Talent, Taxes and Credit Constraints

Explaining Productivity and Investment in Times of Crisis

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Introduction

Many differences about economic policy could be eliminated if we were able to correctly predict the results of any given measure. This is the aim of economics as a positive science, “to provide a system of generalization which can be used to make correct predictions about the consequences of any change in circumstances” (Friedman 1953). Every effort to contribute to positive economics is divided into two steps: to construct a hypothesis which yields an observable prediction and to test its validity with empirical evidence. Both steps have become easier in recent years: first, the advent of simulation in economic theory has made it possible to deduce testable predictions from models which are too complex to be solved analytically. Second, advances in our understanding of identification and statistical theory have increased the credibility of empirical tests. The application of these new quantitative methods is now an important part of modern economic reasoning.

The economic crisis that began in 2007 demonstrated that our knowledge in positive economics is incomplete at best: economists predicted widely different consequences of the financial crisis and the impact of proposed and implemented policies. For example, leading economists claimed that a dollar spent by the government would result either in 1.6 dollar (Romer and Bernstein 2009) or 0.4 to 0.8 dollar (Barro and Redlick 2011) of additional gross domestic product. Such disagreements understandably confused policy makers and the public, leading some commentators to declare the current study of economics broken (Krugman 2009, Stiglitz 2011). At the same time, the apparent absence of knowledge provided a strong incentive for research economists to put the new quantitative methods to work to build new models and to test new predictions.[1]

[1] For example, Christiano, Eichenbaum, and Rebelo (2011) showed with simulations that introducing a binding zero-lower bound on interest rates raises the government spending multiplier to 1.6-2.3 in a DSGE model.

With the help of quantitative economics, this dissertation analyzes three topics which have become particularly relevant in the ongoing economic crisis. In the first chapter, we model theoretically the influence of a credit crunch on investment behavior and market structure. The second chapter is an empirical study concerned with the effects of the business cycle on the allocation of talent within an economy. The last chapter turns to new sources of economic growth by considering the effect of taxes on investment in new companies by venture capital funds. Each chapter is outlined in turn. The chapters are arranged in the order of their inception and can be read independently.

The first chapter of this dissertation examines the effect of a change in borrowing constraints on the equilibrium market structure in a dynamic duopoly model.[2] Recessions caused by banking crises are often accompanied by a credit crunch, the reduction of credit available to companies in the real economy. According to standard macroeconomic models, a lesser amount of available credit leads to a reduction in investment, resulting in turn in lower production. However, these models do not take into account that more severe financial constraints might also lead to fewer firms competing in the product market, i.e., to a change in market structure. For the consumer, market structure is important because it directly influences prices and the available choices.

This chapter contributes to the literature by proposing a computationally feasible model integrating financial constraints in a duopoly framework. To the best of our knowledge, this is the first model to explicitly consider the effect of financial constraints on equilibrium market structure. More concretely, we introduce firms with an endogenous capital structure and an optimizing bank into an Ericson-Pakes framework. To solve this model, a novel learning algorithm is used, based on the Experience Based Markov Equilibrium framework of Fershtman and Pakes (2011). This is necessary because the endogenous capital structure of the firms gives rise to a dynamic optimization problem which cannot be solved with conventional computational methods.

Using this model, we find that credit rationing can amplify the effects of small idiosyncratic shocks to a firm, potentially even causing the firm to exit the market. If a firm loses production capacity through a shock, less profit is available for financing investment.

[2]This chapter is based on the article “Credit Cycles in a Dynamic Duopoly”.

With well-functioning credit markets, the firm can compensate for this reduction in cash flow by taking out more debt. But if credit is rationed, firms might be unable to cover the cost of adding capacity. Without investment, the firm remains at the lower capacity level which is associated with less funds. If the firm is hit by another depreciation shock which further tightens credit constraints, its ability to react by an increase in investment is reduced even more. Eventually, this process can force the firm to exit the market, even if it is equally productive as the remaining firm. The resulting reduction in the number of competitors is (relatively) stable because new entrants cannot enter immediately and replace the failing firm as they face credit constraints, too.

The second chapter analyzes the effect of the business cycle on the distribution of skills across sectors.[3] The ongoing recession led to a growing interest in academia on the effects of downturns on labour market outcomes. In particular, recent studies have found a strong and persistent negative impact of recessions on individuals employment and earnings. Yet, as far as we know, there is no study which examines whether highly skilled individuals react to recessions by changing occupations and the impact these reactions might have on talent allocation across sectors. This chapter fills this gap in the literature by looking at a specific market where skill can be easily measured: the market for academic economists.

We study the impact of recessions on skill allocation by relating the research productivity and career choice of economists graduating from the leading universities to measures of the business cycle during the last 50 years. To guide our empirics, we develop a model of the self-selection of talent into business and academia, where entering academia is competitive but attractive during recessions. This model predicts that fewer economists who faced a recession at time of application to the PhD program stay in academia after graduation. Those who do stay are positively selected on academic productivity. Moreover, if there is a recession at the time of graduation, more economists pursue academic employment, which leads to a higher publication output per PhD graduate.

The results of the empirical analysis support the theoretical predictions. In particular, they show that individuals do react to recession shocks. Economists applying or graduat-

[3]This chapter is based on the article “The Allocation of Talent: Evidence from the Market of Economists” which is joint work with Michael Böhm from the London School of Economics and Political Sciences.

ing during recessions publish significantly more than economists applying or graduating in a boom. A recession at entry leads to fewer PhD students pursuing an academic career, a recession at graduation has the opposite effect. Moreover, the effects are of economically substantial magnitude. Taking our estimates literally, we expect assistant professors from the cohort of graduate students who applied for the PhD during the recession of 2008 (3.5 percentage points increase in unemployment) to be around 24 % more productive than assistant professors from a cohort applying in an average year (0 % unemployment change). We also expect PhD graduates from 2008 to produce on average 20 % more publications in their early careers than economists graduating in an average year. Taken together, it appears to be the case that recessions can lead to a positive selection of talent into academia.

The third chapter turns to new sources of growth by considering the effect of tax changes on the probability of a start-up company receiving investment from a venture capital fund.[4] Around the world, governments introduce policies to promote start-up companies to spur new growth in their economies. These companies are often financed by private venture-capital funds that provide advice and support along with risk capital. Venture capital-backed companies are of special interest for the policy maker because they are particularly innovative. For example, a dollar spent on venture capital yielded more than twice as many patents than a dollar spent on R&D by established companies in the United States in the period from 1983 to 1992 (Kortum and Lerner 2000).

Despite this public interest, it is not completely understood how public policy influences the investment behavior of venture capital investors and thus the entrepreneurial process. In particular, high taxes are supposed to discourage investment from a theoretical perspective, but — to the best of our knowledge — there is no empirical estimate of the size of this effect. In this chapter, we address this gap in the literature by estimating the effect of the capital gains and the dividend tax on the number of firms receiving the first investment and on the probability of a firm receiving a follow-up investment. We expect both tax rates to have a negative impact on the dependent variables because both diminish the profits from investing in new ventures: the capital gains tax, which is levied

[4]This chapter is based on the article “The Effect of Taxes on Venture Capital Investment” which is joint work with Ann-Kristin Achleitner and Carolin Bock of the Technische Universität München.

on a company's sales price, reduces the investor's return. The dividend tax reduces the value of the investee company to the buyer and thus the sales price of an initial public offering (IPO) or a trade sale.

In the first part of our analysis, we measure the effect of taxes on the number of firms receiving their first funding by venture capitalists. We use a negative binomial model to explain the number of new ventures with the two tax rates, year- and country fixed-effects. Our results indicate that an increase in the overall dividend tax rate has a negative effect on the number of companies receiving their first investment. The estimated coefficient is significantly different from zero at the one percent level and implies that a one percentage point increase in the dividend tax rate is associated with approximately two percent fewer companies. At a mean of 131 new companies per country and year, such a tax increase leads to a reduction of about two newly-funded ventures. The mean estimate of the capital gains tax is also negative, but not significantly different from zero at conventional levels.

In the second part of our analysis, we consider the influence of taxes on the probability of venture capital-backed firms receiving a follow-up investment. As empirical model we use a firm fixed-effects panel with probability of investment as the dependent variable and the two tax rates as the independent variables. We find that on average an increase in the capital gains tax rate of one percentage point reduces the probability of venture-capital backed companies receiving a follow-up investment by two percentage points. At a mean probability of investment of 59% in our sample, such a tax increase reduces the likelihood of investment by around four percent relative to the mean. The estimated coefficient of the capital gains tax is significantly different from zero at the one percent level. The mean estimate of the overall dividend tax is negative, but not significantly different from zero at conventional levels.

Taking these three chapters together, this dissertation offers new ideas on the determinants of productivity and investment in times of crisis. Pending rigorous replication studies, all findings should be viewed as preliminary. Nevertheless, we hope to contribute in a meaningful way to positive economics, the description and explanation of economic phenomena (Wong 1987).

Chapter 1

Credit Cycles in a Dynamic Duopoly

1.1 Introduction

In 2007 and 2008 there existed a widespread fear that several OECD countries would suffer from a credit crunch. Loan losses and lower asset prices ate significantly into the equity of the banking sector, a fact which many believed would cause banks to ration credit. According to standard macroeconomic models, a lesser amount of available credit leads to a reduction in investment, resulting in turn in lower production and lower welfare (e.g. Bernanke, Gertler, and Gilchrist 1999). However, these models do not take into account the change in market structure which might result from the financial frictions. For a welfare analysis, market structure is important because it directly influences prices and the available choices for consumers. For example, if in a duopoly a smaller competitor is unable to replace its broken machinery because of a lack of credit, he might exit the market and leave the consumer with a monopoly supplier.

Including financial frictions in any oligopoly model is challenging because investment, financing decisions, and market competition are inherently interdependent and dynamic: past investment decisions determine today's market structure which in turn influences current investment decisions. In addition, a firm can only invest if it can finance the outlays. Investment funds can either come from current profits (determined by today's market structure), retained cash (determined by past financing decisions), or new loans (where the debt capacity is determined by future profits). To complicate matters further, firms rationally anticipate future investment needs and shortages in funding.

This chapter contributes to the literature on financial constraints by proposing a computationally feasible model which takes all these factors into account for the case of a dynamic duopoly. To integrate financing and investment decisions, we introduce firms with an endogenous capital structure and an optimizing bank into an Ericson-Pakes framework. However, including an endogenous capital structure for each firm gives rise to a large state space which makes a calculation of the equilibrium intractable with conventional Gauss-Seidel and Gauss-Jacobi algorithms. Therefore, we use a variant of the novel algorithm introduced by Fershtman and Pakes (2011) to solve our model.

Each firm is characterized by three state variables: capacity, debt level, and cash reserves. Firms accumulate capacity over time and compete repeatedly in the product market to earn profits. In every period, they aim to maximize the net present value of dividend payments. For this purpose, they optimally choose production, investment, the amount of cash to retain, and the size of debt repayments. Whatever is left of the profits after subtracting all incurred costs is distributed as a dividend to the shareholders. Firms can apply for a loan if the current cash flow is insufficient to cover expenses. The loan is provided by a risk-neutral bank given that its expected return exceeds an exogenously set minimum threshold. This threshold parametrizes the amount of credit rationing prevalent in the market.

Using this model, we show that credit rationing serves as a propagation mechanism which amplifies small idiosyncratic shocks to capacity. This mechanism can lead to the monopolization of the market. If a firm loses productive capacity through a depreciation shock, lower current profits are available for financing investment. With well-functioning credit markets, the firm can compensate for this loss in cash flow by increasing the amount of credit financing. But if credit is rationed, firms might be unable to cover the cost of additional capacity. Without investment, the firm remains at the lower capacity level which is associated with less funds. If the firm is hit by another depreciation shock which further tightens credit constraints, its ability to react by an increase in investment is reduced even more. Eventually, this process can lead to the exit of the firm, even if it has the same production costs as the remaining incumbent.

The monopolization of the market is made permanent by two other effects: first, with credit rationing, entrants face financing constraints, too. Therefore, new firms cannot enter because they do not obtain sufficient credit to finance initial outlays. Consequently, the monopolization due to the credit constraints is not quickly reversed by market entry. Second, the competing firm can expand its own capacity and market share. Increased capacity translates into higher profits which eases credit rationing in the competitor's investment process. In the following periods, the monopolist can then finance itself through cash retainment, increase capacity faster, and gain a dominant position in the market.

Given these theoretical results, a recession which is accompanied by a credit crunch might not be only "cleansing," i.e., destroy unproductive firms (as in Caballero and Hammour 1994), but also force viable competitors out of the market. The welfare of the consumer is reduced by higher prices caused by the ensuing monopolization. This observation gives a rationale for government interventions which aim to increase the credit volume available to companies. According to our model, such programs should seek in particular to support small firms to prevent their exit or facilitate their entry. The reason is that small companies (in contrast to large companies) do not have sufficient free cashflow to finance investment and therefore have to rely on a functioning credit market to fund start-up costs or growth plans. If they cannot finance investment with credit they exit or fail to enter the market, what reduces competition and consumer welfare.

This chapter contributes to the growing literature on modeling imperfect competition with heterogeneous firms. It is the first model to introduce financial frictions in an Ericson-Pakes framework.[1] We extend the dynamic duopoly model outlined in Besanko and Doraszelski (2004) and Besanko, Doraszelski, Lu, and Satterthwaite (2010) by firms with an endogenous capital structure and an optimizing bank. The larger state space resulting from the endogenous capital structure makes it is necessary to use the new stochastic algorithm of Fershtman and Pakes (2011) to numerically compute the equilibrium. With this algorithm, we can solve the game much faster than with the commonly used Pakes and McGuire (1994) or Pakes and McGuire (2001) algorithms. To the best of our knowledge, the only other application of the Ericson-Pakes framework to finance is Kadyrzhanova (2009), which models the effect of corporate control imperfections on industry structure.

[1]For a survey on this literature, see Doraszelski and Pakes (2007).

Others have worked on financial frictions in dynamic firm models using the alternative framework of Hopenhayn (1992). In contrast to Ericson-Pakes type models, this framework considers only aggregate firm dynamics by assuming an infinite number of firms with an infinitely small market share. Therefore, it is impossible to consider oligopoly behavior in this framework. In addition, in the model of Hopenhayn (1992), all dynamics are driven by permanent firm specific shocks, because temporary shocks average out. In our model, in contrast to that, temporary idiosyncratic shocks are amplified through the capital structure and competitive behavior. The number of applications of the modeling framework of Hopenhayn (1992) in the finance literature is huge: for instance, Cooley and Quadrini (2001) investigate the effect of financial frictions on firm growth. Gomes (2001) explains the effect of financial frictions on investment. Hennessy and Whited (2005) consider a dynamic trade-off model of leverage, corporate saving, and real investment to explain debt dynamics.[2]

Our results are qualitatively similar to the effects described in Kiyotaki and Moore (1997), which characterizes the emergence of credit cycles. Their main idea is that in downturns, both earnings and the liquidation value of collateral are low because potential buyers are cash-strapped. Due to the lower collateral value credit constrained firms cannot borrow for investment, which in turn further reduces their future earnings. As the liquidation value of the collateral is again reduced by this reduction in expected profits, a reinforcing cycle ensues. In contrast, in our model, firms cannot borrow further money because banks are cash strapped and the effect is transmitted via the expectations of the banking sector and oligopoly behavior.

The remainder of this chapter is organized as follows. We set up the model in Section 2. Sections 3 and 4 present the results and robustness checks. Section 5 concludes.

[2] Other articles modeling the intersection of investment and financial policy are, e.g., Acharya, Almeida, and Campello (2007), Almeida and Campello (2007), Almeida, Campello, and Weisbach (2009) Moyen (2004), Titman and Tsyplakov (2007), and Adam, Dasgupta, and Titman (2007). See Hubbard (1998) and Stein (2003) for reviews of this literature.

1.2 A Duopoly with Endogenous Capital Structure

1.2.1 Static Framework: The Optimization of the Firm

Assume that there are two firms which compete repeatedly in the same market and there exists one risk-neutral bank. Each firm $i \in \{1,2\}$ is fully characterized by its capacity ($\bar{q}_i$), its debt level (d_i), and its cash reserves (c_i). To simplify the notation we combine the value of these state variables of the two firms to the industry state $s = (\bar{q}_1, \bar{q}_2, d_1, d_2, c_1, c_2)$, which is common knowledge.

In every period, each firm can choose an action set $a = (INV, \Delta_{debt}, \Delta_{cash})$ to change the value of its state variable if it has enough funds to cover the associated costs. A firm can decide to add one unit of capacity ($INV = 1$) by incurring the expansion costs η or remain inactive ($INV = 0$). It can pay back the amount Δ_{debt} of debt or increase its cash reserves by Δ_{cash}. The total costs of an action set are the sum of interest payments, the investment cost, the amount used for debt repayment, and the increase of the cash reserve:

$$cost(a,s)_i = r \cdot d_i + \eta \cdot INV_i + \Delta_{debt,i} + \Delta_{cash,i}$$

where r is the interest rate paid by the firm. These costs must be covered with the current profits (π_i), the cash reserves, and the available line of credit ($credit(a,s)_i$). If this is the case, the action set is in the set of feasible actions $A(s)$.[3]

Each firm acts in the interest of its sharholders and chooses the action set a^* which maximizes the expected discounted value of dividend payments in every period:

$$a^* = arg \max_{a \in A(s)} W(a,s).$$

where $W(a,s)$ is the expected value of dividends if action a is chosen in the industry state s. The expected value of this dividend stream is given by

$$W(a,s) = div(a,s) + \beta E_{a',s'}[W(a',s')|a,s]$$

[3] For the sake of readability we suppress the subscript i in the following.

where $E[\cdot]$ is the expectation operator, β is the discount factor, s' is next period's state, and a' is next period's action. The dividend payments are the positive difference of current profits and the costs from the action set

$$div(a, s) = min\{\pi - costs(a, s), 0\}.$$

1.2.2 Dynamic Framework: State to State Transition

In the following, we outline the law of motion for each state variable in turn. At the end of this section, we describe what happens if firms are bankrupt, exit, or enter the market.

☐ **Capacity:** A firm can choose to add one capacity unit ($INV = 1$) or remain inactive ($INV = 0$). With an exogenous probability δ, the current capacity is reduced by one unit because of depreciation. Therefore, the next period's capacity $\bar{q}'$ of a firm with capacity $\bar{q}$ is determined by:

$$\bar{q}' = \begin{cases} \bar{q} + 1 & \text{with probability } (1-\delta) \text{ if } INV = 1 \\ \bar{q} & \text{with probability } \delta \text{ if } INV = 1 \text{ and with probability } (1-\delta) \text{ if } INV = 0 \\ \bar{q} - 1 & \text{with probability } \delta \text{ if } INV = 0. \end{cases}$$

If the firm decides to add capacity and no depreciation shock takes place, the capacity is increased by one. The capacity is decreased if there is no investment and a depreciation shocks hits the firm. It stays constant in all other cases.

As capacity is added and subtracted in discrete steps, it is treated as lumpy in our model. This is in line with the (s, S) modeling tradition of capacity adjustment (e.g. Caballero and Engel 1999, Caplin and Leahy 2010), prior work on Ericson-Pakes models (e.g. Besanko and Doraszelski 2004, Besanko, Doraszelski, Lu, and Satterthwaite 2010), and empirical evidence. For example, Doms and Dunne (1998) show that in U.S. census data a significant amount of investment adjustment takes place in a relatively short period of time, while most periods are characterized by only minor changes. In their sample, 25% percent of total investment derives from firms that adjust their capital stock in a given year by more than 30% percent.

☐ **Debt and Cash reserves:** The costs associated with every action set are financed by current profits, a reduction of the cash reserves and/or with debt (in that order). Accordingly, the law of motion of the cash reserve is given by

$$c' = c + \Delta_{cash} - \min\{\max\{cost(a, s) - \pi, 0\}, c\}$$

Cash tomorrow is cash today plus the additional cash put into reserves less the amount necessary to cover the costs of the action set. If current profits and cash reserves are not sufficient to cover all costs, the firm can finance them with new debt. The law of motion of debt is

$$d' = d - \Delta_{debt} + \min\{\max\{cost(a, s) - \pi - c, 0\}, credit(a, s)\}$$

where $\max\{cost(a, s) - \pi - c, 0\}$ is new borrowing and $credit(a, s)$ is the credit limit. Debt in the next period is debt today minus the amount of debt repaid plus what is left to finance after the cash reserve is used up.

Although this hierarchy of finance looks strict, it is not: for example, firms can at the same time use cash and increase their cash reserves by choosing a high Δ_{cash}, thus increasing the percentage of debt financing. The only thing that is not possible is to rely on cash reserves and debt financing without using all current cash flow π. The hierarchy of finance approach is in line with the pecking order theory of Myers (1984).[4]

☐ **Market exit and entry:** Two exemptions to the laws of motion outlined above exist: the exit and the entry of a firm. A firm exits the market if it is either bankrupt or all its capacity is depreciated. Firm i is bankrupt if it is unable to pay its due interest payments out of current profits and retained cash, i.e.,

$$\pi + c - r \cdot d < 0.$$

The remainder of the cash reserve is given to the bank and the firm vanishes from the

[4] It is necessary to introduce this hierarchy of finance for technical reasons. Restricting the choice space immensely simplifies the calculation of the equilibrium, because it reduces the number of follow-up states that must be considered to compute the continuation value of the firm. An alternative would be to rewrite the model in continuous time (Doraszelski and Satterthwaite 2010).

market. The bankruptcy process imposes an upper bound on the total amount of debt, precludes Ponzi games, and limits the size of the state space. If a firm exits, the possibility arises for an entrant to become the second player in the market. The new player has no capacity and no debt, but has the amount c^e of cash from equity investors.

1.2.3 The Optimization of the Financial Intermediary

In every period, the bank offers the firm a credit limit conditionally on the action taken by the firm, the industry state, and the required minimum return R of the loan. This line of credit is determined by the difference of the expected discounted sum of payments which the bank receives from the firm with the credit ($V_{Bank}(a, s)$) and the amount in case the credit is not granted ($V_{Bank}(\tilde{a}_*, s)$) adjusted by the return R

$$credit(a, s) = \frac{V_{Bank}(a, s) - V_{Bank}(\tilde{a}_*, s)}{R}, \tag{1.1}$$

where $\tilde{a}_*$ is the optimal action the firm would take if no credit is given. Thus the bank is ready to grant a credit limit if it receives at least a return of R per unit of credit in expected repayment from the firm.

The expected discounted sum of payments it will receive from a firm is given by

$$V_{Bank}(a, s) \equiv E\left[\sum_{t=0}^{\infty} \beta_{Bank}^{t}(r \cdot d_t + \Delta_{debt,t} - d_{new})\right]$$

where $\beta_{Bank} = \frac{1}{1+r_{Bank}}$ is the discount factor and r_{Bank} is the interest rate of the savers. In every period, the bank receives interest payments $r \cdot d$ and repayments Δ_{debt} from the firm. To account for the repayment to the savers, we subtract the net present value of all interest payments and the repayment of the principal at the time the loan is granted. By construction, this is exactly the value of the newly obtained credit $d_{new} = \min\{\max\{cost(a, s) - \pi - c, 0\}$.

Credit rationing is more severe if the required return R for loans is larger, i.e., the repayment per unit of credit must be higher. The functional form (1.1) is inspired by the credit crunch model of Holmstrom and Tirole (1997). Assume that there exist three types of agents: a continuum of firms, uninformed investors, and a continuum of banks. In each period, every firm has one project with a different return. The investor would like to invest in these projects, but is unable to prevent the firm from diverting the funds to only privately profitable projects. The bank can perfectly rule out such bad projects by monitoring the firms' efforts. However, it cannot credibly commit to do so because monitoring entails non-verifiable private costs. Consequently, the uninformed investor is willing to employ the bank as a monitor only if the bank invests a fixed amount of its own capital in the firm, too. This makes it privately optimal for the bank to control the firm. Since the bank has only a finite amount of equity, it can only fund a limited number of firms.

In order to choose which project to fund, the intermediary sorts the projects from the highest return to the lowest. Starting with the most profitable project, the bank gives loans to projects with lower and lower returns until all its equity is pledged. The excess return on the loan (corrected for its costs), which just attracts funding is denoted R. This return therefore entails a scarcity rent which might be high if a credit crunch has eaten up all of the bank's equity.

In our model, we set the return R exogenously and time invariant, to parameterize the amount of credit rationing. This implies that throughout the economy, the return distribution of projects is stable and the banks do not raise equity. If a firm in the considered duopoly can deliver in expected value the return R, it gets the loan, otherwise the loan is given to some other firm in the economy.

1.2.4 Timing

At the beginning of each period, the bank decides how much credit it offers to each firm. At the same time, if a firm is unable to pay its due interest payment out of its current cash flow, the firm declares bankruptcy and exits. Next, each firm is privately informed about its cost of capacity addition η. Conditional on these investment costs and the amount of available credit, each firm takes its optimal action. Then both firms compete in the product market. At the end of the period, capacity is subject to depreciation and all decisions are implemented.

1.2.5 Equilibrium Concept and Computation

We focus our attention on a symmetric Experience Based Markov Equilibrium (EBE). An EBE consists of (i) a subset of the set of possible states (the recurrent class), (ii) a vector of strategies which is optimal given the equilibrium continuation values from (iii), and (iii) a vector of continuation values for every state which is consistent with optimal actions defined in (ii). The concept of EBE as defined in Fershtman and Pakes (2011) is a similar, but a weaker concept than Markov Perfect Equilibrium because it is sufficient to calculate optimal policies on the recurrent class of states. A state is a member of the recurrent class if it is visited infinitely often in infinite time.

To solve for the EBE, we use a variant of the reinforcement learning algorithm outlined in Fershtman and Pakes (2011). We describe the computation, the merits and problems of this algorithm in Appendix A.4.

1.2.6 Parameterization

□ **State space & choice set:** To enable computation, we discretize the state space in all three dimensions of the state space to multiples of five units starting with a value of zero. Therefore, a firm in the first capacity state has a capacity of zero, in the second a capacity of 5, in the third a capacity of 10 and so on. The spacing is discretionary but this one is common in the literature (Besanko and Doraszelski 2004). Furthermore, we restrict the maximum capacity to 45, the debt to 195, and the cash to 95 units. These bounds are arbitrary but high enough so that they are never reached in equilibrium play. To ensure that firms stay within the state space, we have to restrict the potential choices of Δ_{debt} and Δ_{cash} to multiples of five with a finite upper bound.

□ **Single period profit:** Firms compete in quantities which are less than or equal to the firm's capacity. Consequently, we use the profit function ($\pi = \pi(\bar{q}_i, \bar{q}_j)$) for capacity constraint quantity competition with the same parameters as Besanko and Doraszelski (2004). The derivation is outlined in Appendix A.1 and illustrated in Figure 1.1.

□ **Investment:** The investment costs η are random and are private information to the

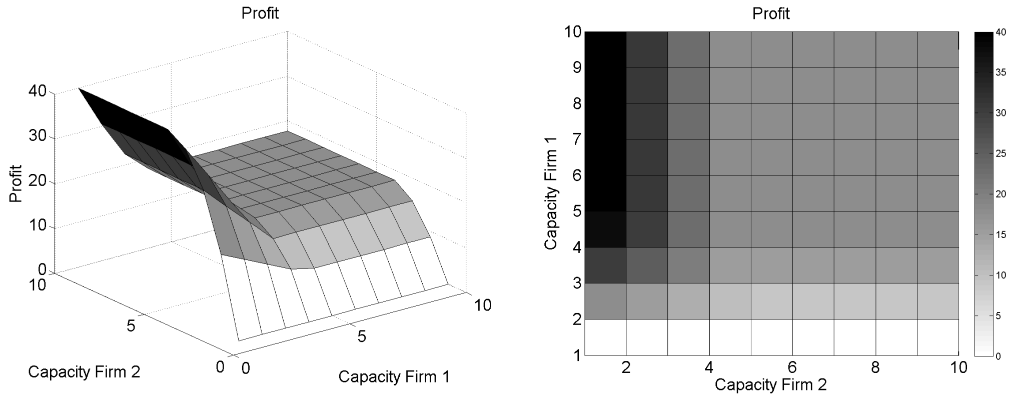


Figure 1.1: Profit of firm 1

firm as in Besanko, Doraszelski, Lu, and Satterthwaite (2010). They are determined by

$$\eta_{i,t} = 50 + 5 \cdot \psi_{i,t},$$

where

- the minimum construction costs are 50, which are the same for both firms and constant over time
- $5 \cdot \psi_{i,t}$ are project specific costs. $\psi_{i,t}$ is a random variable, drawn anew from a Beta(3,3) distribution with support [0,1] independently for each firm and each period. $\psi_{i,t}$ is private information for firm i and captures the idea that project opportunities are not the same for both firms and change over time.

Incorporating random investment costs and incomplete information is now common practice in the simulation of Ericson-Pakes models (e.g. Ryan 2009, Besanko, Doraszelski, Lu, and Satterthwaite 2010). It is realistic that firms do not exactly know the expansion costs of the rival. Furthermore, random investment costs make it possible to use the purification techniques of Doraszelski and Satterthwaite (2010) to ensure the computability of the equilibrium.

Following Gomes (2001), who matches the investment and capital data obtained from Compustat, we set the probability of depreciation to $\delta = 12\%$.

☐ **Entry:** The expected value of the amount of financing available to an entrant, the cash state of the entrant c^e, is set to 50% of the expected average investment costs η. Thus c^e is determined by

$$c^e = 25 + 2.5 \cdot \psi^e_{i,t},$$

where ψ^e_i is a random variable drawn from a Beta(3,3) distribution with support [0,1] in every period. Again this random component of c^e ensures computability. We explore the sensitivity of our results to this assumption in the robustness section.

☐ **Financial parameters:** The yearly interest rate is set to $r = 6.5\%$ and the interest rate for savers to $r_{Bank} = 4.5\%$. This matches the real interest rate over the last century and the average interest rate spread of 2% between 1968 and 1997 (Gomes 2001).

In the simulation we consider two degrees of credit rationing: $R = 5\%$ and $R = 120\%$. These two values are arbitrary but well illustrate the mechanisms at work. We demonstrate the effect of other values of R in the robustness section. Without credit rationing the loan must deliver at least 5% return in net present value terms compared to the case that the loan is not given. The firm must be able to pay interest for two years and return the principal to obtain such a loan. In the case of credit rationing, R is set to 120%. Such a return cannot be met by interest payments on the given credit alone, but there must be an additional future value for the bank. For example, the loan could ensure that a debt-laden firm survives and pays back more of its debt. Another possibility is that the loan helps a new firm to enter which relies heavily on the bank in future play.

1.3 The Effects of Financial Frictions on the Equilibrium Capacity Distribution

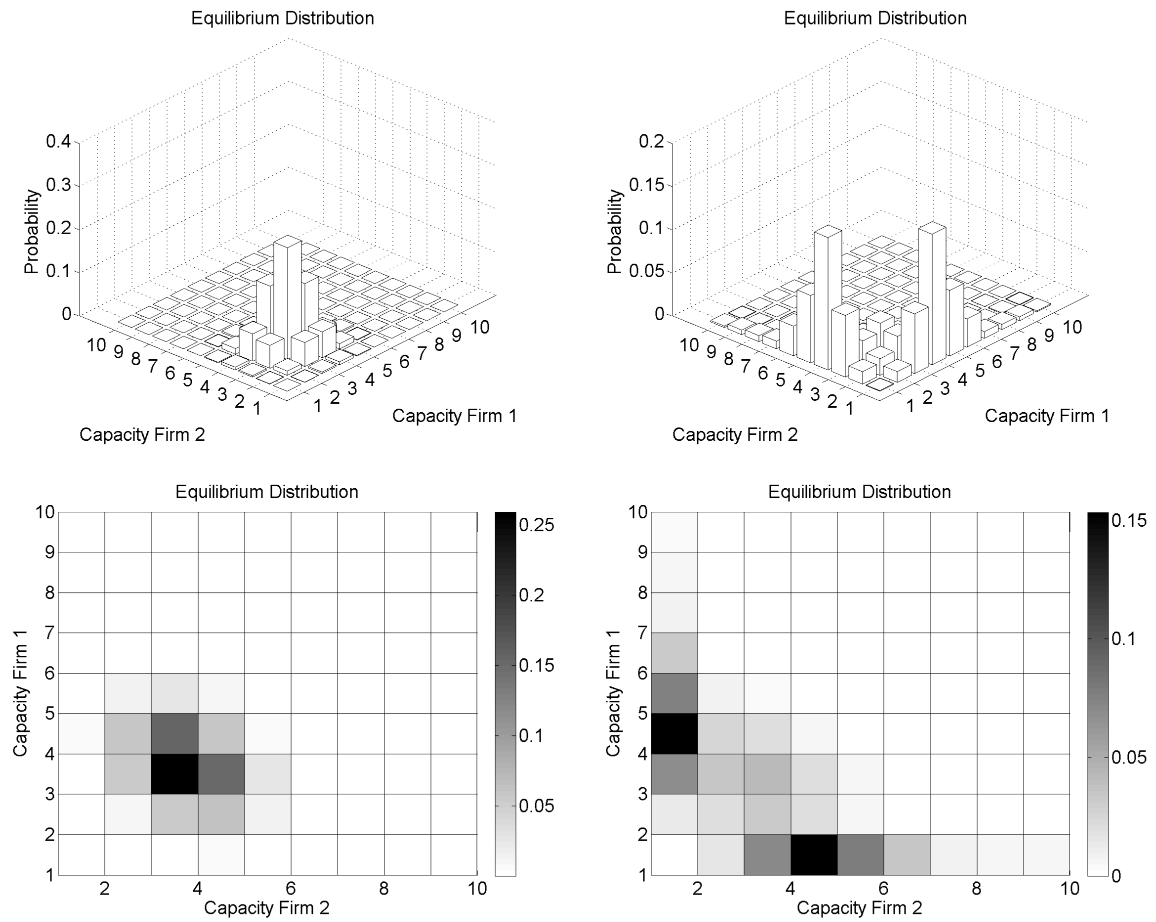
1.3.1 Equilibrium Capacity Distribution and Welfare Results

In this section, we demonstrate that credit rationing can lead to the monopolization of markets and thus to a loss in welfare. To show the effect of financial frictions on the market structure in equilibrium, we discuss in the following the properties of the invariant equilibrium capacity distribution in the market. Table 1.1 and Figure 1.2 picture the equilibrium capacity distribution for the case without credit rationing ($R = 5\%$) on the left hand side and with credit rationing ($R = 120\%$) on the right hand side. A higher probability of a certain industry structure indicates that this industry structure is more likely to occur in equilibrium play. For example, without credit rationing, the industry configuration with firm 1 and a firm 2 in the second capacity state (i.e. both are of size 10) is played with a probability of 25%. With credit rationing, the most likely market structure is one large firm in the third capacity state (with a capacity of 15) and the other firm with no capacity at all.

Credit rationing causes the equilibrium distribution to become skewed: one firm exits the market and the equally productive competitor becomes the monopolist. There is an equal probability that firm 1 or firm 2 is the monopolist, reflecting the symmetric set-up of the model. The large firm is in the fourth capacity state with a capacity of 15 and the small firm has no capacity at all in the most likely industry structure. There is some probability mass in between the two extreme configurations, indicating that leadership changes from time to time. Without financial frictions, the most likely configuration is that both firms have an equal size with a capacity of ten. Due to the randomness in the investment and depreciation process there is also some probability for asymmetric market share configurations.

These findings complement the results of Caballero and Hammour (1994) on the cleansing effect of recessions: they find that a fall in demand during a recession leads to job destruction, which they conjecture is due to the exit of technical inefficient firms. A recession is therefore "cleansing" for an economy. In our model all firms are equally productive in the sense that all firms have the same production costs. Therefore, credit rationing (which often accompanies a fall in demand) leads to the exit of a firm which has the same production costs as the remaining incumbent. This effect bears some resemblance to the "scarring" effect of recessions outlined in Ouyang (2009). In that article, firms' learning-by-doing is reduced by the lower volumes produced in a recession killing potentially good firms in their infancy. In contrast, in the present model, firms are only constrained by financial factors.

Figure 1.2: Equilibrium distribution for $R = 5\%$ (left) and $R = 120\%$ (right)



Note: The capacity states of the two firms are depicted on the x- and y-axis. In the upper panel the probability of a state is displayed on the z-axis. In the lower panel the probability is shown by different colors.

The monopolization of the market leads to a welfare loss (Table 1.2) which is mainly borne by consumers and banks. The welfare loss of the consumer originates from lower capacities and higher prices as shown in the summary statistics of Table 1.3. Banks have lower profits because the amount of credit (on which they earn a fixed income) is smaller (the amount of debt is lower) with credit rationing. In contrast to the reduction of surplus for consumers and banks, the firm surplus stays approximately the same. The reason is simple: with credit rationing, a firm has with (approximately) equal probability monopoly and zero profits, whereas without financial frictions, it has duopoly profits for sure. Thus, in expected value, 50% monopoly profits is a bit larger than 100% of the duopoly profit. Therefore, if firms are risk neutral, they do not suffer from credit rationing.

All other statistics in Table 1.3 are in line with expectations: the average debt level is

Table 1.1: Probability that a state is played in equilibrium (in percentage)

(a) $R = 5\%$

		j=1 $\bar{q}_j = 0$	j=2 $\bar{q}_j = 5$	j=3 $\bar{q}_j = 10$	j=4 $\bar{q}_j = 15$	j=5 $\bar{q}_j = 20$	j=6 $\bar{q}_j = 25$
i=1	$\bar{q}_i = 0$	0	0	0	0	0	0
i=2	$\bar{q}_i = 5$	0	1	5	6	1	0
i=3	$\bar{q}_i = 10$	0	5	25	15	2	0
i=4	$\bar{q}_i = 15$	0	6	15	6	0	0
i=5	$\bar{q} = 20$	0	1	2	0	0	0
i=6	$\bar{q}_i = 25$	0	0	0	0	0	0

(b) $R = 120\%$

		j=1 $\bar{q}_j = 0$	j=2 $\bar{q}_j = 5$	j=3 $\bar{q}_j = 10$	j=4 $\bar{q}_j = 15$	j=5 $\bar{q}_j = 20$	j=6 $\bar{q}_j = 25$
i=1	$\bar{q}_i = 0$	0	1	6	15	7	3
i=2	$\bar{q}_i = 5$	1	1	3	2	0	0
i=3	$\bar{q}_i = 10$	6	3	4	2	0	0
i=4	$\bar{q}_i = 15$	15	2	2	0	0	0
i=5	$\bar{q}_i = 20$	7	0	0	0	0	0
i=6	$\bar{q}_i = 25$	3	0	0	0	0	0

Note: i and j denote the value of the capacity state of firms i and j.

Table 1.2: Welfare effects of credit rationing

Surplus	Consumer	Producer	Bank	Total
Model with credit rationing	14.72	35.95	0.61	51.28
Model without credit rationing	24.19	35.03	2.38	61.60
Difference	-9.46	0.92	-1.77	-10.32

Note: This is the expected welfare over all states. For the calculation of these measures please refer to Appendix A.2.

Table 1.3: Summary statistics

	Capacity	Price	Debt	Cash
Model with credit rationing	8.90	2.35	7.44	18.37
Model without credit rationing	11.25	1.83	26.53	13.20
Difference	-2.35	0.52	-19.09	5.17

lower and the amount of retained cash is higher when credit rationing is present. If the financial market is not working properly firms get fewer and smaller loans and try to finance themselves through the retainment of cash.[5]

[5] Almeida, Campello, and Weisbach (2004) use a similar reasoning to justify cash flow sensitivities of cash as a sensible measure for financial constraints.

1.3.2 Credit Rationing as Propagation Mechanism

Approximately every eight periods a depreciation shock hits each firm. This initially small shock sets a process in motion which results in a skewed equilibrium distribution given that credit rationing is present.

The propagation mechanism works as follows: a shock reduces the capacity of firm i. Lower capacity translates into lower current profits. Because of credit rationing, this loss in profit cannot be compensated by taking out more loans. With lower cash flow and insufficient available credit, the probability that a firm can afford the costs of capacity expansion is reduced. A reduction in investment together with an unaltered probability of depreciation results in less capacity, what again triggers less investment. The competitor benefits from this mechanism: the original shock reduces the capacity on the market and increases the price level. Therefore, the competitor has more profit available for saving and investment. With this additional profit, he can increase his investment in order to further tighten the credit constraints of the smaller firm.

To illustrate, we now compare the different investment probabilities with and without credit constraints given that a firm is hit by a depreciation shock. Assume that in a market with credit rationing, the capacity of a firm in state (3,3) is reduced by one unit so the firm finds itself in state (2,3). Then the investment probability with credit rationing is 27%, much smaller than in the case without, where the firm invests with a probability of 66% (Tables 1.4a and 1.4b). After the first shock, the larger competitor has on average an investment probability of 27%. This is still a reduction, albeit a much smaller one, from the investment probability of 41% without financial frictions. Therefore, the key observation is here that the investment probability of the smaller firm is reduced by $1 - \frac{0.27}{0.66} = 59\%$ while the investment probability of the larger firm is reduced only by 34% compared to the case without credit rationing.[6] This relatively larger reduction in the ability to invest makes it more likely that the smaller firm exits the market: if it fails to reinvest, the firm might be hit by another depreciation shock. Furthermore, if the competitor invests (and the other firm fails to do so), the capacity state evolves to (2,4), reducing the investment probability of the smaller firm further to 15%.

[6] The reduction in the neutral (2,2) state is 40.5% to 44% with credit rationing from 74% without.

Figure 1.3: Investment probabilities for Firm 1, $R = 5\%$ (left) and $R = 120\%$ (right)

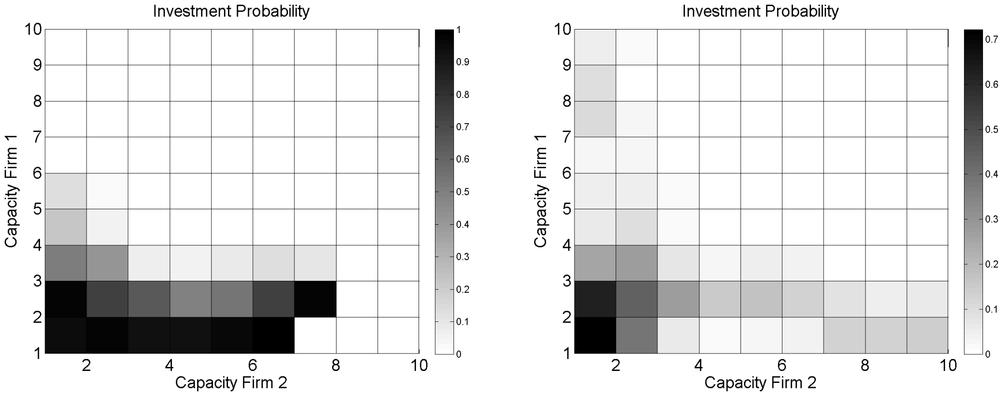


Table 1.4: Investment probability for firm 1 in percentage

(a) $R = 5\%$

		j=1 $\bar{q}_j = 0$	j=2 $\bar{q}_j = 5$	j=3 $\bar{q}_j = 10$	j=4 $\bar{q}_j = 15$	j=5 $\bar{q}_j = 20$	j=6 $\bar{q}_j = 25$
i=1	$\bar{q}_i = 0$	94	98	94	92	96	100
i=2	$\bar{q}_i = 5$	98	74	66	49	54	73
i=3	$\bar{q}_i = 10$	51	41	7	5	8	13
i=4	$\bar{q}_i = 15$	23	6	1	0	0	0
i=5	$\bar{q}_i = 20$	14	2	1	0	0	0
i=6	$\bar{q}_i = 25$	0	0	1	0	0	0

(b) $R = 120\%$

		j=1 $\bar{q}_j = 0$	j=2 $\bar{q}_j = 5$	j=3 $\bar{q}_j = 10$	j=4 $\bar{q}_j = 15$	j=5 $\bar{q}_j = 20$	j=6 $\bar{q}_j = 25$
i=1	$\bar{q}_i = 0$	72	39	7	2	3	4
i=2	$\bar{q}_i = 5$	63	44	27	15	18	14
i=3	$\bar{q}_i = 10$	25	27	8	3	5	4
i=4	$\bar{q}_i = 15$	6	10	1	0	0	0
i=5	$\bar{q}_i = 20$	5	5	1	0	0	0
i=6	$\bar{q}_i = 25$	3	3	1	0	0	0

Note: This is the average investment probability in each capacity state. Investment probabilities also depend on the debt state and the amount of retained cash. States written in grey are played in equilibrium with a probability below 0.1% and are likely calculated with error. i and j denote the value of the capacity state of firms i and j.

The effect is driven by the differing optimal probabilities that investment is carried out with and without credit rationing (Table 1.4). Because the analysis is ceteris paribus, this difference can only originate from the amount of credit available to the firms: with $R = 5\%$, abundant credit is extended in any state (Table 1.6a) and the firm does not need to delay any investment. With credit rationing, only 6 units of credit are offered by

Table 1.5: Sum of current profits, retained cash and credit with $R = 120\%$ for firm 1

		j=1 $\bar{q}_j = 0$	j=2 $\bar{q}_j = 5$	j=3 $\bar{q}_j = 10$	j=4 $\bar{q}_j = 15$	j=5 $\bar{q}_j = 20$	j=6 $\bar{q}_j = 25$
i=1	$\bar{q}_i = 0$	55	40	30	28	28	29
i=2	$\bar{q}_i = 5$	59	39	35	30	30	24
i=3	$\bar{q}_i = 10$	49	48	40	33	31	29
i=4	$\bar{q}_i = 15$	45	49	43	32	30	27
i=5	$\bar{q}_i = 20$	44	52	45	43	0	0
i=6	$\bar{q}_i = 25$	44	61	48	42	0	0

Note: This is the average amount available for investment in each capacity state. This amount is also dependent on the debt state and the amount of cash retained. States written in grey are played in equilibrium with a probability below 0.1% and are likely calculated with error. i and j denote the value of the capacity state of firms i and j.

the financial intermediary (Table 1.6b). This lack of credit drives down the equilibrium investment probability.

Table 1.6: Credit for firm 1

(a) $R = 5\%$

		j=1 $\bar{q}_j = 0$	j=2 $\bar{q}_j = 5$	j=3 $\bar{q}_j = 10$	j=4 $\bar{q}_j = 15$	j=5 $\bar{q}_j = 20$	j=6 $\bar{q}_j = 25$
i=1	$\bar{q}_i = 0$	899	436	338	236	229	308
i=2	$\bar{q}_i = 5$	338	228	198	76	66	37
i=3	$\bar{q}_i = 10$	47	44	14	4	6	4
i=4	$\bar{q}_i = 15$	44	8	0	0	0	0
i=5	$\bar{q}_i = 20$	27	1	1	0	0	0
i=6	$\bar{q}_i = 25$	1	0	0	0	0	0

(b) $R = 120\%$

		j=1 $\bar{q}_j = 0$	j=2 $\bar{q}_j = 5$	j=3 $\bar{q}_j = 10$	j=4 $\bar{q}_j = 15$	j=5 $\bar{q}_j = 20$	j=6 $\bar{q}_j = 25$
i=1	$\bar{q}_i = 0$	27	12	2	0	0	1
i=2	$\bar{q}_i = 5$	20	11	6	3	3	2
i=3	$\bar{q}_i = 10$	3	3	1	0	1	0
i=4	$\bar{q}_i = 15$	1	1	0	0	0	0
i=5	$\bar{q}_i = 20$	1	0	0	0	0	0
i=6	$\bar{q}_i = 25$	1	0	0	0	0	0

Note: This is the average amount of credit offered in each capacity state. The amount of credit is dependent also on the debt state and the amount of cash retained. States written in grey are played in equilibrium with a probability below 0.1% and are likely calculated with error. i and j denote the value of the capacity state of firms i and j.

The described qualitative results are similar to those of Kiyotaki and Moore (1997), however the mechanism is different. In their model, a negative productivity shock reduces the net worth of the credit constrained firm. This leads to a reduction in investment in the productive factor which is also a collateral for credit. The resulting shortfall in demand for the productive factor reduces its value as collateral. Consequently, the firm cannot get as much credit as before. This reduces the demand for the productive factor further, drives down the net worth of the constrained firm again and the firm enters a reinforcing credit cycle.

In our model, firms hit by a depreciation shock are unable to tap the credit market to finance investment. The bank does not offer enough credit because the expected net present value of the investment is not high enough to satisfy the return requirements. Without investment, the firm's capital stock depreciates further resulting again in reduced credit and reduced current profits. In the end, this mechanism can lead to the exit of one firm.

1.3.3 Credit Rationing as Entry Barrier

If one firm exits, the possibility arises for an entrant to become the second firm in the market. However, the monopolization of the market is (relatively) stable because credit rationing also serves as a barrier to entry. Thus, financial frictions lead to lower entry rates which in turn results in a skewed capacity distribution.

In the basic configuration, investment costs are uniformly distributed between 50 and 55 and the amount of start-up financing provided by the equity markets is between 20 and 25. Therefore, the firm has to take at least an amount of 25 as credit to enter the market.[7] If credit rationing is present, the entrant only receives such an amount of credit in case the competitor is out of the market or small, i.e. if the competitor is in the first or second capacity state (Table 1.6). Hence, the investment probabilities are only high in these states, but not when the competitor has more capacity (Table 1.4). The investment probability is 72% for firm 1, given that no firm is in the market. With a competitor in the second capacity state, the investment probability decreases to 39%. The investment probability becomes neglegible if the capacity of the competitor is higher. On the equilibrium path, the monopolist is out of the market or small with only a probability

[7] Profits in the outside state are zero.

of 1% (Table 1.1b). Credit rationing therefore serves as an effective barrier to entry.

In contrast, without credit rationing, the probability to invest for an entrant is always above 90% irrespective of the competitor's capacity (Table 1.4). Consequently, a firm with zero capacity always enters the market immediately.

1.4 Robustness

To show that the outlined results are stable despite the multiplicity of assumptions made, we vary three key parameters in our model: the severeness of credit rationing R, the maximum possible amount of retained cash, and the amount of start-up financing c^e. Furthermore, we explore the implications of incomplete information on the equilibrium capacity distribution.

☐ **Severeness of credit rationing:** In Figure 1.4, we gradually increase the severeness of credit rationing. We find that with an increase in the minimum return R, the probability of an asymmetric equilibrium capacity distribution increases. This is intuitive: the more banks tighten the credit constraint, the more adverse is the effect.

☐ **Maximum amount of retainable cash:** In the preceding analysis, firms were able to accumulate a large amount of cash. The limit was set to 100, the equivalent of two capacity blocks or approximately five periods of profit. However, in reality, shareholders might have an incentive to limit the amount of cash a company can hold, to mitigate moral hazard problems: if a manager must regularly apply for funds, the capital market controls their proper use (Jensen 1986, Easterbrook 1984).

Figure 1.5 presents the equilibrium distribution with varying amounts of maximum retainable cash. The effects of credit rationing become more severe if a company can retain less cash.

☐ **Increase in start-up financing** Throughout the main part of the analysis, entrants only had a limited amount ϕ^e of start-up financing. This can be thought of as the amount a start-up can raise on the equity market. This small scale is intuitive because the monitoring service of the bank is only needed if investment projects without monitoring achieve a negative net present value due to severe moral hazard. Consequently, naive investors

Figure 1.4: Equilibrium distribution with varying amount of credit rationing

(a) $R = 5\%$, Cash=100

(b) $R = 40\%$, Cash=100

(c) $R = 80\%$, Cash=100

(d) $R = 120\%$, Cash=100

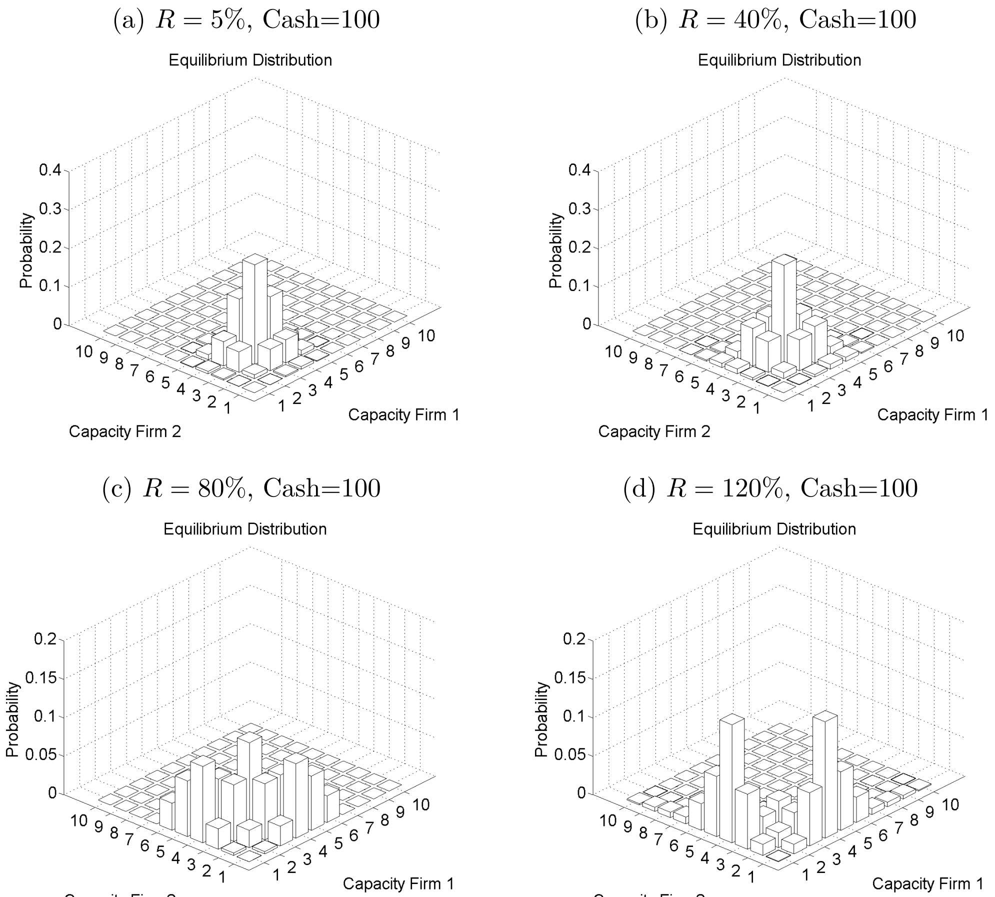


Figure 1.5: Equilibrium distribution with varying amount of retainable cash

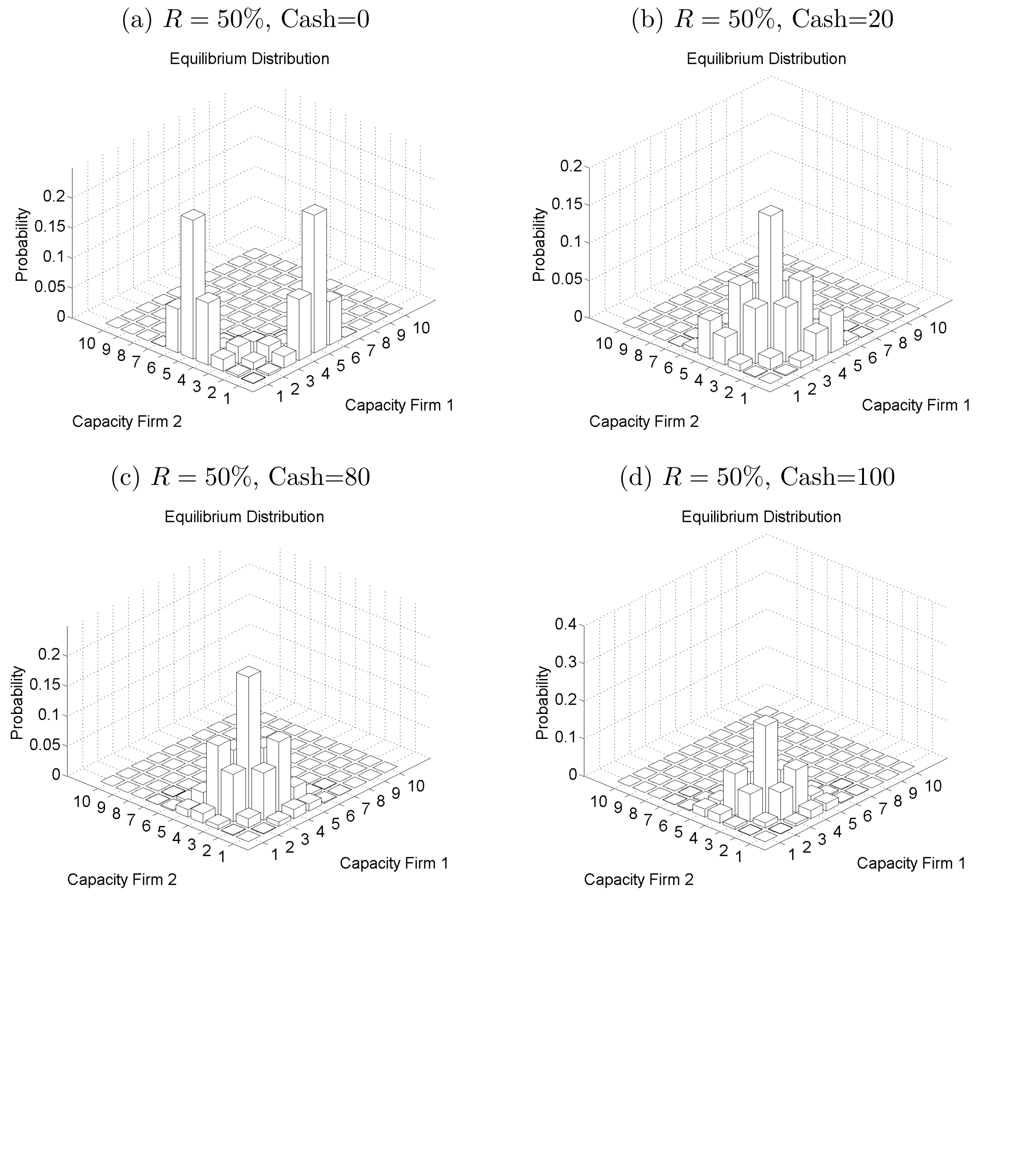
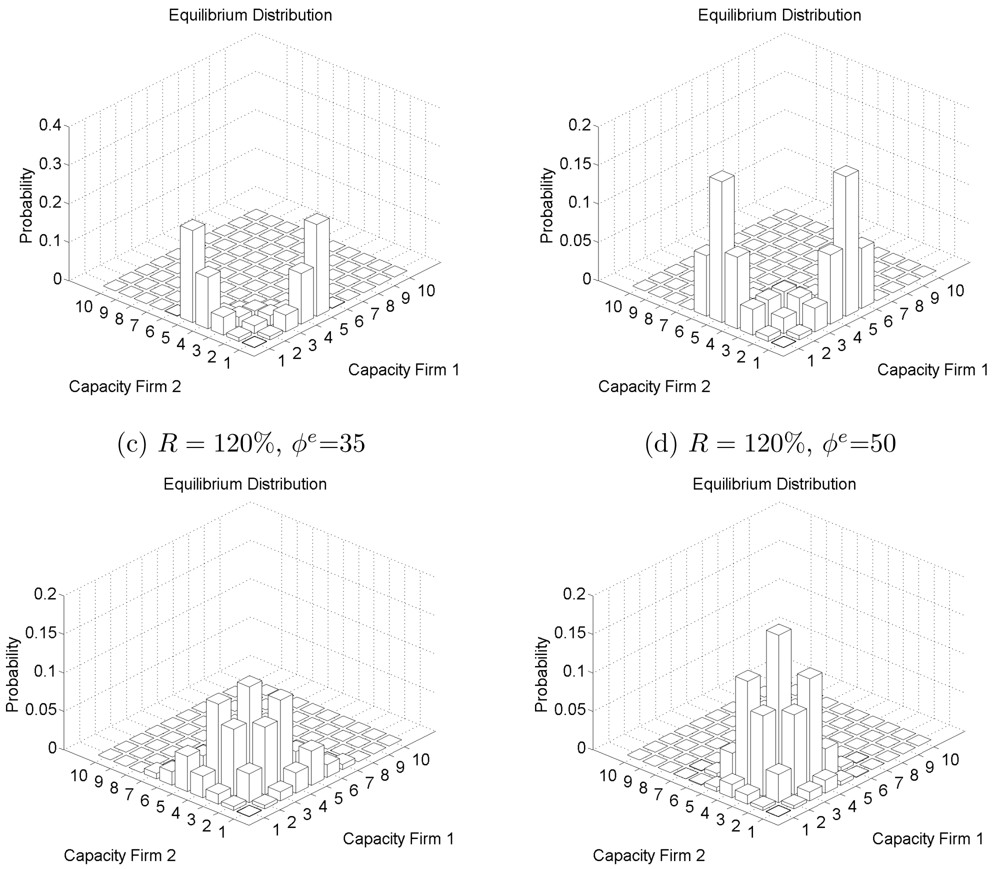


Figure 1.6: Equilibrium distribution with varying start-up financing



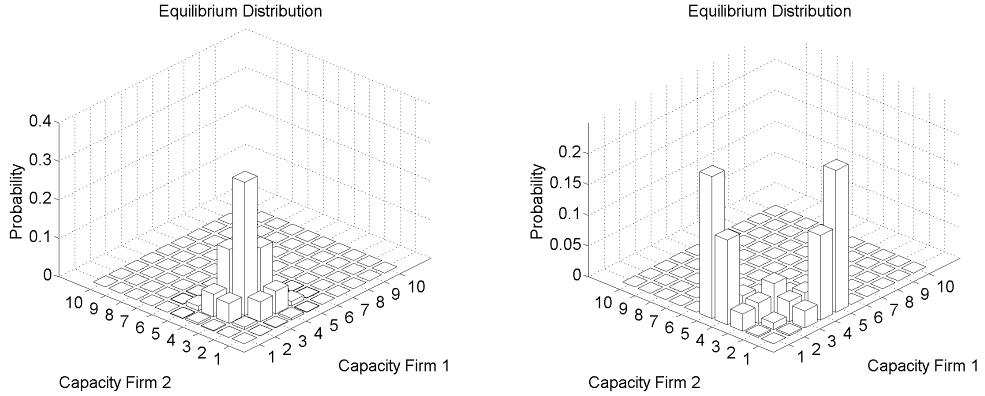
(a) $R = 120\%$, ϕ^e=20 (b) $R = 120\%$, ϕ^e=25 (c) $R = 120\%$, ϕ^e=35 (d) $R = 120\%$, ϕ^e=50

are not willing to finance start-ups on a large scale in such a market.

In our analysis, the size of start-up financing is 50% of the investment an entrant needs to enter the market. If we increase this proportion, the effects of credit rationing are smaller. This result is illustrated in Figure 1.6.

□**Incomplete information:** In the whole analysis, we allow the firms to condition on the complete industry state $s = (\bar{q}_i, \bar{q}_j, d_i, d_j, c_i, c_j)$. However, the assumption that each firm knows the exact financial structure of its competitor might be rather extreme. Fortunately, the Fershtman and Pakes (2011) algorithm allows to introduce incomplete information in the Ericson-Pakes framework. If we let firms condition their strategy only on their own financial structure and the two capacity states, the results are qualitatively similar to the full information case (Figure 1.7).

Figure 1.7: Equilibrium distribution with incomplete information for $R = 5\%$ (left) and $R = 120\%$ (right)



1.5 Conclusion

In this chapter, we describe the effects of credit rationing on the equilibrium market structure in a duopoly. We employ the Experience Based Markov Equilibrium framework presented in Fershtman and Pakes (2011) to extend the model of Besanko and Doraszelski (2004) by an optimizing bank and firms which actively choose their capital structure.

In our model, firms can retain cash, borrow from banks, or use current cash flow to finance themselves. Due to a shortage of capital, banks might be unable to fund every profitable project. Therefore, credit rationing might prevail. If then a small shock reduces the capacity of a firm, this firm might find itself unable to finance capacity expansion. Without investment, it has also less funds to finance investment in future periods. Eventually, this lack of investment can lead to the exit of one firm and monopolization of the market. The monopolization is stable because new entrants also suffer from credit rationing and cannot enter to fill the void.

This chapter shows that in equilibrium, the exit of firms during a recession might not be driven by insufficient productivity but by a lack of credit financing. Therefore, policy makers should put emphasis on the functioning of the credit market during recessions to prevent welfare losses through an increase in market power. For example the government could introduce credit support programs for small companies and start-ups. According to our model, such programs could foster competition and thus increase overall welfare.

Chapter 2

The Allocation of Talent: Evidence from the Market of Economists

2.1 Introduction

There is a growing interest within labor economics in the effect of macroeconomic conditions on microeconomic outcomes. In particular, recent studies have found a strong and persistent negative impact of recessions on individuals' employment and earnings.[1] Yet, to the best of our knowledge, there is no study which examines whether individuals react to these recession shocks in terms of occupational choice and the potential impact the reaction might have on talent allocation and productivity across sectors. Our study fills this gap in the literature by looking at a specific market where individual skills can readily be measured—academia.

We study the impact of the business cycle on skill allocation in the academic labor market. This is done by relating the research productivity and career choice of (potential) economists graduating from the top 30 US universities to measures of the business cycle during the last 50 years. To guide our empirics, we develop a Roy-style model (1951) of the selection of talent between business and academia, where entering academia is competitive but attractive during recessions. This model predicts that fewer economists

[1] See, for example, Oreopoulos, von Wachter, and Heisz (2011), Sullivan and von Wachter (2009), Kahn (2010), Kondo (2008), Oyer (2006), Oyer (2008).

who faced a recession at time of application to the PhD program stay in academia after graduation. Those who do stay are positively selected on academic productivity. Moreover, if there is a recession at the time of graduation, more economists pursue academic employment, which leads to more publications per PhD graduate.

The results of the empirical analysis support the theoretical predictions. In particular, they show that individuals do react to recession shocks. Economists applying or graduating during recessions publish significantly more than economists applying or graduating in a boom. A recession at entry leads to fewer PhD students staying in academia, a recession at graduation has the opposite effect. Moreover, the effects are of economically substantial magnitude. Taking our estimates literally, we expect assistant professors from the cohort of graduate students who applied for the PhD during the recession of 2008 (3.5 percentage points increase in unemployment) to be around 24 percent more productive than assistant professors from a cohort applying in an average year (0 percent unemployment change). We also expect PhD graduates from 2008 to produce on average 20 percent more publications in their early careers than economists graduating in an average year.

Our results contribute to several discussions in the academic literature: First, they show that individuals strongly and persistently react to (temporary) shocks in terms of career choice, which leads to a change in the allocation of talent between sectors. This adds to the broader debate about the allocation of talent, especially in the financial sector and in teaching.[2] Second, by observing that individuals at the top of the skill distribution switch between sectors, we infer that they possess general ex-ante talents and that even ex-post, after six years of specific PhD training, some individuals' skills are general enough to go back to the private sector. This relates to the born versus made debate in labor economics (e.g. Bertrand 2009, Oyer 2008). Third, we note that the predictions of a Roy-style model are supported by the data in our quasi-experimental empirical setting. Fourth, our results imply that it is possible to lure talent to research by increasing compensation.

For our empirical analysis we construct a new dataset of economists' career choices and publication output from publicly available sources. The dataset consists of graduation years and the degree granting universities of 13,624 PhDs since 1955 from the top 30

[2] See, for example, Corcoran, Evans, and Schwab (2004), Bacolod (2007), and Philippon and Reshef (2009).

American institutions. We match each person with all their publications available on JStor and with an indicator for becoming a faculty member or a member of the American Economic Association (AEA) after the PhD. Thus, we can calculate the propensity to stay in academia and the publication output for each economist. Finally, we aggregate each cohort according to university and graduation year, and match different business cycle indicators (recession dummies, GDP growth, and unemployment rates and their changes) at time of application to and at time of graduation from a PhD program. We quantify the influence of the business cycle indicators in both points in time on economists' propensity to decide in favor of academic employment and on their productivity.

Our study is closely related to three distinct strands of the literature. First, as mentioned above, we contribute to the recent literature that analyzes the effect of business cycle shocks on individuals' careers. Kahn (2010) finds large and persistent negative wage effects of graduating from college in a worse economy. Oreopoulos, von Wachter, and Heisz (2011) show that university graduates who enter the labor market during a recession experience a substantial initial loss of earnings, which fades only after 8–10 years, but that more highly skilled graduates suffer less because they switch to better firms rapidly.[3] Our study is the first to look at highly skilled individuals' response to these recession shocks by changing careers and its effect on the skill composition in one of the affected sectors. The results are consistent with those of Oreopoulos, von Wachter, and Heisz (2011), as we find that more highly skilled individuals (are able to) respond more strongly.

The second strand of the literature to which we contribute is concerned with sorting in the labor market. While the papers above generally find that vertical, non-voluntary sorting (i.e., worse job placements whose effects are long-lasting) is the source of the negative impact of recession shocks, we consider horizontal, somewhat more voluntary sorting (i.e., the individual's decision to continue their career in a different sector). In two papers in 2006 and 2008, Paul Oyer estimates the effect of vertical sorting on long term earnings and productivity by instrumenting MBAs' and economists' first placements with the state of the economy at the time of graduation. Combining Oyer's paper and our results on economics PhDs, it may well be that we underestimate the strength of our

[3]Other papers in this strand of the literature include Sullivan and von Wachter (2009),von Wachter, Song, and Manchester (2008), and Kondo (2008).

selection effect because of his placement effect and vice versa.[4]

There are plenty of well-known studies that are concerned with the sectoral selection of skills and the empirical content of the Roy model. Most of these papers employ "structural" econometric techniques while our quasi-experimental study doesn't need to rely on specific distributional assumptions about skills, for example.[5] We nonetheless find strong empirical support for the predictions of the Roy model. Another influential recent study by Philippon and Reshef (2009) describes the relationship between relative wages and human capital in the financial sector in the United States over the last century, but is unable to establish a causal effect of the former on the latter. In contrast, we are able to shed some light on the causal relationship between sectoral attractiveness and talent allocation.[6]

The third strand of the literature this chapter deals with is concerned with the determinants of scientific productivity and their potential policy implications. Our study is most closely related to the papers that examine the impact of science funding on research productivity. Funding increases, like recessions in our context, raise the attractiveness of the academic sector compared to the private sector. Goolsbee (1998) shows that up to 50% of a government spending increase goes into higher salaries for scientists and engineers. Suggesting that the supply of such knowledge workers is relatively inelastic, he argues that a large fraction of governmental research funding may in fact be ineffective and may only constitute a windfall gain for scientists. On the contrary, our results imply that the quantity and/or quality of researchers should strongly and persistently increase with more funding.

The remainder of this chapter proceeds as follows. We derive our theoretical predictions from a modified version of the Roy Model in the next section. Then we describe how we assembled our novel dataset of PhD economists' publication success. Section 2.4 presents and interprets the empirical results, while the conclusion discusses to what extent our results may generalize to other segments of the labor market.

[4] For a more detailed explanation, see Section 2.4.3.

[5] See Heckman and Honoré (1990) and, more recently, Keane and Wolpin (1997) and Lee and Wolpin (2006). An example of another non-structural paper on the Roy model is Borjas (1987).

[6] One paper that uses quasi-experimental identification to study sectoral selection is Bedard and Herman (2008). They examine the impact of economic contractions on the likelihood for enrollment in an advanced university degree program.

2.2 Theory

We are interested in how the selection of skills into academia and business varies with the state of the business cycle. This section modifies a standard Roy (1951) model for the problem at hand. The Roy model analyzes the self-selection of individuals with heterogeneous skills into sectors according to their highest expected earnings. In the following, we model two sectors—academia and business—into which individuals can self-select. Every individual has distinct skills (and therefore different wages) in each sector but can choose only one occupation. The main departure from the original Roy framework is that compensation in business and academia vary with the business cycle and that the number of open positions in academia is assumed to be fixed.

2.2.1 Assumptions

Suppose that individuals are endowed with two skills, an academic skill α and a business skill β. There are two sectors, academia (A) and business (B), which produce outputs utilizing the respective skills. Individuals maximize their expected lifetime compensation by applying for jobs in academia or business. This compensation implicitly consists of a pecuniary and a non-pecuniary component, where the non-pecuniary component might be particularly important in the academic sector (see Stern (2004)).

The business sector is assumed to hire anyone offering a compensation w_t. We assume that the compensation depends linearly on the skill level β of the employee and the state of business cycle $\tilde{y}_t$:

$$w^B(\beta) = \beta + \tilde{y}_t.$$

An employee's lifetime compensation in the business sector is higher in a boom (high $\tilde{y}_t$) and lower in a recession (low $\tilde{y}_t$). In academia, total compensation also varies with the business cycle but is less cyclical than in the business sector:

$$w^A(\alpha) = \alpha + a\tilde{y}_t$$

with $0 < a < 1$.

Two sources might contribute to the variability of compensation over the business cycle: First, in a recession, lower immediate wages can lead to a lower lifetime compensation in both setors. Second, during recessions employees might enter inferior career paths in business or start at a lower ranked institution in academia, which could hurt lifetime income and non-pecuniary benefits. This is consistent with recent articles documenting substantial effects of the current business cycle on long term career outcomes (e.g. Oyer 2008, Oreopoulos, von Wachter, and Heisz 2011). Importantly, we assume that the academic sector is less cyclical than the business sector and we provide empirical evidence supporting this assumption in Appendix B.3.

In order to become an academic, an individual must decide for academia twice: first by applying to a PhD program (at time of application $t = app$) and a second time by pursuing an assistant professorship after the PhD (at graduation $t = grad$). At time of application, we assume that PhD programs admit the best N applicants according to academic skill and that there are always more applicants than available spaces.[7] Thus, the entry into the doctoral program is competitive. This assumption seems reasonable as we consider the top 30 PhD programs in the US only.

At graduation, we assume that the student can choose freely if he wants to stay in academia or enter the business sector instead. This assumption is more disputable: obtaining an assistant professorship at a (top)ranked institution is very competitive. However, conditioned on graduating from one of the top 30 US economics departments, it seems unlikely that a student cannot secure an academic job in a lower ranked institution, a teaching college, a university outside the United States, or a postdoc position even in times of recession.

When taking his decision to apply for a PhD program, the applicant should also take account of the option value of having another choice about his career path after graduation. To simplify our problem, we assume that this option value is a constant, i.e. that it does not vary with the state of the macroeconomy at the time of application.[8] Thus, we

[7] PhD entry cohort sizes are not related to the business cycle in our data (see appendix B.4).

[8] In effect, this assumption amounts to imposing that the business cycle at time of application has no predictive power for the business cycle at graduation. We think that this is defendable as it takes on average six years to complete a PhD and we show in Appendix B.4 that there is no correlation between the business cycle at time of application and graduation in our data. In general, we expect that our results should also hold in all of the cases where there is a reversal in the business cycle during that time

can subsume this constant in the individual's non-varying compensation component, the academic skill level α.

Given these assumptions, an individual compares the expected compensation from academia $\alpha + a\tilde{y}_t$ and business $\beta + \tilde{y}_t$ at time of application and at graduation. He decides to apply for the academic sector (the PhD program or the assistant professorship) whenever

$$\alpha > \beta + y_t. \tag{2.1}$$

where $t \in \{app, grad\}$ and $y_t \equiv (1-a)\tilde{y}_t$. y_t is the relative attractiveness of the business sector that is due to the business cycle.[9]

2.2.2 Predictions

We are interested in how the selection of skills into academia and business varies with the state of the business cycle. To ease the exposition, we compare a generic boom cohort versus a generic recession cohort, i.e. $y^{Boom} > y^{Rec}$. All proofs are relegated to Appendix B.1.

Proposition 2.2.1 *For PhD applicants, the joint distribution of academic and business skills selected into the academic sector during a recession first order stochastically dominates (FSD) the corresponding boom distribution.*[10]

This proposition implies that the academic ability of the least able member of the boom cohort, α^{Boom}, is lower than the academic ability of the least able member of the recession cohort, α^{Rec}.

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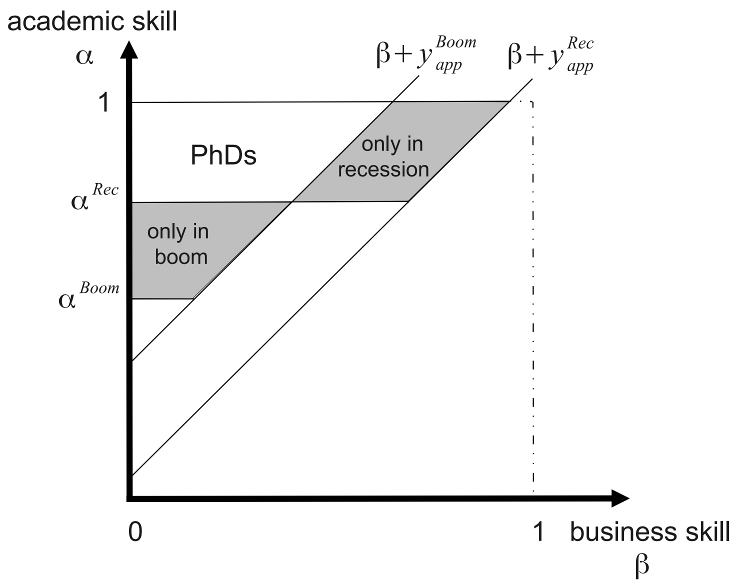
frame, i.e., $Pr(\tilde{y}^{Boom}_{grad}|\tilde{y}^{Rec}_{app}) > Pr(\tilde{y}^{Boom}_{grad}|\tilde{y}^{Boom}_{app})$ and $Pr(\tilde{y}^{Rec}_{grad}|\tilde{y}^{Boom}_{app}) > Pr(\tilde{y}^{Rec}_{grad}|\tilde{y}^{Rec}_{app})$, and in a lot of cases where there is sufficiently strong mean reversion.

[9] We could have added to the model that a PhD constitutes an investment into academic (and business) skills. This is clearly an important feature of obtaining a graduate education and we did this in an earlier version of this section. However, as long as the skill update and the uncertainty about it can be assumed to be independent of the state of business cycle, it does not change the predictions of the model other than by adding noise. Hence, we refrain from defining different (updated) αs, βs, and y_ts at PhD application and graduation.

[10] On the flipside, this implies that the joint distribution of skills selected into business during a boom first order stochastically dominates its recession counterpart. Note that in contrast to the well known result of the general Roy model (e.g. see Heckman and Honoré 1990), we can make a definitive statement about the stochastic dominance for a general distribution of skills here. This is due to the assumption of binding quantity constraints and the resulting competitiveness of the admission into the academic sector.

Figure 2.1 illustrates Proposition 2.2.1 when academic and business skills are distributed uniformly in the unit interval. Given our assumptions, an individual's career choice is governed by a "one-shot" decision, with those individuals for whom $\alpha > \beta + y_{app}$ preferring academia. During a boom (a high y_{app}^{Boom}), fewer individuals apply for academia than during a recession (a low y_{app}^{Rec}), which is depicted by a higher cutoff line for the former than for the latter. Academic employers always hire a fixed number, N, of graduates (PhDs & "only in boom" in boom, PhDs & "only in recession" in recessions) and therefore the distribution of skills for the recession cohort lies to the "North-East" of the corresponding distribution for the boom cohort. However, Proposition 2.2.2 shows that fewer of the

Figure 2.1: Selection with a U(0,1) distribution of both skills at application



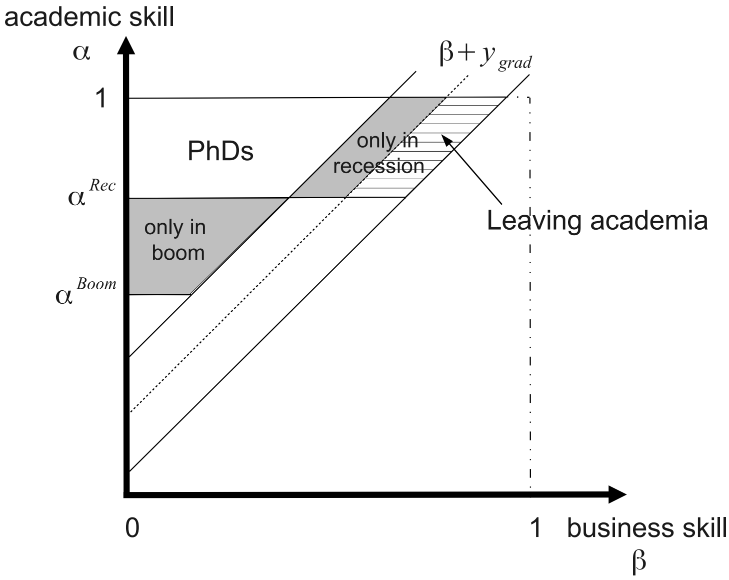
Note.—The "only in recession" area has the same size as the "only in boom" area because the same number of applicants are admitted to the PhD in recessions and in booms.

PhDs who were admitted in a recession will remain in academia and become assistant professors after the PhD.

Proposition 2.2.2 *For every realization of the state of the economy at graduation y_{grad}, a (weakly) higher fraction of the members of a "recession at time of application" cohort will not remain in academia after the PhD.*

The proposition implies that, on average, cohorts of PhD graduates more often leave academia if they experienced a recession at the time of application. Figure 2.2 provides some intuition for the proposition. The academic skill cutoff, above which individuals will prefer academic employment after the PhD, "on average" moves down to the dashed line in the figure for a boom cohort and up for a recession cohort. Thus, in the figure, some individuals of the recession cohort exit academia and enter business after the PhD when the economy is out of recession, while everyone in the boom cohort stays in academia. The recession graduates who leave academia here are the marginal ones who applied for the PhD "because of" the recession in the first place.

Figure 2.2: Selection with a U(0,1) distribution of both skills at graduation



Note.—The "only in recession" area has the same size as the "only in boom" area because the same number of applicants are admitted to the PhD in recessions and in booms.

Proposition 2.2.3 *For any given realization of the business cycle at graduation y_{grad}, the (partial) distribution of academic skills of the members of a "recession at application" cohort who remain in academia after the PhD first order stochastically dominates the distribution of skills of the corresponding members of the "boom at application" cohort.*[11]

Proposition 2.2.3 implies that, no matter how many more recession students than boom students leave academia after the PhD, the recession students who remain in academia are still better in each quantile of their (academic) skill distribution. In our specific

[11]However, the stochastic dominance of the joint distribution of business and academic skills does not feed through in general.

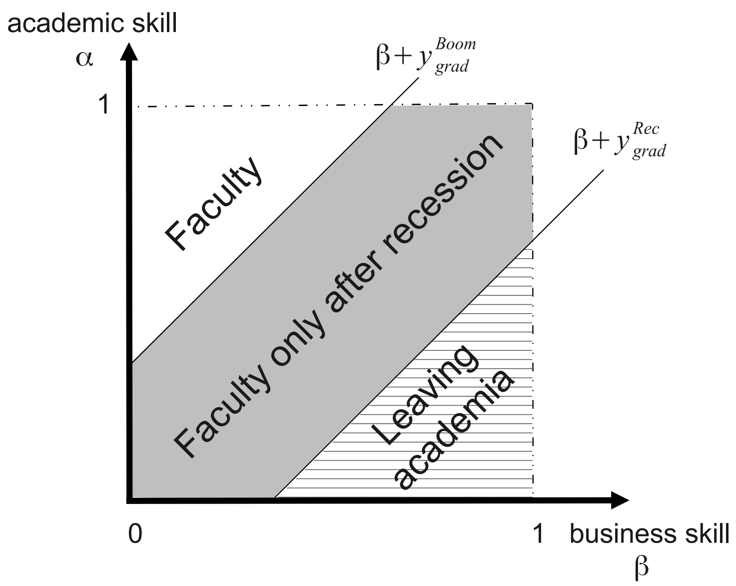
example in Figure 2.2 we see that, although some mass of the recession cohort is cut off, the recession distribution of skills in academia still lies to the "North-East" of the boom distribution.

The effect of the business cycle at graduation (y_{grad}) is more straightforward. In a recession, relatively more graduates take up academic employment than in a boom. For these graduates who end up in academia "because of" the business cycle the following equation holds: $\beta + y_{grad}^{Rec} < \alpha \leq \beta + y_{grad}^{Boom}$.

Proposition 2.2.4 restates this observation and Figure 2.3 provides a graphical representation in the special case of PhD graduates with academic and business skills distributed uniformly in the unit square.

Proposition 2.2.4 *A higher fraction of PhD economists decide to stay in the academic sector if they experience a recession at graduation.*

Figure 2.3: Selection at graduation



Finally, we can reformulate the three propositions of the model into empirical predictions for our data. According to the state of the business cycle, (potential) economists will face options in the academic and the business sector such that:

1. Fewer of the economists who experienced a recession at the time of application to the PhD end up in academia (from Proposition 2.2.2).

2. However, those who remain in academia are better researchers, both on average and in each quantile of their publication distribution (from Proposition 2.2.3).

3. More of the economists who experienced a recession at graduation from the PhD stay in academia (from Proposition 2.2.4),

4. and, therefore, recession PhD graduates publish more on average (also from Proposition 2.2.4).[12]

2.3 Data

We have collected a new dataset of career choices and individual productivity for a large sample of economists in the United States from 1955 to 2004. We aggregate the individuals into university year cohorts and match these with measures of the business cycle in the year of application and the year of graduation.[13]

2.3.1 Economist Sample Selection

The bases of our dataset are the names, graduation years and PhD granting institutions of 13,624 economists who graduated from the top 30 US universities from 1955 to 1994. This data is obtained from the American Economic Association's (AEA) yearly "List of Doctoral Dissertations in Economics", which was published in the Papers and Proceedings issue of the "American Economic Review" until 1986 and in the "Journal of Economic Literature" thereafter. We supplement this information with the tier of the degree granting university according to the ranking of the National Research Council.[14]

[12]We assume that economists which enter the business sector do not publish at all. If more PhD students stay in academic (i.e. if there is a recession at graduation) more of them have a positive publication record. This effect increases — ceteris paribus — the average publication record per PhD graduate.

[13]For the details of the data collection procedure, refer to Appendix B.2.

[14]The National Research Council rankings of economics graduate programs divide programs into tiers. The top three tiers include:

- Tier 1 (ranked 1–6): Chicago, Harvard, MIT, Princeton, Stanford, and Yale;
- Tier 2 (ranked 7–15): Columbia, Michigan, Minnesota, Northwestern, Pennsylvania, Rochester, California-Berkeley, California-Los Angeles, and Wisconsin-Madison;
- Tier 3 (ranked 16–30): Illinois-Urbana, Boston University, Brown, Cornell, Duke, Iowa, Maryland,

2.3.2 Career Choice and Productivity Measures

We add an "academic" indicator which takes the value one if the economist was a faculty member in a US economics, business or finance department in 2001 or listed as a member of the American Economic Association, and otherwise zero. The US faculty directories are compiled by James R. Hasselback and made available on his webpage.[15] AEA Membership data is obtained from the American Economic Association Directory of Members in 1970, 1974, 1981, 1985, 1989, 1993, 1997, 2003 or 2007. AEA membership serves as a proxy for faculty membership outside of the United States, because Hasselback's faculty directories strongly focus on US colleges and feature only very few foreign institutions.

In order to compare the oeuvres of different economists over time we calculate a consistent measure of publication productivity. For all economists in our sample, we collect the publication records in the first ten years after their graduation, multiply each publication of an author by its weight ("publication points") according to a dynamic journal ranking, and divide it by the number of coauthors of the paper. We then sum up all these contributions within the ten years after graduation to obtain a productivity measure for every individual in our sample.

More specifically, we match the PhD graduates with their publications (including journal title, number of pages and the number and identity of co-authors) in 74 journals listed in JSTOR, a leading online archive of academic journals. We select all journals contained in JSTOR for which a ranking was available. Thus we include all major publications in economics and finance except the journals published by Elsevier, most notably the "Journal of Monetary Economics" and the "Journal of Econometrics".[16] To ensure comparability among researchers, we restrict our attention to the first ten years after graduation. JSTOR currently only provides full publication data up to the year 2004. With the ten year requirement we can thus rightfully analyze the sample from 1955 to 1994 without placing

Michigan State, New York University, North Carolina, Texas-Austin, Virginia, California-San Diego, University of Washington, and Washington University-St. Louis.

Source: "The American Economic Association Graduate Study in Economics Web Pages", accessed 2011-02-08, http://www.vanderbilt.edu/AEA/gradstudents/

[15]Source: "Faculty Directories", James R. Hasselback, accessed 2011-02-07, http://www.facultydirectories.com/

[16]Because we do not believe that either recession or boom cohorts systematically prefer or dislike Elsevier journals, this should be of no consequence.

younger researchers at a disadvantage.

Comparing the value of the collected publication records for different researchers over the decades is difficult because the relative impact of economics journals has changed substantially over time (Kim, Morse, and Zingales 2006). Therefore, we construct a dynamic journal ranking with decade specific publication points for each journal from 1950 onwards. For the period from 1960 to the 1989, we use the ranking from Laband and Piette (1994), for the 1990s the equivalent ranking published in Kalaitzidakis, Mamuneas, and Stengos (2003), and for the 2000s the recursive discounted ranking available on the "ideas" webpage.[17] For the 1950s we were not able to find a journal ranking and thus decided to extrapolate a ranking for articles published in the 1950s from our 1960s ranking. A complete list of these journals with their associated publication points can be found in Table $B.2$ of Appendix B.2.4.

In the Appendix B.6.1, we show that our results are robust to the use of other productivity measures.

2.3.3 Macro Data and PhD Entry Date

The main aim of our study is to relate the career decisions and the publication success of economists to a proxy for the state of the macroeconomy at the times of application to and graduation from their PhD program. As our data contains only person-specific graduation dates, we infer the application date by subtracting the median duration of a PhD of 6 years from the graduation date.[18]

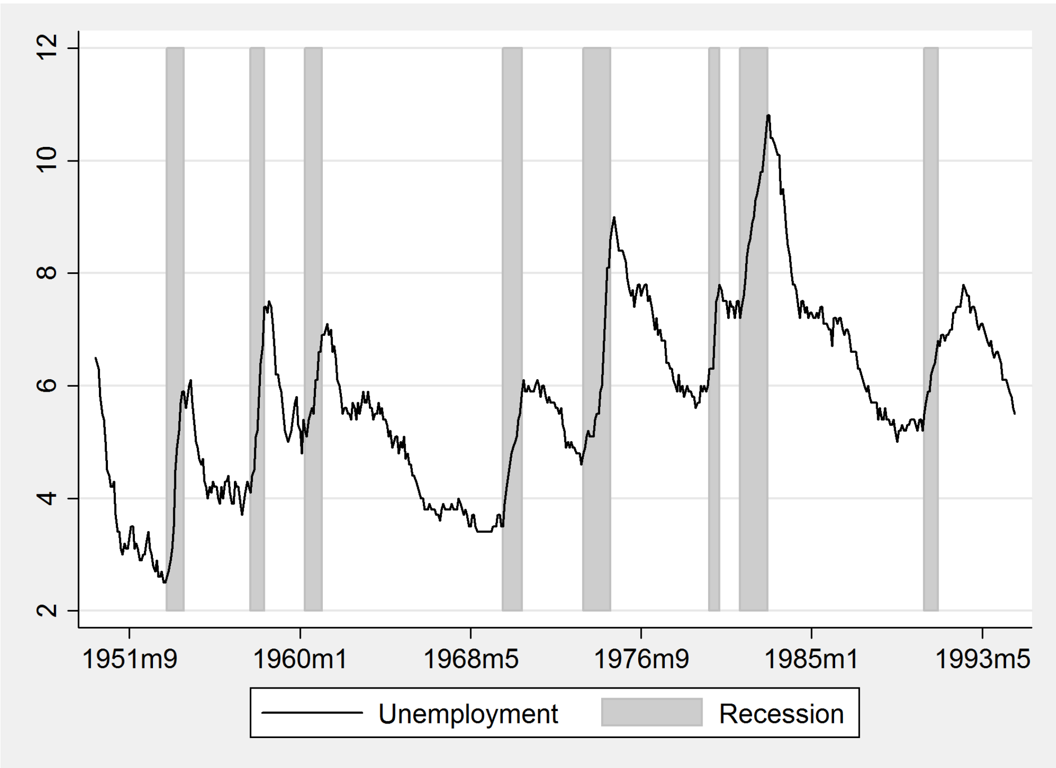
This is a potential problem because the variation in completion times across PhDs is substantial. Section B.2.5 in the appendix reruns our main regressions using the distribution of completion times for the 1997 graduating cohort. The results become stronger, which suggests that measurement error in the business cycle at application potentially biases our estimates in the main part of our analysis.

[17] Refer to "IDEAS/RePEc Recursive Discounted Impact Factors for Journals", last accessed 2009-07-31, `http://ideas.repec.org/top/top.journals.rdiscount.html`. Note, however, that the ranking on the website is updated continuously and thus is not exactly the same as we use in this study. The ranking that we use here was downloaded on 2009-07-31.

[18] The median duration of a PhD stayed almost constant at from five to six years since the 1970s (see Table B.3 in Appendix B.2.5).

Our prefered proxy for the state of the business cycle is the change in the rate of unemployment from June of the preceding year to June of the considered year. The National Bureau of Economic Research (NBER) recession indicators are arguably the most convincing measures of recessions. However, binary indicators cannot carry information about the state of the economy as fine as continuous measures. Unemployment change is such a continuous measure and—out of several candidate variables that are available for the whole of our sample period—it is the most strongly correlated with the NBER recession indicators. For example Figure 2.4 shows that recessions go hand in hand with a large change in unemployment. Unemployment levels are high only after a recession. To demonstrate the robustness of our conclusions, we also estimate all our specifications using unemployment levels and GDP growth as explanatory variables.

Figure 2.4: Unemployment and recessions



We refrain from using some more business sector- or economist-specific measures of the state of the business cycle because they are generally not available for the entire study period. For example, Job Openings for Economists (JOE), a listing of open positions for economists published by the American Economic Assocation, is only available from 1976 onwards. Since our study period ends in 1994, using the JOE listings would reduce the length of our time series to 18 data points (minus six if we used job openings at application to the PhD as well).[19]

2.3.4 Aggregation to University-Year Level

Finally, we group our graduates' publication performances and the indicator for being an academic or not into university-graduation year averages. Thus, we reduce the number of our observations from 13,624 individuals who graduated from institutions in tiers one, two, and three between 1955 to 1994, to 1068 cohort means. Because we do not use any explanatory or control variables that vary below the university-year level, this grouping entails no loss of information.

2.3.5 Descriptive Statistics

Table 2.1 provides summary statistics for the PhD cohorts' average productivity, the average probability to become an academic, and the macroeconomic variation.

The average ten-year productivity of a university-year cohort is about 31.49 publication points. The average probability to become an academic is about 60% and is slightly falling over time as we can see in Figure 2.5a. Conditioned on being an academic, the average ten-year cohort productivity totals 48.14 publication points. This is about 50% of an article in the AER in the 1990s.[20]

Figure 2.5b depicts the average productivity of the PhD cohorts for every year in our analysis, distinguishing between the average productivity of all graduates and graduates that became an academic. As expected, we see that the performance measures move together to a substantial degree.

[19]Nevertheless, in appendix B.3 we can show that job openings and our macroeconomic indicators are correlated using the whole time period from 1976 to 2010. We also want to thank Paul Oyer for sharing his data on financial services activity.

[20]In order to translate these publication points in terms of articles in a certain journal, one has to take into account that the importance of journals changes over time. For example, an article in the American Economic Review (AER) in the 1990s was worth 100 publication points while it was "only" worth 40.2 points in the 1980s. Therefore, the average ten-year productivity of a member of a university-year cohort in the full sample is about the equivalent of one-third of an AER article in the 1990s. Refer to Appendix B.2.4 for a more detailed interpretation.

The change in the unemployment rate, our preferred independent variable, has a mean value of approximately zero. The 10% quantile is -0.9 percentage points and the 90% quantile is 1.5 percentage points for the change in the rate of unemployment. The average unemployment level is 6.1 % and the average GDP growth is 3.4 %. From the 1955 to 1994 the US was in recession 17% of all years. As an example, Figure 2.5c plots the change in the unemployment rate and the GDP growth together with indicator for recessions from 1955 to 1994.

Table 2.1: Summary statistics

	mean	sd	min	max	p10	p90
Productivity	31.49	84.89	0.00	1738.10	0.00	93.80
Productivity (Academic)	48.14	103.84	0.00	1738.10	0.00	144.72
Academic	0.60	0.49	0.00	1.00	0.00	1.00
Unempl Change	0.02	1.03	-2.10	2.90	-0.90	1.50
Unemployment	6.11	1.50	3.50	9.70	3.80	7.70
GDP Growth	3.38	2.29	-1.94	7.20	-0.23	6.42
Recession	0.17	0.37	0.00	1.00	0.00	1.00
Observations	13624					

2.4 Results

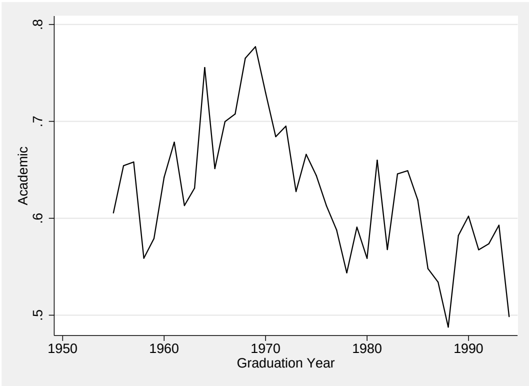
In this section we examine the empirical predictions derived from the modified Roy model. To do this, we estimate the following model in three different specifications:

$$q_{i,t} = \beta \cdot y_{app,t} + \gamma \cdot y_{grad,t} + \delta \cdot \text{controls} + \epsilon_{i,t} \tag{2.2}$$

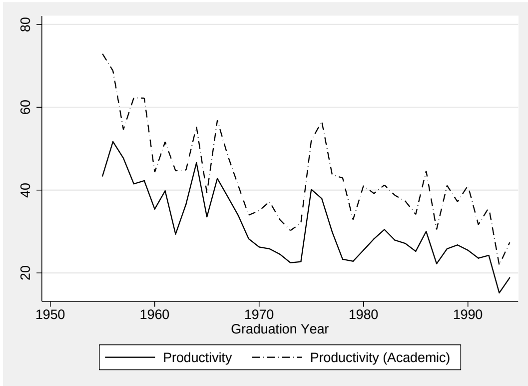
In the first specification, the outcome variable $q_{i,t}$ is the average publication output of a cohort of graduates from university i in year t. In the second specification, it is the average propensity to decide in favor of an academic career after the PhD, and in the third specification, $q_{i,t}$ is the average productivity of those who have decided to stay in academia after the PhD. The unit of observation in all three cases is the average of a given university in a given year, weighted by the amount of underlying individual observations. Moreover, the standard errors are clustered on the graduation year level, in order to allow for contemporaneous correlation between the outcome variables in the presence of

Figure 2.5: Dependent and independent variables over time

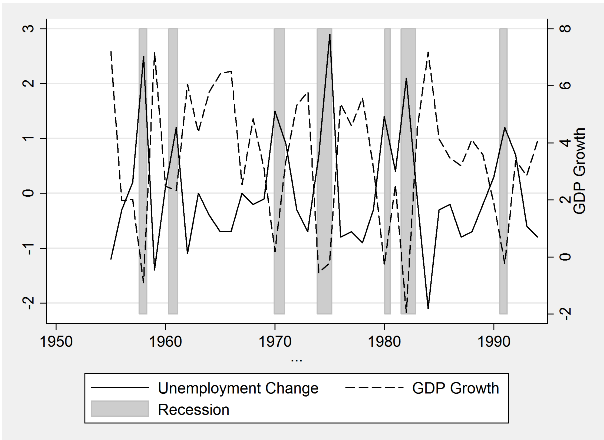
(a) Probability to become an academic



(b) Research productivity



(c) Unemployment Change and GDP Growth



regressors that do not vary within a given year.

The regressors $y_{app,t}$ and $y_{grad,t}$ are a measure of the business cycle at application and at graduation for each cohort. Our preferred regressor is the change in the unemployment rate. To show the robustness of our results we also estimate all specifications with unemployment levels, GDP growth and NBER recession indicators as measures of the business cycle. For conciseness, we focus our interpretation on the effect of unemployment change on our dependent variables and only highlight if differences arise from using one of the other measures. As control variables, we include dummies for the full set of interactions of university and graduation decade. These dummies pick up the (changing) quality differences of PhD education among universities over time and they control for the higher standards of publication in recent decades (e.g. Ellison 2002a, Ellison 2002b).

We estimate Equation (2.2) using linear regressions. To identify the average treatment effect of the business cycle measure on the respective outcome variable, we assume that the productivity and the career decisions of a cohort of (potential) PhD economists do not contemporaneously affect the business cycle in a given year. This assumption excludes potential reverse causality.[21] To be able to interpret β and γ exclusively as the causal parameters of the selection effect discussed in the theory section, we need an additional exclusion restriction to be satisfied: we assume that unemployment change affects a cohort's career decisions and publications only in terms of changing their choice of the sector to apply to (the selection effect). This assumption might not strictly be true in the light of the result of Oyer (2006) that the state of the business cycle affects an economist's first job placement and thus his productivity. We explain in Section 2.4.3 that given Oyer's result we might actually underestimate the causal effect of selection in our regressions due to leaving out the quality of the first job.

Table 2.2 summarizes the main regression results of the three specifications, each in one column. Every column contains four independent regressions each using another business cycle measure for the two explanatory variables. The estimated coefficients of the different regressions are reported one below the other. The following subsections explain the results for the three outcome variables in turn.

2.4.1 Effect on the Publications of all PhDs

The first column of Table 2.2 shows the effect of the business cycle on the publication output of an average PhD graduate in the sample. Unemployment change, both at time of application and at graduation, has a significantly positive effect on research productivity at the five and one percent level, respectively. These two results are also economically substantial: a cohort on the 90% quantile of unemployment change at time of application is expected to achieve 3.7 publication points more than a cohort on the 10% quantile. This is approximately 12% of the mean. Similarly, if we do the same calculation for the graduation cohort, the difference is 5.5 points, which is 17.6% of the mean.[22]

[21]Furthermore, no third factor is allowed to influence both—the business cycle and, the career decisions and productivity—directly.

[22]Referring to Table 2.1 above, the difference between the 10% and the 90% quantiles of unemployment change at time of application is 2.4. Multiplying this by the parameter estimate of 1.54 gives a difference in average productivity between "boom" and "recession" cohorts of 3.7 publication points. Referring to

Table 2.2: The main regression results

	Productivity	Academic	Productivity
Unempl Change (Application)	1.54**	-0.89	3.27***
	(0.66)	(0.58)	(0.94)
Unempl Change (Graduation)	2.31***	1.35**	2.74**
	(0.65)	(0.61)	(1.20)
Unemployment (Application)	1.58**	-0.75	2.98**
	(0.65)	(0.79)	(1.10)
Unemployment (Graduation)	1.80**	-0.25	3.08**
	(0.73)	(0.59)	(1.26)
GDP Growth (Application)	-0.66**	0.47*	-1.46***
	(0.29)	(0.24)	(0.42)
GDP Growth (Graduation)	-0.71**	-0.41	-0.74
	(0.33)	(0.27)	(0.56)
Recession (Application)	2.16	-3.24**	5.38*
	(2.11)	(1.55)	(2.93)
Recession (Graduation)	4.56**	2.15	5.09
	(2.14)	(1.29)	(3.57)
Subsample	All	All	Academic
University-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Note.—Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Using the alternative measures of the business cycle as regressors deliver qualitatively similar results as unemployment change. A higher unemployment rate is associated with higher productivity at application and at exit. Positive GDP growth leads to a lower publication productivity and NBER recessions go hand in hand in hand with more publication success. All coefficients are statistically different from zero at least at the five percent level. The only exception is the estimated coefficient for NBER recessions at application which is not significant at conventional levels.

Therefore, the effect of the business cycle at graduation is in line with empirical prediction 4: PhDs who graduate during a recession publish more on average because more of them decide to stay in academia. Thus, the theoretical effect is at the "extensive margin" as opposed to an "intensive margin" effect in which those PhDs who would have stayed in academia anyway are publishing more if they graduate in recession than if they graduate in a boom.

The theory does not make a prediction which overall effect the business cycle at time of application should have on the publication output of an average PhD graduate. On the one hand, according to Proposition 2.2.1, graduates who experienced a recession at time of application constitute a better selection of individuals. On the other hand, according to Proposition 2.2.2, fewer of these individuals are expected to stay in academia and publish after the PhD. Empirically, it seems that the former effect dominates the latter, as a worse business cycle (measured by a large positive change in the unemployment rate, a higher unemployment rate or lower GDP growth) at time of application is associated with a higher publication output of an average PhD.

2.4.2 Effect on Career Decisions

The second column of Table 2.2 reports how the business cycle is related to economists' career decisions after the PhD. PhD graduates are more likely to stay in academia when the economy is ailing according to our preferred business cycle measure of unemployment

Table B.2 in Appendix B.2.4, this is about the number of publication points one gets assigned for an article in "Economica" during the 1990s. From Table 2.1, we also find that the "average" PhD graduate achieves 31.49 publication points. Similarly, multiplying the difference between the 90% and 10% quantile of unemployment change with the paramter estimate of 2.31 at graduation yields 5.549 publication points. This is about 17.6% of the mean of 31.49.

change at graduation. The estimated coefficient is significant at the five percent level. The mean estimates point in the same direction for two of the three alternative measures, but they are not significantly different from zero on conventional levels.

These findings give qualified support for empirical prediction 3 from the theory section: PhD graduates are more likely to stay in academia if there is a recession at graduation. The increased average productivity of a recession cohort might therefore come from this "extensive margin" effect. Taking the mean estimates for unemployment change literally, a member of the cohort on the 90% quantile of unemployment change at graduation (+1.5%) has a 3.24 percentage points higher probability to become an academic compared to a PhD student graduating on the 10% quantile (-0.9%). The average propensity to become an academic is 60%.

The theory also predicts that economists who experience a recession at application to the PhD are less likely to stay in academia afterwards because some of them will enter only *because* of the recession (prediction 1). The evidence in Table 2.2 suggests the existence of this effect. The estimated coefficient for unemployment change is of the predicted sign but not statistically different from zero. Also the parameter estimates of all other measures are of the predicted sign. For GDP growth and recession indicators they are significantly different from zero at the ten and the five percent level, respectively.

More generally, there are three different concepts conceivable of someone being an "academic": First, one could only consider faculty members of higher learning institutions as academics. This definition leaves out staff at international organizations, central banks and other research-focused (governmental) institutions. Second, one could argue that the relevant distinguishing characteristic of an academic is producing novel and original research. And finally, one could more generally consider anyone an academic who works on research-related topics and upholds a relationship with the academic community.

The evidence reported in Table 2.2 is based on the third notion of an academic by classifying anyone as such who is either a faculty member or a member of the American Economic Association (AEA) after the PhD. Table 2.3 additionally reports the measures of being an academic according to the first two notions.

Column two in this table shows the propensity to become an academic measured by

Table 2.3: Different measures for being classified as an academic

	Academic	Faculty	Publish	Academic
Unempl Change (Application)	-0.89	-0.43	-0.98**	-1.72***
	(0.58)	(0.47)	(0.46)	(0.58)
Unempl Change (Graduation)	1.35**	0.54	0.41	2.87***
	(0.61)	(0.41)	(0.40)	(0.94)
Unemployment (Application)	-0.75	0.08	0.10	-1.23
	(0.79)	(0.38)	(0.42)	(1.03)
Unemployment (Graduation)	-0.25	0.60	0.03	-0.08
	(0.59)	(0.36)	(0.40)	(0.92)
GDP Growth (Application)	0.47*	0.25	0.45**	0.75**
	(0.24)	(0.19)	(0.19)	(0.29)
GDP Growth (Graduation)	-0.41	-0.05	0.05	-1.25***
	(0.27)	(0.19)	(0.23)	(0.36)
Recession (Application)	-3.24**	-1.42	-1.79	-5.73***
	(1.55)	(1.06)	(1.20)	(1.73)
Recession (Graduation)	2.15	1.84**	1.14	3.95**
	(1.29)	(0.76)	(0.84)	(1.67)
Subsample	All	All	All	Tier 1
University-Decade Dummies	Yes	Yes	Yes	Yes
Observations	1068	1068	1068	234

Note.—Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

whether graduates end up as members of faculty at an economics, business or finance department of a college or university in the United States according to the listings published by Hasselback (2001). The direction of the effect is the same as in column one and in the main results table except for unemployment levels. However, the resulting coefficients are not statistically significant for either point in time. The only exception is the estimated coefficient for for recession indicators at graduation from the PhD, which is significant at the five percent level. This might be the case because the employed faculty listings are not exhaustive. For example, faculty on leave are not included and we do not have faculty directories for other departments, such as law and agriculture. Furthermore, our faculty listings are strongly focused on US institutions. Thus, they miss many foreign graduates who become professors in their home countries and are members of the American Economic Association.

Column three defines an academic as an individual who, according to our data, publishes at least one article in a ranked scientific journal after his or her PhD. The estimated effect for the business cycle at application points in the predicted direction for three out of four measures. The estimated coefficients are significantly different from zero on the five percent level for unemployment change and for GDP growth. The business cycle at graduation is weak and not significant for any of the independent variables.[23]

Column 4 in Table 2.3 also shows regressions for the propensity to become an academic (according to our preferred academic measure) for a subsample of graduates from the six top-ranked universities, i.e. the tier one schools. The effect here is significant at least on the five percent level and in the predicted direction for three out of the four business cycle measures. We interpret this as evidence that it is actually the individuals at the very top of the skill distribution which are most able to successfully switch back and forth between academia and business and who thus possess what one could call general skills. Overall, we conclude that the results at lend support to the predictions made by our theory about

[23]This seems to confirm the different reasons for becoming an academic in relation to the two points in time: on the one hand, those individuals who become an academic because the economy is bad at graduation are just added at the extensive margin and some of them might not be able to write a ranked article. On the other hand, those individuals who experienced a recession at time of application and decide against academia after the PhD are of high academic ability according to the theory. Thus, a larger share of them would have been able to write a ranked article had they stayed in academia.

the career decisions of PhD graduates.[24]

2.4.3 Effect on the Publications of Academics

The last column of Table 2.2 shows the results of regressing the publication output of individuals classified as academics on our four business cycle measures. The results here are largely robust to the sample selection according to any of the three definitions of an academic that were discussed above (see Table B.11 in Appendix B.6.3).

For all the different measures, the productivity of academics who experienced a recession at time of application is significantly higher than that of academics who applied during a boom. This is in line with prediction 2 which states that the selection of PhD entrants is better during economically difficult times and that this better selection persists to the PhD graduates who stay in academia. The coefficient is significant at the one percent level for unemployment change and of economically relevant magnitude: comparing the average member of the cohort on the 90% quantile of unemployment change at time of application to a cohort member on the 10% quantile, the former is on average 10.47 publication points better than the latter. This is about 16% of the mean.[25]

In fact, prediction 2 states that a generic recession at time of application cohort should first order stochastically dominate a generic boom at time of application cohort with respect to academic skill. Therefore, not only the mean but the whole distribution of academic skills should shift to the right if the economy worsens. Table 2.4 shows the effect of the

[24] One concern that was expressed to us is that foreign students may go back to their home country after the PhD. For example, Borjas (2006) shows that the share of foreign doctoral students has more than doubled since the 1970s. If hiring in the academic sector in the US is cyclical too, one might imagine that, in recessions, more foreign students go back to academic jobs in their respective home countries. We do not have information about whether students are natives or foreigners in our dataset. In terms of our model, if there are foreign academic programs whose hiring is less correlated with the US business cycle than US schools' hiring, this makes demand for economists more inelastic. If those graduates who take the option to go back more often in recessions appear in the faculty listings, the AEA listings, or if they publish in ranked journals, they are counted as academics. This fits our story. If they are not counted as academics, our estimates in Table 2.2 will understate the effect of the business cycle at graduation on the propensity to become an academic and, depending on whether it is the high-α or the low-α PhDs who react more to this, our estimates will under- or overstate the effect on the publications per graduate. Note that our model does not make predictions on the latter effect.

[25] The 10% quantile of unemployment change at time of application is -0.9 percentage points, the 90% quantile is 1.5 percentage points and the difference is therefore 2.4 percentage points. Multiplying this difference with the mean estimate of 3.27 yields 7.86. The mean productivity for an academic is 48.14 publication points.

business cycle on the distribution of publication output within each cohort using quantile regressions. The unit of observation is now an individual academic's publication output.[26] Among those PhDs who are considered academics according to our "academic" measure, 45 percent do not publish at all. We therefore restrict Table 2.4 to the effect of the business cycle on the median of the publication distribution and above.

The estimates are in the predicted direction and significant for the upper quantiles of the publication distribution, but they become less significant for the lower quantiles. The reason for this is probably that the "academic" measure is not perfect at separating academics who do not publish from individuals who have left academia after the PhD. We know that there are more such individuals among the recession at application cohort, some of which are thus mistaken as low-skill academics. This downward-biases the difference between the publication distributions, most strongly so at the lower quantiles.[27]

Table 2.2 also reports the effect of the business cycle at graduation on the research productivity of academics. According to the evidence in section 2.4.2 more PhDs decide for an academic career if there is a recession at graduation. Without a specific assumption on the distribution of skills of PhD economists, our theory does not make a prediction whether the additional academics who enter at the "extensive margin" are of higher or lower academic skill than the average of those graduates who always decide to stay in academia after the PhD.

The empirical results in Table 2.2 suggest that on average PhD students with higher academic ability decide to stay in academia if the economy is in a state of recession compared to a state of boom. This is in line with the result already noted in Section 2.4.2, that it seems to be the individuals at the top of the skill distribution who are able to successfully move between the sectors. The estimated coefficients are significant at the five percent level for unemployment changes and levels. They are not significant but

[26] We only control for university tier–graduation decade fixed effects and their interactions here, because the quantile estimation becomes much less reliable with a large number of dummy controls. The standard errors are not clustered on the graduation year level as this is not straightforward to implement with quantile regressions.

[27] If we define an academic according to whether he publishes in a ranked journal instead of AEA membership or appearance in a faculty listing, and thus condition on non-zero publications, our quantile regressions yield positive and significant effects of unemployment change in line with the theory over the whole publication distribution.

Table 2.4: Quantile regression for the academic subsamples

	50%	65%	80%	95%
Unempl Change (Application)	-0.00***	0.45	3.70***	9.34*
	(0.00)	(0.67)	(1.30)	(5.02)
Unempl Change (Graduation)	0.00***	1.13	3.87***	0.62
	(0.00)	(0.71)	(1.34)	(5.22)
Unemployment (Application)	-0.00***	0.79*	3.89**	11.22**
	(0.00)	(0.45)	(1.69)	(5.29)
Unemployment (Graduation)	0.00***	2.83***	5.19***	11.58**
	(0.00)	(0.41)	(1.54)	(4.56)
GDP Growth (Application)	0.00***	-0.39	-1.59**	-4.81**
	(0.00)	(0.26)	(0.66)	(2.28)
GDP Growth (Graduation)	-0.00***	-0.04	-1.08	2.11
	(0.00)	(0.27)	(0.68)	(2.28)
Recession (Application)	-0.00	1.10	6.91	17.51
	(0.01)	(1.99)	(4.29)	(14.01)
Recession (Graduation)	0.00	4.88**	8.00*	1.00
	(0.01)	(1.95)	(4.24)	(13.87)
Subsample	Academic	Academic	Academic	Academic
Tier-Decade Dummies	Yes	Yes	Yes	Yes
Observations	8222	8222	8222	8222

Note.—Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in the right direction for GDP growth and the recession indicators. According to our estimates, an academic graduating on the 90% quantile of unemployment change is on average 6.67 publication points better than an academic graduating on the 10% quantile. This is about 13% of the mean of 48.14.

At first glance, the result that academics who experience a recession at graduation are more successful at publishing than those who experience a boom, seems to contradict the findings by Paul Oyer (2006). He shows that PhDs who graduate during a favorable academic job market (which is correlated with economically good times in general) obtain better initial academic placements. He further shows that the first placement has a positive causal effect on an economist's research output by instrumenting the first placement with the state of the academic job market during the graduation year.

However, we think that Oyer's and our result may not be contradictory, but that they could actually reinforce each other: suppose that both effects are relevant in reality—Oyer's placement effect and our selection effect. On the one hand, we would underestimate the effect of the business cycle at graduation on the skills selected into academia. This is because we would not take into account the worse placement a recession economist experiences on average, which would lower our measure of his skill, the publication output. Thus, the individuals selected into academia in recession would actually be better in terms of ex-ante skill than our estimate indicates. On the other hand, Oyer would underestimate the causal effect of the first placement on the research output of an economist. This is because he would not take into account the lower average ex-ante skill of a given economist during boom due to selection.

Finally, it was suggested to us that our results could (partly) be driven by individuals timing their graduation or dropping out of the PhD program at different rates due to recessions. Conceptually, these alternative explanations can be understood as variants of our selection story. Appendix B.4 discusses the alternative explanations and their implications and provides evidence which suggests that they are not important in our data.

2.5 Conclusion

This chapter investigates the effect of aggregate labor market conditions on the career choices and research productivity of economics PhDs in the United States. We document that individuals who applied for—and graduated from—PhD programs during a recession produce substantially more research. Moreover, our results on the economists' career decisions provide evidence that the productivity effects arise from a selection into sectors driven by the state of the economy.

We concede that the market for academic economists is a very particular labor market. Yet, it is uniquely suited for our study because it provides a good output-based measure of skill. Our model is designed to capture key features of this market and it is not necessarily meant to apply broadly. Nevertheless, if (potential) economists react similarly to incentives as talented individuals in other knowledge-intensive occupations, we may be able to draw conclusions for other segments of the labor market from our study.

Our model features talent selection with and without quantity constraints. Selection without quantity constraints appears to be the norm in the private sector and has received a lot of attention in the literature. Without imposing further assumptions on the skill distribution, the only general prediction we can deduct from these models is that more individuals will enter the sector that becomes relatively more attractive (Heckman and Honoré 1990).

Quantity constraints, in the sense that the number of new hires is fixed, are probably more important in the public than in the private sector. Entry is competitive for the top jobs in civil service and therefore clear predictions about the composition of talent arise. For other occupations in the public sector—like teachers and nurses—this does not appear to be the case. In the private sector, the predictions about talent composition are unambiguous if we consider the average skill level of the top N employees only. For example, we expect that the top 100 new hires in the consulting industry to be a better selection of talent if the relative compensation in this occupation rises.

The other specific feature of our setting is its two step selection process with competitive admission and the academic versus non-academic career choice six years later. This is quite unique. However, early careers in other knowledge-intensive industries are not completely dissimilar: for example, starting positions in law or consulting firms feature an informal training phase with a performance appraisal and promotion decision at the end. In many cases the employee decides to leave the industry afterwards.

Overall, we conclude that there are some important specificities in our setting that might impede a broad external validity of our findings. Nevertheless, our key general question of interest is whether there are talent allocation effects in labor markets in response to shocks. Despite all mentioned specificities, the answer to this question is more likely to be yes with the results of our study.

Chapter 3

The Effect of Taxes on Venture Capital Investment

3.1 Introduction

Around the world, governments introduce policies to promote venture capital and thus venture capital-financed start-up companies.[1] These companies are of special interest for the policy maker, because they are particularly innovative: for example, a dollar spent on venture capital yielded more than twice as many patents than a dollar spent on R&D by established companies in the United States in the period from 1983 to 1992 (Kortum and Lerner 2000).[2] Despite this public interest, it is not completely understood how public policy influences the investment behavior of venture capital investors and thus the entrepreneurial process. In particular, high taxes are supposed to discourage investment from a theoretical perspective, but — to the best of our knowledge — there is no empirical estimate of the size of this effect.[3] Our study contributes to closing this gap.

To estimate the effect of taxes on venture capital investment, we match all recorded investments in the Thomson One database with tax rates in 24 countries from 2000 to 2009.

[1]See for example Lerner (2009), Cumming (2010), Da Rin, Nicodano, and Sembenelli (2010), and DeGennaro (2010)

[2]Furthermore, the likelihood of a new product being introduced in the market is three times higher if a start-up receives venture capital (Hellmann and Puri 2000).

[3]There is however a large literature on the effect of taxes on the size of the venture capital industry and the amount of capital commited.

We thus obtain an unbalanced panel of 17,008 companies in 24 different countries with a total of 31,905 funding rounds. The two taxes under consideration are the individual capital gains tax and the overall tax on dividend income. The latter combines the corporate income tax for small and medium-sized companies and the personal income tax on dividend income. We expect both tax rates to have a negative impact on the incentive to invest: the capital gains tax, which is levied on a company's sales price when the investor sells her shares, reduces his return from a potential exit. Similiarly, the overall dividend tax levied on corporate profits and dividends reduces the value of the investee company to the buyer and thus the sales price of an inital public offering (IPO) or a trade sale.

In the first part of our analysis, we measure the effect of these taxes on the number of firms receiving their first funding by venture capitalists. We use a negative binomial model to explain the number of new ventures with the two tax rates, year- and country fixed-effects. Our results indicate that an increase in the overall dividend tax rate has a negative effect on the number of companies receiving their first investment. The estimated coefficient is significantly different from zero at the one percent level and economically large: a one percentage point increase in the dividend tax rate is associated with approximately two percent fewer companies funded. At a mean of 131 new companies per country and year, such a tax increase leads to a reduction of about two newly-funded ventures. The mean estimate of the capital gains tax is also negative, but not significantly different from zero at conventional levels.

In the second part of our analysis, we consider the influence of taxes on the probability of venture capital-backed firms receiving a follow-up investment. As empirical model we use a firm fixed-effects panel with the probability of investment as the dependent and the two tax rates as the independent variables. We find that on average an increase in the capital gains tax rate of one percentage point reduces the probability of venture capital-backed companies receiving a follow-up investment by two percentage points. At a mean probability of investment of 59% in our sample, such a tax increase reduces the likelihood of investment by around four percent relative to the mean. The estimated coefficient of the capital gains tax is significantly different from zero at the one percent level. The mean estimate of the overall dividend tax is negative, but not significantly different from zero at conventional levels.

To the best of our knowledge, this is the first study which analyzes the effect of taxes on the probability of investment in venture capital backed companies. In particular, we are the first to explicitly consider the effect of taxes on the start-up's probability of receiving a follow-up funding. Thus, we are able to trace the influence of taxes over the whole investment cycle from inception to the exit of the venture capitalist.[4] Furthermore, the employed method of a firm fixed-effects panel regression has not been applied to study venture capital backed companies before. This is an improvement on prior work as we can better control for firm-specific heterogeneity compared to previous studies using country fixed-effects. Our study newly assesses the effectiveness of taxes on the creation and the probability of continuing financial support for venture capital-backed companies. It can therefore deliver recommendations for policy-makers on how to enhance the success of new ventures.

The idea of considering the effect of macroeconomic and industry conditions on the investment probability in the first funding round is not new. It was first applied by Gompers, Kovner, Lerner, and Scharfstein (2008). They study the effect of the market-to-book ratio on a venture capital fund's number of investments in newly created companies in a given industry. In contrast to their work, we analyze the effects of tax policy on venture capitalists' investment decisions throughout the investment cycle. Brander, Du, and Hellmann (2010) use the same dataset as we do and analyze the influence of government supported venture capitalists on the probability of venture capital funds realizing a successful exit with their portfolio companies.

Several other studies have considered the effect of taxes on the volume of venture capital committed in a certain country and year (e.g. Poterba 1987, Poterba 1989, Gompers, Lerner, Blair, and Hellmann 1998, Da Rin, Nicodano, and Sembenelli 2006, Bonini and Alkan 2009). They all find a negative impact of taxes on the supply of risk capital. By considering only tax-exempt investors, Gompers, Lerner, Blair, and Hellmann (1998) even show a negative effect on the demand for venture capital. Our study adds to their findings as we analyze the investment decision of the venture capitalists explicitly, and not the overall volume invested by a venture capital fund or in a country. This allows us

[4]Townsend (2010) estimates the effect of the burst of the tech-bubble on the chance of obtaining a follow-up investment. Bergemann, Hege, and Peng (2009) treat the size and frequency of follow-up funding as the outcome of a learning process.

to evaluate the effect of taxes on the survival of start-ups, which cannot be determined by looking at investment volumes alone.

The remainder of this chapter is organized as follows. The next section explains the institutional set-up and the proposed causal channel of taxes on investment activity. In Section 3.3 we discuss our data construction. The empirical specification and the results can be found in Section 3.4. In Section 3.5, we conduct robustness checks on our results and section 3.6 concludes.

3.2 Theoretical Framework

Venture capital (VC) funds are often the only source of funding for young high-risk companies (Elango, Fried, Hisrich, and Polonchek 1995, Gompers, Lerner, Blair, and Hellmann 1998).[5] For such start-up companies, traditional bank financing is unavailable, because they do not have assets which can pledged as collateral. Instead of demanding collateral, a venture capital fund monitors start-ups intensively after the investment, so that the risk of exploitation of private benefits is reduced (Becker and Hellmann 2003, Kaplan and Strömberg 2004, Gompers, Lerner, Blair, and Hellmann 1998). Usually, venture capitalists carefully structure their investments, take seats on the board of directors and concentrated equity positions to obtain control rights (Tirole 2006). To further improve their bargaining position in the monitoring process, they do not invest the required funds all at once but in consecutive funding rounds. In our data, companies receive on average 1.81 funding rounds.

The investment in a start-up is profitable if the investor is eventually able to sell the acquired share of the company to the public in an initial public offering (IPO) or to an established company in a trade sale. Cochrane (2005) estimates that if a firm is acquired or taken public, it delivers to the investor an arithmetic return of 698% with a standard deviation (std) of 3,282%. The average return of all venture capital investments is about 59%, with a standard deviation of 107%. In the first round the average return from investing is 72% (122% std) and decreases to 46% (97% std) in the fourth round mirroring

[5]We use ventures, start-ups, and companies interchangeably throughout the chapter.

the lower risk of investing in later rounds. As an IPO is the most profitable exit route, an active stock exchange is an important determinant of venture capital investment.(Jeng and Wells 2000, Da Rin, Nicodano, and Sembenelli 2006, Gompers, Kovner, Lerner, and Scharfstein 2008)

In our analysis we consider the investment decisions of a representative venture capitalist who aims to achieve a guaranteed minimum return on her investment, the so-called hurdle rate.[6] The venture capitalist closes a funding round for the venture if his expected gains from the investment, i.e. the expected sales price net of taxes less the expected costs associated with the investment, are larger than or equal to his required return.[7] Thus, the probability of venture capitalists providing funding to young companies rises if tax policy is designed in such a way that the venture capitalists' potential returns are high.

We analyze the effect of two tax rates - the capital gains tax and the overall tax rate on dividend income. Each tax influences the net present value of investing through a different channel: the capital gains tax rate is levied on the difference between the sales price and the amount invested. This directly reduces the investor's return and thus the VC's incentive to invest in, to support, and to monitor the venture (Keuschnigg and Nielsen 2004a). Therefore, higher capital gains taxes should reduce the number of start-ups that receive venture capital financing (Keuschnigg and Nielsen 2001, Keuschnigg and Nielsen 2005, Becker and Hellmann 2003) and the probability that entrepreneurial companies' receiving subsequent funding rounds (Keuschnigg and Nielsen 2004a).

The overall tax burden on dividend income is capitalized in the sales price, and thus reduces the potential return for the investor. The value of the company to the potential purchaser, i.e. the maximum sales price, is the net present value of its dividend payments. Dividend payments are taxed by the personal income tax on dividend income (DT) at the investor's level and paid out of net profits. These profits accrue from corporate profits earned in the market, net of the corporate income tax (CIT). Thus both, higher corporate and personal income tax rates diminish the yearly dividend payments and the value which can be realized in the event of an exit (Gompers, Lerner, Blair, and Hellmann

[6]This minimum return is among others influenced by the risk-free return rate and the capital gains tax rate that would have to be paid on the return.

[7]Nanda and Rhodes-Kropf (2011) use a similar thought model for venture capital to explain innovation waves.

1998, Keuschnigg and Nielsen 2004b, Da Rin, Nicodano, and Sembenelli 2006, Bonini and Alkan 2009). Taken together, an increase in the overall tax rate on dividend income should reduce the number of companies receiving their first investment, and the probability of receiving a follow up investment by a venture capital- backed company.

Previous studies have used the investment volumes of venture capital as the dependent variable for analyzing tax policy, implicitly focusing on the incentive of the VC to do fundraising and the limited partners to provide funds (Gompers, Lerner, Blair, and Hellmann 1998, Jeng and Wells 2000, Bonini and Alkan 2009). This makes sense as the raising of funds is a prerequisite for venture capital investments. However, size alone is not a satisfactory measure of the contribution of venture capital markets to the financing of new companies, as no direct conclusion can be drawn on how many firms are created, or whether they persist in the market (Da Rin, Nicodano, and Sembenelli 2006). In our study we focus on the net effect of taxes on the number of newly VC financed ventures and their survival probability, no matter whether this is associated with more or less capital committed.

3.3 Data and Variable Construction

For our dataset we collect tax data for 24 countries over 10 years. We match this data with venture capital investments in these countries in the same period. Data on the individual capital gains tax rate in each year and country is obtained from Ernst & Young “Global Executive” tax guides and the tax handbooks published by the International Bureau of Fiscal Documentation (IBFD). In order to calculate the overall tax on dividend income, we combine the corporate income tax rate and the net personal tax rate on dividend income from the OECD tax database. We collect the data on venture capital investment from Thomson One database (formerly known as VentureXpert) published by Thomson Reuters. The source of each variable is described in Table 3.1.

The individual (instead of the corporate) capital gains tax rate is used in our study because usually “transparent” taxation is applied to capital gains.[8] This means that the

[8]The applicable individual capital gains tax rate is determined for an investor who holds a substantial stake in a company and does not sell her shares for a specific time period, for which usually long-term

Table 3.1: Data description

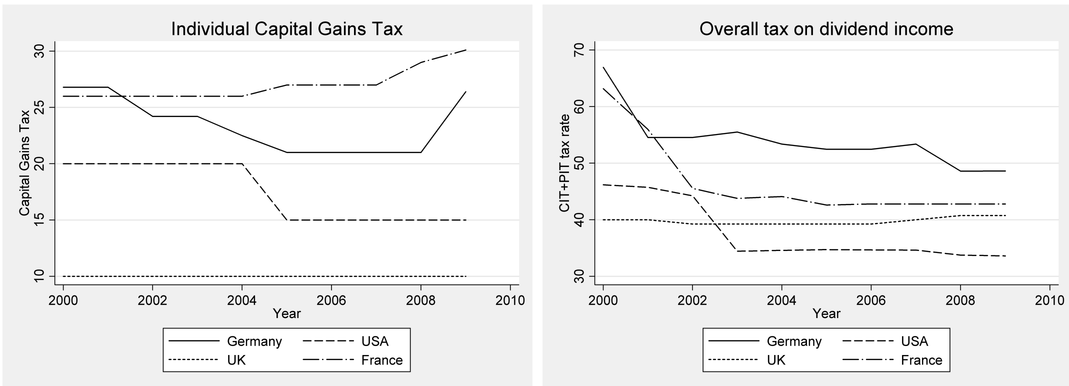
Variable	Description	Source
Capital Gains Tax	Top capital gains tax rate applicable to individuals in the highest income bracket.	Ernst & Young Global Executive Tax guides and tax handbooks published by the International Bureau of Fiscal Documentation.
Net personal dividend tax (DT)	Net top personal tax on dividend income to be paid on shareholder level, taking account of all types of tax relief and gross-up provisions at the shareholder level.	OECD Tax Database available at `http://www.oecd.org/document/60/0,3343,en_2649_34533_1942460_1_1_1_37427,00.html` last accessed on May, 12th 2011. The net personal income tax is taken from table II.4.
Corporate Income Tax (CIT)	Basic combined (central and sub-central statutory) corporate income tax rate for small and medium-size companies.	OECD Tax Database. The general corporate income tax rate can be found in Table II.1 and is substituted by the rate for small and medium-size enterprises from Table II.2 where applicable.
ODT rate	The overall tax rate on dividend income combining the corporate income tax rate for small and medium-size enterprises and the net personal tax rate on dividend income. ODT rate$= 1 - (1 - CIT) \cdot (1 - DT)$	OECD Tax Database. The calculation of the ODT rate is the same as the "Overall Dividend Tax rate" in table II.4.
# Firms	Count of the number of firms receiving the first VC funding round.	Thomson One-Private Equity Module (formerly: VentureXpert).
Investment	Dummy variable, equal to 1 if the company obtains a follow up round or is exited successfully. A successful exit is defined by a trade sale or the company going public.	Thomson One-Private Equity Module (formerly: VentureXpert).

venture capitalists' capital gains are taxed on the individual level even if they execute their investments via funds. The individual capital gains tax rates are taken from the European tax handbooks of the IBFD and the Ernst & Young Global Executive, a guide on taxation of individuals.

Our second independent variable is the overall tax on dividend income (ODT rate). This tax rate is calculated by the following formula: ODT rate = 1-(1-CIT)·(1-DT). Every dollar a company earns in the market is first taxed by the corporate income tax rate (CIT rate). If the resulting profits are distributed, the net personal income tax rate on dividend income (DT rate) further reduces the dividend payout. The overall tax rate on dividend income calculates the total burden of these two tax rates. As corporate income tax rate, we use the top statutory corporate income tax rate applicable to small and medium-size companies according to the OECD tax database. The net personal dividend tax rate (DT) is the net top statutory rate on dividend income to be paid at the shareholder level, taking into account all types of tax relief and gross-up provisions. The evolution of the independent variables is depicted in Figure 3.1.

Figure 3.1: Evolution of tax rates over time

(a) Capital gains tax rate (b) Overall tax rate on dividend income



We get information on consecutive funding rounds for a large sample of venture capital-backed companies with name, country, founding date, date of investment round, round description, and the final company status from the Private Equity module of the Thomson One database published by Thomson Reuters.[9] For our dataset, we select all rounds which are classified as venture capital investment, such as "Seed", "Early Stage", "Expansion",

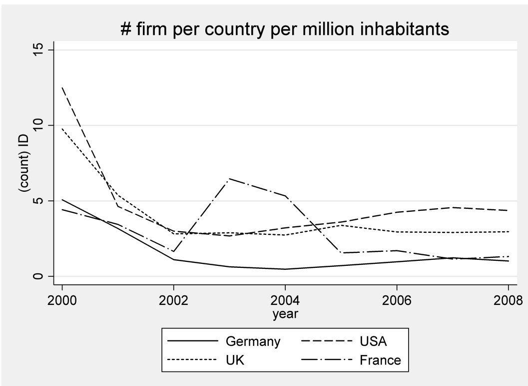
capital gains tax rates apply, e.g. five years.

[9]The total investment of one round is usually not provided by one, but by several venture capitalists.

or "Later Stage". Rounds whose description indicates a relationship with private equity (e.g. "MBO", "LBO", "Bridge Loan", etc.) are deleted. Additionally, we restrict our dataset to companies that received their first investment after 1999 as the Thomson One database has a good international coverage only after this date according to Brander, Du, and Hellmann (2010).

In the first part of our analysis we estimate the effect of taxes on the number of firms receiving their first investment. To do this, we count the number of firms receiving their first investment in each country-year combination and call this variable $\#Firms$. We match this variable with the tax rates in the year before the funding round took place. This is the same timing assumption as in Gompers, Kovner, Lerner, and Scharfstein (2008).[10] As no tax rate varies below the country-year level, we can then aggregate our data without loss of information on this level. The summary statistics for all employed variables in this first dataset in the period from 2000 to 2009 are given in Table 3.2 and the evolution of the number of firms over time for four large economies is depicted in Figure 3.2.

Figure 3.2: The number of firms receiving their first investment over time



In the second part of the analysis we estimate the effect of taxes on the probability of a venture capital-backed company receiving a follow-up investment round. Therefore, our second dependent variable, *Investment*, is a dummy which indicates for every investment

If this is the case, the aggregate these investments to one round. Funding rounds do not necessarily correspond to the development stages of the company, i.e. a start-up can have several funding rounds during its "Early Stage".

[10] In Gompers, Kovner, Lerner, and Scharfstein (2008) the authors match the investment of venture capitalists with the lagged market-to-book of traded technology stocks to estimate the influence of public market signals on investment.

Table 3.2: Summary statistics for the number of firms analysis

	mean	sd	min	max	p10	p90
# Firms	131.36	350.93	0.00	3523.00	7.00	201.00
Capital Gains Tax	19.90	10.93	0.00	45.00	0.00	30.00
ODT rate	43.52	9.46	19.00	72.00	34.39	55.72
Net personal tax (PIT)	24.62	11.48	0.00	60.00	12.50	41.50
Corporate Income Tax (CIT)	24.96	6.66	11.33	52.00	16.00	33.00
Observations	181					

round whether there was a subsequent funding round or whether the venture realized a successful exit. In case a follow-up round or a successful exit occurred, the variable is set equal to one and to zero otherwise.

The following ThomsonOne exit types for the investee company are classified as successful: acquisition, pending acquisition, merger, in registration for an IPO, or went public. In contrast, if an investee company is active, defunct or bankrupt it is regarded as failure. This classification is similiar to the one used by Gompers, Kovner, Lerner, and Scharfstein (2008).[11] This dummy is then matched with the ODT tax rate and the capital gains tax rate. The summary statistics for our second dataset from 2000 and 2007 are given in Table 3.3. In total, our dataset comprises 31,905 funding rounds of 17,008 companies in 24 different countries from 2000 to 2007. Figure 3.3 shows the probability of investment over time.

Table 3.3: Summary statistics for the dependent and independent variables

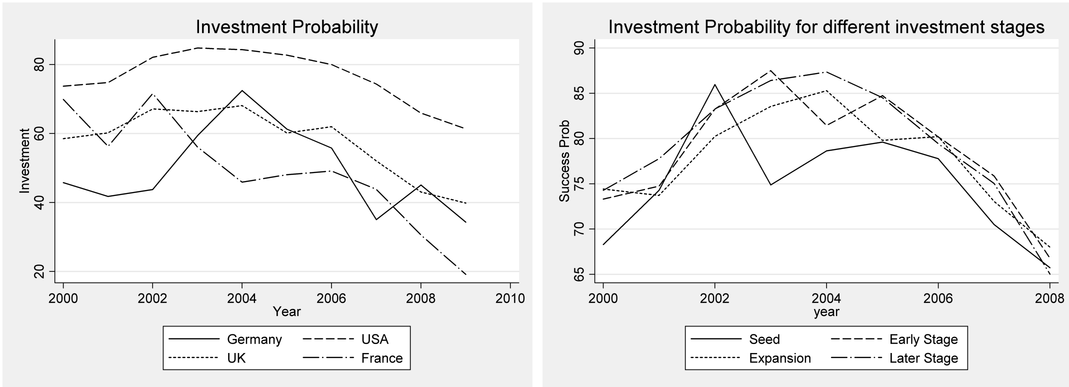
	mean	sd	min	max	p10	p90
Investment	59.29	49.13	0.00	100.00	0.00	100.00
Capital Gains Tax	19.96	6.42	0.00	43.00	10.00	26.80
ODT rate	42.51	7.80	19.00	72.00	34.60	49.60
Net personal tax (PIT)	24.75	7.99	0.00	46.00	17.00	32.30
Corporate Income Tax (CIT)	22.27	6.18	11.33	52.00	18.59	30.00
Duration of successful rounds	365.08	314.66	1.00	2846.00	84.00	747.00
Average Number of rounds	1.81	1.46	1.00	15.00	1.00	4.00
Observations	31905					

A trade sale or an initial public offering are the two most favored exit routes for venture capitalists, yielding the highest returns (Cochrane 2005). In contrast, companies, which

[11] According to the data description Gompers, Kovner, Lerner, and Scharfstein (2008) do not include the category "Pending Acquisition" as a successful exit. It seems logical to include it as "In Registration" for an IPO is also included. A classification for a successful exit similar to ours is also used by other authors (Hochberg and Lu 2007, Brander, Du, and Hellmann 2010).

Figure 3.3: Evolution of the investment probability over time

(a) for different countries (b) for different stages in the US



cannot be sold and stay as "active" companies in the investors' portfolio, are regarded as unsuccessful. However, classifying active companies as a failure might be controversial because a company needs some time to succeed or fail. We cannot determine whether a company, which received its last funding round at the end of our dataset in 2009, gets a subsequent funding round, manages an exit through an IPO or will stay "active" forever. Consequently, we restrict our second dataset to companies that received their last investment round before 2008. Thus, we analyze only complete investment histories of companies from inception to exit: Every company in our sample had at least two years to secure further financing or to exit successfully and we can be reasonably sure that the final company status reflects the exit route.

We match the dependent variable *Investment* with the individual capital gains tax rate and the overall tax rate on dividend income at the date of the current round. This is again the same timing assumption as in Gompers, Kovner, Lerner, and Scharfstein (2008). Our data does not contain the exact date when the investment decision is taken and therefore we cannot exactly determine the relevant tax rate applicable at the date of the decision. We only know that the decision date is weakly after the current round date and weakly before the date of the next round. As we observe only the next round date for firms with a follow-up round we would have to assume an arbitrary round length to impute the relevant tax rate. In order to circumvent this problem, we use the tax rates at the current round date as explanatory variable.

To arrive at our final dataset, we do two more things: First, we set up our panel in funding round time instead of calendar time. To consider the effect of taxes on investment decisions we have to correlate the tax data at the time the investment decision is taken. As we assume that the VC takes the investment decision at the round dates but not in other years, we drop years without a decision by setting the time dimension of the panel to funding round time. This assumption is harmless, as the duration of a successful round is on average about one year and therefore calendar time is approximately equal to funding round time.

Second, we delete all firms in all countries which do not have a stock market with listed technology stocks.[12] We do this by selecting countries and years in which the technology subsector index from the Thomson Reuters "Datastream" database has a non-missing value. If a company is funded in a country without an appropriate stock market, it is not clear whether the venture capitalist expects to take the company public. Therefore, taxes might have no or a much lower effect in such countries and by including them we would estimate a mixture of the coefficient of interest and zero. The excluded countries, which did not have a stock market for technology companies over the whole timespan, are Austria, Greece, Ireland, Luxembourg, Mexico, and New Zealand. Australia is excluded until 2003 and Norway until 2004. An overview of the countries and time span are given in Table 3.4.

3.4 Empirical Specification and Results

3.4.1 The Effect of Taxes on the Number of Companies

To analyze the effect of the overall tax rate on dividend income (ODT rate) and of the individual capital gains tax rate on the number of companies receiving their first investment, we estimate equation (3.1).

$$\#Firms = \beta_0 + \beta_1 \text{Lagged ODT rate} + \beta_2 \text{Lagged Capital Gains Tax} + Controls + \epsilon \quad (3.1)$$

[12] The importance of an active stock market for venture capital investment volumes is shown, for example, by Jeng and Wells (2000), Schertler (2003), and Da Rin, Nicodano, and Sembenelli (2006).

Table 3.4: Sample selection

	Country	Time-Span	#$Firms$
1	Australia	2000-2009	141
2	Belgium	2000-2009	237
3	Canada	2002-2009	794
4	Denmark	2001-2009	212
5	France	2000-2009	1,429
6	Finland	2000-2009	445
7	Germany	2000-2009	1,013
8	Hungary	2000-2009	106
9	Israel	2002-2009	121
10	Italy	2000-2009	266
11	Japan	2000-2009	283
12	Korea	2005-2009	342
13	Netherlands	2000-2009	445
14	Norway	2005-2009	53
15	Poland	2000-2009	95
16	Spain	2000-2009	387
17	Suisse	2000-2009	159
18	Sweden	2000-2009	471
19	Turkey	2000-2009	10
20	United Kingdom	2000-2009	1,756
21	United States of America	2000-2009	8,243

Our preferred estimation method is a negative binomial model (NB2), appropriate for count data with overdispersion, because the dependent variable has a variance approximately three times larger than the mean, as shown in the summary statistics in Table 3.2. In all specifications we use country- and year fixed-effects as controls. Therefore, we identify the parameters β_1 and β_2 with the variation of tax rates within a country over time. The country dummies take up the effect of constant unobserved country-specific factors that might be correlated with the tax rates and thus bias our estimates. For example such factors might include the quality of the university system and the general entrepreneurial attitude. A full set of year dummies control in a nonparametric fashion for a potential time trend in both regressions.

To account for the correlation of tax rates within a country over time, we cluster the standard errors of our estimates on the country level. Thus we allow for an arbitrary correlation structure of the error terms within a country and prevent the over-rejection of the null hypothesis of no effect (Bertrand, Duflo, and Mullainathan 2004).[13] However, this estimation strategy does not take into account that there might be a correlation across countries within a certain year due to common shocks like the burst of the tech bubble in the early 2000s. To show the robustness of our results we use two-way clustered standard errors together with OLS following Cameron, Gelbach, and Miller (2011) in one of the specifications.

We can identify the causal effect of taxes from the coefficients β_1 and β_2, if (and only if) the tax rates are not caused by some other time varying left-out variable that also influences the number of companies receiving their first investment. This seems plausible as we use general tax rates which might be exogenous to decisions in the entrepreneurial sector. If taxes are, for example, raised to reduce a government deficit, it is unlikely that they are accompanied by other measures changing new business creation. In other cases this assumption might be more problematic: If a newly elected policy maker is interested in fostering entrepreneurship, she might lower taxes and at the same time reduce regulation or increase subsidies to entrepreneurship. This being the case, we cannot distinguish the

[13] Unfortunately, a country-fixed effect or an appropriate within transformation does not ameliorate the serial correlation problem in our case like in Da Rin, Giacomo, and Sembenelli (2010). The serial correlation of errors within a country derives from serial correlated levels of taxation and not from a common factor.

Table 3.5: The effect of taxes on the number of companies receiving the first investment

The sample consists of yearly observations for 24 countries from 2000 to 2009. The dependent variable in the first column is the number of companies receiving their first investment in a certain country and year. In the second and third regression the dependent variable is the natural logarithm of companies funded in a country plus one. In the fourth regression we standardize the log of companies plus one with the population size in the country. The independent variables in all regressions below are the capital gains tax rate and the overall tax rate on dividend income (ODT rate) in year t-1, country, and year dummies. Please refer to the text for the construction of these variables and the data sources. The estimation in the first regression is a negative binomial model with dispersion depending on the mean, a NB2 model. In all other regressions we use ordinary least squares.
The standard errors in the third regression are clustered on country and year level. In all other specifications the standard errors reported in parentheses are clustered on the country level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) # Firms	(2) log(# Firms+1)	(3) log(# Firms+1)	(4) log(# Firms per capita)
Lagged Capital Gains Tax	-2.49	-4.13	-4.13	-4.29
	(2.49)	(3.49)	(3.93)	(3.42)
Lagged ODT rate	-2.12***	-1.85**	-1.85**	-1.62*
	(0.75)	(0.81)	(0.74)	(0.80)
Year Fixed Effect	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes
Model	NB 2	OLS	Two-Way	OLS
Log Likelihood	-745.6	-97.3		-90.0
Number of Observations	181	181	181	170

effect of the tax change from the latter two measures. Generally, we have problems with identification, if tax changes are embedded in synchronized programs to help or harm the entrepreneurial sector. In this case, our coefficients estimate the effect of the combined measures. Nevertheless, we think that even in that case such a statistic is of interest to the policy maker in its own right.

The results of the negative binomial model are reported in the first column of Table 3.5. The estimated coefficient of the lagged ODT rate is significantly different from zero at the one percent level in our preferred specification. If we take our estimation at face value, a reduction in the lagged ODT rate of one percentage point increases the number of firms receiving their first investment by 2.12 percent. With a mean of 131 companies funded in every country per year, such a tax reduction results in around two more new ventures funded. The estimated coefficient for the lagged capital gains tax rate is negative. However, as it is not significantly different from zero, we cannot draw any conclusions about its influence.

As robustness checks we estimate in column (2) an OLS regression with the logarithm of the number of companies funded as dependent variable and an OLS model where we standardize the number of companies funded with the size of the population in the fourth column. In the third column we cluster the standard errors on country and year. The log specification is often used for but not tailored to count data and therefore should be interpreted with caution. Nevertheless, the results of all OLS specifications are in line with the findings of the negative binomial model: The estimated coefficient for the overall dividend tax is negative and significantly different from zero at least at the 10% level. The coefficient for the capital gains tax rate is negative but insignificant at conventional levels.

3.4.2 The Effect of Taxes on Follow-Up Investments

In order to appraise the effect of taxes on the probability of receiving follow-up funding, we estimate the following equation:

$$Investment = \beta_0 + \beta_1 \text{ODT rate} + \beta_2 \text{Capital Gains Tax} + Controls + \epsilon \tag{3.2}$$

The dependent variable *Investment* is an indicator that takes a value of one if the company under consideration receives a subsequent funding round or manages a successful exit (and zero otherwise). The overall tax rate on dividend income and the capital gains tax rate at the current round date serve as independent variables.

In our main specification we include firm fixed-effects to control for firm-specific heterogeneity. This is a methodological improvement compared to prior research which often included only country-fixed effects. As we (potentially) observe repeated investments in the same company, it is possible to use firm-fixed effects to control for time-invariant characteristics of the firm such as the quality of the business idea or a key technology (Kaplan, Sensoy, and Strömberg 2009). The company's quality might be positively correlated with the tax burden and bias our estimates when left out. In the second specification, we use OLS with country- and industry-fixed effects as an alternative.[14]

[14]Unfortunately, we cannot include firm fixed effects together with country- and industry-fixed effects in the same regression. No firm in our data changes the industry or the country. Consequently country-

Our estimates show the causal effect of the two taxes on the investment probability if nothing else changes at the same time taxes and the probability of investment. As already noted above, this assumption is dubious if the tax changes are embedded in programs targeted at increasing or decreasing entrepreneurship. However, in this regression the potential endogeneity problem is less severe than in the analysis on the number of companies receiving a first investment, because we consider only companies that already received an investment. These companies, especially in later stages, do not rely much on subsidies like incubators, start-up loans, or coaching provided by state-sponsored programs.

The results of the firm-fixed effects regression and of an OLS regression with country- and industry-fixed effects are reported in Table 3.6. According to our main specification in column (1), we can reject the hypothesis that the individual capital gains tax rate has no influence on the probability of a company receiving a follow-up investment at a significance level of one percent. The probability that a VC backed company receives a follow-up investment is reduced by 2.35 percentage points per percentage point increase in the capital gains tax rate. The regression in the second column shows that the capital gains tax has a negative effect over the whole investment cycle. The estimated coefficients are significantly different from zero at least at the five percent level. In the OLS specification in column (3) the effect is weaker with a mean estimate of around minus one percentage point but is still significant at the ten percent level.

The estimated size of the effect is economically relevant: For example, assume that a country reduces its capital gains tax rate by five percentage points and the average investment probability of receiving a follow-up funding is at the mean of our sample 59% (Table 3.3). After the tax cut, the survival probability is about 69.9% ($59+2.35\cdot5$). Thus, the chance of this company receiving a follow-up investment increases by a total of 10.9 percentage points or about 18% relative to the mean before the tax cut. As mentioned above, our estimates might include the effect of other measures implemented at the same time and therefore should be regarded as an upper bound of the true effect.

The estimated coefficient of the overall tax rate on dividend income (ODT rate) is negative but not significantly different from zero at conventional levels. An increase in the ODT

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and industry-fixed effects are perfectly collinear with the firm-fixed effect and not separately identified.

Table 3.6: The effect of taxes on the probability of receiving a follow-up investment

The unit of observation is a funding round of a VC-backed company. The dependent variable is a dummy which is one if the company under consideration receives a subsequent investment round, goes public, or is acquired. Otherwise the dummy is zero. The ODT rate is the overall personal and corporate income tax on dividends at the current round date. The Capital Gains Tax is the individual capital gains tax rate at the current round date. In specifications (2) and (4) we combine these two tax rates with indicators for the different investment stages to obtain a separate estimate for the "Seed", "Early Stage", "Expansion", and "Later Stage" development stage. We include year, stage, round and firm-fixed effects as controls in the first two columns. In the last two specifications we substitute the firm fixed-effects by dummies for the country and the industry and use a random effects estimator. The standard errors reported in parentheses are clustered on country level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Investment	(2) Investment	(3) Investment	(4) Investment
Capital Gains Tax	-2.35***		-1.12***	
	(0.69)		(0.35)	
Capital Gains Tax - Seed		-1.62**		-0.90**
		(0.77)		(0.36)
Capital Gains Tax - Early Stage		-2.06**		-1.12***
		(0.76)		(0.37)
Capital Gains Tax - Expansion		-2.65***		-1.29***
		(0.67)		(0.45)
Capital Gains Tax - Later Stage		-1.99**		-0.94**
		(0.78)		(0.39)
ODT rate	-0.13		0.00	
	(0.22)		(0.15)	
ODT rate - Seed		-0.04		0.09
		(0.33)		(0.16)
ODT rate - Early Stage		-0.24		-0.07
		(0.18)		(0.13)
ODT rate - Expansion		-0.52*		-0.26
		(0.30)		(0.28)
ODT rate - Later Stage		0.11		0.10
		(0.33)		(0.23)
Year Fixed Effect	Yes	Yes	Yes	Yes
Stage Fixed Effect	Yes	Yes	Yes	Yes
Round Fixed Effect	Yes	Yes	Yes	Yes
Country Fixed Effect	No	No	Yes	Yes
Industry Fixed Effect	No	No	Yes	Yes
Firm Fixed Effects	Yes	Yes	No	No
Model	FE	FE	OLS	OLS
Adj. R-squared	0.340	0.341	0.232	0.232
Number of Observations	31905	31905	31905	31905

rate of one percentage point leads to a reduced probability of receiving another funding round of 0.13 percentage points. According to column (2), the mean estimate of the effect has the largest size and is significantly different from zero at the ten percent level in the expansion stage. In the OLS specification in column (3) we do not find an effect that is significant at conventional levels.

To the best of our knowledge, this is the first study considering empirically the effect of taxes on the re-investment probability of venture capital backed companies. Therefore, we cannot compare our findings with prior estimates on this topic. Theoretically, Keuschnigg and Nielsen (2004b) examined the effect of the considered tax rates on the entrepreneurial effort and advice given by venture capitalists. They find that both, the tax on dividends and the capital gains tax rates reduce entrepreneurial effort and advice. Supposing that a lower effort and advice reduces the probability of receiving a follow-up investment, our results are in line with their theoretical predictions.

3.5 Robustness: Changing the Time-Span

A major concern regarding the robustness of our results is the considered time-span. The dot-com bubble reached its peak in March 2000 and deflated during 2001. At the end of our sample period in 2008 to 2009, the financial crisis broke out. If, for example, during such a crisis the government introduced a series of measures to help the entrepreneurial sector and a tax change happened at the same time, our estimates might wrongly reflect the overall effect of these measures and not only of the tax change. If this is not the case, we might lose information by restricting our sample.

In the main specification of our first analysis we study the number of companies receiving their first funding in the years 2000 to 2009. For convenience reasons, the results of this main specification are again reported in column (1) of Table 3.7. In column (2) we exclude the tech-bubble. The estimated coefficient for the lagged overall dividend tax rate is again statistically different from zero on the one percent significance level. In contrast to our main specification, the estimate for the lagged capital gains tax rate is negative and significantly different from zero at the one percent level. Excluding 2008 to 2009 in column

Table 3.7: Changing the time-span: the number of companies receiving their first funding

The sample consists of yearly observations for 24 countries. The dependent variable in all regressions below is the number of companies funded in a certain country/year. The independent variables in all regressions below are the capital gains tax rate and the overall tax rate on dividend income (ODT rate) in year t-1, country and year dummies. Please refer to the text for the construction of these variables and the data sources. In column (1) the estimation sample covers the years 2000 to 2009. In the second column, the period 2000 to 2001 is excluded. In specification (3) we consider the period 2000 to 2007. In the last column, the estimation sample covers the period 2002 to 2007. The estimation method for all regressions is a NB2 model. The standard errors reported in parentheses are clustered on country level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) # Firms	(2) # Firms	(3) # Firms	(4) # Firms
Lagged Capital Gains Tax	-2.49	-5.55*	-1.56	-4.78*
	(2.49)	(3.17)	(2.45)	(2.61)
Lagged ODT rate	-2.12***	-2.80***	-2.09***	-3.06***
	(0.75)	(0.94)	(0.62)	(0.89)
Year Fixed Effect	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes
Model	NB 2	NB 2	NB 2	NB 2
Time span	2000-2009	2002-2009	2000-2007	2002-2007
Countries	-745.6	-615.0	-588.8	-457.2
Log Likelihood	181.0	154.0	139.0	112.0

(3) delivers the same results for the lagged ODT rate as before. However, the estimated coefficient for the capital gains tax is not significant anymore. If we exclude both time-spans, 2000 to 2001 and 2008 to 2009, as we do in the last column, the resulting coefficients for the ODT are still significant at the one percent level. The estimated coefficient for the lagged capital gains tax rate becomes again significantly different from zero at the ten percent level. In a nutshell we do not find evidence which stand in contrary to our results in the main text.

In the main specification of our second analysis on the probability of a company receiving a follow-up funding round, we analyze the investments of the years 2000 to 2007. If we include companies with an investment in 2008, we potentially mis-classify companies waiting for their next investment round as failures, as we can only see follow-up rounds taking place in 2009. In column (1) of Table 3.8 the results of our main specification are reported for comparison purposes. In columns (2) and (4) we exclude the period of 2000 to 2001 and find similar results as in our main specification. The same is true if we include the year 2008 (columns (3) and (4)). The capital gains tax rate exerts a negative influence on follow-up investments in all specifications that is significant at the one percent level.

Table 3.8: Changing the time-span: the effect of taxes on the probability to receive a follow-up funding

The unit of observation is a funding round of a VC-backed company. The dependent variable is a dummy which is one if the company under consideration receives a subsequent investment round, goes public, or is acquired. Otherwise the dummy is zero. The ODT rate is the overall personal and corporate income tax on dividends at the current round date. The Capital Gains Tax is the individual capital gains tax rate at the current round date. We include year, stage, and firm-fixed effects as controls in all specifications. The estimation sample is for the period 2000 to 2007 in column (1). In the second specification we exclude 2000 and 2001. In the last two columns we include 2008. The standard errors reported in parentheses are clustered on country level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Investment	(2) Investment	(3) Investment	(4) Investment
Capital Gains Tax	-2.35***	-2.89***	-2.66***	-3.41***
	(0.69)	(0.54)	(0.58)	(0.50)
ODT rate	-0.13	-0.45**	-0.24	-0.61**
	(0.22)	(0.21)	(0.23)	(0.23)
Year Fixed Effect	Yes	Yes	Yes	Yes
Stage Fixed Effect	Yes	Yes	Yes	Yes
Round Fixed Effect	Yes	Yes	Yes	Yes
Country Fixed Effect	No	No	No	No
Industry Fixed Effect	No	No	No	No
Firm Fixed Effects	Yes	Yes	Yes	Yes
Model	FE	FE	FE	FE
Time span	2000-2007	2002-2007	2000-2008	2002-2008
Adj. R-squared	0.340	0.419	0.357	0.428
Number of Observations	31905	15131	38175	20309

The coefficient of the ODT rate is negative and significantly different from zero at the 5% level in the second and fourth specification. However, the mean estimate is small and not economically meaningful.

3.6 Conclusion

This chapter offers a new view on tax policy in the entrepreneurial process. The influence of policy interventions can be separated into the effect on the number of companies starting the investment cycle and on the survival probabilities of companies (i.e. the probability of receiving a follow-up investment) within the cycle. We find that higher taxes on dividends lead to a lower number of firms starting the process but do not influence the probability to receive a follow-up funding. The capital gains tax significantly influences the probability of receiving a follow-up investment but does not influence the entry margin. Put in a nutshell, our findings imply that the state can influence entrepreneurial activities by tax policy.

Our study might contribute some empirical evidence to the policy discussion on the taxation of carried interest in the United States which started in the early 2000s. The aim of different legislative proposals was to increase the taxation of capital gains received by the venture capitalist from 15% to the level of 39% on ordinary income. In many other countries similar discussions followed that aimed at adjusting the taxation of carried interest to the regular income tax rate instead of the capital gains tax rate. Our findings imply that such a tax increase might indeed harm the probability of existing companies receiving a follow-up funding round. Unfortunately, we cannot give a quantitative estimate of the expected effect, as we only consider an overall dividend and capital gains tax rate in our study. We also have no data on the differential classification of certain investment returns, as either capital gains or income. Our estimate is a combination of the effect of taxes on the decision of entrepreneurs, the venture capitalists, and the limited partners. Therefore, we cannot isolate the cause of the effect and ascribe it to one special tax treatment. However, we think that limited partners are often tax exempt - especially in the U.S. - and entrepreneurs would always favor additional investments. Thus, our results might be a good approximation of the effects of the proposed tax increase.

Appendices

Appendix A

Appendix to Chapter 1

A.1 Single Period Profit Function

The mode of product market competition is capacity constraint quantity competition as in Besanko and Doraszelski (2004).

The inverse demand function $P(q_i, q_j)$ with P as market price and q_i as quantity produced by firm i is given by

$$P(q_i, q_j) = \frac{a}{b} - \frac{q_i + q_j}{b}.$$

Suppose that firm i and firm j's capacities are given by $(\bar{q}_i, \bar{q}_j)$ and that they compete in the product market by setting quantities (q_i, q_j).

The profit-maximization problem for firm i with $i, j \in (1, 2), i \neq j$ is then given by

$$\max_{0<q_i<\bar{q}_i} P(q_i + q_j)q_i$$

. This maximization problem for i and the symmetric problem for j lead to symmetric reaction functions which are known to have a unique Nash Equilibrium (Vives (2001)). The single period profit function of firm i in the Nash equilibrium of the capacity constrained quantity setting game is therefore

$$\pi_i(\bar{q}_i, \bar{q}_j) = P(q_i^* + q_j^*)q_i^*.$$

The demand parameters used in the simulation are $a = 40$ and $b = 10$ and are thus the same as in Besanko and Doraszelski (2004). These parameters ensure that a company can have more capacity than the entire market demand.

Table A.1: Profit of firm 1

		j=1 $\bar{q_j} = 0$	j=2 $\bar{q_j} = 5$	j=3 $\bar{q_j} = 10$	j=4 $\bar{q_j} = 15$	j=5 $\bar{q_j} = 20$	j=6 $\bar{q_j} = 25$
i=1	$\bar{q_i} = 0$	0	0	0	0	0	0
i=2	$\bar{q_i} = 5$	18	15	13	10	9	9
i=3	$\bar{q_i} = 10$	30	25	20	15	15	15
i=4	$\bar{q_i} = 15$	38	30	23	18	18	18
i=5	$\bar{q_i} = 20$	40	31	23	18	18	18
i=6	$\bar{q_i} = 25$	40	31	23	18	18	18

Note: i and j denote the number of capacity blocks held by firms i and j.

A.2 Welfare Measures

To evaluate the implication of credit rationing on welfare, we calculate the expected consumer surplus and the expected producer surplus of the firms and of the bank.

Expected consumer surplus is calculated by integrating the demand function

$$CS = E\left[\int_{p_{Market}}^{p_{mex}(s)} D(t)dt\right]$$

where $D(\cdot)$ is the demand function, p_{max} is the choke price and p_{Market} is the prevailing market price. The expectation is taken with respect to the probability of the state in equilibrium.

As marginal costs are normalized to zero, expected producer surplus for every state is calculated as the sum of profits minus the financing costs:

$$PS = E\left[\pi(\bar{q}_1, \bar{q}_2) + \pi(\bar{q}_2, \bar{q}_1) - d_1 \cdot r - d_2 \cdot r\right].$$

Expected bank surplus is the interest rate differential multiplied by the sum of debt:

$$BS = E\left[(r - r_{Bank}) \cdot (d_1 + d_2)\right].$$

A.3 Transitory Dynamics

Figure $A.1$ shows the distribution after 10, 20, and 50 periods, starting from the initial value of zero capacities for both players. The distribution without credit rationing evolves directly towards symmetry and stays there forever. With credit rationing, first a symmetric configuration with equal capacity for both firms is reached and then the distribution becomes asymmetric. There is a large probability that one firm exits the market on the equilibrium path.

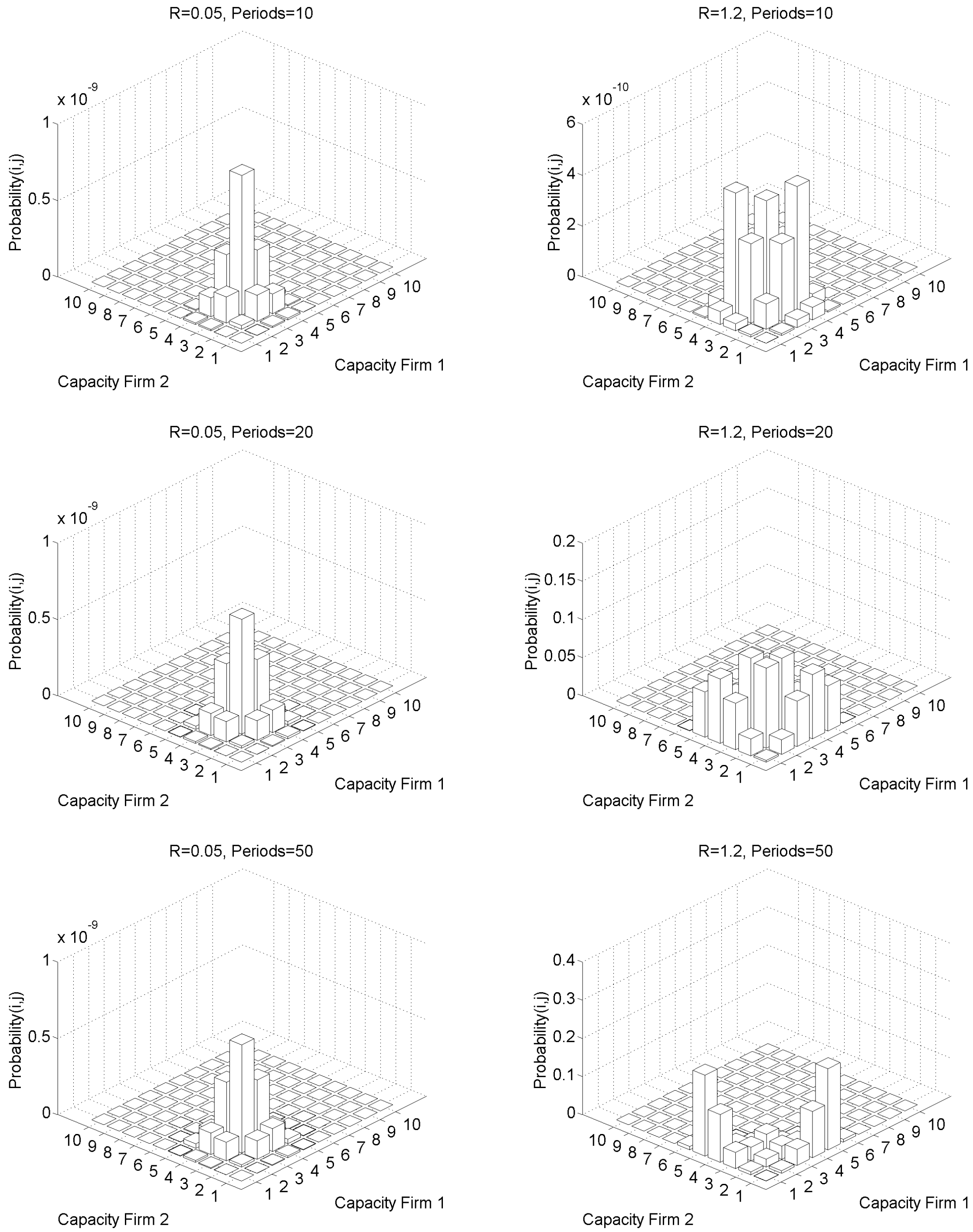
A.4 The Reinforcement Learning Algorithm

In this section, we outline the reinforcement learning algorithm used in the first chapter. It is a variant of the algorithm described in Fershtman and Pakes (2011), to which the reader should refer for an extensive description.

Intuitively, the algorithm employed works as follows: a firm starts in state s and time t. For every potential action a and state s, the firm holds beliefs $W(a_t, s_t)$ about the expected discounted sum of cash flows the action will yield. The firm then chooses the best action a^* according to its beliefs and receives an instant payoff of $div(a_t^*, s_t)$. The actions together with the law of motions of the state variables prescribe the next state. In the next state, the firm chooses again its best actions according to its belief $W(a_{t+1}, s_{t+1})$. At this point, the algorithm can update the belief $W(a_t^*, s_t)$ because $div(a_t, s_t)$ and $W(a_{t+1}^*, s_{t+1})$ are part of the discounted sum of cash flows originating in s_t if a_t is chosen. This procedure is repeated for $Iter$ periods. The optimal actions a_t in every period are stored in memory for use in the equilibrium testing procedure. To test for an equilibrium, the algorithm simulates a large number of periods with the stored optimal actions and checks whether the resulting beliefs $W^{test}(a, s)$ are the same as the beliefs $W(a, s)$ which justified the actions in the first place.

A tentative example: Assume that the player is in state s. Assume further that the player is under the impression that storing five more units of cash starting from state s gives—for the sake of illustration—a continuation value of 2000. This is better than

Figure A.1: Transitory dynamics for $R = 5\%$ (left) and $R = 120\%$ (right)



Note: The capacity states of the two firms are depicted on the x and y axes. The probability of a state is displayed on the z-axis. On the left hand side, the evolution without credit rationing is pictured. On the right hand side, severe credit rationing prevails.

the alternative of not doing so as he believes that this gives him a continuation value of 1500. He stores five more units and then finds out during the play that this decision only resulted in a continuation value of 1600. So he adjusts his expectation of storing five units in state s downwards to 1800. He does not adjust it downwards to 1600 as he cannot perfectly distinguish if this was just a matter of bad luck or truly the consequence of his actions. The benefit of this solution algorithm is that it can accommodate larger state spaces than the commonly used Pakes and McGuire (1994) algorithm. This algorithm only calculates policies on the recurrent state space and therefore ignores states which are never played in equilibrium. To give an idea, the state space in our calculation has about $6.25 \cdot 10^{12}$ states. By selecting only those states relevant to the equilibrium, we only have to calculate equilibrium policies for around one million states, which is still large but manageable. The idea of calculating policies in an Ericson-Pakes model only for a sample of states is gaining prominence in numerical analysis, e.g., another algorithm using this method is Farias, Saure, and Weintraub (2010).

There are also several known problems for this kind of algorithms and numerical simulations of imperfect competition in general:

1. It is not guaranteed that an equilibrium exists. Even if one exists, the algorithm does not necessarily converge to it.

2. There might be multiple equilibria for reasonable parameter values. Besanko, Doraszelski, Kryukov, and Satterthwaite (2009) offer a possible solution, however, we did not explore this issue up to now.

3. There might be more than one recurrent class associated with a set of policies.

4. It is not clear that the off-equilibrium beliefs are irrelevant for the equilibrium play. This is known as the problem of insufficient exploration.

In line with common practice, we check if the algorithm converges to the same equilibrium for different starting values. Although this appears to be the case, the above mentioned issues should be kept in mind.

Scheme of the algorithm: The algorithm requires the following inputs:

- A set of beliefs about the continuation value for every action in every state $W(a, s)$

- A counter $h(a, s)$ for every state and action which measures how often the action was taken
- An arbitrary initial state $\breve{s}$ and an arbitrary initial action $\breve{a}$
- An instant return function $div(a_t, s_t)$ for every action and state
- A function assigning the next period's state s' conditional on today's state s and action a, $f(\cdot)$.
- Technical parameters: length of iteration ($Iter$), ϵ precision of the approximation, and the discount factor β

Algorithm for calculating EBE

$s_t = \breve{s}$, $a_t = \breve{a}$ {Set initial state and initial actions }
repeat
t:=0 {Set index t for best simulation}
while t<=Iter {Begin learning process, last for T periods}
$t = t + 1$
$s_{t+1} = f(a_t, s_t)$ {Assign next state in $t+1$ according to the optimal actions and state in t }
Load $W(\cdot, s_{t+1})$ for all a_{t+1} from memory if already visited, otherwise assign initial values.
$a^*_{t+1} = arg\max_{a_{t+1}} W(a_{t+1}, s_{t+1})$
{Calculate the optimal action}
$h(a^*_{t+1}, s_{t+1}) = h(a, s) + 1$
{Increase the counter of the state s_{t+1} and action a_{t+1} by one. }
$\hat{W}(a^*_t, s_t) = div(a^*_t, s_t,) + \beta W(a^*_{t+1}, s_{t+1})$
{Calculate the continuation value in t according to the next period's action and state. $W(a_{t+1}, s_{t+1})$ is a draw of the integral governing the continuation value. }
$W(a^*_t, s_t) = W(a^*_t, s_t) + \frac{1}{h(a^*_{t+1}, s_{t+1})}[W(a^*_t, s_t) - \hat{W}(a^*_t, s_t)]$
{save the updated belief $W(a^*_t, s_t)$ to memory and store the optimal a^*_t action}
set $s_t = s_{t+1}$ and $a^*_t = a^*_{t+1}$
end
$t = 0$
while t<=T{Begin test procedure}
$s_{t+1} = f(a^*_t, s_t)$ {Assign new state}
Load a^*_{t+1} and $W(a^*_{t+1}, s_{t+1},)$ from memory
$h(a^*_{t+1}, s_{t+1}) = h(a, s) + 1$
{Increase the counter of the state s_{t+1} and action a_{t+1} by one. }
$\hat{W}^{test}(a^*_t, s_t) = div(a^*_t, s_t) + \beta W(a^*_{t+1}, s_{t+1})$
{Calculate the continuation value in t according to the next period's action and state. }
$W^{test}(a^*_t, s_t) = W^{test}(a^*_t, s_t) + \frac{1}{a^*_{t+1}, h(s_{t+1})}[W^{test}(a^*_t, s_t) - \hat{W}^{test}(a^*_t, s_t)]$
{Update the belief about the continuation value. Also do the procedure for the square of $W^{test}(.)$ to calculate the sampling variance.}
store $W^{test}(a^*_t, s_t)$
set $s_t = s_{t+1}$ and $a^*_t = a^*_{t+1}$
end
$Bias(s, a) = \frac{W^{test}(a,s)}{W(a,s)}^2 - Var(\frac{W^{test}(a,s)}{W(a,s)})$
{Calculate for every state and action visited on the equilibrium path a bias statistic. The variance term is used to adjust for sampling variance. }
$T = \left\| \sum_a \frac{h(a,s)}{\sum_a h(a,s)} Bias(a, s)|| \right\|_{L^2_{P(s)}}$
{The test statistic is then an L^2 norm in the bias term where $P(s)$ is a measure for the fraction of time s is visited on the equilibrium path. The test statistic measures if the stored optimal action can replicate the continuation values. }
until $T < \epsilon$ {The algorithm has converged if T is below the required precision ϵ. }

Appendix B

Appendix to Chapter 2

B.1 Formal Results and Proofs

Without loss of generality, we define the density function of academic and business skills on the unit square, i.e. $f(\alpha, \beta) \geq 0$ for $\alpha, \beta \in [0, 1]$ and zero otherwise. Furthermore, rather than treating N as the *absolute* number of PhD places like in the main text, it is convenient here to redefine it to be the number of places in the PhD programs as a fraction of the whole population. As in the main text, we compare a generic boom to a generic recession cohort, i.e. $y^{Boom} > y^{Rec}$. Furthermore, a person applies for a PhD if he has skills such that $\alpha > \beta + y$.

In order to facilitate the proofs in the following, we do three more things: First, we define different sets of applicants to keep our notation concise in the rest of this section. Second, we define conditional probabilities to be able to compare different sets with each other. Third, we show that the least able (in terms of academic skills) individual admitted into academia in a recession is academically more able than the least able individual admitted in a boom. This result is used repeatedly in the proofs of the propositions.

1. The following distinct sets of applicants are used in the proofs and illustrated in Figure B.1:

    - C(onstant) applicants, who enter academia no matter what happens in the business cycle.

$$C = \{(\alpha, \beta) | \alpha \geq \alpha^{Rec} \wedge \alpha > \beta + y^{Boom}\}$$

- B(usiness inclined), who only select themselves into academia if the business climate necessitates it.

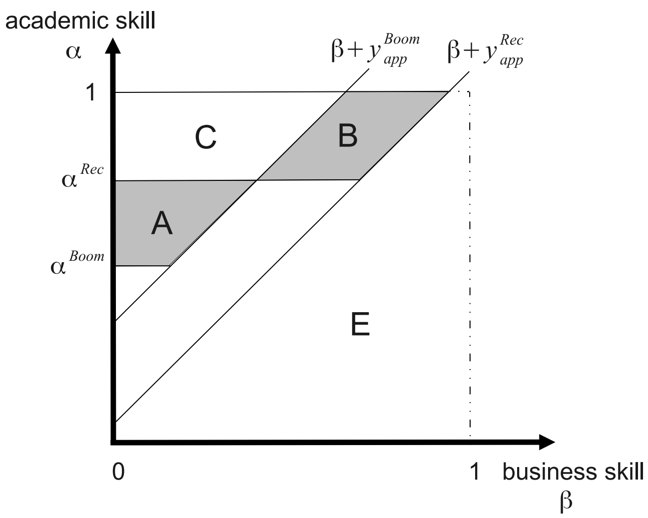
$$B = \{(\alpha, \beta) | \alpha \geq \alpha^{Rec} \wedge \beta + y^{Rec} < \alpha \leq \beta + y^{Boom}\}$$

- A(cademically inclined), who want to go to academia but only have the chance to if the group B members don't apply.

$$A = \{(\alpha, \beta) | \alpha^{Boom} \leq \alpha < \alpha^{Rec} \wedge \alpha > \beta + y^{Boom}\}$$

- E(xternals), who never go to academia.

Figure B.1: Example with a U(0,1) distribution of both skills



Note that $A \cup C$ is the boom cohort and $B \cup C$ the recession cohort. Furthermore, from our assumption that there are always more people applying for a PhD-program than there are spaces, it follows that y has an upper bound.

2. We introduce the following notation for the probability of being member of the set

X (or fulfilling the condition X) conditionally on being member of the set Y:

$$P_Y(X) = \frac{P(X \cap Y)}{P(Y)}.$$

This conditional probability is always within [0,1] and can be interpreted as the fraction of members of Y who are member of X. If the subscript Y is dropped, we refer to the fraction X compared to all potential applicants. As mentioned above, N is the the fraction of individuals actually entering the academic sector, i.e. in a recession $N = P(C \cup B)$ and in a boom $N = P(C \cup A)$.

3. We show that the cut-off value α^s is weakly higher in recession than in boom. A higher cut-off value implies that the least able (in terms of academic skills) individual admitted into academia in a recession is academically more able than the least able individual admitted in a boom.

Lemma B.1.1 $\alpha^{Boom} \leq \alpha^{Rec}$.

Proof of lemma B.1.1: Let $g_y(\alpha) := \int_0^{\alpha-y} f(\alpha, \beta)\, d\beta$ be the percentage of students with academic skill α who will apply to the PhD-program. Obviously $y^{Boom} > y^{Rec} \Rightarrow g_{y^{Boom}} \leq g_{y^{Rec}}$ as $f \geq 0$ for all (α, β). Therefore $\alpha^{Rec} \geq \alpha^{Boom}$ as the equality $\int_{\alpha^{Rec}}^1 g_{y^{Rec}}\, d\alpha = N = \int_{\alpha^{Boom}}^1 g_{y^{Boom}}\, d\alpha$ has to hold. ∎

Proof of proposition 2.2.1: : First, note that by the definition of A and B, $P_A(x \geq \alpha) = 0$ if $\alpha > \alpha^{Rec}$ and $P_B(x \geq \alpha) = 1$ if $\alpha \leq \alpha^{Rec}$. Second, as $P(A) = P(B) = N - P(C)$ it follows that $P_{A \cup C}(x \geq \alpha) \leq P_{B \cup C}(x \geq \alpha)$, which is the definition of first order stochastic dominance. As the argumentation holds analogously for the business skills, this implies a joint stochastic dominance of academic and business skills of the recession cohort compared to the boom cohort. ∎

Proof of proposition 2.2.2: In case of $y_{grad} < y^{Boom}$ some or no people in set B leave the recession cohort and nothing changes in the boom cohort. If $y_{grad} \geq y^{Boom}$, all people in B leave. All remaining members of the recession cohort (who are member of set C and may or may not leave) are a subset of the boom cohort and therefore behave alike. Note that, as P(B) = P(A) and all members of B, but potentially only some members of A, leave for $y_{grad} \geq y^{Boom}$, there are always more leavers in the recession than in the boom cohort. ∎

Proof of proposition 2.2.3: Let B' be a subset of B. We show that $C \cup B'$ first order stochastically dominates $C \cup A$ in the partial distribution of academic skill, which is the proposition for $y^{grad} < y^{Boom}$. It follows for all α that

$$P_{C \cup B'}(x \geq \alpha) = P_{C \cup B'}(C) P_C(x \geq \alpha) + P_{C \cup B'}(B') P_{B'}(x \geq \alpha),$$

and analogously $P_{C \cup A}(x \geq \alpha) = P_{C \cup A}(C) P_C(x \geq \alpha) + P_{C \cup A}(A) P_A(x \geq \alpha)$. This means that the percentage of members in C and B' who have an academic skill larger than some arbitrary α is the weighted sum of the percentage of members in C and of the percentage of members in B' who have at least such a high academic skill. The respective weights are the percentage of members of C in C union B' and the percentage of B' in C union B'. (Remember that $P_{C \cup B'}(C)$ is the percentage of members of C in the union of C and B'.)

Now one can show as in Proposition 2.2 :

- $P_{C \cup B'}(x \geq \alpha) \geq P_{C \cup B'}(C) P_C(x \geq \alpha) \geq P_{C \cup A}(C) P_C(x \geq \alpha) = P_{C \cup A}(x \geq \alpha)$ for $\alpha \geq \alpha^{Rec}$.
  The first inequality holds by the decomposition of $P_{C \cup B'}(x \geq \alpha)$ above, the second inequality holds because $P(A) = P(B)$ and the equality holds because $P_A(x \geq \alpha) = 0$ for $\alpha \geq \alpha^{Rec}$ by definition of the set A.

- $P_{C \cup B'}(x \geq \alpha) = 1 \geq P_{C \cup A}(C) \underbrace{P_C(x \geq \alpha)}_{=1} + P_{C \cup A}(A) P_A(x \geq \alpha) = P_{C \cup A}(x \geq \alpha)$ for $\alpha < \alpha^{Rec}$. The first equality holds by the definition of C and B', the first inequality by the definition of probability measures (it cannot exceed one) and the second equality holds by the definition above.

These two statements taken together prove the first order stochastic dominance in the partial distribution of the academic skill for the recession cohort compared to the boom cohort.

Note, that the same argument can be made if $y^{grad} \geq y^{Boom}$ with A' and C' being subsets of A and C, respectively, and $B' = \emptyset$. This completes the proof. ∎

For the proof of the last proposition we require one further piece of notation: Let y^{Boom}_{grad} denote the business cycle variable if there is a boom at graduation and y^{Rec}_{grad} if there is a recession at graduation. Note that $y^{Boom}_{grad} > y^{Rec}_{grad}$ and therefore $w^B_{Boom} = \beta + y^{Boom}_{grad} > w^B_{Rec} = \beta + y^{Rec}_{grad}$.

Proof of proposition 2.2.4: The PhD students with $\{\alpha, \beta) | \beta + y^{Rec}_{grad} < \alpha \leq \beta + y^{Boom}_{grad}\}$ leave academia when there is a boom instead of a recession at graduation. As this set can be non-empty, weakly more students leave in a boom than in a recession. ∎

B.2 Data Collection and Processing

This section explains in detail the data collection and processing procedure. Specifically, we explain how the sample of economists and their background variables were acquired and how we computed measures of publication success. An overview of the data sources is given in Table B.1.

All employed programs are available from the authors upon request.

B.2.1 Database for Economics PhD Graduates

To construct our sample of economists, we downloaded the PDF version of all issues of the American Economics Association's (AEA) yearly "List of Doctoral Dissertations in Economics" from JSTOR, an online journal repository, from 1950 to 2006. The list was published in the Papers and Proceedings issue of the "American Economic Review" until 1986 and in the "Journal of Economic Literature" thereafter. The AEA "List of Doctoral Dissertations in Economics" specifies doctoral degrees conferred by U.S. and Canadian universities for every year since 1906. The name of the degree recipients and the year of

Table B.1: Data sources

Variable	Description	Source
Personal information of graduates	Name, University and Graduation year	AEA "List of Doctoral Dissertations in Economics" of 1955 to 2004
Faculty membership	Faculty directory of (mainly American) Economics, Business and Finance departments by John R. Hasselback	"Faculty Directories," James R. Hasselback, accessed 2011-02-07, `http://www.facultydirectories.com/`
Membership in the AEA	Membership data of the American Economic Association in 1970, 1974, 1981, 1985, 1989, 1993, 1997, 2003 and 2007	Supplement to the Papers and Proceedings Issue in the respective year digitalized by JSTOR
University ranking	Tier of a university according to the National Research Council	"The American Economic Association Graduate Study in Economics Web Pages," accessed 2011-02-08, `http://www.vanderbilt.edu/AEA/gradstudents/`
Publication records	Publications in 74 journals listed in the JSTOR online repository, from 1955 to 2004	"JSTOR Data for Research," last accessed 2011-02-07, `http://dfr.jstor.org/`.
Journal rankings	Citation ranking of journals in Economics, Business and Finance from 1950 to 2000	Laband and Piette (1994), Kalaitzidakis, Mamuneas, and Stengos (2003), Kim, Morse, and Zingales (2006) and "IDEAS/RePEc Recursive Discounted Impact Factors for Journals," last accessed 2011-02-07, `ideas.repec.org/`
Measure of the business cycle	seasonally adjusted change in unemployment, unemployment levels and GDP growth from 1949 to 1994	Thomson Reuters Datastream
Recession Indicators	NBER recesssion indicators from 1949 to 1994	"The NBER's Business Cycle Dating Committee," last accessed 2011-08-09 `http://www.nber.org/cycles/recessions.html`
Duration of the PhD	Median years between registration and graduation from the PhD for 1977, 1986, 1996, 1997, 2001	National Science Foundation, Stock and Siegfried (2006), Hansen (1991)
Number of Graduates (NSF list)	Number of admitted and graduating PhDs according to the "NSF Survey of Earned Doctorates/Doctorate Records File" of the National Science Foundation	"WebCASPAR Integrated Science and Engineering Resource Data System - NSF Survey of Earned Doctorates/Doctorate Records File," National Science Foundation, last accessed 2011-02-08, `https://webcaspar.nsf.gov/`
econphd.net ranking	University ranking according to econphd.net	"Rankings." last accessed 2011-02-07, `http://econphd.econwiki.com/rankings.htm`

graduation is provided to the American Economic Association by each degree granting university.

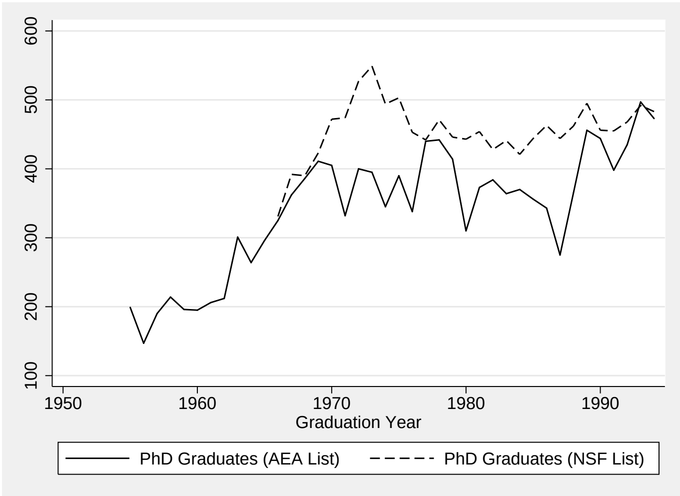
To convert the available PDF version of the AEA doctoral list into a text file, we used the optical character recognition (OCR) program included in the Adobe Acrobat 8 Professional Suite. The quality of the Adobe technology was best compared to several other programs we have tried. This read-in procedure worked well in general and it accelerated the compilation of the dataset but, as every automated procedure, it also entailed several problems and imperfections. In some cases the original PDFs were scans of old printed versions and, therefore, due to the quality of the source files, the character recognition of some records was erroneous.

Particularly, there were problems with the letter “r”, which was mistaken as “n” or “i” from time to time. “O” was sometimes read as zero, “H” as “II”, and “M” as “IVI”. Also, dots sometimes were not readily recognized. We were able to correct faulty university names and graduation years because the set of those is finite. For example, we always replaced “IVIichigan” by “Michigan”. Due to limited resources, we were not able to correct all errors in the name spellings. We decided to drop observations with names that contain characters or sequences of characters that are highly unlikely to be correct and thus had no chance to return accurate results in a query for publications in JSTOR.

In the next step we used regular expressions, a way to assign database fields for some string combinations, to convert the text file into a database format. The data structure of the AEA doctoral list is quite regular so this procedure worked reasonably well. On some instances, the employed regular expression was not able to determine the end of a data entry due to missing dots. However, this did not happen systematically.

As mentioned above, the read-in procedure delivered some faulty results. We believe that all these errors are orthogonal to our effect of interest and that they thus just add noise to our data. Nevertheless we want to test how many read in names are faulty: To do this, we first correct some years (perfectly) by hand and compare the resulting “complete” graduation numbers to graduation numbers published by the National Science Foundation (NSF). We find that the “complete” graduation numbers from the AEA list are about 90% of the NSF graduation numbers. Then, for every year, we compare the fraction of the “not corrected” number in our database to the number in the NSF data. This fraction fluctuates from 0.6 to 0.9, which suggests that in the worst case we lose about 40% of graduates due to the imperfect automated read-in procedure. In Figure B.2 the number of NSF graduates and of graduates from our AEA list are plotted over time.

Figure B.2: Number of graduates according to the NSF and the AEA list over time



In the next step we supplemented the information with the respective tier of the degree granting university according to the National Research Council. The National Research Council rankings of economics graduate programs divide programs into tiers.

We dropped all graduates from universities not represented in this NRC ranking because we are not sure if the application process and research environment in these institutions are comparable to the universities in the first three tiers. In order to ensure robustness we also considered the Top 30 US universities according to the econphd.net ranking (as in Oyer 2006), which yielded the same results. The econphd.net ranking is available online on `http://econphd.econwiki.com/rankings.htm` (last accessed 2011-02-07).

B.2.2 Indicator for Being an Academic

To complete the person-specific background variables, we add an indicator if a PhD graduate became an “academic” later on. We define “academics” according to the three concepts explained in section 2.4.2 - those who are faculty members, those who are faculty members or AEA members, and those who publish at least one ranked article. While the last concept derives from our publication measure explained in the next subsection, the data collection for the first two measures is described here.

Data about faculty membership in US economics, business or finance departments is acquired from the webpage of James R. Hasselback from the University of West Florida who regularly compiles U.S. faculty directories.[1] Unfortunately, there is no comprehensive database about faculty members of non-US universities, researchers in other US university departments, like law and agriculture, and academics in institutions other than universities, e.g. World Bank researchers. To construct a proxy for belonging to these groups, we analyze the membership records of American Economic Association. We think that the likelihood of being an AEA member is higher, if the graduate decided to become a member of the academic community.[2]

The faculty listings and the AEA membership directories are only available as PDF. Therefore, we again use the Adobe OCR program and regular expressions to translate them into a database file. We use Apache Lucene, an information retrieval library, to match the data on graduates with the faculty listing and the AEA membership. This is necessary because some students drop their second name over the years or abbreviate it. As is common for search engines, Lucene employs a scoring algorithm based on the similarity of the name of the graduate and the name in the documents.[3] For the faculty directory (and a sample of the AEA members), we checked the matches found by hand to ensure accuracy.

B.2.3 Publications

After compiling the database of graduates, we used a program to match each entry with its publication record in JSTOR. To do this, we use the newly available XML application

[1] "Faculty Directories," James R. Hasselback, accessed 2011-02-07, `http://www.facultydirectories.com/`

[2] Specifically, we take the AEA directory of members in 1970, 1974, 1981, 1985, 1989, 1993, 1997, 2003 and 2007.

[3] For a discussion of the scoring algorithm of Lucene please refer to "org.apache.lucene.search - Class similarity," last accessed 2011-02-07, `http://lucene.apache.org/java/2_4_0/api/org/apache/lucene/search/Similarity.html`.

programming interface of JSTOR, called “Data for Research” (DfR).[4] Specifically, we entered the names and given names of all researchers contained in our database and extracted all recorded publications with journal title, number of pages and the number and identity of coauthors in the first 10 years after their graduation. To be as specific as possible, we restricted our search to articles classified as “research articles” published in English language in the fields of economics, business and finance.

The restriction to articles published ten years after graduation (as in Oyer 2006), has three reasons: First, it improves the specificity of the data processing, because economists with the same name who were born in different decades are not merged but kept as different persons. Second, the quality of an economist is arguably best revealed in the first decade after PhD graduation. Academic researchers are highly motivated (incentivized) in this period because their tenure decision depends on the publication record of these first years. Finally, graduates from more recent years would be disadvantaged if we did not restrict the time frame. Currently JSTOR provides full publication data up to the year 2004, so the last individuals we can rightfully analyze following our ten year requirement are those who graduated in 1994.

B.2.4 Ranking Methods and Interpretation of the Productivity Measure

To measure the productivity of each individual on a cardinal scale, we have to value each publication in the record. This poses three challenges: First, the relative weight of an article in a certain journal compared to an article in another journal is a constant matter of discussion in the profession. Second, comparing the value of publications over the decades is difficult because the relative impact of economics journals has changed substantially over time (Kim, Morse, and Zingales 2006). Third, by summing up the contributions of different publications over ten years, the resulting number becomes hard to interpret. We adress these challenges by showing the robustness of our result for several ranking

[4]JSTOR (`http://www.jstor.org/`) (last accessed 2011-02-07) is a leading repository for archiving academic journals which contains (in July 2010) around 3.1 Million research articles for all sciences with the first article published in 1545. For the DfR interface please refer to “JSTOR Data for Research,” last accessed 2011-02-07,`http://dfr.jstor.org/`.

methodologies with different strengths and weaknesses below.

Our preferred method is a citation ranking based on the methodology of Laband and Piette (1994). The authors of this study use the citations to articles in a particular journal (excluding self-citations) as a measure of its quality or impact. Their paper presents the journal impact factors from the 1960s to the 1980s, while Kalaitzidakis, Mamuneas, and Stengos (2003) use the same method for the 1990s and the recursive discounted ranking on the ideas.org ranking page delivers us the impact factors for the 2000s.[5] For the 1950s we were not able to find a journal ranking and thus decided to extrapolate our 1960s ranking back to articles published in the 1950s. In total, we collect impact factors of 74 ranked journals in economics, business and finance for five decades. Table B.2 provides an overview of the dynamic ranking of the top forty journals used in this study.

The outcome measure in Table B.2 is denominated in publication points. The best journal in each decade receives 100 points and all others are scaled accordingly. For example, in the 1960s, a single-authored Econometrica article is worth 46.6 points while it is worth 96.8 points in the 1990s. The impact of the American Economic Review (AER) changed even more dramatically: It has been the leading journal in the 1960s and 1990s with 93.3 and 100 respectively. In contrast, in the 1970s, 1980s and 2000s it was "only" a top tier journal with 30-40 publication points. Consequently, when trying to interpret our results above in terms of actual papers, we need to mention the journal and the decade (e.g. "one third of an AER article in the 1990s").

Reassuringly, we show in section B.6.1 that our results are extremely robust to using several other intuitive productivity measures: publication points assigned according to the currently very popular h-index, raw counts of articles written, and, most notably, counts of articles in the five top economics journals (as in Oyer 2006) plus the Journal of Finance.

[5]"IDEAS/RePEc Recursive Discounted Impact Factors for Journals," last accessed 2011-02-07, `http://ideas.repec.org/top/top.journals.rdiscount.html`. Note, that this ranking is updated continuously and thus its online version at the time of reading is not exactly the same as the one we use.

Table B.2: Ranking of journals in different decades.

Rank	Journal (ordered by 2000 rank)	1960	1970	1980	1990	2000
1	The Quarterly Journal of Economics	65.6	16.2	41.6	58.1	100
2	Econometrica	46.6	31.6	78.4	96.8	68.7
3	Journal of Economic Literature	-	100	100	18.8	63.5
4	The Review of Economic Studies	100	30.7	40.7	45.2	54.3
5	Brookings Papers on Economic Activity	-	96.9	15.9	0.7	51.5
6	The Journal of Political Economy	63.5	59.1	63	65.2	49.8
7	Economic Policy	-	-	-	-	45.7
8	Journal of Labor Economics	-	-	15.4	12.8	45.5
9	The American Economic Review	93.3	34.5	40.2	100	39.9
10	The Journal of Economic Perspectives	-	-	23.3	34.3	39.8
11	The Review of Financial Studies	-	-	-	-	39.2
12	Journal of the European Economic Association	-	-	-	-	38.6
13	The RAND Journal of Economics (Bell Journal of Economics)	-	39.5	40.2	11.4	38.2
14	The Journal of Finance	37.8	14.6	34.1	34.1	31.1
15	The Review of Economics and Statistics	59.8	12.4	6.5	28	21.7
16	Journal of Business & Economic Statistics	-	-	7.9	38.4	20.8
17	The Economic Journal	47.5	28	23.9	20.7	20.5
18	Journal of Applied Econometrics	-	-	-	16.6	19.1
19	Journal of Money, Credit and Banking		18.5	22.1	18.6	18.6
20	The World Bank Economic Review	-	-	-	5.7	18.5
21	International Economic Review	35.1	19	12.3	23	18.4
22	IMF Staff Papers	-	-	-	5.1	18.3
23	Journal of Law, Economics, & Organization	-	-	-	4.1	16.1
24	Journal of Law and Economics	51.8	43.3	33.1	3.9	14.1
25	The Journal of Human Resources	-	13.6	4.6	21.3	13.4
26	Journal of Population Economics	-	-	-	2.41	10.6
27	The Scandinavian Journal of Economics	2.5	7.1	2.1	10.7	9.2
28	The Journal of Business		18.5	37.4	8.7	8.7
29	The Journal of Industrial Economics	14.9	16.4	16	3.85	8.7
30	The World Bank Research Observer	-	-	-	0.9	8.5
31	The Journal of Financial and Quant. Analysis	-	10.8	20	2.1	7.9
32	Oxford Economic Papers	35.2	16.8	25	3.7	7.9
33	Economica	20.7	36.2	4.1	4.5	7.2
34	Economic Theory	-	-	-	22.4	6.8
35	Industrial and Labor Relations Review	17	18.8	23.4	-	6.1
36	Econometric Theory	-	-	3.3	45.8	5.9
37	The Canadian Journal of Economics	-	11.8	10.2	5.09	5.6
38	The Journal of Legal Studies	-	-	51.6	5.4	5.4
39	Financial Management	-	-	-	-	5.1
40	Journal of Accounting Research	-	-	-	-	4.2

Note.—These are the first 40 out of 74 journals. The rankings for the 1960s, 1970s and 1980s are taken from Laband and Piette (1994) and the ranking for the 1990s is from Kalaitzidakis, Mamuneas, and Stengos (2003). For the 2000s, we normalize the current discounted recursive impact factors ranking from the IDEAS RePEc website (`http://ideas.repec.org/top/top.journals.rdiscount.html`, last accessed 2011-02-07) to make it comparable to the other rankings.

B.2.5 Imputing the PhD Entry Date

Our data only contains the graduation date of each PhD student. Therefore we have to impute the PhD entry date to relate the macroeconomic variation at application to each PhD's lifetime research productivity.

In our main analysis we substract six years, the median duration of a PhD, from the graduation date and then use our measure of the business cycle at this date as macroeconomic variation at entry. The median duration of a PhD stayed almost constant around five to six years since the 1970s according to the data assembled in Table B.3. Unfortunately we could not find evidence for the 1950s and 1960s.

Table B.3: Duration of a PhD

Year	1977	1986	1996	1997	2001
	5.7	6.3	5.3	5.25	5.5
	Median years of registered time to PhD	Median years of registered time to PhD	Time to degree	median time-to-degree	Time to degree
Source	Hansen (1991)	Hansen (1991)	NSF*	Stock, Siegfried, and Finegan (2011)	NSF*

Note.—*NSF duration data includes masters degrees, therefore we subtract 1.5 years.

Using the median duration might be questionable, because there is considerable variation in the length of PhD across individuals. For the 1997 graduating cohort, Stock, Siegfried, and Finegan (2011) documented the distribution of completion times of those PhDs who graduated within eight years: 14 percent graduated within four years, 25 percent within five, 28 percent within six, 13 percent within seven, and 20 percent within eight or more years. This substantial variability (standard deviation of 1.32 years) in the time to graduation adds measurement error to our business cycle variation at application to the PhD.

We therefore repeat our main analysis with a weighted average of the respective business cycle measure at application according to the distribution of completion times for the year 1997. The results are reported in Table B.4. Note that the regressors have a much lower variation because we compute moving averages here. Thus, if we want to compare the results in Table B.4 to our main regressions in Table 2.2, we need to divide the point estimates for unemployment levels by about 1.2 and for the other regressors by about 2.6. Nonetheless, the mean estimates in Table B.4 are larger and more significant than in the main text. This suggests that the latter might be downward biased due to measurement error.

Table B.4: The regression results using "weighted average" of PhD entry

	Productivity	Academic	Productivity
Unempl Change (Application)	4.05**	-5.99***	10.18***
	(1.71)	(1.52)	(2.89)
Unempl Change (Graduation)	2.33***	1.26***	2.93**
	(0.65)	(0.45)	(1.19)
Unemployment (Application)	2.37**	-1.18	4.54***
	(0.96)	(1.44)	(1.64)
Unemployment (Graduation)	1.90***	-0.36	3.43***
	(0.66)	(0.67)	(1.17)
GDP Growth (Application)	-1.33	2.55***	-3.41**
	(0.85)	(0.58)	(1.29)
GDP Growth (Graduation)	-0.70**	-0.38	-0.80
	(0.34)	(0.25)	(0.60)
Recession (Application)	15.16**	-14.49**	34.26***
	(6.41)	(6.03)	(10.35)
Recession (Graduation)	5.33***	1.32	7.03**
	(1.84)	(1.25)	(2.98)
Subsample	All	All	Academic
University-Decade Dummies	Yes	Yes	Yes
Observations	1023	1023	1005

Note.—Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Cyclicality of Academia versus Business

In our theory section we assume that compensation in the academic sector is less cyclical than in the business sector. In this section we provide evidence that this is a reasonable assumption. We focus on the cyclicality in the attractiveness of academia versus business only at graduation from the PhD. At application, graduate school seems to be clearly less cyclical than business—as was illustrated by the flood of applications to masters and PhD programs during the crisis of 2008/09 (see Bedard and Herman (2008) for systematic evidence for the period from 1993 to 2001).

Ideally, we would like to compare the variability of the total expected lifetime compensation (consisting of pecuniary and non-pecuniary benefits) for the two sectors over the business cycle. Unfortunately, this is not possible for two reasons: First, (variabilities in) non-pecuniary benefits are hard to observe and difficult to compare across jobs. Second, even the monetary component of compensation is difficult to obtain or to approximate. Wage data for the business sector is not consistently available on a yearly basis over longer time periods for Economics PhDs.[6] Furthermore, even if wages were available, they are a result of the selection process we are trying to explain (e.g. Solon, Barsky, and Parker 1994). Consequently, it would be sensible to focus on wage offers in both sectors as used by Scott Stern in a similar setting (Stern 2004). Unfortunately we are unable to find such data.

In the following we approximate the relative attractiveness of the academic sector by comparing the number of academic versus non-academic job offers for economists over the business cycle.[7] The underlying assumption is that an additional vacancy (weakly) increases a sectors' relative attractiveness. The number of new jobs is published annually in the Job Openings for Economists (JOE) director's report in the American Economic Review's Papers and Proceedings issue in May. The academic and non-academic openings are broken up by new and total jobs and listings (employers). Since we want to approximate the decision situation of a graduate in year t during his job market year, we focus on the sum of new job offers from August in year t-1 to July in year t.[8] [9]

Figure B.3 plots the yearly sums of job offers over the years from 1977 to 2010. Academic jobs are displayed in the upper-left panel and non-academic jobs in the upper right panel. In the lower panel the overall number of job offers is plotted together with the number of academic per non-academic jobs. Academic and non-academic jobs move together in lockstep, which shows that the academic sector is in fact quite cyclical. However, the relative number of academic jobs to non-academic jobs appears to be countercyclical: even

[6] We do not have access to any employer-employee matched dataset as in Oreopoulos, von Wachter, and Heisz (2011).

[7] Oyer (2006) uses the academic job offers as a measure of demand for economists in academia.

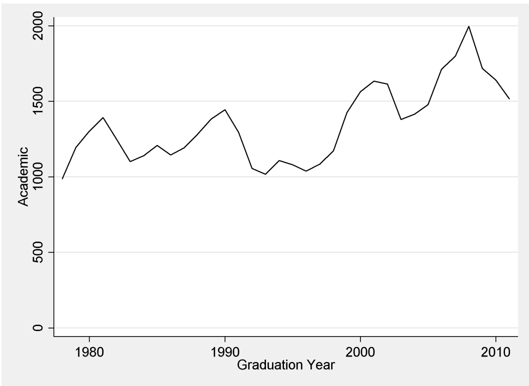
[8] The seasonality of job offers within a given year follows the job market for each cohort, especially for academic jobs. Job offers reach their trough in June after which they start rising. They literally jump up in October and stay high during fall after which they decline. We therefore define each yearly sum of job offers according to job market years instead of calender years.

[9] We do not use total jobs as we do not know if these jobs are double counted in several months.

when the number of academic jobs rise, the number of non-academic jobs rises relatively more. The reverse is true in recessions. Therefore, graduates have relatively more business jobs (compared to academic jobs) to chose from in booms than in recessions.

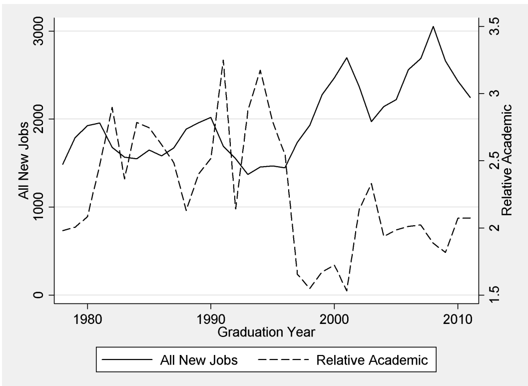
Figure B.3: Academic and non-academic job offers over time

(a) Academic Job Offers



(b) Non-Academic Job Offers

(c) Overall Job and Relative Academic Job Offers



To formally test if business jobs are indeed more pro-cyclical than academic jobs, we estimate the following system of equations

$$\log(\#\text{ Academic jobs})_t = \beta_{Academic} \cdot \mathrm{y}_t + \delta \cdot \text{controls} + \epsilon_t \tag{B.1}$$

$$\log(\#\text{ Non-Academic jobs})_t = \beta_{Non-Academic} \cdot \mathrm{y}_t + \delta \cdot \text{controls} + \epsilon_t \tag{B.2}$$

where the dependent variables are the log of the number of new academic and non-academic jobs, respectively, and y_t is a measure of the business cycle. Then we test if the business cycle has a larger influence on the number of non-academic jobs than on the number of academic jobs, i.e. if $\beta_{Non-Academic}$ is larger than $\beta_{Academic}$ in absolute values.

The regressor y_t is one of four business cycle measures: recession indicators, unemployment levels and changes, and the log of GDP. The business cycle variables are measured in October in the year before graduation when the mode of job offers for each cohort comes in. The controls include dummies for the switch from seven to ten monthly reports of job offers in 1999 and the JOE going online in 1995 interacted with a linear time trend. We estimate the outlined specification in levels with a time trend and in first differences. We do this to control for the potential trend or the non-stationarity of dependent and independent variables.

Table B.5: Differing cyclicality of academic and non-academic jobs—levels

	log(# Academic Jobs)	log(# Non-Academic Jobs)	z-Value
Unemployment	-0.05***	-0.09***	2.23**
	(0.01)	(0.02)	
GDP	1.96***	4.06***	-2.32***
	(0.62)	(1.08)	
Recession	0.02	-0.08	1.57*
	(0.05)	(0.09)	

Note.—Standard errors in parentheses. The z-Value is the test statistic of a one-sided test for $|\beta_{Non-Academic}| > |\beta_{Academic}|$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5 and Table B.6 report the results of these regressions in levels and in first differences. Unemployment and GDP are significantly related to academic and non-academic job offers in the way that we would have expected from figure B.3. Moreover, in levels, the relationship is significantly stronger for non-academic than for academic jobs. For example, a one percentage point increase in unemployment is approximately associated

Table B.6: Differing cyclicality of academic and non-academic jobs—first differences

	FD log(# Academic Jobs)	FD log(# Non-Academic Jobs)	z-Value
Unempl Change	-0.05***	-0.06**	0.58
	(0.01)	(0.03)	
GDP Growth	2.57***	3.09**	-0.39
	(0.62)	(1.34)	
FD Recession	-0.00	-0.09	1.66**
	(0.03)	(0.06)	

Note.—Standard errors in parentheses. The z-Value is the test statistic for a one-sided test for $|\beta_{Non-Academic}| > |\beta_{Academic}|$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

with a nine percent decrease in the number of non-academic jobs and "only" a five percent decrease in academic jobs. Recession indicators do not work that well. Although they are significantly different from each other in the right direction, the estimated coefficients are not significantly different from zero on their own. These results are qualitatively robust to using total job openings instead of focusing on new ones, variations in the control variables (e.g. including quadratic time trends), and a sensible alternative timing of the business cycle variables.

Overall, we would state that we find reasonable support for the assumption that the academic sector is less cyclical than the non-academic sector in the job openings for economists. We think this is some prima facie evidence for our assumption that in downturns the academic sector becomes relatively more attractive as an employer compared to the business sector. Moreover, we think that the above exercise is conservative because of the following reason: the (variation in the) number of job offers is unlikely to approximate well the (variation in) non-pecuniary benefits, which are substantial and probably stable in research related jobs (see Stern 2004). Thus, total compensation in the academic sector might be less cyclical than indicated by the number of jobs openings.

B.4 The Relationship Between (Potentially) Confounding Factors and the Business Cycle

This section addresses potential concerns about factors that might confound our results and analyzes possible impacts on our estimates. In the following we address concerns about the size of the entry and exit cohort, the attrition rate and the timing of graduation. Lastly, we adress a potential correlation of the business cycle at application and graduation.

In order to do this, we calculate the number of graduates from our dataset (in the following listed as "# of graduates (AEA)") and match it with the business cycle at application and at graduation. For conciseness, we focus on unemployment change as our preferred measure for the business cycle. Then, we supplement this data with data from the National

Science Foundation's "Survey of Earned Doctorates".[10] From there we obtain the number of PhD entrants and graduates for our top 30 universities since 1977. Using this data, we are able to estimate the attrition (dropout) rate of each cohort as the difference of the number of entrants minus graduates divided by the number of entrants. We report the partial correlation coefficient of unemployment change at application and at graduation with application and graduation numbers in Table B.7. In order to obtain the correct standard errors we aggregate the data to yearly averages. To keep this section concise, we only report for unemployment change and not for all four business cycle measures. These correlation tables are available on request from the authors.

[10]This survey is publicly available through the WebCASPAR Interface: "WebCASPAR Integrated Science and Engineering Resource Data System - NSF Survey of Earned Doctorates/Doctorate Records File," National Science Foundation, last accessed 2011-02-08, `https://webcaspar.nsf.gov/`.

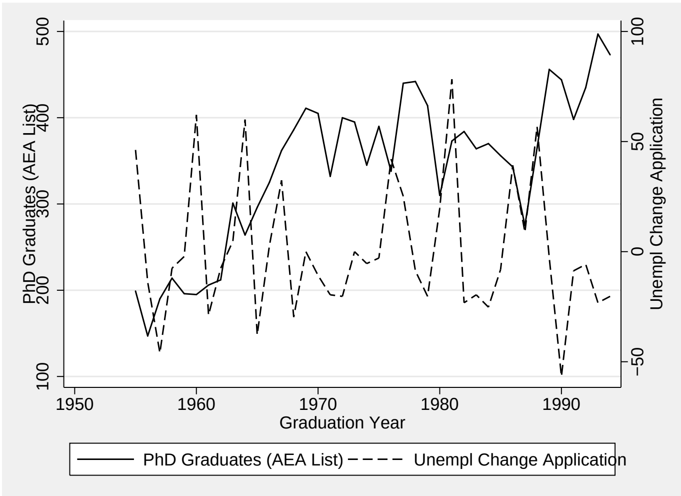
Table B.7: Correlation of unemployment change with attrition, the number of entrants and graduates (year level)

	Unempl Change (Grad.)	Unempl Change (App.)	# Graduates (AEA)	# Graduates (NSF)	# Entrants (NSF)	Attrition (NSF)
Unempl Change (Grad.)	1.00					
Unempl Change (App.)	-0.13	1.00				
	(0.42)					
# Graduates (AEA)	0.02	-0.17	1.00			
	(0.91)	(0.30)				
# Graduates (NSF)	0.15	-0.08	0.35*	1.00		
	(0.44)	(0.69)	(0.06)			
# Entrants (NSF)	-0.08	0.08	0.14	-0.02	1.00	
	(0.70)	(0.67)	(0.47)	(0.91)		
Attrition (NSF)	0.20	0.39	-0.40	-0.32	0.25	1.00
	(0.43)	(0.12)	(0.12)	(0.12)	(0.24)	
Observations	53					

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first concern one might have is that the number of students admitted to the PhD systematically increases (decreases) in recessions. Within the framework of our model, this would weaken (strengthen) the selection effect at application. The estimated coefficient of unemployment change at application might then be underestimated (overestimated). According to Table B.7, we cannot reject that the relation of the number of entrants to the PhD and the change in unemployment differs from zero on conventional significance levels (p-value of 67.5%). In Figure B.4 the number of graduates in our data and the unemployment change at application are depicted.

Figure B.4: Number of graduates and unemployment change at application



Second, one might be concerned that the attrition (or dropout) rate during the program may systematically differ between recession and boom cohorts. On the one hand, some business-inclined individuals who entered the PhD in order to bridge a recession might return to the private sector before they actually obtain the PhD. If this were the case, we would underestimate the effect of unemployment change at application on economists' career decision after the PhD (the "academic" variable). The reason is that many of those who would want to switch would have already done so before we consider them in our population of graduates. On the other hand, there might be a higher dropout rate for the boom cohort because its individuals are of lower academic quality. In this case, our parameters would underestimate the effect of unemployment change at application on the performance of graduates and academics. According to the correlation Table B.7, our estimate of the attrition rate is not significantly correlated with unemployment change at application or graduation.

Third, PhDs might time their graduation in order to circumvent entering the private or the academic job market during a time of recession.[11] The effect of such a graduation timing on our parameter estimates would depend on whether the high- or the low skilled bring their graduation date forward (or delay it). For example, if in a recession students with low academic talent delay their end of the PhD, we overestimate the effect on productivity at graduation, but underestimate the effect on becoming an academic. Table B.7 reports the correlation of graduation numbers and unemployment change according to the NSF data and the AEA doctoral listings, respectively. Reassuringly, graduation numbers seem not to be at all related to the state of the business cycle.

Finally, a last concern might be that, contrary to our assumption in the model, the business cycle is systematically correlated with itself in the six years between a cohort's application and graduation. Table B.8 reports this and the contemporaneous correlation exemplary for unemployment change and GDP growth. The correlation table with unemployment levels and recession indicators are available on request from the authors. Unsurprisingly both measures are strongly contemporaneously related. However, there is no significant correlation, neither of unemployment change nor GDP change, between the time of application and graduation. If at all, there may be a very slightly reversing relationship over the six years. This could imply that we potentially underestimate the effect of the business cycle on academic performance because a recession cohort at graduation is more likely a boom cohort at application (and thus is inherently not as able) and vice versa for a boom cohort at graduation. For the same reason we might in this case overestimate the effect of the business cycle on the career decision (i.e. the academic variable) at application and at graduation.

[11] In Appendix B.3 we document that also academic job offers decline during recession.

Table B.8: Correlation of unemployment change and GDP change at application and at graduation (university-year level)

	Unempl Change (App.)	Unempl Change (Grad.)	GDP Growth (App.)	GDP Growth (Grad.)
Unempl Change (App.)	1.00			
Unempl Change (Grad.)	-0.15	1.00		
	(0.27)			
GDP Growth (App.)	-0.79***	0.16	1.00	
	(0.00)	(0.25)		
GDP Growth (Grad.)	0.13	-0.86***	-0.11	1.00
	(0.34)	(0.00)	(0.41)	
Observations	57			

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Supporting Evidence for the Selection Channel

In the theory section of the main text we hypothesize that during downturns more individuals want to enter academia and, due to a fixed number of open spaces at entry to the PhD, only a favorable selection with superior ability is admitted. Unfortunately, however, we see ourselves unable to provide direct evidence for the selection mechanism at work. This is for the following reason:

In order to gather evidence, we were looking for data that provides observable ex ante characteristics of the students admitted to the PhD programs which we could then relate to the state of the business cycle. We obtained Graduate Record Examination (GRE) scores for a non-US PhD program that is comparable to a tier two school. The GRE consists of three sections: quantitative, verbal and analytical writing. In all universities, GRE scores are considered an obligatory part of the application documents and it is generally agreed that it is almost exclusively the quantitative section that matters for admission. For this reason, our GRE scores proved to be uninformative. We found that, independently of the state of the business cycle, virtually everyone accepted to the PhD as well as most applicants had the highest possible mark (800 points) in the quantitative section.

In general, we are very skeptical that easily observable ex ante characteristics, such as GRE data or undergraduate GPAs, of applicants or entrants would be informative about the selection into the programs because many successful and unsuccessful applicants do not differ in these dimensions. The truly informative quality differences of applicants and entrants are most likely to be more subtly hidden in “softer” information such as reference letters, research assistantships and types of courses taken during the undergraduate degree. This kind of information is very hard to obtain and to process in an objective way.

Although we are unable to present direct evidence for our hypothesized channel, Kelly Bedard and Douglas Herman published a study in the Economics of Education Review (2008) that documents supporting evidence for our main selection channel. They use data on recently graduated science and engineering Bachelor and Master students from

1990 to 2000 which is provided in the 1993 to 2001 National Survey of Recent College Graduates (NSRCG). Exploiting the variation in state-level unemployment rates, Bedard and Herman find that male PhD enrollment is counter-cyclical and the counter-cyclicality is driven by students with a high GPA in the hard sciences.[12] They state that the unemployment rate responses for this group are fairly precisely estimated and that their estimates imply a one-percentage point increase in the unemployment rate increases "high GPA" male Ph.D. enrollment by 0.356 percentage points.

In another paper, Fougere and Pouget (2003) find that the applications per spaces ratio in the French public sector rises strongly in economically hard times. Unfortunately they do not provide a quality measure of French public sector workers.

B.6 Robustness Checks

In this section we show that our results are robust when we use several different measurement concepts for publication productivity. We also consider briefly the subsample of graduates from the elite tier one institutions and productivity of academics selected under different criteria for becoming an academic.

B.6.1 Alternative Measures for Productivity

One might be concerned that our dynamic productivity measure does not properly capture the actual achievements of an academic. We consider three alternative measures of academic productivity in Table B.9: the number of top journal articles, the h-value and the raw number of articles. We classify articles in the "Econometrica", "The American Economic Review", "The Quarterly Journal of Economics", "The Review of Economic Studies", "The Journal of Political Economy" and "The Journal of Finance" as top journal articles. The h-index (Hirsch index or Hirsch number) is a currently very popular

[12] They look at entry into all PhD programs in terms of quality and subject and not only the top 30 economics programs. Therefore, quantity constraints at entry to the PhD should matter much less and it is not surprising that they not only find the expected quality differences of entrants with respect to the business cycle, but also quantity differences. Moreover, it is also not surprising that GPAs matter (more strongly) for engineering and science majors and for a broader range of graduate schools than just the top 30 departments.

measure based on citations and number of articles. An economist has index h if h of his N papers have at least h citations each, and the other N - h papers have at most h citations each. The last measure is the raw number of articles written as recorded in JSTOR. In Table B.9 we report the results for these three alternative productivity measures for the full and the academic subsample. All mean estimates for every business cycle measure point in the same direction as the dynamic performance measure in the main text and as the selection theory predicts. The only exceptions are the estimated coefficients for the recession indicator for the full sample at application but in fact the theory makes no prediction on the effect of the business cycle at application on productivity for all PhDs. Furthermore, in many cases the coefficients are statistically significant at conventional levels. Thus, our results appear largely robust to the use of different productivity measures.

Table B.9: Alternative productivity measures

	Top Five	h-index	# of Articles	Top Five	h-index	# of Articles
Unempl Change (Application)	1.55	1.17	1.23	3.53**	3.16**	5.68
	(1.00)	(1.11)	(3.21)	(1.35)	(1.56)	(4.75)
Unempl Change (Graduation)	3.97***	3.98***	5.02**	4.97***	4.84***	4.67
	(0.90)	(0.87)	(2.17)	(1.37)	(1.55)	(4.41)
Unemployment (Application)	0.66	1.02	3.40	1.98	2.59	7.75
	(1.09)	(1.14)	(2.77)	(1.75)	(1.90)	(4.95)
Unemployment (Graduation)	0.80	1.27	2.30	1.68	2.53	5.54
	(1.13)	(1.15)	(2.64)	(1.66)	(1.75)	(4.28)
GDP Growth (Application)	-0.60	-0.47	-0.46	-1.50**	-1.36*	-2.63
	(0.44)	(0.48)	(1.40)	(0.61)	(0.69)	(2.17)
GDP Growth (Graduation)	-1.28**	-1.24**	-1.22	-1.54**	-1.37*	-0.85
	(0.48)	(0.48)	(1.16)	(0.71)	(0.78)	(2.11)
Recession (Application)	-0.51	-0.60	-1.39	1.88	2.10	5.44
	(3.45)	(3.51)	(8.58)	(5.00)	(5.06)	(12.51)
Recession (Graduation)	6.30**	6.60**	7.12	7.01	7.26	4.62
	(2.82)	(2.82)	(6.13)	(4.45)	(4.86)	(11.27)
Subsample	All	All	All	Academic	Academic	Academic
Univ-Decade Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1068	1068	1068	1047	1047	1047

Note.—Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.6.2 The Tier 1 Subsample

In this section we consider the subsample of economists who graduated from the elite tier 1 schools and repeat all our regressions for these highly skilled individuals. According to Table B.10, the magnitude of the effects appears to be larger in all considered dimensions. The estimated coefficients are in some specification more, and in some specification less, significant than in the main text. Taken together, the results for the Tier 1 graduates support our findings in the main text.

Table B.10: Main regression results (Tier 1)

	Productivity	Academic	Productivity
Unempl Change (Application)	5.39**	-1.72***	9.86***
	(2.12)	(0.58)	(2.93)
Unempl Change (Graduation)	4.35*	2.87***	3.97
	(2.39)	(0.94)	(3.45)
Unemployment (Application)	3.19	-1.23	5.91*
	(2.03)	(1.03)	(3.15)
Unemployment (Graduation)	2.55	-0.08	3.73
	(2.44)	(0.92)	(3.95)
GDP Growth (Application)	-1.98**	0.75**	-3.67***
	(0.89)	(0.29)	(1.24)
GDP Growth (Graduation)	-1.25	-1.25***	-0.84
	(1.10)	(0.36)	(1.57)
Recession (Application)	7.51	-5.73***	16.88*
	(6.15)	(1.73)	(8.51)
Recession (Graduation)	5.40	3.95**	4.06
	(6.88)	(1.67)	(9.91)
Subsample	Tier 1	Tier 1	Tier 1 Academic
University-Decade Dummies	Yes	Yes	Yes
Observations	234	234	232

Note.—Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.6.3 Productivity of Academics Selected Under Different Criteria

In the main text, we report three different measures which might indicate that an individual is an academic: Our standard "academic" measure equals one if he is a faculty member or a member of the American Economic Association after graduation from the PhD. The second measure is one if the PhD student becomes a faculty member at a US business, economics or finance department and the third one shows if the student is able to publish in one of our ranked journals after graduation. In the main text, due to conciseness, we left out the robustness of our productivity regressions of academics with regard to the last two measures. In Table B.11, we report this robustness check for completeness. All coefficients have the same sign as when selection is according to our standard "academic" measure with the exception of GDP Growth at graduation for the faculty measure. However, in fact the theory makes no prediction on the effect of the business cycle at graduation on the productivity of academics. Some coefficients are more and some are less significant than in the main text. Overall, our results on the productivity of academics seem quite robust with respect to how we identify academics.

Table B.11: Alternative measure for being an academic: productivity

	Productivity	Productivity	Productivity
Unempl Change (Application)	3.27***	6.80***	5.63***
	(0.94)	(2.49)	(1.29)
Unempl Change (Graduation)	2.74**	2.08	4.35***
	(1.20)	(1.86)	(1.09)
Unemployment (Application)	2.98**	6.54**	4.10**
	(1.10)	(2.84)	(1.55)
Unemployment (Graduation)	3.08**	4.58	4.44***
	(1.26)	(2.80)	(1.57)
GDP Growth (Application)	-1.46***	-2.64**	-2.39***
	(0.42)	(1.00)	(0.58)
GDP Growth (Graduation)	-0.74	0.06	-1.55**
	(0.56)	(0.91)	(0.60)
Recession (Application)	5.38*	7.73	7.70
	(2.93)	(6.14)	(4.68)
Recession (Graduation)	5.09	1.85	8.07**
	(3.57)	(5.61)	(3.57)
Subsample	Academic	Faculty	Publish
University-Decade Dummies	Yes	Yes	Yes
Observations	1047	903	974

Note.—Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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