Reallocation and Learning over the Business Cycle *

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Abstract

This paper shows how cyclical aggregate shocks can stimulate structural reallocation activities, which in turn amplify the effect of the shock. It analyses the *informational aspects* of restructuring activities and their interplay with aggregate shocks. A model is developed in which production units are uncertain about the value of staying in the market and learn about it over time in a Bayesian fashion. In addition to their own private assessment, they can also learn from observing other units' decisions. Given that adjusting is costly, each unit has an incentive to delay action and wait for other players to act in order to make a better informed decision. If delay is more costly in a downturn, a negative aggregate shock can break the inertia and induce the most pessimistic agents to exit. The information released by such actions will induce more action, thus generating a burst in restructuring activities that reinforces the initial effect of the aggregate shock. This process of information accumulation and revelation offers both a powerful amplification mechanism of relatively modest aggregate shocks and a potential explanation of why restructuring tends to be concentrated in recessions.

Keywords: Aggregate fluctuations; Amplification; Job destruction; Strategic learning.
JEL classification numbers: E32, D83, L16, J65, C73.

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1 Introduction

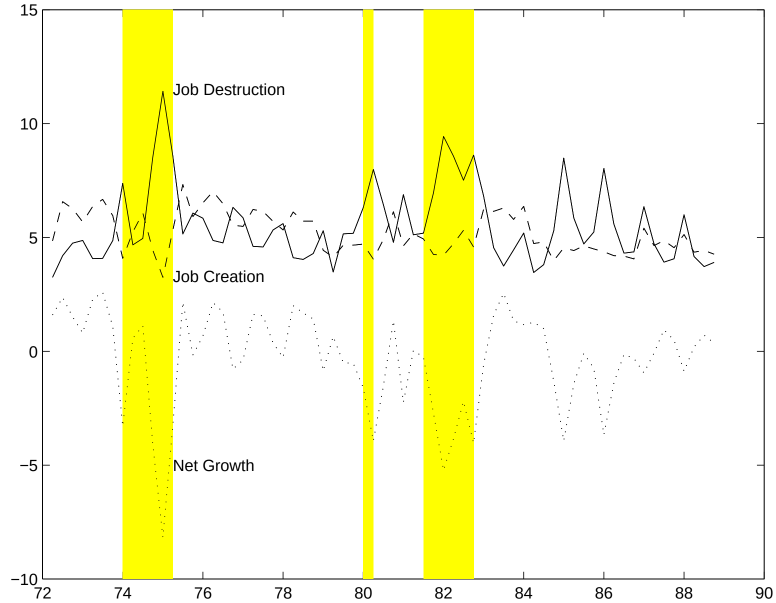
A substantial body of recent empirical work has challenged the traditional neoclassical view of the business cycle. On one side, the empirical literature on aggregate fluctuations has been unsuccessful in identifying impulses that can account for the large variations in macroeconomic time series over the cycle (Cochrane (1994)). Figure 1 reports Davis-Haltiwanger's quarterly data for job creation, job destruction and employment growth for the period 1972-1988. The prominent features of the figure are the spikes in job destruction, and the corresponding decrease in employment, that characterize the troughs. The lack of obvious large impulses points to the importance of identifying *amplification mechanisms* that can explain such spikes. On the other side, the body of work initiated by Blanchard and Diamond (1990) and Davis and Haltiwanger (1990), based on the analysis of gross flows of workers in and out of unemployment, has suggested that a substantial part of the job destruction that takes place in a recession is related to reallocation of workers from one production unit to another, rather than to cyclical fluctuations in the demand and supply of labor.[1] This observation suggests a powerful amplification mechanism: relatively small aggregate shocks could trigger a process of reallocation activities during a concentrated period of time that amplify the overall effects of the initial shock.

Research on the interrelation between aggregate and allocative shocks,[2] and on their respective roles in generating employment fluctuations, was initiated by Lilien (1982), who showed that during recessions the variance of employment growth rates across sectors increases substantially. Since then, a consensus has emerged that a considerable part of the employment changes taking place in a recession has a structural rather than a cyclical character. Identifying the direction of causality has turned out to be a harder task, as argued, among others, by Loungani (1996): is the reallocation a driving force of aggregate fluctuations or is it that the economy takes advantage of the low level of economic activity to carry out necessary restructuring activities?

[1] See Caballero and Hammour (1994) for a model of "creative destruction" along these lines.

[2] I refer to allocative shocks as shocks that change the long run desired allocation of resources in the economy, and to aggregate shocks as having only a temporary and symmetric impact on all production units.

Figure 1: Net and Gross Job Flow Rates in Manufacturing, 1972:1988



Shaded regions represent recessions.
Source: LRD data.

The quantitative assessment of the role of aggregate and allocative shocks in generating the increase in unemployment in recessions is still an open issue. However, a growing body of literature shows that allocative shocks play an important role in determining the behavior of both net (unemployment) and gross (job creation and job destruction) flows.[3] Indeed, the characterization of the economy that emerges from this literature is one in which heterogeneous units with changing desired employment follow nonlinear adjustment policies that induce large and infrequent downward adjustments, maybe due to the presence of kinked adjustment costs, with a tendency to concentrate such adjustments in recessions. It is important then to understand how the timing and the intensity of reallocation activities interact with aggregate shocks to determine the movements in employment over the business cycle.

I build a model of endogenous revelation of information to explain the sudden increase in job destruction that characterizes a recession. I set up an economy in which production is carried out using different technologies. Production units are divided into subsectors,

[3]Recent studies that address these issues are Caballero, Engel and Haltiwanger (1997), Campbell and Kuttner (1996) and Davis and Haltiwanger (1999).

with all units in a given subsector sharing the same technology. They are uncertain about the efficiency of their technology, and consequently about the optimality of remaining in production, and learn about it over time in a Bayesian fashion, in the spirit of Jovanovic's selection model (1982). Units' assessments are private information, but they can observe the decisions of similar units and infer useful information from that. If shutting down is costly, there is an incentive to wait for somebody else to exit in order to make a better informed decision. As a consequence, the model generates *delay* in adjustments: units tend to postpone costly restructuring activities. In the presence of aggregate shocks, it turns out that the cost of delaying is lower in booms, so that even production units that are quite pessimistic about their prospects might find it preferable to wait; on the contrary, a negative aggregate shock makes delaying more costly, thus prompting the most pessimistic units to act. Once some agents undertake adjustment, the number of liquidations releases information that might induce others to shut down. Aggregate shocks therefore trigger a process of information revelation and actions that speeds up learning and culminates in a large number of units undertaking adjustment in a short period of time. The role of the shocks is not confined to reducing overall productivity: rather, they influence the economy mainly by breaking the inertia that characterizes agents' behavior.

A number of recent papers have studied the problem of information accumulation and endogenous revelation in a strategic context.[4] By studying the connection between aggregate shocks and exit decisions, this paper formally applies the insights of this literature to the explanation of the business cycle. The model builds on Caplin and Leahy's (1994) model of a multi-stage investment project, which is generalized along two dimensions. First, I introduce an aggregate state to account for aggregate shocks; second, I model entry over time, allowing for correlation in the type selection process. These features allow me to study the time series properties of the economy and the concentration effect on exit induced by aggregate shocks.

The paper contributes to two distinct strands of literature. First, by tackling the tech-

[4]For a diverse range of models and applications, see Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992), Caplin and Leahy (1994,1998), Chamley and Gale (1994), Horvath, Schivardi and Woywode (1998), Rob (1991).

nical problems related to the introduction of an aggregate state and of entry with correlated types, it contributes to the theoretical literature on information spillovers. In particular, I show that the second feature makes the model an hybrid of models of simultaneous actions and of sequential actions, and that informational cascades can occur when the correlation of types of different subsectors is above a certain threshold.[5] Second, it offers a new characterization of aggregate shocks as having informational effects which induce restructuring activities, identifying an amplification mechanism coherent with the concentration of reallocation activities in recessions. The model therefore supplies a theoretical framework that can help the empirical analysis on gross job flows and on the role of aggregate and allocative shocks over the business cycle.[6]

Very little work has been done on the empirical relevance of information spillovers, arguably because of the problems connected to the measurement of information flows. Guiso and Schivardi (1999) carry out a first attempt at testing their relevance for firms' labor adjustments. Their results, briefly summarized in Subsection 5.1, are supportive of the theoretical predictions of the paper, both for the relevance of information spillovers and for their role in amplifying aggregate shocks.

The rest of the paper is organized as follows. Section 2 describes the model, and section 3 solves for the equilibrium. Section 4 illustrates the role of aggregate shocks in determining the timing of reallocation activities, while section 5 investigates the implications of the interaction between aggregate shocks and reallocative activity. In a simulation exercise, I show that the model generates concentration of reallocation activities that amplifies the effect of the aggregate shocks. Section 6 contains some concluding remarks.

[5]See Vives (1996) and references therein for a discussion of the conditions required for informational cascades to arise.

[6]For example, Davis and Haltiwanger (1999) draw theoretical restrictions from the model that help to identify the relative roles of aggragate and allocative shocks in driving business cycle fluctuations.

2 The Model

2.1 The Single Production Unit Problem

I start by describing the single production unit problem and introduce the strategic aspects after that. Time is discrete; a production unit is uncertain about the efficiency of its technology and learns about it over time. The unit has to decide whether to remain active or to exit. In every period the unit receives an idiosyncratic profit realization, drawn from a binary random variable $Z = \{z_g, z_b\}$, with $z_g > z_b$.[7] The production unit is one of two types $\{\theta_l, \theta_h\}$ ("high" and "low"), where the type determines the probability of the realizations of the shock. A θ_h production unit is more efficient in the sense that it is more likely to experience the good realization of the idiosyncratic shock:

$$\Pr\{Z = z_g|\theta_l\} < \Pr\{Z = z_g|\theta_h\} \tag{1}$$

At time zero the production unit holds prior beliefs and updates them over time in a Bayesian fashion according to the realizations of Z. Given that the unit can be only one of two types, the prior is the probability assigned to being type θ_l: $\lambda_0 = \Pr\{\theta = \theta_l\}$. Given the discrete nature of the prior distribution, the posterior will also be a discrete distribution: in any period, the unit's beliefs are summarized by a value λ representing the probability assigned to the event $\{\theta = \theta_l\}$. In fact, given n_g good and n_b bad realizations of the productivity shock, Bayes rule gives:[8]

$$\begin{gathered}\lambda(n_g, n_b; \lambda_0) \equiv \Pr\{\theta = \theta_l|n_g, n_b; \lambda_0\} = \\ \frac{\Pr\{z_g|\theta_l\}^{n_g}\Pr\{z_b|\theta_l\}^{n_b}\lambda_0}{\Pr\{z_g|\theta_l\}^{n_g}\Pr\{z_b|\theta_l\}^{n_b}\lambda_0 + \Pr\{z_g|\theta_h\}^{n_g}\Pr\{z_b|\theta_h\}^{n_b}(1-\lambda_0)}\end{gathered} \tag{2}$$

[7] For example, the shock could be the realization of the production costs, with cost being inversely proportional to the realizations of Z.

[8] Formally, given a random sample from a Bernoulli distribution with unknown parameter, the family of priors from the n-values discrete distribution is (trivially) a conjugate family. Note that Z behaves like a Bernoulli random variable, apart from the fact that the values of the realizations are $\{z_g, z_b\}$ rather then $\{0, 1\}$.

For a given λ, the expected value of profits is

$$\pi(\lambda) = E(Z|\theta_l)\lambda + E(Z|\theta_h)(1-\lambda) \tag{3}$$

where, for $i = \{l, h\}$,

$$E(Z|\theta_i) = z_b \Pr\{Z = z_b|\theta_i\} + z_g \Pr\{Z = z_g|\theta_i\} \tag{4}$$

Given the assumption that a θ_l production unit is more likely to receive a bad realization of the shock, we have $E(Z|\theta_l) < E(Z|\theta_h)$, so that $d\pi/d\lambda < 0$: the expected value of profits is decreasing in the probability assigned to being type θ_l.

A production unit starts at time zero with a prior λ_0. Future profits are discounted at rate β. Upon exit, a unit pays a scrapping cost k or receives a salvage value $-k$;[9] exit is an irreversible decision. The exit cost is intended to capture the degree of labor market flexibility. Parameters of the model are selected such that, conditional on types, it is optimal for a low type to exit and for a high type to stay. The unit solves the following dynamic programming problem:

$$v(\lambda) = \max\{-k, \pi(\lambda) + \beta E v(\lambda')\} \tag{5}$$

Standard arguments ensure existence and uniqueness of a solution. At this point, I do not directly tackle the problem, but note that the solution of similar problems is well known (Sargent,1987). Beliefs constitute a martingale that evolves according to the realizations of Z and the production unit solves an optimal stopping problem; the optimal policy takes the form of a threshold level for beliefs, above which it is optimal to shut down.

[9]What is essential is the relative value of k compared to the expected profits from remaining in the market. Abusing notation, define $\pi(\theta_i)$ as the expected profit for a unit known to be of type θ_i (so that, for example, $\pi(\theta_l) \equiv \pi(1)$; then, a unit that knows its type will remain in the market if and only if $\pi(\theta_i) \geq (1-\beta)k, i = \{\theta_l, \theta_h\}$, *i.e.* if the expected profits are at least as large as the flow revenue coming from exit.

2.2 The Aggregate State

In each period the economy can be in one of two states $s = \{n, d\}$, where n denotes "normal" and d denotes "downturn". The aggregate state is realized and observed *before* the production unit makes its decision, so that there is no uncertainty about the state of the economy in the current period.[10] The aggregate state influences the average productivity by determining the values that the idiosyncratic shock can take. A downturn lowers both values of the shock: $z_j^d < z_j^n$ for $j = \{g, b\}$; the probability of each realization is independent of the aggregate state.[11] As a consequence, the expected profits are lower in a downturn for all values of λ:

$$\pi(\lambda, n) > \pi(\lambda, d) \tag{6}$$

where

$$\pi(\lambda, s) = E(Z^s|\theta_l)\lambda + E(Z^s|\theta_h)(1-\lambda) \tag{3'}$$

and

$$E(Z^s|\theta_i) = z_b^s \Pr\{Z = z_b^s|\theta_i\} + z_g^s \Pr\{Z = z_g^s|\theta_i\} \tag{4'}$$

The aggregate state evolves according to a Markov transition matrix. I use the notation $\gamma_t(s'|s)$ to indicate the probability that t periods ahead the state is s', given that the current state is s. I assume that it is more likely that the aggregate state will be n next period if it is n today:

$$\gamma_1(n|n) > \gamma_1(n|d) \tag{7}$$

[10] The emphasis of the model is on idiosyncratic rather than on aggregate uncertainty. Gonzales (1996) develops a model in which the evolution of the aggregate state is unobservable and agents can costly experiment to obtain information about it.

[11] This assumption makes the pace of learning independent of the aggregate state. An interesting alternative would be one in which the probabilities of receiving a certain shock also change over the business cycle. For example, one could argue that a downturn is more effective at discriminating among efficient and inefficient production units and model the probabilities accordingly.

The introduction of the aggregate state necessitates that the unit's problem be reformulated contingent on the aggregate state itself:

$$v(\lambda, s) = \max\{-k, \pi(\lambda, s) + \beta E \sum_{s'} v(\lambda, s')\gamma_1(s'|s)\} \tag{5'}$$

The solution is characterized by a couple of state-contingent threshold values for beliefs, $\{\lambda_d^*, \lambda_n^*\}$, above which the unit leaves the market.

2.3 The Game

Consider now an economy populated by a continuum of units. The problem of the single unit is identical to the one described in the previous section. There are m *ex-ante* identical sectors in the economy. In each period a nonzero mass of units enter in each sector. Let's define the units that entered a sector in a given period as a *subsector*. At time t, each subsector is identified by a couple (j, τ), where $j = 1, 2, ..., m$ is the "cross-sectional" or sectoral index and $\tau = 0, 1, ...$ indicates the age. The subsector of belonging of a unit is publicly observable. I make four important assumptions about the interaction among units and about their evolution.

Assumption 1. *There is no interaction at the level of payoff: the profits of one unit do not depend either on the actions or on the number of other units.*

Assumption 2. *Signals are private information: a unit can only observe other units' actions.*

Assumption 3. *The realizations of signals are independent across production units and over time.*

Assumption 4. *In addition to the endogenous exit decision, there is an exogenous probability of death δ.*

The first assumption serves to simplify the analysis, and emphasizes the informational aspects of the model. While desirable, the endogenization of profits would make the model intractable. The second assumption is indeed the critical one, which gives rise to the strategic behavior of the units: it generates an incentive to observe other units' actions in order to gain information from them. The last assumption ensures that the economy will be characterized by positive entry and exit in the long run.

The two fundamental assumptions on the information structure are the following.

Assumption 5. *It is common knowledge that all units in a subsector share the same unknown type.*

Assumption 6. *Types are independently drawn across sectors; within sector, draws can be correlated over time.*

Assumption 5 gives rise to the fundamental strategic interaction between units. Given that it is common knowledge that all units in a subsector share the same type, each one of them can in fact obtain useful information about itself from observing the behavior of the other units in the same subsector.[12]

Assumption 6 concludes the description of the informational structure. First, given that types are independently drawn across sectors, we can concentrate on a representative sector to solve the model. Indeed, multiple sectors are assumed only to avoid that any particular draw of types influences the business cycle properties of the model. Second, the assumption allows for correlation of draws of subsectors in the same sector. Given that, as discussed at the end of the section, the type captures a common feature of the units, it seems natural to assume that the degree of similarity declines with age differences. In our contest, this corresponds to assuming that the amount of information that a unit of age τ can extract from the type of the units of age τ' decreases with $|\tau - \tau'|$. I formalize this by assuming that nature selects the type of the entering subsector according to a probability that evolves as a Markov chain with the following structure:

$$\Pr\{\theta_t = \theta_l | \theta_{t-1}\} = \lambda_0 + \rho(1_{\{\theta_{t-1}=\theta_l\}} - \lambda_0) + u_t \tag{8}$$

[12]The assumption that units that enter a sector in a given period are endowed with the same technology is used, in a different setting, in vintage capital models that study the relation between technological innovation and macroeconomic fluctuations (Caballero and Hammour, 1994). As discussed at the end of this section, in this contest the identification between period of entry and type should be seen as a modeling device.

where $0 \leq \rho \leq 1$, θ_t is the type of the subsector that entered at t, u_t is a random variable with zero mean and support over the interval $-[\lambda_0(1-\rho), 1-(\lambda_0+\rho(1-\lambda_0))]$ and $1_{\{x=y\}}$ is the indicator function taking value 1 if $x = y$ and zero otherwise. Equation (8) models the type selection process as a mean-reverting process, with the long run value equal to λ_0. It implies that the probability of being a low type given that the subsector that entered the previous period is low is higher than λ_0 and vice-versa. In the particular case of $\rho = 0$ and with u characterized by a degenerate distribution identically equal to zero, the types are drawn independently with $\Pr\{\theta_t = \theta_l\} = \lambda_0$ for all t.

The correlation in the type-selection process implies that a unit can extract useful information about its type by considering also the type of units of other subsectors. To rule out the unstable solution of the stochastic difference equation (8), I impose the restriction that a unit of age τ only considers the information coming from units older then herself, in addition to that from units in the same subsector. Define $x_s(t)$ as the mass of units of subsector s in the market at time t, and $\mathbf{x_s(t)} = \{x_{s-l}(t-l)\}_{l=0}^{\infty}$ as the subsectoral history.[13] The public information of units of age τ at time t is given by $\Omega_t^\tau = \{\mathbf{x_s(t)}\}_{\mathbf{s}>\tau}$. This information is common to all units in a given subsector. They will use it to better asses the distribution from which their type was drawn. On this account, prior beliefs of units of subsector τ at t based on public information are given by the expected value of (8):

$$\begin{aligned}\lambda(\Omega_t^\tau) \equiv \quad & E[\Pr\{\theta_t = \theta_l|\Omega_t^\tau\}] = \lambda_0 + \rho(E[1_{\{\theta_{t-1}=\theta_l\}}|\Omega_t^\tau] - \lambda_0) \\ & = \lambda_0 + \rho(\Pr\{\theta_{t-1} = \theta_l|\Omega_t^\tau\} - \lambda_0) \qquad (9)\end{aligned}$$

Given $\lambda(\Omega_t^\tau)$ and their private signals, units use Bayes rule according to equation (2) with λ_0 substituted by $\lambda(\Omega_t^\tau)$ to form their posterior beliefs.

As suggested above, the autoregressive structure of type selection implies that the impact of information about the type of a given subsector is decreasing in the temporal distance between subsectors. For example, if the common information of units in a subsector is simply the type of a subsector that entered the market q periods before, then their prior

[13]Note that, by comparing $x_s(t)$ and $x_{s-1}(t-1)$ one can immediately recover the mass of exit from a subsector between $t-1$ and t.

beliefs will be given by

$$\lambda(\theta_{t-q} = \theta_i) = \lambda_0 + \rho^q(1_{\{\theta_{t-q}=\theta_l\}} - \lambda_0) \tag{10}$$

Consider now the m sectors. Define $x_{j\tau}(t)$ as the mass of units of subsector (j, τ) that are in the market at the beginning of period t. The total mass of incumbents at the beginning of the period (i.e. before entry takes place) is given by:

$$\Phi(t) = \sum_{\tau=1}^{\infty} \sum_{j=1}^{n} x_{j\tau}(t) \tag{11}$$

I assume that the there is an upper bound to the measure of units in the economy, which is normalized to 1: $\forall t, \quad \Phi(t) \leq 1$. This is intended to represent the maximum number of "production sites" available, and deviation from the bound will be interpreted as a measure of economic slackness.

The timing of events is the following:

1. The aggregate state is revealed and entry takes place;

2. Exit decisions are made and observed;

3. Idiosyncratic signals and profits are realized;

4. Natural deaths occur.

To complete the description of the environment, the entry process and the strategic aspects of the exit decision must be illustrated.

Entry is modeled in an *ad hoc* way: it is assumed that the mass of entering units is a deterministic function of the difference between the maximum potential measure of the market and the actual measure of incumbents at the beginning of the period.[14] In each

[14] This assumption is made for the sake of simplicity. It would be interesting to extend the model to endogenize entry, for example along the lines of Hopenhayn (1992). This possibility is left to future work.

period a fraction $\alpha \in (0,1)$ of the difference is filled:[15]

$$y(t) = \alpha * (1 - \Phi(t)) \tag{12}$$

where $y(t)$ is the measure of entrants at time t and. The total mass of entry is equally distributed across the m sectors: $x_{i0}(t) = y(t)/m$.

Exit is determined partially exogenously, as a consequence of natural death, and partially endogenously, as the deliberate choice of incumbent units. The exit choice involves strategic considerations that are at the heart of the model, given that a unit can extract useful information from the behavior of units in the same sector. I concentrate on the informational aspects involved in the process of discovering types, that is, on how production units learn about their type and how the speed and timing of learning and reallocation interact with the aggregate state. The extensive form of the game is the following. At each point in time a *history* $h^t \in H^t$ is a sequence recording the actions of units currently and previously in the market and the realizations of exogenous events up to the point when the units must act.[16] The action space after history h^t for a unit that has entered the market at or before period t is defined as:

$$A(h^t) = \begin{cases} \{\text{stay,exit}\} & \text{if not previously exited} \\ \emptyset & \text{otherwise} \end{cases} \tag{13}$$

Exit constitutes an irreversible decision, and one can think of it as the liquidation of the unit. Given that units that have exited the market have no further role in the model, in what follows I will refer only to incumbent players. The *information partition* is a partition I_i of H whose elements I_i are the *information sets* for player i. Whereas H is the complete history of the game, I_i represents the information available to player i when making a

[15] This assumption is motivated by the large body of literature on matching models of the labor market (Mortensen and Pissarides, 1994), in which it is assumed that in each period a vacancy is filled with a given probability. This representation of the functioning of the labor market is in accordance with many "stylized facts" as presented, for example, in Blanchard and Diamond (1990).

[16] Given the timing convention, a history contains signals, natural deaths and exit decisions up to the previous period, and entry and the aggregate states up to the current one.

decision. Given my assumptions on the informational structure, the information sets do not contain all the signals, but only those of player i. The per period payoff function is constituted by the expected profits if the production unit stays in the market and by an exit cost if the unit decides to shut down:

$$u(a,h) = \begin{cases} \pi(\lambda, s) & \text{if } a = \text{stay} \\ -k & \text{if } a = \text{exit} \end{cases} \tag{14}$$

where I exploit the fact that π depends on history only through the current belief and aggregate state. In case of natural death, it is assumed that the unit pays no exit cost (or gets no scrap value).

A *strategy* for player i is a collection of functions mapping from information sets to probability distributions over actions. Given that there are only two possible actions, I adopt the convention that a strategy at t is the probability assigned to action $\{exit\}$: $\sigma_i^t : I_i^t \to [0,1]$. Given a strategy profile σ, the expected payoff for any player after history h^t is given by:

$$U(\sigma, h^t) = E\sum_{i=0}^{\infty} \beta^i (1-\delta)^i u(a_{t+i}, h^{t+i}) \tag{15}$$

where the expectation is taken with respect to the probability distribution induced by the strategy σ and by the stochastic evolution of the exogenous variables. The future is discounted for the possibility of natural death.

2.4 Discussion: the reference group

The crucial assumption in the model, that gives rise to the strategic interaction, is that firms in the same subsector share the same type. It is therefore important to understand what the reference group, that is the group from which each individual can extract useful information, is meant to indicate. For the analysis of this paper, that considers the effects of information spillovers on reallocation timing and intensity, it seems appropriate to think at the reference group as units using a very similar technology and operating in the same market, among which the information flows for restructuring activities are more likely to matter. This is captured by the fact that in the model all learning takes place at the sectoral level. The fact that all units that enter at the same time share the same type should instead be seen as a modelling device. In fact, one could assume that the time frequency for entry in a sector is substantially lower than the business cycle frequency. Similarly, it could be assumed that entry in a sector continues over its entire life-cycle. Another possibility is that the type is not fixed forever upon entry, but can change over time, also in relation to the adoption of competing technologies. These modifications would substantially increase the complexity of the model, without adding anything substantial to the argument, and are therefore not pursued in this paper. The general principle at work it that of a common unknown factor linking a group of units, possibly but not necessarily related to the period of entry; such principle should be used to select the relevant reference group for a production unit when interpreting the model and considering its empirical applicability.

3 Characterizing the Equilibrium

The strategic aspects of the model are complex, entailing the solution of an extensive form game of incomplete information with a continuum of players, who are divided among an infinite number of groups of initially unknown type. However, I show that, by introducing appropriate restrictions on strategies and on the equilibrium concept, a solution can readily be identified. Given that all interaction at the level of payoff has been excluded, we only need to consider that at the informational level. Moreover, given that all sectors are *ex-ante* identical and that assumption 6 has excluded interaction across sectors also at the informational level, we can concentrate on the solution for a representative sector and solve the strategic aspects of the game within this narrower environment. Given that all sectors face the same problem, once the solution for a representative sector has been found, the evolution of the economy can be obtained by applying it to all sectors and aggregating over them.

Another restriction relates to the equilibrium concept: I concentrate on *Symmetric Nash Equilibria*, in which units at the same information set choose the same strategy, and define a symmetric equilibrium as a strategy σ^* such that no production unit can increase its expected payoff by using an alternative strategy $\hat{\sigma}$ when all other units use σ^*. The symmetry restriction implies that the identity of the units taking a given action has no informational content: only their measure is relevant.

Once these restrictions are introduced, the model can be solved along the lines outlined by Caplin and Leahy (1994).[17] The assumption that there is a continuum of agents is the key one. It in fact guarantees that, while the single unit faces uncertainty, at the aggregate level (that is at the subsector level) the distribution of signals, conditional on types, is non-stochastic. As a consequence, the measure of players at each information set is a deterministic function of the type. This imposes a very strong restriction on the pace of information revelation: if a strategy prescribes exit for different measures of units according to their types, then by observing this measure one can infer the type of the sector, and uncertainty is immediately resolved. The process of information revelation has a discontinuous character. As long as no unit from a given subsector decides to exit, only the information possibly coming from other subsectors can be obtained by observing actions; but if the strategy prescribes exit for units of the same subsector at a particular information set, then generally the mass of exiting units will reveal types immediately. I introduce the following definition to formalize this concept.

Definition 1. *A strategy is defined to be type-revealing if for any history H and any subsector there exists a τ^* at which the strategy induces different measures of exit for the different types.*

The definition establishes that, if players follow a type-revealing strategy, then at some point the type will be revealed by the measure of exiting units. An example of a strategy that is not type-revealing is one that prescribes first exit for *all* units in the same subsector (independently of the signals received) at some age τ.

Consider now the following strategy.

[17]Caplin and Leahy (1994) construct a model of a multi-stage investment project, with the initial measure of investors determined by a zero expected profit condition. With respect to their model, here there is multple entry with correlated types and the economy is characterized by the presence of an aggregate state.

Definition 2. *A cutoff strategy is a strategy that, when prescribing exit, does so for all units with beliefs exceeding a state contingent threshold* $\lambda(s) \in (0,1)$, $s = \{n, d\}$

A cutoff strategy is characterized by a vector $\Lambda = \{\lambda(n), \lambda(d)\}$. For cutoff strategies the following result holds.

Proposition 1. *Cutoff strategies are type-revealing if, for* $s = \{n, d\}$,

$$\rho \leq \frac{\lambda(s) - \lambda_0}{1 - \lambda_0} \tag{16}$$

Proof: see appendix A.1.

If condition (16) is met, then $\lambda_0 + \rho(1 - \lambda_0) < \lambda(s)$: the beliefs of a unit before receiving any signal and knowing that the previous subsector was a low type do not exceed the cutoff value. The proposition establishes that, for cutoff strategies to be type-revealing, it is enough that units are willing to stay in the market for at least one period under the worst informational scenario, that is knowing that the previously entered subsector is a low type. If this were not the case, then there would be circumstances in which all units would exit immediately after entry and no information would be revealed about the type. If this condition is satisfied upon entry, then in any period before type-revealing actions the most optimistic units will hold beliefs below the threshold, given that $\lambda(n_g, 0; \cdot)$ is decreasing in n_g. This ensures that the first exit will not involve all units in the subsector.

Condition (16) highlights the effects of allowing for correlation between subsectors. Such correlation makes the model a hybrid of models with simultaneous actions, such as Caplin and Leahy (1994) and Chamley and Gale (1994), and of sequential actions, such as Bikhchandani *et al.* (1992) and Banerjee (1992). Indeed, proposition 1 establishes the condition under which *informational cascades* never occur. An informational cascade occurs when an agent takes an action only on the basis of public information, disregarding her own private information. In such case, actions will not reveal private information and nothing can be learned by observing the behavior of others. In terms of the model, this occur if the observation of public history makes everybody so pessimistic to be willing to exit independently from the private signals.[18] Given that, conditional on knowing that the previous subsector is a low type, the units become more pessimistic the higher ρ, cascades might occur if the correlation between subsectors is sufficiently high. When correlation is below the level of condition (16), it will influence the timing of type revelation but, given that the strategy is type-revealing, the true type will be discovered with probability one. We will focus our attention on such cases.

To determine the equilibrium strategy I concentrate on the problem of an individual unit with beliefs λ, who has to decide her action conditional on being at an information set at which she knows that the type will be revealed. This is the crucial property of the game. It implies that the continuation values from next period onward are independent from other units' strategy. Given such values, then, the unit uses current beliefs to evaluate the payoff from continuing and from exiting, so that the only variable needed to determine equilibrium strategy are the beliefs. The payoff from exit is given by the exit cost:

$$r(\lambda, s) = -k \tag{17}$$

Given that next period the type will be known, the payoff from staying depends on the continuation value of a unit that finds out that she is a θ_h type in state s. This is the present discounted value of profits for a high type given the aggregate state s:

$$v(s) = \sum_{i=0}^{\infty} \beta^i (1-\delta)^i [\pi(\theta_h, n)\gamma_i(n|s) + \pi(\theta_h, d)\gamma_i(d|s)] \tag{18}$$

For a θ_h unit the expected value of being in the market tomorrow, given the aggregate state s today, is therefore given by

$$V(s) = v(n)\gamma_1(n|s) + v(d)\gamma_1(d|s) \tag{19}$$

[18] Bala and Goyal (1998) identify conditions on the structure of the reference group under which a similar result obtains. Vives (1996) studies the convergence of social learning equilibria to rational expectations equilibria and stresses that cascades can arise only in the presence of a discrete action space and of signals of bounded informativeness.

$V(s)$ plays a fundamental role in determining the equilibrium strategy. It allows us to determine the payoff from staying, given by the expected profits for the current period plus the continuation payoffs:

$$\tilde{r}(\lambda, s) = \pi(\lambda, s) + \beta(1-\delta)[-\lambda k + (1-\lambda)V(s)] \tag{20}$$

Equation (20) states that the payoffs from waiting, given beliefs λ and aggregate state s, are equal to the current expected profits plus the discounted expected continuation values; these, in turn, are determined by the fact that the production unit expects to be type θ_l with probability λ, in which case she will pay the exit cost and leave, and θ_h with probability $(1-\lambda)$, in which case the expected continuation value is $V(s)$ as defined in equation (19). The condition for λ to be such that a production unit would rather shut down is:

$$r(\lambda, s) \geq \tilde{r}(\lambda, s) \tag{21}$$

Equation (21) can be used to determine the equilibrium strategy. By showing that $\tilde{r}(\lambda, s)$ is continuously decreasing in λ and that there is one and only one value for which $r(\lambda, s) = \tilde{r}(\lambda, s)$, the following proposition, characterizing equilibrium strategies, can be established.

Proposition 2. *Equilibrium strategies are cutoff strategies.*

Proof: see appendix A.1.

Let $\Lambda^* = \{\lambda_n^*, \lambda_d^*\}$ denote the pair of values that satisfies (21) with equality. Λ^* is obtained by solving (21), for each of the aggregate states, as an equality and by applying the definition of $\pi(\lambda, s)$:

$$\lambda_n^* = \frac{k + \pi(\theta_h, n) + \beta(1-\delta)V(n)}{\pi(\theta_h, n) - \pi(\theta_l, n) + \beta(1-\delta)(k + V(n))} \tag{22a}$$

$$\lambda_d^* = \frac{k + \pi(\theta_h, d) + \beta(1-\delta)V(d)}{\pi(\theta_h, d) - \pi(\theta_l, d) + \beta(1-\delta)(k + V(d))} \tag{22b}$$

I have established the existence of cutoff values for beliefs after which a production unit would rather exit than wait. For them to be an equilibrium couple it is also necessary that no production unit would rather exit for less pessimistic beliefs. It could be that a production unit that is sufficiently pessimistic about its type would find it preferable to shut down before reaching the threshold. To eliminate this possibility, it is sufficient to check that the most pessimistic production units are willing to continue for all periods preceding the first exit time: for any τ, for any s and public history, the value of continuing for the most pessimistic production units, when the equilibrium strategy prescribes so, must be at least as large as the cost of leaving the market:

$$U_\tau(\Lambda^*, s) \geq -k \tag{23}$$

The complete expression for this value is rather cumbersome, having to take into account the expected payoffs for any possible evolution of the game. An example of its derivation for the case with $\rho = 0$ is confined to appendix A.2. Numerical analysis of the game show that existence is indeed a serious issue, and that an equilibrium fails to exist in many instances. The problem is particularly severe for some regions of the parameter values. The existence problem is typical in this class of models with a continuum of agents. I discuss the issue at more length in appendix A.2, where I also point to an additional assumption on the structure of exit costs that would ensure existence for any possible configuration of the model without modifying the equilibrium analysis.

4 Aggregate Shocks and Reallocation Timing

In this section I analyze more closely the implications of the model, concentrating on the interrelation between aggregate shocks and reallocation activity. We have seen that at the heart of the model is the incentive for production units to free-ride in terms of production of information. As a consequence, even production units that have a high confidence of being of type θ_l might still find it optimal to delay adjustment, in the hope that others will go first. One important question is then how this incentive varies over the business cycle: pessimistic production units might find it relatively cheap to postpone restructuring in normal periods, while this might become more expensive in a downturn.

Before addressing this question, I introduce a further simplifying assumption. In the previous section we have derived the equilibrium strategy allowing for correlation in the type selection process at the sectoral level. For tractability reason, for the rest of the paper I will shut down this channel, assuming that $\rho = 0$ so that the learning process is confined within each subsector. This assumption greatly simplifies the analysis and allows for an intuitive characterization of the equilibrium in terms of first exit time. Note that the results would be reinforced in terms of amplification if we would explicitly allow for this channel.[19] Once the correlation across subsectors is shut down, the prior is independent from history and constant at λ_0. The condition for a strategy to be type-revealing reduces to $\lambda_0 < \lambda(s)$, $s = \{n, d\}$.

they all have the same prior λ_0 which is independent from the evolution of other subsectors. We can therefore concentrate on a representative subsector and characterize the solution for it without having to consider the sectoral history.

The characterization of the equilibrium strategy in proposition 2 lets us concentrate attention on the most pessimistic production units. Given that there exists a continuum of production units, in each period there will be a nonzero measure of units that has received all possible combinations of signals. In any period, therefore, the beliefs of the most pessimistic production units are the beliefs of those that have received all bad signals, given λ_0. One can then uniquely determine the minimum number of bad signals, and therefore of periods, required for the beliefs of a subset of units to exceed some λ:

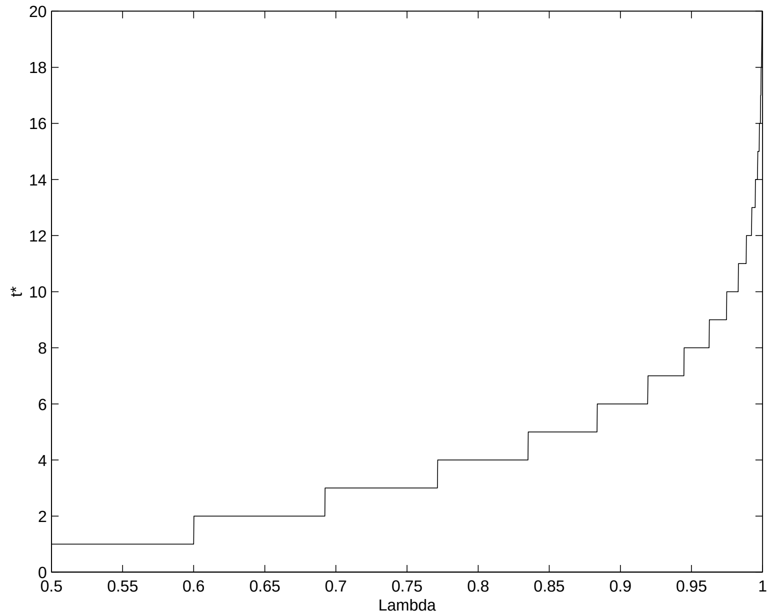
$$\tau(\lambda) \equiv \text{Inf}\{m \in \mathcal{N}_+ : \frac{\Pr\{z_b|\theta_l\}^m \lambda_0}{\Pr\{z_b|\theta_l\}^m \lambda_0 + \Pr\{z_b|\theta_h\}^m (1-\lambda_0)} \geq \lambda\} \tag{24}$$

where N_+ is the set of nonnegative integers. It is easy to show that the fraction in (24) is increasing in m so that $\tau(\lambda)$ is uniquely determined. By equation (24) we can associate with Λ^* a vector $T^* = \{\tau_n^*, \tau_d^*\}$, where, abusing notation, I use τ_s^* for $\tau(\lambda_s^*)$. This vector

[19] Such correlation will reinforce the effects of strategic learning in terms of concentration of reallocation activities. When a given mass of first exit signals that a subsector is a low type, it will also signal to other subsectors that they are more likely to be low type as well, increasing the likelihood of a further adjustments in such subsectors.

determines the two first stopping times: it indicates the aggregate state-contingent minimum number of periods at which the first exit wave could take place in equilibrium. Figure 2 plots $\tau(\lambda)$ for $\lambda \geq 1/2$ for the following parameter values: $\lambda_0 = 1/2, Pr\{Z = z_b|\theta_l\} = .6, Pr\{Z = z_b|\theta_h\} = .4$. Note the discontinuous character of the function $\tau(\lambda)$.

Figure 2: Minimum number of bad signals required to reach a certain beliefs level



We are now ready to formally determine the effects of aggregate shocks on the adjustment threshold.

Proposition 3. *The equilibrium level of pessimism at which it is optimal to exit is lower in a downturn than in a normal period:*

$$\lambda_d^* < \lambda_n^* \tag{25}$$

or, in terms of first adjustment time,

$$\tau_d^* \leq \tau_n^* \tag{25'}$$

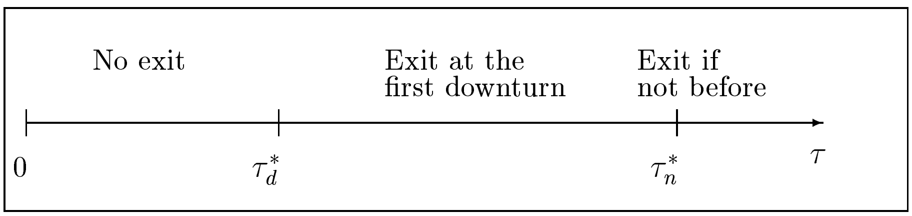
Proof: see appendix A.1

Proposition 2 dictates the following characterization of the evolution of a given subsector:

- For $\tau < \tau_d^*$, no production unit voluntary exits and, therefore, no private information is revealed;
- for $\tau_d^* \leq \tau < \tau_n^*$, production units with beliefs greater than or equal to λ_d^* will choose to shut down if in any period the economy is in a downturn;
- for $\tau = \tau_n^*$, exit will take place anyway, if it has not already taken place previously.

The evolution is graphically represented in Figure 3.

Figure 3: Evolution of a given subsector: first exit times



The mass of units shutting down during the first exit wave is small. For example, if the downturn hits exactly at τ_d^*, then the percentage of units in the subsector that will exit equals $Pr\{z_b|\theta_l\}^{\tau_d^*}$ if the subsector is θ_l and $Pr\{z_b|\theta_h\}^{\tau_d^*}$ if it is θ_h. This is in fact the probability of receiving all bad signals conditional on types. For values of τ_d^* sufficiently high, these numbers are small. However, the exit induced by the downturn has the important effect of revealing types. If the type is θ_l, then in the following period all units exit, with exit taking place independently of the aggregate state.[20] It could well be that the largest share of job destruction takes place in a period in which the state has reverted to normal. If the exit wave is large, however, the economy will suffer a recession. A recession is therefore a joint consequence of cyclical and structural events. The effect of a downturn is primarily that of breaking the inertia induced by the joint presence of microeconomic (unit level)

[20] Recall that by construction it is optimal for a θ_l unit to exit irrespective of the aggregate state. Of course, this need not be necessarily the case.

uncertainty and unrecoverable costs: it influences the economy mostly through the informational changes that it induces. This view of aggregate shocks overcomes the difficulties of the traditional one, in which the shocks influence the economy only through their direct effect on productivity, and can reconcile both the need for amplification mechanisms and the extent of reallocation activities that characterize recessions. Note that I obtain this result without going as far as the literature on sunspots (Farmer, 1993), in which aggregate shocks only have a role as coordination devices: in my model, the shocks do have a concrete informational effect.

4.1 Comparative Statics

It is important to understand what determines the difference between the two threshold values, defined as $\Delta\Lambda^* \equiv \lambda_n^* - \lambda_d^*$. The higher this difference, the more likely that the reallocation activity takes place following a negative aggregate shock. To analyze this point, I refer to equation (20), which determines the payoffs from waiting at a particular belief and state, given that some units will exit today. The difference in the threshold values depends on two elements: the continuation value and current profits. Lemma 1 in the appendix shows that $v(n) > v(d)$, that is, the expected continuation payoff for a θ_h unit is higher in a normal period than in a downturn. This, together with the assumptions about the structure of the Markov chain governing the evolution of the aggregate state, implies that if the state today is n, then the continuation value conditional on being θ_h is higher than if the state is d, that is $V(n) > V(d)$. This means that a mistake (exiting when type θ_h) is more costly in a normal period, thus increasing the equilibrium level of pessimism in normal times. In the same way, given that $\pi(\lambda, d) < \pi(\lambda, n) \quad \forall\, \lambda \in [0,1]$, the lower expected revenue in a downturn makes it more costly to delay adjustment, thus inducing production units to act sooner.

A larger difference between current expected profits in the two states, as well as between continuations, implies a larger $\Delta\Lambda^*$. Equation ($3'$) shows that when a production unit places a high probability on being type θ_l, the expected value of its profits depends in large measure on $E(Z^s|\theta_l)$, as defined in equation ($4'$). The model predicts larger differences in the threshold beliefs if θ_l production units experience a large drop of productivity in downturns, that is if $\pi(\theta_l, n) - \pi(\theta_l, d)$ is large. This feature suggests a characterization of the economy as a system with heterogeneous production units with different efficiency levels, in which inefficient production units might be able to remain in production in normal periods, but are more adversely affected by cyclical downturns than efficient ones.

While the threshold levels are important for understanding the functioning of the model, in terms of describing the evolution of the economy we need to consider the first exit times τ_d^*, τ_n^* and their difference ΔT^*. I have shown that, for $s = \{n, d\}$, τ_s^* is monotonically increasing in λ_s^*, so that all the considerations of the previous paragraph apply to the analysis of the first exit times. However, the informativeness of the signals plays a fundamental role in determining the first exit time: the more informative the signals, the shorter the time needed to reach a given threshold of beliefs. By manipulating equation (2) for the case of n_b bad and no good signals, we obtain:

$$\lambda(0, n_b; \lambda_0) = \left\{ 1 + \left(\frac{\Pr\{z_b|\theta_h\}}{\Pr\{z_b|\theta_l\}} \right)^{n_b} \left(\frac{1-\lambda_0}{\lambda_0} \right) \right\}^{-1} \tag{26}$$

It is apparent from equation (26) that, given n_b and λ_0, the level of pessimism only depends on the ratio $\frac{\Pr\{z_b|\theta_h\}}{\Pr\{z_b|\theta_l\}}$. I formalize this concept in the following definition.

Definition 3. *The informational content of the signals is defined as the ratio between the probability of receiving a bad signal conditional on types:*

$$\eta \equiv \frac{Pr\{z_b|\theta_l\}}{Pr\{z_b|\theta_h\}} \tag{27}$$

When η is close to 1, a realization of z_b is not much more likely for a θ_l production unit than for a θ_h, so that the informational content is low.[21] A given number of bad signals will

[21]It is interesting to relate this definition to the general notion of Blackwell's information principle, which allows for the comparison of different information structures (in our case, the information stucture is the set of probability of signals given types). To compare information structures in Blackwell sense, in addition to η one also need to consider $\nu \equiv \frac{\Pr\{z_g|\theta_l\}}{\Pr\{z_g|\theta_h\}}$. Information structure A is then said to be more informative than information structure B if and only if both $\eta_A > \eta_B$ and $\nu_A > \nu_B$ (Nermuth (1982), pp. 12-37). Our definition coincides with Blackwell's for the probability distribution of bad signals. This is indeed a natural result, given that the first exit time depends on agents that received only bad signals, so that the distribution of good signals plays no role for this particular aspect.

generate more pessimistic posterior beliefs the higher η: put differently, a given threshold value for beliefs will be reached with fewer signals.[22] As a consequence, a given gap between λ_n^* and λ_d^* will induce a higher difference between the two first exit times when signals are less informative:

$$\left.\frac{\partial \Delta T^*}{\partial \eta}\right|_{\Delta \Lambda^*} < 0 \tag{28}$$

Less informative signals therefore imply a higher probability that the reallocation process occurs after an aggregate downturn.

Finally, we note that an increase in k increases both threshold values. This means that an economy with higher adjustment costs will be characterized by an average lower turnover rate. The consequences of this fact reach beyond the scope of this paper, which focuses on the cyclical aspects of production units' turnover. This would be an interesting direction in which to extend the analysis.

5 The Concentration of Reallocation Activities

After the discussion of the single subsector problem, I revert to the whole economy and analyze the implications of aggregate downturns for the process of aggregate entry and exit, which are intended to be proxies for job creation and job destruction. The composition of units in the economy at the beginning of time t is represented by the sequences of subsectors' masses $\{x_{j\tau}(t)\}_{\tau=1}^{\infty}$, $j = 1, ..., m$. Such a description contains redundant information. From the equilibrium characterization it is known that, for any subsector, the type will be revealed at age τ_n^* at the latest, so that subsectors of age $\tau_n^*+1, \tau_n^*+2, ...$ are of known type. But once the type is revealed, there is no need to keep track of each individual subsector's evolution: if the type is θ_l, all units will exit and will play no further role in the economy; if the type is θ_h, all units will stay until natural death occurs, with the probability of death being independent of age. We can therefore aggregate all units that are known to be type θ_h at time t and denote their mass by $X_{\theta_h}(t) \equiv \sum_{j=1}^{m} \sum_{\tau > \tau_n^*} x_{j\tau}(t)$. Then, we only need to keep track of

[22] In terms of Figure 2, this means that the steps become longer as η increases.

the mass and type of subsectors of age τ_n^* and younger, whose type might still be unknown. A more parsimonious representation of each sector is therefore constituted by a couple of τ_n^* dimensional vectors $X_j(t) = \{x_{j1}(t), ..., x_{j\tau_n^*}\}$ and $\Theta_j(t) = \{\theta_{j1}(t), ..., \theta_{j\tau_n^*}(t)\}$, $j = 1, ..., m$, recording the mass and the type of subsectors of age $1, ..., \tau_n^*$. The economy is then described by the collection of such vectors $X(t) = \{\{X_j(t)\}_{j=1}^m; X_{\theta_h}\}$, $\Theta(t) = \{\Theta_j(t)\}_{j=1}^m$. These variables, together with the current aggregate state, allow the determination of entry and, given equilibrium strategies, of both voluntary and involuntary exit, so that they are sufficient to determine the evolution of the economy.

Consider now the *concentration effect* of aggregate shocks. I define the subsectors within the age interval $[\tau_d^*, \tau_n^*]$ as vulnerable to aggregate downturns, and units in them as *fragile*, in the sense that an aggregate downturn will induce type-revealing actions, potentially inducing mass exit from such subsectors. If the economy is in a normal period, then only the subsectors of age τ_n^* will undertake an adjustment. If the aggregate state switches to a downturn, however, all the vulnerable subsectors will have their types revealed. As a consequence, the following period will on average be characterized by a high mass of units exiting, thus inducing a concentration of restructuring activities within one period.

To provide a quantitative assessment of the "pooling" of reallocation activities induced by aggregate downturns, I simulate the model numerically, after having obtained the equilibrium first adjustment times for the set of parameter values reported in table 1. For these parameters, there exists an equilibrium with first adjustment times $\tau_n^* = 8$ and $\tau_d^* = 4$. I set $m = 50$, a number large enough to smooth out the consequences of the random draws of types. The results are reported in Figure 4. To allow for comparisons, I also construct an economy without an aggregate state. In such an economy, the equilibrium strategy is described by a single threshold value, which I obtain as a simple average of the economy with the aggregate state.

The simulation is carried out by fixing an initial value for the state variables, generating a sequence of values for the aggregate state, drawing types of entering subsectors and computing the corresponding evolution for the economy. I let the model run for 2000 periods to eliminate the effects of the initial conditions. Figure 4 plots the paths for entry,

Table 1: Parameter Values

λ_0	k	β	δ	$\Pr\{z_b\|\theta_l\}$		$\Pr\{z_b\|\theta_h\}$
.5	3.10	.98	.03	.6		.25
$\gamma_1(n\|n)$	$\gamma_1(d\|d)$	z_b^n	z_b^d	z_g^n	z_g^d	α
.93	.3	-.6	-1	.5	.1	.5

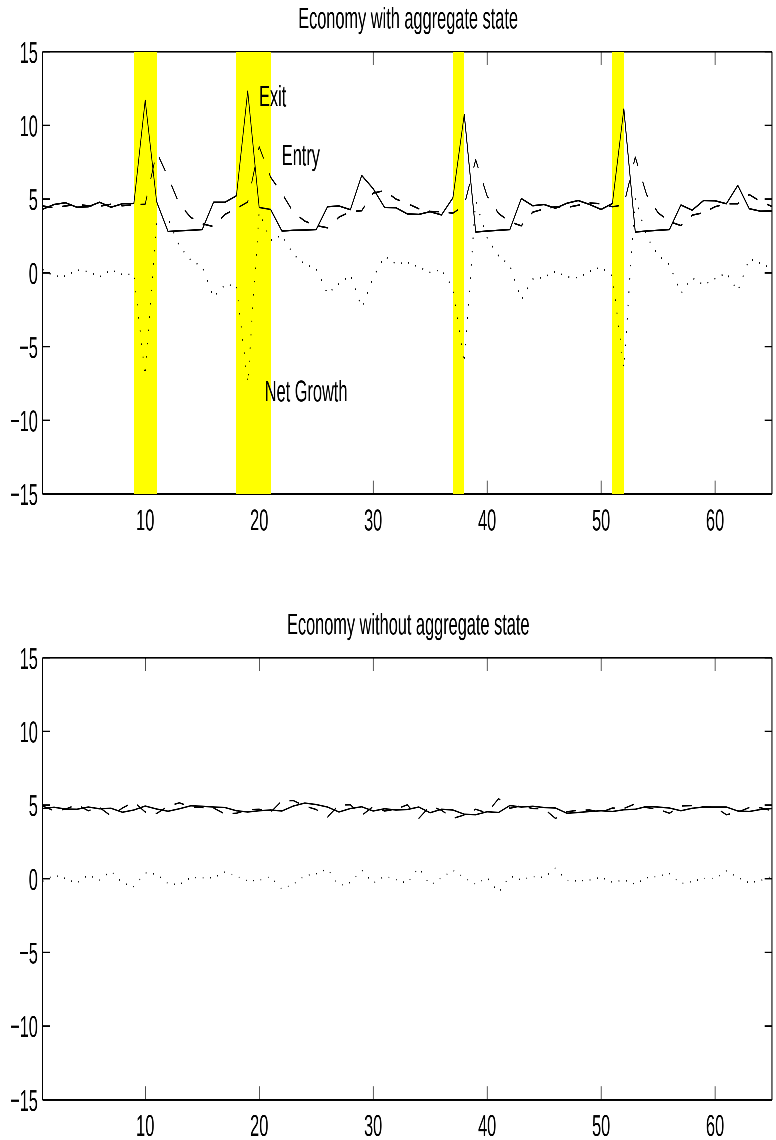
for exit and for the net flow. The aim is to compare the model economy with the real one shown in Figure 1. The y-axis indicates values as a percentage of the total size of the economy at its full employment level.[23]

The series in the upper panel of Figure 4 show that the presence of an aggregate state induces the concentration of reallocation activities within a short period of time. When the aggregate state switches to a downturn, all the vulnerable subsectors will undertake the adjustment, so in the following period there will be a spike in exit at the aggregate level, inducing the spike in job destruction that, as shown in Figure 1, characterizes recessions in real economies. Note that in the period in which the exit rate reaches its peak the aggregate state might have reverted to normal: this is the sense in which downturns and recessions are distinct concepts in the model. In terms of comparison, the lower panel of the figure shows that, without the concentration effects induced by the switches of the aggregate state, the economy tends to be characterized by stable flows of entry and exit that offset each other, without the peaks of the upper panel: without the concentration effects of aggregate shocks, reallocation activities are spread over time and cannot account for the burst in job destruction characterizing the series in Figure 1.

The simulations also point to other interesting implications of the model. To explore these further, I carry out an experiment in which I choose a particular series for the aggregate state rather than randomly generating it. The series has an initial long sequence of normal periods, followed by a combination of downturns and normal periods. The behavior of the economy in the second phase is reported in Figure 5. First, I stress the cleansing effect of

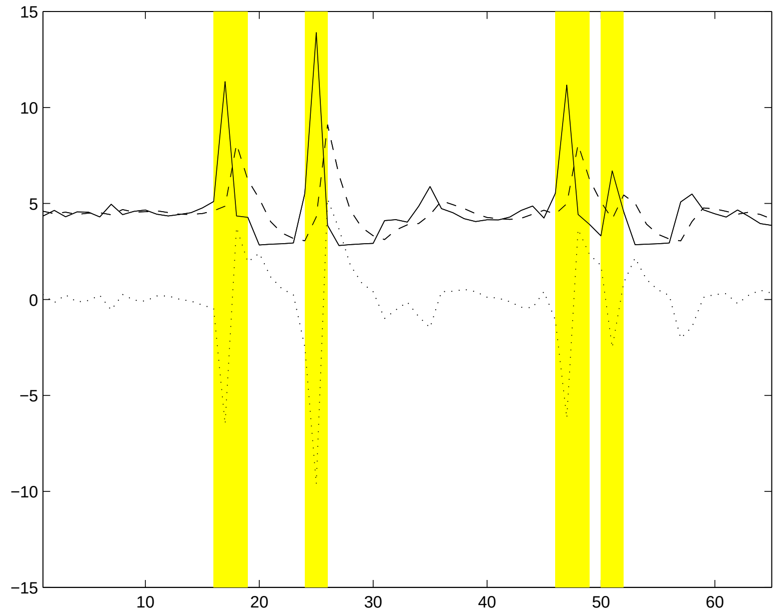
[23]Given the high level of stylization of the model, no attempt is made to carry out a more careful calibration exercise. The aim is rather to asses the capacity of the model to account for some qualitative features of the data.

Figure 4: Net and Gross Job Flow Rates for the Model Economies



Shaded regions represent downturns (not necessarily recessions)

Figure 5: Experiments

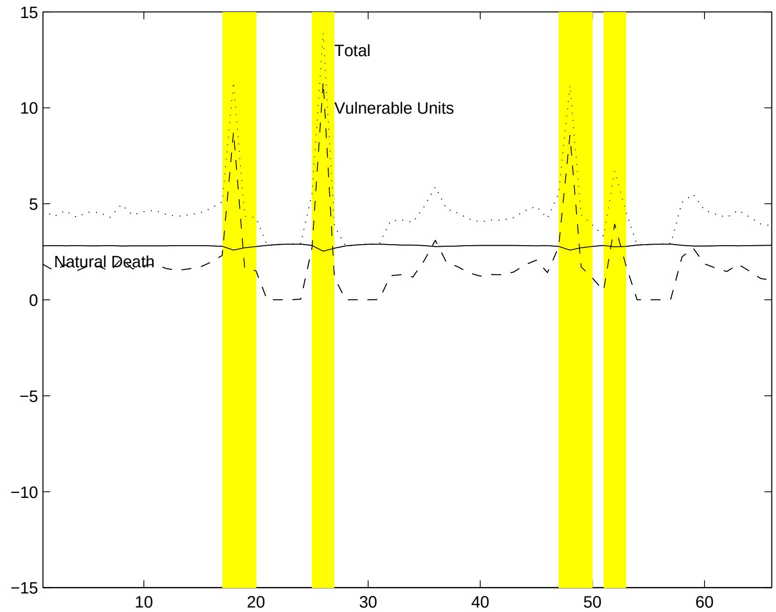


downturns: a downturn induces a period of intense reallocation activity, during which all vulnerable units discover their type and act accordingly. This implies that in the next few periods the mass of vulnerable units will be low.[24] Therefore, a downturn closely following another one will not induce high exit, as the two close downturns in periods 46-52 in the figure show.

The aspects illustrated so far would remain true also in a model in which fragile units are not necessarily the young ones. If we take the age aspect literally, we can make a point on the intensity of the effects of a downturn and length of the expansion phase. Consider the first thirty periods in Figure 5. With no downturns, the economy behaves in a fashion that closely matches that of the economy without the aggregate state, as the first 15 periods in the figure show. The effects of the first downturn are represented by the first spike in exit. I then inflict a second downturn 9 periods later. The figure shows that the second recession is indeed deeper than the first one, with a higher spike in job destruction. This result is due to the fact that the exit wave following the first downturn induces some periods of high entry as the economy fills up again, so that the subsectors that enter after the recession will

[24]In terms of the state vector $X(t)$, the revelation of types for all units of age τ_d^* and older implies that at the end of next period all the subsectors of age $\tau_d^* + 1$ or more will be empty.

Figure 6: Decomposition of the exit flow



be larger than average; the second downturn hits when such large subsectors are vulnerable, thus inducing a particularly high level of exit.[25] This feature of the model accords with the particular severity of the 1981-82 recession as illustrated in Figure 1: this recession was in fact preceded by a short and sharp one at the beginning of 1980. Many observers claim that the recession of 1981-82 was characterized by a high level of restructuring activities. Taking the assumptions of the model literally, much of such restructuring should be attributed to units that entered during the recovery following the previous recession.

The previous observation leads to one final point, which relates aggregate downturns to the composition of exit. A downturn induces a surge in voluntary exit by fragile units, but not a change in natural death. This implies that the ratio of fragile to mature units exiting is noticeably higher than average after a downturn. To make this point clear, Figure 6 plots the decomposition of the exit flow of Figure 5. Recessions are induced by a surge in exit of vulnerable units, with the ratio of voluntary to natural exit going from less then one for the initial period to approximately four in the period immediately following a downturn.

[25]This is also apparent in the echo effects generated by recessions: a prolonged series of normal periods will induce a surge in exit some periods after the downturn, when the large subsectors that entered immediately after the recession undertake adjustment.

5.1 Discussion: Empirical Evidence

There is little work that directly addresses the empirical relevance of information spillovers, due to the difficulties in identifying information flows. A distinct but related literature suggests that knowledge and technological spillovers matter for firms' location decisions (see for example Feldman and Audretsch, 1999; Jaffe *et al.*, 1993). Anderson and Holt (1997) show that information cascades, a particular form of information spillovers (Bikhchandani *et al.*, 1992), tend to arise frequently in controlled experiments. Goolsbee and Klenow (1999) find evidence that local spillovers are important in determining the diffusion of home computers for a sample of US households. More to the point of this paper, Guiso and Schivardi (1999) directly address the issue of the role of information spillovers in shaping firms' factor adjustments, using a unique dataset containing balance-sheet data on approximately 7,000 Italian manufacturing firms for the period 1982-1996. They identify the reference group in terms of firms' *similarity*, related to the product brand, and *proximity*, measured by geographical distance. The dataset allows the selection of a group of firms located in industrial districts[26] that are more likely to be exposed to information spillovers because they satisfy both criteria. They study the process of labor adjustment in relation to information spillovers, considering both positive and negative aggregate shocks. The results are supportive of the theoretical predictions. Even after controlling for sectoral and local shocks, individual labor adjustments are strongly influenced by different measures of adjustment of firms that satisfy both the similarity and the proximity conditions, while no effects are exerted by firms not satisfying either of them. Moreover, measures of the most extreme adjustments, such as the 10th and the 90th percentile of the distribution of adjustments, have a stronger explanatory power than the average adjustment, arguably because large changes in the labor force have a proportionally higher informational content. Another finding relates to firms' response to aggregate shocks. In accordance with the predictions of the model, the response to aggregate shocks in terms of labor adjustment is approximately three times as large in periods of intense relocation activity (the "recessions") than in nor-

[26]An industrial district is a relatively small geographical area characterized by a strong concentration of firms producing similar goods.

mal periods. Interestingly enough, for firms that are less likely to be subject to information spillovers (firms not located in an industrial district), no difference is found in the response between the two periods. This evidence supports the view that information spillovers play an important role in shaping firms' decisions and can constitute a powerful amplification mechanism of aggregate shocks.[27]

6 Conclusions

I have studied the effects of aggregate shocks on the level of restructuring activities, showing how modest aggregate shocks can induce a burst in relocation activities that magnify the response of the economy to the shock. The model stresses the informational aspects of restructuring activities. Aggregate shocks trigger an endogenous increase in the amount of information available to decision makers, which stimulates reallocation. The model offers both an amplification mechanism and an explanation of why restructuring activities tend to be concentrated in recessions.

While the extreme level of stylization leaves room for generalizations, such as endogenizing entry and studying the welfare implications of the pace of restructuring activities, it will be essential to assess the empirical validity of the model. This can be done at two levels. The first is to consider the relation between aggregate shocks and restructuring activities, and analyze how the level and pace of the restructuring activities vary over the business cycle. This is an area of increasing interest in the empirical analysis of the business cycle (Davis and Haltiwanger (1996;1999), Campbell and Kuttner (1996), Caballero, Engel and Haltiwanger (1997)). While the model does have distinctive restrictions, such as the amplification of shocks and the age composition of exit over the cycle, some of its predictions would be shared by a traditional Ss model without learning. A direct test of the learning mechanism is then warranted. This is a challenging task. The results of Guiso and

[27]Davis and Haltiwanger (1999) use the predictions of this model to obtain theoretical restrictions on the sign of the covariance between aggregate and allocative shocks in a structural VAR for job creation and destruction for the US manufacturing sector in the postwar period. Given that the predictions are used as identifying assumptions for the VAR, their results cannot be seen as direct evidence in support of information spillovers. They however offer evidence that allocative shocks are an important driving force of employment fluctuations over the cycle.

Schivardi (1999), based on a panel of firms that are classified according to their exposure to information spillovers, are supportive of the theoretical predictions, suggesting that this is a direction of research worth further exploration. Another, complementary way to tackle the issue would be to undertake case studies of specific episodes of massive restructuring, such as the one of the US steel industry in the 1981-82 recession as documented by Barnett and Crandall (1986) and popularized by Davis, Haltiwanger and Schuh (1996).

A Appendices

A.1 Proofs

I begin with a lemma that will be used to prove proposition 1.

Lemma 1. *Consider two discrete probability functions f and g, with corresponding cumulative distributions F and G, defined over a common support $X = \{x_1, x_2, ..., x_n\}$, where $x_1 < x_2 < ... < x_n$. Assume that there exists an $\bar{\imath}$ such that $f(x_i) > g(x_i)$ for $i < \bar{\imath}$, and $f(x_i) < g(x_i)$ for $i > \bar{\imath}$. Then, $\forall\ i < n,\ F(x_i) > G(x_i)$.*

Proof. First, for any $i < \bar{\imath}$, $f(x_i) > g(x_i)$ implies that $\sum_{j=1}^{i} f(x_j) > \sum_{j=1}^{i} g(x_j)$, or $F(x_i) > G(x_i)$. For $\bar{\imath} < i < n$, $f(x_i) < g(x_i)$ implies $\sum_{j=i}^{n-1} f(x_j) < \sum_{j=i}^{n-1} g(x_j)$ or $1 - F(x_i) < 1 - G(x_i)$. Finally, for $i = \bar{\imath}$, if $f(x_{\bar{\imath}}) \neq g(x_{\bar{\imath}})$, the same argument can be extended to such a point, while if $f(x_{\bar{\imath}}) = g(x_{\bar{\imath}})$, then, given that $F(x_{\bar{\imath}-1}) > G(x_{\bar{\imath}-1})$, it follows that $F(x_{\bar{\imath}}) = F(x_{\bar{\imath}-1}) + f(x_{\bar{\imath}}) > G(x_{\bar{\imath}-1}) + g(x_{\bar{\imath}}) = G(x_{\bar{\imath}})$. □

Proof of Proposition 1. Consider a generic subsector τ at t. First, note that from equation (10), $\lambda(\Omega_t^\tau) \leq \lambda_0 + \rho(1 - \lambda_0)\ \ \forall\ \Omega_t^\tau$. If $\lambda(s) > \lambda_0 + \rho(1 - \lambda_0)$ for $s = \{n, d\}$, then it follows that $\lambda(s) > \lambda(\Omega_t^\tau)\ \ \forall\ \Omega_t^\tau)$. As a consequence, no matter what the public history, all units will stay in the market at least one period, so that each of them receives a signal. Consider now a generic period t before which no voluntary exit has taken place, τ periods after entry. Given the continuum of units assumption, there will be a non-zero mass of units that will have received all possible combinations of signals. For Bayesian updating, we only need the total number of bad and good signals, given that the order in which they are received does not matter. There will be $\tau + 1$ points for beliefs with a non-zero mass of units, corresponding to having received $0, 1, ..., \tau$ bad signals out of τ total signals. For n_b bad signals, the value of the posterior is $\lambda(n_b) \equiv \lambda(\tau - n_b, n_b; \lambda(\Omega_t^\tau))$ as calculated according to Bayes rule in (2). Clearly, in any period τ, $\lambda(0) < \lambda(\Omega_t^\tau) < \lambda(\tau)$. Define $f_\tau(n_b|\theta)$ as the discrete density function of the *share* of units at belief $\lambda(n_b)$, and $F_\tau(n_b|\theta)$ as the cumulative density function. Then, we want to show that $\forall\ n_b < n_\tau,\ F_\tau(n_b|\theta_h) > F_\tau(\lambda_{n_b}|\theta_l)$. If this is the case, the mass of units at or above a given beliefs level will be different for the two types, which is enough to prove the proposition. To ease notation, define $p_h \equiv \Pr\{z_b|\theta_h\}$ and $p_l \equiv \Pr\{z_b|\theta_l\}$. Given that there is a continuum of units, the share of units with belief $\lambda(n_b)$ is the probability of n_b successes in τ trials for a binomial distribution:

$$f_\tau(n_b|\theta_h) = \binom{\tau}{n_b} p_h^{n_b}(1 - p_h)^{\tau - n_b} \tag{A-1}$$

$$f_\tau(n_b|\theta_l) = \binom{\tau}{n_b} p_l^{n_b}(1 - p_l)^{\tau - n_b} \tag{A-2}$$

Consider the inequality $f_\tau(n_b|\theta_h) > f_\tau(n_b|\theta_l)$. Taking the logarithm of both sides and rearranging, we get:

$$dlf_\tau(n_b) \equiv \tau log\left(\frac{1-p_h}{1-p_l}\right) + n_b log\left(\frac{p_h}{1-p_h}\frac{1-p_l}{p_l}\right) \tag{A-3}$$

For $n_b = 0$, $dlf_\tau(0) = \tau log\left(\frac{1-p_h}{1-p_l}\right) > 0$ given that $p_h < p_l$. For $n_b = \tau$, $dlf_\tau(\tau) = \tau log\left(\frac{p_h}{p_l}\right) < 0$. Finally, given that $\frac{p_h}{1-p_h}\frac{1-p_l}{p_l} < 1$ it follows that

$$log\left(\frac{p_h}{1-p_h}\frac{1-p_l}{p_l}\right) < 0 \tag{A-4}$$

This implies that $dlf_\tau(n_b)$ is monotonically decreasing in n_b, from which it follows that $f_\tau(n_b|\theta_h)$ and $f_\tau(n_b|\theta_l)$ satisfy the condition of lemma 1, so that $F_\tau(n_b|\theta_h) > F_\tau(n_b|\theta_l)$ $\forall\ \lambda < \lambda_\tau$. Finally, given that $\forall\ \Omega_t^\tau, \lambda(0) < \lambda(\Omega_t^\tau) < \lambda(s),\ \ s = \{n, d\}$, it follows that $\forall\ \tau > 0$, there is a non-zero mass of units below the exit cutoff, which excludes the possibility that the full mass of units undertake first exit simultaneously. □

Proof of Proposition 2. I show that any best response strategy is a cutoff strategy. Consider $\tilde{r}(\lambda, s)$ as defined in equation (20). First, note that the assumption that it is optimal for a θ_l unit to leave the market implies that $\pi(\theta_l, s) < -(1-\beta(1-\delta))k$, which in turn implies that $\tilde{r}(1, s) = \pi(\theta_l, s) - \beta(1-\delta)k < -k$. Second, given that it is optimal for a θ_h unit to stay, we have $\tilde{r}(0, s) = v(s) > -k$. If we show that $\tilde{r}(\lambda, s)$ is monotonically decreasing and continuous in λ, then there exists a $\bar{\lambda}(s)$ such that

$$r(\bar{\lambda}, s) = \tilde{r}(\bar{\lambda}, s) \tag{A-5}$$

and

$$r(\lambda, s) > \tilde{r}(\lambda, s) \qquad\qquad \forall\ \lambda > \bar{\lambda} \tag{A-6}$$

From equation (3′) it is immediate that $\pi(\lambda, s)$ is continuous and decreasing in λ. Moreover, given that $v(s) > -k$ for $s = \{n, d\}$ and that $\sum_{s'} \gamma_1(s', s) = 1$, it follows that $V(s) > -k$, which implies that the second term on the right hand side of (20) is decreasing and continuous. Therefore, for all $\lambda > \bar{\lambda}$ it is optimal to exit even if the type will be revealed next period. This means that the best response is in cutoff strategies. Given that, under the condition discussed above, cutoff strategies are type revealing, the equilibrium must be in cutoff strategies. □

The proof of proposition 3 will follow immediately from this rather obvious lemma. To ease notation, define $a \equiv \gamma_1(n|n)$ and $b \equiv \gamma_1(d|d)$. Note that $\gamma_1(d|n) = 1 - a$ and

$\gamma_1(n|d) = 1 - b$.

Lemma 2. *The value of being a θ_h type is higher in a normal period than in a downturn: $v(n) > v(d)$.*

Proof. First, note that $\{v(n), v(d)\}$ must satisfy the following system of equations:

$$v(n) = \pi(\theta_h, n) + \beta(1-\delta)[av(n) + (1-a)v(d)] \tag{A-7}$$
$$v(d) = \pi(\theta_h, d) + \beta(1-\delta)[(1-b)v(n) + bv(d)] \tag{A-8}$$

Solving this system, the implied values for $v(n), v(d)$ are:

$$v(n) = \frac{(1-b\beta(1-\delta))\pi(\theta_h, n) + (1-a)\beta(1-\delta)\pi(\theta_h, d)}{(1-a\beta(1-\delta))(1-b\beta(1-\delta)) - (1-a)(1-b)(\beta(1-\delta))^2} \tag{A-9}$$
$$v(d) = \frac{(1-a\beta(1-\delta))\pi(\theta_h, d) + (1-b)\beta(1-\delta)\pi(\theta_h, n)}{(1-a\beta(1-\delta))(1-b\beta(1-\delta)) - (1-a)(1-b)(\beta(1-\delta))^2} \tag{A-10}$$

Then, given that $\gamma_1(s'|s) \in (0,1) \quad \forall s, s'$, and that $\beta(1-\delta) < 1$, the denominator of the expression is positive. Comparing the numerators, after collecting terms we obtain that $v(n) > v(d)$ if and only if $[\pi(\theta_h, n) - \pi(\theta_h, d)](1 - \beta(1-\delta)) > 0$, or equivalently if $\pi(\theta_h, n) > \pi(\theta_h, d)$. □

Proof of Proposition 3. It is easier to resort to $\tilde{r}(\lambda, s)$ rather that using directly the values of $\{\lambda_n^*, \lambda_d^*\}$ as obtained in equations (22a,22b). First, note that given the assumption that $\gamma_1(n|n) > \gamma_1(n|d)$ and the result established in lemma 2, it is immediate to show that $V(n) > V(d)$, with $V(s)$ defined in equation (19). In addition, I have shown that $\pi(\lambda, d) < \pi(\lambda, n)$, so that

$$\tilde{r}(\lambda, n) > \tilde{r}(\lambda, d) \;\; \forall \lambda \in [0,1] \tag{A-11}$$

Consider λ_d^*. Given what established in equation (A-11), and given that $\tilde{r}(\lambda_d^*, d) = -k$, it must be that

$$\tilde{r}(\lambda_d^*, n) > -k \tag{A-12}$$

Therefore, given that $\tilde{r}(\lambda, n)$ is decreasing in λ, it follows that $\lambda_n^* > \lambda_d^*$. □

A.2 Existence Discussion and No-Deviation Condition

In terms of existence, the numerical solution of the model shows that it is indeed an issue. In particular, the cost of exit needs to be relatively large for a pessimistic unit to be willing to wait for the first exit times. The problem is particularly severe when η is low, arguably because in that case, for given Λ^*, a unit needs to wait longer. For higher values of η equilibria exist for a large selection of parameter values.

The existence issue is a very important problem for the model. However, as already noted by Caplin and Leahy (1994), it seems more a technical issue than a substantive one. The problem arises because of the continuum of units assumption, which implies that the information cannot be realized at any rate other than "all" or "nothing". With a discrete number of units, it would be possible to choose (mixed) strategies that control the amount of information being released and can therefore keep pessimistic units from exiting.[28] While it would be interesting to pursue a formulation of the model along these lines, there seems to be no easy way to tackle the problem once we dismiss the continuum of units assumption.

A drastic way to solve the existence issue is to increase the cost of exit in periods when no other unit voluntarily exits. Formally, if we define the mass of voluntary exit from the sector in period t with e_t, then we impose

$$k(e_t) = \begin{cases} k & \text{if } e_t > 0 \\ k' & \text{otherwise} \end{cases} \tag{A-13}$$

This assumption does not modify the previous analysis. Then, for suitable values of k', such as for all $k' > \pi(\theta_l, d)$, it is easy to show that an equilibrium exists.

For the no deviation condition, I only sketch the derivation[29] of the condition for $\tau < \tau_d^*$. The one for $\tau_d^* \le \tau < \tau_n^*$ follows the same logic. Consider a generic period $\tau_0 < \tau_d^*$. I have argued in the text that we only need to worry about the value of continuing for the most pessimistic units, that is, for those that have received all bad signals. Therefore, all the expectations in the following derivation are conditional on current beliefs $\lambda_{\tau_0} = \lambda(0, \tau_0; \lambda_0)$. The conditioning is not explicitly reported to ease the notation. By linearity of $\pi(\lambda, s)$ in λ and by the martingale property of the beliefs, we have:

$$E(\pi(\lambda_\tau, s)) = \pi(\lambda_{\tau_0}, s) \tag{A-14}$$

where λ_τ is the belief at τ. Define the following truncated expectations and probabilities:

$$\lambda_\tau^s = E(\lambda_\tau | \lambda_\tau < \lambda_s^*) \tag{A-15}$$

$$P_\tau^s = Pr\{\lambda_\tau \ge \lambda_s^*\} \tag{A-16}$$

λ_τ^s is the expected value for beliefs at time τ conditional on the fact that beliefs are below

[28] Models with a discrete number of agents can be found in Horvath, Schivardi and Woywode (1998) and Chamley and Gale (1994). Those models are however simpler in that, in addition to not having an aggregate state, either there is no private information (the former) or there is no arrival of new information over time (the latter).

[29] Detailed calculations are available upon request.

the equilibrium threshold, and P_τ^s the probability that beliefs are above the threshold.

Define $\Gamma_\tau(s'|s)$ as the probability that the first adjustment takes place at time τ in state s' given that the state at τ_0 is s. For example, for $s = d, \tau_d^* < \tau < \tau_n^*$, we have:

$$\Gamma_\tau(d|s) = \gamma_{\tau_d^* - \tau_0}(n|s)\gamma_1(n|n)^{\tau - \tau_d^* - 1}\gamma_1(d|n) \quad \text{(A-17)}$$

$\Gamma_\tau(d|s)$ is the probability that the first downturn in the interval $[\tau_d^*, \tau]$ hits the economy at τ. Then, we obtain:

$$\begin{aligned} U_{\tau_0}(\Lambda^*, s) = & \sum_{\tau=0}^{\tau_d^*-1} \{(\beta(1-\delta))^{\tau-\tau_0} \textstyle\sum_{s'} \pi(\lambda_{\tau_0}, s')\gamma_{\tau-\tau_0}(s'|s)\} + \\ & \sum_{\tau=\tau_d^*}^{\tau_n^*} (\beta(1-\delta))^{\tau-\tau_0}\pi(\lambda_{\tau_0}, n)\gamma_{\tau-\tau_0}(n|s)\gamma_1(n|n)^{\tau-\tau_d^*} + \\ & \sum_{\tau=\tau_d^*}^{\tau_n^*} (\beta(1-\delta))^{\tau-\tau_0}\Gamma_\tau(d|s)\{-kP_\tau^d + \\ & (1-P_\tau^d)[\pi(\lambda_\tau^d, d) + (\beta(1-\delta))(-k\lambda_\tau^d + (1-\lambda_\tau^d)V(d))]\} + \\ & (\beta(1-\delta))^{\tau_n^*-\tau_0}\Gamma_{\tau_n^*}(n|s)\{-kP_\tau^n + \\ & (1-P_\tau^n)[\pi(\lambda_{\tau_n^*}^n, n) + (\beta(1-\delta))(-k\lambda_{\tau_n^*}^n + (1-\lambda_{\tau_n^*}^n)V(n))]\} \quad \text{(A-18)} \end{aligned}$$

The first two lines represent the expected payoff from the pre-adjustment periods, the third and fourth that from the adjustment period with adjustment taking place in a downturn and the last two that from adjustment taking place in a normal period.

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