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Subsidizing startups under imperfect information[☆]

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How is firm creation affected by imperfect information? Our model of rational inattention generates inefficient entry and labor misallocation, because startups make error-prone decisions. Learning decisions of prospective entrepreneurs alter the effects of lump-sum transfers to startups: the total employment gain is amplified due to an unintended increase in inefficient entry, most entrants hire fewer workers, and misallocation goes up. The transfer changes the learning incentives and makes even productive startups lean towards more conservative hiring. We show that this novel information channel works against well-known mechanisms, and thus can help reconcile recent empirical evidence on startup policies.

1. Introduction

Startups are a crucial driver of aggregate job creation and productivity growth; consequently, many countries devise policies to promote their formation and success. Recent research has highlighted the importance of startups' growth potential, and initial size, for their future performance. Sterk et al. (2021), for instance, find that ex-ante factors explain a large share of the cross-sectional dispersion of employment even many years after firm entry. This form of ex-ante heterogeneity, however, is difficult – and costly – to observe; not only by researchers and policymakers, but arguably by startups themselves. Indeed, information frictions have been empirically shown to be one of the most sizable firm-level costs – see Zbaracki et al. (2004) – and firm managers' beliefs are consistent with models of information rigidity and inattention in particular, see Coibion et al. (2018).

Motivated by these considerations, we build a model of startup creation with imperfect information, following the theory of rational inattention developed by Sims (2003). Consistent with empirical evidence, our model implies that some entrepreneurs start a firm although they should not (i.e, inefficient entry) and under- or over-hire relative to the first best of perfect information (i.e., labor misallocation). We document that allowing prospective entrepreneurs to choose the precision

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and the amount of information to acquire alters the effects of lump-sum transfers to startups. While the total employment effects are amplified, three unintended consequences arise: transfers may amplify inefficient entry, reduce the initial size of most startups, and increase misallocation. We first isolate this new channel in a simple static model, and then explore how firm dynamics and financial frictions affect our conclusions. In these richer environments, the information decision dampens the intended effects of startup policies, and has markedly heterogeneous effects. As such, our mechanism can help explain why cash transfers to startups are sometimes empirically found to have limited effects.

In light of the empirically documented importance of ex-ante heterogeneity, we focus our analysis on the very early stages of firm creation.[1] To this end, we begin with a deliberately simple static model in which potential entrants differ ex-ante in their idiosyncratic productivity. If firms decide to enter the market, they hire labor, which is the only factor of production, pay wages and a fixed cost. When information is complete, startups can observe their productivity beforehand, and the fixed cost implies that there exists a minimum level of productivity below which entry is not profitable. Moreover, all startups that enter the market hire optimally. When information is incomplete, however, rationally inattentive startups only observe noisy signals about their true productivity. Learning is costly but endogenous and completely flexible, as firms decide which actions to learn about, the specific structure of the signals they aim to collect and how much information to acquire about the realization of productivity. In our model firms learn "actively" as the quality of such noisy signals is chosen by the firm itself. Moreover, the full flexibility of information acquisition implies that there are no parametric assumptions on the distribution of signals chosen by startups. In this context, we study how rational inattention *simultaneously* affects the decision to enter the market and how many workers to hire.[2] Applying insights from Matějka and McKay (2015) and Caplin et al. (2019) to our framework, we add the discrete choice of firm entry, as an additional action, to the full set of employment choices.

Our calibrated model highlights two key implications of rational inattention. First, there is inefficient entry. Under imperfect information there is now a share of startups whose productivity is below the profitable cutoff but decide nevertheless to enter. Mistakes, however, happen also among profitable startups, some of which decide to stay out of the market although they would be making positive profits if they operated. We show under which conditions inefficient non-entry dominates. Second, rational inattention also distorts the intensive margin of hiring. Some startups over-hire relative to first best, while some under-hire. This generates a large dispersion in marginal products of labor, quantitatively consistent with the contribution of information frictions to empirically observed misallocation assessed by David and Venkateswaran (2019). We also show how higher information frictions exacerbate entrepreneurs' mistakes, thus increasing inefficient entry and misallocation.

We then use our theoretical framework to investigate how information frictions alter the effects of a homogeneous lump-sum transfer to startups. Policies of this sort are common across the globe. They often take the form of R&D grants, as studied by Howell (2017), but can also have a broader scope and loose requirements to meet.[3] The empirical evaluation of these policies, however, is particularly difficult, given the scarcity of identified exogenous variation and the limited observable information on startups, especially those that eventually do not enter the market. Moreover, some of these startup fundamentals, such as their growth potential, are likely to be imperfectly observed even by the entrepreneurs. We therefore see our model – and subsequent extensions – as a useful laboratory to outline the theoretical mechanisms that characterize the effects of startup policies, especially the allocative implications across the size and productivity distribution. Our framework also fits into a long-standing literature studying the consequences of policy when agents have imperfect information, such as Lucas (1972) and Woodford (2001). Under full information, the mechanism is simple: the transfer shifts the profitability cutoff to the left. It therefore increases entry, but leaves the intensive-margin hiring decisions of all startups unaffected.

We uncover three main unintended consequences of lump-sum transfers under rational inattention. First, while they generate an increase in firm entry more than twice as large as with full information, this amplification is driven by additional inefficient entrants. Although rationally inattentive startups do not observe the exact distance between their productivity and the profitability cutoff, they know with certainty that some actions can be ruled out ex-ante, i.e., they are dominated. The transfer makes some previously dominated actions feasible, changing the cutoff and boosting inefficient entry.

This channel lies at the core of the second unintended consequence: most startups *reduce* hiring when receiving a lump-sum transfer. The transfer adds actions that were previously dominated to the set of possible actions of startups. Due to the absence of regularity, typical of rational inattention models, the policy has an effect on the *entire* learning strategy of firms and thus on the chosen employment distribution. The closer the perceived productivity is to the cutoff, the higher weight the potential entrant will put on the new, low-employment, actions made feasible by the transfer. A transfer equal to 5% of the fixed cost reduces average employment by 1.5%, among startups that would have already entered without the transfer. Finally, the lump-sum transfer increases misallocation, in the form of dispersion of marginal products of labor. This is caused by a reduction in information acquisition after the policy. Hence, the endogenous acquisition of information does

[1] Therefore, we do not study learning over the entire firm life cycle, as instead done by Jovanovic (1982) and Arkolakis et al. (2018). We discuss the extent to which this ex-post channel is complementary to our ex-ante learning mechanism and how it can deliver different policy implications.

[2] Woodford (2009) and Acharya and Wee (2020) study the extensive margin in isolation. The former in the context of firms' decisions to adjust existing prices, the latter in a search and matching framework where the decision to hire a worker is made under rational inattention.

[3] Caliendo and Tübbicke (2020) study a German start-up subsidy program targeted to the unemployed and show that similar policies are common in OECD countries. Such policies often come in the form of equity-free grants (e.g.: Start-up Chile, Bourse French Tech).

not only matter for resource misallocation per se, but also for how it is affected by policy.[4] Excessively large transfers are sometimes blamed for artificially keeping alive inefficient, "zombie", firms. We show how our novel information channel can lead to similar conclusions among young firms, as transfers may induce inefficient startups to enter the market and hire suboptimally.

The amplified effect along the entry margin, operating through enhanced inefficient entry, dominates the negative effects on initial size. As a result, transfers increase total employment of startups by more when information is imperfect. Importantly, most of the rich implications just discussed do not simply arise from generic information frictions; instead, they are the direct result of active learning under flexible information. Since startups tailor the characteristics of acquired signals, and these ultimately shape their actions, transfers alter both the learning and hiring strategies of the firm.

Next, we consider various extensions of the baseline model that make startup decisions richer and investigate how our conclusions are affected. First, startups may take into account future expected profits when deciding to enter the market. To explore this, we consider a two-period model in which operating firms pay a cost of adjusting labor between the first and the second period. Although we assume that productivity is fully revealed in the second period, mistakes made upon entry endogenously generate sizable exit rates and persistent misallocation. For an empirically plausible range of parameters, we find that RI can explain between 15 and 25% of the empirically observed young firms' exit rates. In addition, survival rates fall with the cost of information; we provide new empirical evidence that supports these findings. The unintended consequences of startup transfers are still present in this dynamic setup, although quantitatively attenuated; while average employment falls by 0.5–1%, entry goes up by more than with full information. We discuss how the choice of parameters affects our results and, in particular, their persistence. Importantly, we intentionally set up the model to focus on the very early stages of firm creation and thus see additional mechanisms, such as learning over the firm life cycle as in Jovanovic (1982), as complementary to our channel.[5]

We then augment the dynamic setting with financial frictions. Startups are typically limited in their ability to access external financing; indeed, grants and similar policies are often thought to operate via the relaxation of credit constraints that hamper startup creation and growth.[6] We assume that there is a cash-flow mismatch between the payment of the wage bill, which happens at the beginning of the period, and the realization of revenues, at the end of the period. We discuss various financial frictions that can affect startups' ability to satisfy this liquidity need and focus our analysis on earnings-based constraints, as recently studied by Drechsel (2019) and Lian and Ma (2021). With full information, lump-sum transfers not only stimulate firm entry, but now also boost hiring of financially constrained startups, since they improve their financial position.

The novel information channel previously discussed, and the associated unintended consequences, are however still present. The transfer increases inefficient entry, thus amplifying the entry margin effect relative to the full information benchmark, albeit to a lesser extent than without financial frictions. Along the intensive hiring margin, financially constrained startups face two counteracting effects. On the one hand, they want to increase employment, because they can borrow more. On the other hand, the transfer makes new, low-size, actions feasible; this alters startups' entire learning strategy and makes them lean towards less hiring. The former channel prevails for higher-productivity firms, whereas smaller, unproductive startups choose a smaller initial size. On average, our novel information channel is quantitatively substantial, such that it can overturn the positive employment effects stemming from the financial friction: employment to cash flow elasticities are close to zero, and thus much smaller than in full information. Hence, our theoretical framework provides an explanation for why cash transfers have been empirically found to have limited effects on startups performance, see Howell (2020) and Gonzalez-Uribe and Leatherbee (2018). Their findings suggest that information frictions may be important for startups; we formally outline a mechanism through which information rigidities can affect the effectiveness of startup policies and work against well-known (financial) channels.[7]

The paper is organized as follows. In Section 2 we describe the baseline static model and Section 3 shows how RI generates inefficient entry and suboptimal hiring. We present the effects of a startup transfer in Section 4. We explore how our findings change in a dynamic model in Section 5.1 and adding financial frictions in Section 5.3. Section 6 concludes.

2. A model of startups

We consider a one-period framework in which a unit measure of potential entrants chooses the amount of labor n, among a discrete set of alternatives, and face decreasing returns to scale. The model is in partial equilibrium and zeroes in on the early stages of firm creation.

Potential entrants are heterogeneous with respect to idiosyncratic productivity z. With productivity z we think of any idiosyncratic fundamental that may introduce heterogeneity in performance across startups: for instance, demand compo-

[4] Similarly, Gondhi (2021) studies how rational inattention affects misallocation over the business cycle.

[5] We discuss how extending the model to more periods does not unambiguously soften the effects upon entry. To maintain our focus on the early stages of firm creation, we always make the conservative assumption that firms observe their productivity in their second year of life.

[6] This channel is often discussed in the context of R&D grants to young firms, as in Howell (2017). Albert et al. (2020) study loan and wage subsidies in a model with heterogeneous firms, financial constraints and firm entry, and assess their effects during the COVID-19 recession.

[7] Empirical work also highlights the effectiveness of non-monetary components of startup policies. We discuss this, through the lens of our model, in Appendix D.4.

nents, productive efficiency, entrepreneurial ability or managerial talent. Given our focus on the early stages of firm creation, z aims to represent the form of ex-ante heterogeneity recently studied by Sterk et al. (2021) and Felix et al. (2021), and shown to be a crucial driver of employment differences across U.S. firms.

There is a finite amount of possible realizations for the idiosyncratic productivity, described by the set Ω_z. A hiring decision (i.e., an action) is a mapping from the potential productivity realizations to firm profits. Let Ω_n denote the set of possible actions, where $\pi : \Omega_n \times \Omega_z \to \mathbb{R}$ determines the firms profit of each hiring decision in each possible outcome for the productivity. Each unit of labor is paid at a competitive wage w. When a startup decides to enter the market, they must pay a fixed cost ϕ which is known with certainty. Finally, τ is an exogenous transfer, which we set to 0 for now and discuss later in Section 4.

Profits of a startup i are defined as:

$$\pi_i = \begin{cases} z_i n_i^{\alpha} - w n_i - \phi + \tau & \text{if} \quad n_i > 0 \\ 0 & \text{if} \quad n_i = 0 \end{cases} \tag{1}$$

As noticed, the possibility of not entering the market is included in the set of possible actions and delivers zero profits. We consider two possible states of the world, one in which startups have Full Information (henceforth, FI) about $z \in \Omega_z$, and another where information is imperfect. In the latter case, we assume that, prior to making a hiring decision, startups can acquire costly information about their idiosyncratic productivity z, following the theory of Rational Inattention (henceforth, RI).

2.1. Full information

When information is complete, potential entrants observe z exactly. Given the fixed cost ϕ, the optimal hiring decision is defined by a cutoff rule of productivity $n(\underline{z})$. Below this cutoff, startups do not enter because they make negative profits. Above this level, they choose employment to maximize profits. Hence, our FI framework can be seen as a simplified version of Lucas (1978), where there is an observed distribution of managerial talent and the fixed cost can be interpreted as a fixed outside opportunity cost of managers' time.

Optimal employment with full information looks as follows:

$$n^*(z_i) = \begin{cases} \left(\frac{\alpha z_i}{w}\right)^{\frac{1}{1-\alpha}} & \text{if} \quad z_i^{\frac{1}{1-\alpha}} w^{\frac{\alpha}{1-\alpha}} \left(\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}\right) \geq \phi - \tau \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Therefore, $\underline{n} = \underline{z}^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{w}\right)^{\frac{1}{1-\alpha}} = \frac{\phi-\tau}{\alpha^{-1}-1} w^{\frac{-1-\alpha}{1-\alpha}}$ defines the minimum production scale.

2.2. Rational inattention

In the RI setting, we assume that firms imperfectly observe the idiosyncratic draw $z \in \Omega_z$. Information frictions have been shown to be one of the most sizable costs faced by firms. They affect firms' ability to observe their idiosyncratic fundamentals, such as demand and productive efficiency, see David et al. (2016), as well as the ability to identify productivity-enhancing managerial practices, as in Bloom et al. (2013). Startups are no exception. In fact, it is even more likely to expect that potential entrepreneurs do not observe their true ability/productivity before entering the market, or at least do not anticipate exactly how their own growth potential, z, will unfold. However, entrepreneurs have the incentive to acquire information about their growth prospects, and thus we employ a model that allows for endogenous learning.

Since z is imperfectly observed, profits associated to each possible action are unknown. We can interpret the framework as one in which each prospective entrant only observes noisy signals about its true z, similarly to Clementi and Palazzo (2016). However, differently from their setup, signals are not drawn from an exogenous distribution, but startups actively choose the signal structure. Before choosing the amount of labor, the startup can collect information about the realization of z by designing an "information strategy", which consists of what specific information to learn and how much information to acquire. As we think about the information strategy as a set of signals, there is a stochastic mapping between the true productivity and these signals. The firm will, however, face a tradeoff. While more precise signals allow it to make fewer error-prone decisions (on average), a higher precision requires a higher cost. Following the literature on RI, we measure this cost based on Shannon mutual information between signals and the unobserved productivity.

The startup decision problem under RI is given by a prior distribution $g \in \Delta(\Omega_z)$ over the set of possible values of productivity, the set of actions Ω_n and the marginal cost of information $\theta > 0$. An important implication of decision-making under RI is that for a strategy to be optimal, each possible action is selected by no more than a single posterior probability. Hence, each possible signal maps to just one possible action.[8] In turn, rather than choosing the possible quality of signals, we merge the information and decision strategies into a single problem consisting of choosing the probability of each action

[8] Intuitively, if the agent chooses to receive different signals that lead to the *same* action, she will be acquiring costly information that is not ultimately used. See Lemma 1, in Matějka and McKay (2015).

in each state, as outlined in Matějka and McKay (2015). Therefore, the firm chooses $F: \Omega_z \to \Delta(\Omega_n)$, i.e., the probability of $n \in \Omega_n$ in each possible state z. We denote $F(n|z)$ the probability of action n given z.

Startups choose F to maximize the expected value of profits minus the product of the marginal cost of information, θ, and the total amount of acquired information, κ. As standard in RI, κ is measured based on Shannon mutual information between states and actions:

$$\kappa \equiv -\sum_{n\in\Omega_n} F(n)\ln(F(n)) - \sum_{z\in\Omega_z} g(z)\left(\sum_{n\in\Omega_n} F(n|z)\ln(F(n|z))\right) \tag{3}$$

where $F(n) = \sum_{z\in\Omega_z} g(z)F(n|z)$ is the marginal probability of each possible action n. The first term on the right hand side of (3) corresponds to the ex-ante (i.e., prior to information) uncertainty of the unconditional distribution $F(n)$ measured by its entropy. The second term in (3) corresponds to the ex-post (i.e.: after receiving new information) uncertainty of the posterior distribution $F(n|z)$. The hiring decision problem of startups under RI is given by:

$$\max_F \sum_{z\in\Omega_z} g(z)\left(\sum_{n\in\Omega_n} F(n|z)\pi(z,n)\right) - \theta\kappa \tag{4}$$

The fact that the final decision is drawn from $F(n|z)$ reflects the nature of the problem. Due to the imperfect information, the startup produces stochastic error-prone decisions. Full Information, in contrast, can be approximated by $\theta = 0$. In this world, for a given realized productivity z', the posterior probability would necessarily degenerate in the optimal decision $F(n'|z') = 1$, where n' is the FI hiring choice defined in Eq. (2).

Following Matějka and McKay (2015), the optimal hiring policy under RI must satisfy:

$$F(n|z) = \frac{F(n)exp(\pi(n,z)/\theta)}{\sum_{n'\in\Omega_n} F(n')exp(\pi(n',z)/\theta)} \tag{5}$$

The posterior probability is a function of the unconditional probabilities $F(n)$ and the normalized payoffs of each actions $exp(\pi(n,z)/\theta)$. Eq. (5) implies that each payoff is weighted by $F(n)$, which are independent of z and total information acquired. Hence, when a particular action n seems ex-ante very attractive (the firm is somehow predisposed to choose this specific action), then it has a relatively high probability of being chosen, although its actual payoff is low.

We can substitute Eq. (5) in (4) to get an alternative formulation for the RI problem as a function of the unconditional probabilities:

$$\max_{F(n)} \theta \sum_{z\in\Omega_z} g(z)\left(\sum_{n\in\Omega_n} F(n)exp[\pi(z,n)/\theta]\right) \tag{6}$$

This alternative formulation is what we will use to solve the problem numerically. As one of the possible actions is to not enter the market ($n = 0$), this complicates the computational intensity of the problem greatly. By solving (6) instead of (4), we gain some numerical tractability, which allows us to solve for the two decision margins.

3. Quantitative exploration

We set $\alpha = 0.8$, implying the same returns to scale as in Clementi and Palazzo (2016) and on the lower end of estimates by Basu and Fernald (1997). We show in Appendix B.2 that our results are robust to alternative values. The wage is normalized to 1. We calibrate ϕ to match the within–first–year survival rate, interpreting non–entry as exit within the first year as in Sedláček and Sterk (2017). Using quarterly data from the Business Employment Dynamics (BDM), we find that this probability averaged 35.7% between 1994 and 2017. Conditional on ϕ, we calibrate the productivity distribution as a Gamma distribution with shape parameters $\lambda_g = 0.028$ and scale parameter $\delta_g = 0.190$. We choose the parameters to match, under FI, average employment, the standard deviation, and the 75th and 95th percentile of the firm size distribution of startups in the U.S. In implementation, we discretize the productivity space such that $|\Omega_z| = 1500$ and, hence, $|\Omega_n| = 1501$. We provide additional details on the calibration and underlying data in Appendix A.

While it is well known in the literature that choosing the cost of information, θ, is difficult (see Maćkowiak et al. (2021)), we discipline our choice of $\theta = 0.001539$ with a key empirical observation. By solving a static RI problem with flexible information acquisition, as in our model, Stevens (2020) finds that information acquisition is equal to 0.7% of firm's average revenues in the US. Thus, we calibrate θ to exactly match this ratio.[9] Given the calibration, we start by setting the startup transfer τ to 0 and explore in Section 4 the effects of transfers to startups, i.e., $\tau > 0$.

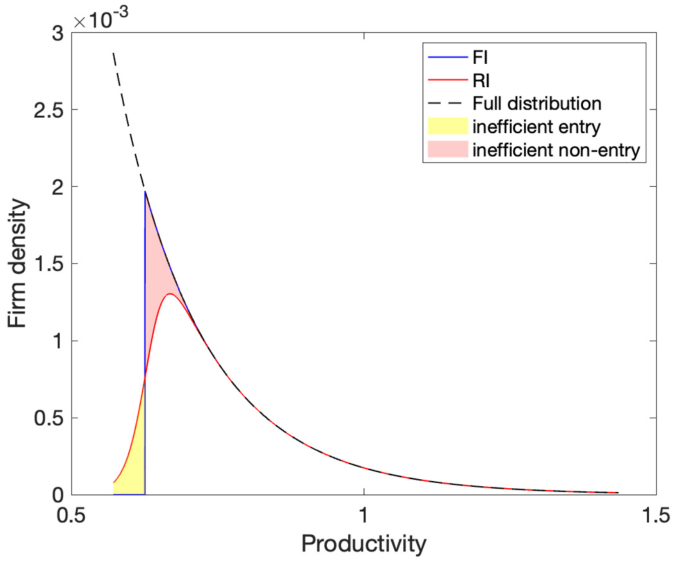


Fig. 1. Productivity distribution of entrants. *Notes*: The figure plots the prior distribution of productivity (dashed black line), the productivity distribution of entrants with full information (solid blue line) and the productivity distribution of entrants under rational inattention (solid blue line). Model described in Section 2 and 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.1. Rationally inattentive startups

In Fig. 1 we show the productivity distribution of startups that decide to enter the market. With full information, there is a clear entry cutoff (blue line in the figure); some states (z), below this cutoff, are never associated with a decision to enter the market. This latter result, in contrast, breaks down under RI.

With FI, there is a one-to-one mapping between productivity and employment, both along the intensive (hiring) and extensive (entry) margin. In RI, this mapping is fuzzy and the sharp cutoff disappears, as shown by the red solid line. Some firms, whose productivity is so low that they should not enter, decide nevertheless to start up. Hence, RI generates inefficient entry. Moreover, some productive firms, which instead would enter if they observed their true productivity, do not hire any worker. Hence, RI implies inefficient "non-entry".[10] As a result, the entrants' productivity distribution does not display a cutoff, but it is hump-shaped. For our calibrated θ, inefficient non-entry dominates, implying that information frictions slightly depress firm entry; we show in Section 3.2 that this conclusion depends on the value of θ. Finally, inefficient entry is empirically consistent with low survival rates of startups, as we discuss later in the two-period model.

Information frictions also affect the intensive margin of hiring. Since z is observed (known) under FI, the size distribution of firms reflects the shape of the productivity distribution. This one–to–one mapping between z and n breaks under RI, and the firm size distribution degenerates into fewer employment values. The fact that RI brings discreteness in actions is an important result in this literature and has been formally proven by Jung et al. (2019). The intuition is that costly information forces the firm to focus only on a subset of actions, leaving the rest unconsidered. As previously mentioned, our choice of θ generates a firm size distribution that remains consistent with the empirical counterpart. However, as we show later, implausibly high information costs are associated with too little learning and, in turn, excessive degeneration of hiring decisions.

To better understand the results of this paper, it is particularly important to focus on hiring decisions at the lowest productivity level. We have previously discussed how, in FI, there exists a productivity cutoff below which firms decide not to enter: i.e., $n^*(z) = 0$. As a result, there exists a minimum operating scale, $\underline{n}$, which pins down the minimum size of entrants. In other words, the subset of actions $\Omega_n^d \equiv (0, \underline{n})$ delivers a lower payoff – than alternative actions – for all realizations of z. Hence, it will never be selected by the firm. We label Ω_n^d as the set of dominated actions. While obvious under FI, through Eq. (6) we notice that firms under RI will also ex ante remove Ω_n^d from the set of possible actions. In particular, if $n' \in \Omega_n$ is a dominated action, i.e. if $\pi(n', z) < \pi(n, z)$ for all z, the objective function can always be increased by shifting probability mass from $F(n')$ to $F(n)$. Hence, the set of *relevant* actions under both FI and RI is given by $n \in \Omega_n \setminus \Omega_n^d$.

[9] As a further validation, in Appendix A we show that our calibrated θ delivers startup shares by size bins in line with what is observed in the U.S. data. Moreover, in Appendix B we argue that excessively high costs of information imply counterfactual firm size distributions.

[10] We assume that all potential entrants take their decisions independently and at the same time, and therefore abstract from other channels like strategic deterrence of entry (e.g., Salop (1979)) and learning under sequential entry (e.g., Rob (1991), Chamley and Gale (1994)).

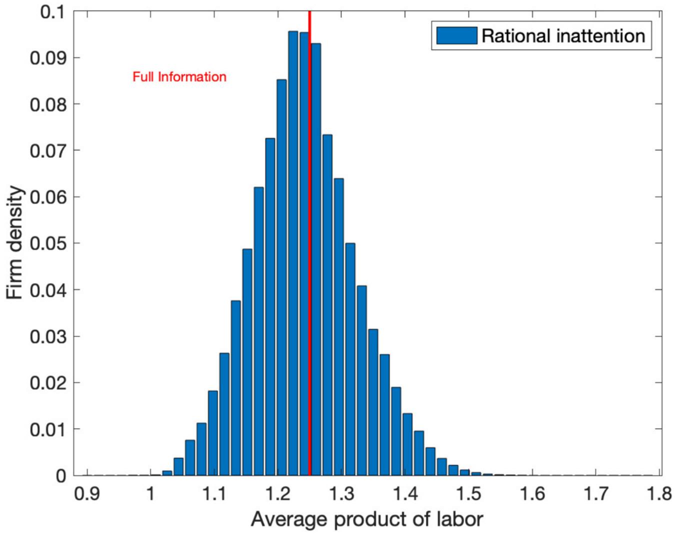


Fig. 2. The distribution of the average products of labor. *Notes*: Average product of labor defined as the firm-level ratio of output y to employment n. Model described in Section 2 and 3.

Following Caplin et al. (2019), we label the subset of hiring decisions that are chosen with positive probability Ω_n^c as the firm's *Consideration Set*. In particular $\Omega_n^c = \{n \in \Omega_n \setminus \Omega_n^d | F(n) > 0\}$. While under FI all possible firms' sizes are considered, the presence of imperfect information leads the firms to endogenously rule out some possible sizes ex-ante and focus on a small subset of alternatives. As a result, and in spite of the presence of inefficient entry, the minimum operating scale in RI is weakly larger than in FI.

The fact that the minimum operating scale persists under rational inattention, while the minimum productivity does not, also has more subtle implications for misallocation and efficiency losses across firms. In our simple baseline model, conditional on entry, all firms choose employment optimally under FI, i.e., there is no dispersion in MPL or in labor productivity, which is equal to $\frac{w}{\alpha}$. This is shown by the vertical red line in Fig. 2. In the same figure we show that RI introduces instead a large degree of dispersion in labor productivity, consistent with empirical evidence even within narrowly defined industries, see Syverson (2004). Startups do not exactly observe their productivity, thus breaking the one–to–one mapping with size. Although firms rationally choose the set of alternatives to maximize expected profits – i.e., the consideration set –, decisions are ultimately stochastic as they reflect the impossibility of perfectly observing z. We find that some firms under-hire (MPL higher than the wage) with respect to the first best, while some other firms over-hire under RI (MPL lower than the wage). Low average products of labor could be engineered in FI by introducing overhead labor in the production function. Adding financial frictions instead, can generate under-hiring, which we discuss in Section 5.3. Interestingly, the information friction alone can endogenously generate both deviations at the same time.

Hiring mistakes are also not evenly distributed across the productivity distribution. We find that productive firms typically under-hire relative to first best, because higher information frictions shrink the consideration set. In contrast, low-productivity firms over-hire. The intuition for this result builds on the minimum operating scale $\underline{n}$, which *censors* the possibilities of under-hiring for unproductive firms close to the cutoff. We show the quantitative extent of these hiring inefficiencies, and their correlation with productivity and size, in Appendix D.2.

The degree of misallocation generated by information frictions is also quantitatively non-negligible. Indeed, we find that it accounts for 11% of the empirically observed standard deviation of log revenue labor productivity in the U.S. measured by Bartelsman et al. (2013).[11] Our findings are consistent with results by David and Venkateswaran (2019), who show that imperfect information accounts for 7% of the dispersion of average revenue products of capital among publicly traded firms in the U.S., and 10% for Chinese manufacturing firms. We interpret the ability of our model to replicate the contribution of information frictions to misallocation as a further validation of our calibrated cost of information.

Finally, in Appendix C.1 we present an extension of our baseline model in which we add an additional, undistorted, input to the production function. We show the conditions under which, in this framework, misallocation driven by information frictions can be attenuated, although it remains present.

[11] Young firms are likely to display larger dispersion in revenue labor productivity than average (see for example Foster et al. (2019)), thus suggesting that the actual contribution of information frictions to misallocation is probably slightly lower than 11%.

Table 1
The employment and productivity effects of startup transfers.

	% Change due to a 5% transfer	
	Full Information	Rational Inattention
Entrants	5.0	11.3
Average Employment	- 3.5	- 7.7
Average Employment (conditional on entry pre-transfer)	0	- 1.5
Total Employment of startups	1.3	2.7
Average Productivity	- 0.8	- 1.8
St. Dev. MPL	–	3.8
Total acquired information	–	- 3.0

Notes: Effects of a lump-sum transfer τ on the number of entrants and hiring as described in Section 4.

3.2. Sensitivity to the cost of information

In this section we summarize how our results change for different values of θ and use this sensitivity analysis to elaborate on our theoretical results. We provide a more detailed analysis in Appendix B.1.

The importance of information frictions for rationally inattentive startups can be spanned over a domain that ranges from $\theta = 0$, i.e., full information (in which the posterior probability degenerates exactly at the optimal choice of n), to a value of θ so high that prospective entrepreneurs do not acquire any information at all (in which the posterior probability is exactly the same as the prior distribution). We label this latter state, and the associated level $\overline{\theta}$, as the "uninformed choice" (UC). In this state, all prospective entrepreneurs choose the same size, n^{UC}, maximizing the expected profit function under no learning.

As the cost of information falls from $\overline{\theta}$, the dispersion of startup sizes increases around n^{UC}. This has three main implications. First, the previously discussed "consideration set" shrinks with the information cost. Second, chosen startup sizes become sparser the higher the information cost. Third, the minimum startup size is affected, as it generally increases with the information cost.

Given our choice of α and the distribution of z, it holds that $n^{UC} > 0$. As a result, for all $\theta \geq \overline{\theta}$, all prospective entrepreneurs enter the market. This clarifies how θ affects the relative strength of inefficient entry vs inefficient non-entry. Inefficient entry unambiguously increases with θ, as a higher cost of information induces more entrepreneurs to make mistakes. However, it also makes more entrepreneurs enter the market, as the dispersion around n^{UC} shrinks with θ. The two forces push in opposite directions, implying that inefficient non-entry initially increases for small values of θ, before falling to 0.

Finally, a higher cost of information is also associated with higher misallocation. Intuitively, greater θ increases the extent to which entrepreneurs make mistakes and hire labor that is far from optimal.

4. Policy experiment: A startup transfer

In this section we investigate the effects of a lump-sum transfer to startups. Policies of this type are common across the globe and take different forms; in particular, they often feature an equity-free cash infusion, which motivates our analysis.[12,13] We model this as a homogeneous monetary transfer equal to 5% of the fixed cost ϕ.

The effects of this policy when information is complete are straightforward. The transfer shifts the productivity cutoff to the left, making it profitable for more startups to enter the market. As a result, the average size of startups falls; startups that would have entered the market even without the transfer, however, do not adjust their employment decisions when receiving additional cash, since they are already operating at the optimal scale.[14] We summarize these effects in the FI column of Table 1.

Under RI, however, even such a simple policy can have complex effects. First, as discussed, the FI productivity cutoff is also observed under RI (recall that $\underline{n}$ is a function of known parameters). Thus, the presence of a lump sum transfer implies that firms are certain that the cutoff has "moved to the left". As a result, some actions that previously delivered negative payoffs now become more attractive because of the transfer. In other words, there is a subset of actions that is no longer

[12] In Appendix D.4, we relate the theoretical channels discussed in this section with empirical evidence on cash grants to startups. In the simple version of the model discussed here, a transfer τ can also be interpreted as a reduction in the entry cost ϕ. Branstetter et al. (2014) find that a reform that decreased entry costs in Portugal boosted firm entry; however, startups were smaller, less productive and with lower survival probability. Our model is consistent with these facts.

[13] In Appendix C.2 we investigate how RI startups respond to wage subsidies.

[14] We abstract from general equilibrium effects and keep the wage constant, under the assumption that the startups' contribution to aggregate employment is not big enough to meaningfully affect the aggregate wage. Endogenous price movements could imply that some startups lose from the transfer. We show that rational inattention implies unintended firm-level effects even with fixed prices.

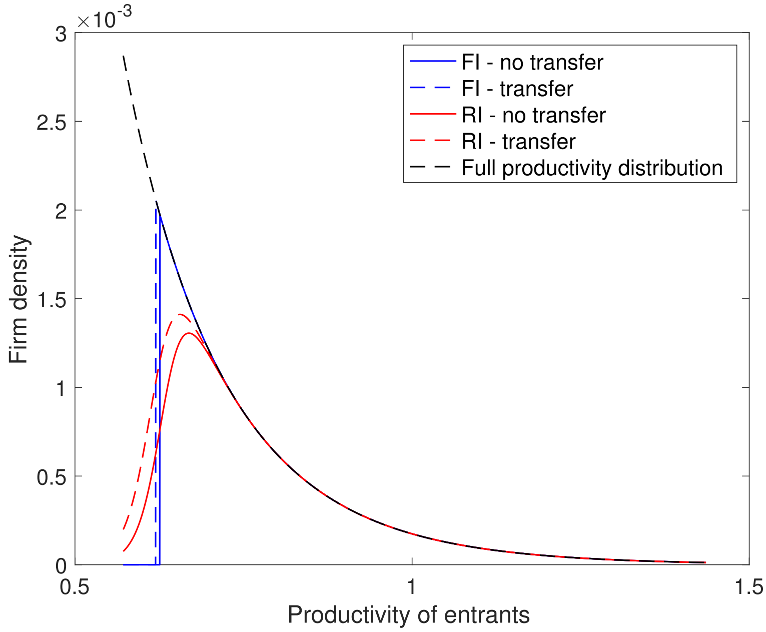


Fig. 3. Productivity distribution of entrants with transfer.

dominated, hence they are added to the set of considered alternatives $\Omega_n \setminus \Omega_n^d$. In addition, because of the shape of the prior distribution of productivity, the new set of added actions are unconditionally more likely to happen than already existing alternatives.

These two effects non-trivially affect the learning problem and, in turn, the hiring decisions. This is the result of two theoretical features of rational inattention, as studied by Matějka and McKay (2015): lack of regularity and monotonicity. The absence of regularity in RI problems implies that adding new alternatives to a choice set can alter the likelihood of existing alternatives being chosen. Such behavior is inconsistent with models of fixed attention, as well as with Random Utility Models. Rational inattention, in contrast, is consistent with such behavior because agents internalize the informational spillovers that arise from the addition of new objects to the choice set. Moreover, rationally inattentive agents attach greater unconditional probability of selecting actions that are relatively more attractive. This feature is known as the monotonicity of RI problems.

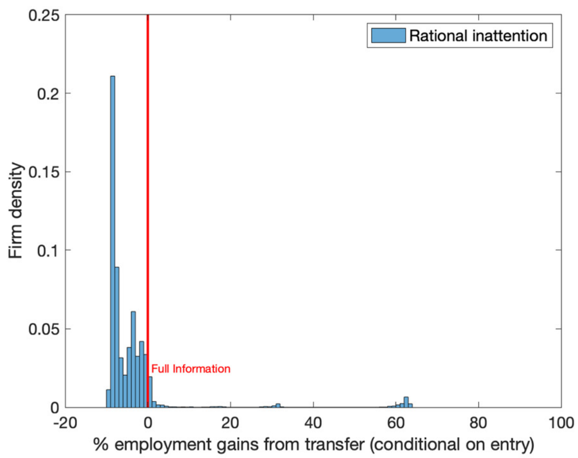
We summarize the employment effects of the transfer, under RI, in the last column of Table 1, and discuss them in detail next. First, RI amplifies the entry margin effect. 11.3% additional startups enter the market thanks to the transfer, more than twice as many as with FI. Fig. 3 shows the underlying sources of the adjustment. On the one hand, startup transfers reduce inefficient non-entry (i.e.: productive firms that should enter but choose not to) stemming from information frictions. On the other hand, they amplify information-related distortions by boosting inefficient entry (i.e.: low-productivity startups that should not enter). Put together, both effects amplify the effects on the extensive margin.

The intuition for these effects relies on the *perceived* position of the unobserved productivity relative to the cutoff. Imagine a firm that before the transfer conjectures to have a low realization of z and then decides not to enter the market. The policy reduces the perceived distance between its belief about z and the cutoff, given the known reduction in $(\phi - \tau)$. As firms are certain that the cutoff moved to the left, more low-productivity startups decide to enter, although it is still not profitable to do so.

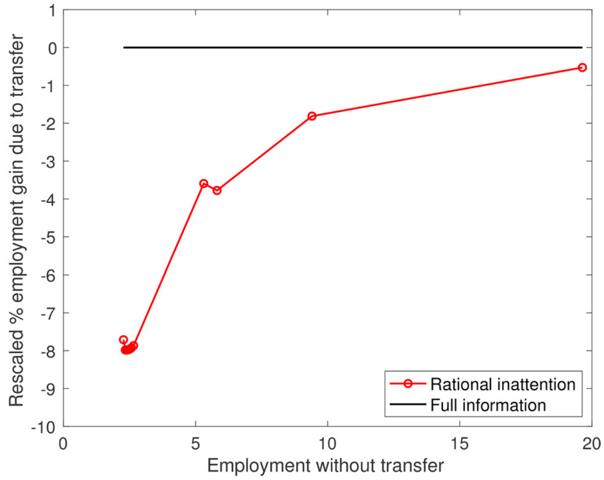
Turning our attention to the intensive margin of hiring decisions, we focus on startups that entered even when $\tau = 0$. Under FI, those firms do not adjust employment in response to a lump-sum transfer, and therefore the intensive margin is zero, as reported in Table 1. Intuitively, τ does not enter the first order condition which governs labor demand. Under RI, however, the transfer generates a large dispersion in employment net gains. This is shown in Fig. 4a. Some firms gain with the policy, but the vast majority loses.[15]

What lies behind these unintended consequences of startup transfers? We rationalize this result in light of the aforementioned absence of regularity in RI problems. Let us focus on the hiring decisions of a startup whose productivity is higher than the entry cutoff. In principle the lump-sum transfer should not affect its hiring decision. However, the new set of hiring alternatives introduced by the policy changes the information strategies for *all* firms. In particular, the added actions

[15] To make sure that this is not the result of random error-prone decisions, our simulation ensures that, for each startup, the realization of productivity is the same with and without the transfer. The same applies to the random signal about z.



(a) Distribution of employment gains



(b) Employment gains by size quantile

Fig. 4. Employment gains from transfer: intensive margin. *Notes*: 50 simulations of a panel of 100,000 firms. For each economy, we draw the same set of realized productivity shocks with FI and RI, with and without the transfer. We then restrict the attention to startups that operate even when $\tau = 0$. For this subset of firms, Fig. 4a shows the distribution of percent employment gains due to transfer. In Fig. 4b, we group entrants by deciles of their chosen size without the transfer. Each dot represents a decile; on the horizontal axis, we report the median size in the decile, without the transfer. On the vertical axis the within-decile median employment gains due to the transfer, rescaled by the median size. The figure plots averages across 50 simulations.

alter what to learn about and how much information to acquire. The higher unconditional probability of the newly added alternatives makes them very attractive, which pushes the firm to learn more about them while sacrificing learning about other (already existing) alternatives. Hence, as firms now focus more attention on these actions with lower employment levels, average employment drops by 1.5% with the policy, among firms that were already deciding to enter.

The information effect of the new alternatives, made feasible by the transfer, gradually fades away for larger, and thus more productive, startups. We show this in Fig. 4b, which plots the median employment gains by quantiles of startups size. Small, unproductive startups typically lose from the transfer. As productivity increases, the negative effects gradually dissipate, although they persist even for large startups. These results highlight the gravity effect exerted by the newly added actions, which binds more the closer productivity is to the entry cutoff.

Finally, we turn to the productivity effects of the transfer, which we summarize in the lower panel of Table 1. Average productivity drops, even in full information, because less productive firms now find it profitable to enter. Nevertheless, it drops more under Rational Inattention, because inefficient entry has increased when $\tau > 0$, as previously discussed.

Misallocation, measured by the standard deviation of MPL of entrants, increases in RI following the transfer, while it is obviously zero in FI. As shown in the last row of Table 1, and in line with the fact that the policy changes the learning strategies of the firm, total acquired information decreases relative to $\tau = 0$. This happens because the transfer increases firms' ex-ante profits with full certainty for all prospective entrepreneurs that wish to enter. As such, it makes the entry decision less costly for rationally inattentive startups, and therefore less "sensitive" to mistakes, thus making prospective entrepreneurs decide to acquire less information. Such behavior is consistent with findings by Mackowiak and Wiederholt (2012), who show that, under RI, agent facing limited liability processes less information than an agent with unlimited liability. In our framework the transfer bounds negative profits from below, which is qualitatively akin to a reduction in expected losses borne by the startup. As the subsidy crowds out information acquisition, error-prone decisions are amplified relative to the baseline scenario, leading to an increase in misallocation.

Our findings on inefficient entry and misallocation also relate to recent discussions on "zombie" firms. In particular, it may be possible that excessively high subsidies could keep inefficient firms artificially alive. The policies implemented in the aftermath of the COVID-19 pandemic have revived this debate, as discussed for instance by Zoller-Rydzek and Keller (2020). The literature has typically focused on policies that delay efficient exit of old and unproductive firms. In contrast, we introduce a new (information) channel that affects young and unproductive firms; transfers might inefficiently push entrepreneurs to start up a firm and distort the efficient allocation of labor.

5. Extensions

In this section we extend the simple, frictionless, static model in two ways. First, we extend the time horizon taken into account by startups and introduce labor adjustment costs. Second, we add financial frictions into this dynamic framework.

5.1. A two period model

Potential entrants arguably take into account future expected profits when deciding whether to enter the market and at what initial size. Our baseline model can be reinterpreted as a multi-period collection of static problems, but doing so would not change any of the conclusions previously discussed. In order to illustrate how firm dynamics can affect the interaction between information frictions and responses to transfers, we therefore consider a tractable two period model.

As in the baseline model, each firm must choose its optimal size, but now the decision is taken over both the current ($t = 0$) and future period ($t = 1$), which we label as n_0 and n_1, respectively. The instantaneous profit function in period $t = 0$ is the same as in the static problem in Section 2. Startups discount the future at a rate $\frac{1}{\beta} - 1$ and, during the second period, all incumbent firms must pay a labor adjustment cost if they decide to modify n_1 relative to the previous size n_0. The cost of the size adjustment is given by $\gamma\left|\left(\frac{n_1}{n_0} - 1\right)\right|$. We assume that productivity z is time invariant. Startups pay a fixed cost of entry, ϕ_0, in the first period, but they also face a operational cost ϕ_1 in the second period. We assume that the transfer is, however, only received in the first period.

Before entering the market, potential entrants indexed by i maximize discounted profits:

$$\pi_i^* = \max\left\{\max_{n_{i0}}\left[\pi_{i0} + \beta\max\left\{\max_{n_{i1}}[\pi_{i1}], 0\right\}\right], 0\right\} \tag{7}$$

where $\pi_{i0} = z_i n_{i0}^\alpha - wn_{i0} - \phi_0 + \tau$ and $\pi_{i1} = z_i n_{i1}^\alpha - wn_{i1} - \gamma\left|\left(\frac{n_{i1}}{n_{i0}} - 1\right)\right| - \phi_1$. The discrete choice associated with 0 profits is achieved when the startup decides to not operate in that period (i.e., $n = 0$). Indeed, no startup will choose to operate only in the second period, as this would deliver an infinite cost of adjusting labor. It could be, however, that $n_{i0} > 0$ and $n_{i1} = 0$, i.e., the firm decides to exit after the first period. In this case, $\pi_i^* = \pi_{i0}$. We come back to this case later.

The model is solved backwards. At the beginning of period $t = 1$, even under rational inattention, startups observe their productivity without any uncertainty. This is because, given n_{i0} and by observing period $t = 0$ profits, all surviving firms are able to back out their true level of productivity in period $t = 1$. We set up the problem such that the full information solution is as simple as possible, and any interesting dynamics is entirely isolated by information frictions. In particular, our choice of labor adjustment costs implies that, with FI, π_i^* is maximized when $n_{i1} = n_{i0}$. Hence, without the ex-ante uncertainty about productivity, the size of startups will remain constants over the periods. When $\phi_1 < \phi_0$, no FI startup decides to exit in the second period, whereas some efficient exit takes place in the alternative case. We provide details in Appendix C.3.

Let us now turn to the rational inattention problem. First of all, since we can express optimal n_{i1} in closed form, we can write total profits as a function of n_{i0} and z_i only, and then solve the RI problem. We have seen that labor adjustment costs are inconsequential for the full-information solution. However, with RI, their presence implies that choosing the initial size incorrectly will have persistent consequences, as n_{i1} is a function of n_{i0}. For instance, a startup might choose an inefficiently low initial size n_{i0}, and then find it optimal to remain small in the second period, even after knowing z_i with certainty.

Information frictions also affect the entry-exit dynamics. We know from our static model that potential entrants will not be able to observe their position relative to the entry cutoff, given the noisy signals about their productivity. Moreover, in this dynamic framework, they will also imperfectly observe, in period-0, where they expect to stand relative to the productivity cutoff in the following period. As such, some startups may enter in the first period and then exit after realizing that their productivity is too low, even if $\phi_1 < \phi_0$.

We start by showing, in Fig. 5, how startup exit rates change with $\frac{\phi_1}{\phi_0}$. When the operational cost is below the entry cost, information frictions are the only source of exit, with inefficient entrants leaving the market after knowing their productivity. Even when $\frac{\phi_1}{\phi_0} > 1$, and thus there is efficient exit in FI, information frictions account for approximately one-fourth of the total exit in the second period. Hence, our mechanism offers an endogenous, and quantitatively relevant, reason for the relatively low survival rates of startups observed in the data (e.g., Dunne et al. (1989)).

In the dynamic setting considered here, higher information costs θ are still associated with greater labor misallocation, as we have previously shown in Section 3.2. Moreover, we find that survival rates fall with θ; intuitively, when it is costly to acquire information, a larger share of potential entrepreneurs will inefficiently start a business, exiting the market shortly thereafter as they learn their productivity. We show this sensitivity analysis in Appendix B.1, while in Section 5.2 we provide empirical support for these results.

Turning to the intensive margin hiring decision of startups, we find that labor misallocation in the first period is lower than in the static model. This is due to the fact that adding the forward-looking component acts as an "attention-grabbing" device in the RI model: the persistence in the hiring decision forces the firm to learn more. The total acquired information is higher than in the static model of Section 2, more so when $\phi_1 < \phi_0$. While initial labor misallocation is lower, it persists in the following period, even when productivity is observed by all startups, due to the labor adjustment cost.

Our conservative assumption of revealing productivity in the second period implies that firms would make full-information decisions after learning their productivity even if they considered a longer horizon $T > 2$. A higher T may change startups' learning and action strategies, but it would not necessarily lower the quantitative relevance of imperfect information upon entry. In fact, startups could face a trade-off between the amount of information to acquire and the number of periods they expect to operate. On the one hand, the possibility of operating for several periods could propitiate

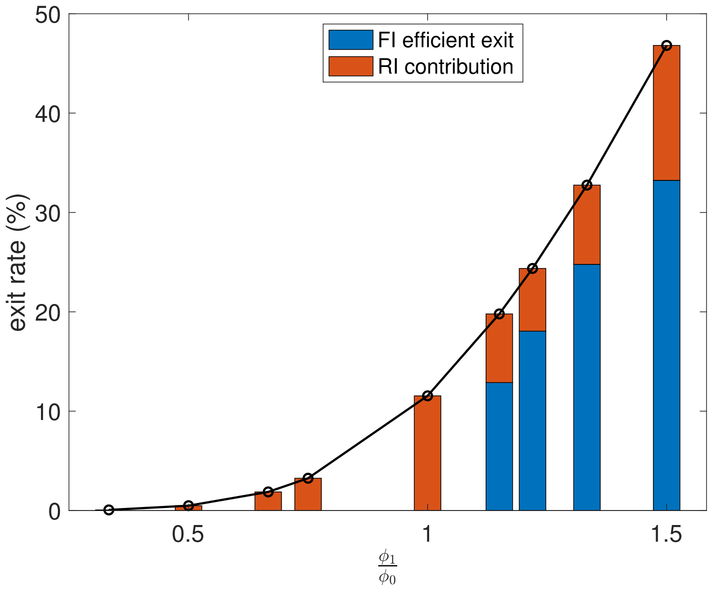


Fig. 5. Startups' exit hazard rates by ϕ_1. *Notes*: Share of t_0 entrants that exit in t_1. Parameters set to their calibrated values discussed in Section 5.1. The figure is barely affected when considering higher values of γ (rather than $\gamma = 0.005$ as done here), in line with what shown in Appendix B.1.

further learning, in line with the results of the two-period model. On the other hand, total acquired information could also decrease with T because the possibility of operating for several periods gives startups more flexibility to amend possible mistakes over time. In this case, it may be sufficient to devise a simple learning strategy in which information is collected only to determine whether they should enter the market or not in $t = 0$. If this channel prevails, inefficient entry and initial misallocation could even increase with T.

Our model is intentionally set up to focus on information frictions upon entry; as such, as firms age, mistakes done early in life are amended, more quickly if $\phi_1 > \phi_0$ and efficient exit dominates. Additional information–driven mechanisms, such as learning over the life cycle, may also affect firm behavior; we see these forces as complementary to ours. For example, Jovanovic (1982) builds a model in which as firms spend more time producing in an industry, they progressively learn how to separate their inherent (time-invariant) productivity from the common random business fluctuations. This dynamic learning delays the process of exiting, whose persistence is disciplined by the assumed rate at which firms uncover their true productivity. In our framework, we obtain similar patterns even though firms can immediately back out their productivity in the second period because labor adjustment costs make the consequences of incomplete learning at the time of starting up long-lasting. Recent empirical evidence has supported the idea that it is the selection of skilled owners, rather than learning over the life-cycle of the firm, which determines the ultimate success of a startup, see Felix et al. (2021). This is relevant for our model since, although we are abstracting from gaining business skills over time, the assumed dispersion in z_i allows us to capture time-invariant skills or manager–specific characteristics, which are then crucial for the future of any startup.

Finally, we discuss the effects of startup transfers in a dynamic setup. In order to sharpen our quantitative conclusions, we discipline the new parameters to empirical observations. As shown by Barseghyan and DiCecio (2011), entry costs can be higher or lower than fixed operating costs in the data. Hence, we focus on two choices of $\frac{\phi_1}{\phi_0}$. First, we set the ratio to $\frac{3}{4}$, which corresponds to the lowest ratio reported by Barseghyan and DiCecio (2011). Besides being empirically plausible, this case is also theoretically relevant since it implies that no FI startup exits in the second period.[16] We then set $\gamma = 0.005$, to match empirical estimates by Feng (2018) of the drop in labor misallocation between the first and the second year of firm age. Second, we also consider $\frac{\phi_1}{\phi_0} = \frac{1}{0.82}$, equivalent to the preferred choice by Barseghyan and DiCecio (2011).[17] Since we wish to isolate the effects of labor adjustment costs and forward-looking behavior, we keep θ equal to its original value in the baseline static model. Finally, we set the discount factor $\beta = 0.95$, a standard value in the range of parameters used in the literature of young firm dynamics.

Our range of values for ϕ_1 allows us to be more explicit about the role of information frictions for firm survival. When there is no efficient exit, RI still accounts for about 15% of the empirically observed exit rate in the second period. This share increases to 25% in our alternative calibration with $\frac{\phi_1}{\phi_0} > 1$.

[16] Trade models of firm dynamics often assume $\phi_1 < \phi_0$, see Alessandria and Choi (2007) or Ghironi and Melitz (2005) for an example.

[17] We keep γ unchanged but discuss in Appendix B.1 how the results are little sensitive to this parameter.

Table 2
The effects of startup transfers: static vs dynamic .

		FI			RI		
		Static	Dynamic		Static	Dynamic	
			$\frac{\phi_1}{\phi_0}=\frac{3}{4}$	$\frac{\phi_1}{\phi_0}=\frac{1}{0.82}$		$\frac{\phi_1}{\phi_0}=\frac{3}{4}$	$\frac{\phi_1}{\phi_0}=\frac{1}{0.82}$
Entrants	$t=0$	5.01	2.80	4.93	11.29	5.06	11.58
	$t=1$		2.80	0		3.48	1.57
Average employment	$t=0$	0	0	0	-1.45	-0.45	-1.02
(entrants with $\tau=0$)	$t=1$		0	0		-0.42	-0.46
Total Employment	$t=0$	1.35	0.76	1.29	2.75	1.43	3.29
of startups	$t=1$		0.76	0		0.82	-0.19
St. Dev. MPL	$t=0$	-	-	-	3.82	3.19	3.35
	$t=1$		-	-		1.45	3.13
Total information		-	-	-	- 3.05	- 1.19	- 4.32

Notes: $t=0$ refers to newborn firms, whereas $t=1$ to one-year-old firms entered in $t=0$. The transfer is equal to 5% of the fixed cost of entry.

Table 3
Internet access and startups' survival rates .

	Startups' survival rates				
	(I)	(II)	(III)	(IV)	(V)
% with internet	0.024***	0.024***	0.025**	0.041***	0.039***
	(0.006)	(0.006)	(0.010)	(0.008)	(0.008)
State fixed effects		✓	✓	✓	✓
Startups' sectoral composition			✓	✓	✓
Unemployment rate				✓	✓
House price growth					✓
Observations	1150	1150	1150	1029	1029

Notes: Standard errors, reported in parentheses, are robust to heteroskedasticity and autocorrelation.

While the unintended consequences of startup transfers that we have previously shown remain, they are quantitatively less pronounced. Table 2 reports the effects of this policy in the static and the dynamic framework. RI still amplifies the entry effect of startup transfers regardless of the choice of $\frac{\phi_1}{\phi_0}$. The amplification is larger when fixed operating costs are greater than entry costs. In fact, the transfer increases entry by 2.3 times more than under FI in this scenario, while it increases by 1.8 times more when $\phi_1 < \phi_0$. The static model lies in between. The negative employment effects conditional on entry are also bigger for relatively larger fixed operating costs, but lower than in the static model. These effects are, however, less persistent when $\phi_1 > \phi_0$, because a higher operational cost in the second period increases the incentives to correct mistakes made upon entry, including those associated with the transfer. For example, all inefficient entrants immediately exit in period 2 when $\phi_1 > \phi_0$, while only half do in our alternative choice of ϕ_1. Due to this different persistence, startups' total employment remains above its level without transfer in the second period when ϕ_1 is relatively low, whereas the negative intensive margin effect prevails in the alternative case.

We have shown how our model of endogenous pre-entry learning on ex-ante heterogeneity implies that lump-sum transfers can increase inefficient entry and misallocation. As previously discussed, models of *ex-post* learning over the firm life cycle are complementary to ours. In this context, Arkolakis et al. (2018) find that transfers allow existing firms to stay afloat, observe additional signals and improve their knowledge about the unobserved market conditions they face. These findings are only apparently in contrast with ours; indeed, we find that transfers may lead inefficient startups to enter when they should not. Ex-post learning implies that transfers can mitigate inefficient exit later in the firm life cycle.

5.2. Empirical validation of the model mechanisms

In this section, we discuss empirical evidence that supports our theoretical findings. We follow Dasgupta and Mondria (2018) and approximate the (inverse of) cost of information using data on international bandwidth for various countries. Intuitively, higher internet penetration lowers firms' costs of processing information. As a first approach, using evidence at the cross-country level, we find a strong negative correlation (- 0.56), between startup survival rates and the cost of information. Then, we turn to panel data for US states between 1997 and 2019, this time proxying information costs with data from Tolbert and Mossberger (2015) on the population share with access to the internet, and startups' one–year survival rates from the U.S. Census. In Table 3, we again confirm that startup survival rates are positively and significantly related to internet access. In particular, states with a ten percentagepoint higher share of individuals having internet access are associated with a 0.24 percentagepoint higher survival probability of startups after one year of life. As shown in column (II) of Table 3, the latter result is quantitatively the same if we control for state fixed-effects. In the other columns, we also control for additional confounding factors such as startups sectoral composition, local unemployment rates, and house price growth: our results are robust to the inclusion of these additional covariates.

Finally, our finding that misallocation increases with the cost of information is consistent with evidence from David et al. (2016), who find that misallocation differences between China, India and the U.S. are at least partly explained by differences in firm private information. To provide our own additional, albeit suggestive, evidence, we use cross–country data on the standard deviation of revenue labor productivity from Bartelsman et al. (2013). We find that this measure of labor misallocation is strongly inversely related to the population share using internet and with access to fixed broadband, supporting our model implications. Appendix D.5 provides further detail on all the empirical exercises outlined in this section.

5.3. Financial frictions

So far we have assumed that, under full information, entering startups achieve the first-best employment level; we have used this framework to cleanly show how, in contrast, information frictions distort hiring elasticities to the transfer. In this section, we assume that startups do not have unlimited access to funding; as a result, in FI, employment is positively elastic to cash flow and thus transfers boost startup hiring.

We augment the two-period model assuming that there is a cash-flow mismatch between the payment of the wage bill, which happens at the beginning of the period, and the realization of revenues, at the end of the period. This liquidity need can be fulfilled by raising external finance, which is however limited by a financial friction. For simplicity, we assume that the financial constraint is only present in the first period. Following recent work on earning-based constraints (EBC) – see for instance Lian and Ma (2021) and Drechsel (2019) – the intra-period loan $wn_0 - \tau$ is limited to be smaller or equal than a multiple of first-period profits. Imposing credit rationing would undo information frictions, because startups can learn about their true productivity when observing that their credit has been rationed. Therefore, we assume that startups can breach the EBC (i.e., borrow more than a multiple of their profits in the first period), but when they do so they incur a cost. In Appendix C.4 we discuss alternative ways of modeling financial frictions.

Potential entrants still maximize discounted profits as described in Eq. (7); however, we now assume that the first period profits are:

$$\pi_{i0} = z_i n_{i0}^{\alpha} - wn_{i0} - \phi_0 + \tau - \eta(wn_{i0} - \tau)^{\sigma}\,\mathbb{1}((wn_{i0} - \tau) > \xi\widetilde{\pi}_{i0}) \tag{8}$$

where $\widetilde{\pi}_{i0} = \max\left\{z_i n_{i0}^{\alpha} - wn_{i0} - \phi_0 + \tau, 0\right\}$. We set $\eta = 1$ and $\sigma = 2$: a convex cost of this type can be reinterpreted as an interest rate on the intra-period loan that is linearly increasing with the size of the loan.[18] This specification effectively nests the standard EBC with an infinitely high η. Indeed, we numerically confirmed that the extent of inefficient entry in RI decreases with η and σ. Following Drechsel (2019), we set $\xi = 4.6$.

How does the financial friction interact with RI? Inefficient entry is still present, although it is lower than in the dynamic model without financial constraints. The financial cost further depresses negative profits of inefficient entrants, making them more aware of their mistakes. In the limit, there is no inefficient entry if the financial cost becomes excessively high. While financial frictions generate labor misallocation even with FI, the dispersion of MPL is twice as high with RI. Moreover, misallocation is one-sided with FI, as all constrained startups under-hire. In contrast, RI still generates over-hiring for more than 20% of startups.

The transfer studied in Section 4 now stimulates hiring, under FI, even among startups that would have entered the market with $\tau = 0$. This operates through two channels. First, a higher τ decreases the number of constrained firms, both by reducing the liquidity need and expanding the maximum amount beyond which borrowing is costly. Second, it lowers the borrowing cost for constrained firms.

How does this liquidity channel interact with RI? We show how the negative information channel described in the previous sections, and the positive effects just described, co-exist and act in opposite directions. Table 4 summarizes the main results. As done previously, we consider the same range of ratios of operating to entry costs. The effects on the extensive margin of entry are similar to what discussed in the previous section, with entry increasing by more when information frictions are present.

The most interesting interactions operate along the intensive margin. With FI, the transfer increases the average size of entrants, by relaxing the financial frictions. This effect persists over time due to the labor adjustment costs. Under RI, this positive effect is still present. However, it co-exists with the negative information channel discussed in the previous sections and brought about by the fact that the transfer expands the set of available actions. Quantitatively, the RI channel barely prevails with $\phi_1 > \phi_0$, while the opposite is true, in t_0, in the alternative case. In both instances, however, the net effect is close to 0. This result confirms that our channel is quantitatively substantial, since it can overturn the positive employment effects stemming from the financial friction. As such, our information channel provides an explanation for why cash transfers have been empirically found to have limited effects on startups' performance. We expand on this discussion in Appendix D.4.

The two counteracting channels have heterogeneous effects along the size distribution of startups, as can be seen in Fig. 6. With FI, only firms below a certain productivity level (and thus size) are constrained. The smallest startups react

[18] Similar quadratic costs are often assumed in the corporate finance literature, for equity issuance and debt financing, see Bond and Söderbom (2013).

Table 4
The effects of startup transfers: financial and information frictions.

		FI		RI	
Panel A: $\frac{\phi_1}{\phi_0} = \frac{3}{4}$		Dynamic	Dynamic + EBC	Dynamic	Dynamic + EBC
Entrants	$t = 0$	2.80	3.12	5.06	4.98
	$t = 1$	2.80	3.12	3.48	4.29
Average Employment	$t = 0$	0	0.65	-0.45	0.12
(entrants with $\tau = 0$)	$t = 1$	0	0.38	-0.42	-0.18
Total Employment	$t = 0$	0.76	1.49	1.43	1.94
of startups	$t = 1$	0	1.21	0.82	1.32
St. Dev. MPL	$t = 0$	-	-2.16	3.19	1.05
	$t = 1$	-	1.12	1.45	2.07
Total information		-	-	-1.19	0.35
Panel B: $\frac{\phi_1}{\phi_0} = \frac{1}{0.82}$					
Entrants	$t = 0$	4.93	5.97	11.58	9.17
	$t = 1$	0	0	1.57	2.35
Average Employment	$t = 0$	0	0.54	-1.02	-0.29
(entrants with $\tau = 0$)	$t = 1$	0	0.38	-0.46	-0.29
Total Employment	$t = 0$	1.29	1.95	3.29	2.93
of startups	$t = 1$	0	1.77	-0.19	0.39
St. Dev. MPL	$t = 0$	-	-1.91	3.35	3.48
	$t = 1$	-	3.28	3.13	0.67
Total information		-	-	-4.32	-1.99

Notes: $t = 0$ refers to newborn firms, whereas $t = 1$ to one-year-old firms entered in $t = 0$. The transfer is equal to 5% of the fixed cost of entry.

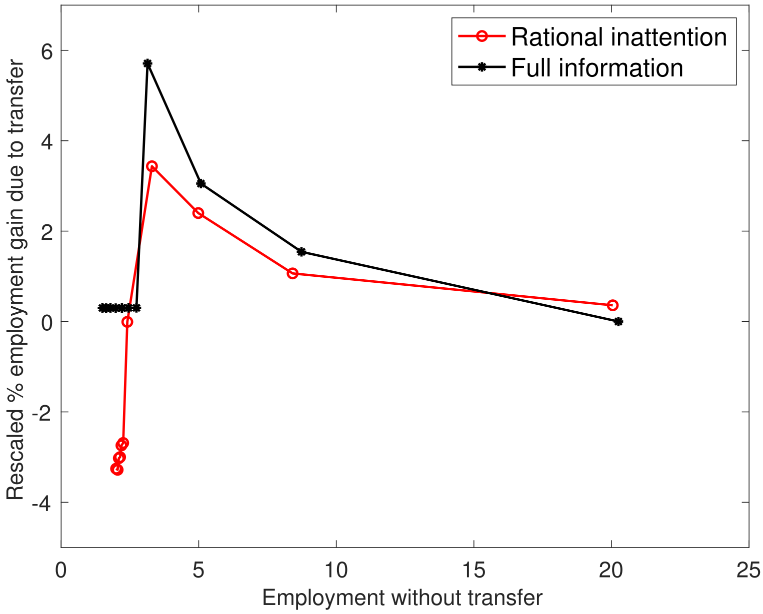


Fig. 6. Heterogeneous employment gains from transfer. *Notes*: Same notes to Fig. 4 apply, for the EBC model outlined in the text. The figure reports results for $\frac{\phi_1}{\phi_0} = \frac{3}{4}$, but it is qualitatively unaffected when considering $\frac{\phi_1}{\phi_0} = \frac{1}{0.82}$. We report this in Figure D.4 of Appendix D.3.

little, because the transfer only affects their financial cost. Medium-sized startups are affected the most, because they are closer to the binding EBC; by affecting that margin, the transfer can result in sizable employment gains for these startups, as it makes them move to the unconstrained space. Largest startups are already unconstrained and thus unaffected by τ. The positive effect on medium-sized startups is still present under RI, and more productive entrants are affected too since their decisions are error-prone. Smallest startups, however, are negatively affected by the transfer. These firms are the closest to the entry cutoff and therefore the most influenced by the addition of newly available feasible actions. Nevertheless, this negative information channel is dampened by the forward-looking setting and, most importantly, the financial frictions; indeed, their employment losses are half what shown in Fig. 4.

Combining the intensive and extensive margins, the total employment effects of the transfer are still larger under RI relative to FI. Misallocation still increases, driven by a fall in information acquisition, but this unintended consequence of the transfer is mitigated by the positive allocation effects stemming from a relaxation of financial frictions.

6. Conclusions

We have built a model that allows us to study how information frictions affect firm entry, as well as hiring choices of startups. Rational inattention is a source of empirically observed inefficient entry and misallocation, as inattentive startups do not observe exactly their own growth potential. Using this theoretical framework, we have documented a novel information channel that alters the effects of policies targeted at startups. Lump-sum transfers, such as equity-free grants, induce more firms to enter, as lower initial sizes are now profitable. This shift, however, alters the endogenous ex-ante learning process, resulting in three unintended consequences: inefficient entry increases, productive startups choose a lower initial size, and misallocation goes up.

This negative information channel dampens the positive effects of transfers which arise from other frictions. As such, it can provide a rationale for limited employment effects of cash transfers to startups.

Data availability

Data will be made available on request.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.06.008

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