European Commission

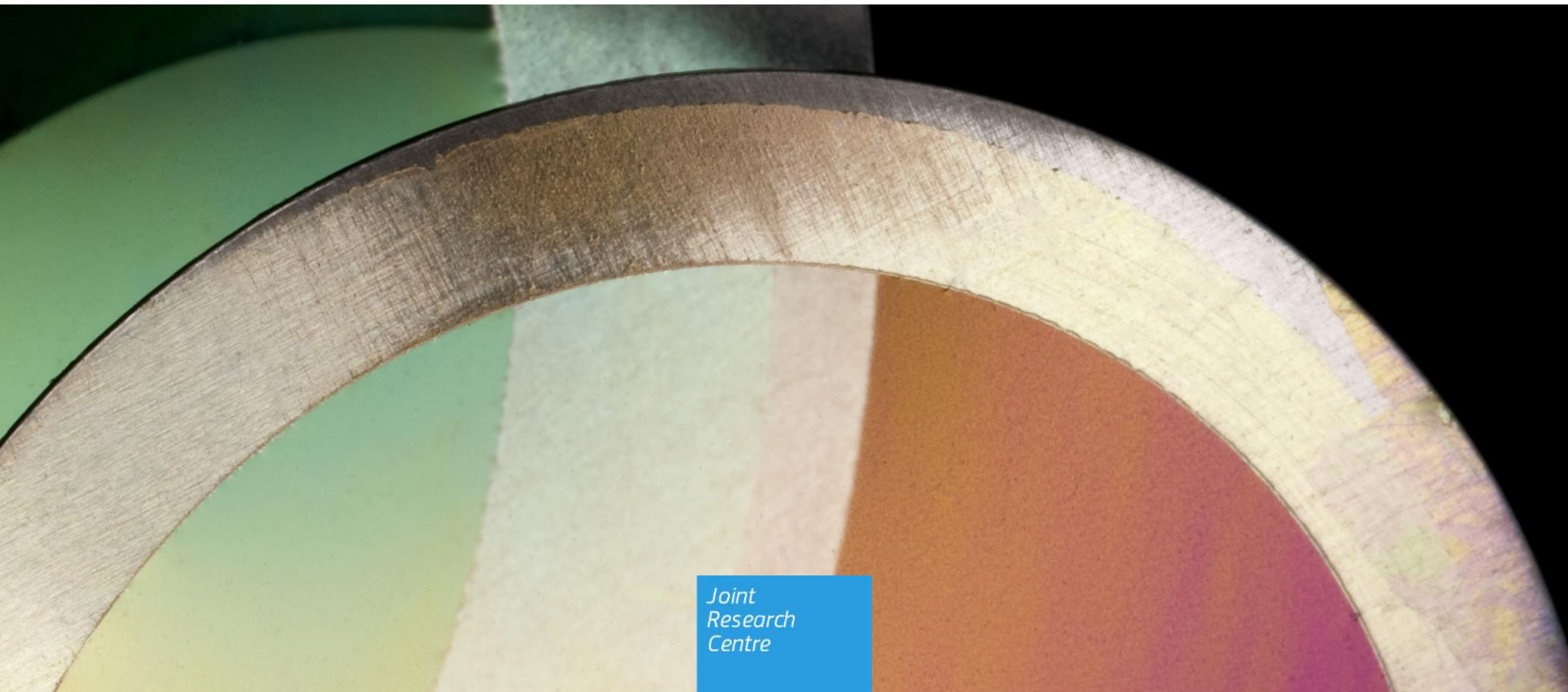
JRC TECHNICAL REPORTS

Tax policy and entrepreneurial entry with information asymmetry and learning

JRC Working Papers on Taxation and Structural Reforms No 1/2017

Diego d'Andria

February 2017



Contact information
Name: Diego d'Andria
E-mail: Diego.D'ANDRIA@ec.europa.eu

JRC Science Hub
https://ec.europa.eu/jrc

JRC105841

ISSN 1831-9408

Sevilla, Spain: European Commission, 2017

How to cite: d'Andria, D. (2017), "Tax policy and entrepreneurial entry with information asymmetry and learning"; JRC Working Papers on Taxation and Structural Reforms No. 1/2017, European Commission, Joint Research Centre, Seville

Tax policy and entrepreneurial entry with information asymmetry and learning

Diego d'Andria*

This version: February 2017

Abstract

We study a market with entrepreneurial and workers entry where both entrepreneurs' abilities and workers' qualities are private information. We develop an Agent-Based Computable model to mimic the mechanisms described in a previous analytical model (Boadway and Sato 2011). Then, we introduce the possibility that agents may learn over time about abilities and qualities of other agents, by means of Bayesian inference over informative signals. We show how such different set of assumptions affects the optimality of second-best tax and subsidy policies. While with no information it is optimal to have a subsidy to labour and a simultaneous tax on entrepreneurs to curb excessive entry, with learning a subsidy-only policy can be optimal as the detrimental effects of excessive entrepreneurial entry are (partly or totally) compensated by surplus-increasing faster learning.

JEL classification: D82, D83, G14, H25.

Keywords: Entrepreneurship, Taxation, Asymmetric Information, Learning, Adverse Selection, Agent-Based Computational Model.

---

*European Commission Joint Research Centre (JRC), Unit B2 fiscal Policy Analysis. Calle Inca Garcilaso 3, 41092 Seville (Spain). Email contact: diego.d'andria@ec.europa.eu
The findings, interpretations, and conclusions expressed in this paper are entirely those of the author. They should not be attributed to the European Commission. Any mistake and all interpretations are his and his only.

1 Introduction

At least since Schumpeter (1934) entrepreneurial entry have been seen as a major driver for economic growth. Entrepreneurs challenge incumbent firms thus stimulating improvements and productivity gains, and can themselves bring innovations into the market in the form of new products or processes. A reflection of this view is the widespread existence of policies designed to foster entrepreneurship, to support small young firms and to ease credit constraints. At the hearth of the market failure that these policies try to solve is asymmetric information. First, there is an intrinsic riskiness in starting a new venture which makes investors require a risk premium thus raising the cost of capital. Second, the chances of entrepreneurial success depend on a number of factors including the entrepreneur's human capital, which is not directly observable thus giving rise to adverse selection. Third, the entrepreneur himself faces asymmetric information at the time of acquiring input factors, notably when hiring personnel and in cases when third-party technologies have to be employed.

This paper focuses on simultaneous informational asymmetries in the credit market and in the labour market. We develop an agent-based computational model which is designed to mimic the mechanisms described in Boadway and Sato (2011). Our novel contribution lies in explicitly taking into account learning over time and its consequences on the effects of tax and subsidy policies. Simulation analysis is here used as a means to falsify the generality of Boadway and Sato (2011)'s optimal policy made of a tax on entrepreneurs and a subsidy to labour income: in a slightly more realistic setting where a market is not in an extreme condition of either full or no information, excess entry favours learning and thus produces more information in less time.

The intuition behind our claim is rather straightforward. If agents learn about other agents' ability or quality, then having more entrants in earlier periods increases the amount of information available and leads the market closer to a condition of full information. Consequently, the optimal level of entry with learning is larger than in a first-best scenario with full information, as the loss in surplus suffered as more bad entrepreneurs enter the market is (partly, or entirely) compensated by an increase in future surplus due to more efficient market conditions.

In our model entrepreneurs and workers decide whether to enter or not an entrepreneurial market, entrepreneurs hire workers and fund investment costs by means of external financing, and a government may levy taxes or subsidies on both entrepreneurial income and labour costs. The estimated entrepreneur's ability[1] affects the cost of financing she faces, while the estimated worker's quality affects his expected wage. After replicating the main features of a market as described in Boadway and Sato (2011) for the polar cases with full information and with no information available, we then introduce the possibility that agents may learn over time thus better estimating abilities and qualities thanks to informative signals. We challenge the optimal policy found in Boadway and Sato (2011) which is made of a tax on entrepreneurs and a subsidy to labour, and instead point to the fact that including learning a tax on entrepreneurs may be detrimental welfare-wise. Our claim is that the optimality of the tax and subsidy policy only holds under specific circumstances and is not general, thus the optimality of a tax on entrepreneurs should be evaluated based on the empirical evidence about how the market produces information.

In the following, Section 2 summarises the relevant previous literature. Section 3 describes the model, and Section 4 discusses the simulation results. Section 5 concludes and points to future avenues for research.

[1] We keep throughout the paper the convention to use male pronouns for workers and female pronouns for entrepreneurs. Also following the original convention in Boadway and Sato (2011), the term ability refers to entrepreneurs while quality refers to workers.

2 Related literature

This paper draws from several previous research contributions. The literature on adverse selection in credit and entrepreneurial markets, particularly with regard to new ventures, poses the basis for the analysis of the asymmetric information on the side of entrepreneurs (Stiglitz and Weiss 1981). The main message from this literature often closely resembles Akerlof (1970) in predicting underinvestment and less than optimal (from a social planner's point of view) entry of new ventures, though subsequent research (De Meza and Webb 1987, Boadway and Keen 2006) finds conditions under which this outcome can be reversed to overinvestment.

Adverse selection on the side of labour inputs acquisition and its effects on new firms is relatively less studied. Weiss (1980) analyses a market with unobservable workers' quality and shows how adverse selection would draw more workers with low skills from the pool of candidates, with overall lower employment than optimal. Most other studies focused on moral hazard in the form of unobservable effort provision (Shapiro and Stiglitz 1984, Holmstrom and Milgrom 1991).

The taxation literature has analysed tax and subsidy policies that may be employed to obtain first– or second–best optimality (good summaries of results and open questions are found in Rosen 2005, Keuschnigg and Nielsen 2003, Henrekson and Sanandaji 2011). Most of these, though, again focus on the problem of non-monitorable effort, for instance Keuschnigg and Nielsen (2003) develops a model where venture capitalists and entrepreneurs jointly provide effort, and they find how taxes on labour, capital and capital gains income should be designed. The effects of specific types of taxes on bonus compensation with unobserved work effort have been studied with regard to managers (Radulescu 2012, Dietl et al. 2013), and with regard to innovative employees where also corporate taxes and tax incentives are levied (d'Andria 2016).

The possible interactions between the two informational asymmetries, however, remain largely unexplored. One exception is of course Boadway and Sato (2011) which we are employing here as a basis to develop our own agent-based computational model. Boadway and Sato (2011) discuss a theoretical model where entrepreneurs with unknown ability decide whether to start a risky project. Those that decide to start such a project hire workers whose quality is, as well, unknown. This kind of market generates inefficient levels of entrepreneurial activity and adverse selection simultaneously on the side of entrepreneurial borrowing and on the side of labour supply. Policy-wise one of the main results is that, in a scenario where adverse selection in credit markets induces excessive entry of low-ability entrepreneurs and mitigates adverse selection in labour markets thus hiring too many low-quality workers, the second-best optimal policy is made of a subsidy to labour (which serves the purpose to attract high-quality workers) paired with a tax on entrepreneurs (which curbs the excessive entry of entrepreneurs, the latter being further increased by the labour subsidy).

Methodologically our choice is Agent-Based Computational Economics (ACE) modelling, see Tesfatsion and Judd (2006) for an in-depth description and a number of examples taken from the literature. The rationale for using agent-based computational modelling techniques has been widely discussed already, for example in Tesfatsion (2003) and Judd (2005). In our case as we aim at introducing learning over time – which is intrinsically a stochastic path-dependent process – together with heterogeneous agents, we believe this comes as a rather natural choice. We can then deal with multiple equilibria using a Montecarlo approach and study the way the simulated model converges, on average, to different outcomes. We believe we avoid the critique, common to many agent-based models, of a lack of generality of the results stemming from simulated runs of the model with specific parametrizations, as in this specific paper our intent is exclusively to falsify the generality of another claim (we use here the term "falsification" as in Popper 2005), previously made through the use of classical analytical modelling tools.

Agent-based models have been employed in the past (though only occasionally) to study labour markets (i.e. in Tesfatsion 2001 and Neugart 2008) and taxation (mainly in relation to tax evasion, see for instance Bloomquist 2006, Hashimzade et al. 2015 and Warner et al. 2015). A relevant example is d'Andria and Savin (2015) where an agent-based model was developed to study a market for innovative workers with unobserved effort and workers' qualities, multiple job tasks and taxes both at the corporate and personal level. We follow here a philosophy similar to d'Andria and Savin (2015) in first developing a model that resembles as close as possible the features and mechanisms of a corresponding analytical model (in the case of the present paper the analytical model of reference is Boadway and Sato 2011), then we change only one key assumption (by introducing learning) to see how the behaviour of the model changes. A similar approach has been used in the past in Yildizoglu (2002) where an Agent-Based model was developed that first follows an existing and well-known model (in that case, Winter and Nelson 1982), then a different element is introduced (in Yildizoglu 2002 the new element consists of a different set of assumptions about investment behaviour based on a learning mechanism), finally the convergence of the model is computed across several replications and compared with and without the new assumptions.

3 The Model

3.1 Overview of the model

The model[2] generates a population of entrepreneurs at the beginning of each simulation, drawing for each entrepreneur an ability value a from a uniformly distributed continuous interval [0, 1]. Similarly, a population of workers is generated with qualities q drawn from a uniformly distributed continuous interval [0, 1].[3] Each entrepreneur may hire a fixed number n of workers and by assumption the number of workers is n times the number of entrepreneurs. Ability/quality is assigned to each agent and stays constant across the simulation. Ability represents the probability of success for an entrepreneur in sector E[4], while quality is an index of productivity of a worker in both sectors E and T.

Each simulation runs for a fixed number of periods. In each period, each worker decides to enter the entrepreneurial sector E if, and only if, he expects his wage to be not lower than an exit option wage he can obtain with certainty from working in a traditional sector T. The wage in sector T is made equal to the worker's quality and is known to him. The expected wage from working in sector E depends from the scenario that is being simulated. If full information

[2]The model code was written in Matlab/Octave. It was tested in Matlab (R2015a) and GNU Octave (4.0.3). To improve reproducibility of results, we used Octave to produce the figures reported in the following text, running on an Intel Xeon E5-2690 2.60GHz CPU with 14 cores, 128 Gb of RAM memory and under Microsoft Windows Server 2008 R2 Enterprise. All source code is made available at the URL: `https://ec.europa.eu/jrc/sites/jrcsh/files/code.zip`

[3]In the actual code the values of abilities and qualities are rounded down to the nearest second decimal for coding convenience. For the same reason, abilities and qualities equal to zero are converted to 0.01. This way of coding introduces a very minor bias in the learning algorithm, which we tested to be of trivial importance and in no way affecting our arguments.

[4]An alternative interpretation of the values a assigned to entrepreneurs, which we will not pursue here, would be as probabilities of success for an underlying entrepreneur-specific project that requires repeated financing over time to be completed, and which discloses information about such probability over time as it gets developed.

is assumed then the true quality of each workers is common knowledge, and each workers knows that, if hired in E, the wage he will be paid is equal to his quality. If the scenario is of no information, all workers are always assigned the average quality calculated across the workers population employed in E (as assumed in the no-information case in Boadway and Sato 2011). If the scenario allows for learning, wage is equal to the estimated quality for each worker (the learning algorithm that generates such estimated qualities is described below). Wages are assumed to be paid upfront and therefore do not depend upon the probability of entrepreneurial success (again the latter assumption is taken to follow Boadway and Sato 2011 closely).

In each period, each entrepreneur is assigned a gross interest rate $r \geq 1$. Entrepreneurs face a probability of success equal to their ability a. If they fail they are assumed to go bankrupt and repay nothing to the bank. If they succeed, they repay to the bank the cost of labour times r. As the risk-free interest rate is assumed constant and equal to a value ρ, the interest rate for an entrepreneur is simply ρ divided by the entrepreneur's estimated ability, $\frac{\rho}{a_e}$, so that higher-ability entrepreneurs face lower interest rates.[5] As per workers, the estimated ability a_e for entrepreneurs depends upon the scenario of choice. With full information it is equal to the true ability value. With no information, it is equal to the average across the population of entrepreneurs. The latter is equivalent to assuming that the distribution of abilities and qualities in sector E is common knowledge. Finally, with learning, estimated ability a_e changes over time based on a learning algorithm. Given a true ability a and an estimated ability a_e, the expected profit of an entrepreneurial project from the point of view of banks is:

$$E_{banks}(\pi) = a_e(R\bar{q_e}^{\alpha} - r(a_e)n\bar{q_e}) \tag{1}$$

[5]In the simulation code a cap is put on the maximum value of r to avoid infinite values, which we arbitrarily set equal to the interest rate that would be offered to an entrepreneur with ability $a = 0.1$ under full information.

where $\bar{q}$ is the mean estimated quality of hired workers, and $0 < \alpha < 1$. As said before, the value of r depends on the estimated ability a_e that other agents believe the entrepreneur to possess. From the point of view of an entrepreneur, her expected profit is:

$$E(\pi) = a(R\bar{q_e}^{\alpha} - r(a_e)n\bar{q_e}) \tag{2}$$

the difference being that the entrepreneur is assumed to know his own ability value a. Entrepreneurs have too an external option of value π_0 which is interpreted as a risk-free investment opportunity, and they decide to enter sector E if, and only if, $E(\pi) \geq \pi_0$.

After entry is determined for all agents, a matching algorithm assigns the n workers having the best-looking estimated qualities q_e to the entrepreneur having the best-looking estimated abilities a_e. The reason for assuming a ranked-matching stems from the fact that better-looking entrepreneurs can always offer a slightly larger wage to a better-looking worker (this point was already demonstrated in Boadway and Sato 2011, for the cases with full and no information).

Finally, each enterprise enters the production phase and can either be successful (with probability a) or fail (with probability $1 - a$). The cost of production is determined by the sum of the estimated qualities of employees, times r (there are no capital costs other than what constitutes the net interest paid to banks in case of success). Revenues are determined by the true qualities of employees, meaning that better quality implies larger productivity.

Without learning, the model is parametrized such that it replicates Boadway and Sato (2011) (in the case they examined where the employment rate of workers who opted for entry in sector E is not 100%, therefore some of them will not be hired in E and will work in sector T instead), and in the scenario with full information such parametrization makes about 50% of entrepreneurs enter sector E and the same share of workers to be hired there. The total surplus of this market is maximised without policy intervention. In the scenario with no information, on the contrary, a “market for lemons” dynamics occurs and less than 50% of workers are employed in E while entrepreneurial entry exceeds 50% (as the worse-ability ones enjoy lower interest rates), resulting in lower total surplus.

3.2 Learning algorithm

The scenarios with learning feature a learning algorithm. At the beginning of a simulation all agents are assigned the mean value from their respective population (as per the scenario with no information). Then in subsequent periods a noisy informational signal is observed by all agents and used to infer the true underlying value of ability or quality. Both parameters σ_a and σ_q, which represent the standard deviations of the noise factors, are assumed constant over time and equal for all entrepreneurs and workers, respectively.

In each simulated period each entrepreneur who entered sector E is observed to be either successful or not successful. The number of successes in past periods divided by the number of total entrepreneurial projects started, plus a noise $\sim \mathcal{N}(0, \sigma_a)$, is used as an estimation for the true underlying probability of success (which is just equal to the ability value a). The noise parameter is such that a high-ability entrepreneur may look, after some periods of learning, as an average-ability one but very unlikely as a low-ability one (the opposite holds for low-ability entrepreneurs).

For workers, an informative signal of their quality is observed in each period, regardless whether they entered or not sector E. This signal is equal to their true quality q plus a noise $\sim \mathcal{N}(0, \sigma_q)$. The vector of such signals obtained in the past, $\bar{q}_e$, is used within a Bayesian inference algorithm. The value for q corresponding to the largest estimated probability $P(q|\bar{q}_e)$ is picked as best-guess and assigned as the estimated quality q_e to the worker (if multiple q values are associated with an equal probability, their mean is taken instead).

As stated we employ Bayesian learning. This is interpreted as an as-if representation of rational expectations (see Feldman 1987) formed over a worker's quality, given a set of observed signals. The prior belief on (conditional) quality distribution is assumed to be correct and common knowledge among all agents, that is, the probability $P(\bar{q}_e|q)$ for each possible q is obtained from the Normal probability density function of $\mathcal{N}(q, \sigma_q)$. The learning algorithm is "non-adaptive" in the sense explained in Marimon (1996), and disregards the possibility that Bayesian predictions are somewhat affected by reinforcement-based predictions (Charness and Levin 2005).

With learning, therefore, the estimated values for abilities and qualities on average converge toward their true values. Also the longer the simulation, the more observation points are available to the agents so that the closer estimated values will be to the true ones. As entrepreneurs gain more observations if they enter sector E, increasing entry may make the market converge faster to a higher informational level. For workers on the contrary we assume that workers produce signals about their quality even when working in the traditional sector T: this assumption represents the idea that in most cases workers can build up their curriculum vitae regardless of being hired by a new entrepreneurial firm. While debatable in principle, the latter assumption runs against our claim that the optimal entry level is larger with learning, so it does not really bear any implication for optimal policy (other than, possibly, strengthening our point).

3.3 Policy

As in Boadway and Sato (2011) the model allows for two types of policy instruments. The first is a tax or subsidy σ on labour income. The other instrument is a tax or subsidy τ on entrepreneurs. Both instruments are taxes if negative and are subsidies if positive. As there is no explicit bargaining process in the model to endogenously determine the split of profit between entrepreneurs and workers we assume that any tax or subsidy σ on labour is split between the two parties in fixed shares (which in our calibration is 50%).

A tax on entrepreneurs $\tau < 0$ is meant to represent, in a very synthetic way, the combined effects of the personal and corporate tax system on the individual choice to enter entrepreneurship. It can be viewed as a "success tax" as explained in Gentry and Hubbard (2000) exceeding personal taxation (if one assumes that the risk-free investment is taxed under personal taxation), or as a tax design for corporate taxation that penalises new entrepreneurial firms (for example by having an imperfect loss offset). Agents in the model are assumes risk-neutral, so the tax on entrepreneurs should not be interpreted as a device affecting risk-taking choices akin to Domar and Musgrave (1944).

The effects of a subsidy $\sigma > 0$ to labour are to induce more workers' entry (by raising the expected wage in sector E), and also to induce more entrepreneurial entry (because of lower investment costs). A tax on labour $\sigma < 0$ would bear the opposite effects. Differently from σ, a tax or subsidy to entrepreneurs only affects their entry decision. Boadway and Sato (2011) (see their Proposition 3.i) argue therefore for a policy that is made of a subsidy to labour, and a tax on entrepreneurs meant to reduce excessive entrepreneurial entry stemming from the combined effects of no information and labour subsidy.

4 Simulation results

The model is run for several replications (we chose 50) using the same parameters. Then, average values are taken across periods and replications (this is the case for entry and employment figures) or summing up across periods and then averaging across replications (for surplus). the latter average values are what we refer to as results in the follwing text.

We first run the model assuming full or no information to calibrate it. We chose parameters that make the model on average obtain an entry of 50% for both types of agents under full information. We then looked for a subsidy to labour that made workers' entry in the no-information scenario close[6] to the full information scenario, which we found to be $\sigma = 0.2$. Then we searched for a tax on entrepreneurs that, together with the subsidy on labour, would bring the entry levels in the no information scenario close to the full information scenario, which we found to be $\tau = -0.8$. This tax and subsidy policy represents a policy that would be optimal in the no information scenario described in Boadway and Sato (2011), under the condition that the number of workers seeking employment in sector E in the optimum is at least as great as the demand for workers by active entrepreneurs (which is the case we are looking at here). It is just the case to stress that the parameters used here are not meant to resemble any level of realism: they are meant to make the model behave in a certain way in order to support a theoretical argument. Table 1 summarizes the set of parameters employed.

The measure used to evaluate policies is total surplus (again following Boadway and Sato 2011), calculated as the sum across all entrepreneurs of the net profit earned minus the alternative no-risk investment, plus the sum across all workers employed in sector E of the wage earned less the alternative wage they could earn in T, which by assumption is just equal to q.

Table 2 summarizes the average outcome of the simulations across all the replications. The model is such that with no information there is excess entrepreneurial entry (because low-ability entrepreneurs enjoy better financial conditions thanks to the pooling with higher-ability entrepreneurs, as banks can only apply to all the same interest rate $r = \frac{\rho}{\bar{a}}$ with $\bar{a}$ being the average ability of active entrepreneurs in sector E). The average quality of both entrepreneurs and workers in E is lower than the case with full information.

[6] We here write "close" because due to the stochasticity of the model one can never be warranted that end values are exactly corresponding to a specific number, unless a very large number of replications is used which would make simulations last for too long.

Label	Base value	Sensitivities	Description
replications	50		No. of replications
periods	10	from 7 to 30	No. of periods
No. of workers	1000		Initial population of workers
No. of entrepreneurs	100		Initial population of entrepreneurs
R	36.2		Revenues multiplier
α	0.7		Revenues exponent
ρ	2		Risk-free interest rate
π_0	1		Profit from risk-free investment
n	10		No. of employees per firm
learning (starts at)	3		Initial periods without learning
σ_a	0.25	0.35 and 0.15	Std. dev. of abilities
σ_q	0.15	0.25 and 0.05	Std. dev. of qualities
interest cap	20		Maximum interest rate allowed
τ	0 or -0.8		Subsidy or tax on entrepreneurs
σ	0 or 0.2		Subsidy or tax on workers
$\sigma_{\text{incidence}}$	0.50		How σ is distributed

Table 1: Parameters used

As in Boadway and Sato (2011) total surplus is greatest, in the no information scenario, with the tax and subsidy policy as compared to the subsidy-only policy and the no-policy scenario.

	Entrepren. entry	Empl. rate	Surplus
Full information	50.7%	50.7%	48,264
No information and no policy	56.7%	43.2%	16,572
No information + subsidy	69.1%	53.3%	20,743
No information + tax + subsidy	56.1%	49.8%	21,109
Learning and no policy	43.9%	40.0%	25,246
Learning + subsidy	55.1%	49.6%	34,154
Learning + tax + subsidy	44.4%	42.5%	31,501

Table 2: Summary of simulation results

We then allowed for agents to learn, and run simulations first without any policy, then with a subsidy to labour $\sigma = 0.2$, and finally with both a tax on entrepreneurs $\tau = -0.8$ and a subsidy to labour $\sigma = 0.2$. Table 2 summarizes these results. With learning and without policy actions the market produces sub-optimal entry for both types of agents. The reason lies in the noisiness of ability and quality estimates, such that there is always a share of agents who are undervalued and thus do not enter sector E, and this share decreases in time as better estimates of abilities and qualities are available.

Contrary to the no information scenario, having learning agents implies that a policy made only of a labour subsidy is surplus-improving over the tax and subsidy policy, and it leads the level of workers' employment close to the level obtained in the optimal case with full information. Note that this is true even if the subsidy-only policy produces some level of excessive entrepreneurial entry: as explained, the efficiency gains from accelerated learning more than compensate the efficiency losses due to more low-ability entrepreneurs entering sector E. The optimality of a no-tax policy though is not warranted and in real economies having excess entrepreneurial entry (that is, excessive as compared to the ideal full information scenario) must be traded-off against its social costs. Thus, our claim is not that the optimal policy always implies no taxation in the presence of learning. Rather, our claim is that the existence of learning implies a lower tax (eventually down to zero), than in the scenario with no information.

4.1 Sensitivity analyses

Our argument is that the optimality of the tax and subsidy policy stated in Boadway and Sato (2011) is not robust to the inclusion of learning over time. Therefore, whatever combination of parameters we used to obtain a different ranking welfare-wise of the policies, it would be sufficient as a falsification device. Still, sensitivity analysis over some key parameters can be used to shed more light on the conditions that would make such falsification more likely in real economies.

One seemingly important key parameter is the number of periods included in the simulations. As the improvements in the estimation of abilities and qualities become marginally smaller in later periods, a longer time span means that the positive effects of learning on total surplus will decrease relative to the total effect from having larger entrepreneurial activity (the latter depresses surplus as more low-ability entrepreneurs are led into sector E). We thus changed the number of periods from 7 to 30 (from our central case with 10 periods).[7] Table 3 reports the results divided by policy. Indeed looking at the last column in Table 3, the longer the number of periods considered, the larger the welfare gain from the policy relative to the no-action scenario. Although the relationship between the number of periods and wel-

[7] Our model in Octave takes about three days to perform 50 replications with 30 periods each. As the amount of calculations needed for each additional period increase more than proportionally because of the Bayesian learning algorithm, we decided to stop the analysis at 30 periods.

fare gains is not in itself robust (for example in Table 3 one can see that the gains from the tax and subsidy policy peak at 20 periods and then decrease), the subsidy-only policy always outperforms the alternative policy in terms of surplus gains.

	A: with subsidy	B: with tax and subsidy	Difference (A-B)
7 periods	1.43	1.34	0.10
10 periods	1.35	1.25	0.11
20 periods	1.63	1.49	0.14
30 periods	1.64	1.46	0.17

Table 3: Sensitivity on the number of periods in the scenario with learning: total social surplus divided by total social surplus in the corresponding scenario with no policy action.

Another set of sensitivity analyses relates to the variance of the informational signal about abilities and qualities. We built two series of simulations that, in comparison to our central scenarios, only differ because the parameters σ_a and σ_q are either both increased by $+0.10$, or decreased by -0.10. We refer to these new sensitivity scenarios as "high-noise" and "low-noise". Table 4 summarizes the results. As can be seen changing the standard deviation of the distributions from which the noise values for estimated ability and quality are drawn does not meaningfully affect the results. Also the relative magnitude of the welfare gains from the two alternative policies (subsidy only, or tax and subsidy) are very similar.

A third set of sensitivity analyses relates to the level of the tax on entrepreneurs. It might be the case that learning entails a lower optimal tax, but not a zero tax. We reduced the tax from -0.8 to -0.1 stepwise (each step being +0.1) and we found that total surplus was always lower than the scenario with a subsidy-only policy, and decreasing with the tax rate. While we cannot exclude that some level of tax rate (smaller than 0.1) might be surplus-improving compared to a subsidy-only policy, that optimal tax would

	Entrepren. entry	Empl. rate	Surplus	Change in surplus
High-noise sensitivity				
No policy action	43.7%	40.0%	24,114	*(n.a.)*
Subsidy	55.0%	49.1%	31,623	1.31
Tax + subsidy	43.6%	42.0%	29,036	1.20
Low-noise sensitivity				
No policy action	42.5%	39.2%	26,796	*(n.a.)*
Subsidy	53.5%	48.0%	35,582	1.32
Tax + subsidy	44.3%	42.3%	33,674	1.26

Table 4: Sensitivity on noise in the scenario with learning: Summary of simulation results. The last column reports the ratio of total surplus over total surplus in the corresponding scenario with no policy action.

be very small in our simulations, and any way much smaller than the optimal tax found for the scenario with no information.

5 Conclusions

We developed a simulation exercise to mimic in an agent-based fashion a market with adverse selection both on the side of entrepreneurial entry and on the input market for workers, in this following the theoretical work of Boadway and Sato (2011). Our simulation results show that the introduction of learning over time can affect the optimality of tax and subsidy policies. A policy made of a subsidy to labour and a simultaneous tax on entrepreneurs, which would be socially second-best under a no-information scenario, was shown to be inferior welfare-wise to a policy made only of a labour subsidy when agents are allowed to learn about other agents' characteristics.

The intensity of information asymmetries probably varies across industries, countries and times. Highly innovative sectors are likely to be more plagued as it takes time to evaluate the capacity of a technical employee to innovate, an example of this being the highly skewed distribution of patent applications among the population of inventors where most employees never patent anything or at most manage to patent once in a lifetime. In such cases the economy is likely to be represented quite closely as a polar scenario with no information, with the exception of "star" scientists and entrepreneurs for whom a sizable number of observations may exist about their performance so that other agents may evaluate them accordingly. The latter observation points to a candidate extension of this research by assuming a segmented market with learning over ability/quality happening only above a threshold number of observed successes or failures.

References

Akerlof, George A (1970). "The market for" lemons": Quality uncertainty and the market mechanism". In: *The quarterly journal of economics*, pp. 488–500.

Bloomquist, Kim M (2006). "A comparison of agent-based models of income tax evasion". In: *Social Science Computer Review* 24.4, pp. 411–425.

Boadway, Robin and Michael Keen (2006). "Financing and taxing new firms under asymmetric information". In: *FinanzArchiv: Public Finance Analysis* 62.4, pp. 471–502.

Boadway, Robin and Motohiro Sato (2011). "Entrepreneurship and asymmetric information in input markets". In: *International Tax and Public Finance* 18.2, pp. 166–192.

Charness, Gary and Dan Levin (2005). "When optimal choices feel wrong: A laboratory study of Bayesian updating, complexity, and affect". In: *The American Economic Review* 95.4, pp. 1300–1309.

d'Andria, Diego (2016). "Taxation and Incentives to Innovate: A Principal–Agent Approach". In: *FinanzArchiv: Public Finance Analysis* 72.1, pp. 96–123.

d'Andria, Diego and Ivan Savin (2015). *Motivating innovation in a knowledge economy with tax incentives*. Tech. rep. Jena Economic Research Papers.

De Meza, David and David C Webb (1987). "Too much investment: a problem of asymmetric information". In: *The Quarterly Journal of Economics* 102.2, pp. 281–292.

Dietl, Helmut M et al. (2013). "Incentive effects of bonus taxes in a principal-agent model". In: *Journal of Economic Behavior & Organization* 89, pp. 93–104.

Domar, Evsey and Richard Musgrave (1944). "Effects of proportional taxes on risk-taking". In: *Quarterly Journal of Economics* 59, pp. 338–422.

Feldman, Mark (1987). "Bayesian learning and convergence to rational expectations". In: *Journal of Mathematical Economics* 16.3, pp. 297–313.

Gentry, William M and R Glenn Hubbard (2000). "Tax policy and entrepreneurial entry". In: *The American economic review* 90.2, pp. 283–287.

Hashimzade, Nigar et al. (2015). "The use of agent-based modelling to investigate tax compliance". In: *Economics of Governance* 16.2, pp. 143–164.

Henrekson, Magnus and Tino Sanandaji (2011). "Entrepreneurship and the theory of taxation". In: *Small Business Economics* 37.2, pp. 167–185.

Holmstrom, Bengt and Paul Milgrom (1991). "Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design". In: *Journal of Law, Economics, & Organization* 7, pp. 24–52.

Judd, Kenneth L (2005). "Computationally intensive analyses in economics". In:

Keuschnigg, Christian and Soren Bo Nielsen (2003). "Tax policy, venture capital, and entrepreneurship". In: *Journal of Public Economics* 87.1, pp. 175–203.

Marimon, Ramon (1996). *Learning from learning in economics*. European University Institute Florence.

Neugart, Michael (2008). “Labor market policy evaluation with ACE”. In: *Journal of Economic Behavior & Organization* 67.2, pp. 418–430.

Popper, Karl (2005). *The logic of scientific discovery.* Routledge.

Radulescu, Doina (2012). “The effects of a bonus tax on manager compensation and welfare”. In: *FinanzArchiv: Public Finance Analysis* 68.1, pp. 1–16.

Rosen, Harvey S (2005). “Entrepreneurship and taxation: Empirical evidence”. In: *Venture capital, entrepreneurship and public policy*, pp. 251–279.

Schumpeter, Joseph Alois (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle.* Vol. 55. Transaction publishers.

Shapiro, Carl and Joseph E Stiglitz (1984). “Equilibrium unemployment as a worker discipline device”. In: *The American Economic Review* 74.3, pp. 433–444.

Stiglitz, Joseph E and Andrew Weiss (1981). “Credit rationing in markets with imperfect information”. In: *The American economic review* 71.3, pp. 393–410.

Tesfatsion, Leigh (2001). “Structure, behavior, and market power in an evolutionary labor market with adaptive search”. In: *Journal of Economic Dynamics and Control* 25.3, pp. 419–457.

— (2003). “Agent-based computational economics: modeling economies as complex adaptive systems”. In: *Information Sciences* 149.4, pp. 262–268.

Tesfatsion, Leigh and Kenneth L Judd (2006). *Handbook of computational economics: agent-based computational economics.* Vol. 2. Elsevier.

Warner, Geoffrey et al. (2015). “Modeling tax evasion with genetic algorithms”. In: *Economics of Governance* 16.2, pp. 165–178.

Weiss, Andrew (1980). “Job queues and layoffs in labor markets with flexible wages”. In: *Journal of Political economy* 88.3, pp. 526–538.

Winter, Sidney G and Richard R Nelson (1982). "An evolutionary theory of economic change". In:

Yildizoglu, Murat (2002). "Competing R&D strategies in an evolutionary industry model". In: *Computational Economics* 19.1, pp. 51–65.

JRC Mission

As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

Joint Research Centre

EU Science Hub