said, the effects of the various policies on the responses are effectively the same regardless of whether output or employment drops are used to calibrate λ.

[36] These difference in incidence rates will matter when we consider alternative targeting of the policies.

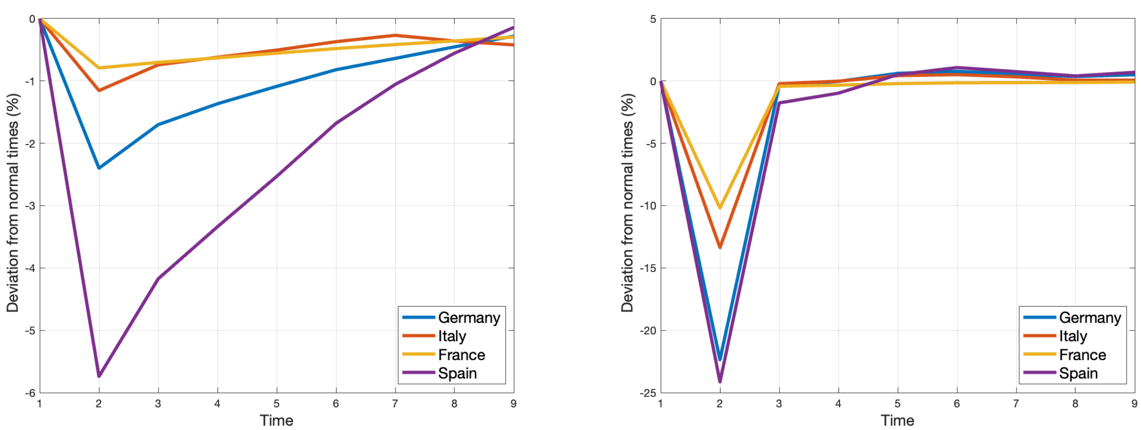
Table 8: Covid-19 Shock and Policies

	Fraction STW (%)	Hours sharing (%)	Employment drop			λ
			Data	Model	Fit	
Germany	15.8	28.1	-2.40	-2.40	3.719e-06	0.79
France	14.0	31.0	-0.79	-0.79	2.123e-06	0.90
Italy	57.2	13.0	-1.10	-1.11	2.046e-04	0.87
Spain	38.0	24.1	-5.71	-5.73	7.431e-04	0.79

Notes — For this table, "Fraction STW (%)" refers to the fraction of firms making use of short-time work during the Covid-19 crisis. "Hours sharing (%)" refers to the average fraction by which firms reduced hours worked. See Appendix section H for data sources.

The column labeled "λ" in Table 8 shows the calibrated country-specific revenue reduction needed to match the employment drop in the data. λ is country specific for three reasons. First, the policy interventions were country specific. Second, the observed employment reductions differed across countries. This is shown in the column termed "Data". Third, because of parameter differences, the response to a revenue shock is country specific. From this table, the shock was largest in Spain and smallest in France. The actual and the model-generated employment drops are quite close as reflected in the near-zero model fit for all four countries.

6.4 Responses



(a) Employment (b) Output

Figure 2: Employment and Output Responses

Notes — The figure shows the employment and output responses to the Covid-19 shock and interventions in the estimated models. These responses are measured as percent deviations from normal times.

Given the revised decision rule of firms, we simulate a baseline economy for ten periods in which the disaster state occurs in period 2 and lasts for one year. When simulating the economies we always start them in the stationary distribution of the economy with aggregate shocks over the state-space, where exiting firms are replaced by new firms to retain stationarity.

Figure 2 shows the employment and output responses by country predicted by the model with policy interventions. Note that the vertical axis measures percent deviation from a baseline economy that has not been hit by the shock.

The employment response is country specific. The employment loss is largest in Spain, with a deviation of nearly 6% below baseline. In contrast, employment falls by a little more than 2% in Germany, less than half of that in Spain, and closer to 1% in France and Italy. To be clear, these employment effects at impact reflect the calibration of the shock.

While the employment response was matched through the choice of λ, the output effects were not targeted. They are a consequence of the persistence of the shock and the relatively slow adjustment of employment. The model produces a relatively quick recovery in output. Though the shock lasts only one period, the employment effects are long-lived. This comes from the model. The presence of the adjustment costs leads to a gradual employment response to the temporary large shock. Looking again at Spain, employment is still about 3.5% below baseline two years after the shock.

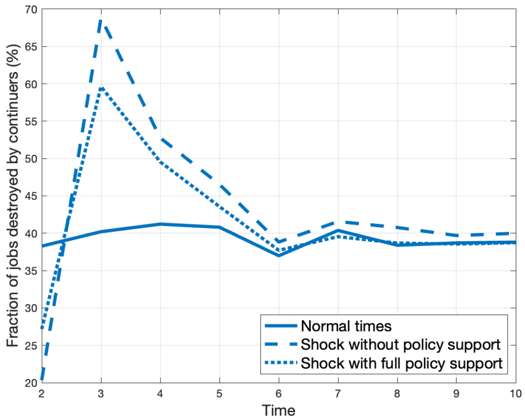
There are two margins for the job loss. One is a contraction in employment of continuing firms. The second is job destruction due to exit. Figure 3 shows the job destruction for continuing firms and, as a residual, from exit. On impact, the fraction of job destruction by continuers was well below normal times. In Italy, as an extreme, the job loss by continuing plants was near zero with the policy support, indicating the importance of firm exit for job destruction. After the initial exit, the job destruction rates by continuing plants are higher than normal times for a large number of periods in all countries.

Finally, it is useful to compare the responses from the model with those found in the data. Figure 4a shows the output and employment reductions in the four countries. The output loss is about 20% on impact and, with the exception of France, is close to what the model produces. But, there is an important issue of frequency. The data is quarterly and clearly these economies recovered relatively quickly, at least in terms of output. The model is annual and thus unable to match the relatively high frequency movements in output. But it does capture both the magnitude of the output fall and its quick recovery.

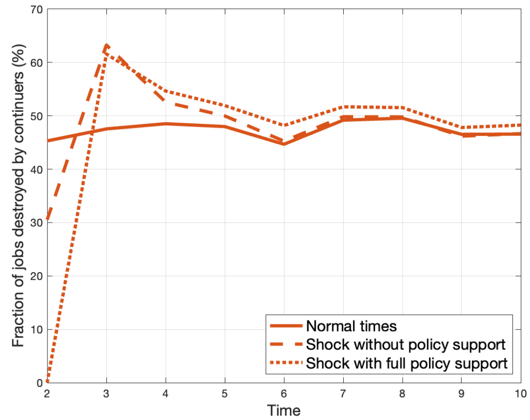
In contrast, from Figure 4b, the employment recover in the data, as in the model, is relatively slow. Interestingly, the employment recovery is fastest in Italy, perhaps due to the "no firing" restriction.

6.5 Evaluating the Impact of Policy Interventions

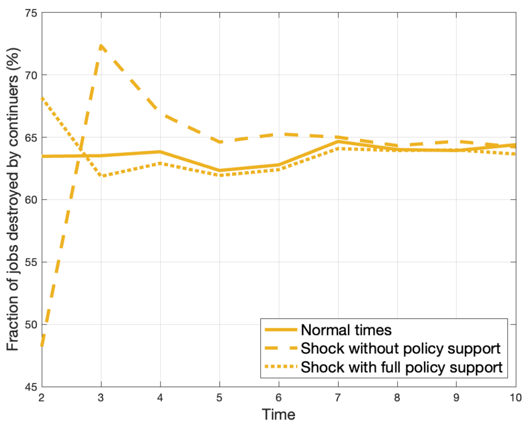
The model is used here to evaluate the effects of the policy interventions. These responses are included in the analysis since they are needed to match the observed employment reductions. They



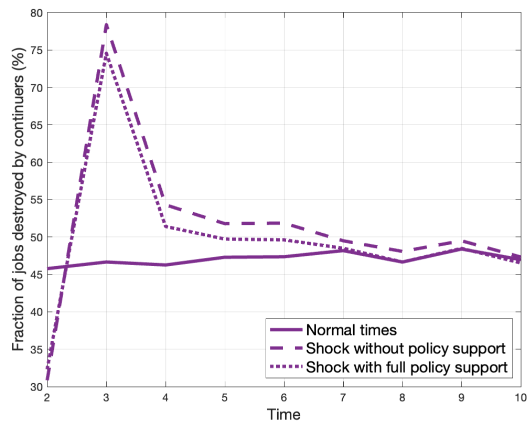
(a) Germany



(b) Italy



(c) France



(d) Spain

Figure 3: Sources of Job Destruction

Notes — The figure shows job destruction rates (in percent) by continuing firms in normal times and during the crisis, both with and without policy support.

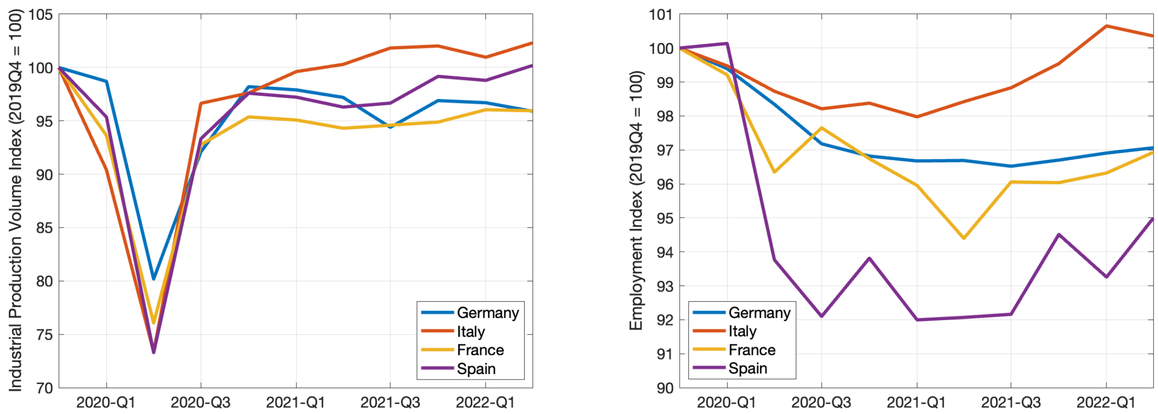
are removed here as a counterfactual to determine their impact.[37]

Focusing on Germany and Italy, Figure 5 compares the employment response with and without policy interventions.[38] The solid curve response includes the shock as well as the policies outlined above. The counterfactual for Germany eliminates the policy support, as indicated by the dashed curve. In terms of the STW policy, this means that $\tau = 0$ for all firms.

For Germany, the effect of the shock without policy interventions reduces employment by 4%, compared to a 2.5% with the policies in place. For Italy, the elimination of all policy support almost triples the employment fall. Clearly these policies mattered.

[37] This is, of course, impossible to do without a model.

[38] Here we focus on only two countries and present the graphs for all in Appendix section C. We highlight Germany given the immense detail about its policy program. Italy is important to study because it was the only country with a no firing clause.

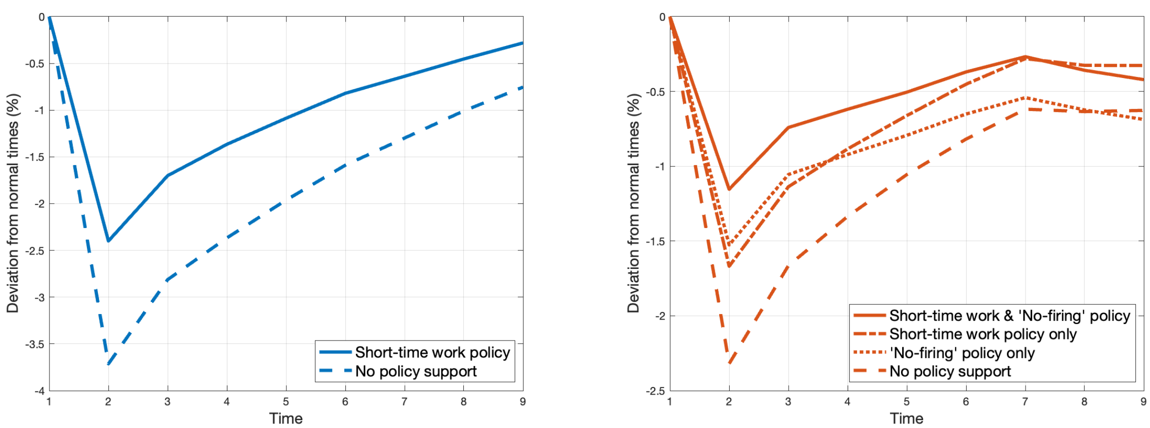


(a) Output in Data

(b) Employment in Data

Figure 4: Employment and Output Responses from the Data

Notes — Panel (a) shows production output in the manufacturing sector in Germany, Italy, France, and Spain. Values are obtained from Eurostat's "Production in industry - quarterly data" table. Panel (b) shows total employment in the manufacturing sector in Germany, Italy, France, and Spain. All values, except for France, are obtained from Eurostat's Quarterly National Accounts. Values for France are obtained from Eurostat's Labor Force Survey data. All series are normalized to 100 in 2019q4.



(a) Germany

(b) Italy

Figure 5: Employment Responses

Notes — The figure shows employment responses in Germany (with and without policy support) and Italy (for alternative interventions). These responses are measured as percent deviations from normal times.

Italy was the only country introducing a "no firing" obligation during the pandemic.[39] From Figure 5, with STW in place, the employment drop in Italy would have been considerably bigger than the baseline response if firms had not been subject to a "no-firing" obligation, reaching about

[39] Unless stated otherwise, the policy simulations and calculations for Italy all include this no-firing clause.

2.4% reduction relative to the baseline. If instead the only policy in place was the "no-firing" obligation, then the employment drop would have only been slightly larger than the baseline. Clearly, at least for Italy, the "no-firing" obligation was an important part of the package.

Returning to the extensive margin, as shown in Figure 3 and discussed above, the exit rate rose considerably at the time of the shock. From that figure the policies impacted the form of job destruction. These margins are affected by the policies in two ways. First, the STW program increases the value of continuing operations. Second, a restriction on firing, such as that in Italy, makes exit the only option for large reductions in the work force.

Table 9 compares the employment-weighted exit rates for Germany and Italy. From the table, if no policy support had been in place, the employment-weighted exit rate would have been almost 70% higher than the actual rate in Germany and almost 20% higher in Italy. If the only policy in Italy was a "no-firing" obligation, then the exit rate would have indeed been even higher.

Table 9: Employment-weighted exit rates

	Germany	Italy
Normal times	0.386	0.563
Shock with full policy support	1.933	1.768
Shock with only short-time work policy	1.933	1.760
Shock with only 'No-firing' policy	–	2.154
Shock without policy support	3.235	2.073

Note—This table summarizes the effect of the policy support on employment losses (in percentage points) due to exit.

6.6 Sensitivity to Parameters

This section returns to the earlier discussion about alternative parameterizations of the model. The focus here is not on the parameters *per se*, but in the employment response to the Covid-19 shock and associated policies.

The first exercise, summarized in Table 10, examines the employment response during the period of the Covid-19 shock to changes in each individual parameter for Germany and Italy. This exercise varies each of the baseline parameters individually and studies the maximal effect of the Covid-19 shock on employment. The point is to understand which parameters are most important for determining the response of the economy to this shock and which matter most for the effects of the policy intervention.

From this experiment, variations in the serial correlation of the shock have the largest effect on the magnitude of the employment response in both countries. The fixed costs of employment adjustment matter much less. Comparing the employment loss with and without interventions, again the serial correlation is essential. We explore this further in the discussion of the sensitivity of the employment response to the perception of the permanence of the Covid-19 shock.

Table 10: Sensitivity of Employment Response to Parameter Variation

		Baseline	α	ρ	σ_η	ν	F_m	F_p	Γ
Germany	Shock w/o pol. supp.	-3.714	-3.882	-4.047	-3.687	-3.582	-3.670	-3.588	-3.777
	Shock w/ pol. supp.	-2.400	-2.431	-2.909	-2.392	-2.293	-2.410	-2.342	-2.444
Italy	Shock w/o pol. supp.	-2.320	-2.328	-2.213	-2.254	-2.330	-2.307	-2.313	-2.310
	Shock w/ pol. supp.	-1.154	-1.156	-0.796	-1.016	-1.150	-1.154	-1.121	-1.224

Notes — This table computes the employment response as percent deviations from normal times during the period of the Covid-19 shock to changes in each individual parameter for Germany and Italy. We here consider a 1% increase in each parameter separately.

The second exercise builds on the alternative parameterizations, either through estimation with a weighting matrix or through the calibration of α, presented in Appendix A. Using the same magnitude of the shocks reported in Table 8, we report, in Table 11, the response of employment, with and without policy interventions, to the Covid-19 shock.[40]

Table 11: Employment Response: Alternative Estimation

		Baseline	W	α
Germany	Shock w/ policy support	-2.400	-0.277	-11.031
	Shock w/o policy support	-3.714	-0.566	-11.846
Italy	Shock w/ policy support	-1.154	-0.318	-1.847
	Shock w/o policy support	-2.320	-1.118	-4.504

Notes — This table computes the employment response as percent deviations from normal times during the period of the Covid-19 shock to two alternative parameterizations for Germany and Italy. The column denoted "W" using the estimates from a weighting matrix and the column denoted "α" is based on calibrated rather than estimated values of the curvature parameter.

Compared to the baseline, for both Germany and Italy the job loss from the shock is much lower based upon the estimates using the weighting matrix. The opposite is true for the estimation using the calibrated curvature of the revenue function. The key to these differences is in the responsiveness produced by these alternatives to the baseline. The model-produced responsiveness moments, particularly β_1^{int}, are much larger for the case of the calibrated α and much smaller in the weighting matrix case compared to the baseline.

Comparing the rows with and without policy support provides insights into how the parameterization affects the response to the policy. Though the magnitude of the response differs with the estimation, the contribution of the policy to reducing the job loss remains apparent.

[40] Appendix subsection D presents an alternative where λ is calibrated to maintain the same employment drop under the policy. The qualitative effects of the policy remain the same.

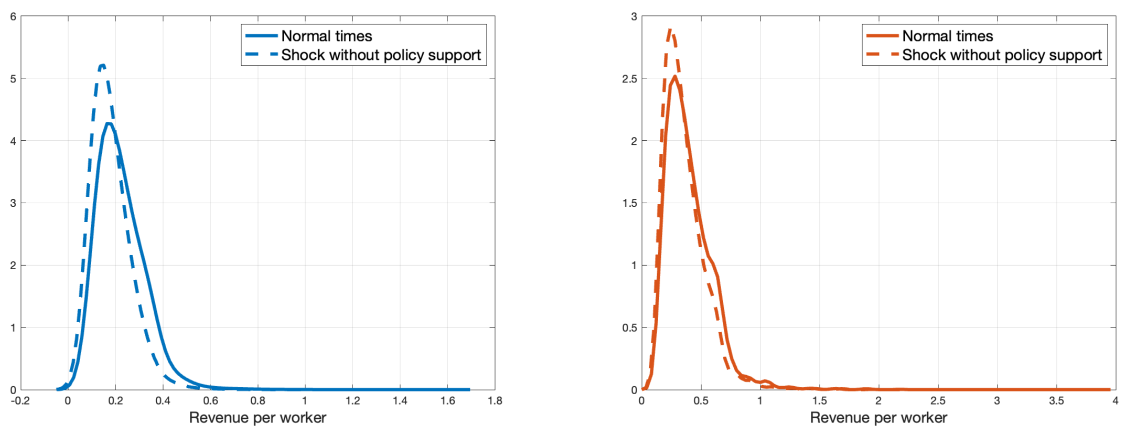
6.7 Productivity Implications

The Covid-19 shock had big effects on firms' employment choices. The shock and the ensuing policy support, however, may have also impacted productivity by impeding beneficial factor reallocation across firms. This would clearly be a cost of the interventions. In this section we analyze the effect of the Covid-19 shock as well as the policy support on firm-level and aggreagte productivity.

There is of course a direct and substantial effect of the Covid-19 shock on profitability. Beyond that, there are indirect effects coming from reallocation. The pace of reallocation, in turn, is impacted by both the shock itself as well as the policy interventions, some of which may have limited reallocation.

6.7.1 Firm Level Responses: Productivity Distributions

First, to isolate the effect of the Covid-19 shock on productivity, we compare the distribution of revenue per worker in an economy with the Covid-19 shock with a counterfactual economy without the shock. We do so for the case with and without policy support.



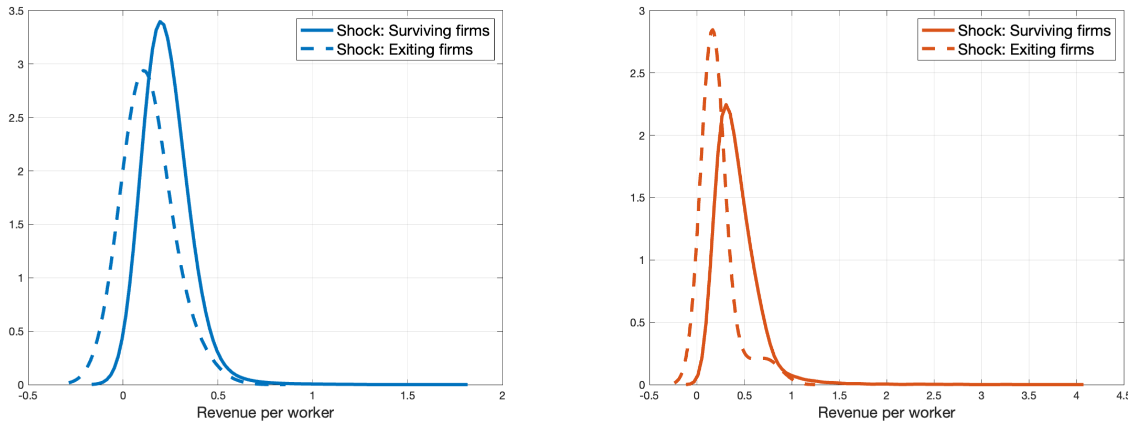
(a) Germany (b) Italy

Figure 6: Surviving firms during shock period with no policy support

Notes — The figure shows the distributions of revenue per worker in Germany and Italy in normal times and with the Covid-19 shock but without policy interventions.

Without Policy Support Figure 6 shows the distribution of the revenue per worker in normal times and in the shock period without any policy support in place. What emerges from Figure 6 for both countries, Italy and Germany, is that the shock negatively affected the productivity distribution of surviving firms. This net effect is, however, driven by multiple forces.

On the one hand, recessions can have a positive impact on aggregate productivity since it pushes the least productive firms out of the market and the remaining firms are usually the better performing ones (Caballero and Hammour (2005); Foster, Grim, and Haltiwanger (2016)). This "cleansing" effect is also present in our setting, as can be seen from Figure 7. In both countries, exiting firms are on average less productive, compared to surviving firms.



(a) Germany

(b) Italy

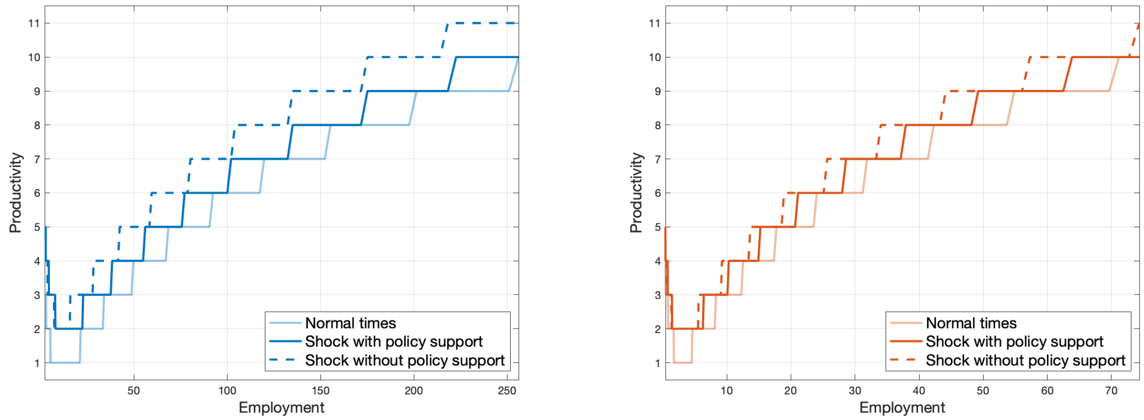
Figure 7: Exiting vs surviving firms

Notes — The figure shows the distributions of revenue per worker in Germany and Italy, comparing surviving and exiting firms in the period of the Covid-19 shock without policy interventions.

Another way to see how a recession can impact the pool of operating firms is through the discrete policy functions for exit decisions. Figure 8 plots the critical productivity level at which firms decide to exit under the two alternative scenarios, in normal times and during the Covid-19 shock. For each employment level, the firm remains active if (and only if) realized profitability exceeds the critical level shown in the graph. Clearly, the Covid-19 shock increases the productivity threshold for all levels of employment implying that, for a given firm size, the Covid-19 shock induced firm exit at levels of productivity that would have not triggered exit during normal times.

On the other hand, recessions can have a negative effect on productivity in the presence of high labor adjustment costs. In our framework, the aggregate shock shifts down the revenues of all firms by a fraction λ. In order to keep the same level of productivity in terms of output per worker, firms would need to respond by firing workers in the same proportion. The presence of high labor adjustment costs, however, makes the employment response sluggish, leading to a large fraction of firms operating at an inefficient scale.

The overall effect of the aggregate shock on productivity is, hence, the sum of the positive cleansing effect of the recession induced by selection and the negative effect generated by adjustment costs and the resulting inability of firms to adjust their workforce. From Figure 6 we see that in our case, the negative effect is dominating. To make this point clear, Figure 9 compares the productivity distribution of firms in the shock period and in normal times in the absence of labor adjustment costs. Without adjustment costs the two distributions overlap, meaning that absent adjustment costs firms are able to respond efficiently and preserve their productivity in terms of output per



(a) Germany (b) Italy

Figure 8: Productivity threshold of exit

Notes — For each country, this figure displays the critical level of productivity below which a firm with a given level of employment decides to exit.

worker.

With Policy Support Using the estimated model, we evaluate the effect of the policies on firm productivity given that the policy support enacted in response to the Covid-19 pandemic has been effective in preventing aggregate employment losses. In Figure 10 we plot firms' productivity distribution in normal times and during the shock period when policy support is active.

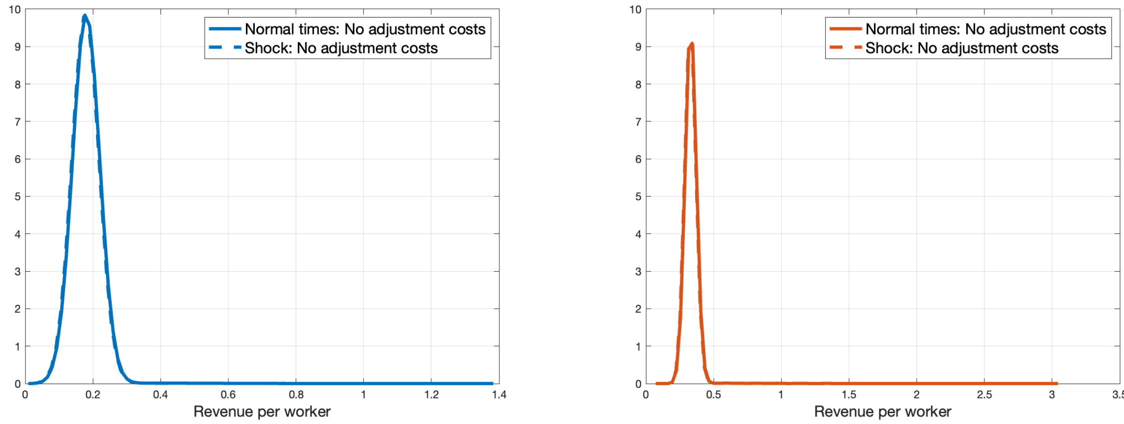
We do not see major differences compared to Figure 6, suggesting that the policy interventions alone did not distort firm productivity too much. To further support this idea we check how firm productivity is affected in a counterfactual case in which the policies are introduced in normal times. We plot the results from this exercise in Figure 11.

Compared to the effect of the recession on productivity, the effect of the policy support is rather minor even if slightly negative. The reason why the policy support only modestly distorts firms' optimal decisions is the presence of high adjustment costs. High adjustment costs imply large regions of inaction for firm behavior. As a consequence, the policy support does not change firms' policy function much, leaving the productivity distribution largely unaffected.

6.7.2 Aggregate Productivity

Finally, we analyze the aggregate productivity implications of the Covid-19 shock and the related policy support. Table 12 and 13 report statistics of aggregate productivity.

"APL" refers to the aggregate revenue per worker. This measure of aggregate productivity, which is a revenue-based measure of total factor productivity, includes both the direct effects of common shocks as well as the allocation of labor across heterogeneous plants. Thus, this measure



(a) Germany

(b) Italy

Figure 9: Surviving firms normal vs shock period with no adjustment costs

Notes — The figure shows the distributions of revenue per worker in Germany and Italy in normal times and with the Covid-19 shock without adjustment costs.

is endogenous and impacted by labor misallocation.[41]

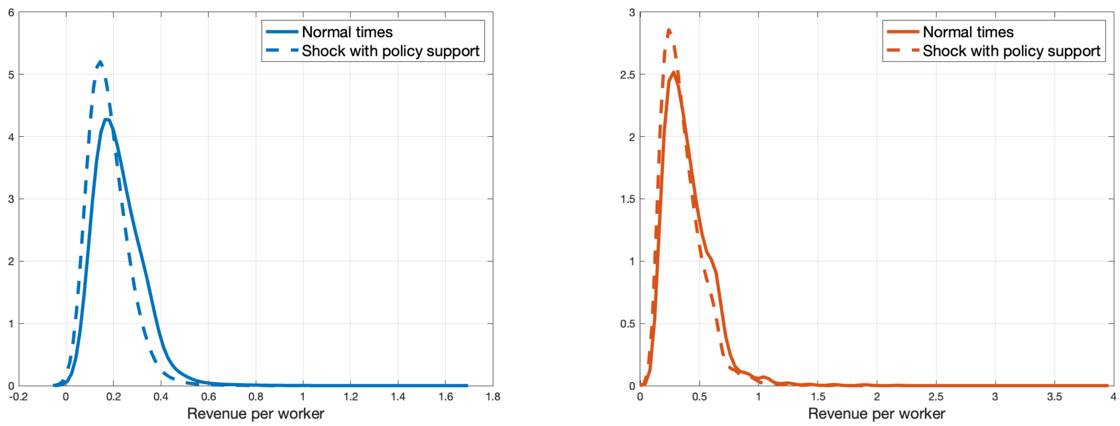
Another key metric for this misallocation of factor inputs is the standard deviation in the revenue product of labor, denoted "Std". In an efficient allocation, i.e. when labor input factors are allocated optimally across firms, the "Std" should be zero. Due to the presence of adjustment costs at the individual firm level, however, the standard deviation of the average revenue product will not be zero. This statistic summarizes the dispersion in the revenue per worker distributions discussed in Section 6.7.1.

Table 12 displays these aggregate statistics for an economy in normal times, during the shock period absent any policy support, and during the shock period when policy support is active. In both Germany and Italy, aggregate revenue per worker drops by 20% and 12%, respectively, during the recession. The "Std" falls, indicating less dispersion across firms in both countries. This reduction in dispersion reflects, in part, the exit of relatively low profitability firms with large numbers of workers.

Comparing the second and the third column of Table 12, there are no major differences in aggregate productivity with and without policy intervention. From the perspective of productivity, this shows that policy support through short-time work schemes can be an effective tool to limit employment losses and firm exit while at the same time does not generate strong negative effects on aggregate productivity through factor misallocation. The limited impact of the policy support on factor misallocation is consistent with the findings of Altomonte, Demertzis, Fontagné, Müller, et al. (2021).

Finally, Table 13 highlights the role of adjustment costs in affecting aggregate productivity. We

[41] Recall that the mean of profitability is normalized to unity in both the data and the model so that differences in this measure across countries is not necessarily informative.



(a) Germany (b) Italy

Figure 10: Surviving firms normal vs shock period with policy support

Notes — The figure shows the distributions of revenue per worker in Germany and Italy for surviving firms in normal times and with the Covid-19 shock with policy interventions.

Table 12: Productivity measures

		Normal times	Shock	Shock + targeted pol. supp.	Shock + untargeted pol. supp.
Germany	APL	0.211	0.169	0.168	0.169
	Std	0.098	0.079	0.079	0.079
Italy	APL	0.384	0.339	0.336	0.337
	Std	0.201	0.179	0.179	0.179

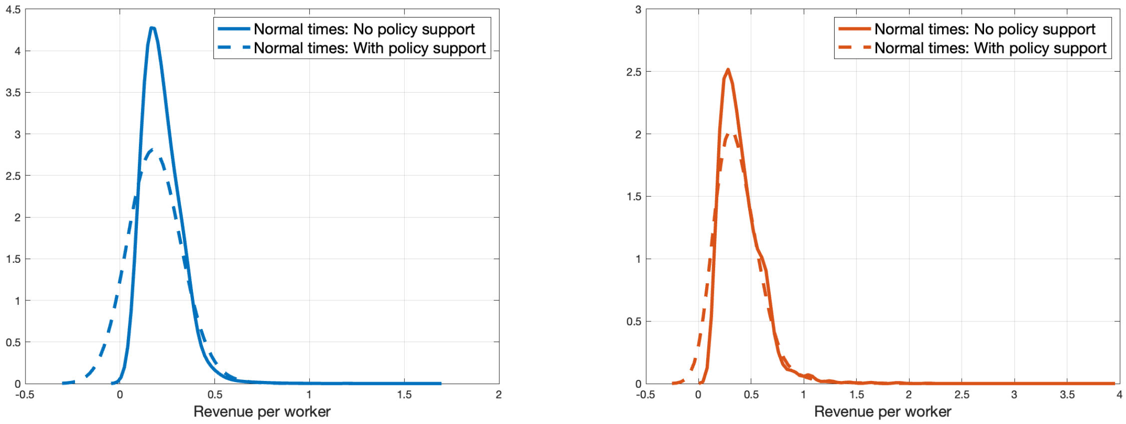
Notes — This table summarizes aggregate productivity through the average revenue per worker (APL) and the standard deviation of the average revenue product, (Std). These measures are for normal and crisis times with and without targeted policy interventions.

see that an economy without adjustment costs, through the ability of firms to immediately adjust its workforce to the new optimal size, displays higher aggregate productivity during shock periods as well as considerably less factor misallocation. Further, relative to normal times, the Std measure with adjustment costs is lower in both countries reflecting the reallocation due to adjustment in response to the Covid-19 shock.

6.8 Investment Implications

Though there are no costs associated with capital adjustment, the model nonetheless has implications for the demand for capital and thus investment. A version of the model with capital is provided in Appendix F, showing that capital demanded is a log linear function of employment and the profitability state.

From simulation of the estimated models in normal times, we can generate a cross-sectional distribution of steady state investment rates. Simulating the model including the Covid-19 shock and policies, furthermore, allows us to isolate the impact of the shock and the policies on firm-level



(a) Germany (b) Italy

Figure 11: Surviving firms in normal times with policy support

Notes — The figure shows the distributions of revenue per worker in Germany and Italy in normal times with and without policy interventions.

Table 13: Productivity measures

		Normal Times		Shock	
		AC	No AC	AC	No AC
Germany	APL	0.211	0.183	0.169	0.181
	Std	0.098	0.029	0.079	0.029
Italy	APL	0.384	0.341	0.339	0.337
	Std	0.201	0.079	0.179	0.079

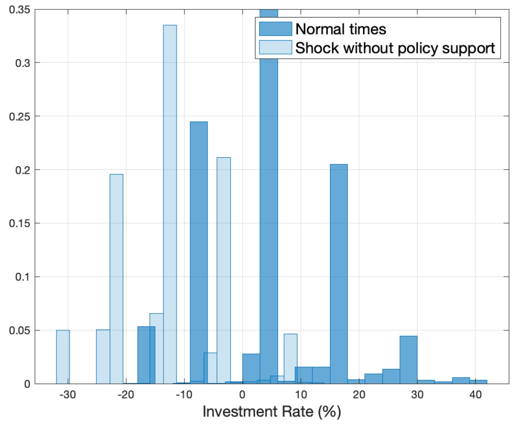
Notes — This table summarizes aggregate productivity through the average revenue per worker (APL) and the standard deviation of the average revenue product, (Std). These measures are for normal and crisis times with and without adjustment costs (AC).

and aggregate investment rates.

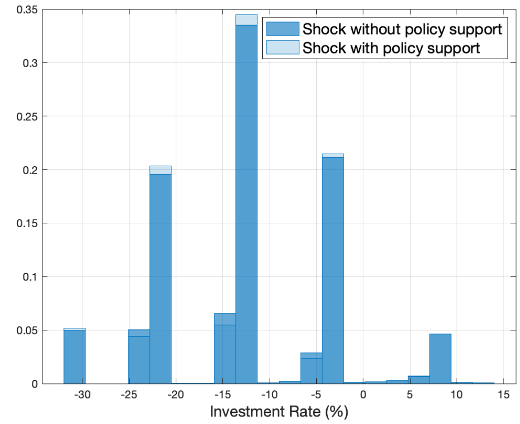
Figure 12a shows distributions for Germany, in normal times and with the Covid shock. The ample dispersion in investment rates even in normal times reflects the underlying joint distribution of profitability shocks and employment which determine capital demand and thus investment. Importantly, the investment rate distributions also depend on the labor adjustment costs.[42]

The large reduction in profitability stemming from the Covid-19 shock shifts the distribution of investment rates to the left. Given the ample heterogeneity across firms, there are, of course, still firms with positive investment rates even in the shock period. From Figure 12b, it becomes clear that the policy support does very little to stabilize the distribution of investment rates in the

[42]The addition of quadratic adjustment costs for capital would tend to reduce the dispersion of investment rates while non-convex costs of capital adjustment can create more dispersion.



(a) Impact of Shock



(b) Impact of Policy

Figure 12: Investment Rates

Notes — The figure shows the distributions of gross investment rates in Germany for normal times as well as in response to the Covid shock, with and without policy interventions.

shock period.

Figure 13 looks at aggregate investment in Germany, documenting the predicted fall in investment rates due to the shock.[43] In line with the cross-sectional evidence at the firm level, the fall in the aggregate investment rate is little impacted by the policy support.

[43]The aggregate investment response for the other countries are in Appendix section F.

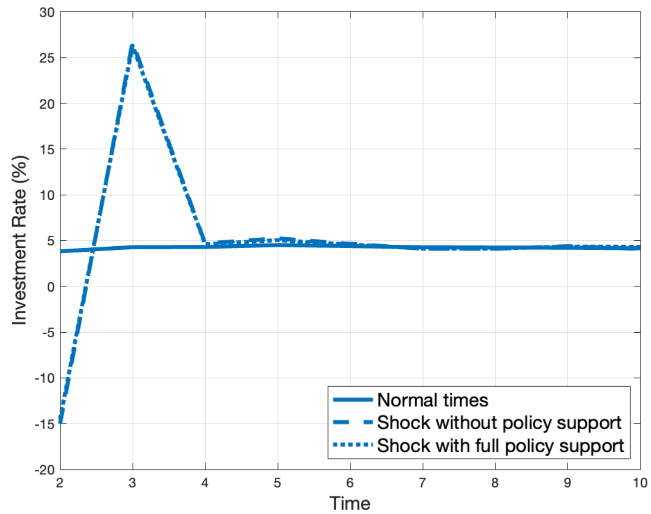


Figure 13: Germany: Investment Rates

Notes — The figure shows the aggregate gross investment rates (in percent) for Germany with and without policy support.

7 Additional Policy Experiments

This final section studies two extensions of the model. Both extensions are directly related to the effects of the policy support. The first extension considers alternative targets for the wage subsidies, beyond the subsidization of low profitability firms assumed in the baseline. The second exercise focuses on the sensitivity of firms' choices to their beliefs. There is an important policy dimension here as well: interventions can influence firms' beliefs which, as we demonstrate, can have a sizeable effect on their choices.

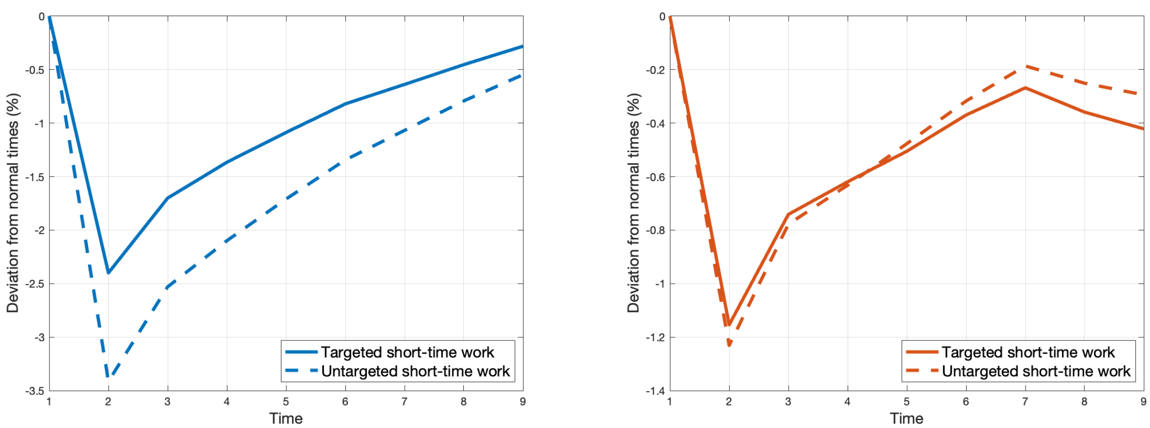
7.1 The Importance of Targeted Policies

The policy measures introduced above were targeted towards low-profitability firms that destroyed jobs due to the Covid-19 shock. In the simulated data those are easy to identify and they were all given a subsidy at the country specific rate of τ. This type of intervention may be difficult to implement in reality given limited information and incentive problems. This section looks at the implications for employment and productivity of alternative policy implementations. First, we consider, a scenario in which the policy support is completely un-targeted. Second, we consider the case in which the policy support is targeted to firms based on its revenue per works rather than their profitability shock which is difficult to observe in practice. And third, we allow the policy support to be targeted to high- instead of low-profitability firms.

7.1.1 Untargeted Policies

In this section, we study interventions that are completely un-targeted so that firms have an equal chance of obtaining a subsidy. This is simulated in our model by providing the subsidy to the same aggregate fraction of firms receiving the subsidy in the targeted policy treatment but now the treatment is state-independent.

From Figures 14, the effect of non-targeted policy support is not nearly as effective in limiting job loss in a recession. Recall from Table 8, that the fraction of firms treated under the STW plan was more than 3 times higher in Italy compared to Germany. For Germany, the employment drop under untargeted policy support is very close to the employment drop without any policy in place. For Italy, the difference in the employment responses policy is much smaller. This, again, seems to be the consequence of the "no-firing" clause which, by design, only impacts those firms who are truly in a low-profitability state. In that sense, the restriction on firing is a very targeted instrument.



(a) Germany

(b) Italy

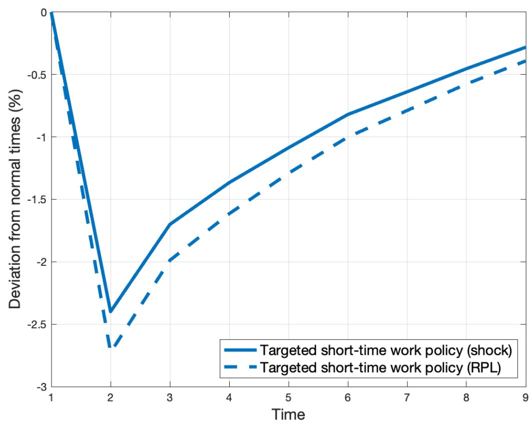
Figure 14: Employment Response: Untargeted support

Notes — The figure shows the employment response in Germany and Italy, comparing targeted and untargeted policy interventions. These responses are measured as percent deviations from normal times.

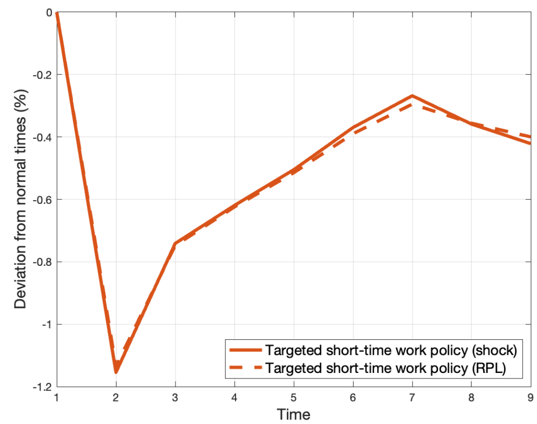
7.1.2 Alternative targeting strategies

Profitability shocks are not easy to observe. An alternative is to use the revenue product of labor as a measure of firm productivity. These are not the same measures as the revenue per worker includes the firm response to the shock. In the simulated data, the correlation of these measures is positive but far from one. Figure 15 plots the employment response when firms are targeted in terms of their productivity shock vs their revenue per worker.

In Germany, this alternative creates a larger employment drop in response to the shock compared



(a) Germany



(b) Italy

Figure 15: Employment Response: Targeted support based on Revenue per Worker

Notes — The figure shows the employment response in Germany and Italy, comparing interventions with targets based on profitability compared to revenue per worker. These responses are measured as percent deviations from normal times.

to the baseline policy of targeting low profitability firms. Evidently, some of the firms with low profitability had sufficiently high revenue per worker that they did not receive a subsidy and responded by reducing employment. For Italy, in contrast, there is not much of a difference.

At last, from the perspective of aggregate productivity, promoting employment at high profitability firms might dominate the alternative of trying to save jobs at low profitability firms. With this in mind, Figure 16 plots the employment response when the short-time work subsidy is given to the most rather than the least productive firms.

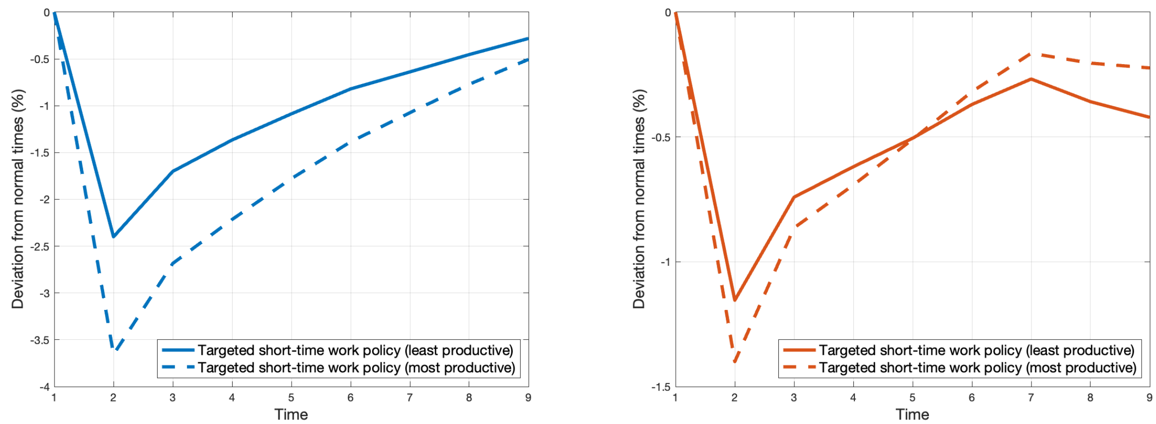
In this case the employment drop is much larger in both countries. Evidently, the job destruction from firms that need the subsidy to avoid layoffs (but do not get it) dominates the job creation from the more productive firms that do receive a subsidy.

7.2 The Role of Heterogenous Beliefs

We have so far assumed that firms have homogeneous beliefs about the persistence of the aggregate Covid-19 shock. Using responses from a survey among a large panel of German firms, however, Buchheim, Dovern, Krolage, and Link (2022) show that, at the onset of the crisis, there was substantial heterogeneity in firms' expectations about the duration of restrictions imposed on public life.[44] Moreover, the authors show that firms' beliefs are an important determinant of their crisis response. Specifically, they show that more pessimistic firms, i.e. firms that expected the shutdown to last longer, were more likely to fire workers or cancel investment projects.

Taking this survey evidence as motivation, this section sheds light on the role of dispersion in

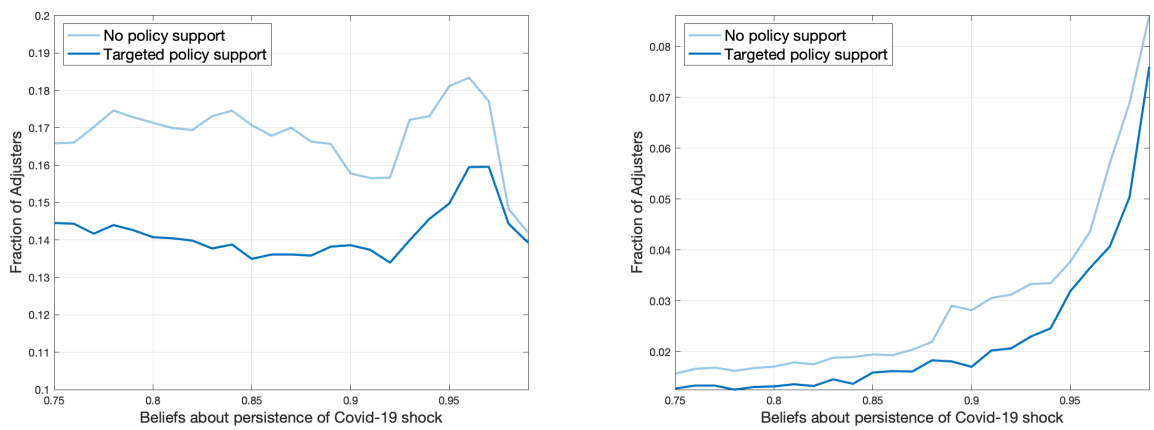
[44]We are grateful to Lukas Buchheim and Sebastian Link for sharing these data with us.



(a) Germany (b) Italy

Figure 16: Employment Response: Targeted support to most profitable firms

Notes — The figure shows the employment response in Germany and Italy, comparing interventions with targets based on least profitability compared to most profitable firms. These responses are measured as percent deviations from normal times.



(a) Fraction of Firms Adjusting Employment (b) Exit Margin

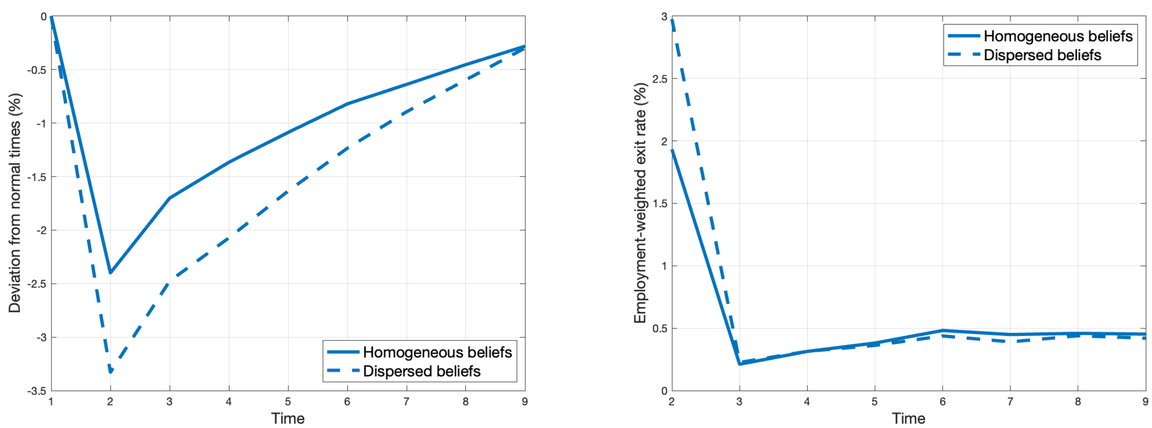
Figure 17: Beliefs and employment decisions

Notes — The figure illustrates the dependence of employment adjustment and exit on the perceived serial correlation of the Covid-19 shock.

expectations about the duration of the shock for aggregate dynamics. We do not rely on the survey expectations directly for two reasons. First, the survey elicits expectations about the duration of the lockdown in spring 2020 instead of the recession induced by the Covid-19 shock. And second, the survey elicits beliefs on a monthly basis while our model is annual. Therefore, there is no direct mapping between the survey responses and firms' expectations about the duration of the "disaster" state in our model. However, we still find it instructive to study whether and how dispersion in firms' expectations matter for aggregate outcomes.

The first exercise illustrates the dependence of firm choices on their beliefs about the persistence of the shocks at the time of the Covid-19 shock.[45] Figure 17 shows the responses in employment adjustment (the fraction of firms adjusting employment) and exit margins to the perceived persistence of the shock. Clearly, there is a critical level of persistence where the response increases rather quickly. This is quite apparent on the exit margin where at $\pi_{dd} = 0.95$, the exit rate goes from near 0.03% to about 0.08%. The fraction of firms exiting increases with the persistence of the shock. This is sensible given that exit is a forward looking decision that depends on the probability distribution of future states. The probability of employment adjustment, however, is not monotone. For high enough values of believed persistence, the likelihood of adjustment falls. One possibility is composition effects: as the exit rate increases with π_{dd}, the remaining firm are less likely to adjust.

For a second exercise we consider an alternative economy with dispersed beliefs that are modeled as a mean-preserving spread around the baseline expectations. Specifically, we assume there are two types of firms in the economy, "optimists" who believe the aggregate disaster state has persistence $\pi_{dd} = 0.93$ and "pessimists" who believe the aggregate disaster state has persistence $\pi_{dd} = 0.99$. To isolate the effect of dispersion rather than more optimistic average beliefs, we assume optimists and pessimists have equal shares in the overall population of firms, $s_{optimists} = s_{pessimists} = 0.5$, such that the average belief coincides with the baseline value.[46]



(a) Employment (b) Employment-weighted Exit Rate

Figure 18: Germany: Homogeneous versus Dispersed Beliefs

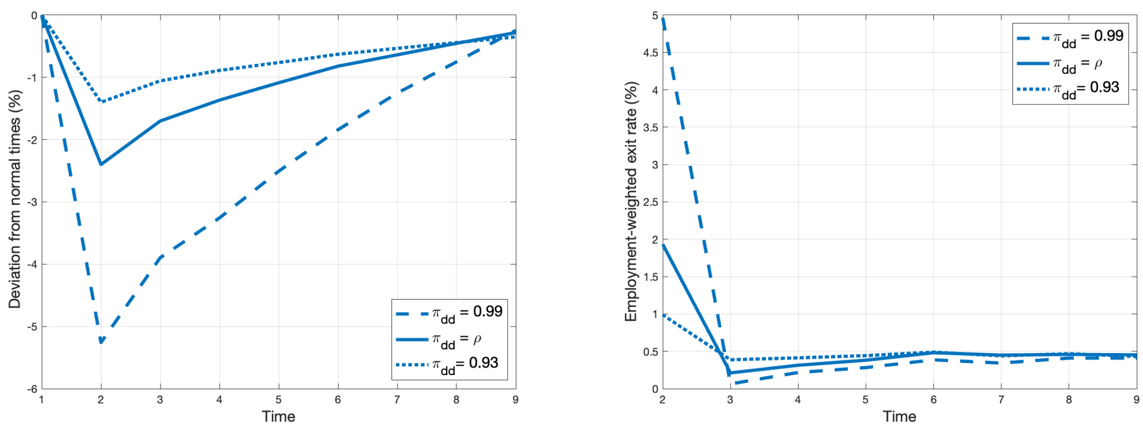
Notes — The figure illustrates employment adjustment and exit in Germany with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).

In Figure 18 we plot aggregate employment and size-weighted exit rates under the two different assumptions about firms' expectations, homogeneous versus dispersed beliefs, in the case of full

[45]These figures come from simulations for Germany.

[46]In this section, we focus on one country, Germany, and report the results for the other countries in the Appendix.

policy support. We find that the dispersion of beliefs matters for our results. This reflects the non-linearity of firms' decision rules with respect to their beliefs about the future aggregate state. Consistent with the empirical evidence of Buchheim, Dovern, Krolage, and Link (2022), we find that more optimistic firms are more likely to "look through" the shock and, hence, to adjust their employment less (see Figure 19).[47] Conversely, more pessimistic firms are more prone to adjust employment. Given the non-linearity of decision rules, employment decisions of pessimistic firms have a stronger influence on aggregate outcomes than employment decisions by relatively more optimistic firms (see Figure 18).



(a) Employment

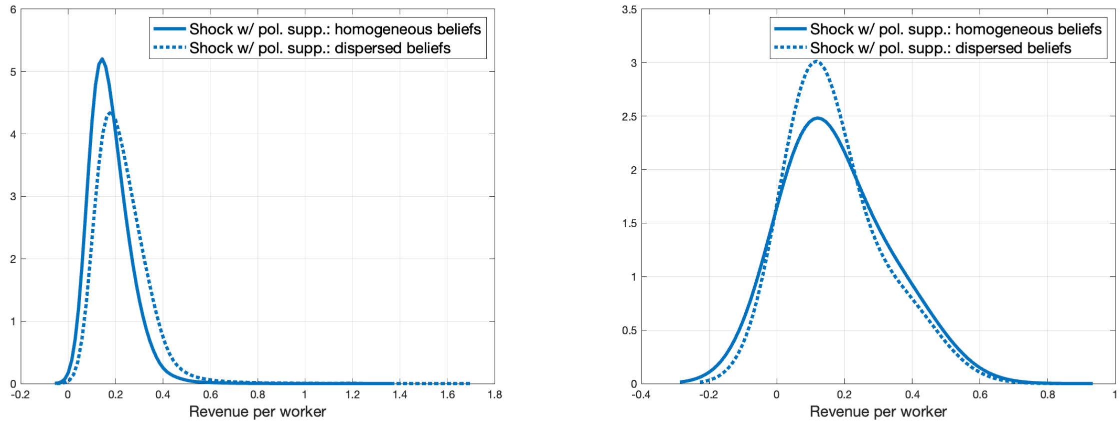
(b) Employment-weighted Exit Rate

Figure 19: Germany: Optimists versus Pessimists

Notes — The figure illustrates employment adjustment and exit in Germany for optimists and pessimists concerning the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).

Figure 20 plots the distribution of output per worker across surviving and exiting firms in the baseline of homogeneous beliefs and the economy with dispersed beliefs. Dispersion in beliefs has a rather small effect on the productivity distribution of both surviving and exiting firms. This is also reflected in the comparison of aggregate productivity measures across the two economies in Table 14.

[47]Figure 19 plots the employment and exit responses in economies populated entirely with one of the three types.



(a) Surviving firms

(b) Exiting firms

Figure 20: Germany: Productivity Distribution with Homogeneous vs. Dispersed Beliefs

Notes — The figure illustrates the distributions of revenue per worker for surviving and exiting firms with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock.

Table 14: Productivity measures

		Normal times		Shock		Shock + policy support	
		Homogeneous	Dispersed	Homogeneous	Dispersed	Homogeneous	Dispersed
Germany	APL	0.211	0.211	0.169	0.170	0.168	0.169
	Std	0.098	0.098	0.079	0.078	0.079	0.079

Notes — The table shows the aggregate productivity implications of dispersion in beliefs in normal times, during the period of the shock absent any policy support, and during the period of the shock when policy support is activated. Homogeneous beliefs refers to the baseline economy. Dispersed beliefs refers to the economy described in section 7.2.

8 Conclusion

This paper explores the effects of the Covid-19 shock on manufacturing firms in four European countries. It does so through the lens of responsiveness: the extent to which employment adjustment responds to variations in profitability at the firm level.

We first document pre-existing differences across European firms in the intensity of firm employment responses to unanticipated changes in their profitability. Part of these differences reflect the cross-country heterogeneity in the magnitudes of labor adjustment costs. We then argue that these responsiveness measures are key to understand the different effects of the Covid-19 shock on aggregate employment and productivity in Europe. We do so through a quantitative firm dynamics model with endogenous exit and non-convex labor adjustment costs. The model is brought to the data through a simulated method of moments exercise in which the responsiveness coefficients are used as moments to identify the model's structural parameters. The estimation isolates differences across countries in market power, adjustment costs and the stochastic processes for the shocks.

Using the estimated model, we then study the effects of the Covid-19 shock and related labor market policy interventions. To that end, we use our model to calculate the effect the Covid-19 shock would have had on aggregate employment, absent any policy intervention. In terms of labor market interventions, our simulations suggest that the policies, in particular work-retention schemes, can be successful in preventing the large drop in employment that would have arisen in their absence, without major negative effect on factor allocation. We also show that the firing restrictions, if not coupled with a wage subsidy, would generate even more job destruction since firms in distress that are not able to fire would decide to exit the market. Though aggregate investment responds to the adverse shock, the policies have little effect on capital accumulation.

In additional policy experiments, we highlight the importance of being able to target policies towards firms that would have otherwise destroyed jobs through a contraction of employment or exit. Though still effective, untargeted policies offset less of the adverse effects of the shock. We, furthermore, discuss the role of firms' beliefs about the persistence of the aggregate shock. We show that "pessimistic" firms are more likely to adjust employment than relatively more "optimistic" firms. The dispersion of beliefs across firms, hence, has important implications for the response of aggregate employment to the Covid-19 shock.

Finally, we also show that the aggregate shock and related policy interventions have consequences for aggregate productivity and affect factor allocation across firms. The presence of large labor adjustment costs, which lead to inefficient allocation of resources even absent an exogenous shock, amplify the negative productivity consequences of the aggregate shock as captured by the distribution of revenues per worker. While our simulations suggest that aggregate productivity falls during the Covid-19 recession, we do not find strong effects of policy interventions on aggregate productivity or the extent of factor misallocation.

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Appendix

The Appendix contains additional estimation exercises as well as results for countries not reported in the text.

A Further Estimation

This section presents two additional estimation exercises. One uses a weighting matrix and the other calibrates rather than estimates the curvature of the revenue function.

A.1 Weighting Matrix

Here we present the results for estimation of the model with the optimal weighting matrix as described in the main text.

Table A.1: Moments: Weighting Matrix

		Revenue Function			Responsiveness			Exit	£
		$\tilde{\alpha}$	$\tilde{\rho}$	$\tilde{\sigma}_\eta$	β_1^{int}	β_2^{int}	β_1^{ext}	ξ	
France	Data	1.040	0.920	0.301	0.343	0.255	-0.005	0.698	
	Model	1.030	0.899	0.301	0.335	0.160	-0.083	0.433	284.595
Germany	Data	1.012	0.926	0.299	0.168	0.053	0.021	0.210	
	Model	0.988	0.923	0.298	0.177	0.009	-0.017	0.000	180.914
Italy	Data	1.042	0.870	0.365	0.242	0.022	0.002	0.882	
	Model	0.807	0.844	0.365	0.226	-0.090	0.030	0.255	1016.478
Spain	Data	1.091	0.885	0.352	0.300	0.054	0.019	1.442	
	Model	1.128	0.877	0.351	0.327	-0.075	0.012	0.000	1416.111

Notes — The moments here are: $\tilde{\alpha}$ = curvature of revenue function estimated via OLS, $\tilde{\rho}$ = persistence of idiosyncratic profitability shock obtained from the OLS revenue function estimation and assuming that idiosyncratic profitability shocks evolve according to an AR(1), $\tilde{\sigma}_\eta$ = standard deviation of profitability innovations η, $(\beta_1^{int}, \beta_2^{int}, \beta_1^{ext})$ = responsiveness regression coefficients, ξ = employment-weighted exit rate. "£" refers to the minimum distance between data and simulated moments achieved in the estimation.

A.2 Calibrated Curvature

Here we present the results for estimation of the model with the externally calibrated value for the curvature of the revenue function α as described in the main text.

A.3 Adding Exogenous Exit

To address the issue that moments estimated on the simulated data are subject to attrition bias coming from endogenous exit choices, we evaluate how moments change in an alternative model with both endogenous and exogenous exit. In this alternative framework when we simulate the

Table A.2: Parameters: Weighting Matrix

Country	Parameters						
	ν	F_p	F_m	α	ρ	σ	Γ
France	3.622	0.431	0.041	0.569	0.965	1.098	0.110
Germany	2.666	0.303	0.060	0.323	0.942	0.872	0.097
Italy	3.607	0.429	0.114	0.471	0.869	0.743	0.321
Spain	3.057	0.442	0.350	0.390	0.898	0.797	0.041

Notes — The parameters here are: ν = quadratic adjustment cost, (F_p, F_m) = fixed hiring and firing costs, (α, ρ, σ) = curvature of revenue functions, serial correlation of profitability shocks and the standard deviation of the innovation to profitability shocks. Γ denotes the fixed operating costs.

Table A.3: Moments: Calibrated Curvature

		Revenue Function			Responsiveness			Exit	£
		$\tilde{\alpha}$	$\tilde{\rho}$	$\tilde{\sigma}_\eta$	β_1^{int}	β_2^{int}	β_1^{ext}	ξ	
France	Data	1.040	0.920	0.301	0.343	0.255	-0.005	0.698	
	Model	0.896	0.895	0.173	0.222	0.032	-0.005	0.476	1.190
Germany	Data	1.012	0.926	0.299	0.168	0.053	0.021	0.210	
	Model	0.873	0.913	0.105	0.353	0.062	0.024	0.647	6.037
Italy	Data	1.042	0.870	0.365	0.242	0.022	0.002	0.882	
	Model	1.003	0.802	0.242	0.442	-0.060	0.000	1.526	16.092
Spain	Data	1.091	0.885	0.352	0.300	0.054	0.019	1.442	
	Model	1.025	0.838	0.189	0.602	0.051	0.018	1.609	1.257

Notes — The moments here are: $\tilde{\alpha}$ = OLS estimate of curvature of revenue function, $\tilde{\rho}$ = persistence of idiosyncratic profitability shock obtained from the OLS revenue function estimation and assuming that idiosyncratic profitability shocks evolve according to an AR(1), $\tilde{\sigma}_\eta$ = standard deviation of profitability innovations η, $(\beta_1^{int}, \beta_2^{int}, \beta_1^{ext})$ = responsiveness regression coefficients, ξ = employment-weighted exit rate. "£" refers to the minimum distance between data and simulated moments achieved in the estimation.

Table A.4: Parameters: Calibrated Curvature

Country	Parameters						
	ν	F_P	F_M	α	ρ	σ	Γ
France	4.792	0.122	0.019	0.518	0.959	0.594	0.238
Germany	5.557	0.262	0.019	0.727	0.981	0.508	0.181
Italy	5.416	0.319	0.031	0.830	0.858	0.478	0.015
Spain	4.300	0.195	0.027	0.771	0.947	0.578	0.135

Notes — The parameters here are: ν = quadratic adjustment cost, (F_P, F_M) = fixed hiring and firing costs, (α, ρ, σ) = calibrated curvature of revenue functions, serial correlation of profitability shocks and the standard deviation of the innovation to profitability shocks. Γ denotes the fixed operating costs.

model we allow for an exogenous probability p that firms in any given time period can be hit by an exit shock. We calibrate the probability p such that in our simulated data the correlation between productivity shocks and exit is close to zero, as in the Orbis data (it is -0.2 in the baseline model). Below we compare the moments of our baseline economy to this alternative framework.

Table A.5: Moments

		Revenue Function			Responsiveness			Exit	£
		$\tilde{\alpha}$	$\tilde{\rho}$	$\tilde{\sigma}_\eta$	β_1^{int}	β_2^{int}	β_1^{ext}	ξ	
Germany	Data	1.012	0.926	0.299	0.168	0.053	0.021	0.210	
	Baseline	0.808	0.928	0.144	0.209	0.047	0.019	0.386	1.089
	With exogenous exit	0.809	0.928	0.143	0.208	0.049	0.013	0.386	1.203

Notes — The moments here are: $\tilde{\alpha}$ = curvature of revenue function estimated via OLS, $\tilde{\rho}$ = persistence of idiosyncratic profitability shock obtained from the OLS revenue function estimation and assuming that idiosyncratic profitability shocks evolve according to an AR(1), $\tilde{\sigma}_\eta$ = standard deviation of profitability innovations η, $(\beta_1^{int}, \beta_2^{int}, \beta_1^{ext})$ = responsiveness regression coefficients, ξ = employment-weighted exit rate. "£" refers to the minimized distance between data and simulated moments achieved in the estimation.

B Responsiveness Across Countries

Table B.1 illustrates the effects of replacing German with French and Spanish parameters.

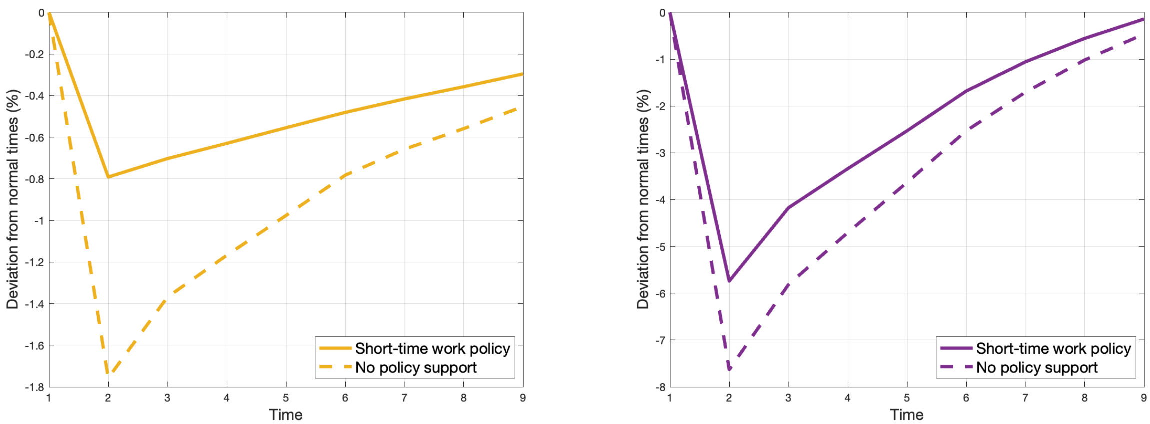
Table B.1: Replacement of German with French and Spanish Parameters

	Baseline (Germany)	Curvature (α)	Adj. costs (ν, F_m, F_p)	Stoch. process (ρ, σ)
France				
Responsiveness coefficient adjusters (β^{int})	0.209	0.208	0.205	0.189
Responsiveness coefficient adjusters (β_2^{int})	0.047	0.047	0.033	-0.034
Responsiveness coefficient extensive margin (β^{ext})	0.019	0.019	-0.030	0.084
Size-weighted exit rate (ξ)	0.386	0.386	0.313	0.519
Curvature revenue function ($\tilde{\alpha}$)	0.808	0.808	0.922	0.796
Autoregressive coefficient ($\tilde{\rho}$)	0.928	0.928	0.917	0.919
Standard deviation innovation ($\tilde{\sigma}$)	0.144	0.144	0.144	0.172
Stat. Value	1.089	1.089	6.722	14.039
Spain				
Responsiveness coefficient adjusters (β^{int})	0.209	0.210	0.231	0.204
Responsiveness coefficient adjusters (β_2^{int})	0.047	0.014	0.018	-0.001
Responsiveness coefficient extensive margin (β^{ext})	0.019	0.035	-0.024	0.032
Size-weighted exit rate (ξ)	0.386	0.484	0.319	0.453
Curvature revenue function ($\tilde{\alpha}$)	0.808	0.817	0.900	0.811
Autoregressive coefficient ($\tilde{\rho}$)	0.928	0.922	0.918	0.926
Standard deviation innovation ($\tilde{\sigma}$)	0.144	0.143	0.144	0.151
Stat. Value	1.089	3.079	5.775	3.006

Notes — This table shows the moments from replacing German with French and Spanish parameters, respectively, with each change studied independently, not cumulatively.

C Evaluating the Impact of Policy Interventions

This section compares the employment response with and without policy intervention for France and Spain.



(a) France

(b) Spain

Figure C.1: Employment Responses

Notes — The figure shows employment responses in France and Spain (with and without policy support). These responses are measured as percent deviations from normal times.

Table C.1: Employment-weighted exit rates

	France	Spain
Normal times	0.463	0.875
Shock with full policy support	0.538	4.662
Shock with only short-time work policy	0.538	4.662
Shock with only 'No-firing' policy	–	–
Shock without policy support	1.410	6.276

Note—This table summarizes the effect of the policy support on employment losses (in percentage points) due to exit.

D Alternative Employment Response

Table D.1: Employment Response: Alternative Estimation

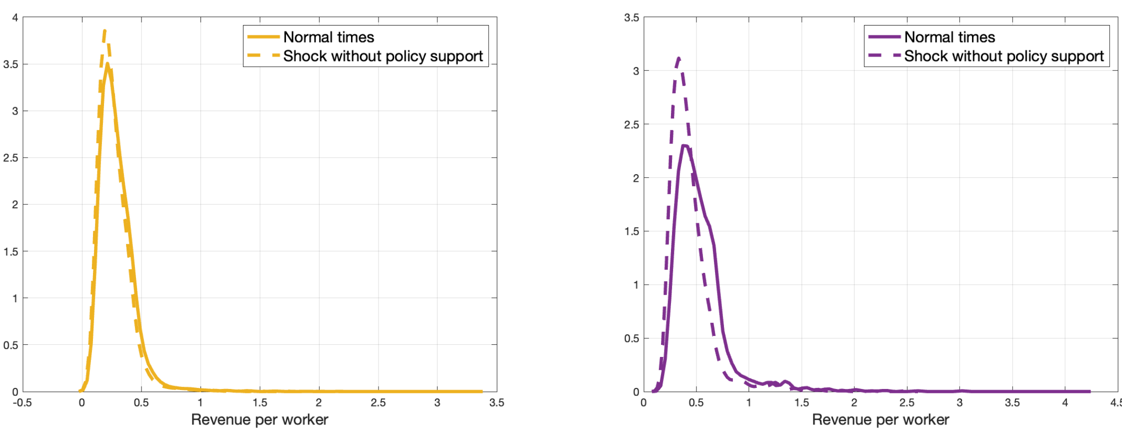
		Baseline	W	α
Germany	Shock w/ policy support	-2.400	-2.400	-2.400
	Shock w/o policy support	-3.714	-3.008	-3.148
Italy	Shock w/ policy support	-1.154	-1.154	-1.154
	Shock w/o policy support	-2.320	-1.731	-4.131

Notes — This table computes the employment response as percent deviations from the baseline during the period of the Covid-19 shock to two alternative parameterizations for Germany and Italy. The column denoted "W" using the estimates from a weighting matrix and the column denoted "α" is based on calibrated rather than estimated values of the curvature parameter. Here λ changes with the alternative estimates so that the employment with policy support remains essentailly the same as the baseline.

E Productivity Implications

This section shows productivity responses at the firm level and in the aggregate for France and Spain.

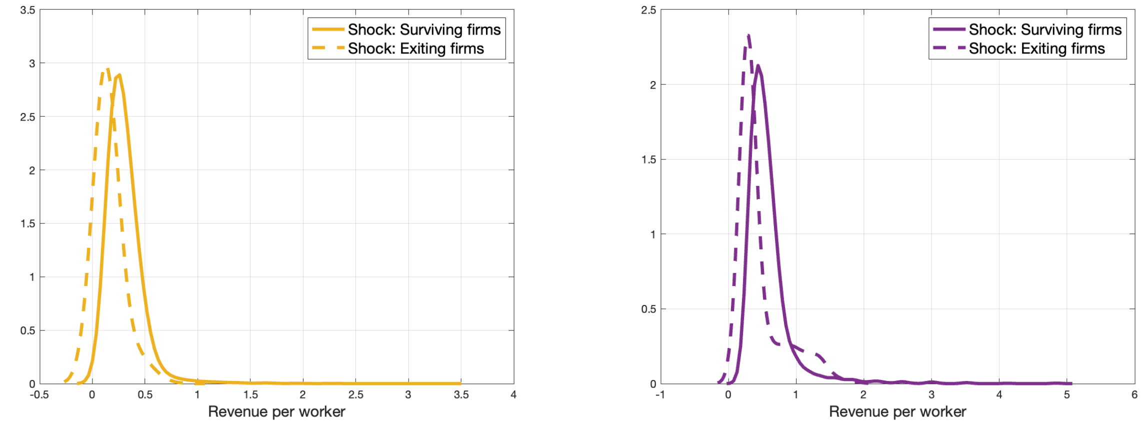
E.1 Firm Level Responses: Productivity Distributions



(a) France (b) Spain

Figure E.1: Surviving firms during shock period with no policy support

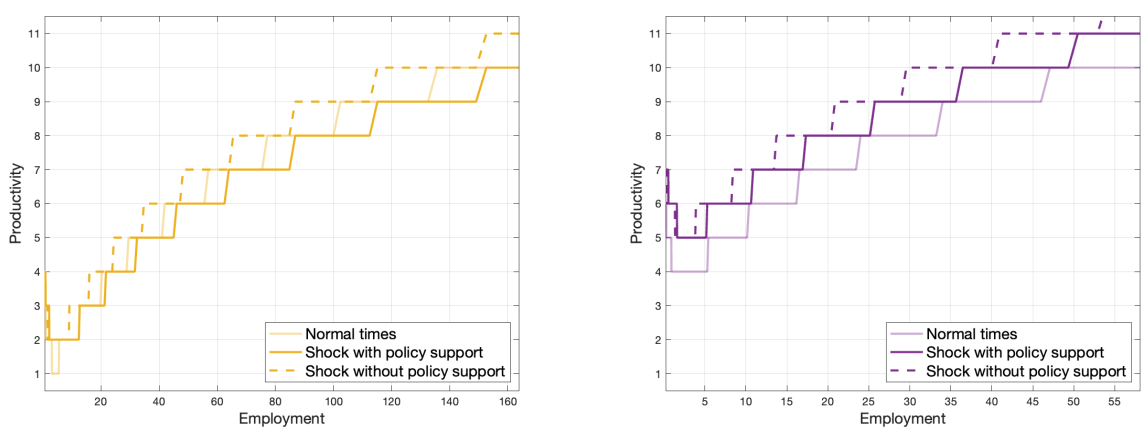
Notes — The figure shows the distributions of revenue per worker in France and Spain in normal times and with the Covid-19 shock but without policy interventions.



(a) France (b) Spain

Figure E.2: Exiting vs surviving firms in shock period

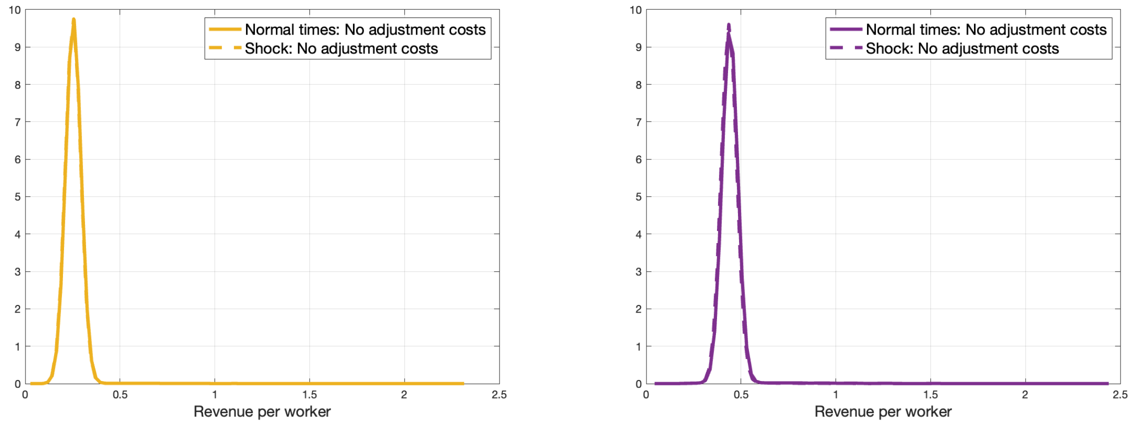
Notes — The figure shows the distributions of revenue per worker in France and Spain, comparing surviving and exiting firms in the period of the Covid-19 shock without policy interventions.



(a) France (b) Spain

Figure E.3: Productivity threshold of exit

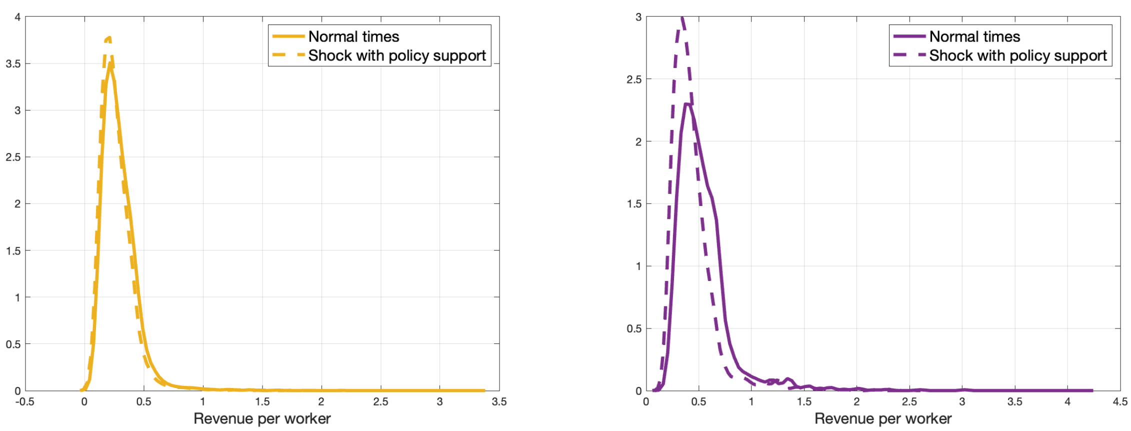
Notes — For each country, this figure displays the critical level of productivity below which a firm with a given level of employment decides to exit.



(a) France (b) Spain

Figure E.4: Surviving firms normal vs shock period with no adjustment costs

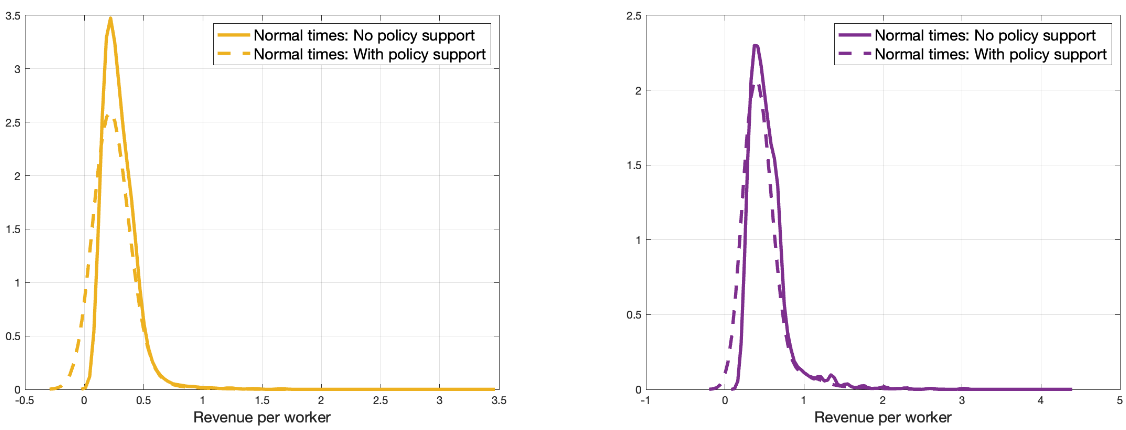
Notes — The figure shows the distributions of revenue per worker in France and Spain in normal times and with the Covid-19 shock without adjustment costs.



(a) France (b) Spain

Figure E.5: Surviving firms normal vs shock period with policy support

Notes — The figure shows the distributions of revenue per worker in France and Spain for surviving firms in normal times and with the Covid-19 shock with policy interventions.



(a) Germany (b) Italy

Figure E.6: Surviving firms in normal times with policy support

Notes — The figure shows the distributions of revenue per worker in France and Spain in normal times with and without policy interventions.

E.2 Aggregate Productivity

Table E.1: Productivity measures

		Normal times	Shock	Shock + targeted pol. supp.	Shock + untargeted pol. supp
France	APL	0.283	0.258	0.257	0.258
	Std	0.151	0.138	0.139	0.137
Spain	APL	0.491	0.400	0.395	0.397
	Std	0.263	0.214	0.215	0.214

Notes — This table summarizes aggregate productivity through the average revenue per worker (APL) and the standard deviation of the average revenue product, (Std). These measures are for normal and crisis times with and without targeted policy interventions.

F Capital Implications

The static choice of capital is given by this optimization problem:

$$R(A,e) = max_k R(A,e,k) - rk$$

where r is the rental rate on capital. The outcome depends on the state of profitability and employment, (A,e). The first-order condition is simply $R_k(A,e,k) = r$. If the inverse demand curve has an elasticity of $-\eta$, then revenue can be written as

$$R(A,e,k) = q^{(1-\eta)}$$

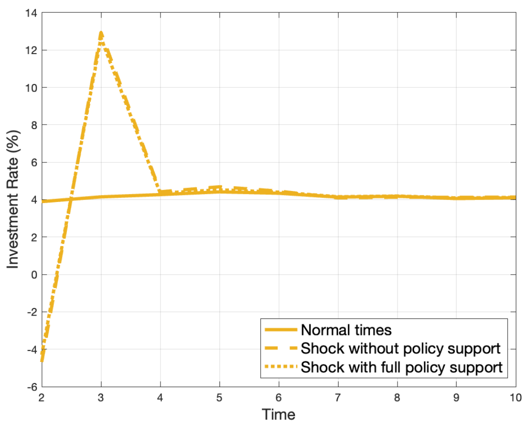
where

$$q = Ak^{\gamma}e^{\zeta}.$$

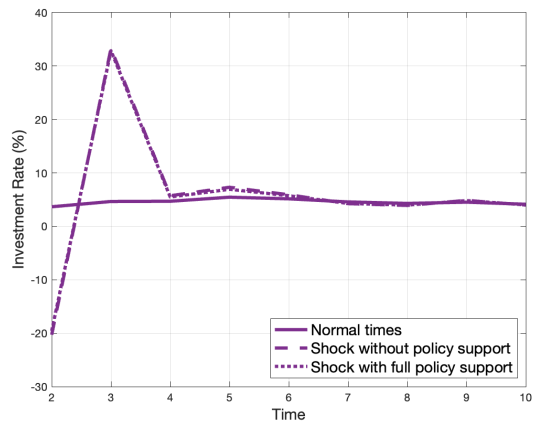
From this:

$$k = \frac{r}{\tilde{\gamma}A^{1-\eta}e^{\tilde{\zeta}}}^{\frac{1}{\tilde{\gamma}-1}}$$

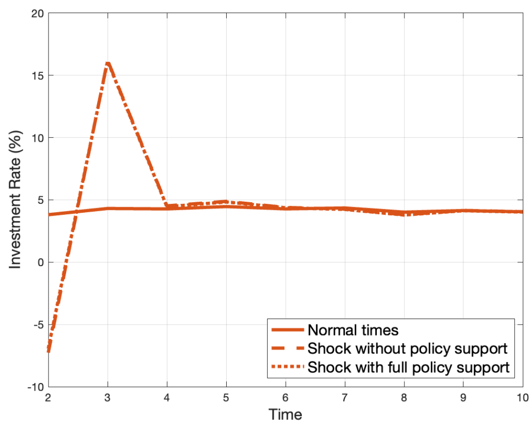
where $\tilde{\gamma} = \gamma(1-\eta)$ and $\tilde{\zeta} = \zeta(1-\eta)$. The parameterization is discussed in the text. The investment rate is independent of r.



(a) France



(b) Spain



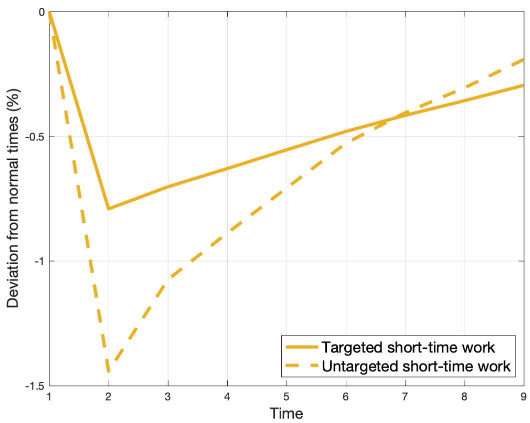
(c) Italy

Figure F.1: Investment Rates

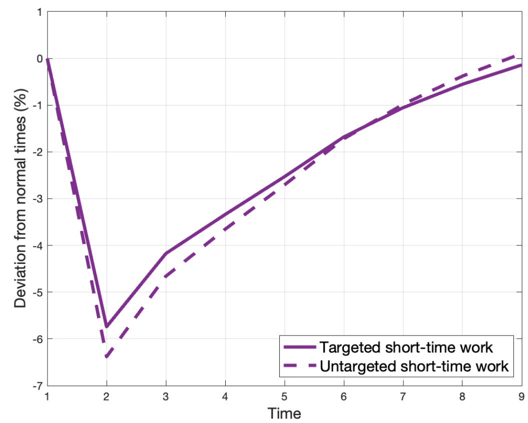
Notes — The figure shows the aggregate gross investment rates (in percent) for France and Spain with and without policy interventions.

G Additional Policy Experiments

G.1 The Importance of Targeted Policies



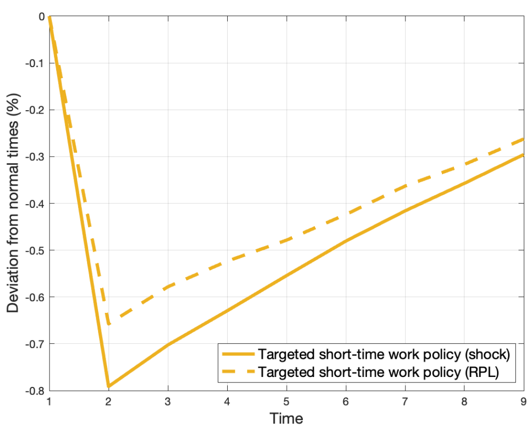
(a) France



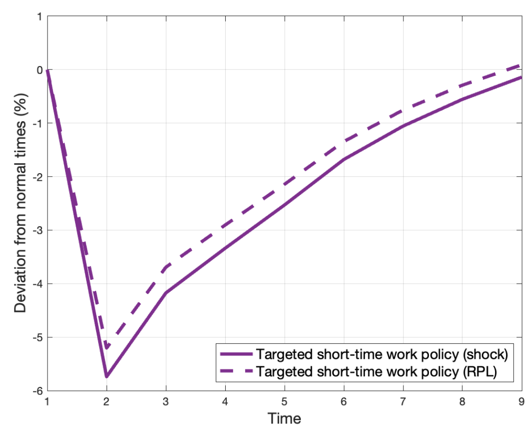
(b) Spain

Figure G.1: Employment Response: Untargeted support

Notes — The figure shows the employment response in France and Spain, comparing targeted and untargeted policy interventions. These responses are measured as percent deviations from normal times.



(a) France

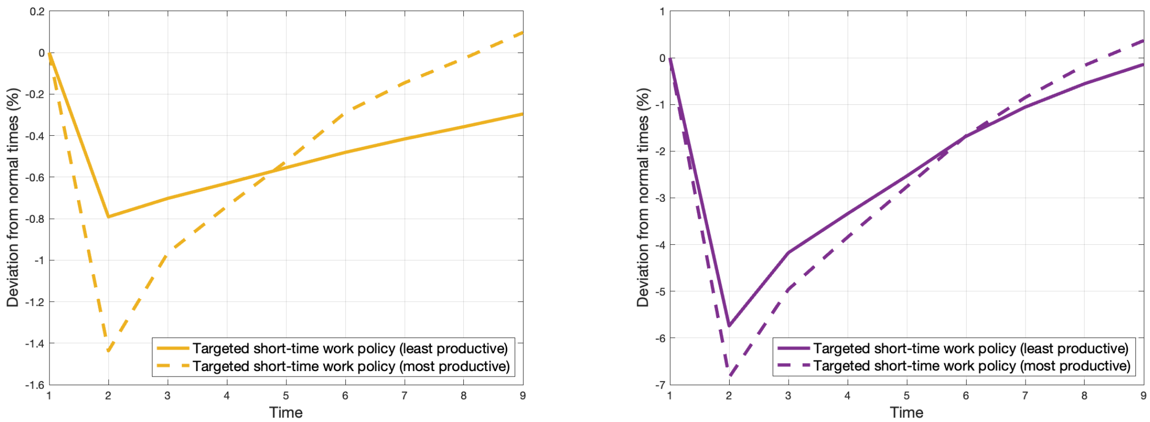


(b) Spain

Figure G.2: Employment Response: Targeted support based on Revenue per Worker

Notes — The figure shows the employment response in France and Spain, comparing interventions with targets based on profitability compared to revenue per worker. These responses are measured as percent deviations from normal times.

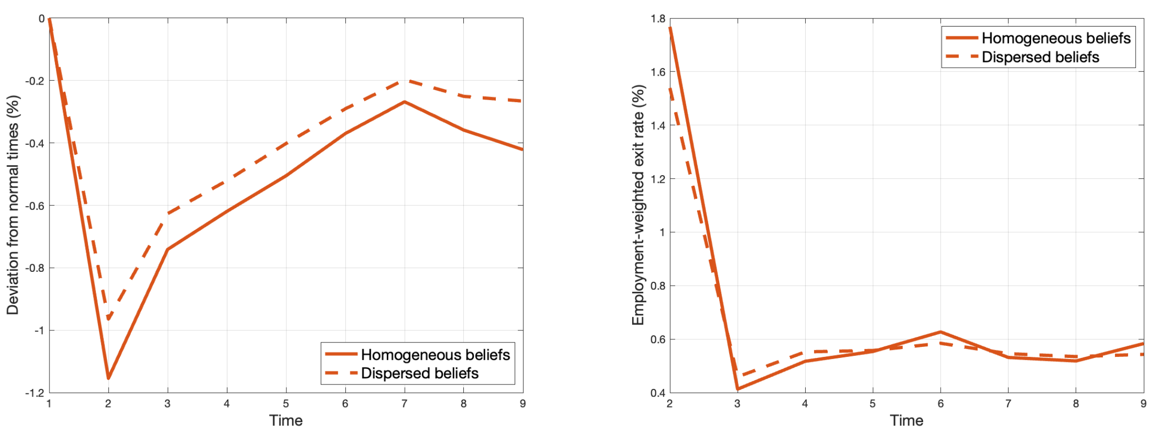
G.2 The Role of Heterogenous Beliefs



(a) France (b) Spain

Figure G.3: Employment Response: Targeted support to most profitable firms

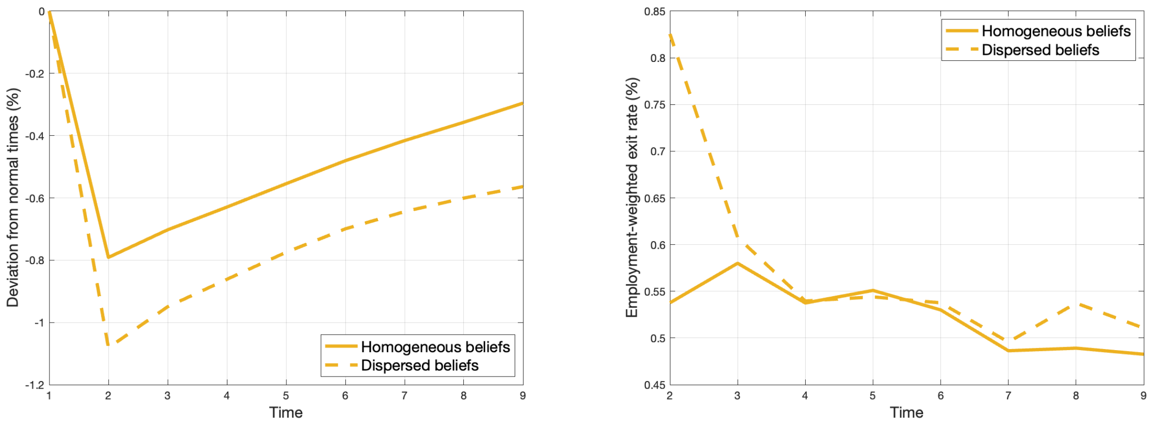
Notes — The figure shows the employment response in France and Spain, comparing interventions with targets based on least profitability compared to most profitable firms. These responses are measured as percent deviations from normal times.



(a) Employment (b) Employment-weighted Exit Rate

Figure G.4: Italy: Homogeneous versus Dispersed beliefs

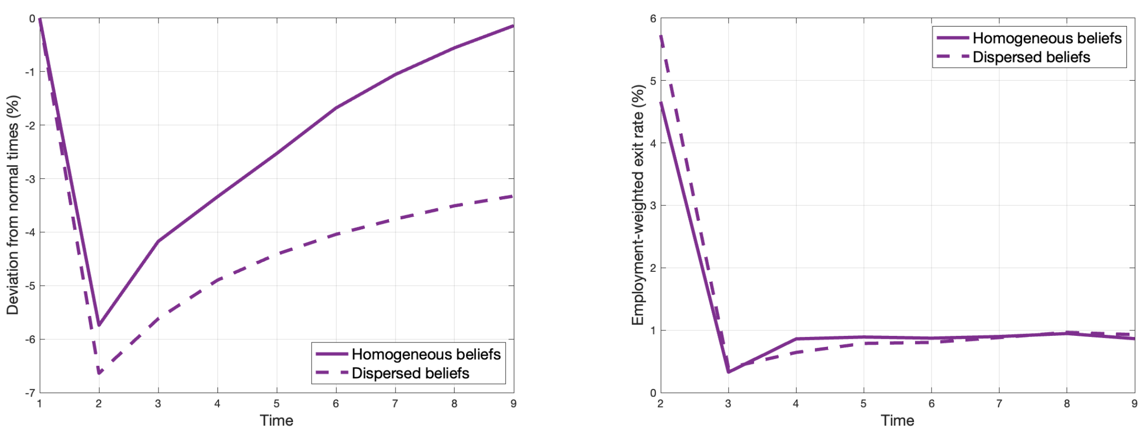
Notes — The figure illustrates employment adjustment and exit in Italy with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).



(a) Employment (b) Employment-weighted Exit Rate

Figure G.5: France: Homogeneous versus Dispersed beliefs

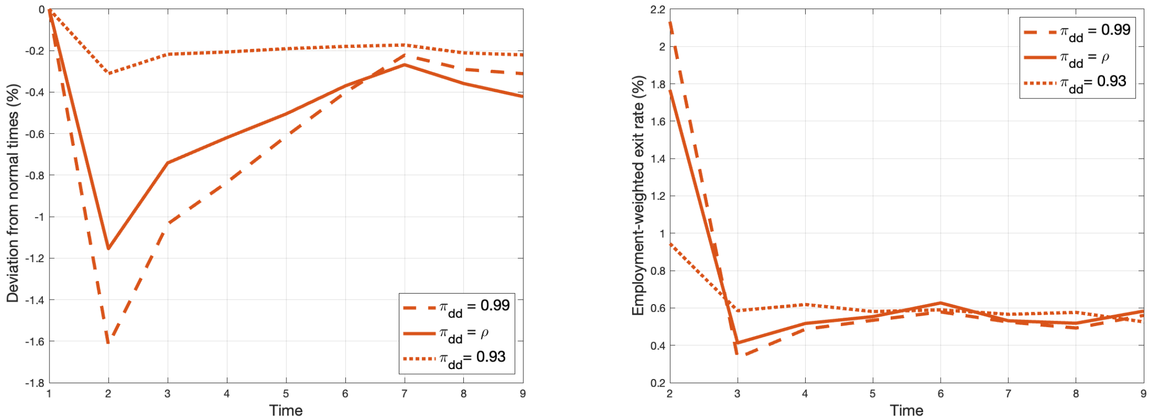
Notes — The figure illustrates employment adjustment and exit in France with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).



(a) Employment (b) Employment-weighted Exit Rate

Figure G.6: Spain: Homogeneous versus Dispersed beliefs

Notes — The figure illustrates employment adjustment and exit in Spain with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).

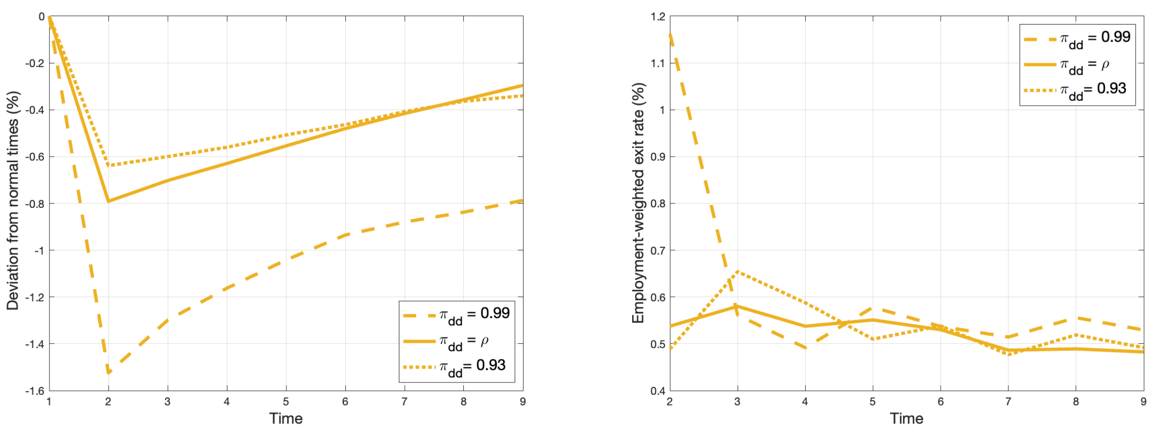


(a) Employment

(b) Employment-weighted Exit Rate

Figure G.7: Italy: Optimists versus Pessimists

Notes — The figure illustrates employment adjustment and exit in Italy for optimists and pessimists concerning the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).

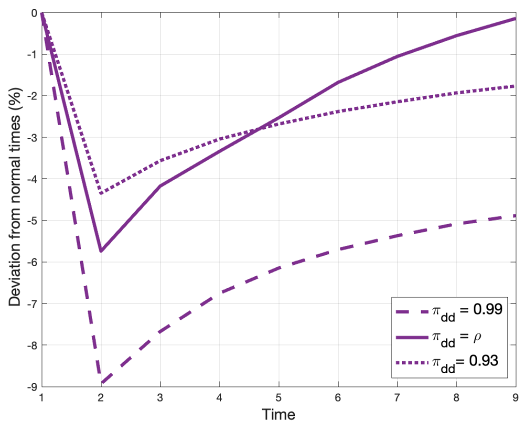


(a) Employment

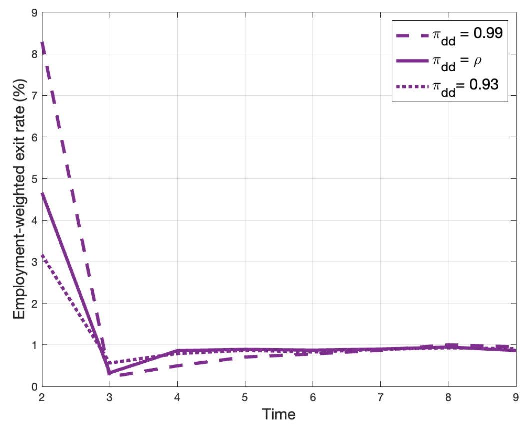
(b) Employment-weighted Exit Rate

Figure G.8: France: Optimists versus Pessimists

Notes — The figure illustrates employment adjustment and exit in France for optimists and pessimists concerning the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).



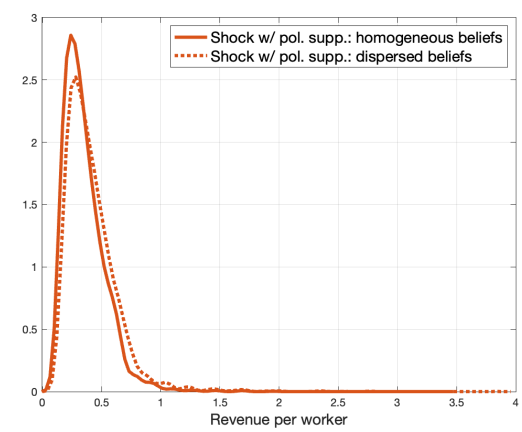
(a) Employment



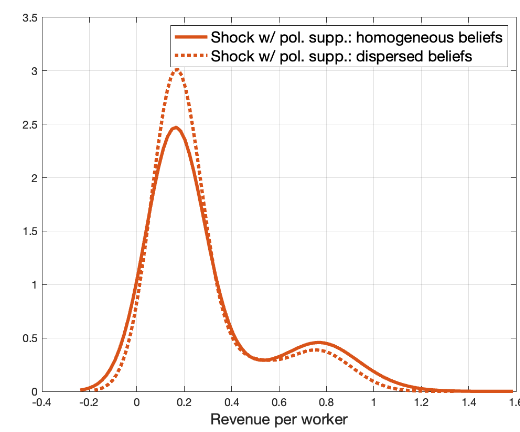
(b) Employment-weighted Exit Rate

Figure G.9: Spain: Optimists versus Pessimists

Notes — The figure illustrates employment adjustment and exit in Spain for optimists and pessimists concerning the perceived serial correlation of the Covid-19 shock. These responses are measured as percent deviations from normal times (left panel) and as percentages (right panel).



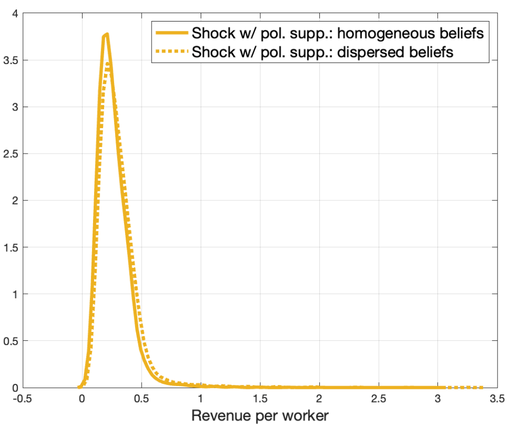
(a) Surviving firms



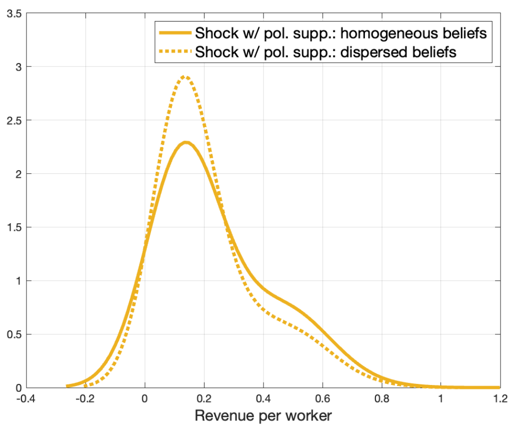
(b) Exiting firms

Figure G.10: Italy: Productivity Distribution with Homogeneous vs. Dispersed Beliefs

Notes — The figure illustrates the distributions of revenue per worker for surviving and exiting firms with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock.



(a) Surviving firms

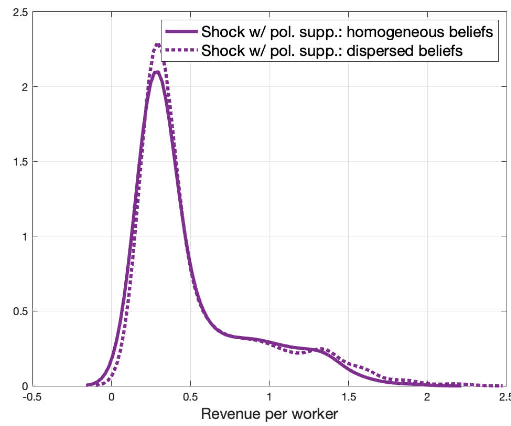


(b) Exiting firms

Figure G.11: France: Productivity Distribution with Homogeneous vs. Dispersed Beliefs

Notes — The figure illustrates the distributions of revenue per worker for surviving and exiting firms with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock.

(a) Surviving firms



(b) Exiting firms

Figure G.12: Spain: Productivity Distribution with Homogeneous vs. Dispersed Beliefs

Notes — The figure illustrates the distributions of revenue per worker for surviving and exiting firms with homogeneous and dispersed beliefs about the perceived serial correlation of the Covid-19 shock.

Table G.1: Productivity measures

		Normal times		Shock		Shock + policy support	
		Homogeneous	Dispersed	Homogeneous	Dispersed	Homogeneous	Dispersed
Italy	APL	0.384	0.384	0.339	0.339	0.336	0.336
	Std	0.201	0.197	0.179	0.176	0.179	0.177
France	APL	0.283	0.283	0.258	0.258	0.257	0.257
	Std	0.151	0.154	0.138	0.137	0.139	0.137
Spain	APL	0.491	0.492	0.400	0.403	0.395	0.397
	Std	0.263	0.265	0.214	0.213	0.215	0.212

Notes — The table shows the aggregate productivity implications of dispersion in beliefs in normal times, during the period of the shock absent any policy support, and during the period of the shock when policy support is activated. Homogeneous beliefs refers to the baseline economy. Dispersed beliefs refers to the economy described in section 7.2.

H Parameterizing the Covid Shock and Interventions

These are the notes that underlie the entries in Table 8. Data for both "Fraction STW (%)" and "Hours sharing (%)" are collected from country-specific sources.

- Germany

  Federal Employment Agency ("Bundesagentur für Arbeit") monthly short-time work statistics. "Hours sharing (%) is calculated as the ratio of the full-time equivalent number of workers in short-time work to the number of workers in short-time work. "Fraction STW (%)" is the monthly number of firms using short-time work averaged over the year 2020 relative to the total number of firms in the manufacturing sector in 2019. The total number of firms comes from Eurostat's Structural Business Statistics, Business Demography Table (online data code: BD_9BD_SZ_CL_R2).

- Italy

  National Statistical Agency (ISTAT). "Fraction STW (%) is collected from the statistical appendix of the first and second edition of the report "Situazione e prospettive delle imprese nell'emergenza sanitaria Covid-19" (`https://www.istat.it/it/archivio/244378` and `https://www.istat.it/it/archivio/251618`, respectively). We use the variable "Utilizzo della Cassa Integrazione Guadagni" in percent and construct a weighted-average of the reporting periods. "Hours sharing (%) comes from the table "Overtime hours and short-time work allowance" from ISTAT's data for short-term economic analysis in Italy (`https://dati-congiuntura.istat.it`). Due to a lack of more granular data, the reported number refers to the total industry excluding construction, i.e. NACE Rev. 2 codes B-E.

- Spain

  National Statiscal Agency (INE). "Fraction STW (%)" comes from the "Notas de prensa" (`https://www.ine.es/daco/daco42/ice/ice_mod_covid_0121.pdf`), p.4. "Hours sharing (%)" is not available for Spain. We, therefore, use the average across the other three countries.

- France

  Directorate for Research, Studies and Statistics (DARES) of the Ministry of Labour, Social Relations, Family and Solidarity (`https://dares.travail-emploi.gouv.fr/donnees/le-chomage-partiel`). "Hours sharing (%) is calculated as the ratio of the full-time equivalent number of workers in short-time work ("ETP en DI") to the number of workers in short-time work ("Effectif en DI"). We average the available monthly data for March 2020 to December 2020. "Fraction STW (%) is calculated as the average number of establishments filing at least one request for STW ("Nombre en DI") relative to the total number of firms in the manufacturing sector in 2019. The total number of firms comes from Eurostat's Structural Business Statistics, Business Demography Table (online data code: BD_9BD_SZ_CL_R2).