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Kiel Working Paper No. 1191

Distribution Dynamics in European Venture Capital

by

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December, 2003

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Abstract:

This paper evaluates the evolution of European venture capital investments since 1990, using the distribution dynamics methodology. It tests and rejects the hypothesis that the international allocation of venture capital investments is driven by a path-dependent process of agglomeration, in which a country's initial advantage is transformed into a long-term lead. Instead, the evidence from a cross section of 13 European countries is more favourable for the alternative hypothesis, which explains international variations in venture capital investments as part of countries' different patterns of specialization. The robustness of these findings and implications for government policy are discussed.

Keywords: Distribution dynamics, Markov chains, New technology-based firms, Venture capital

JEL classification: F21, F43, G20

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1. Motivation

A widening gap has separated Europe's venture capital sector from that in the US throughout the 1990s. Large international differences in venture capital activity are also apparent within Europe's common market. The literature has suggested a variety of partially competing and partially complementary explanations for these differences (see Bottazi and DaRin 2002, among others). Policy makers, both at the national and at the European level, have sought to find policy instruments that can seed and nurture an emerging venture capital industry where it has failed to develop on its own. Yet, before efficient policies can be devised, one must ask the normative question: How much venture capital should an economy ideally have? One size cannot fit all. Instead, the optimal level of venture capital activity will depend on country-specific opportunities and constraints that determine the demand and the supply of venture capital.

In essence, the potential – and the need – for government subsidies to seed an emerging venture capital industry rests on the hypothesis that different initial conditions, coupled with positive feedback in the venture capital cycle, can create path dependence, akin to hysteresis, at the country-level. According to this hypothesis, venture capital will evolve like an *agglomeration* in space: the volume of venture capital investments will tend to grow faster in countries with an initial advantage. Countries lacking a sufficient initial endowment with venture capital will fall behind, and this may motivate governments to create an artifical endowment by using taxpayers' money to subsidize a nascent venture capital industry.

However, even if venture capital accumulates in line with the agglomeration hypothesis, not all governments should strive to build their own national venture capital industry. If too many governments jump on the bandwagon at the same time, there is likely to be a coordination failure and an oversupply of venture capital that would result in disappointing rates of return. Instead, governments must recognize that the agglomeration of venture capital in an *open* economy may pave the path towards new patterns of specialization in the tradables sector and may thus create welfare gains by enhancing and deepening the international division of labour. Because dynamic economies of scale are relevant in the venture capitalist's own learning as well as in the creation and application of knowledge in the industries that venture capital supports, an *uneven* international distribution of venture capital may actually be required to maximize the global trade-related welfare gains from exploiting the inherent increasing returns to scale in venture capital. Temporary subsidies that succeed in tipping the balance of venture capital's accumulation towards one or a few countries may ultimately generate benefits for all.

No such strategic role for targeted government subsidies is implied by theoretical explanations that lack positive feedback and path dependence, but see international differences in venture capital activity as fully reversible when the initial conditions, the regulatory choices and factor endowments, of similarly sized countries are reversed. The older literature has emphasized the influence of capital gains taxation and other regulations (Poterba 1989), but in a large cross-country study, Jeng and Wells (2000) have found no statistically significant influence of different capital gains tax rates on venture capital. A more fundamental explanation is in terms of *specialization*: being a highly specialized form of financial intermediation, with high initial set-up costs, venture capital will develop where there is a sufficient demand for it. The demand for venture capital is a derived demand that depends primarily on the level of entrepreneurial activity in a small number of highly competitive high-tech industries where bank credit fails to finance the rapid expansion that innovative start-ups often require to benefit from first mover advantages. If a country's level of entrepreneurial activity in high technology changes, so will the demand and the observed level of venture capital activity.

The present paper uses the distribution dynamics methodology to study the role of path dependence in the allocation of European venture capital empirically. This methodology has previously been used to study international convergence and divergence in economic growth (Quah 1993a and 1996) and the dynamics of technological specialization in open economics (Mancusi 2003 and Stolpe 1995). The findings of the present paper, however, cast doubt on the hypothesis that the international distribution of venture capital is driven by a pathdependent historical process of agglomeration. I do not observe strong persistence in empirical measures of relative venture capital activity in the European country cross-section. This is consistent with explanations in terms of demand-driven specialization amid rapid structural change: the cross-country distribution of venture capital investments in any given period does not predetermine the allocation of venture capital in the future.

Previous empirical studies of international variation in venture capital activity have been silent on this issue, because they have concentrated on exogenous and mostly time-invariant determinants. Examples of such immutable structural conditions are the economy's exogenous endowments with primary factors of production and the legal system, including accounting standards and labour market rigidities. To be sure, the influential study by Jeng and Wells (2000) has also included dynamic variables, such as GDP growth, the growth of stock market capitalization and the importance of initial public offerings (IPOs) relative to GDP, within a panel regression framework. They find that IPOs are the strongest driver of venture capital investing, while private pension fund levels are a significant determinant over time, but not across countries.

However, even Jeng and Wells (2000) provide little insight when some of the driving forces of venture capital are at least partially endogenous themselves. Recognizing this shortcoming, Leleux and Surlemont (2003) use Granger causality tests within a vector autoregression to discriminate between exogenous and endogenous driving forces of national venture capital investments.

Controlling for the time-invariant characteristics of countries' legal system, which La Porta et al. (1997) have found to affect the size and breadth of national capital markets through their differential effectiveness in protecting investors' rights, Leleux and Surlemont (2003) find a negative correlation between large public participation in venture capital funding and the size of the national venture capital industry. On the other hand, public investment seems to spur greater subsequent amounts of private investments in an established venture capital industry, but not in a nascent one. Yet, this conclusion is compatible with either agglomeration, starting after a national venture capital industry has surpassed a critical size, or with specialization, emerging only gradually so that targeted public investments may have misallocated resources by failing to anticipate the long-run pattern of specialization in the case of a fledgling venture capital industry. There is thus a clear need for more research.

The remainder of this paper is structured as follows: Section 2 provides an extended discussion of the agglomeration and specialization hypotheses and derives testable empirical implications. Section 3 introduces empirical methods that can discriminate between the two hypotheses. Section 4 presents the empirical findings. Section 5 concludes.

2. The Dynamics of Venture Capital Investments: Agglomeration versus Specialization

The contribution of venture capital to economic growth derives from its role in financing the expansion of start-up firms in fast growing high-tech industries that are driven by new ideas and the accumulation of human capital. Venture capital combines temporary equity participation in young privately held firms with management services designed so that exiting via an IPO or a trade sale can be expected to return a profit after the portfolio firm has established a track record. In addition, buyout financing for older firms is often counted as venture capital in Europe.

The specialization hypothesis

According to the *specialization hypothesis*, the level of investments is driven primarily by the *demand* for venture capital. No assumption about geographic mobility is required to explain large international differences in venture capital activity. Instead, the hypothesis is based on the idea that venture capital firms will seek to improve their own efficiency in screening, supporting and controling portfolio firms by becoming technologically specialized themselves. Mature venture capital will concentrate on certain subsets of high technology. The demand for venture capital will therefore depend on a country's industry-specific needs for external finance – that bank credit fails to meet – when start-up firms have the potential to either grow rapidly or face extinction if they cannot do so. For example, in the software industry, network externalities, scale economies and rapid product cycles combine to turn competition among new entrants into a game of the winner-takes-all variety. Industries, by contrast, where young firms' expansion is more organic and largely financed from retained earnings may never develop a demand for venture capital.

The paradigm of *incomplete contracts*, formally introduced by Grossman and Hart (1986), can be invoked to explain the very different roles that entrepreneurial start-ups play in the innovation process of different industries.[1] All innovation is to some degree governed by incomplete contracts, which assign ownership rights and decision-making authority to the various parties involved, because neither the characteristics, nor the timing of genuine innovations can be specified in advance. The optimal assignment of ownership

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[1] For a more comprehensive account of economic theories that address the role of new firms in technological innovation, see Schertler and Stolpe (2000).

and decision rights will depend on risk aversion and on the relative efficiency of the parties' efforts in finding the innovation, as described in the principal-agent literature.[2] Beyond that, the assignment will also depend on technology-specific conditions, like the relative importance of complementary investments in the case of systemic innovations, and on the conditions for transmitting proprietary information to the producers and users of the innovation, like the technical and legal feasibility of avoiding knowledge spillovers to competitors. The structure of *optimal* contracts governing innovation in a second-best world of fundamental uncertainty varies with these conditions so as to minimize the overall costs of achieving technological and commercial success.

These incomplete contracts typically involve the creators of new ideas, often specialists with the necessary skills to do pertinent research, as one party, and the manufacturers or users of an innovation as the other party. Ideally, the contracts distribute the private incentives so that each party makes the socially optimal effort in line with its comparative advantages. When *ownership* is the best arrangement to incite effort, property rights should be assigned to the party whose input, including knowledge, is more important for successful innovation. In software and biotechnology, for example, individual ingenuity is paramount and new ideas often threaten to make proprietary technologies of established firms obsolete. This is one reason why the incentives to innovate can be stronger in entrepreneurial start-ups and why new firms have generated many of the most visible and profitable innovations in these areas of technology. To incite the socially optimal effort, researchers with special skills and the originators of radically new business ideas may actually need to own their business, as a start-up enables them to do.

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[2] See Aghion and Howitt (1998) for an introduction.

Of course, creativity or research is not always the most important input. In many established manufacturing industries, like automobiles and aircraft, product development, production and marketing capabilities are more important for the ultimate success of an innovation. And these capabilities are often subject to economies of scale at the plant level, which can account for a highly concentrated market structure and the absence of independent owner-innovators in many established manufacturing industries. A further reason for this absence is that the cost of transmitting new – and often tacit – knowledge needed to produce or use an innovation tends to be lower when the innovator is integrated into a large manufacturing firm or user organization. An example are the in-house R&D departments in the chemical and machinery industries where the transmission of tacit knowledge plays an important role in setting up complex manufacturing processes. In the case of software, by contrast, the production and distribution of fully equivalent copies of the original product does not require any understanding of its content so that the developer and manufacturer can work completely separate. *Codified* knowledge can often be transmitted at arms length and at much lower costs than *tacit* knowledge. Similar reasoning may apply to large parts of the biotechnology industry, where innovation is largely driven by the start-up firms of star scientists (Zucker et al. 1998).

To sum it up, the paradigm of incomplete contracts predicts that the importance of new firms in technological innovation is contingent on economic characteristics of the respective area of technology. Only industries whose innovation process is driven by new firms will in turn develop a significant *demand* for venture capital. According to the specialization hypothesis, an economy's *supply* of venture capital is fully endogenous and will change with any changes in demand-side determinants, such as the economy's pattern of production specialization, which in turn is partly driven by export demand. The normative implications of the specialization hypothesis do not assign a special role to government subsidies. Instead, a relatively small or non-existing venture capital market is seen as a benign consequence of the international division of labour, as part of a national pattern of specialization in tradables that is assumed to maximize a country's welfare.

The agglomeration hypothesis

According to the *agglomeration* hypothesis, the level of venture capital is primarily driven by forces that affect its *supply*. Existing venture capitalists are geographically bounded in their ability to support and control the management of portfolio firms effectively. A persistent level of venture capital activity can therefore be interpreted as an endowment of locations and as a source of comparative advantage in specific high-tech industries. Moreover, since many of the high-tech goods and services brought to market with the support of venture capital are traded globally, the spatial distribution of venture capital can not only help to explain international patterns of trade, but may also be reinforced by established trade patterns. Only at the beginning of a venture capital agglomeration will industry-specific financing gaps, such as credit market constraints, determine how important the availability of venture capital would be as a source of comparative advantages for different categories of tradeables. Venture capital will be more important, the riskier an investment and the higher the share of intangible capital is. An abundant supply of venture capital can therefore help to establish a broad comparative advantage in the export of technologies whose development and production entails supernormal financial risks and requires a high share of intangible investments, as in the case of software and biotechnology. But once the agglomeration has gathered sufficient momentum, venture capital will spread to other industries and may become a generic financing instrument for technology-based start-ups across the board.

The main difference vis-à-vis the specialization hypotheses is that in the agglomeration hypothesis localization advantages are *self-reinforcing* and one country may attract a vibrant venture capital industry at the expense of others, which introduces a potentially important zero-sum aspect into international trade relations. This is the case of hysteresis, or path dependence, in which *temporary* government subsidies may succeed in establishing an efficient domestic venture capital industry that moves the economy onto a superior path in terms of growth and welfare. On the other hand, the agglomeration hypothesis also implies that a coordination failure resulting in an insufficient local supply of external finance for new technology-based firms may prevent a country from developing the optimal industrial organization in high technology. The literature on endogenous growth in open economies has long recognized the possibility of dynamic inefficiency in the presence of positive externalities from private investments. Grossman and Helpman (1991) showed that the domestic accumulation of important inputs with public goods characteristics, such as a stock of technological knowledge required for the production of certain tradeable goods, can change an economy's factor endowment over time and may result in pathdependent patterns of trade and growth. The agglomeration hypothesis sees venture capital as a largely non-tradeable input that combines private and public goods characteristics and can serve as a source of dynamic comparative advantages. This point is reinforced by the observation that a viable venture capital industry itself relies on several important public goods that are of a *local* nature – specific to a region or country in which a certain critical amount of venture capital has been accumulated.[3]

The *first* instance of a local public good is related to venture capitalists' desire for syndicated financing contracts. When each individual venture capital firm is

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[3] Schertler and Stolpe (2000) spell out parts of this argument in greater detail. In the context of a closed economy model, Schertler (2003) uses stochastic simulations to show that path dependence can create dynamic inefficiency by slowing down venture capitalists' accumulation of experience. The public good aspect in these simulations is that capital providers only observe the average return on all venture capital-backed firms in a particular period, but not the different returns realized on individual investments.

specialized, syndication presupposes the existence of other venture capitalists with a similar profile of technological specialization. Bygrave (1987, 1988) has suggested that venture capital firms' primary objective in syndication is local networking which can help to recruit experienced professionals, like managers and engineers with special skills, on behalf of portfolio firms as well as to informally trade information about management practices and investment opportunities among otherwise competing venture capitalists. In a highly competitive environment, access to insider knowledge is often critical and many venture capital firms simply cannot afford to stay out of syndicating networks. In these networks, individual venture capital firms may alternate between taking the lead and taking a complementary role in co-financing new technology-based firms which are located both within a venture capitalist's geographic and technological domain. The inevitable partial synchronization of investment priorities implicitly serves as a co-ordinating mechanism for the technological specialization chosen by venture capital firms within a region or country. This may establish a virtuous circle because technological coordination can further increase the opportunities for syndication and raise the productivity of local venture capital.

The *second* local public good is a liquid stock market with a lively primary equity market, so that venture capital firms have the option to exit their portfolio firm through an IPO, or after an applicable lock-up period ends. Jeng and Wells (2000) provide empirical evidence of the positive impact of IPOs, measured by their total market value relative to a country's GDP, on the volume of venture capital investments in a cross-country study. However, to argue that a liquid domestic stock market provides a local public good requires two clarifications: First, what *public* goods characteristics of a stock market are relevant for venture capital? And second, why can a foreign stock market not provide the same public good services as a *local* stock market? The answer to both of these questions has to do with the inevitable public revelation of private information about equity issuers in the stock market. In general, the greater a stock market's liquidity, the more frequently are individual stocks traded and the more accurate does the price of a stock convey the dispersed private information about the firm's true value. Liquidity considerations thus give large 'global' stock markets a competitive advantage over small 'local' ones. In primary equity markets, however, the efficiency of the IPO process depends on the accuracy of valuation when the IPO candidate is still in private hands and – apart from the legally required information in the prospectus – only private information is available. In this case, the accuracy of valuation will depend primarily on the contributions of underwriters, such as investment banks, and of professionals, such as analysts, accountants and lawyers, who all have an incentive to taylor their services for clients in the local market. By specializing on a localized market, they can profit from decreasing average costs in researching, processing and selling private information about local firms. This effect tends to give local primary equity markets a competitive advantage over global stock markets: many IPO candidates may be too small to get global recognition, but can provide a profitable business opportunity for local information providers in primary equity markets.

Having established the local nature of information revelation in primary equity markets, it is easy to see the special relevance for venture capital. Black and Gilson (1998) have argued that the IPO exit channel is critical for an efficient venture capital industry for two main reasons: First, an IPO offers venture capital firms a unique opportunity to build *reputational* capital, which can help to attract new funds from outside investors and facilitate the screening and contracting with new start-up firms. And second, the prospect of an IPO improves the entrepreneur's incentives because it can be the basis for a self-enforcing implicit contract over control, which provides for the return of control from the venture capital firm to the entrepreneur upon exit through an IPO, which is chosen only in case of a successful development of the start-up.

Without a liquid stock market, exit would have to be via a trade sale that would prevent the entrepreneur from regaining the control ceded to the venture capitalist in exchange for his financial and non-financial support. Only the prospect of an IPO can hence give the entrepreneur the call option on control which provides a large reward in the event of success (Black and Gilson 1998: 261). The higher the reputation which the venture capitalist has already acquired through his track record of past IPOs, the lower are the costs of an IPO to the entrepreneur because underpricing in primary equity markets tends to decrease with the reputation of the venture capital firm involved. For outside investors, the advantage of dealing with a reputable venture capital firms not only that the expected rate of return on future portfolio investments may be higher, but also the expectation that a larger share of the venture capitalist's future portfolio firms will be divested through an IPO, so that more public information is available when the outside investor wishes to withdraw capital from venture capitalists that turn out to be less successful, for example because their industry-specific expertise and technological specialization may have become obsolete as a result of technological change.

A *third* local public good is a local job market in which venture capital firms can recruit the experienced professionals they need to screen, support and control their portfolio firms effectively. Not all of these people must be experts in the portfolio firm's area of technology, but they cannot be successful without specific management skills and specialized knowledge of financial contracts and markets, which must be acquired through learning-by-doing. An emerging venture capital industry cannot simply rely on, but must build a supportive local job market itself – as in Krugman's (1991) well-known model of labour market pooling: A professional who leaves his job after acquiring skills and expertise in a certain area of technology may well find a higher-paying job at another firm, but will never be fully compensated for the true value of the acquired skills and knowledge to his new employer. However, he can expect to do better in a local labour market pool in which many potential employers compete for his scarce skills than in a labour market dominated by a single employer with monopolistic pricing power. Labour market pooling is a direct and an indirect source of agglomeration economies in venture capital. Not only does it force venture capital firms to locate in clusters, but also their portfolio firms often depend on the local availability of the specialized research and engineering skills that high technology requires.

To sum it up, the agglomeration hypothesis sees venture capital as a source of comparative advantages in open economies for two main reasons: first, because the active involvement in the management of portfolio firms limits the geographic space within which each individual venture capitalist can operate effectively, and second, because the long-term accumulation of venture capital is driven by strategic choices of competing venture capitalists that are often interdependent. The agglomeration hypothesis therefore predicts that venture capital is accumulated in a pathdependent process with considerable persistence over time.

[insert Figure 1 here]

Testable implications

With the aid of Figure 1, the *empirical* implications of the agglomeration and specialization hypotheses can be summarized as follows: Agglomeration implies persistence, above all in early stage investments and in the volume of investments provided by independent venture capital firms. These two segments of venture capital are the ones that require the longest time to establish. Figure 1 captures this by showing a supply curve for venture capital that is completely price inelastic in the short run, at X^A. The economy's short-run demand for venture capital, d_1, is downward sloping because the efficiency of venture capital varies across the set of short-run investment opportunities. p* is the short-run equilibrium price of venture capital, at which the market clears (point A). It equates the rate of return required by outside investors in venture capital with venture capital users' willingness to pay. Exogenous shocks that affect users' willingness to pay will shift the demand curve, say to d_2 in the case of a positive shock. Such a shock may be triggered, for example, by a change in relative prices that makes starting a new firm more profitable. However, only the price of venture capital will increase in the short run. The volume of investments will be constrained by the inelastic supply of venture capital. In B, the new short-run equilibrium price, p**, exceeds the rate of return required by outside investors, p*, and this will set in motion an extended process of accumulation during which the relevant public goods – that define the localized venture capital market – will also expand, until the new equilibrium in C is reached. But the short-run mobility in the volume of venture capital investments will be minimal.

By contrast, the specialization hypothesis does not imply persistence. Instead, it predicts as much mobility in venture capital as there is in the host country's entrepreneurial activity within high technology, since this is thought to be driving the demand for venture capital. The short-run supply curve of venture capital can thus be thought as horizontal, indicating perfect price elasticity. The response to exogenous shocks will be a high degree of mobility in the volume of venture capital investments, such as a swift expansion from A to C without any change in the short-run equilibrium price of venture capital, at X^s. Pertinent empirical studies on the basis of patent data, such as Mancusi (2003) and Stolpe (1995), have found that the dynamics of countries' technological specalization are indeed characterized by a high degree of mobility, with evidence of persistence confined to just a few limited areas like electronics. These empirical studies imply that new opportunities to enter emerging areas of technology arise in many different countries at different points in time. Since entrepreneurs will want to profit from these opportunities wherever they may arise, the specialization hypothesis predicts that venture capital is quite mobile and quickly diffuses best practices, such as syndication. As a further empirical implication, the specialization hypothesis does not provide any reason to assume that different segments of the venture capital industry exhibit different degrees of persistence.

3. Empirical Methods

To assess the evidence on the agglomeration and specialization hypotheses, I choose the distribution dynamics methodology because it has been especially developed to address intertwined questions like the following two empirically: On the one hand, we must ask whether the distribution of selected measures of countries' propensity to invest in venture capital has been stable or instable over time, in the sense that these measures have shown tendencies either towards a more even or a more polarized distribution across countries. To see this, the focus of analysis must be on the *external* shape of the cross-country distribution and its evolution over time. On the other hand, we must also ask whether the evolution of *individual* countries propensity to invest in venture capital is characterized by *relative* stability and persistence or by tendencies towards either forging ahead or falling behind, in short by individual mobility. Increasing returns to scale and positive feedback in the allocation of venture capital investments might imply that individual countries come to cluster at the extreme ends of either far-above or way-below average volumes of venture capital investments, after scaling these on an appropriate benchmark such as GDP. To address the question of individual persistence and mobility at the country level, the focus of analysis must be on the *intra-distribution* dynamics.

The distribution dynamics methodology, developed by Quah (1993a, 1993b and 1996), provides the information to answer these two fundamental questions by simultaneously exploiting the cross-section and time-series variation in the data. The agglomeration hypothesis has two implications – the a priori unspecified form of time-heterogeneity in the distribution and the non-ergodicity in the temporal dependence structure – that prevent classical statistical-inference techniques from providing a proper test. These techniques are, after all, based on specific assumptions about the nature of the underlying distribution: Classical tests generally require that the type of the distribution is known and that it is of a sort whose exact shape can be described by a small set of parameters. But when state dependence, or hysteresis, is thought to be present in the data, the unknown distribution of the variables describing the stochastic process must be allowed to evolve over time, which generally rules out any standard distribution. The fact that no particular assumption about the type of the underlying distribution or its parametric description would be appropriate as an a priori restriction, calls for the adoption of non-parametric methods and the use of data from more than one realisation of the stochastic process. The best available empirical model is a Markov process whose evolving distribution can be estimated non-parametrically from parallel realization in the cross section of countries. Before turning to the details of this methodology, it may be useful to clarify the general structure of Markov processes more formally, and to discuss how ergodicity and non-ergodicity would manifest themselves in a finite number of observations.

Non-Ergodicity in Markov Processes

In general, a stochastic process can be modelled as a sequence of transition functions, in which an operator T^* maps the space of probability measures λ on some measurable space $(Z,\Im)$ into itself. Stokey and Lucas (1989), p. 213, suggest to interpret $(T^*\lambda)(A)$ as the probability that a state in set A will be realised after the transition if the preceding state is drawn according to the probability measure λ. Although the transition functions of a stochastic process can have arbitrary arguments, it is often assumed that the current realisation of the process is the only argument. This defines a first-order[4] Markov process, for which the conditional probability of the event $\{\omega \in \Omega : [\sigma_{t+1}(\omega),...,\sigma_{t+n}(\omega)] \in C\}$, given that the event $\{\omega \in \Omega : \sigma_\tau(\omega) = a_\tau, \tau = t-s,...,t-1,t\}$ has occurred, can be written as (Stokey and Lucas, 1989, p. 223): $P_{t+1,...,t+n}(C|a_{t-s},...,a_{t-1},a_t) = P_{t+1,...,t+n}(C|a_t)$, with $t = 2,3,...;\ n = 1,2,...;\ s = 1,2,...,t-1;$ and $C \in \Im^n$. If these conditional probabilities are independent of time t for all $a \in Z$ and $C \in \Im$, the Markov process is said to have stationary transitions. Of course, this does not necessarily imply a stationary stochastic process; the stationarity of a Markov process does not depend in any way on whether the process has stationary transitions. Stationarity instead requires that the sequence of probability measures λ_t converges, in some sense, to an invariant probability measure λ^*, defined as a fixed point of the operator T^*, so that $\lambda^* = T^*\lambda^*$. Thus, λ^* is the probability measure over the state s_{t+1} in period *t+1* if it is the probability measure over the state s_t in period *t*.

For the empirical implementation, I will use a *finite-state* Markov process, also called a Markov *chain*, which is defined on a denumerable space with a finite number of states. It will exhibit basically the same long-run behaviour patterns as a general Markov process, defined on a continuous state space, and can be identified empirically if stationary transition probabilities can be assumed or data from more than one sample path is available. If, as in Stokey and Lucas (1989: 320), a suitable probability measure for the finite state space $S = \{s_1,...,s_l\}$ is given by a vector p in the l-dimensional unit simplex: Δ^l = $\{p \in R^l : p \geq 0 and \sum_{i=1}^{l} p_i = 1\}$, a transition function P can be represented by an 1×1

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[4] In higher-order Markov processes, the transition function would have as its arguments realisations of some finite number of periods into the past. But the assumption of a *first-order* Markov process does usually not constitute a serious restriction. Stokey and Lucas (1989) show in section 8.4 of their book, second- or higher-order Markov processes can be written as a first-order process after suitably redefining the state space.

Markov transition matrix $\Pi = \lfloor \pi_{ij} \rfloor$, with elements $\pi_{ij} = P(s_i, \{s_j\})$. The *i*th row of this matrix gives the probability distribution over the post-transition states conditional upon the ante-transition state being s_i. With $p \in \Delta^l$, denoting the probability distribution over the state in period *t*, the probability distribution in period *t+1* can be determined by matrix multiplication as $\hat{p} = p\Pi$, and the behaviour of the sequence $\{\Pi^n\}_{n=0}^{\infty}$ reveals the long-term behaviour of the Markov chain. Stokey and Lucas (1989), pp. 326, show that the sequence of *averages* $\{A^{(n)}\} = \{(1/n)\sum_{k=0}^{n-1} \Pi^k\}$ necessarily converges, as $n \to \infty$, to a limiting Markov matrix *Q*, whose rows are *invariant* distributions with respect to time. Thus, one can be sure that there always exist time-invariant distributions of the long-run average probabilities over all states of a (finite) Markov chain with stationary transitions, and that these invariant distributions are given for each initial state s_i by the corresponding row of *Q*. I will invoke this convergence result to draw inferences on persistence versus mobility in empirically estimated transition matrices.

Mobility requires ergodicity in the long-term behaviour of the Markov process, whereas persistence is compatible with non-ergodicity. Ergodicity of a Markov chain implies irreducibility so that each state is accessible from all others, even if not necessarily by one-step transitions: if the entire state space is to form an *ergodic* set, denoted *E* and defined by the condition that $p(s_i, E) = 1$, for $s_i \in E$, no non-empty subset of *E* can itself be ergodic. If a Markov chain has two (or more) ergodic subsets, the system may converge to two (or more) *different* invariant distributions depending on the system's initial state, or on the particular sample path realised. In this case, the Markov chain as a whole is said to be *non-ergodic*; and the different invariant distributions might correspond to different steady-state equilibria in a related deterministic model. It follows that the assumption of stationary transitions may not suffice to estimate all transition probabilities from a single realisation of the process. I therefore adopt the ensemble view, which assumes that the venture capital investment dynamics in different countries are independent realisations of the same underlying Markov process. Under this assumption, one can estimate the transition probabilities for all states even if an individual country's investment path gets locked into one of the extreme states at an early date within the observation period.

Finite Markov Chains with Fixed States

My estimation strategy approximates the operator *T** by a finite Markov chain transition matrix for a discretised state space. An empirical estimate of the transition matrix can give useful information on the *intra-distributional* mobility of individual countries between different degrees of venture capital investment over time, and can be used to calculate long-run stationary distributions of the specialisation indicator – provided they exist – according to the Chapman-Kolmogorov equation: $\Pi^s = \Pi^r \cdot \Pi^{s-r}$ with the time period index $s \to \infty$, where Π denotes the transition probability matrix; its rows contain the conditional probabilities that a transition beginning in a certain discrete state (row *i*) will end after one step (in event time) or one period (in historical time) at a certain state (column *j*). Π^r consequently has the probabilities of moving from initial states to intermediate states after *r* steps or periods of time.

To discretise the continuous state space of the venture capital investment measure, three states are defined – somewhat arbitrarily – by setting upper boundaries so that the distribution of sample realisations over all years from 1990 to 2002 is approximately uniform across the three states. The corresponding 3×3 Markov chain transition matrix is estimated by maximising the log-likelihood function $\log L = \log p_i(1990) + \sum_{i,j} h_{ij} \log p_{ij}$ with respect to $p_{i\_}$ and subject to the restriction $\sum_j p_{ij} = 1$, where $p_i(1990)$ are the initial probabilities of having a realisation of the venture capital investment measure in state *i*, $p_{i\_}$ are the probabilities of having a realisation in state *j* after a specified transition period, conditional upon a prior realisation in state *i*, and $h_{i.}$ are the observed frequencies of transitions from state *i* to state *j* in that period. Ignoring any information about transition probabilities, which may be contained in the initial probability distribution, and assuming that the transition probabilities are invariant with respect to time as well as across countries, the Maximum Likelihood estimator can be readily computed as: $\hat{p}_{ij}=h_{ij}/h_i$, where $h_i=\sum_j h_{ij}$. This estimator is consistent and has an asymptotic normal distribution (see Basawa and Prakasa Rao, 1980, pp. 54).

To check the robustness of the estimation results for one-year transition matrices, I will compare these with estimates of four-year transitions and with the estimation results from so-called fractile Markov chains. Experimenting with different time intervals and different ways of discretising the state space is generally recommended as a test for robustness of Markov chain estimates. Arbitrary discretisation without considerion of plausible alternatives could be a source of spurious results.

Fractile Markov Chains

The estimation of transition matrices for *fractile* Markov chains, named so by Quah (1993b), and originally proposed by Geweke, Marshall and Zarkin (1986) can be viewed as way of checking the robustness of the estimated transition matrices with respect to the delineation of states. Instead of using an arbitrary grid to discretise the continuous state space of the specialisation indicators, one can fix a set of increasing, non-redundant probabilities, equally spaced on the open unit interval, say $P = \{1/3, 2/3, 1\}$, and let this determine for each period *t* a corresponding set of quantiles. The sequence of quantile sets {Q(t): integer *t*} then parametrises movements in the entire distribution, while the estimated *fractile* transition probability matrix parametrises intra-distribution mobility.

The simple Maximum Likelihood estimator is again based on the assumption of invariance of the transition probabilities with respect to time and the relevant cross section dimension. If the estimated fractile matrix is ergodic, its stationary distribution will be uniform relative to the quantiles *Q* (see Quah 1993b). Estimates of intra-distribution mobility may be higher or lower since the fractile method basically implies a redefinition of the grid discretising the state space in each period of time. In order to relate the stationary distribution to the original state space, one has to consider – in addition to intra-distributional mobility – movements in the entire distribution as estimated in the sequence of quantile sets $\{Q(t)\text{: integer } t\}$.

In the present context, it will suffice to examine whether the interquantile range increases, decreases or remains constant over time. This can be done by running a simple linear regression of the interquantile range on time and testing for the significance of the slope coefficient. A significant positive time trend in the interquantile range combined with high persistence in terms of large entries on the main diagonal – especially at the ends – of the estimated fractile matrix would lend support to the agglomeration hypothesis, whereas a negative or no time trend in the interquantile range and low persistence in the transitions matrix would contradict the idea of pathdependence implied by the agglomeration hypothesis, but would be consistent with specialization.

4. Empirical Findings

Descriptive statistics

Data on annual investments flows in European venture capital are provided by the EVCA (2003). A short series of graphs can be used to summarize the gross patterns of development and distribution in the 13 countries included in this study: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden und the United Kingdom.[5] Figures 2 to 7 show density estimates for various measures of the cross country distribution of venture capital investments. All of these densities are estimated by kernel smoothing, as described in Silverman (1986), using the Epanechnikov kernel with STATA's automatic bandwidth choice. As the graphs show, all cross-section distributions have a very high peak close to zero[6]: Most countries have very small investment volumes in venture capital, especially during the 1990 to 1996 period. The high peaks at low values are less pronounced for the later period covering the years 1997 to 2002, suggesting that the distribution of venture capital has become more even in those later years, which coincided with the technology bubble in the stockmarket and its aftermath.

Taking a closer look, Figure 2 shows the distribution of total venture capital investments per mil of GDP for the two periods 1990 to 1996 and 1997 to 2002. The much lower peak at small values during the later period and the peak's rightward shift suggest that countries with a low initial volume of venture capital investments have begun to catch-up during the 1990s. Figure 3 shows the distribution of *early stage* venture capital investments per mil of GDP and suggests that the catch-up of less-developed venture capital markets in this segment has been much more pronounced than with respect to total venture capital investments. In fact, the very high peak in the distribution of early stage venture capital investments at low values shows that most countries had almost no early stage venture capital investments to begin with. Figure 4 shows a

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[5] For most countries – Germany, the Netherlands, Belgium, Spain, Sweden, Ireland, Denmark, Finland, Portugal and Austria – the dataset was incomplete in some of the time series used and several gaps had to be filled by intrapolation.

qualitatively similar picture for the distribution of *expansion stage* venture capital investments per mil of GDP. The high peak at low values during the early period is again more pronounced than in the case of total venture capital investments, but not nearly as pronounced as in the case of early stage venture capital investments. Qualitatively, the overall picture is similar: the peak is lower in the second period and has shifted towards larger values of expansion stage venture capital investments per mil of GDP.

Figures 5 to 7 are from a different point of view. They show the relative distributions of venture capital investment volumes across countries for different sources of funds. Figure 5 shows the distribution of *independent* venture capital investments across countries. The density estimate roughly indicates what proportion of countries accounts for different shares of the total volume across countries; these shares are plotted on the horizontal axis. The distribution is of course influenced by country size. In both periods, there is a very high peak at low values: most countries have relatively small volumes of independent venture capital investments; and overall, the distribution has not changed much between the two periods.

However, substantial change is evident in Figures 6 and 7. Figure 6 shows the distribution of *captive* (including semi-captive) venture capital investments across countries. These are venture capital investments made by subsidiaries of established industrial corporations or financial institutions, like banks. Compared to the 1990 to 1996 period, the peak at low values during the 1997 to 2002 period is much lower suggesting that the relative concentration of captive venture capital investments in small venture capital markets has declined. This could be either due to slow growth in these markets or due to rapid growth of

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[6] Unfortunately, the STATA program used for these estimates lacks the option to impose a non-negativity limit on the domain of the base variable, so that the non-parametric density

captive investments in the larger markets. Ireland, for example, saw a tenfold increase in its ratio of captive venture capital investment to GDP between 1990 and 1999, followed by an almost total collapse of this market segment in 2000. Other countries with large increases in the ratio of captive venture capital investment to GDP in the late 1990s included the Untited Kingdom, France, Sweden, Belgium and especially the Netherlands – with a tenfold increase between 1990 and 2000.

Interestingly, the opposite development is shown for *public* venture capital investments in Figure 7. Like the previous figures, the distribution of public venture capital investments across countries has a very high peak at low values: much of the volume of public venture capital investments in Europe is concentrated in small markets. However, what is most notable here, is that the concentration in small markets has substantially increased between the 1990 to 1996 and 1997 to 2002 period. Belgium, Sweden and Germany were among the countries with the largest relative increase of public venture capital investments in the late 1990s, but not the Netherlands.

Another picture of the evolution of cross country dispersion in venture capital investments can be obtained from the calculation of Gini coefficients for each year during the sample period, as in Table 1 and Figures 8 and 9. The question asked here is whether different measures of venture capital investments have basically the same *or* different characteristics and *how* the dispersion of these measures varies over time. The Gini coefficient is a widely used inequality measure that ranges between 0 and 1 and is equal to twice the area between the 45-degree line and the Lorenz curve obtained by plotting the cumulative share of venture capital investments against the cumulative percentage of countries, ordered by increasing share of their venture capital investments. The Gini

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estimator shown in Figures 2 to 7 erronously allocates some density mass to negative volumes of venture capital investment.

coefficient thus compares the distribution of country shares in venture capital investments to a uniform distribution, giving a measure of cross-country concentration. While Figure 8 looks at the dispersion of aggregate venture capital investments, Figure 9 takes a closer look at the dispersion of several structural characteristics of national venture capital markets. Figure 8 reveals that the concentration country share in all countries' total *early stage* investment has been lower than the concentration of country share in all countries' total venture investments throughout the observation period. This is notable because the agglomeration hypothesis implies the opposite, assuming that early stage investments are the least mobile segment in the short run. Figure 8 also presents a piece of information suggesting that professional management methods are widely diffused in European venture capital: A low share of non-syndicated venture capital investments in the total volume of national venture capital investments can be considered as a measure of the professional sophistication of venture capital. It is remarkable that the Gini coefficient for this measure is very low throughout the sample period. Apparently, countries had very similar shares of non-syndicated venture capital investments.

Figure 9 shows that the cross country dispersion of venture capital investments *by source of funds* is much larger than the cross country dispersion of venture capital investments *by stage focus*. But these differences are blurred in the later years when the Gini coefficients for both captive and public venture capital investments per mil of GDP drop markedly. One explanation might be that countries which had relatively little captive and public venture capital investments per mil of GDP until 1999, suddenly boosted these ratios in the year 2000. Alternatively, countries with relatively large captive and public venture capital investment may suddenly have seen them drop, as it actually happened in the case of Ireland.

Markov chain estimates

Tables 2 to 5 present estimates of first-order, time-stationary transition probabilities over periods of one and four years – for the entire data set of aggregate venture capital investment measures from all thirteen countries. To facilitate the estimation, all variables have been entered after logarithmic transformation. The total numbers of observed one year and four years transitions are 156 and 117, respectively. The first panel of each table gives the one-step annual transition matrix, whose (*i, j*) entry is the conditional probability that the measure of venture capital investment in a certain country has transited from state *i* to state *j* after one year. Entries on the main diagonal are the probabilities that the measure of venture capital investment observed in a certain interval of the state space will *not* have moved out of that interval after one year. Entries to the right of the main diagonal give the probabilities that the measure increases its relative weight in a country, whereas entries to the left of the main diagonal are the probabilities for the measure to loose ground in a country, relative to the entire sample of countries.[7]

Each panel in Tables 2 to 5 contains the transition matrix, the sample distribution across states, the stationary distribution computed according to the Chapman-Kolmogorov equation and several specification test statistics: a test for the independence of individual rows of the transition matrix, a test for equality of each row with the sample distribution and a test for the simultaneous equality of all rows with the sample distribution. Moreover, each panel also provides three mobility indices, based on the trace, the eigenvalue and the determinant of the estimated transition matrix.[8] Each row of the transition matrix sums to one. The stationary distribution can be interpreted as the implied

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[7] Entries are rounded to two decimal places.

ergodic distribution, the asymptotic unconditional probability that a country falls into one of the three states, provided the underlying Markov chain is irreducible, and positively recurrent. These probabilities are independent of the initial state that a country occupies, provided there is no lock-in at one end of the extreme states. The panels reporting the non-fractile results also report the state, defined in terms of their logarithmic values.[9] The salient feature of the estimated transition matrices are the entries on the main diagonal: the larger these values, the greater the persistence in countries' relative venture capital investment. The larger the off-diagonal entries, the larger is the mobility. The mobility indices try to express these characteristics in one parameter taking values between zero and one.

In the three panels stacked in the left part of Table 2, I present the results for individual countries' different shares in the total venture capital investment volume of all sample countries combined. The persistence of countries' relative position, as revealed in the large entries on the main diagonal and the low values of the mobility indices, is very high. The off-diagonal entries furthest away from the main diagonal are in fact zero. This is not very surpirising since the relative size of each country's economy will have a large influence on the relative size of its venture capital sector, and this influence will not change much during the sample period. The finding of high persistence in the distribution of aggregate venture capital investments is thus not very informative with regard to the hypotheses of agglomeration and specialization. More important is the observation that the implied ergodic distribution is not very different from the sample distribution. In the fixed states estimates, the implied probability of ending up in the lowest state is somewhat lower than in the sample and the

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8 See Shorrocks (1978) and Geweke et al. (1986).

9 The upper bounds have been chosen so as to ensure an approximately equal number of realisations for each state in the sample period.

probability of ending up in the highest state in slightly higher. This could be an indication that many of the more numerous small venture capital sectors are catching up with the leaders. But as a caveat, the ergodic distribution implied by the estimated transition matrix for the fractile Markov chain does not show any noticeable deviation from the sample distribution. However, a positive time trend in the interquantile range, albeit a mild one, is found to be significant at the 5 % level.

The right panel of Table 2 shows results for countries' shares in the total volume of early stage investments of all sample countries combined. To control for the influence of country size, each country's share in early stage venture capital is expressed as a ratio in which the early stage share is divided by the share of each country's total venture capital investment in the aggregate venture capital investment volume of the sample countries. These estimates reveal much lower persistence; all the elements on the main diagonal of the transition matrix and the values of the three mobility indices are lower. The estimated coefficient for the influence of time on the size of the interquantile range is negative. And the implied ergodic distribution is similar to the sample distribution, except in the case of the four-year transition matrix. There, the long term probability of being in a state with relatively low levels of early stage investments is larger than the relative frequency of that state in the sample, whereas the long term probability of having relatively high levels of early stage investments is lower. This observation may reflect the fact that emerging venture capital markets often develop by first increasing the volume of venture capital that is targeted at the expansion stage of portfolio firms and at late stage deals, such as management buy-outs; the development of a venture capital market for early stage investments often takes much longer.

A simpler way of controlling for country size is to divide each country's venture capital investment volume by its GDP. Using GDP as a scaling factor results in transition probability matrices that indicate venture capitals's evolving *relative* importance in different countries. Both Table 3 and Table 4 are based on the normalization relative to GDP. The three panels stacked on the left side present the results for *early stage* investments, the three panels in the middle those for *expansion* stage investments and the three panels on the right those for *total* venture capital investment, in each case per mil of GDP. In all three estimated transition matrices for early stage investment, persistence is lower than in the corresponding transition matrices for expansion stage and total venture capital investments. This conclusion is supported both by the relatively *low* entries on the main diagonal of the early stage transition matrices and by the relatively *high* values of the three mobility indices for early stage investment shares in GDP. The stationary distribution for early stage investments implies a greater probability for countries to be in the high-level state than suggested by the sample distribution. The observed mobility in the transition matrix may thus be mainly due to small venture capital sectors catching up in early stage investments. In total venture capital investments, by contrast, the ergodic distribution is almost exactly the same as the sample distribution. However, the regression of interquantile range on time suggests that the variance of the scaled measure of expansion stage and total venture capital across countries has shrunk slightly over the course of the observation period.

Table 4 reports estimated transition probability matrices for the three major organizational forms of venture capital – independent, captive (including semi-captive) and public – which are defined on the basis of their respective principal capital *sources*. The agglomeration hypothesis implies that persistence is particularly pronounced in *independent* venture capital investments, because the accumulation of the pertinent skills and experiences to manage these relies to a much larger extent on the three local public good inputs responsible for path dependence, as I explained in section 2. *Captive* venture capital firms, by contrast, are much less dependent on those three public inputs: with a clear mandate to target technologies related to their corporate parent's priorities, they rarely syndicate; with a reliable stream of capital infusions from their coporate parent, IPOs of portfolio firms are not important as a signal to attract outside investors for future funds; and with recruitment of personnel from their corporate parent, they do not require a well-developed local labour market for venture capital professionals. Analogous arguments apply in the case of public venture capital.

In the two panels on the left, Table 4 shows the results for independent venture capital, in the middle those for captive (and semi-captive) venture capital and on the right those for public venture capital investments, all scaled by GDP. Mobility is quite similar across organizational forms, and in all three cases, it is higher in four-year transitions than in one-year transitions. The observed mobility is similar to the degree of mobility found in total venture capital investment per mil of GDP, as shown in Table 3.

Table 5 presents similar results for syndicated and non-syndicated venture capital investments. This can be interpreted as an important structural indicator of the maturity of a national venture capital industry; syndication is the preferred strategy of venture capital firms that are highly specialized in their focus on one or a few narrow areas of high technology and thus have to rely on syndication as a strategy to diversify their investments across portfolio firms. Non-specialized venture capital firms, by contrast, can diversify by choosing portfolio firms in different areas of technology, so that the overall riskiness of the portfolio is reduced. The agglomeration hypothesis can be interpreted as implying persistence in national patterns of syndication. A more sophisticated venture capital industry distinguishes itself by a higher propensity to syndicate; and such structural differences should persist over time if the agglomeration hypothesis is true.

The two left panels of Table 5 show the one-year and four-year transition matrices for national shares in the aggregate volume of syndicated venture capital investments, scaled by countries' total venture capital investments.

Persistence does not appear to be high, except in the lowest state: Even after four years, almost three in four countries starting in that state have not moved to a higher state. But persistence does not seem to be a general characteristic of lowly syndicated venture capital markets. On the contrary, the right panel of Table 5, showing the estimated transition matrices for countries' different shares of non-syndicated venture capital investment in their respective total volume of venture capital investments, provides further evidence of considerable mobility. Even countries that have initially had relatively little syndication in venture capital appear to be catching up, which casts further doubt on the agglomeration hypothesis.

5. Concluding remarks

In the 1990s, governments in many European countries have tried to seed and foster the development of domestic venture capital industries, sometimes lavishly spending taxpayers' money. This policy is, often explicitly, based on the assumption that venture capital provides an efficient financing solution for young technology-based firms when credit markets fail to make sufficient external funds available. But the evident success of venture capital in a few high-tech industries and a small number of fast-growing regions and countries need not imply that governments' role is to bring this form of financial intermediation to life everywhere. Instead, government policy should be based on a tested theory that can predict the likely success of targeted support for venture capital by identifying the relevant economic pre-conditions.

The present paper has considered and tested two competing hypotheses. The agglomeration hypothesis effectively links the dynamics of venture capital to a historical process driven by dynamic scale economies akin to learning-by-doing in infant-industry models of international trade. This implies that there may be scope in principle to enhance an economy's welfare through targeted support for venture capital. The specialization hypothesis, by contrast, has no such normative implication. Instead, venture capital investment patterns are seen as driven by demand, which in turn is largely determined by a country's institutional environment and by the evolving technological specialization of its economy. The evidence I have found in a cross section of 13 European countries is largely in favour of the specialization hypothesis. Not even in *early stage* and *independent* venture capital investments, the two segments where the empirical implications of the agglomeration hypothesis are expected to have their strongest impact, do I find evidence of persistence, or path dependence, in the cross-country allocation.

In future research, the distribution dynamics methodology should also be applied to the sectoral distribution of venture capital investments. Since many individual venture capital firms tend to specialize in one or a few narrow areas within high technology when selecting their portfolio firms, one should expect to find more detailed evidence on the hypothesis of agglomeration and path dependence from the evolution of sectoral investment patterns over time. The empirical methodology described in the present paper can be readily adapted to the case of categorical variables. The EVCA (2003) already publishes the required data annually, in its venture capital yearbook, for each of the European countries in which such data are regularly collected.

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Table 1: The standard Gini coefficient for different measures of VC investment

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	1990–1996	1997–2002
Country share in all countries' total VC investment	0.78	0.71	0.73	0.73	0.74	0.75	0.71	0.73	0.75	0.71	0.69	0.61	0.68	0.69	0.66
Country share in all countries' total early stage investment	0.69	0.53	0.58	0.60	0.62	0.64	0.63	0.65	0.58	0.60	0.62	0.60	0.54	0.59	0.57
Early stage per mil of GDP	0.46	0.39	0.37	0.41	0.42	0.50	0.53	0.53	0.42	0.45	0.28	0.36	0.44	0.44	0.47
Expansion stage per mil of GDP	0.50	0.41	0.43	0.40	0.41	0.45	0.41	0.39	0.37	0.36	0.29	0.33	0.29	0.41	0.37
Total VC investment per mil of GDP	0.53	0.46	0.48	0.47	0.48	0.52	0.52	0.48	0.49	0.46	0.45	0.39	0.43	0.48	0.46
Independent VC investment per mil of GDP	0.87	0.79	0.89	0.89	0.95	0.89	0.97	0.91	0.71	0.92	0.66	0.67	0.59	0.90	0.79
Captive investment per mil of GDP	0.84	0.73	0.73	0.79	0.89	0.83	0.77	0.89	0.86	0.86	0.43	0.32	0.55	0.79	0.75
Public VC investment per mil of GDP	0.97	0.91	0.75	0.77	0.80	0.77	0.82	0.95	0.82	0.94	0.60	0.67	0.46	0.93	0.87
Share of non-syndicated investment in total national VC investment	0.21	0.20	0.24	0.25	0.15	0.15	0.18	0.19	0.10	0.18	0.14	0.15	0.21	0.19	0.16

Table 2: Estimated Transition Probability Matrices for the Allocation of Total and Early-stage VC Investment Across Countries

	National share in total VC investment			National share in total early stage VC investment, standardized*		
One-year transitions						
Upper endpoint (ln)	-5	-2.5		0.25	1	
Transition matrix	0.91	0.09	0	0.65	0.23	0.12
	0.06	0.86	0.08	0.29	0.52	0.19
	0	0.09	0.91	0.11	0.42	0.47
Sample distribution	0.29	0.42	0.29	0.38	0.37	0.24
Ergodic distribution	0.27	0.40	0.33	0.39	0.39	0.22
Test statistics for:						
independence[1]	223.19			39.52		
equality with sample distr.[2]	79.67	69.59	79.67	25.76	9.44	16.16
overall equality of rows[3]	228.94			51.36	51.36	51.36
Mobility indices[4]	0.16	–	0.30	0.69	–	0.91
Four-year transitions						
Upper endpoint (ln)	-5	-2.5		0.25	1	
Transition matrix	0.82	0.18	0	0.56	0.34	0.1
	0.12	0.76	0.12	0.36	0.5	0.14
	0	0.12	0.88	0.24	0.41	0.35
Sample distribution	0.29	0.43	0.28	0.35	0.36	0.29
Ergodic distribution	0.26	0.38	0.37	0.42	0.42	0.16
Test statistics for:						
independence[1]	128.93			17.97		
equality with sample distr.[2]	44.63	35.05	54	12.68	7.79	2.53
overall equality of rows[3]	133.68			23		
Mobility indices[4]	0.27	–	0.48	0.80	–	0.96
Fractile Markov chain						
Transition matrix	0.94	0.06	0	0.54	0.31	0.15
	0.06	0.88	0.06	0.35	0.38	0.27
	0	0.05	0.95	0.08	0.29	0.63
Sample distribution	0.31	0.31	0.38	0.33	0.33	0.33
Ergodic distribution	0.31	0.31	0.38	0.31	0.31	0.38
Test statistics for:						
independence[1]	243.53			33.75		
equality with sample distr.[2]	86.03	68.96	90.41	11.38	0.88	21.5
overall equality of rows[3]	245.4			33.75		
Trend regression for inter-quantile range[5]	-127.83	0.06	0.02	93.07	-0.05	0.02
Mobility indices[4]	0.12	0.12	0.23	0.73	0.73	0.97

*divided by national share in total VC investment. – [1]Asymptotically χ^2 with 4 degrees of freedom. – [2]The test statistics – for the first, second and third row – are asymptotically χ^2-distributed with 2 degrees of freedom. – [3]Asymptotically χ^2 with 6 degrees of freedom. – [4]The following three mobility indices are given that evaluate the trace of the transition matrix, tr(Π), the eigenvalues, λ_j, and the determinant, det(Π), respectively: $\mu_1 = n - \mathrm{tr}(\Pi)/(n-1)$; $\mu_2 = n - \sum_m |\lambda_m|/(n-1)$; $\mu_3 = 1 - |\det(\Pi)|$. – [5] The entries of this row give the estimated constant, the coefficient and the coefficient's standard error from a regression of the interquantile range on time.

Table 3: Estimated Transition Probability Matrices for VC Investment by Stage-focus

	Early stage*			Expansion stage*			Total*		
One-year transitions									
Upper endpoint (ln)	-3.3	-2.5		-1.33	-0.5		-1	-0.33	
Transition matrix	0.6	0.23	0.16	0.7	0.24	0.06	0.72	0.21	0.08
	0.21	0.43	0.36	0.15	0.56	0.3	0.1	0.58	0.33
	0.03	0.17	0.8	0.02	0.29	0.69	0.01	0.1	0.88
Sample distribution	0.28	0.27	0.46	0.35	0.35	0.31	0.25	0.26	0.49
Ergodic distribution	0.17	0.24	0.58	0.22	0.38	0.40	0.11	0.22	0.68
Test statistics for:									
independence[1]	67.88			83.4			117.97		
equality with sample distr.[2]	19.16	5.64	60.07	34.85	13.34	35.38	39.15	20.38	83.39
overall equality of rows[3]	84.87			83.58			142.92		
Mobility indices[4]	0.59	–	0.86	0.53	–	0.81	0.41	–	0.67
Four-year transitions									
Upper endpoint (ln)	-3.3	-2.5		-1.33	-0.5		-1	-0.33	
Transition matrix	0.28	0.26	0.47	0.38	0.34	0.28	0.37	0.26	0.37
	0.13	0.18	0.7	0.2	0.39	0.41	0.11	0.3	0.59
	0.12	0.21	0.68	0	0.3	0.7	0	0.14	0.86
Sample distribution	0.37	0.34	0.29	0.45	0.38	0.17	0.32	0.32	0.36
Ergodic distribution	0.14	0.21	0.65	0.11	0.33	0.56	0.03	0.17	0.80
Test statistics for:									
independence[1]	64.12			67.47			58.35		
equality with sample distr.[2]	3.49	23.77	21.76	5.55	3.58	38.12	0.89	14.18	49.58
overall equality of rows[3]	49.02			47.25			64.64		
Mobility indices[4]	0.93	–	0.99	0.77	–	0.97	0.74	–	0.95
Fractile Markov chain									
Transition matrix	0.65	0.21	0.15	0.71	0.21	0.08	0.75	0.21	0.04
	0.29	0.38	0.33	0.21	0.56	0.23	0.19	0.58	0.23
	0.08	0.58	0.33	0.04	0.38	0.58	0.08	0.28	0.64
Sample distribution	0.44	0.44	0.11	0.4	0.4	0.2	0.36	0.36	0.27
Ergodic distribution	0.37	0.37	0.27	0.32	0.40	0.28	0.36	0.36	0.27
Test statistics for:									
independence[1]	44.67			52.24			69.29		
equality with sample distr.[2]	20.03	4.38	29.5	27.85	11.08	24.32	36.57	12.85	22.44
overall equality of rows[3]	53.91			63.25			71.86		
Trend regression for inter-quantile range[5]	16.93	-0.01	0.02	156.3	-0.08	0.02	112.84	-0.06	0.02
Mobility indices[4]	0.82	0.73	0.96	0.57	0.57	0.85	0.51	0.51	0.79

*VC investment per mil of GDP. – [1]Asymptotically χ^2 with 4 degrees of freedom. – [2]The test statistics – for the first, second and third row – are asymptotically χ^2-distributed with 2 degrees of freedom. – [3]Asymptotically χ^2 with 6 degrees of freedom. – [4]The following three mobility indices are given that evaluate the trace of the transition matrix, tr(Π), the eigenvalues, λ_j, and the determinant, det(Π), respectively: $\mu_1 = n - \mathrm{tr}(\Pi)/(n-1)$; $\mu_2 = n - \sum_m |\lambda_m|/(n-1)$; $\mu_3 = 1 - |\det(\Pi)|$. – [5] The entries of this row give the estimated constant, the coefficient and the coefficient's standard error from a regression of the interquantile range on time.

Table 4: Estimated Transition Probability Matrices of VC Investment by Source of Funds

	Independent*			Captive*			Public*		
One-year transitions									
Upper endpoint (ln)	-1.66	-0.33		-2	-0.50		-4	-2	
Transition matrix	0.73	0.25	0.02	0.77	0.20	0.04	0.83	0.12	0.05
	0.17	0.60	0.23	0.13	0.62	0.24	0.17	0.67	0.17
	0.02	0.06	0.92	0	0.20	0.8	0.04	0.21	0.75
Sample distribution	0.36	0.31	0.33	0.36	0.29	0.35	0.42	0.27	0.31
Ergodic distribution	0.17	0.17	0.63	0.20	0.34	0.46	0.39	0.32	0.29
Test statistics for:									
independence[1]	140.81			121.39			127.95		
equality with sample distr.[2]	41.73	17.78	81.5	46.5	21.43	54.25	62.72	27.92	43.1
overall equality of rows[3]	141.01			122.19			133.74		
Mobility indices[4]	0.38	–	0.65	0.41	–	0.67	0.38	–	0.63
Four-year transitions									
Upper endpoint (ln)	-1.66	-0.33		-2	-0.5		-4	-2	
Transition matrix	0.52	0.31	0.17	0.44	0.44	0.13	0.58	0.27	0.15
	0.13	0.38	0.49	0.06	0.38	0.56	0.21	0.61	0.18
	0.04	0	0.96	0.03	0.20	0.77	0.13	0.13	0.73
Sample distribution	0.44	0.33	0.22	0.47	0.27	0.26	0.50	0.24	0.26
Ergodic distribution	0.08	0.04	0.88	0.07	0.26	0.67	0.29	0.33	0.38
Test statistics for:									
independence[1]	104.99			76.48			60.71		
equality with sample distr.[2]	11.46	8	73.68	14.02	16.19	36.66	21.44	16.33	30.16
overall equality of rows[3]	93.14	93.14	93.14	66.86	66.86	66.86	67.93	67.93	67.93
Mobility indices[4]	0.57	–	0.85	0.71	–	0.93	0.54	–	0.80

*VC investment per mil of GDP. – [1]Asymptotically χ^2 with 4 degrees of freedom. – [2]The test statistics – for the first, second and third row – are asymptotically χ^2-distributed with 2 degrees of freedom. – [3]Asymptotically χ^2 with 6 degrees of freedom. – [4]The following three mobility indices are given that evaluate the trace of the transition matrix, tr(Π), the eigenvalues, λ_j, and the determinant, det(Π), respectively: $\mu_1 = n - \mathrm{tr}(\Pi)/(n-1)$; $\mu_2 = n - \sum_m |\lambda_m|/(n-1)$; $\mu_3 = 1 - |\det(\Pi)|$. – [5] The entries of this row give the estimated constant, the coefficient and the coefficient's standard error from a regression of the interquantile range on time.

Table 5: Estimated Transition Probability Matrices for Syndicated and Non-syndicated VC Investment

	National share in total syndicated VC investment of all sample countries, standardized*			Share of non-syndicated in total national VC investment		
One-year transitions						
Upper endpoint (ln)	-0.33	0.33		-0.55	-0.3	
Transition matrix	0.77	0.18	0.05	0.69	0.25	0.06
	0.4	0.45	0.15	0.23	0.38	0.4
	0.02	0.36	0.62	0.04	0.38	0.58
Sample distribution	0.39	0.34	0.27	0.33	0.34	0.33
Ergodic distribution	0.38	0.34	0.28	0.52	0.29	0.18
Test statistics for:						
independence[1]	76.36			58.04		
equality with sample distr.[2]	47.62	8.05	29.69	32.17	2.72	23.23
overall equality of rows[3]	85.36			58.12		
Mobility indices[4]	0.58	–	0.86	0.68	–	0.98
Four-year transitions						
Upper endpoint (ln)	-0.33	0.33		-0.55	-0.3	
Transition matrix	0.73	0.17	0.1	0.46	0.31	0.23
	0.51	0.36	0.13	0.2	0.5	0.3
	0.36	0.38	0.26	0.16	0.29	0.55
Sample distribution	0.26	0.38	0.36	0.33	0.34	0.32
Ergodic distribution	0.25	0.37	0.38	0.63	0.24	0.13
Test statistics for:						
independence[1]	56.55			18.14		
equality with sample distr.[2]	30.42	9.36	1.16	3.23	5.49	9.48
overall equality of rows[3]	40.93			18.19		
Mobility indices[4]	0.83	–	0.98	0.75	–	0.94

*scaled by total national VC investment. – [1]Asymptotically χ^2 with 4 degrees of freedom. – [2]The test statistics – for the first, second and third row – are asymptotically χ^2-distributed with 2 degrees of freedom. – [3]Asymptotically χ^2 with 6 degrees of freedom. – [4]The following three mobility indices are given that evaluate the trace of the transition matrix, $\mathrm{tr}(\Pi)$, the eigenvalues, λ_j, and the determinant, $\det(\Pi)$, respectively: $\mu_1 = m - \mathrm{tr}(\Pi)/(m-1)$; $\mu_2 = m - \sum_j |\lambda_j| / (m-1)$; $\mu_3 = 1 - |\det(\Pi)|$. – [5] The entries of this row give the estimated constant, the coefficient and the coefficient's standard error from a regression of the interquantile range on time.

Figure 1: *Short-run Dynamics in a Venture Capital Market*

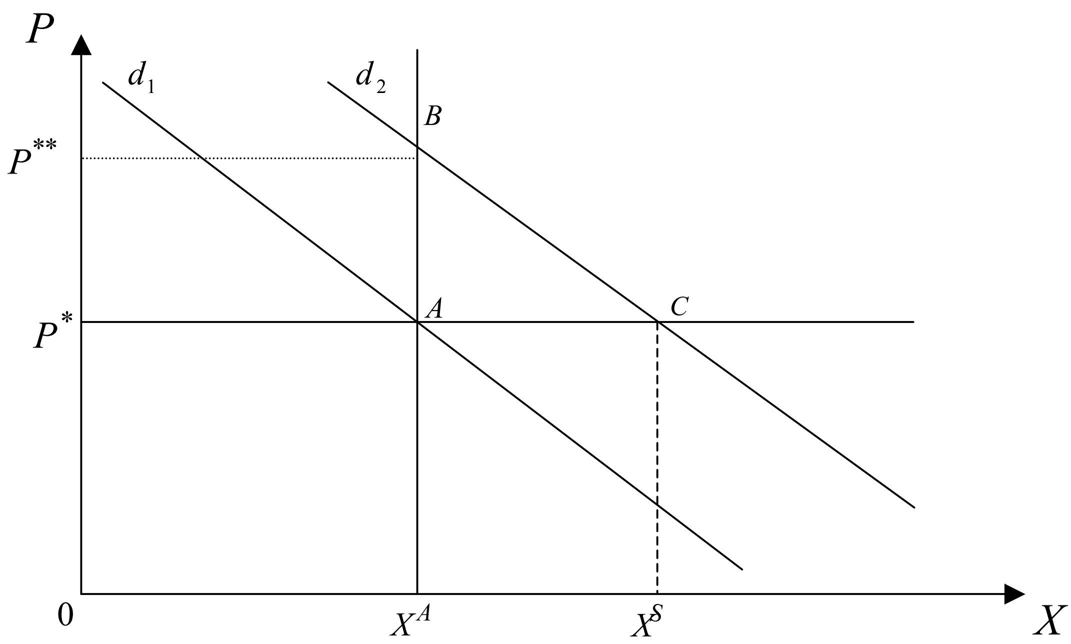

Figure 2: *The Distribution of Total Venture Capital Investments per mil of GDP*

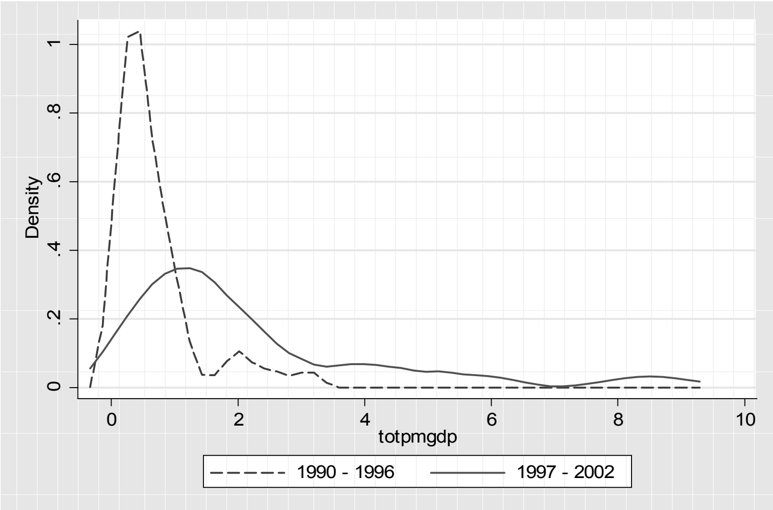

Figure 3: *The Distribution of Early Stage Venture Capital Investments per mil of GDP*

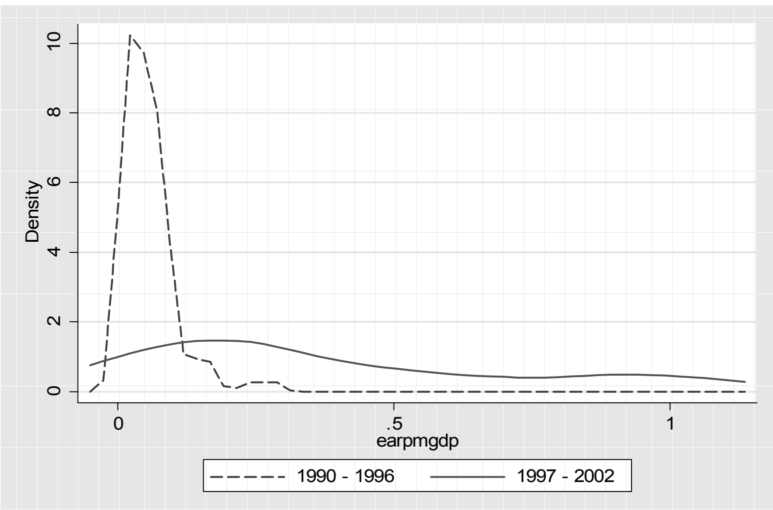

Figure 4: *The Distribution of Expansion Stage Venture Capital Investments per mil of GDP*

Figure 5: *The Distribution of Independent Venture Capital Investments Across Countries*

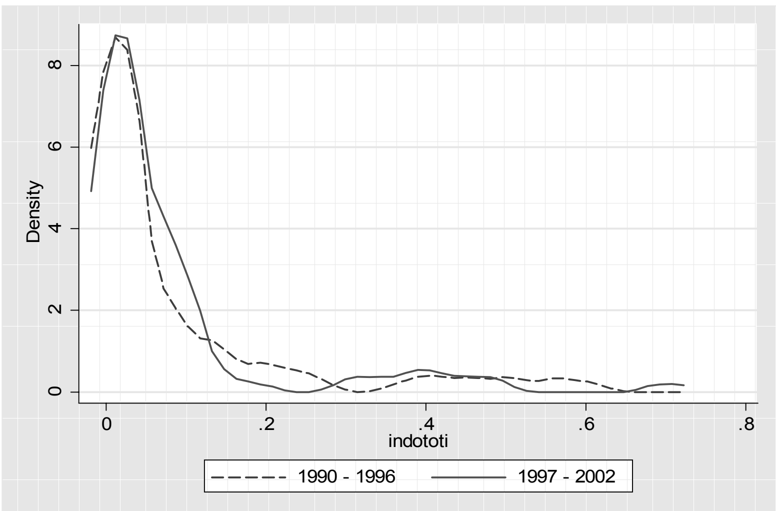

Figure 6: *The Distribution of Captive Venture Capital Investments Across Countries*

Figure 7: *The Distribution of Public Venture Capital Investments Across Countries*

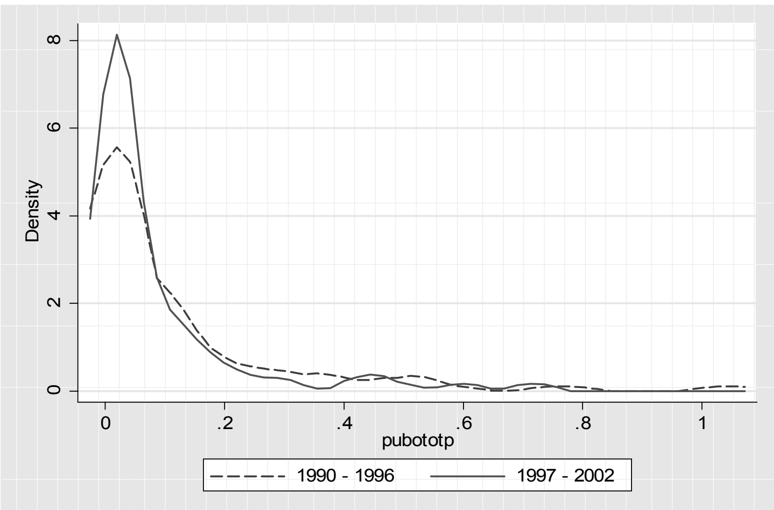

Figure 8: Cross-country Dispersion of Aggregate Venture Capital Investments – the evolution of Gini coefficients from 1990 to 2002

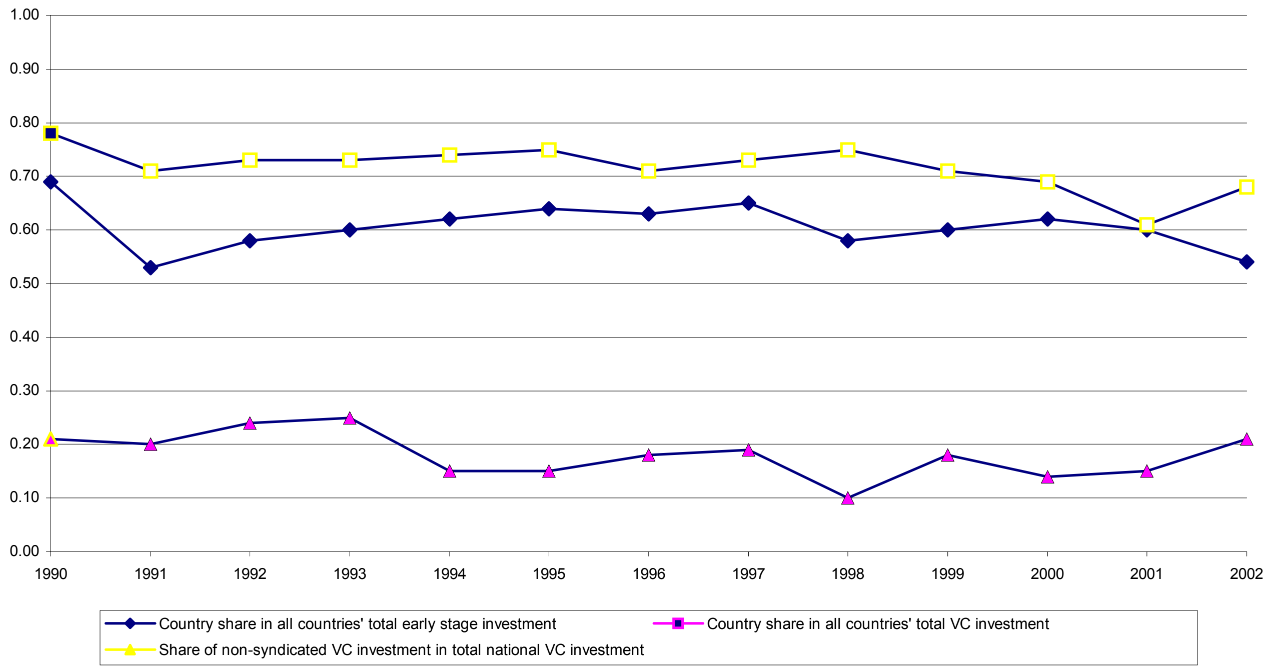

Figure 9: Cross-country Dispersion of Structural Characteristics in National Venture Capital Investments – the evolution of Gini coefficients from 1990 to 2002