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Non-Market Interaction in Primary Equity Markets: Evidence from France and Germany

by

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Abstract:

This paper provides micro-econometric evidence on the relevance of non-market interaction for the timing of initial public offerings (IPOs) in the French and German primary equity markets. The surge of IPO volume in the late 1990s appears to be consistent with rational expectations, not with adaptive expectations derived from the performance of past IPOs. This finding tends to support the hypothesis that hot issue markets are endogenous and that they may generate large welfare gains by boosting the incentives for technological innovation in start-up firms, potentially creating a self-fulfilling prophecy. A variety of empirical approaches and policy implications are discussed.

Keywords: Initial public offerings, New technology-based firms, Information spillover, Hot issue market, Non-market interaction

JEL Classification: G12, G14, G18

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Contents

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Figures

Tables

I. Motivation

Non-market interaction in issuers' and investors' decision making is a key element of primary equity markets. The notion of non-market interaction is central to recent explanations of volatility in primary equity markets that allow for significant welfare *gains* from bubbles manifesting themselves as hot issue markets. The conventional perception of stock market bubbles has focused on the large wealth *losses* suffered by investors who buy at or near market peaks as well as on the additional investment risks and economic instability that bubbles tend to generate. But this view has overlooked the potential for welfare gains from temporary reductions in the private costs of raising equity finance. As long as the private costs of equity finance exceed the social costs of capital in normal times, a bubble in the primary equity market may help to bring private and social costs into line and may thus enhance welfare by improving the allocation of capital. Non-market interaction may create a social multiplier, or multiple equilibria, and large variances in aggregate investment volumes across time and space. Stolpe (2004) argues that this can explain Europe's experience with venture capital in the 1990s, in which a temporary surge of investment volumes across countries has not eliminated persistent international differences in investment levels.

In the present paper, I distinguish initial public offerings (IPOs) according to their issuer's area of technology in order to examine the empirical relevance of non-market interaction within different technological neighbourhoods. For a variety of reasons, the difference between the private and the social costs of equity capital is likely to be particularly large for start-up firms from the most dynamic areas of high technology, such as biotechnology and software. Due to the inability of using human capital as collateral for bank credit, these firms are more dependent on equity capital to finance their expansion when they have a profitable product. However, equity investors will require higher rates of return because the prospects of high-tech start-ups are particularly uncertain and much of the available information is distributed more unevenly among potential investors as well as between the entrepreneur and any outside investor. The required rate of return is part of the cost of raising capital. In the absence of a bubble, these firms are hence likely to face suboptimal access to equity finance, and the rate of innovation is likely to be too small.

The idea that bubbles in primary equity markets can remedy this market failure – at least partially – rests on three stylized facts: First of all, these bubbles tend to be concentrated in the very same subsectors of high technology that are likely to face the highest cost of equity capital during normal times. Secondly, hot issue markets are typically accompanied by a rapid shortening of firms' average lifetime before the IPO. And thirdly, the observation that average underpricing tends to increase with the aggregate volume of IPOs suggests that hot issue markets boost investors' willingness to buy IPO shares so that the need and opportunity for rationing increases. In a similar vein, increased average underpricing may indicate an increased willingness to bet on more risky firms, whose IPOs are normally shunned. The social returns from the real investments financed with issuers' proceeds often exceed their private returns by a substantial margin. In the context of high technology, private research and development (R&D) often generates positive technological externalities in the form of knowledge spillovers for other firms and the introduction of radically new products can generate substantial pecuniary externalities such as product complementarities and system-wide increasing returns to scale. Hot issue markets in high technology are therefore likely to yield welfare gains that exceed the private wealth losses suffered by investors who buy at the peak of the bubble when almost all IPOs under-perform the general stock market price index in the long term – over periods of three to five years – as shown by Ritter (1991).

The literature has not dealt comprehensively with these issues. The few studies that do examine welfare gains from bubbles have mainly been theoretical, almost none – to my knowledge – have been done on the empirical end. In earlier theoretical analyses, Samuelson (1958) showed that speculative bubbles could be welfare-enhancing if they completed a limited set of existing markets and Tirole (1985) argued that bubbles in non-productive assets could help to reduce the over-accumulation of physical capital in dynamically inefficient economies. More recently, Olivier (2000) argued that a speculative bubble in equities may reduce the cost of capital and showed that this may raise the sustainable market value of firms and so encourage entrepreneurship, investment and growth. In a more comprehensive model, Caballero and Hammour (2002) have analysed the possibility of extended episodes of economic growth driven by the formation of a bubble in stocks of firms that belong to a newly emerging industry based on radical technological innovation.

Looking at the impact of information technology in the 1990s, this analysis provides an explanation for the acceleration of productivity growth in the US, in which the stock market bubble is part of a feedback mechanism that raises savings in response to improved growth prospects. The bubble essentially facilitates the real investments required for faster productivity growth. In a cross-section of countries, Harris (1997) found evidence that stock market activity is indeed positively correlated with investment, as predicted by Olivier's and Caballero and Hammour's models of speculative growth, but not with the marginal productivity of capital, as it would be if stock markets' impact on investment was mainly via their role in improving the selection of investment projects (Greenwood and Jovanovic 1990) and in diversifying away any remaining risks (Saint-Paul 1992b).

The remaining sections of the paper are organized as follows. Section II discusses competing explanations of bubbles with special reference to primary equity markets and policy implications. Section III discusses the testable implications and choice of empirical methods. Section IV provides descriptive statistics. Section V presents the results from statistical inference. Section VI discusses related literature and Section VII concludes.

II. Exogenous and Endogenous Explanations of Bubbles – Review and Synthesis

Economists' conventional definition of a bubble is that prices for a certain class of assets deviate from these assets' fundamental value for an extended period of time. Observed stock prices P_t are thus made up of two components – the fundamental value P_t^f and the bubble B_t: $P_t = P_t^f + B_t = \sum_{i=1}^{\infty} \delta^i E_t D_{t+i} + B_t$ where $E_t D_{t+i}$ is the dividend payment in the period between *t* and *t+i* expected on the basis of information at time *t* and δ is the discount factor. In practice, this implies that fundamental value is determined by a firm's price history in the stock market and by the prices of shares in similar firms observed over the long term. This definition largely relates to secondary equity markets: a bubble is viewed as a market-wide phenomenon, a period of abnormally high stock prices in general. It is often explained as a consequence of irrational behavior on the part of investors. But beginning with Blanchard and Watson (1982), economists with a penchant for self-consistent explanations have learned to model stock market bubbles in the context of rational behaviour. A bubble can arise when the solution to a rational expectations equilibrium is indeterminate and the socalled Euler equation, $P_t = \delta(E_t P_{t+1} + E_t D_{t+1})$, fails to give a unique price level at each point in time. The bubble is then a case of self-fulfilling expectations, which create the opportunity of making a profit from stock bought at a price above fundamental value because someone else will pay an even higher price in the future. This sort of bubble is clearly exogenous to the prediction of stock returns on the basis of fundamentals.[1] An alternative model of a rational bubble, also consistent with the Euler equation, has been developed by Froot and Obstfeld (1991) and dubbed an intrinsic bubble because it is a non-linear function of the level of dividends and thus driven by fundamentals. For an excellent review, see Shiller (2000), chapter 9.

In primary equity markets, the concept of fundamental value is elusive. The main problem in any IPO is in fact how to determine the true value of the issuing firm and to find an offer price which closely approximates this value by discounting long term prospects for profitability. Neither a price history, nor a sufficient number of comparable IPOs will normally be observed for an individual IPO firm. There will thus be no basis to quantify the bubble component in actual prices. This casts doubt on the validity of theoretical models, such as Ljungqvist et al. (2001), in which "irrationally exuberant investors" are a source of inefficiency that provides a single explanation for the three phenomena underpricing, temporal clustering and long-term underperformance. Instead of using market prices, bubbles in primary equity markets are better defined with reference to IPO volume, the number of IPOs during a given interval of time. Bubbles are therefore synonymous with hot issue markets, characterized by an unusually high volume of offerings, large underpricing, frequent over-subscription of offerings, a preponderance of small issues and often by concentrations in particular industries, as described in Helwege and Liang (1996), p. 1, and more up-to-date in Ploog and Stolpe (2003), pp. 129. The intervening periods, known as cold issue markets, have much lower issuance, lower underpricing, fewer instances of over-subscription and larger offerings on average.

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[1] As Cuthbertson (1996), p. 159, notes, this model of a rational bubble satisfies the martingale property and is uninformative about the cause, size, beginning and end point of the bubble.

To gain some insight into the potential welfare benefits from hot issue markets, I propose to distinguish between *exogenous* and *endogenous* sources of bubbles. Exogenous sources lie outside the stock market and expansive monetary policy is a prime example. Endogenous sources, by contrast, arise from some kind of feedback between stock market prices and the real economy that turns rising prices into a self-fulfilling prophecy. For example, the interdependence of timing choices by individual investors and issuers planning to list in the stock market can lower the cost of raising equity capital and therefore expand the scale at which innovative firms exploit their ideas. This interdependence is a form of non-market interaction, a natural implication of externalities associated with the revelation of private information through investors' and issuers' choices.

Exogenous and endogenous sources of bubbles are not mutually exclusive, but making the distinction helps to define the conditions under which a hot issue market may have welfare benefits. The exogenous bubble is not expected to generate welfare gains. Instead, it is likely to cause welfare losses. Endogenous bubbles, by contrast, reflect the presence of multiple equilibria with different welfare levels. For reasons spelled out below, an endogenous bubble concentrated in high technology may be interpreted as a focusing device that coordinates individual behaviour so that it becomes consistent with the efficient equilibrium. It is of course an empirical question which source of bubbles dominates in a given situation. An empirical assessment is therefore indispensable to solve a variety of policy issues, including the regulation of markets and the oversight of financial intermediaries.

Exogenous Bubbles. The classic analysis of a bubble in *non-productive* assets has emphasized the additional demand for savings and the implied increase in the cost of capital for productive investments. In the absence of production externalities, this may actually be a boon since bubbles can only arise in economies that are dynamically inefficient at the outset: obviously a bubble cannot grow faster than the economy's growth rate in the long term, yet the growth rate must equal the interest rate in equilibrium. Since the bubble's crowding out of real investment will increase the interest rate, this rate must fall short of the economy's growth rate before the bubble starts, which implies that capital has been accumulated at a rate in excess of its rate of return.

Olivier (2000) departs from the classic analysis by focusing on bubbles in productive assets whose prices directly enter agents' maximization problem. When agents have the choice of being either workers or entrepreneurs, an IPO market price of firms above their 'fundamental' value will affect the optimal choice, with implications for wages, the rate of firm formation and the growth rate of the economy. Olivier's model builds on Romer's (1990) model of endogenous technological change in which long-term growth is sustained by positive externalities from private firms' R&D. The larger the bubble and the lower the interest rate, the more valuable is each firm. The growth-enhancing effect is therefore unambiguous when the interest rate is constant, as it is in a small open economy. However, when the interest rate is flexible, as it must be in a closed economy model, the impact of the bubble on growth is ambiguous, because increased asset prices will tend to raise the interest rate via the implied increase in consumer demand and real investments.

In either case, Olivier's (2000) model highlights the salient feature of exogenous bubbles that they are not specific to any particular industry or area of technology; the general optimism rather improves the opportunities for all firms seeking expansion finance in primary equity markets. Yet, the assumption of non-diminishing social returns in excess of the private returns on investment – the driving force in Olivier's model – is more likely to be relevant in the small number of high-tech industries where positive externalities from the creation of knowledge and a perpetual flow of new ideas are strong.[2]

Although an economy need not be dynamically inefficient to accommodate a rational bubble in the presence of externalities (Saint-Paul 1992a), the economy as a whole is likely to see over-investment and excess capacity as a result of an exogenous bubble that reduces the private costs of capital for all firms, if most firms are outside of high technology and do not face a market failure. With over-investment in IPOs of low-tech firms accompanied by under-investment in IPOs from high-tech industries, the existing distortions in favour of low-tech firms remain in place and capital continues to be wasted. The relative number of high-tech IPOs is too small, and the relative number of low-tech IPOs is too large. Hence, the smaller the share of high technology the larger is the waste of capital in other sectors that an exogenous bubble will cause. This intersectoral distortion is likely to be further exacerbated by a decrease in the average quality of investment projects that are selected during an exogenous bubble. Entrepreneurs both within and outside the high-tech sector will usually be uncertain about the economic prospects of their ideas. When a bubble makes it easier to raise funds through an IPO, the entrepreneurs may feel less pressure to generate the best ideas. Instead, they may be tempted to rush to the market with premature and possibly bad ideas so that an increasing share of the available capital is allocated to firms that turn out to be failures.

Endogenous Bubbles. Over-investment is much less likely in an endogenous bubble where growth effects are mainly due to a reduction of the capital market's inherent distortion against high-tech firms. Given that the creation of high technology is often associated with strong increasing returns to scale, it is natural to assume that there are at

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2 See Peri (2003) for a comprehensive empirical study and Griliches (1992) for an earlier survey.

least two equilibria of steady state growth when a new high-tech industry is about to emerge: a distorted market equilibrium in which the level of high-tech investment is too low and the undistorted social planner equilibrium in which the optimal level is reached. Within a model that allows for these two equilibria, the endogenous bubble may serve as a catalyst, a kind of self-fulfilling prophecy, that facilitates the transition to the more efficient equilibrium with higher growth, as in Krugman (1991). In the following, I will argue that the bubble can only play this role if there is an effective feedback mechanism between the valuation of firms in the stock market and the real economy. Such a feedback mechanism may take a variety of forms, based either on linkages in macroeconomic aggregates or on non-market interdependence in microeconomic choices due to the co-ordinating role of information revealed in primary equity markets.

Whatever feedback mechanism is in force, the theory of self-fulfilling prophecies must be clearly distinguished from theories of information cascades in which multiple equilibria in stock market prices arise without any feedback from the real economy. Banerjee (1992) and Bikhchandani et al. (1992), have developed models of herdlike behaviour arising from an information cascade where it is rational for an individual, possessing only partial information, to take into account the judgments revealed by other people's choices, even if the group behaviour is known to result in a suboptimal, and hence irrational equilibrium. If hot issue markets were pure herding under unobservable private information, as in Banerjee (1992), a privately held firm would decide about going public or staying private under the condition that it possesses an exclusive signal with a certain probability α_f which is expected to be correct with probability ξ_f. By the same token, investors would decide about buying stock from a particular IPO after receiving a private signal with probability α_i that is correct with probability ξ_i. On either side, a second agent will follow the first if she has no signal; and after a sufficient number of agents act in a certain way, all following agents will do the same. Lock-in at a suboptimal activity is therefore possible, in which case a pure information externality would have persistent negative welfare implications.

These results are not inconsistent with the observed clustering and underperformance of IPOs: a bubble may simply indicate the enforcement of the subjective probabilities ξ_f and ξ_i after a certain number of agents have bet on rising prices. It is clear that such a temporary lock-in at unsustainable valuation levels is a market failure. It results from the inefficient generation of new information when free-riding decision makers cease to engage in socially valuable experimentation and from the incomplete diffusion of information when the range of observable actions is too small to reveal the full set of private information, as in Morris and Shin (2002), p. 1523. Ultimately, this market failure hypothesis rests on the idea that fundamental value is exogenous and stays constant through the bubble. As Shiller (2000), p. 152, notes "all information cascade theories are theories of the failure of information about true fundamental value to be disseminated and evaluated".

The essential difference in an endogenous bubble is that the seemingly irrational group behaviour is subsequently justified by a rise in the fundamental value of the assets that are subject to the bubble. Within an endogenous bubble, it is precisely the appropriate valuation of new issues that is endogenous because lower costs of equity capital enable firms to better exploit the increasing returns to scale inherent in high technology. Obviously, the expected valuation in the primary equity market plays a crucial role in high-tech firms' decision to go public. During a bubble, firms can expect to receive higher proceeds from the IPO and to finance operations on a larger scale. With a faster build-up of capacity, they can expect greater profitability and a higher rate of return on their original investment, which justifies at least part of the higher market valuation of the IPO (see Olivier 2000). Because in high-tech firms, fixed costs from R&D account for a bigger share of total cost, average costs can decline more as output is increased.

The ability to expand quickly and to appropriate as much as possible of a new product's social value is the principal reward for innovation in high-tech firms. A larger scale and a higher fundamental value is more likely to be achieved in hot issue markets than in cold issue markets where prices are depressed, because in the absence of information spillovers, risk averse investors often do not know how to value an individual IPO. It is for this endogeneity of fundamental value that an endogenous bubble cannot be fully explained as an information cascade.

A generic model. To define more precisely the conditions under which endogenous bubbles can arise, consider a reinterpretation of Krugman's (1991) stylized model of a stochastic allocation process in which multiple equilibria are selected either by historical events, reflected in an economy's initial conditions, or by self-fulfilling prophecies, formed by collective expectations. This model features a two-sector open economy model with labour as the only factor of production and has two long-term stable equilibria – motivated by the assumption that workers' decentralized decision making is interdependent through positive feedback, with labour productivity in one sector being an increasing function of the sector's total labour input due to positive externalities. Workers will tend to move to the sector offering the higher wage, but individual decisions may be subject to some noise so that the allocation must be modelled as a stochastic process.

Krugman (1991) establishes three conditions for collective expectations to play a decisive role in the selection of long-term equilibria in such a stochastic allocation process: (i) The speed with which resources can be reallocated must be high relative to the rate of time preference with which future income differentials are discounted. The potential future benefits of the first-best long-term allocation must outweigh the benefits of whatever allocation may be initially realized. In other words, the cost of reallocating resources and the real rate of interest must be low. (ii) There must be increasing returns to scale of sufficient strength in one sector so that a redirection to this allocation lets incomes rise rapidly. (iii) The initial historical situation must not already be irreversibly 'locked' into the inferior long-term equilibrium.

These insights are sufficiently general to hold also if we consider a fixed number of new entrepreneurs K, with limited access to capital as their only factor of production, who must decide in which industry to set up as an initially unlisted firm. Given the common denial of bank credit for human capital investments and the practice of rationing and staging in the venture capital sector, it is plausible to assume that entrepreneurs indeed have limited financing for each project in an emerging high-tech industry. The story can then be summarized as follows: The economy with an initial real capital endowment $\bar{\kappa}$ distributed equally among the given number of start-up firms produces two kinds of goods for which prices are fixed at world market levels: a basket of conventional goods C with constant returns and a variety of high-tech goods X with increasing returns to scale and subject to a positive externality. In the context of this model, the externality can provisionally be thought of as sector-specific knowledge spillovers from R&D for the creation of new product varieties. More specific mechanisms, which I will describe below, can replace the rather general assumption of knowledge spillovers. Formally, the larger the number of start-up firms in X, the higher the rate of return in that sector: $\pi = \pi(K_X)$ with $\pi(K_X)$ being continuously differentiable so that $\pi' > 0$, $0 < \pi(0) < 1$, $1 < \pi(\bar{\kappa}) < +\infty$. The world market rate of interest is fixed at $r > 0$. As long as discounted present values of future capital income in the high-tech industry exceed that in the low-tech industry, entrepreneurs will want to start a high-tech venture, but they are slowed by positive adjustment costs since R&D and learning-by-doing take time to bear fruit.

For simplicity, the economy's total cost of moving a start-up into high-tech, instead of low-tech, can be assumed to be quadratic in the rate at which start-ups are set up, reflecting the 'congestion' from parallel R&D and parallel learning. The more start-ups go into high technology, the more likely will be the involuntary and wasteful duplication of research projects and the larger will be the percentage of start-ups that fail due to the obsolescence of their investments. The set-up cost for each entrepreneur is $|\dot{K}_X|/\gamma > 0$ where γ is an inverse index of the adjustment cost that determines the speed of adjustment. The economy is therefore described by the dynamic system $\dot{K}_X = \gamma q$ and $\dot{q} = rq - \pi(K_X) + 1$, where q is the present value of a start-up located in the high-tech industry instead of the established industry and $\dot{q}$ is the rate of capital gains on this value. The qualitative laws of motion of this dynamic system are as follows: whenever q is positive, K_X is rising; whenever it is negative, K_X is falling. A higher value of q can result only if q is expected to rise, a lower value only if q is expected to fall. No movement is expected at the critical allocation, $K_X = K_X^*$, where $q = 0$ and an unstable equilibrium is reached. In the long term, only two equilibria are stable, one where all start-ups are in the established industry and one where they are all in high technology.

To understand how one of these equilibria gets selected through history or expectations, I follow Krugman (1991), pp. 661, and adopt a simple linear function for $\pi(K_X)$, such that $\pi = 1 + \beta(K_X - K_X^*)$, where β represents the strength of the external economies in high technology. The dynamic system now consists of two linear differential equations and – as shown by Krugman (1991) – self-fulfilling expectations can only play a role in the selection of a long-term equilibrium if $r^2 < 4\beta\gamma$, that is if the future is not heavily discounted (r must be small), if interdependence among decisions is strong (β must be sufficiently large), and if the economy does not adjust too slowly (γ must be sufficiently large).

It is clear that the last two conditions are more likely to be met in the case of an emerging high-tech industry than in long-established industries. Because R&D and learning-by-doing take time, there are significant adjustment costs, but they are not prohibitive. In the absence of adjustment costs, either equilibrium could be obtained as a self-fulfilling prophecy from any initial position of the economy. With adjustment costs, the decision of an entrepreneur to set up in the high-tech sector instead of the established industry will depend on both the current rate of return differential and on expected future rates of return. In the high-tech industry, these depend on expectations about the decisions of other entrepreneurs and this is where the valuation of firms in the primary equity market comes in. A change in collective expectations can be brought about by price movements in the stock market, which immediately changes q by changing the prospects of high-tech start-ups to finance their expansion through an IPO.

The formal analysis of the linearized system's transitional dynamics (Fukao and Benabou 1993) reveals that the equilibrium adjustment paths of K_X towards the two long-term stationary equilibria E_X and E_C can be either *steady* in the sense that the adjustment is monotonous or *oscillating* in the sense that the path changes its direction several times. Starting from the unstable stationary point at $q = 0$, $K_X = K_X^*$, the system will diverge in expanding oscillations if $r^2 < 4\beta\gamma$. It is in this case that there will not only be two long-term stable equilibira, but also *multiple* equilibrium adjustment paths so that collective expectations can be self-fulfilling if the initial K_X lies inside a certain range around the unstable stationary point K_X^*. This range is defined by the condition that the adjustment costs are not yet so large that the current rate of return differential dominates any difference in the discounted present value of future rates of return.

In line with Krugman (1991), p. 663, the economic intuition behind the oscillating, and thus potentially cyclical, adjustment paths is that due to the positive externalities and scale economies in high technology, every entrepreneur wants to set up in the industry chosen be everybody else. If an entrepreneur believes the others will switch industries, she will do the same; and if they all act on the same expectation, their shared belief will in turn be validated. However, the existence of several cyclical equilibrium paths need not imply that cyclical adjustments are actually observed. Instead, there may be additional stochastic paths that jump to one of the deterministic paths with a positive probability. For example, even if the rate of return at the current allocation is higher in the established industry, entrepreneurs may not move into that sector if they believe that high technology will begin to attract all other entrepreneurs at same point in the future.

It is natural to assume that the valuation of high-tech IPOs in primary equity markets is the place where collective expectations are formed and then spread to entrepreneurs and other investors. Hot issue markets can therefore be represented by sudden jumps in q that are consistent with a stochastic equilibrium and with perfect rationality on the part of market participants. Because these self-fulfilling prophecies influence the number of start-up firms and the rate of return in high technology, they do affect the real economy and may therefore validate the initial jump in the market value of IPOs. This clearly distinguishes self-fulfilling prophecies from information cascades, which can be a source of welfare losses if they reinforce false expectations about the future. In the recent literature, both macroeconomic and microeconomic mechanisms have been invoked to justify the existence of multiple equilibrium paths and their selection through self-fulfilling expectations that are formed and spread through a stock market bubble.

Feedback mechanisms. Consider first the hypothesis of macroeconomic feedback from the real economy. In a theoretical contribution, Caballero and Hammour (2002), pp. 15, argue that the emergence of a new production sector creates a natural feedback from growth to investment funding in support of a potentially efficient speculative growth equilibrium. They draw this conclusion from an endogenous growth model in which a speculative bubble in productive assets that are specific to the emerging sector may lead to accelerated productivity growth. The feedback that validates the bubble results from the additional savings generated by the economy’s emerging sector. Moreover, the model predicts a negative feedback from the speculative growth to the interest rate so that investment volume can expand in a highly elastic fashion as new investment opportunities are opened by the emerging area of technology. Key to the model is that only an emerging high-tech sector provides these conditions and is thus poised to trigger an episode of speculative growth: Successful IPOs will help to finance the expansion of high-tech firms and lead to an increased demand for skilled labour that drives up wages and enlarges the amount of savings available for investment. Due to larger economies of scale in the high-tech sector, the returns on capital will diminish at a smaller rate than in established industries, or not at all. For a given investment volume, the interest rate will hence be lower if the capital is invested in the emerging high-tech industry. The bubble facilitates the transition from a high-cost-of-capital equilibrium, in which a relatively large share of capital is invested in the slow-growing established sector, to a low-cost-of-capital equilibrium, in which a larger share of capital is invested in the fast-growing high-tech sector. In the presence of an externality, such as technological spillovers in the high-tech sector, the bubble can be shown to enhance welfare provided it is sustainable (Caballero and Hammour 2002, p. 25).

The hypothesis of microeconomic feedback in an endogenous bubble is best understood on the basis of Tobin's Q. A firm will expand and invest when its market value exceeds the replacement costs of its capital. By implication, a privately held firm will seek expansion finance through an IPO if the expected market value of the firm exceeds the costs of expanding the firm's operations. Private expectations about market value are formed on the basis of information revealed by previous IPOs of similar firms. Firms' timing choices in primary equity markets are therefore interdependent, and this may give rise to multiple equilibria even if macroeconomic feedback mechanisms are absent. A bubble can then be interpreted as an equilibrium outcome of a very specific kind of endogenous non-market interaction.

Two channels of interdependence in issuers' timing choices have been the focus of the recent literature on primary equity markets. On the one hand, firms will seek to time their issues so as to take advantage of fluctuations in the demand for equity shares. On the other hand, firms will seek to time their issues so that expansion finance arrives when the prospects for growth are favorable. Information externalities in investors' choices are thus part of the story. They can induce investors to reduce their individual effort to search for independent information about specific IPO candidates. But information externalities can also induce firms to change the timing of a planned IPO by helping them to predict investor sentiment and the demand for equity shares more accurately and by providing information about investment volumes and expansion plans of other firms in the industry.

When the externalities reveal good news about the prospects of an industry, privately held firms may seek to exploit the opportunity by speeding up an IPO that will help to finance a timely expansion. A hot issue market may hence be set off by a short series of successful IPOs from one particular industry where an unexpectedly high degree of underpricing is interpreted as a clue to positive prospects for the entire industry. In the model by Hoffmann-Burchardi (2001), firms go public as soon as the proceeds from selling shares begin to exceed the expected utility from the uncertain stream of future profits that accrues to these shares. The expected utility will be lower, the more risk averse the party offering the shares. The perception of improved industry prospects will be reflected in an increase in the average prices at which shares can be sold during the bubble. Moreover, consistent with stylized facts, the average underpricing will also rise because outside investors must be compensated for taking the additional risk of buying stock without scrutinizing each issuing firm individually.

In contrast to the case of macroeconomic feedback, the microeconomic interdependence of issuers' choices implies that hot and cold issue markets are opposite sides of the same coin. During a cold issue market, many firms are waiting for conditions to improve and no IPO may be observed for a prolonged period of time. Although each entrepreneur evaluates her own firm's prospects separately, the foreknowledge that there will be another hot issue market at some point in the future serves as a coordinating mechanism even during long spells of inactivity.

The special case of high technology. A closer look at the rationale behind the behaviour of issuers and investors is required to understand why the cycles in IPO markets are particularly pronounced in high-tech industries. From the point of view of the entrepreneurs, they face a fundamental trade-off with respect to their timing decisions of going public. On the one hand, a firm may want to rush the IPO since delaying it might give a competitor the chance to be the first to receive scarce expansion finance. In this vein, Maksimovic and Pichler's (2001) formal model predicts that hot issue markets will occur in industries where a technological pioneer faces a significant risk of reduced profits through the entry of imitators. On the other hand, a firm may want to delay going public in order to avoid revealing information that may help competitors. Both the prospectus and the valuation of the firm by investors in primary and secondary equity markets often reveal specific information that competitors might use. From an economic point of view, there is an information spillover – a technological externality because the issuing firm cannot charge a price for it. This lets entrepreneurs hold back the IPO in order to minimize the spillovers.

Under an endogenous bubble, this tradeoff will be relaxed and many firms will be enticed to go public. The information revealed in the IPOs of the firms going public early will enable followers to predict more accurately the valuation that their own firm will experience in its IPO. By giving away valuable information to potential competitors, the earliest firms bear most of the cost of information revelation during a hot issue market. As more and more firms go public, these costs will decrease since any additional information from an IPO at a later date will only be incremental compared to what the investing public already knows at that point in time. Hence, the gains from going public will be higher than the informational costs for most of the firms, giving them strong incentives to rush to the market. Yet, the improved incentive to go public does not only rest in the decreasing cost of information revelation, but also in an increasing likelihood that an IPO will be successful. The IPO market can support more firms going public during a hot issue market because more capital is made available to firms in a particular field of technology when investors benefit from the greater availability of public information that lowers the costs of valuing the individual IPO.

This adds a further reason why hot issue markets are more pronounced in high-tech industries: High-tech investors rely to a greater extent on the information revealed by early high-tech IPOs than investors do in the case of IPOs from an established industry. Without any public information, it would be much more costly for an investor to acquire accurate information for the valuation of IPOs in high-tech industries than in long established industries. The latter can be easily valued, for example by looking at similar firms in the secondary market, but there are no track records or useful benchmarks for an emerging high-tech industry. The information spillovers during a bubble reduce the costs of investors' search for information and lure them into investing in the IPOs of firms belonging to the area of technology in which recent IPOs have provided the largest public pool of relevant information. Like privately held firms, investors thus face a trade off in their timing of investments that is relaxed during a hot issue market: on the one hand, investors want to buy early when prices are still low; on the other hand, they want to wait until the hot issue market has created more public information on specific areas of technology.

Since most of the relevant information spillovers are within narrowly defined areas of technology, rather than across different fields of technology, endogenous bubbles arise in much the same way as localized externalities create spatial clustering, only that IPO volumes concentrate over time rather than geographically.[3] This suggests that a long-term view should be taken on the efficiency of primary equity markets. Just as spatial agglomerations, in which cities are catalysts of economic growth because they help to exploit knowledge spillovers more efficiently[4], hot issue markets can be viewed as an implication of agents' attempt to internalize information spillovers. This idea is supported by the empirical observation that financial intermediaries are actively involved in the timing decisions revealed in hot issue markets (Benveniste et al. 2002, 2003). Moreover, when financial intermediaries, such as investment banks and venture capital firms, have reputational capital at stake, they can be expected to take a long-term view, at least on average.

This may serve as a cushion against the adverse selection in favour of premature business ideas and against the general over-investment that is endemic during an exogenous bubble. In a sufficiently competitive underwriter market, financial intermediaries would have stronger incentives than one-time actors in primary equity markets to avoid falling prey to temporary fashions of the kind generated by information cascades (see Ploog and Stolpe 2003, pp. 143). Instead, there is evidence of underwriters attempting to internalize information spillovers by bundling the IPOs of their client firms in a specific area of technology and by scheduling them in a temporal sequence so that public information generated by the earlier IPOs is optimally exploited by those coming later (Benveniste et al. 2002, 2003). Obviously, individual IPO firms cannot

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3 A similar comparison between spatial agglomerations and the general business cycle was made by Hall (1991).

4 See Glaeser et al. (1992) for empirical evidence.

themselves internalize the information externalities because they go public only once. Hence, the role of financial intermediaries in primary equity markets is a bit like that of real estate developers in economic geography, which make a living from finding the mix of shops in a mall that provides optimal variety and maximizes overall value to consumers within a given region. Underwriters often appear to provide an equivalent service for outside investors in primary equity markets, which may be efficient because the social risk of aggregate over-investment is thus linked with underwriters' private risk of loosing their reputation. By the same token, it is clear that financial intermediaries cannot mitigate over-investment during an *exogenous* bubble or during a hot issue market not driven by information spillovers. The behaviour of financial intermediaries can therefore help to distinguish between exogenous and endogenous bubbles in empirical data.

Policy implications. I propose to distinguish between exogenous and endogenous bubbles not only for the sake of academic curiosity, but also because these hypotheses have rather different policy implications. The idea that exogenous bubbles create welfare losses can justify government intervention to suppress or pop such a bubble, for example through a sharp tightening of monetary policy. By contrast, the potential welfare gains of endogenous bubbles suggest that policies should be designed to allow them to take place and perhaps even to facilitate them. The essential difference in the welfare implications of exogenous and endogenous bubbles is that the former lowers the cost of raising equity capital for all firms equally, while the latter lowers the costs of raising equity capital merely for high-tech firms. The endogenous bubble may thus help to mitigate a market failure that is specific to high-tech firms in primary equity markets. The inherent uncertainty about new technology and about the prospects of individual high-tech firms makes information spillovers particularly important for the valuation of high-tech IPOs by their issuers, underwriters and by outside investors.

As pointed out above, the role of financial intermediaries in internalizing information spillovers also gives them special incentives to avoid excessive investment in the aggregate. Were some underwriters to encourage reckless over-investment in an endogenous bubble, they would lose their reputation and would have difficulty finding outside investors for client firms wishing to go public in the future. In turn, they would also cease to be an attractive partner for privately held firms planning an IPO. However, while reputational capital can be considered a conditio sine qua non for the internalization of information externalities, it also endows individual underwriters with varying degrees of monopoly power. But the extraction of excessive monopoly rents would drive a wedge between the available gross volumes of investment and the net proceeds obtained by the issuers in primary equity markets. The hypothesis of endogenous bubbles therefore suggests that government policy should be designed to safeguard a sufficiently competitive underwriter market, especially against incipient monopoly power due to the accumulation of reputational capital.

At the same time, policy makers must note that the role of financial intermediaries in processing and evaluation decentralized information about investment opportunities is indispensable and that the monopoly power this creates cannot be completely eliminated. One may wish to accommodate an endogenous bubble by regulating primary equity markets so that issuers must disclose more of the relevant valuation information; the information used by investors might then be more accurate and complete and the influence of financial intermediaries might be reduced. However, Morris and Shin (2002) have shown that the welfare effect of increased public disclosures is ambiguous when agents possess independent private information as well as a motive to seek the coordination of their individual choices. In this case, agents will place more weight on the public information than a social planner would do so that the negative consequences of errors in the public information are exacerbated. The same caveat also applies to the public dissemination of information about broad technological developments in an attempt to provide a basis for 'realistic' expectations.

Policy action at the industry level, such as changes in intellectual property rights, may be required when there is widespread uncertainty about the private appropriability of the social returns to innovation in an emerging field of technology. Such uncertainty may not only increase private investor risk for a given information set, but may also frustrate investors' efforts to improve the valuation of individual IPOs by searching for additional private information. Moreover, my framework suggests the possibility that an aggregation of endogenous bubbles in different industries looks like an exogenous bubble and therefore erroneously triggers policies that suppress potential welfare gains.

III. Empirical Methods and Hypotheses

In this section, I introduce and discuss the methods that can be used to test the empirical implications of competing explanations for bubbles. Due to data limitations and the lack of a fully fledged econometric model, one cannot examine the impact of different bubbles on real economic activity over a sufficiently long time to come up with a full quantitative comparison of the welfare benefits and costs from different types of bubbles. Moreover, there are inherent limits to the empirical identification of a model that is based on multiple equilibria when only one historical realization of the stochastic process is available.

An appropriate time series model must therefore have some cross section dimension in order to exploit the available evidence fully and to clearly distinguish the empirical implications of the no-bubble benchmark case, the exogenous bubble scenario and the endogenous bubble hypothesis. Five methods will be used to present the evidence: descriptive statistics, an exploratory regression analysis of the determinants of time distances between arbitrarily paired IPOs, the Markov chain model of stochastic processes, duration models for independent observations and duration models with non-market interaction.

Distribution of IPOs in time. In the absence of any bubbles in primary equity markets, I would expect a uniform distribution of IPOs over time; within any given time interval, IPOs would occur with equal probability. This is the no-bubble benchmark case. By definition, the presence of a bubble implies an unequal distribution over time. In the case of exogenous bubbles, the peaks of IPO activity and of the general price index in the secondary market would occur in the same sub-period; moreover, the peaks of IPO activity would not vary across time for the different areas of technology to which IPO firms may belong. In the case of endogenous bubbles, I expect the peaks for different technology areas at different points in time. Moreover, since they are driven by information spillovers, the technology-specific peaks in primary equity market activity will not necessarily coincide with high market valuations in the secondary market. Thus, in a disaggregated analysis, the observed clustering of IPOs will be revealed as a sequence of sectoral clusters where each area of technology concentrates its IPOs in a certain interval of time. To uncover these patterns, I will look at area-specific histograms of the length of time between consecutive IPOs and equally disaggregated histograms of the duration from the market opening to the IPO date.

Determinants of time distance between paired IPOs. A simple linear regression analysis of the determinants of duration between arbitrary pairs of IPOs provides a first look at the role of financial intermediaries in the formation of IPO clusters. It is natural to consider the process of intermediation as a potential co-determinant of hot issue markets – in addition to issuers' characteristics and investors' choices in primary equity markets. In a preliminary test of the influence of financial intermediaries, I will ask whether the equality of underwriters or of venture capital firms backing any two randomly selected IPOs has a significant influence on the time distance between them. Besides controlling for the influence of technology focus, additional interaction terms will be used to study the influence of financial intermediaries in different areas of technology. However, unless the temporal sequence of IPOs is explicitly specified, causal relationships cannot be tested rigorously. In the following, I will therefore introduce two empirical models which do take the sequence of IPOs into account – the Markov chain, which analyses a sequence of discrete events in discrete time, and the survival model, which analyses discrete events in continuous time.

State-dependent probabilities of IPOs from specific areas of technology. The Markov chain[5] is a simple formalization of the idea that clustering can be defined as the increase of the probability that the next firm going public is from the same area of technology as the last IPO at any given point in time. I thus consider the technology area observed for each in a series of IPOs as the outcome of a stochastic process with a finite number of states. The essence of a Markov chain is that the probabilities of the recurrence of events in a discrete stochastic process depend on the state of the system after the preceding event. These conditional probabilities are called transition probabilities. How they are to be estimated depends on whether there are additional exogenous explanatories.

The most general Markov chain model has a multitude of elements which may or may not experience a transition during any given interval of time. Tracking all firms simultaneously, the general Markov chain model could in principle be applied to our problem by defining the process $y_j^i(t) = 1$ if the *i*th firm is listed in the stock market at time t and $y_j^i(t) = 0$ otherwise (unlisted) – like a generalized qualitative response (QR) model. The standard QR model would require that the realizations of $y_j^i(t)$ are independent over t, but this assumption would rule out the possibility of state

5 See Basawa and Rao (1980) and Amemiya (1985), chapter 11, for rigorous introductory surveys.

dependence. A more useful variant is the first-order Markov model, in which the distribution of $y_j^i(t)$ depends on $y_k^i(t-1)$, so that the model is completely characterized by the set of transition probabilities $P_{jk}^i(t)$, defined as the probability that the ith firm is in state j at time t given that it was in state k at time t–1 and by the distribution of initial conditions, $y_j^i(0)$. The matrix $P^i(t)$ of the nonnegative transition probabilities is called the Markov matrix, in which the entries of each row sum to unity. In a stationary Markov model $P_{jk}^i(t) = P_{jk}(t) \quad \forall t$ and in a homogeneous model $P_{jk}^i(t) = P_{jk}(t) \quad \forall i$. While a general Markov model can be parameterized similar to QR models by specifying $P_{jk}^i(t) = F_{jk}\left\lfloor x^i(t)'\beta \right\rfloor$ for some function F_{jk} such that $\sum_{k=1}^{M} F_{jk} = 1$, the simplest case of a Markov model that is both homogeneous and stationary is given by $P_{jk}^i(t) = P_{jk} \quad \forall i, t$. Because the stationary Markov chain does not consider time-varying exogenous variables as determinants of the transition probabilities, one can estimate these probabilities using a simple non-parametric maximum likelihood estimator (MLE).

However, since each firm going public does so only once, one cannot hope to identify a fully parameterized Markov model in the data. Instead, one must rely on homogeneity and stationarity, although the latter assumption will be somewhat relaxed below where I include time-varying determinants of the transition probabilities. For now, I ignore all exogenous or predetermined explanatories except for the technology area of the preceding IPO. I thus rely on groupwise homogeneity as an identifying assumption. Two different methods can then be used to estimate the transition probabilities: First, assuming that the IPO process gives us the proportion of firms within a technology area that are either listed or still unlisted at varying times, I can use least-squares or minimum-χ-squared methods, as described in Basawa and Rao (1980), pp. 72. Second, I can consider the technology area of the preceding IPO as the only determinant of the (conditional) probabilities with which the present IPO falls into each of the technology areas. Essentially, this is like assuming that the same stochastic process holds for every firm, as implied by homogeneity and stationary. If I let the observed sequence of n+1 consecutive IPOs, characterized by their affiliation to $k=\{1, 2, \ldots, m\}$ areas of technology, be contained in $\mathbf{x}_{n+1} = (x_0, x_1, \ldots, x_n)$, the likelihood function for an ergodic Markov chain is given by $L = P_{x_0}^{(0)} \prod_{h=1}^{n} P_{x_{h-1}x_h} = P_{x_0}^{(0)} \prod_{j,k=1}^{m} P_{jk}^{n_{jk}}$, where $P_{x_0}^{(0)}$ is the vector of initial probabilities. P_{jk} are the probabilities of transition from the j^{th} to the k^{th} area of technology between any two consecutive IPOs, and n_{jk} is the frequency of the one-step transitions from state j to k in the sample $\mathbf{x}_{n+1}$. After taking logs, the log-likelihood function, $\log L = \log P_x^{(0)} + \sum_{j,k} n_{jk} \log P_{jk}$ is straightforward to maximize with respect to the P_{jk}'s, conditional on $\sum_k P_{jk} = 1$, so that the maximum likelihood estimators are $\hat{P}_{jk} = n_{jk}/n_j$ where $n_j = \sum_k n_{jk}$. Since n is large, I can ignore the effect of the first term of the log-likelihood function.

Various hypotheses tests in the homogeneous stationary Markov model – and the asymptotic properties of the MLE estimator given by $\hat{P}_{jk} = n_{jk} / \sum_k n_{jk}$ – are discussed in Anderson and Goodman (1957). For example, if the homogeneous and stationary Markov model is to be tested against a homogeneous but non-stationary model the likelihood ratio test uses the statistic $-2\log \prod_t \prod_j \prod_k \left[\hat{P}_{jk} / \hat{P}_{jk}(t)\right]^{n_{jk}(t)} \sim \chi^2_{(T-1)m(m-1)}$, where $\hat{P}_{jk}(t) = n_{jk}(t) / \sum_{k=1}^{m} n_{jk}(t)$ is based on the number of IPOs, n (t), during each of t = 1, 2, …, T time intervals, since normally no more than one IPO is observed at each point in time. Apart from this specification tests, it will be useful to test the hypothesis that the transition probabilities for the different technology areas are independent random variables $\{x_k\}$, k = 1, 2, …m under the assumption of stationarity. Basawa and Rao (1980), p. 62, show that the test statistic $V = \sum_{j,k} \left(n_{jk} - n_j n_k / n\right)^2 \Big/ \left(n_j n_k / n\right)$ has a limiting χ^2-

distribution with $(m^2–m)–(m–1)=(m–1)^2$ degrees of freedom. Finally, one row or the entire transition matrix consists of certain prespecified values P^*_{jk}. Anderson and Goodman (1957) show that under the null hypothesis $P_{jk} = P^*_{jk} \neq 0$ for k = 1, 2, …m and for a given j the test statistic $S_j \equiv \left(\sum_{k=1}^{m} n_{jk}\right)\sum_{k=1}^{m}\left(\hat{P}_{jk} - P^*_{jk}\right)^2 / P^*_{jk} \overset{A}{\sim} \chi^2_{m-1}$, where $\hat{P}_{jk}$ is the MLE. The null hypothesis $P_{jk} = P^s_k$, where P^s_k may be defined as the sample distribution or the stationary distribution to which the Markov chain will converge after a sufficient number of iterations, is rejected for large values of the test statistic. If the null hypothesis cannot be rejected, the stationary distribution should equal the population distribution: $P^s_k = n_k / n$. If P^*_{jk} is prespecified for j = 1, 2, …. m as well as k, the appropriate test statistic is $\sum_{j=1}^{m} S_j \overset{A}{\sim} \chi^2_{m(m-1)}$.

In the no-bubble scenario, the probability of the next IPO being from any particular area of technology will be independent of the previous IPO's technology area and the estimated probabilities in each row of the transition matrix will equal the population distribution. The same holds under exogenous bubbles. But the endogenous bubble is characterized by persistence in the sense that the probability of the next IPO coming from the same area of technology as the current IPO will be higher than the relative frequency of that area in the sample. This is the observational equivalence of sectoral clustering defined by an increase in probability that a second firm goes public from an area of technology that has already had an IPO recently.

Markov models with exogenous variables. There may be several reasons why estimation of the stationary Markov model fails to detect persistence. The most important is that transition probabilities cannot be expected to be stationary over the course of a hot issue market confined to any one particular area of technology. For a complete cycle in technology-specific IPO activity that is not fully synchronized with the overall bubble, persistence must be *more* pronounced before the peak of the hot issue market and *less* pronounced thereafter. The transition probabilities must therefore be allowed to change in response to changes in exogenous variables, including – for example – the degree of lagged underpricing observed in the IPOs from a given area of technology and – as a control – the general stock market price index. This requires a non-stationary Markov model that tries to explain the transition probabilities on the basis of their exogenous determinants.

Toikka (1976) has proposed an estimator for a homogeneous and non-stationary Markov model in which transition probabilities are assumed to depend *linearly* on the exogenous variables. With m being the number of technology areas to which an IPO firm may belong, the model comprises m–1 equations, because the mth equation – a linear combination of the others – can be eliminated: $\bar{y}^i(t)' = \left[y^i(t-1)' \otimes x_t'\right]\Pi + \bar{u}^i(t)'$. This in turn is a multivariate heteroscedastic linear regression equation for which two asymptotically efficient estimators of Π are available. *First*, as Amemiya (1985), p. 429, shows, a generalized least squares estimator $\hat{\Pi}$ is given by $\hat{\Pi} = \left[\sum_{t=1}^{T}(Y_{t-1}'Y_{t-1} \otimes x_t x_t')\right]^{-1} \sum_{t=1}^{T}\left(Y_{t-1}'\bar{Y}_t \otimes x_t\right)$ where Y_t is $N \times M$ matrix with rows $y^i(t)'$ and $\bar{Y}_t$ is the $N \times (M-1)$ matrix made up of the first M–1 columns of Y_t. To derive a feasible generalized least squares estimator, Amemiya uses a consistent estimator of the variance–covariance matrix of the error term. *Second*, Toikka's own estimator of Π, denoted $\tilde{\Pi}$, is given by $\tilde{\Pi} = \left[\sum_{t=1}^{T}(I \otimes x_t x_t')\right]^{-1} \sum_{t=1}^{T}\left[(Y_{t-1}'Y_{t-1})^{-1} Y_{t-1}'\bar{Y}_t \otimes x_t\right]$. Amemiya argues that this estimator can be interpreted as the least squares estimator in the regression of $\hat{P}(t)$ on x_t, because $(Y_{t-1}'Y_{t-1})^{-1} Y_{t-1}'\bar{Y}_t$ contains the first m–1 columns of the unconstrained MLE of the Markov matrix $P(t)$. Alternatively, Toikka's estimator can be interpreted as applying least squares after premultiplying

$$\begin{bmatrix}\overline{Y}_1\\ \overline{Y}_2\\ \cdot\\ \cdot\\ \cdot\\ \overline{Y}_T\end{bmatrix}=\begin{bmatrix}Y_0\otimes x_1'\\ Y_1\otimes x_2'\\ \cdot\\ \cdot\\ \cdot\\ Y_{T-1}\otimes x_T'\end{bmatrix}\Pi+\begin{bmatrix}\overline{U}_1\\ \overline{U}_2\\ \cdot\\ \cdot\\ \cdot\\ \overline{U}_T\end{bmatrix}$$ by $$\begin{bmatrix}(Y_0'Y_0)^{-1}Y_0' & & & \\ & (Y_1'Y_1)^{-1}Y_1' & & \\ & & \ddots & \\ & & & (Y_{T-1}'Y_{T-1})^{-1}Y_{T-1}'\end{bmatrix}$$, a block-diagonal matrix, where $\overline{U}_t$ is analogous to $\overline{Y}_t$. In our application, these formulae can be greatly simplified because there is never more than one contemporaneous observation, so that N=1 and $Y_t, \overline{Y}_t$ and $\overline{U}_t$ have only one row.

Two exogenous variables should be considered to determine the transition probabilities for a given technological affiliation of the current IPO: Besides the stock market price index as a control for general market conditions and the degree and differential of underpricing observed in the two preceding IPOs from the given area of technology. Under the endogenous bubble hypothesis, persistence should be positively correlated with the observed prior underpricing, but not necessarily with the general stock market price level. In the no-bubble case, there should be no significant influence of the exogenous variables on the transition probabilities, and just as in the stationary Markov model, the estimated transition probabilities should equal the population distribution of IPOs. In an exogenous bubble, persistence should also be absent from narrowly defined areas within high technology.

Duration analysis of independent observations. An obvious weakness of the Markov model is that it does not account properly for the time dimension, but only for the sequence of events assumed to take place in discrete time. To analyze the empirical determinants of the length of time between two events, a model of duration in continuous time is needed. Of interest here is the duration between the opening of the Neuer Markt and Nouveau Marché, respectively, and the IPO date of a specific firm. Given the pre-announcement more than two years before the opening of these markets, one can safely assume that a large number of firms had already anticipated to go public when the markets were launched. Empirical duration models can thus be used to understand what factors have influenced the subsequent waiting time of the many different firms that have eventually gone public. Some of the reasons for timing a specific IPO, relative to other IPOs, will be related to time-invariant characteristics of the individual IPO firm, so that my estimates of the influence of previous IPOs within the same technology area might be biased if I did not explicitly consider the influence of those exogenous firm characteristics. In this vein, Bottazi and DaRin (2003) have studied the impact of venture capital-backing on the time-to-listing of firms going public on the Euro.nm group of stock markets, controlling for the sector of activity, for country of origin, for the return on asset, and for leverage, measured at the IPO. They do not find a significant influence of the return on asset and leverage, but estimate that the time-to-listing is about 60 percent longer on the Nouveau Marché.

Duration models are derived from the probability distribution of a random variable T, the time at which a particular firm decides to go public. If I let T denote the duration from the start of the two markets until the date of the firm's IPO, three equivalent ways of describing the probability distribution can be used: The *first* is the cumulative distribution function (CDF), $F(t) = \Pr(T \leq t)$, defined as the probability that T will be smaller than or equal to the value t, and its complement, the survival function $S(t) = \Pr(T>t) = 1 - F(t)$, the probability that T will be greater than t. *Secondly*, a probability distribution function (PDF) or density function can be defined as $f(t) = dF(t)/dt = -dS(t)/dt$, by taking the first derivative of the CDF. *Thirdly*, a hazard function can be derived, which gives the *conditional* probability that a firm will go public in the next infinitesimally short period given that it has stayed private as long as it has. Since the hazard function describes the probability distribution *conditional* on $T \geq t$, it has the form $h(t)=\lim_{\Delta t\to 0}\Pr(t\le T<t+\Delta t|T\ge t)/\Delta t=F'(t)/(1-F(t))=f(t)/S(t)$, where h(t) is the hazard rate and Δt is the next short time interval.

In general, firm i's hazard function of going public can be written: $h_i(t)=h(x_i,f(t))$, where x_i are time-invariant characteristics of the firm and f(t) are time-varying variables, such as exogenous market conditions measured by the relevant market price index[6]. The time-invariant and exogenous firm characteristics, observed at the market opening date, include firm age as a measure of maturity, employment as a measure of size as well as the growth rate of sales over the growth rate of employment and the debt-equity ratio as two measures of financing constraints before the IPO. The larger the debt-equity ratio and the greater the rate of sales growth relative to employment growth, the less binding should be the financing constraint. In addition, a dummy variable for the area of technology is expected to have an influence if IPOs from different areas of technology cluster in time, as implied by the endogenous bubble hypothesis.

I hypothesize that the firm-specific hazard rate will be greater, the more conventional its technology, the older the firm, the larger the firm, the lower the debt-equity ratio and the lower the ratio of sales growth over employment growth. In the no-bubble case, I do not expect the hazard to be correlated with the general stock market price index. In the exogenous bubble, the hazard rate of going public is hypothesized to increase for all firms with the stock market price index since this raises the expected market valuation of firms still privately held. In the endogenous bubble, not the general stock market price index, but price indices of shares from the specific area of technology to which an IPO candidate belongs may be expected to have a positive impact on the hazard rate.

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[6] Direct estimation of the influence of the market price index on the hazard rate of going public requires a parametric model, such as an accelerated failure model, in which the distribution of the baseline-hazard over time can be specified.

However, this theoretical distinction provides little opportunity to discriminate between the endogenous and exogenous bubble hypotheses empirically, since most of the subindices will be strongly correlated with the general stock market price index during the sample period. A more appropriate test will therefore be proposed next.

Duration models with non-market interaction. Although the Markov chain and the duration analysis of independent observations are both apt to capture potentially important aspects of the timing of IPOs, they cannot directly discriminate between the influence of exogenous characteristics of an IPO firm and information spillovers from previous IPOs. Only within a model that encompasses exogenous characteristics *and* endogenous spillovers can a nested test of the endogenous and exogenous bubbles hypotheses be constructed. For this purpose, I propose to use a new method of duration analysis that allows for non-market interaction in the time dimension, so that the impact of endogenous interactions on the timing of IPOs can be estimated explicitly. In this new class of duration models with non-market interaction, developed by Brock and Durlauf (2001), the payoff function of any given agent takes as direct arguments the choices of other agents. This captures the idea of social interactions not mediated through the market via a change in relative prices. The primary objective of these models is to identify the aggregate properties that emerge in a population of agents with non-market interaction. In the timing of IPO decisions, non-market interaction stems from the information inevitably revealed by each IPO of a high-tech firm, since this new information can give valuable clues to subsequent issuers and investors in primary equity markets. Since they cannot be charged a price for receiving and using this information, the revealing firm cannot appropriate the benefits to others and the aggregate outcome may be inefficient.

It follows that the hazard function for firm i – defined as $\lambda_i = \lambda(x_{i,}\, y_{m(i)}, s^e_{m(i)})$ – depends on covariates that include the exogenous characteristics of the firm, x_i, its neighbourhood characteristics, $y_{m(i)}$, and its subjective expectation of a neighbourhood behavioral measure, $s^e_{m(i)}$. The exogenous characteristics from the conventional duration analysis – age, employment, debt-equity ratio and sales over employment growth of each firm – are retained. The neighbourhood of firm i, denoted by m(i), is assumed to be its area of technology. To account for time-invariant neighbourhood characteristics, m–1 dummy variables for technology areas are employed. The term $s^e_{m(i)}$, finally, is a vector of neighbourhood behavioral measures that vary with time. For example, $s^e_{m(i)}$ may be the expected value of either the within-neighbourhood duration or the median group duration.[7] Alternatively, one could use the average duration until the IPO in a given area of technology, the median time of privately held firms from the beginning of the two markets to the date of their IPO, or the number of prior IPOs in the respective area of technology relative to some general benchmark as a measure of neighbourhood behaviour.

Following the exposition in Brock and Durlauf (2001), pp. 3338, the density function now has the form, $f(t \mid x_i, y_{m(i)}, s^e_{m(i)}) = \lambda(x_{i,}\, y_{m(i)}, s^e_{m(i)}) \exp\ (-\lambda(x_i, y_{m(i)}, s^e_{m(i)})\, t)$, and the expected duration for firm i, conditional on specific realizations of the covariates, is $E\left(t \,\middle|\, x_i, y_{m(i)}, s^e_{m(i)}\right) = \lambda\left(x_i, y_{m(i)}, s^e_{m(i)}\right)^{-1}$. The median of the duration is given by the solution t^* of $\exp\left(-\lambda\left(x_i, y_{m(i)}, s^e_{m(i)}\right) t^*\right) = 1 - F\left(t^*\right) = 1/2$, which is found by solving $\log 2 = \lambda\left(x_i, y_{m(i)}, s^e_{m(i)}\right) t^*$ for t^*. This condition defines two requirements for self-consistent estimates. Self-consistency with respect to expected duration requires that $s^e_{m(i)} = s_{m(i)} = \int \lambda\left(x_i, y_{m(i)}, s_{m(i)}\right)^{-1} dF_x$ and self-consistency with respect to the

[7] Although the neighbourhood characteristics and my neighbourhood behavioral measure are time-varying variables, the time index has been suppressed for notational convenience.

neighbourhood median requires that $s^e_{m(i)} = s_{m(i)} = \log 2 \int \lambda\left(x_i, y_{m(i)}, s_{m(i)}\right)^{-1} dF_x$, where F_x is the probability distribution of characteristics within neighbourhood n(i) and $s^e_{m(i)}$ is the expected value of either the within-neighbourhood duration or the median group duration.

It seems natural to assume adaptive expectations, so that the expected neighbourhood behavioral measure depends on previous realizations of observable variables. Intuitively, the assumption of adaptive expectations is consistent with the selection of multiple equilibria by historical event or initial conditions. Agents adapt their behaviour according to the prior behaviour of other agents, which in turn can be traced back to the initial conditions of the system. By contrast, assuming rational expectations implies that the firms' expectations are subsequently realized on average; rational expectations are therefore consistent with the selection of multiple equilibria by self-fulfilling prophecies since it is the essence of a self-fulfilling prophecy that individual expectations are validated ex post – at least on average.

The simplest *parametric* specification of the duration model for estimation purposes would be the exponential. If the hazard function for firm i is assumed to be, $\lambda_i = \exp(\alpha' x_i + \beta' y_{m(i)} + J' s^e_{m(i)})$, the likelihood function for a given data set will then be $L = \prod_i \exp(\alpha' x_i + \beta' y_{m(i)} + J s^e_{m(i)}) \exp[-\exp(\alpha' x_i + \beta' y_{m(i)} + J s^e_{m(i)})\, t_i]$, where α, β, and J are the parameter estimates that maximize the likelihood function. However, since this paper is concerned with testing hypotheses, not with making quantitative forecasts, I will only provide semi-parametric estimates, which are much simpler to compute, because the baseline hazard is left unestimated. Consider the following specification of the Cox (1972) proportional hazard model: $\lambda\left(t, x_i, y_{m(i)}, s^e_{m(i)}\right) = \lambda_0(t) \exp\left(\alpha' x_i + \beta' y_{m(i)} + J' s^e_{m(i)}\right)$, where x_i is the vector of time-invariant firm characteristics, $y_{m(i)}$ is the vector of neighbourhood characteristics and $s^e_{m(i)} = \left(\upsilon^e_{m(i)}, w^e_{m(i)}, v^e_{m(i)}\right)'$ is the time-varying neighbourhood behavioural measure. It includes for each firm the expected number of IPOs by some duration τ, denoted $\upsilon^e_{m(i)}$, the average duration $w^e_{m(i)}$, and the median duration within the neighbourhood. These measures can be obtained either under the assumption of rational expectations, as in Sirakaya (2003), or under adaptive expectations, as in Nigmatullin (2003). In either case, expectations must be formed under the constraint that the solution is self-consistent.

Under rational expectations, agents' subjective beliefs are the best prediction of future events, based on the available information.[8] Hence,

$$s^e_{m(i)} = s_{m(i)} = \begin{pmatrix} \int dF_x \sum\limits_{i \in m(i)} F\left(\tau \middle| x_i, y_{m(i)}, s_{m(i)}\right) \\ \int \mathrm{II}_{\{i \in \psi_{m(i)}\}} E\left[t \middle| x_i, y_{m(i)}, s_{m(i)}\right] dF_x \\ \arg\min\limits_{v} \left| \int dF_x \sum\limits_{i \in m(i)} F\left(t > v \middle| x_i, y_{m(i)}, s_{m(i)}\right) - \int dF_x \sum\limits_{i \in m(i)} F\left(t \le v \middle| x_i, y_{m(i)}, s_{m(i)}\right) \right| \end{pmatrix}$$

where F_x is the probability distribution of individual characteristics within neighbourhood m(i), $\psi_{n(i)}$ is the set of firms going public by duration τ in neighbourhood m(i), and

$$\mathrm{II}_{\{i \in \psi_{m(i)}\}} = \begin{Bmatrix} 1 \text{ if } i \in \psi_{m(i)}, \\ 0 \text{ else} \end{Bmatrix}.$$

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[8] Kalai and Lehrer (1993) derive conditions for observational learning to generate rational expectations and a Nash equilibrium.

Under adaptive expectations, the neighbourhood behavioural measures are a function of the prior realizations of the corresponding observables. For example, the measures could be based on the average or median time distance of past IPOs within the neighbourhood or on the observed underpricing.

Both types of expectations offer a way to solve the identification problem which arises when the same observed outcome may be due to a multitude of alternative interaction processes. For example, Manski (1993) found that observed equilibrium outcomes do not allow the researcher to distinguish endogenous interaction from contextual interactions when the data generating model is linear in means, such that individual behaviour varies linearly with mean behaviour and mean values of exogenous characteristics within a neighbourhood. Since in this case, mean behaviour is itself determined by the individual behaviour in the neighbourhood, the observations cannot reveal whether the group behaviour actually affects individual behaviour or whether group behaviour is simply the aggregation of individual behaviours (Manski 2000, p. 25). This is known as the ‘reflection problem’.

As a caveat, I note that the assumption of adaptive expectations can only solve the identification problem if the lag length of mean behaviour is known with which individual behaviour in a neighbourhood varies. To solve the identification problem, the lag must be correctly specified. The assumption of rational expectations, by contrast, makes no such demands for solving the identification problem because it lets individual behaviour vary with mean behaviour in the neighbourhood in a nonlinear fashion – determined by the probability distribution of individual characteristics within neighbourhood m(i).[9] Rational expectations guarantee global identification since group

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[9] As a third alternative, according to Manski (2000), the identification problem may be solved by letting individual behaviour vary with the median, instead of the mean of neighbourhood behaviour.

and individual determinants of individual behaviour are nonlinearly related – according to a specified function (see Manski 2000, p. 26, or Brock and Durlauf 2001, p. 3340).

For the case of rational expectations, I follow Sirakaya (2003) and define $z_i = \left(x_i', y_{n(i)}', s_{m(i)}^e\right)'$ and $\theta = (\alpha', \beta', J')'$. The Cox likelihood function for the data can then be written as $L = \prod_{i=1}^{n} \lambda_0(t_i) \exp(\theta' z_i) \exp[-\Lambda_0(t_i) \exp(\theta' z_i)] \quad \prod_{i=s+1}^{I} \exp[-\Lambda_0(t_i) \exp(\theta' z_i)]$, where t_i for i=1, 2, …, n are the completed spells (firm i went public at time t_i) and $\Lambda_0(t) = \int_0^t \lambda_0(z) dz$ is the integrated baseline hazard. Identification requires that the expected value of the Hessian matrix of log L is nonsingular at the self-consistent solution.

The empirical predictions from my hypotheses about the nature of bubbles can be tested under either adaptive or rational expectations. In the no-bubble case, the hazard rate is only influenced by time-invariant and exogenous characteristics of the individual firm. In an exogenous bubble, I expect the hazard rate to be influenced by neighbourhood characteristics, in addition to firm characteristics, but not by our neighbourhood behavioral measure. I will therefore interpret a significant impact of the neighbourhood behavioral measure as evidence in support of the endogenous bubble hypothesis. Moreover, the impact of the expected duration of IPOs should be *negative* in an endogenous bubble: The shorter the expected time of the next IPO within the neighbourhood, the higher should be the propensity to go ahead with the IPO of one's own firm.

IV. Descriptive Statistics

The creation of France's Nouveau Marché in March 1996 and Germany's Neuer Markt in 1997 has been a real-life experiment waiting to be evaluated. These new markets set out to improve the access of small and young, but innovative firms without a track record of performance to the primary equity market and therefore adopted more stringent reporting requirement and disclosure regulations as well as rules to limit opportunistic behaviour by insiders. Because the creation of these market segments was preannounced, it is reasonable to assume that a large number of firms anticipated to go public even before the start of these new markets. The empirical analysis thus has a natural starting point for the build-up of the bubble at the end of the 1990s and for testing the implications of my hypotheses on the bubble's causes.[10] My disaggregated data set reveals considerable variance in the primary equity market experience of firms that differ in terms of the technological focus of their business activity.

IPO volumes and percentage shares by technology area. Figures 1a and b plot the number of IPOs (IPO volume) per month in the Neuer Markt and Nouveau Marché from the start of these two markets until December 2000. A low level of IPO activity during the early months was followed by a rapid increase in IPO volume between the end of 1998 and 2000. This hot issue market was less pronounced in France than in Germany. Juxtaposing the average monthly level of the respective market index (dotted lines), the NEMAX Overall Performance Index of the Neuer Markt and the Nouveau Marché Indice, generates a graph suggesting that IPO volume is positively correlated with high market valuations, albeit with a lag of several months. By contrast, low and flat levels of the indices are associated with low IPO volumes. Prima facie, exogenous market conditions reflected in the general market price index seem to be driving the number of IPOs.

Table 1 presents the number of IPOs and the percentage shares of IPOs by area of technology. I classify the issuing firms into six categories based on the field of technology that defines the firm's dominant business activity. The first five areas –

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[10] See Stolpe (2003) for a detailed description of the various data sources.

Software, *IT Services*, *Hardware & Telecomms*, *Internet & Media*, and *Biotechnology* – are subsectors within high technology whereas *Industrial & Financial Services* can be considered a low-tech sector. *Internet & Media* accounted for 30 percent of the overall share of IPOs in the Neuer Markt with most of them occurring in 1999 and 2000. In the Nouveau Marché, *Software* and *Internet & Media* accounted for the highest overall shares: Table 1 reveals that in the Neuer Markt, *Internet & Media* and *Biotechnology* had the highest increase in the number of IPOs in 1999 and 2000 from 39 to 49 IPOs and 10 to 18 IPOs, respectively. In the same period *Industrial & Financial Services* had a drop in the number of IPO from 36 to 25. In the Nouveau Marché, *Software* and *Internet & Media* experienced the biggest increases in IPO volume in the years 1999 and 2000, from 6 to 12 IPOs for *Software* and 5 to 12 IPOs for *Internet & Media*, taking their shares of all IPOs to 41.4 percent (*Software*) and 57.1 percent (*Internet & Media*) in the year 2000.

The last two years in both markets were characterized by the internet boom in which high-tech IPOs had the largest increases in number and reached their peak both in absolute terms and relative to total IPO volume. But no clear pattern can be detected for individual years when sectors are ranked according to their percentage shares of all IPOs in the year. In each year, a different area of technology claims the highest percentage share of all IPOs. In the Neuer Markt, *Hardware & Telecomms* was top at 6.1 percent in 1997, *Industrial & Financial Services* at 22.4 percent in 1998, *Software* at 45 percent in 1999, and *Biotechnology* at 60 percent in 2000. Similarly, in the Nouveau Marché, *Biotechnology* was top at 25 percent in 1997, *Industrial & Financial Services* at 40.9 percent in 1998, *IT Services* at 36 percent in 1999, and *Internet & Media* at 57.1 percent in 2000. The same lack of persistence in the rankings is found when one looks for the area of technology with the lowest shares of all IPOs.

These observations of fluctuating percentage shares for any given area of technology suggests that industry-specific characteristics may help to explain why hot issue markets take place in certain areas at different points in time. Moreover, in both markets the IPOs during the first two years of the sample period mainly came from *Industry & Financial Services*, a low-tech area, but in the last two years mainly from high-tech areas, above all *Internet & Media*. That the years of low IPO activity coincide with IPOs mostly coming from low-tech areas and the bubble years coincide with IPOs mostly coming from high-tech areas lends further support to the idea that a pent-up supply of high-tech IPOs has required a critical IPO volume to burst out. Indeed, this appears to distinguish high-tech from low-tech IPOs – fully in line with the endogenous bubble hypothesis.

Time patterns in going public. More descriptive evidence in favour of the endogenous bubble hypothesis can be obtained by looking at the rather distinct time patterns of the IPO series from different areas of technology. Table 2 presents a comparison of the observed average length of time between two consecutive IPOs that would be expected in the absence of a bubble. Without a bubble, IPOs can be assumed to be evenly spread throughout the entire sample and the expected number of days between two IPOs is simply the number of days in the whole period divided by the total number of IPOs. Looking at the whole sample of IPOs in the Nouveau Marché, the observed average and expected length of time between two consecutive IPOs is almost equal, as if no-bubble had occured. However, the observed average time between two consecutive IPOs was much smaller than the length of time expected in the absence of a bubble. Moreover, the *average* time was considerably lower than the *expected* length of time between IPOs for all areas of technology except for *Hardware & Telecomms* in the Neuer Markt and *IT Services* in the Nouveau Marché, both of which had similar average and expected values. The degree of clustering, measured by the ratio of average to expected length of time between consecutive IPOs also varies considerably across areas of technology, which is again consistent with the idea that hot issue markets are driven by technology-specific factors.

Furthermore, the Nelson-Aalen cumulative hazard estimates, by area of technology as shown in Figure 2a, and the smoothed hazard estimates, shown in Figure 2b, both indicate that the hazard rate for firms from the *Industrial and Financial Services* sector increased earlier in the analysis time than for the other sectors. The real latecomers were the firms from the *Biomedical* industry. The most pronounced clustering, as shown in the smoothed hazard estimates, is evident for the *Internet & Media* sector. The lowest peak in the smoothed hazard estimates is recorded for the *Hardware & Telecoms* sector. Figures 3a to 3c show Kaplan-Meyer survival estimates for the three areas of technology *Biomedical*, *Internet & Media* and *Software*. The survival estimates for *Biomedical* and *Internet & Media* differ significantly from those of other firms. But in the case of *Software*, the Kaplan-Meyer survival estimates are almost indistinguishable from those of other firms.

For a more detailed look at time patterns, Figure 4 plots histograms of the observed length of time between two consecutive IPOs by area of technology, counting the number of IPO pairs which fall into different intervals of approximately equal time distances. These histograms thus display the frequency distribution of time distances between any two consecutive IPOs. In both markets, the interval with the shortest time distances, has the highest count of consecutive IPO pairs, except for the case of *Biotechnology* in the Nouveau Marché. As the upper and lower time distances defining the intervals are increased, moving to the right end of the histograms, fewer and fewer consecutive IPO pairs are observed, sometimes none at all.

In panel A, for example, 25 pairs of consecutive *Software* IPOs are separated by an intervening period of time that falls within the interval of 0 to 25 days. Only 6 pairs of IPOs fall into the next interval of 26 to 50 days. For *Internet & Media*, an even higher number of IPO pairs fall under the first interval: 33 IPO pairs are separated by only two days; but there is a sharp drop in the frequency counted in the second interval. For *Industrial & Financial Services*, 25 IPO pairs fall into the 0 to 5 days interval followed by 20 pairs in the 6 to 10 days interval, suggesting that the extent of clustering is less pronounced in this area of technology. In panel B, most areas of technology exhibit similar patterns of clustering with the exception of *Biotechnology* where time distances between consecutive IPO pairs appear to be evenly distributed. *Industrial & Financial Services* also show relatively little clustering. *IT Services* shows a striking pattern with 23 IPO pairs falling into the 0 to 100 days interval, followed by a sudden drop to 3 pairs in the next interval.

Although the graphs in Figure 4 are suggestive of clustering, a more careful comparison across different areas of technology requires the calculation of *relative* frequencies for the time distances between consecutive IPO pairs falling in standardized intervals. These relative frequencies, expressed as percentage shares of all consecutive IPO pairs within a given area of technology are shown in Tables 3 and 4 for the Neuer Markt and Nouveau Marché, respectively. The first column shows the upper bounds of the equal-length intervals in days, while the succeeding columns show the percentage shares of consecutive IPO pairs falling in the corresponding interval for different areas of technology and for the sample as a whole (last column). Among *Software* IPOs in the Neuer Markt, for example, 64.1 percent of the consecutive IPO pairs are separated by an intervening period between 0 to 25 days, 15.4 percent between 26 to 50 days 10.3 percent between 51 to 75 days, 7.7 percent between 76 to 100 days, and 2.6 percent of consecutive IPO pairs are more than 150 days apart.

Again, most of the observations fall into the first interval, but the extent of this clustering varies across areas of technology. On the Neuer Markt, Internet & Media has the highest degree of clustering with 90.5 percent in the first interval followed by *Industrial & Financial Services* with 85.7 percent. *Hardware & Telecomms* has the lowest clustering at 50 percent. Combining all areas, fully 97.2 percent of the observations fall into the first interval – clearly a reflection of the larger number of IPOs in the total sample. On the Nouveau Marché, *IT Services* has the highest first interval percentage at 70.8 percent followed by *Internet & Media* at 65 percent and *Software* at 60.7 percent. The lowest first interval percentage is recorded for *Biotechnology*, which has relatively large entries in intervals up to 250 days. However, when all areas are combined, the concentration in the first interval is almost as high as on the Neuer Markt.

The bottom panels of Tables 3 and 4 show the differences between the percentage shares for the combination of all areas and the percentage shares for each of the specific areas to highlight the sector-specific clustering against overall clustering. For both markets the overall clustering is more pronounced than the clustering in specific areas of technology. However, this impression may simply be caused by the fact that each area has a different number of observations. Since I am looking at intervals of equal length in time, areas with fewer observations will naturally be spread farther apart, and areas with many observations may show spurious clustering. To correct for this distortion, the intervals must be adjusted so as to control for the differences in the number of IPOs from different areas of technology. In effect, the adjustment must widen the base intervals by an area-specific factor determined by the share of the area in the total number of IPOs on the Neuer Markt or Nouveau Marché, respectively. This factor is calculated by dividing the number of days defining the base interval by the relative share of the corresponding area of technology in the total number of IPOs. The results are presented in Tables 5 and 6 for the Neuer Markt and the Nouveau Marché, respectively, where the left column refers to the base intervals, and not to the adjusted intervals since these are different for each area of technology. The remaining columns show the relative frequencies of time distances between consecutive IPO pairs in the adjusted intervals.

Prima facie, the clustering patterns revealed in Tables 5 and 6 look more pronounced than those in Tables 3 and 4 for most areas of technology, with a larger percentage of IPOs falling in the first interval. But comparing patterns across areas of technology, the clustering looks more similar, with smaller differences from the overall distribution (shown in the lower half of the Tables). The lion's share of the observations still belongs to the first interval, with rapidly declining shares in the subsequent intervals and almost none after the third. In the Neuer Markt, the highest first interval share still comes from *Internet & Media* at 83.2 percent, while the lowest still comes from *Hardware & Telecomms* at 71.9 percent. In the Nouveau Marché, the highest first interval share comes from *IT Services* with 52.2 percent while the lowest is from *Biotechnology* at 9.1 percent. Despite the adjustment of the length of intervals, clustering patterns are still different across areas of technology. These different patterns are highlighted in the lower halves of the Tables, which present the differences in percentage points between the relative frequency distribution across the adjusted intervals for each area of technology and the relative frequency distribution across the unadjusted intervals for the overall sample.

Finally, different clustering patterns for different areas of technology can also be detected when the duration from the market opening date to the date of each firm's IPO is examined. Figure 6 plots the histograms of these durations by area of technology. For the Neuer Markt, there appear to have been two peaks in IPO activity, which were particularly pronounced in the high-tech areas. The pattern is less clear-cut in *Industrial & Financial Services*. For the Nouveau Marché, IPOs in the *IT Services* and *Internet & Media* areas show a unimodal pattern with a steep ascent, suggesting that firms in these sectors waited longer so that IPOs clustered at the end of the observation period. These findings lend further support to the idea that IPOs from different areas of technology cluster around different peaks in time – in line with the endogenous bubble hypothesis.

Tables 7 and 8 and the corresponding figures 7a and 7b confirm these findings. They show the distribution of IPOs in terms of percentage shares of all IPOs from a given area of technology falling within fixed intervals of duration from the start of the Neuer Markt and Nouveau Marché, respectively. As before, the left column shows the upper boundary of each time interval of equal length. The middle panels show the cumulative percentage shares of IPOs at the upper boundaries of each interval. In the Neuer Markt, IPOs from different areas of technology concentrate in three intervals: 401 to 600 days, 701 to 900 days, and 1101 to 1300 days. But within these intervals, patterns of IPO timing vary considerably across sectors, suggesting that both the overall market peak, but also technology-specific factors determine clustering.

For example, in the interval of 1200 days not only the all-area share of IPOs was at its peak, but also *Internet & Media* and *Software* recorded their peak in IPO activity, with 22.9 percent and 22.5 percent of all IPOs from these technology areas falling into the interval. By contrast, the lowest area-specific percentage share in that interval was recorded for *IT Services* with only 5.4 percent of all IPOs from that area. *IT Services* instead had its peak in the 900 days interval. In the Nouveau Marché, overall IPO activity has peaked in three intervals with a longer lag from the market's (earlier) opening date: 801 to 1000 days, 1001 to 1200 days, and 1401 to 1600 days. As on the Neuer Markt, the peaks for different areas of technology vary in time, but still fall within one of the three intervals. The area-specific differences in the relative frequency distribution of IPOs vis-à-vis the total sample distribution are shown in the bottom panels of Tables 7 and 8. While these differences are often large, no clear pattern can be detected, so that technology-specific factors – in line with the endogenous bubble hypothesis – are the most plausible explanation.

V. Results from Statistical Inference

Linear Regression Analysis. For a first test of the empirical determinants of clustering and the role of financial intermediaries in the timing of IPOs, simple regression analysis can be used. Tables 9 and 10 present the results of a least squares regression using the length of time between the dates of arbitrarily paired IPOs as the dependent variable. These time distances are now calculated not only for two consecutive IPOs, but for all possible pairs of IPOs in the sample from the Neuer Markt or Nouveau Marché, respectively. This regression model addresses the question which of the characteristics observed in earlier IPOs has a significant influence on the timing of subsequent IPOs. More specifically, is the timing of going public sped up by previous IPOs from the same area of technology, as implied by the endogenous bubble hypothesis? Inclusion of a technology dummy as a regressor – with the value 1 if both IPOs in a pair belong to the same area of technology and 0 otherwise – allows us to test whether a subsequent IPO from the same area of technology is indeed more likely than would be expected if each IPO's area of technology were drawn from an independent random variable: The time distance between any two IPOs should be negatively correlated with the technology dummy.

However, a proper test of this hypothesis must control for other potential determinants of the time distance between arbitrary pairs of IPOs. I control for exogenous firm characteristics by including the time interval between firms' founding dates as an explanatory variable: Firms that started out around the same time are more likely, ceteris paribus, to go public at about the same time. The influence of financial intermediaries on the timing of IPOs is taken into account by including dummies for the equality of lead underwriters and for the equality of any of the venture capitalists involved in the two IPOs whose distance in time is the explanandum. These two types of intermediaries may have a role to play in determining the lengths of time between two IPOs because they would both benefit – although perhaps in different ways – from the internalization of information spillovers emanated by earlier IPOs. In particular, underwriters with some market power may sequence the IPOs of their client firms so that they achieve a greater private appropriation of the inherent information externalities in order to maximize their private returns from a series of IPOs.

My regression analysis reveals that the empirical influence of venture capitalists and underwriting is mostly in line with expectations on the Nouveau Marché, but it is strikingly at odds on the Neuer Markt. In Table 9, columns 1 and 2 report estimation results for the Neuer Markt and column 3 for the Nouveau Marché. The regression of column 1 includes only the set of IPO pairs obtained by matching each IPO from 1998 and 1999 with all of the preceding IPOs since the start of the Neuer Markt. Likewise, the regression of column 2 includes only those pairs in which an IPO from the first 300 days in 1999 is matched with one of the preceding IPOs on the Neuer Markt. Limited computer processing capacity prevented me from including all possible matches of IPOs from the Neuer Markt. For the Nouveau Marché, by contrast, the entire sample of IPOs could be utilized to assemble the set of matched IPO pairs.

In the Nouveau Marché sample, all explanatory variables are significant and have the expected sign. The time interval between firms' founding dates has a positive sign, while the three other explanatories have negative signs. This is consistent with the implication of an endogenous bubble that underwriters and venture capital firms will seek to maximize their returns by scheduling IPOs so that information spillovers are at least partially internalized. Moreover, the negative coefficient on the technology dummy suggests that IPO candidates themselves have an incentive to accelerate a planned IPO after other IPOs from the same area of technology have taken place.

But in both regressions for the Neuer Markt, the time interval between firms' founding dates, underwriter equality and the technology dummy turn out to be positive influences on the time distance between IPOs, while the dummy for VC equality is insignificant. It is of course surprising that the length of time between two IPOs from the same area of technology is larger than between two IPOs coming from different areas and that also the equality of lead underwriters is associated with a larger time distance between the paired IPOs. The Neuer Markt evidence thus contradicts the hypothesis of technology-specific information spillovers, causing IPOs from the same area to cluster in time and providing underwriters with an incentive to schedule their client firms' IPOs so as to internalize these spillovers. Acceptance of the spillover hypothesis would require that at least one of the coefficients on the equality of technology areas, equality of lead underwriters and equality of venture capital firms is significantly negative.

Since the evidence from the Neuer Markt is puzzling, I will now report the results from a more detailed analysis, using additional dummy variables that distinguish between different areas of technology and interaction effects between these areas of technology and the dummy for underwriter equality. I drop the technology dummy for *Financial Services* IPOs because else there would be perfect multicollinearity. The original dummy for the equality of technology focus now captures the impact of the equality of technology focus only in the case of *Financial Services*. All other areas of technology have their own dummy variable. Tables 10a to c examine the differential impact that the equality of the lead underwriter may have on the area effects in the timing of IPOs. Because there might still be considerable multicollinearity, I test the robustness by re-estimating the full model with only one set of dummies, first without the interaction terms and then with the interaction terms only.

The results reported in Table 10a for the 1998 to 1999 sample from the Neuer Markt show the influence of the *Financial Service* dummy as highly significant, but negative – with an estimated coefficient of minus 95.32. The time distance between any two IPOs from the *Financial Services* industries seems to be much smaller than the average time distance between arbitrary paired IPOs. None of the other coefficients for the technology area dummies indicate such a small time distance. Coefficients that exceed 95.32 indicate that the time distance between any two IPOs is larger than the average time distance between arbitrary paired IPOs. A larger than average time distance is evident for *Hardware*, *Telecom*, and *Industry & Services*. A much smaller time distance is significant in the case of *Software* and *Media*.

In addition, the regression reported in Table 10a controls for the influence of the equality of the lead underwriter in the IPO pairs. Here again, I distinguish between the different areas of technology. Only two coefficients are noteworthy: in the case of *Telecom*, there is a highly significant negative influence of the equality of lead under-writers on the time distance between any two IPOs. In the case of *Hardware*, there is a highly significant positive influence. The regressions reported in the second and third column of Table 10a show that the estimated coefficients are largely robust when dummy variables for underwriter equality in specific areas of technology are dropped and when the area specific technology dummies are dropped. But in the latter case, I do find a significant negative influence of underwriter equality on time distance between *Software* IPOs.

Table 10b shows the results for the 1999 sample from the Neuer Markt. Overall the estimated coefficients are similar to those obtained for the larger sample. However, a highly significant negative influence of underwriter equality is now revealed in the case of *Biomedical* IPOs. The second and third columns of Table 10b again confirm that the coefficients are robust when the set of dummy variables is reduced. *Telecom* and

Biomedical seem to be the areas of technology in which underwriters coordinate the timing of IPOs so as to bring them closer together in time and exploit the implied information externalities. Table 10c reports the results from the Nouveau Marché. Here, the technology dummy for *Internet* IPOs, *Hardware* IPOs and *Media* IPOs have highly significant negative influences on the time distances within IPO pairs. However, only in the case of *Telecom*, *Biomedical*, and *Industrial Services* is there a significant negative impact of underwriter equality on the time distance between arbitrary paired IPOs. In the case of *Internet* IPOs, the estimated coefficient suggests that underwriter equality results in a larger time distance within the IPO pairs. The second and third column of Table 10c confirm the robustness of these findings. The influence of the venture capital dummy is highly significant and negative in all three regressions. Once again, the relevant financial intermediaries in primary equity markets, underwriters and venture capital firms, seem to be more successful in internalizing information externalities on the Nouveau Marché than on the Neuer Markt.

These contradictory results from the Neuer Markt and the Nouveau Marché call for a cautious interpretation of the evidence. Three basic methodological problems must be considered: Firstly, the classification of IPO firms into the six areas of technology may be misleading. Many firms are involved in more than one line of business so that the categories are less homogeneous than they ideally should be in order to delineate senders and recipients of the same information spillovers. Moreover, the information spillovers may not always be limited to firms focused on the same area of technology. Secondly, I have already provided descriptive evidence of several subsequent hot issue markets in some areas of technology on the Neuer Markt, but not on the Nouveau Marché.[11] If a sufficient number of the IPO pairs from one of these areas of technology

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[11] See Figures 1 and 2 and especially Tables 8 and 9.

combine IPOs from different hot issue markets in the Neuer Markt, the average time distance may indeed be larger than in the control pairs that match IPOs from different areas of technology. This could result in a significant positive coefficient on the dummy for equality of technology, but there would be a distortion since the regressions do not control for the number of hot issue markets within an area of technology. Lastly, the contradictory results may be due to international differences in market characteristics and investment practices. For example, the puzzling result for the Neuer Markt may mean that the German primary equity market is less efficient – an interpretation which will require further examination. In spite of these caveats, the message of this exploratory regression analysis is that the technological focus of IPO firms does have an impact on the timing of IPOs in France and Germany. To what extent that impact determines the temporal sequence of IPOs from different areas of technology will be analysed next.

Transition probabilities in the Markov chain model. First for the stochastic IPO process on the Neuer Markt and then for that on the Nouveau Marché, a matrix with non-parametric estimates of the transition probabilities between technology areas is presented in Table 11a. Each element in the matrix is the estimated conditional probability that the next IPO will come from the area of technology in the column headings given that the most recent IPO has come from the area of technology in the row headings. Iteration of the transition matrix yields the stationary distribution and predicts the long term distribution of IPOs across technology areas to which the transitional dynamics will converge in the absence of any exogenous shocks to the system. The stationary distribution is given in the last row of each panel in Table 11a. In both cases the stationary distribution equals the sample distribution, given in the penultimate row of each panel. Since there are no absorbing states, the estimated Markov chain is found to be an ergodic stochastic process: The memory of the process fades in the sense that the covariance between observations converges to zero with increasing distance in time.

This aggregate property, however, does not rule out persistence in individual areas of technology in the sense that the conditional probability of the next IPO coming from the same technology area is significantly higher than would be expected from the sample distribution. Persistence in an ergodic Markov chain simply requires that the diagonal elements of the transition matrix are higher than the elements in the sample distribution. However, only two areas – *Software* in the Neuer Markt and *Internet & Media* in the Nouveau Marché sample – appear to have this kind of persistence. Visual inspection thus suggests that there is clustering in some areas, but not in all.

However, the visual evidence does not stand a formal statistical test. Persistence as implied by the endogenous bubble hypothesis would require that the entries in rows and columns of the transition matrix are *independent* random variables. The independence of the transition probabilities can be tested using the test statistic proposed by Basawa and Rao (1980), p. 62, which is χ^2-distributed with $(m–1)^2 = 25$ degrees of freedom since we have six areas of technology defining the possible states of the system. For the Neuer Markt as a whole, we get V = 16.09 (p = 0.91), so that the hypothesis of independence is clearly rejected.[12] On the other hand, equality tests of the kind proposed by Anderson and Goodman (1957), testing the equality of the transition matrix rows one by one against the sample distribution, yields test statistics in excess of 23.4 and therefore much larger than the critical value of $\chi^2_{5;95} = 11.07$ so that the hypothesis of equality is clearly rejected for all rows. For the Nouveau Marché, by contrast, the test of independence

[12] Looking only at *Software* against all other IPOs yields: V = 4.2 (p = 0.04), so that persistence appears to be confirmed in the case of *Software* IPOs on the Neuer Markt. But looking only at one individual sector selected after a visual inspection of the estimated transition matrix amounts to data mining.

yields V = 33.22 (p = 0.13), which can be interpreted as weak evidence in favour of persistence, although the equality between individual rows of the transition matrix and the sample distribution is only rejected for the *Biomedical* sector.

As a further check on the robustness of my estimates, I provide a time-interval interpretation of the Markov chain shown in Table 11b. One problem with the event-based Markov chain estimates of Table 11a is that the time distance between two consecutive IPOs varies widely and the timing of the next IPO may already have been decided before or long after the preceding IPO took place. In either case, it is doubtful that an IPO's area of technology is influenced by the immediately preceding IPO. Although we do not directly observe *when* the decision to go public is taken, it will usually be fixed one month before the IPO date. Table 11b is therefore based on the assumption that the percentage distribution of IPO across areas of technology in the course of one month will determine the percentage distribution of IPOs in the next months. The estimates are coefficients from a systems regression of current percentage shares of IPOs in the six technology areas on the lagged percentage shares. I tested for serial correlation, which would bias the lagged endogenous regressor, using the Brensch-Godfrey LM test statistics, but I did not find it to be a big problem in most of the individual equations.[13]

Exogenous determinants of transition probabilities. As I pointed out above, the stationary Markov model may fail to detect persistence because endogenous bubbles, in which hot issue markets are confined to one or a few separate subsectors of high technology, do not imply that transition probabilities are stationary. Instead, persistence is expected to be larger before the peak of a hot issue market and lower thereafter. The likelihood ratio test proposed by Anderson and Goodman (1957) yields 22.63 for the Neuer Markt count data model of Table 11a and 9.84 for the Nouveau Marché, so that

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[13] Detailed results are available from the author.

the stationarity assumption cannot be rejected in either sample. However, this aggregate property of the transition matrix may mask non-stationarity in the transition probabilities from individual areas of technology. The endogenous bubble hypothesis would be consistent with transition probabilities that change in response to the prior level of underpricing that IPOs within a given area of technology have incurred. I therefore use Toikka's estimator to identify technology-specific hot issue markets in the Neuer Markt on the basis of two exogenous variables[14]: first, the average level of underpricing, or initial return, observed in the two preceding IPOs from the current IPO's technology area as a measure of the market's sentiment towards that area; and second, the stock market price index as a control for general market conditions. Table 11c presents the results for a three state model in which the area *Computer* comprises *Hardware*, *IT Services* and *Software* IPOs, whereas *Mediacom* comprises *Internet*, *Media* and *Telecoms*. The category *Other* comprises all other IPOs, namely those from the *Industrial & Financial Services* and from the *Biomedical* areas.

The first panel of Table 11c presents the estimated transition probability matrix for the three-state model whose entries were used as endogenous variables in regressions on the two explanatories *Index* and *Underpricing*. The regressor *Index* is defined as the four-week average of the NEMAX performance index lagged one month. The regressor *Underpricing* is defined as the average underpricing observed in the two preceding IPOs from the same area of technology as the one in the current transition's initial state. The estimated regression equations are reported in the bottom panel of Table 11c. Only two regressions are reported for each row since the third would just be a linear combination of the first two. The seemingly unrelated regression model has been employed. The results show that *Index* has a highly significant, but quantitatively similar influence on

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[14] I have not applied Toikka's estimator to the Nouveau Marché sample because the number of IPOs is relatively small.

all of the transition probabilities. *Underpricing*, by contrast, is not only significant, but also quantitatively distinct. In line with expectations, the impact of area-specific prior underpricing on the transition probabilities is larger on the main diagonal than in the off-diagonal entries of the transition matrix. Underpricing thus explains part of the observed persistence in the three-state model for the Neuer Markt.

The estimated coefficients from the regressions explaining the observed transition probabilities have then been used to calculate ex post predictions, first on the basis of the *observed* initial states (panel 2 in Table 11c), and second on the basis of the *predicted* initial states (panel 3). The second approach has a better theoretical foundation since it attempts to make a long-term prediction of the implications contained in the estimated econometric model. The disadvantage of a multi-step recursive prediction is that errors in the estimation of Toikka's coefficients will accumulate over time. It is therefore useful to report also the transition probability matrix implied by one-step predictions starting at the observed initial values for each transition. The true transition matrix taking the empirical changes in the exogenous determinants of transition rates into account should lie *between* the two predicted matrices of panel 2 and 3. Panel 2 implies lower persistence in the *Computer* and *Mediacom* areas, but higher persistence in the *Other* area. The implied stationary distribution assigns a higher probability to being in the *Other* area and in the *Computer* area than the sample distribution does. By contrast, the *recursive* ex post prediction, reported in panel 3 implies higher persistence in the *Computer* and *Mediacom* areas, but lower persistence in the *Other* area. In the implied stationary distribution, only the higher probability of being in the *Other* area represents a striking difference from the sample distribution.

For further evidence on the determinants of transition probabilities, Table 11d provides a brief look at the role of individual underwriters in the Neuer Markt. To this end, I have applied the estimator after ordering all IPOs with the same lead underwriter in temporal sequence according to their IPO dates. The results indicate lower persistence than in the unconditional Markov chain estimates of the three state model (first panel in Table 11c), especially in the case of *Mediacom*. This casts some doubt on the hypothesis that hot issue markets are the work of underwriters specializing on one or a few selected areas of technology in order to exploit area-specific information spillovers. However, I must note that I have ignored the potentially important influence of co-underwriters since the multidimensionality of the estimation problem would then require a more general statistical model, like a random field estimator, beyond the scope of the present paper.

Table 11e presents three mobility indices for the various transition matrices I have estimated. These mobility indices attempt to express the mobility with a Markov chain in terms of a standardized number that evaluates the trace of the transition matrix, $\mathrm{tr}(\Pi)$, the eigenvalues, λ_j, and the determinant, $\det(\Pi)$, respectively. They consistently indicate a very high degree of mobility in all of the estimated transition matrices and thus rule out persistence of the kind implied by the endogenous bubble hypothesis.

Duration analysis. To analyse the empirical determinants of IPO timing in continuous time, I use the Cox (1972) proportional hazard model. There is neither right-censuring since the data set excludes firms that might have gone public after the end of the sample period, nor is there left truncation since the observation period has no gap after the onset of risk. In the basic Cox model, $h_i(t|x_i) = \eta_0(t)\exp\{\beta_1 x_{i1} + ... + \beta_c x_{ic}\}$, the hazard of going public is the product of two factors: a baseline non-negative hazard function $\eta_0(t)$ at time t, which is common for all IPOs, and the exponential of a linear function with c covariates, which are specific to each IPO and are summarized in the vector x_i. The semi-parametric Cox model does not specify $\eta_0(t)$ and estimates only the β coefficients, using the partial maximum likelihood method (PMLE). This estimator is generally consistent and asymptotically normal.

In our context, the choice of a semi-parametric model is preferred to either fully parametric or non-parametric models. Non-parametric methods can be used to compare survival experiences observed for different values of qualitative covariates that are time-invariant. Table 12 reports three non-parametric tests for the equality of the survivor functions for firms from different technology areas and for firms with and without venture capital-backing: the log-rank test, the Wilcoxon and a stratified Wilcoxon, in which the equality of the survival functions for venture backed and non-backed firms is tested separately for different technology areas and then combined into one overall statistic. These tests provide consistent evidence that the survivor functions for *Biomedical* firms and for *Industry & Financial Services* firms in both the Neuer Markt and the Nouveau Marché are clearly distinguished from the other firms in the respective sample. But the survivor functions for the other areas of technology, including a broad category comprising all information and communications technologies, do not seem to differ from the survivor function of firms *not* falling into the respective area of technology. Looking next at venture capital-backed and non-backed firms, the survivor functions differ only in the Neuer Markt sample. This is not necessarily inconsistent with Bottazi and DaRin (2002) who fail to find a statistically significant effect of venture capital-backing on the hazard rate in the much larger sample of 488 IPOs from the entire Euro.nm group of markets. My stratified Wilcoxon reveals that *Industry & Financial Services* is the only category in the Neuer Markt where venture capital-backing makes a significant difference.

I have not estimated a fully parametric model, although such a model could in principle provide direct estimates of the influence of time-varying variables on the hazard rate. Besides qualitative and time-invariant characteristics of individual firms, the hypothesis of endogenous bubbles assigns an important role to time-varying variables, such as the general price level in the stock market and various measures of expectations. However, *unless* the distribution of the baseline-hazard over time is known with a high degree of accuracy, any choice of a specific distribution from the standard menu, such as the exponential, will be ad hoc and may introduce an unnecessary source of error. While in theory, parametric estimation can be efficient if the correct distribution of the baseline-hazard of going public is assumed, that distribution cannot *a priori* be known under the hypothesis of endogenous bubbles. It is the essence of non-market interaction that the shape of the density of IPOs from different technology areas will evolve as the bubble forms. Any test based on parametric estimates would therefore be misleading.

The Cox proportional hazard model obtains estimates by pooling over the risk groups based on ordered survival times and therefore does not require inclusion of the stock market price index as a time-varying covariate. The baseline hazard, $h_0(t)$, is left unestimated; it could be any function of time and will therefore automatically reflect the influence of market conditions that affect all firms equally. The price to be paid for ignoring the baseline hazard is a loss in the efficiency of estimating the coefficients of the time-invariant covariates. In our context, the main advantage of choosing the Cox proportional hazard model is that it allows us to test hypotheses on covariates that are either time-invariant or depend only on the temporal ordering of the IPO events, not on the time distances between them. The validity of these tests will be unaffected by the underlying temporal distribution of IPOs. The ordering of the IPOs, our failure events, determines the analysis time in the Cox model.[15]

To account for non-market interaction in the Cox (1972) proportional hazard model, $\lambda(t, z_i) = \lambda_0(t)\exp(\theta' z_i)$, the vector z_i will include up to three different within-neighbourhood expectations as the neighbourhood behavioural measure for each area of

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[15] The values of time-varying covariates have to be introduced as a function of analysis time. The neighbourhood expectations derived from the endogenous bubble hypothesis are a case in point.

technology at the relevant failure times. Under rational expectations, the neighbourhood behavioural measures are based on separate Nelson-Aalen estimates of the forward-looking cumulative baseline hazard from the current observation to the end of the sample. I thus assume that rational expectations are formed with full knowledge of the probability distribution of the relevant time-invariant characteristics of all the firms within their respective neighbourhood.

The calculation of the neighbourhood behavioural measures generates step functions because the nonparametric Nelson-Aalen estimator of the baseline hazard does not produce a continuous function, but a function with steps occurring at each observed failure time within the neighbourhood. Recall that our behavioural measure has three components under rational expectations: the expected number of IPOs by some duration τ, the average duration of all future IPOs within a neighbourhood and their median duration. I set $\tau = 4$ months. Implicitly, all three components take the total number of IPOs in each neighbourhood into account.

The most comprehensive test of the neighbourhood behavioural measure's relevance would ideally call for the inclusion of all non-neighbourhood expectations as control variables. However, a model with so many variables suffers from severe multicollinearity. I therefore proceed stepwise and test only against the alternative hypothesis for one technology area at a time. At the observed IPOs of one specific technology area, I include the expections within each of the other five technology-based neighbourhoods at that point in analysis time. This is a stepwise test because it shows whether the going public decision is based on expectations within the neighbourhood or on more general expectations that a shared by two or more neighbourhoods at the same time. My empirical findings, as shown in Tables 13 for the Neuer Markt and Tables 14 for the Nouveau Marché, are unequivocal in their support for the within-neighbourhood hypothesis.

Table 13a reports the results from the Cox proportional hazards model with social interaction under rational expectations in the Neuer Markt. Model 1 includes the most comprehensive set of variables, comprising exogenous characteristics of issuing firms, such as their age at the time of the IPO, the number of employees, a dummy variable for venture capital-backing, the debt-equity ratio at the time of the IPO, the rate of sales growth over the rate of employment growth and a dummy for each of the following five technology areas: *Software*, *ITservices*, *Biomedical*, *Hardware & Telecoms (Hardwtel)* and *Internet/Media (Intmedia)*. The technology dummies are to capture the relevant time-invariant neighbourhood characteristics.

In addition, there are four sets of time-varying variables, one of which is used to estimate interaction effects between the technology areas and the general stock market price index. The other three sets of time-varying variables serve as neighbourhood behavioural measures. They include the expected number of IPOs pertaining to the technological neighbourhood within the next four months, the expected mean time distance of future IPOs and the expected median time distance of future IPOs in the technology neighbourhood.

None of the time-invariant firm and neighbourhood characteristics are significant except for the *Hardwtel* dummy. Nor are the interaction terms between the technology dummies and the market price index significant. However, because there is likely to be multicollinearity in these estimates, it would be futile to interpret the size of the estimate obtained for individual dummy variables. Looking at the neighbourhood behavioural measures, I do not find a significant impact of the expected number of IPOs within the next four months or of the expected mean time distance of future IPOs in the technology neighbourhood. But I do find a significant negative influence of the expected median time distance of future IPOs within the technology neighbourhood on the hazard rate of current IPOs.

To examine this further, I adopt the general–to–specific methodology and successively eliminate variables that are the least significant in my regressions. Model 2 eliminates the debt-equity ratio and the interaction terms between technology dummies and market price index as well as the interaction with the expected mean time distance of future IPOs in the technology neighbourhood. Again, it turns out that the interaction with the expected median time distance of future IPOs in the technology neighbourhood is the only significant influence on the hazard rate of current IPOs. Model 3 confirms this once more after eliminating the interaction of technology dummies with the expected number of IPOs within four months. Model 4 shows that the age of a firm at its IPO is significant and increases the hazard rate and that venture capital-backing and the size of the venture capital stake before the IPO are jointly significant, and so are the technology dummies.

The observation that the interaction of technological dummies with the expected median time distance of future IPOs in the technology neighbourhood is highly significant and negative in all four regressions should not be attributed to the general surge in IPO activity during the bubble. Of course, there will be a natural decline in the mean time and median time distance of future IPOs during the bubble. But because the Cox proportional hazard model does not estimate the base-line hazard, which is allowed to vary over time, it will automatically capture all time-variant influences on the hazard rate that affect firms in the various areas of technology equally. Only the neighbourhood-specific impact of the changing median duration is estimated. All fixed effects, including different starting levels for the neighbourhood behavioural measures, are captured by the technology area dummies.

Table 13b provides further tests for the area-specificity of the expectations impact in the Neuer Markt. The regressions reported in this table are designed to test separately for each area of technology the hypothesis that the expected median time distance of future

IPOs in the technology neighbourhood explains the hazard rate *against* the hypothesis that the same kind of expectations for other technology areas have equal explanatory power. The column headings give the name of the technology neighbourhood for which the test is performed. Model 1 includes time-invariant firm and neighbourhood characteristics, the full set of interaction terms between technology dummies and the expected median time distance of future IPOs in the technology neighbourhood, and five additional interaction terms between the *Biomedical* dummy and the expected median time distance of future IPOs in each of the other five areas of technology. Model 2 reports the same sort of test for hardware and telecom IPOs, using interaction terms between the *Hardwtel* dummy and the expected median time distances of future IPOs in each of the other five areas of technology. Model 3, 4, 5 and 6 report the test for *IT Services*, *Intmedia*, *Ind.&Financial Services* and *Software*. To calculate interaction terms between the dummy for the technology area stated in the column heading and the median duration expectations for all the dates of IPOs in the other areas of technology, I have had to augment the information contained in the step functions based on my nonparametric estimates of the area-specific cumulative hazard rate in order to obtain the appropriate values at the IPO dates in those other areas of technology. I have filled in these values so as to take into account that the median duration of future IPOs expected at the current date will decline with time even if no new IPO takes place within a technology neighbourhood. The decline will be proportional to the total number of IPOs within the technology neighbourhood. The same logic has been applied to obtain values for dates before the first IPO in a technology neighbourhood took place.[16]

Each of the regression models reported in Table 13b confirms the highly significant negative impact of the expected median time distance of future IPOs in the technology

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[16] Details are available from the author upon request.

neighbourhood. Moreover, it turns out that none of the expectations for the other areas of technology have a significant influence on the hazard rate of current IPOs within a given technology neighbourhood, which provides compelling evidence of the significance of the neighbourhood behavioural measure. I conclude that it is not the general median time distance of future IPOs that is influencing the hazard rate within any of the chosen areas of technology, but only the expected median time distance of future IPOs *within* the technology neighbourhood.

Next, I examine the possibility that neighbourhood behaviour is driven by adaptive expectations. Table 13c estimates an adaptive expectations model for the Neuer Markt and tests it against the rational expectations model. Besides the time-invariant firm and neighbourhood characteristics, the regressions include interaction terms between technology dummies and the median time distance of past IPOs in the technology neighbourhood as well as interaction terms between the technology dummies and the average area-specific underpricing over two months lagged one month. As in the case of rational expectations, I have filled in the values of the adaptive expectations measures at dates not directly supported by the cumulative hazard estimates for a given technology neighbourhood. The average area-specific underpricing is held constant until the information is updated by a new IPO in the technology neighbourhood. However, my measures of adaptive expectations for the median duration of future IPOs – the median time distance of past IPOs – changes also when new IPOs are not forthcoming during a given lapse of time since the last observed IPO in the technology neighbourhood. The expected median duration until future IPOs will increase during those time lapses in proportion to the number of days that have passed since the last observed IPO. At dates before the first IPO within a technology neighbourhood the actual duration of the first IPO since the start of the Neuer Markt is used as a neasure of expectations. Inevitably, these starting values are somewhat arbitrary, but that should not invalidate the coefficients estimated for the time-varying variables in a regression that includes additional neighbourhood dummies to control for fixed area-effects.

If past underpricing influences decisions of privately held firms to go public, it seems reasonable to assume that these decisions are made one month before the IPO and will therefore be influenced by underpricing observed before that point in time. One could argue that a longer history of underpricing within a neighbourhood is relevant and test this hypothesis using Bayesian model averaging techniques[17]. But the overall number of observations in our sample period is too small to make this estimation strategy practical.

In Table 13c, Model 1, 2 and 3 show that neither the median time distance of past IPOs within a technology neighbourhood, nor the average area-specific underpricing is a significant determinant of the current hazard rate. Moreover, Models 4 and 5 show that the neighbourhood behavioural measure from the rational expectations specification, the expected median time distance of future IPOs within a technology neighbourhood, retains its significant influence on the current hazard rate even if a measure of adaptive expectations is included. This lends further report to the hypothesis of non-market interaction driven by rational expectations.

Table 14a reports the results from the Cox proportional hazards model with social interaction under rational expectation for the Nouveau Marché. The estimation strategy is essentially the same as in the case of the Neuer Markt. Each regression model includes a set of time-invariant firm and neighbourhood characteristics as well as neighbourhood behavioural measures, defined as interaction terms between technology dummies and (i) the expected number of IPOs within the next four months, (ii) the expected mean time distance of future IPOs within the technology neighbourhood and (iii) the expected

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[17] See Volinsky et al. (1997) for an introduction.

median time distance of future IPOs in the technology neighbourhood. The only difference between Model 1 and 2 is that the two insignificant time-invariant firm characteristics employment and the debt-equity ratio have been eliminated in the latter model. As in the case of the Neuer Markt, only the expected median time distance of future IPOs in the technology neighbourhood provides a significant neighbourhood behavioural measure.

This finding is further confirmed by Model 3 and 4 which eliminate successively the set of expected mean time distances of future IPOs in the technology neighbourhood and the set of expected IPO numbers from the technology neighbourhood within the next four months. Model 5 shows that venture capital-backing and the size of the venture capital stake before the IPO can count as jointly significant time-invariant firm characteristics that help to explain the hazard rate of IPOs in the Nouveau Marché although it is possible that this impression is only created by the elimination of the technology area dummies. In contrast to the Neuer Markt, venture capital-backing tends to increase the hazard rate of going public in the Nouveau Marché, so that venture capital-backed firms will tend to go public earlier than those without venture capital-backing.

Table 14b provides further tests for the area specificity of the expectations impact in the Nouveau Marché. The results are largely similar to those found in the Neuer Markt. Interaction terms between the technology dummy and the expectations for non-neighbourhood technology areas do not have explanatory power in addition to the interaction between technology dummies and the expected median time distance of future IPOs in the technology neighbourhood.

Table 14c presents estimates of the adaptive expectations model for the Nouveau Marché. As in the Neuer Markt sample, the results show that neither the median time distance of past IPOs in the technology neighbourhood, nor the average area-specific underpricing over two months, lagged one month, are significant influences on current hazard rates. Moreover, the negative influence of the rationally expected median time distance of future IPOs in the technology neighbourhood on the hazard rate is shown to be unaffected by the inclusion of interaction terms between technology dummies and the median time distance of past IPOs. As in the Neuer Markt sample, the evidence is thus strongly in favour of the rational expectations model to explain the influence of time-varying neighbourhood behavioural measures.

VI. Related Literature

Most work on bubbles in primary equity markets has been theoretical. It is part of a burgeoning literature on more general herd behaviour in financial markets that is reviewed in Hirshleifer and Hong Leoh (2003). Herd behaviour may arise from a variety of causes, including payoff externalities and reputational interactions, social learning, and informational cascades. Hirshleifer and Hong Leoh (2003) propose a simple taxonomy of effects to evaluate how alternative theories explain the evidence on the behaviour of investors, firms and analysts. They discuss both the private incentives to engage in herding or cascading and the incentives to protect against or take advantage of herding or cascading by others.

To understand what is actually driving an endogenous bubble matters because the welfare implications can be very different. The literature has made only partial progress in understanding how a bubble can be recognized before it bursts, how bubbles in financial markets are related to technological innovation and whether bubbles may be efficient from a social point of view. However, it has already become clear that rational behaviour, such as rational learning, does not guarantee an optimal allocation. Informational cascades, in which agents ignore their own private information and imitate others with certainty, have been shown to aggregate information inefficiently and to create the idiosyncrasies, fragility and simultaneity of endogenous moves that are characteristic elements of any stock market bubble. Moreover, it is clear that long periods with individual herding upon bad decisions are not an exclusive implication of informational cascades, but may also occur in rational learning theories with incomplete information blockage.

Primary equity markets offer a particularly suitable setting for informational cascades because the IPO decision is always discrete. By contrast, in a continuous and unbounded action space, private information never ceases to have at least a small impact on individual decisions. Overshooting is a natural implication of informational cascades (Grenadier 1999), but can also occur without full information blockage, as in Caplin and Leahy (1993). In a formal model of the IPO decision, Nelson (2002) develops the hypothesis that informational cascades can by asymmetric and that going public is more likely to be driven by informational cascades than the decision to stay private. On balance, informational cascades may thus be a good feature of primary equity markets, because they may enable firms to go public and finance projects that have a social rate of return in excess of the social cost of capital, but cannot attract investors in the absence of the informational cascade. By implication, some systematic failure in the capital market must be present, and as Hirshleifer and Teoh (2003) point out, some such failure is also required for herding to affect prices and to cause the excess volatility and temporary predictability of private rates of return that is often observed during hot issue markets.

The potential endogeneity of private rates of return during and after a bubble renders an ex ante definition of a bubble virtually impossible. Siegel (2003) argues that any definition must be based on an assumption of irrational expectations with regard to cash flows or with regard to the rate used to discount the discount expectations. The problem then is to determine what can reasonably be expected of the future. The current price of an asset may be justified not only by cash flows in the next few years, but by cash flows several decades later. Siegel (2003) argues that stock prices in 1929 may not have been justified by the returns in the early 1930s, but – with hindsight – by the cash flows some thirty years later. To make the definition of a bubble operational, a time limit must be placed on the period over which future cash flows are considered. Siegel proposes that the future realized return of the asset justifies the original price over a time period long enough so that the present value of cash flows received by investors during this period constitutes at least one half of that price. A measure of this length of time is the duration of the asset, the time-weighted average of all future expected cash flows. Siegel (2003), p. 14, argues that a bubble is present if the realized return is more than two standard deviations from the expected return, given the risk and return conditions present up to the time when the price is being examined. While it is hence impossible to know immediately after a market price index falls whether there was a bubble or not, the definition can be used to argue that the great crashes of 1929 and 1987 have not really been bubbles. Moreover, as Siegel (2003) argues, the low point in stock prices in 1932 may well have been a 'negative bubble'.

Some recent explanations of hot issue markets. Attempts to analyze the empirical implications of theoretical models more carefully have been at the core of the most recent literature. Some findings can be interpreted as support for exogenous bubbles, others as support for endogenous bubbles. In a pioneering empirical study of US biotechnology IPOs, Lerner (1994) has found that venture capitalists often take their portfolio firms public at times of high industry valuations. In a more comprehensive study, Lowry and Schwert (2002) find a significant positive relation between initial returns to IPO investors and future IPO volume in the US, which can account for the cyclical nature of the IPO market. Based on evidence that includes the entire IPO process of each firm, positive information during the registration period appears to explain the observed propensity of IPOs to cluster during periods of high initial returns. However, another study by Lowry (2003) investigating the large volatility of IPO volume in the US casts some doubt on the hypothesis that information spillovers drive the observed clustering. Instead, Lowry (2003) argues that a much larger part of this volatility can be explained as a consequence of the changing demand for capital during the business cycle, and as a consequence of changes in investor optimism, than would be consistent with explanations emphasizing asymmetric information and adverse selection in the IPO market.

Exogenous bubbles may imply pseudo market timing of the kind studied by Schultz (2003). Using simulations that are based on the distribution of market and IPO returns and the relationship between IPO clusters and overall price levels actually observed in the US stock market from 1973 to 1997, Schultz (2003) finds long-term underperformance of more than 25 percent to be neither surprising nor unusual in an efficient market. This finding raises the methodological question how best to measure the long-term underperformance of IPOs. It is an established empirical regularity that underperformance of IPOs is much greater when calculated in event time, weighting all offerings equally (as if equal amounts were invested in each offering), than for calendar time, weighting each month equally (as if equal amounts were invested each month regardless of the number of IPOs). As a caveat, however, the theory of pseudo market timing cannot account for the stylized fact that initial returns (the underpricing) increase with the aggregate IPO volume, as they do during a bubble.

Another class of recent papers has provided empirical support for an explanation which is consistent with increasing initial returns during a bubble and which I would call a theory of semi-endogenous bubbles. Increasing initial returns may be due to the divergent incentives for the production of private information used in the valuation of an

IPO candidate by the underwriter – in line with a principal agent theory of underwriting. Ploog and Stolpe (2003), pp. 135, provide a detailed summary of the principal-agent theory of underwriting. The basic idea is that the issuer will allow underpricing of his shares in order to set optimal incentives for the underwriter to acquire information from dispersed investors that is relevant for the valuation of the firm. Hot issue markets thus need not always be caused by a bubble in the secondary market; they may also arise due to other exogenous changes that alter the agency conflict between issuers (the principals) and underwriters (the agents). According to Ljungqvist et al. (2003), the ownership structure of IPO firms became more fragmented shortly before and during the dot-com bubble of the late 1990s. Moreover, since there was less insider selling at the typical dot-com-IPO, pre-IPO owners became more complacent about underpricing. The larger initial return in turn attracted more demand for shares in the primary equity market and thus inflated the bubble, as suggested by Lowry and Schwert (2002). In effect, outside investors suddenly viewed IPOs as less risky. Offer prices could thus increase as underpricing increased, and the incentive of pre-IPO owners to bargain with underwriters about the best offer price could decline further.

Finally, there is the recent study of Benveniste et al. (2003) which I interpret as an exploration of endogenous bubbles based on information spillovers. They confirm Schwert and Lowry's (2002) finding that the decision to carry through with a planned IPO is influenced by the performance of other IPOs that have taken place at almost the same time. However, they show that initial returns and IPO volume is negatively correlated among those contemporaneous IPOs that are subject to a common valuation factor although the correlation in the aggregate of all IPOs is positive. The authors argue that these findings can be reconciled if underwriters with some market power, such as investment banks, seek to bundle offerings that are subject to a common valuation factor in order to internalize the information spillovers from the earlier IPOs during a hot issue market. This private response to the coordination problem in the underwriting process, first analyzed in Benveniste et al. (2002), could be an important source of welfare benefits from endogenous bubbles in primary equity markets.

VII. Concluding Remarks

In this paper, I have sought to provide a fresh perspective on the genesis of bubbles in primary equity markets, also known as hot issue markets in the literature. I have suggested an analytical distinction between hot issue markets driven by exogenous changes in the economy, such as an unexpected expansion in monetary policy, and those driven by endogenous forces, such as information spillovers from individual IPOs that can alter the choice of timing for subsequent IPOs through non-market interaction. Positive information spillovers can greatly improve the opportunities of privately held firms that plan to go public. The distinction I propose helps to define conditions for hot issue markets to generate welfare gains by boosting the incentives for technological innovation. The main contribution of the paper has been to develop an econometric framework to test the empirical implications of the endogenous and exogenous bubble hypotheses. Using firm-level data from Germany's Neuer Markt and France's Nouveau Marché, I have provided descriptive evidence that firms belonging to the same area of technology tend to cluster their IPOs around peaks whose timing varies across different technology areas.

Hot issue markets may generate important welfare benefits primarily because they provide a window for new technology-based firms to be rewarded for their innovation and to embark on a large-scale expansion. Similar rewards would not be available during normal times when the market's valuation of IPOs, in particular from high-tech start-ups, is often too low, relative to their potential long-term performance, to be an attractive source of expansion finance. IPOs from certain subsets of high-technology are therefore absent during cold issue markets. The notion of an endogenous bubble summarizes the key arguments why hot issue markets may be welfare-enhancing. Endogeneity is a natural implication of information spillovers and non-market interaction in firms' timing of going public during the build-up of a bubble. Endogenous bubbles are relatively more likely to benefit firms generating social returns in excess of the returns that can be privately appropriated, while exogenous bubbles are relatively more likely to waste capital on firms that will turn out to be failures.

The evidence from Germany's Neuer Markt and France's Nouveau Marché is predominantly in favour of the hypothesis that the hot issue market of the late 1990s has been an endogenous bubble, driven by forward-looking rational expectations, not by adaptive expectations derived from the performance of past IPOs. I draw this conclusion primarily on the basis of a Cox proportional hazards model with non-market interaction that explains the empirical determinants of the waiting time, or duration, of specific privately held firms before their IPO. The expected median duration of future IPOs within the technological neighbourhood is the most important explanatory of a firm's hazard rate of going public. Neither the general stock market price index, nor most of the exogenous firm characteristics that I considered were significant determinants of the hazard rate in my empirical model. However there is some evidence from the Neuer Markt that venture capital-backed firms go public later.

Because the empirical behaviour of the relevant financial intermediaries can help to distinguish between exogenous and endogenous bubbles in primary equity markets, I have sought to estimate the influence of lead underwriters and venture capitalists on the time distance between arbitrarily paired IPOs, using a simple linear regression framework. My evidence from the Nouveau Marché is consistent with the implication of an endogenous bubble that underwriters and venture capital firms will seek to maximize their private returns by scheduling IPOs so that information spillovers are at least partially internalized. Moreover, the evidence suggests that IPO firms themselves have an incentive to accelerate a planned IPO after other IPOs from the same area of technology have taken place. But the Neuer Markt evidence contradicts the hypothesis of technology-specific information spillovers, causing IPOs from the same area to cluster in time and providing underwriters with an incentive to schedule their client firms' IPOs so as to internalize these spillovers. Both underwriters and venture capital firms thus appear to be more successful in internalizing information externalities in the Nouveau Marché than in the Neuer Markt.

Future empirical research should study the role of financial intermediaries in primary equity markets in much greater detail. For example, my duration analysis with non-market interaction could be extended to consider the influence of financial intermediaries on the timing of IPOs. This might be done either by including interaction terms – multiplying the neighbourhood behavioral measure with a dummy variable that identifies the financial intermediaries backing a given IPO – or by simply redefining the notion of a firm's neighbourhood in terms of the associated financial intermediaries. Further research on these issues could have important practical implications for the regulation of financial intermediaries in primary equity markets. Underwriters with market power may benefit from greater profits during a hot issue market, and they may thus have a special interest in helping to create a pattern of hot and cold issue markets. Cold issue markets might even serve as a barrier to entry because a relatively small number of the largest underwriters may have a much better chance of surviving the long cold issue markets between bubbles.

References

Anderson, T.W. and L.A. Goodman (1957), 'Statistical Inference about Markov Chains'. *Anuals of Mathematical Statistics* **28**: 89–110.

Amemiya, T. (1985), *Advanced Econometrics*, Cambridge, MA: Harvard University Press.

Amemiya, T. (2001), Endogenous Sampling in Duration Models. *Monetary and Economic Studies* **19** (3): 77–96.

Basawa, I.V. and B.L.S. Prakasa Rao (1980), *Statistical Inference for Stochastic Processes*, London: Academic Press.

Benveniste, L., W. Busaba and W. Wilhelm Jr. (2002), Information Externalities and the Role of Underwriters in Primary Equity Markets. *Journal of Financial Intermediation* **11**: 61–86.

Benveniste, L., A. Ljungqvist, W. Wilhelm and X. Yu (2003), Evidence of Information Spillovers in the Production of Investment Banking Services. *Journal of Finance* **58** (2): 577–608.

Bottazi, L., and M. DaRin (2003), Venture Capital in Europe and the Financing of Innovative Companies. *Economic Policy* **34**: 231–269.

Blanchard, O. and M.W. Watson (1982*),* 'Bubbles, Rational Expectations and Financial Markets', in P. Wachtel (ed.), *Crises in the Economic and Financial Structure*, Lexington, MA: Heath.

Brock, W. and S. Durlauf (2001*),* 'Interactions-Based Models', in J. Heckman and E. Leamer (eds.), *Handbook of Econometrics V*, **54**: 3297–3380, Amsterdam: Elsevier.

Caballero, R.J. and M.L. Hammour (2002*),* Speculative Growth. NBER Working Paper series 9381. National Bureau of Economic Research. Cambridge, Mass.

Caplin, A. and J. Leahy (1993), Sectoral Shocks, Learning and Aggregate Fluctuations. *Review of Economic Studies* **60**: 777–794.

Cleves, M.A., W.W. Gould and R.G. Gutierrez (2002*), An Introduction to Survival Analysis Using Stata*, College Station, Texas: Stata Press.

Cornelli, F. and D. Goldreich (2003*),* Bookbuilding: How Informative Is the Order Book? *The Journal of Finance* **58** (4): 1415–1443.

Cuthbertson, K. (1996*), Quantitative Financial Economics*, Chichester: John Wiley & Sons.

Froot, K.A. and M. Obstfeld (1991), Intrinsic Bubbles: the Case of Stock Prices. *American Economic Review* **81** (5): 1189–1214.

Fukao, K. and R. Benabon (1993), History versus Expectations: A Comment. *Quarterly Journal of Economics* **108** (2): 535–542.

Glaeser. E.L., H.D. Kallal, A. Scheinkman and A. Schleifer (1992), Growth in Cities. *Journal of Political Economy* **100** (6): 1126–1152.

Glaeser, E.L., B. Sacerdote and J. A. Scheinkman (1996), Crime and Social Interactions. *Quarterly Journal of Economics* **111** (2): 507–548.

Grenadier, S.R. (1999), Information Revelation through Option Exercise. *Review of Financial Studies* 12: 95–129.

Griliches, Z. (1992), The Search for R&D Spillovers. *Scandinavian Journal of Economics* **94** (supplement): 24–47.

Hall, R.E. (1991), *Booms and Recessions in a Noisy Economy*, New Haven: Yale University Press.

Harris, R.D.F. (1997), Stock Markets and Development: A Re-Assessment. *European Economic Review* **41** (1): 139–146.

Helwege, J. and N. Liang (1996), *Initial Public Offerings in Hot and Cold Markets*. Finance and Economics Discussion Paper Series **96** (34). Board of Governors of the Federal Reserve System, Washington, D.C.

Hirshleifer, D. and S. Hong Teoh (2003), Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis. *European Financial Management* **9** (1): 25–66.

Hoffmann-Burchardi, U. (2001), Clustering of Initial Public Offerings, Information Revelation and Underpricing. *European Economic Review* **45**: 353–383.

Krugman, P.R. (1991), History versus Expectations. *Quarterly Journal of Economics* **106** (2): 651–667.

Lerner, J. (1994), Venture Capitalists and the Decision to Go Public. *Journal of Financial Economics* **35**: 293–316.

Ljungqvist, A.P. and W. Wilhelm, Jr. (2003), IPO Pricing in the Dot-com Bubble. *Journal of Finance* **58** (2): 723–752.

Ljungqvist, A.P., V. Nanda and R. Singh (2001), *Hot Markets, Investor Sentiment and IPO Pricing*. CEPR Discussion Paper 3053. Centre for Economic Policy Research. London.

Lowry, M. (2003), Why does IPO Volume Fluctuate So Much? *Journal of Financial Economics* **67**: 3–40.

Lowry, M. and G. Schwert (2002), IPO Market Cycles: Bubbles or Sequential Learning? *Journal of Finance* **57**: 1171–1200.

Maksimovic, V. and P. Pichler (2001), Technological Innovation and Initial Public Offerings. *The Review of Financial Studies* **14** (2): 459–494.

Manski, C.F. (2000), Economic Analysis of Social Interactions. *The Journal of Economic Perspectives* **14** (3): 115–136.

Morris, S. and H.S. Shin (2002), Social Value of Public Information. *The American Economic Review* **92** (5): 1521–1534.

Nelson, L.B. (2002), Persistence and Reversal in Herd Behaviour: Theory and Application to the Decision to Go Public. *Review of Financial Studies* **15**: 65–95.

Nigmatullin, E. (2003), *Neighbourhood Interactions and Fertility Dynamics*, Department of Economics, University of Wisconsin-Madison. Mimeo.

Olivier, J. (2000), Growth-Enhancing Bubbles. *International Economic Review* **41** (1): 133–151.

Peri, G. (2003), *Knowledge Flows, R&D Spillovers and Innovation*. ZEW Discussion Paper 03–40. Zentrum für Europäische Wirtschaftsforschung, Mannheim.

Ploog, C. and M. Stolpe (2003), Die Fehlbewertung junger Aktiengesellschaften beim Gang an die Börse – Ursachen und wirtschaftspolitische Konsequenzen. *Zeitschrift für Wirtschaftspolitik* **52** (1): 128–151.

Ritter, J.R. (1991), The Long-Run Performance of Initial Public Offerings. *Journal of Finance* **46** (1): 3–27.

Romer, P.M. (1990), Endogenous Technological Change. *Journal of Political Economy* **98**: 71–102.

Saint-Paul, G. (1992a), Fiscal Policy in an Endogenous Growth Model. *The Quarterly Journal of Economics* **107** (4): 1243–1259.

Saint-Paul, G. (1992b), Technological Choice, Financial Markets and Economic Development. *European Economic Review* **36** (4): 763–781.

Samuelson, P. (1958), An Exact Consumption Loan Model of Interest With or Without the Social Contrivance of Money. *Journal of Political Economy* **66**: 467–482.

Schertler, A. and M. Stolpe (2000), *Venture Mania in Europe: Its Causes and Consequences*. Kiel Discussion Paper 358. Institut für Weltwirtschaft, Kiel.

Schultz, P. (2003), Pseudo Market Timing and the Long-Run Underperformance of IPOs. *Journal of Finance* **58** (2): 483–517.

Siegel, J. J. (2003*),* What Is an Asset Price Bubble? An Operational Definition. *European Financial Management* **9** (1): 11–24.

Shiller, R. (2000*), Irrational Exuberance*, Princeton: Princeton University Press.

Sirakaya, S. (2003*), Recidivism and Social Interactions*, Department of Economics, University of Wisconsin-Madison. Mimeo.

Stolpe, M. (2003*), Learning and Signalling in the French and German Venture Capital Industries*. Kiel Working Paper 1156. Institut für Weltwirtschaft, Kiel.

Stolpe, M. (2004*), Europe's Entry into the Venture Capital Business: Efficiency and Policy*. Institut für Weltwirtschaft, Kiel. Mimeo.

Toikka, R.S. (1976*),* A Markovian Model of Labor Market Decisions by Workers. *American Economic Review* **66**: 821–834.

Van Den Berg, G. (2001*),* 'Duration Models: Specification, Identification, and Multiple Durations', in J. Heckman and E. Leamer (eds.), *Handbook of Econometrics V*, Amsterdam: Elsevier.

Volinsky, C.T., D. Madigan, A.E. Raftery and R.A. Kronmal (1997*),* Bayesian Model Averaging in Proportional Hazard Models: Assessing the Risk of a Stroke. *Applied Statistics* **46** (4): 433–448.

Figure 1a: Monthly IPO volume and market price index in the Neuer Markt

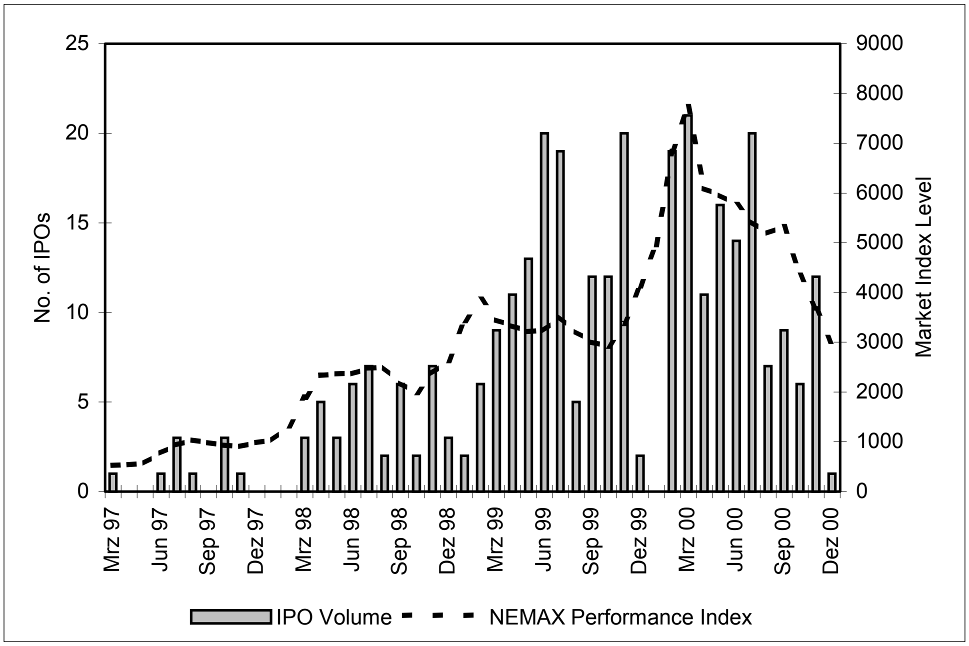


Figure 1b: Monthly IPO volume and market price index in the Nouveau Marché

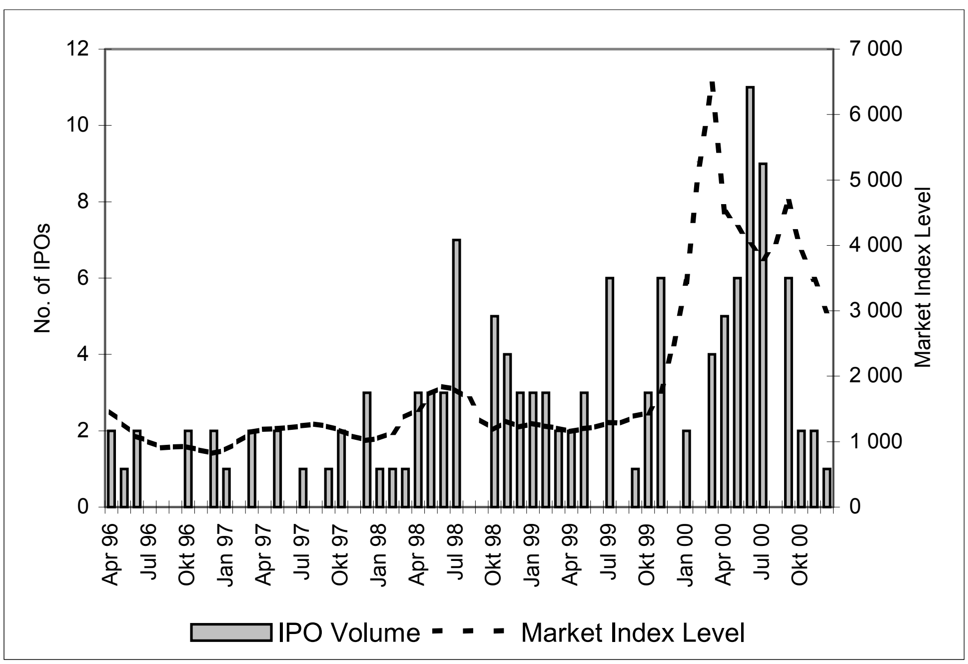


Figure 2a: Nelson-Aalen cumulative hazard estimates for Neuer Markt IPOs, by technology area

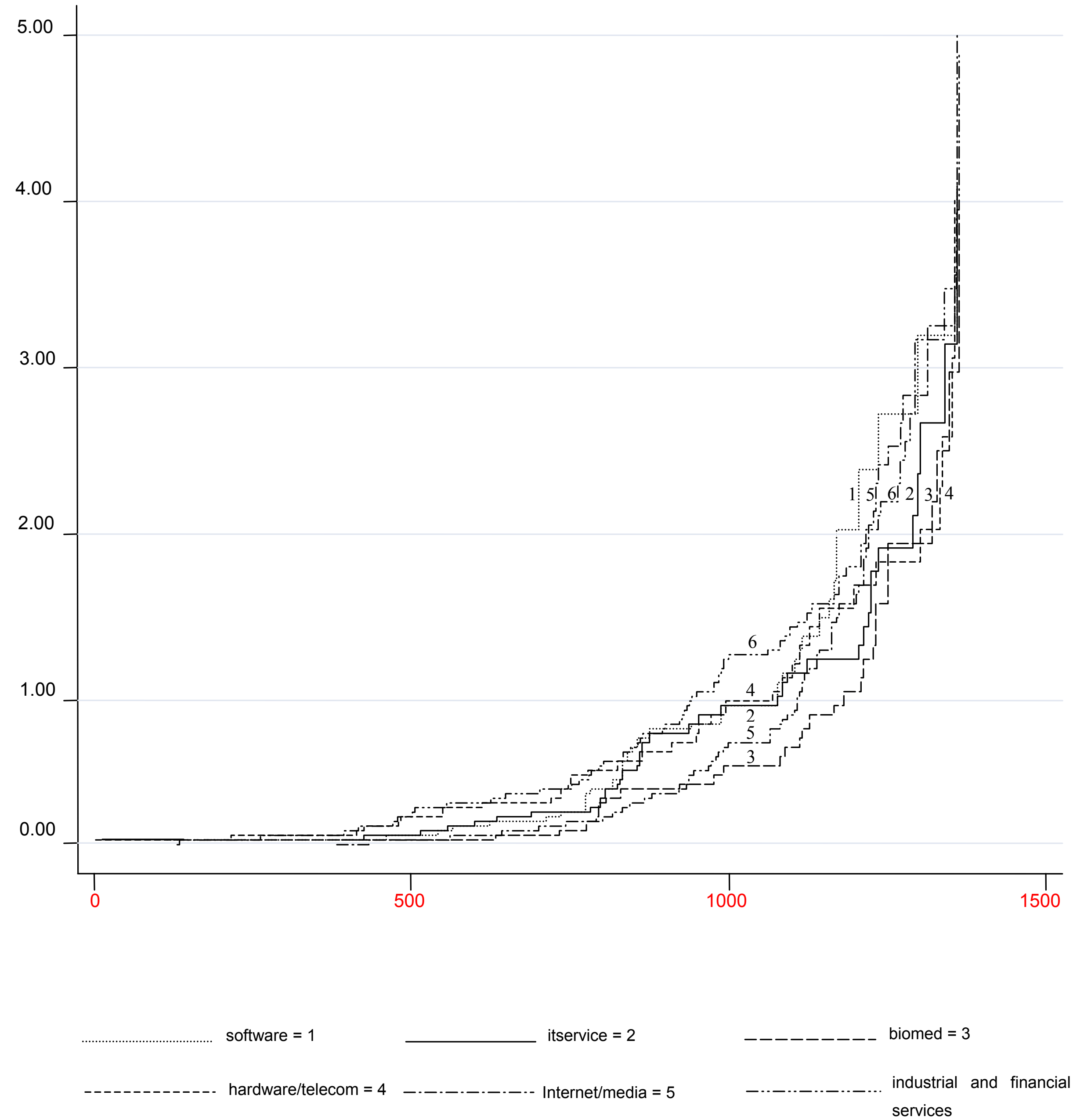


Figure 2b: Smoothed hazard estimates for Neuer Markt IPOs, by technology area

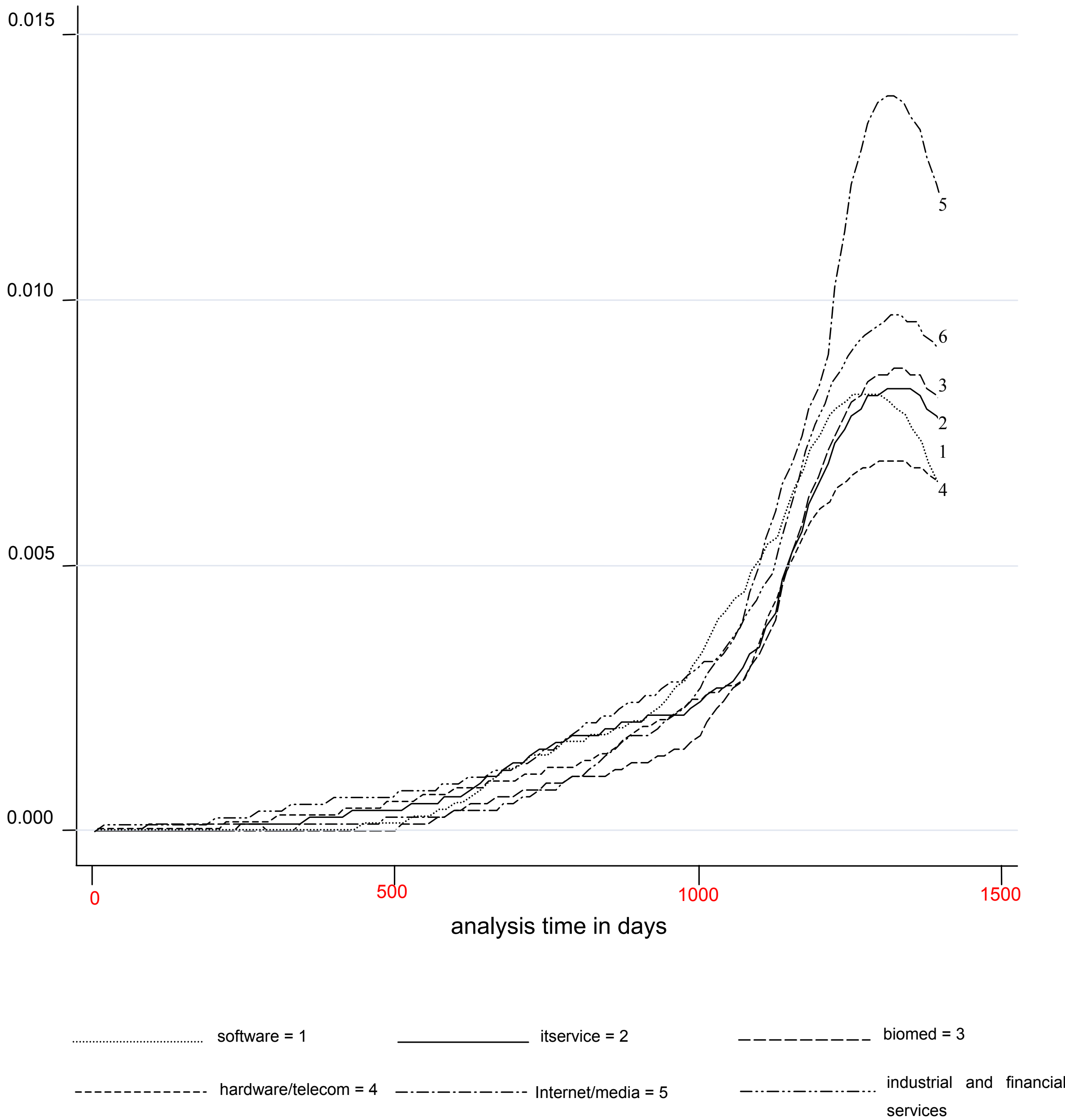


Figure 3a: Kaplan-Meier survival estimates for Neuer Markt IPOs

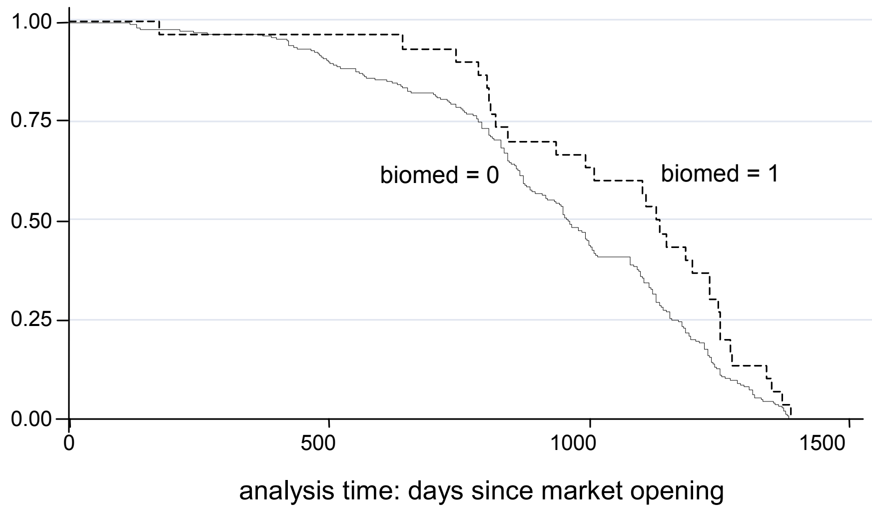


Figure 3b: Kaplan-Meier survival estimates for Neuer Markt IPOs

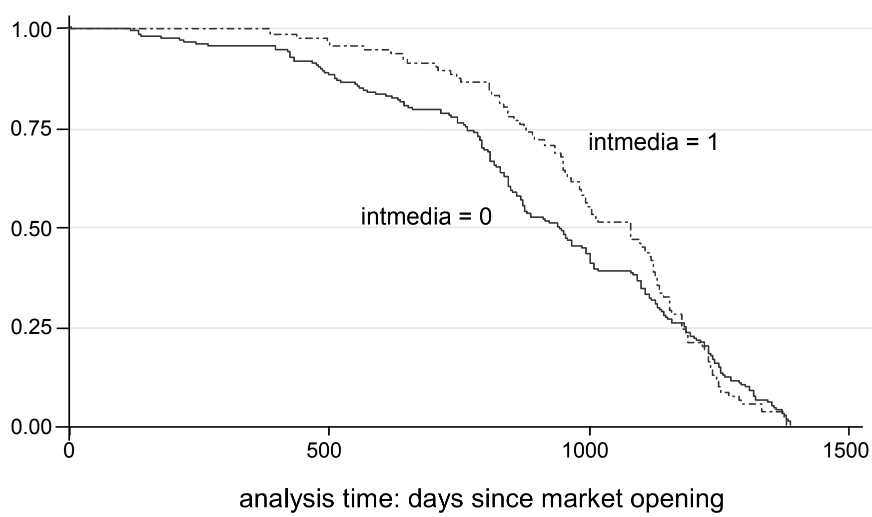


Figure 3c: Kaplan-Meier survival estimates for Neuer Markt IPOs

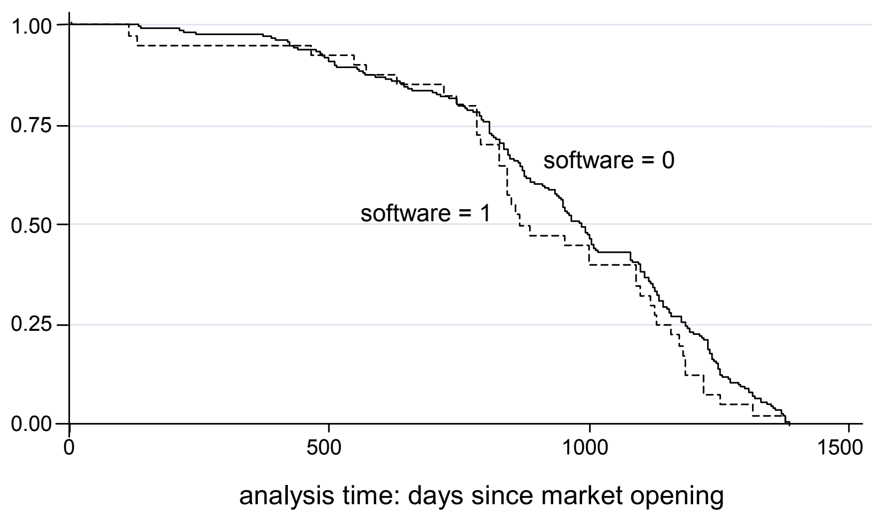


Figure 3d: Kaplan-Meier survival estimates for Neuer Markt IPOs

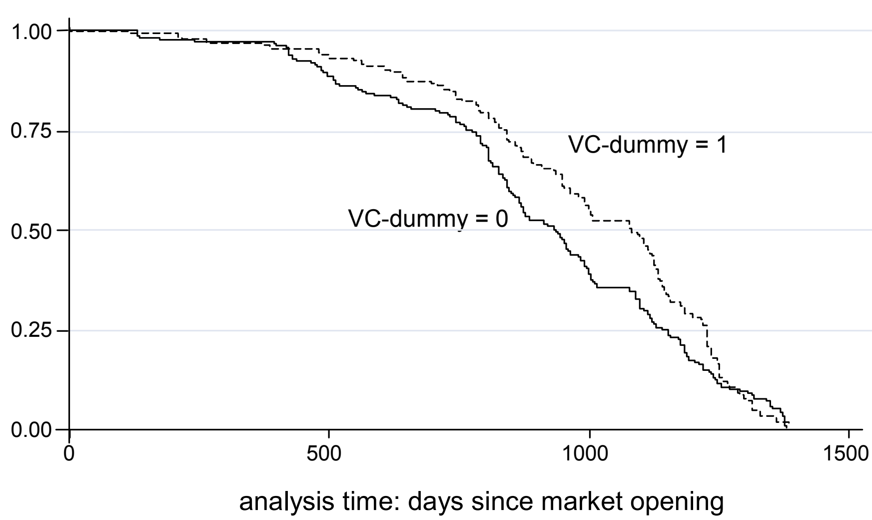
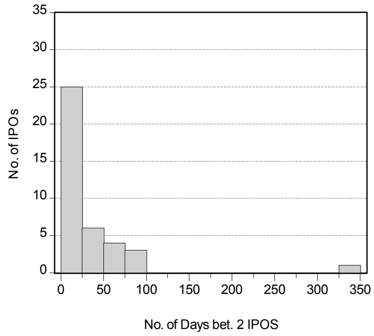


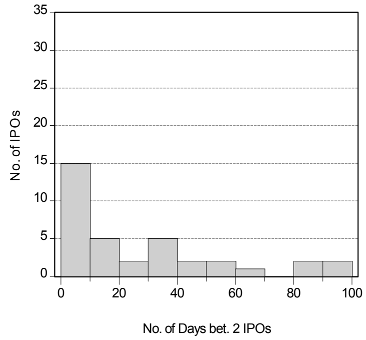
Figure 4: Histograms of the length of time between two consecutive IPOs, by technology area

Neuer Markt

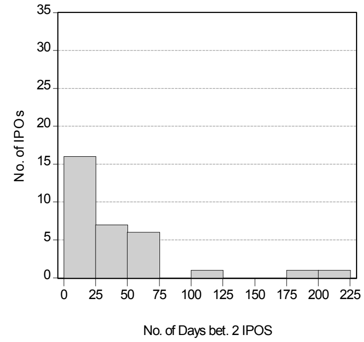
a. Software



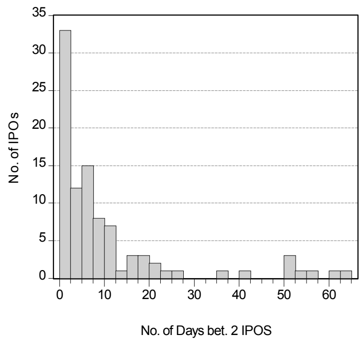
b. IT Services



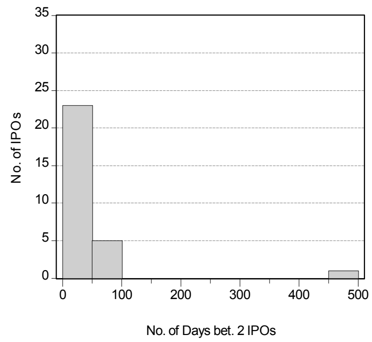
c. Hardware & Telecomms



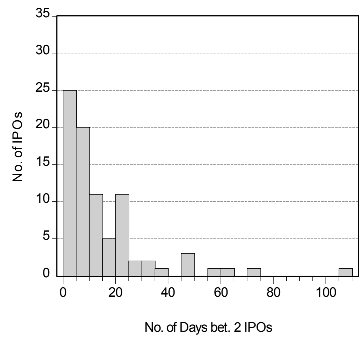
d. Internet & Media



e. BioTechnology

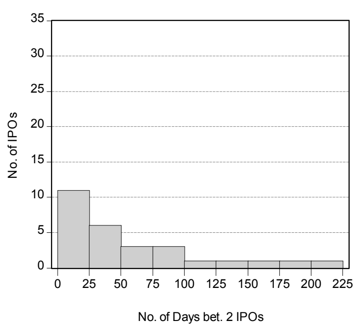


f. Industrial & Financial Services

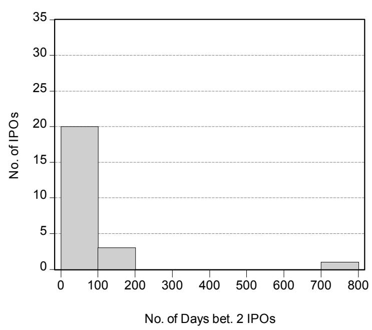


Nouveau Marché

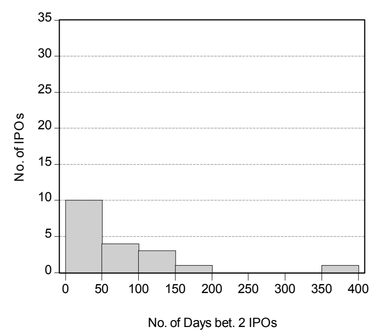
a. Software



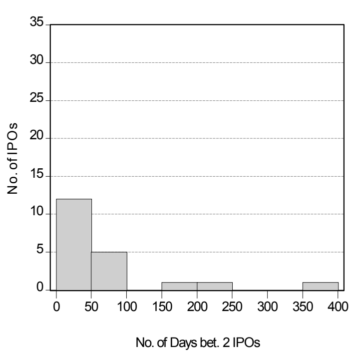
b. IT Services



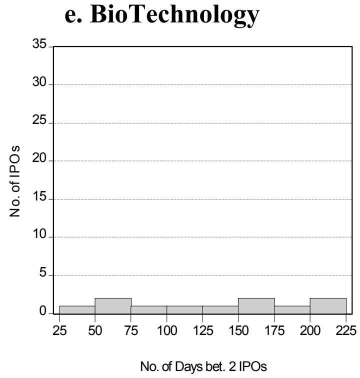
c. Hardware & Telecomms



d. Internet & Media



e. BioTechnology



f. Industrial & Financial Services

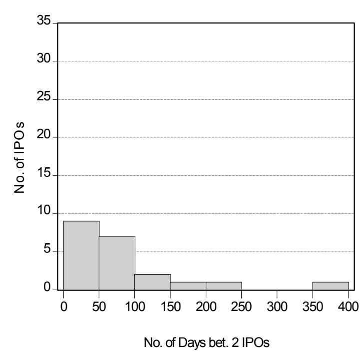


Figure 5a: Frequencies of different time intervals between two consecutive IPOs, Neuer Markt

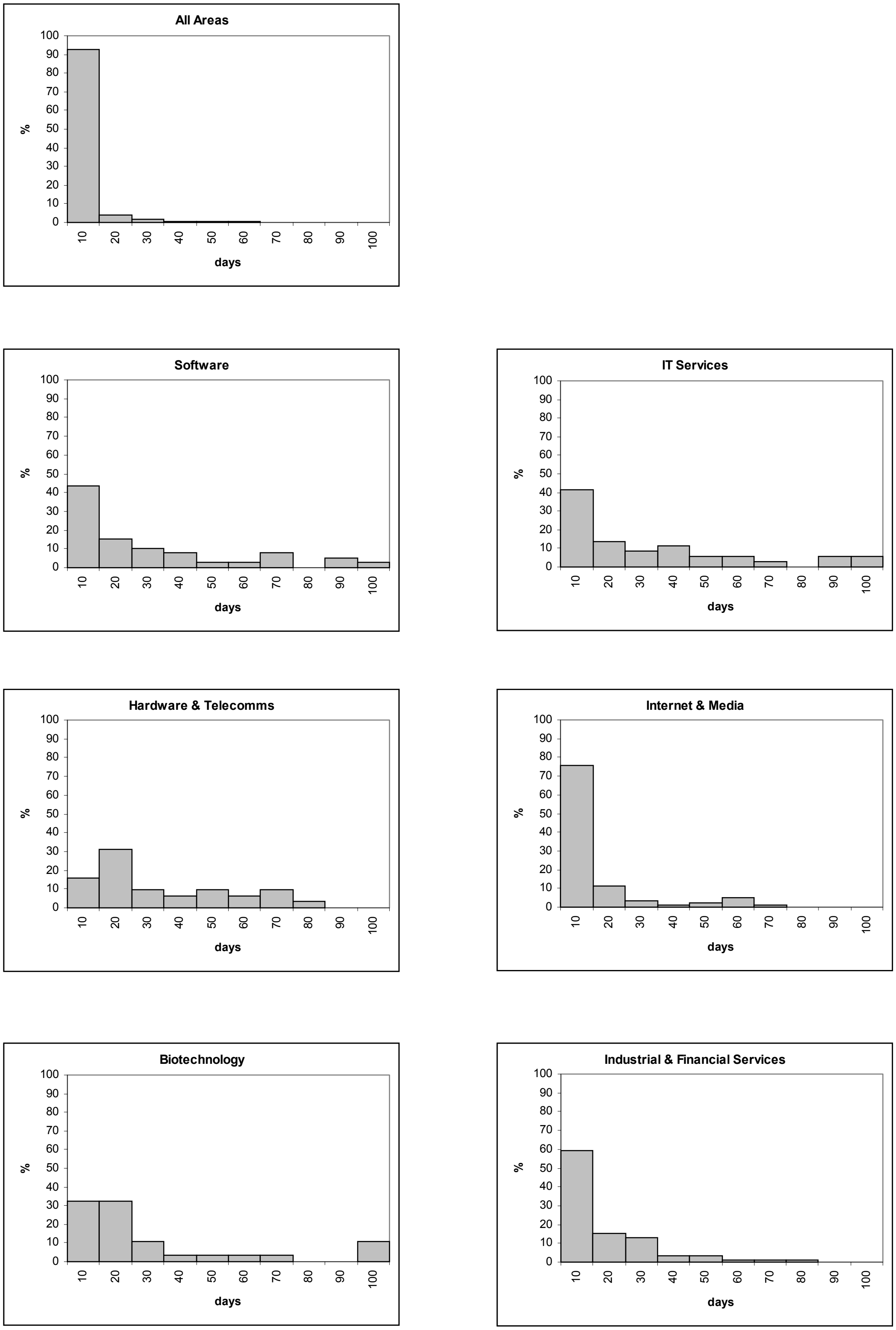


Figure 5b: Frequencies of different time intervals between two consecutive IPOs, Nouveau Marché

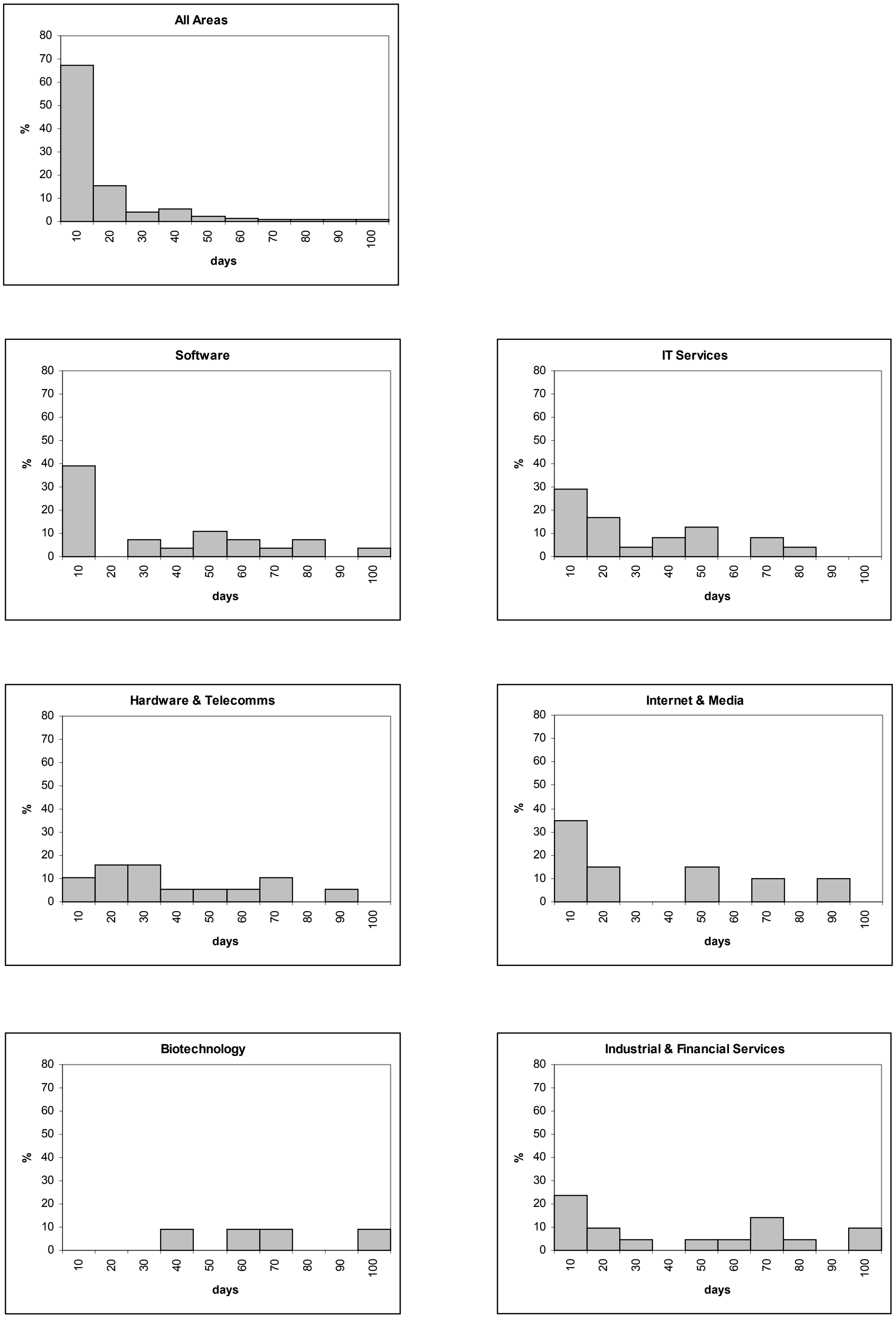
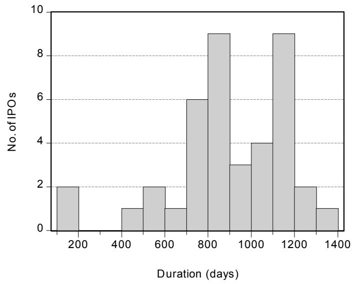


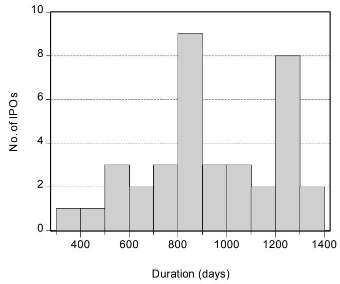
Figure 6: Histograms of the duration from market opening day to date of IPO

A. Neuer Markt

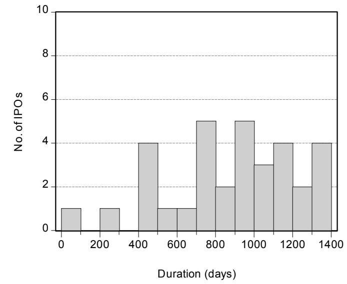
a. Software



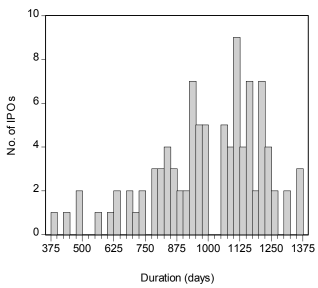
b. IT Services



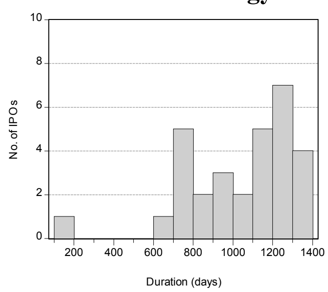
c. Hardware & Telecomms



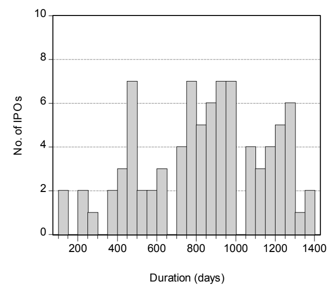
d. Internet & Media



e. BioTechnology

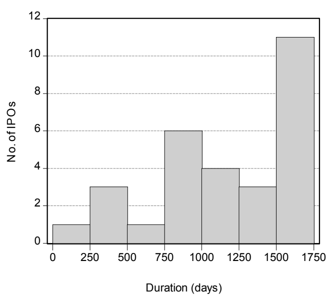


f. Industrial & Financial Services

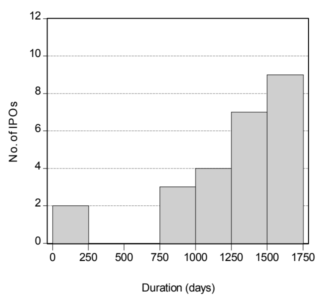


B. Noveau Marché

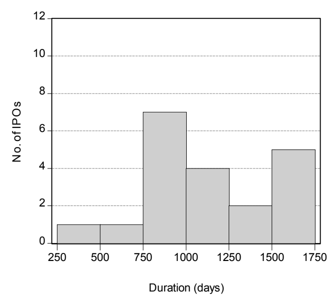
a. Software



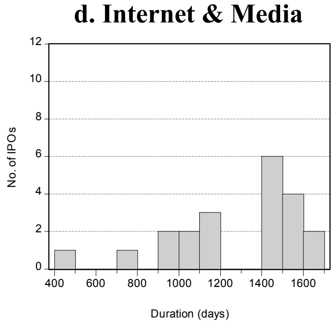
b. IT Services



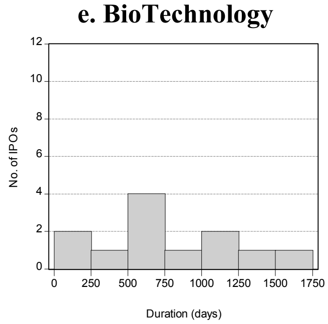
c. Hardware & Telecomms



d. Internet & Media



e. BioTechnology



f. Industrial & Financial Services

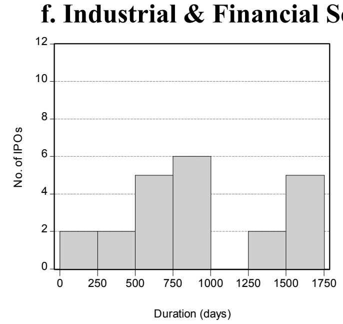
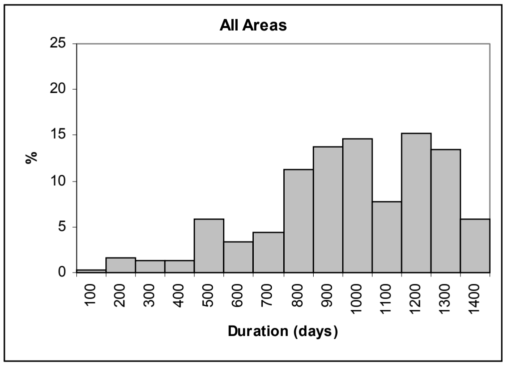
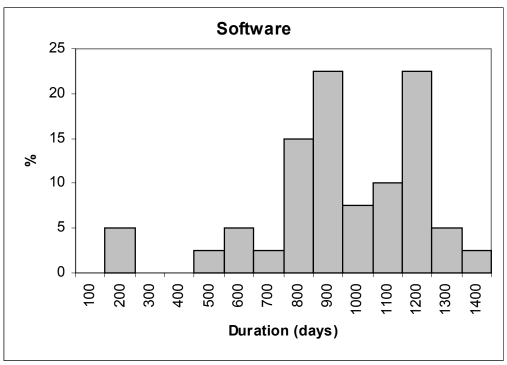
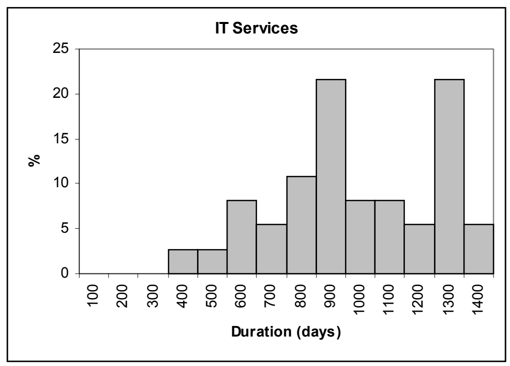
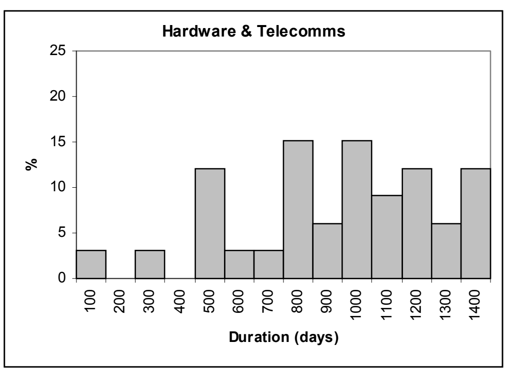


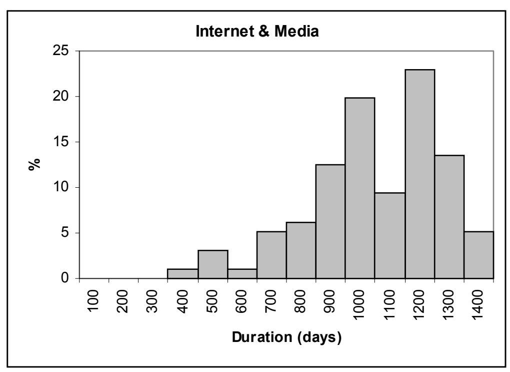
Figure 7a: Duration frequencies from Neuer Markt opening day to date of IPO

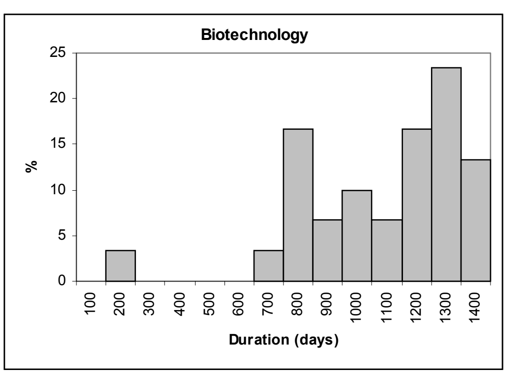












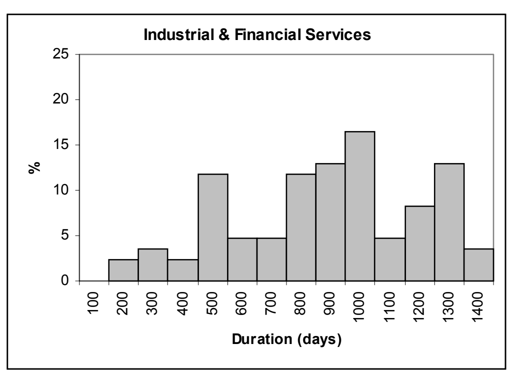


Figure 7b: Duration frequencies from Nouveau Marché opening day to date of IPO

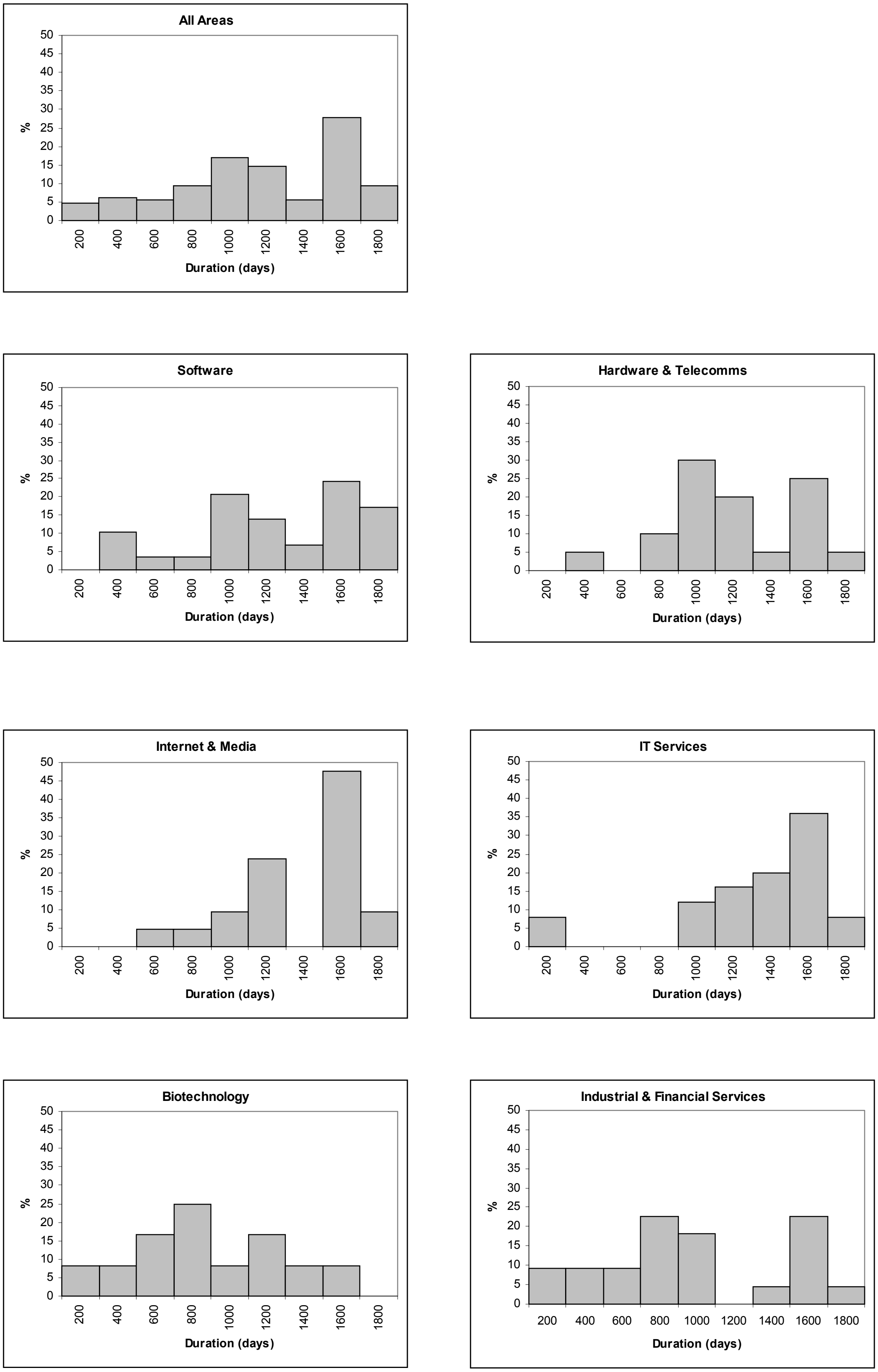


Table 1: Number and percentage shares of IPOs by technology area

Neuer Markt (opened March 10, 1997)

	1996	1997	1998	1999	2000	Total
Software		2	4	18	16	40
IT Services		0	6	16	15	37
Hardware & Telecomms		2	6	12	13	33
Internet & Media		0	8	39	49	96
Biotechnology		1	1	10	18	30
Industrial & Financial Services		5	19	36	25	85
Total		10	44	131	136	321

Nouveau Marché (opened March 20, 1996)

	1996	1997	1998	1999	2000	Total
Software	2	3	6	6	12	29
IT Services	2	0	3	9	11	25
Hardware & Telecomms	1	1	7	5	6	20
Internet & Media	0	1	3	5	12	21
Biotechnology	2	3	3	3	1	12
Industrial & Financial Services	2	4	9	1	6	22
Total	9	12	31	29	48	129

Percent Shares*

Neuer Markt (opened March 10, 1997)

	1996	1997	1998	1999	2000	Total
Software (12.5)		5.0	10.0	45.0	40.0	100.0
IT Services (11.5)		0.0	16.2	43.2	40.5	100.0
Hardware & Telecomms (10.3)		6.1	18.2	36.4	39.4	100.0
Internet & Media (29.9)		0.0	8.3	40.6	51.0	100.0
Biotechnology (9.3)		3.3	3.3	33.3	60.0	100.0
Industrial & Financial Services (26.5)		5.9	22.4	42.4	29.4	100.0

Nouveau Marché (opened March 20, 1996)

	1996	1997	1998	1999	2000	Total
Software (22.5)	6.9	10.3	20.7	20.7	41.4	100.0
IT Services (19.4)	8.0	0.0	12.0	36.0	44.0	100.0
Hardware & Telecomms (15.5)	5.0	5.0	35.0	25.0	30.0	100.0
Internet & Media (16.3)	0.0	4.8	14.3	23.8	57.1	100.0
Biotechnology (9.3)	16.7	25.0	25.0	25.0	8.3	100.0
Industrial & Financial Services (17.1)	9.1	18.2	40.9	4.5	27.3	100.0

*Figures in parentheses are percent of total number of IPOs.

Table 2: Average and expected length of time between two IPOs

	Neuer Markt		Nouveau Marché	
	Average*	Expected**	Average*	Expected**
Software	31.8	34.8	54.04	60.2
IT Services	26.9	37.6	69.46	69.9
Hardware& Telecomms	42.2	42.2	75.84	87.4
Internet & Media	10.3	14.5	61.25	83.2
Biotechnology	41.2	46.4	133.09	145.6
Industrial& Financial Services	14.7	16.4	77.62	79.4
Total	4.26	5.4	13.30	13.5

* Days

** Total number of days in sample period divided by total number of IPOs

Table 3: Relative frequency of the lengths of time between two consecutive IPOs within fixed intervals in the Neuer Markt

Percentage shares within each area of technology

	SOFTWARE	ITSERVICE	HRDW&TEL	INT&MEDIA	BIOMED	IND&FIN	ALL AREAS
Obs.	[39]	[36]	[32]	[95]	[29]	[84]	[320]
Interval in days*							
25	64.1	61.1	50.0	90.5	71.4	85.7	97.2
50	15.4	19.4	21.9	3.2	10.7	9.5	1.9
75	10.3	8.3	18.8	6.3	7.1	3.6	0.3
100	7.7	11.1	0.0	0.0	10.7	0.0	0.0
125	0.0	0.0	3.1	0.0	0.0	1.2	0.6
150	0.0	0.0	0.0	0.0	0.0	0.0	0.0
>150 days	2.6	0.0	6.3	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Difference from shares in all areas in percentage points							
25	-33.1	-36.1	-47.2	-6.7	-25.8	-11.5	0.0
50	13.5	17.6	20.0	1.3	8.8	7.6	0.0
75	9.9	8.0	18.4	6.0	6.8	3.3	0.0
100	7.7	11.1	0.0	0.0	10.7	0.0	0.0
125	-0.6	-0.6	2.5	-0.6	-0.6	0.6	0.0
150	0.0	0.0	0.0	0.0	0.0	0.0	0.0
>150 days	2.6	0.0	6.3	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 4: Relative frequency of the lengths of time between two consecutive IPOs within fixed intervals in the Nouveau Marché

Percentage shares within each area of technology

	SOFTWARE	ITSERVICE	HRDW&TEL	INT&MEDIA	BIOMED	IND&FIN	ALL AREAS
Obs.	[28]	[24]	[19]	[20]	[11]	[21]	[128]
Interval in days*							
50	60.7	70.8	52.6	65.0	9.1	42.9	94.5
100	21.4	12.5	21.1	20.0	27.3	33.3	4.7
150	7.1	12.5	15.8	0.0	18.2	9.5	0.8
200	7.1	0.0	5.3	5.0	27.3	4.8	0.0
250	3.6	0.0	0.0	5.0	18.2	4.8	0.0
300	0.0	0.0	0.0	0.0	0.0	0.0	0.0
>300 days	7.1	0.0	5.3	5.0	0.0	4.8	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Difference from shares in all areas in percentage points							
50	-33.8	-23.7	-41.9	-29.5	-85.4	-51.7	0.0
100	16.7	7.8	16.4	15.3	22.6	28.6	0.0
150	6.4	11.7	15.0	-0.8	17.4	8.7	0.0
200	7.1	0.0	5.3	5.0	27.3	4.8	0.0
250	3.6	0.0	0.0	5.0	18.2	4.8	0.0
300	0.0	0.0	0.0	0.0	0.0	0.0	0.0
>300 days	0.0	4.2	5.3	5.0	0.0	4.8	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 5: Relative frequency of the lengths of time between two consecutive IPOs within fixed intervals (adjusted) in the Neuer Markt

Percentage shares within each area of technology

	SOFTWARE	ITSERVICE	HRDW&TEL	INT&MEDIA	BIOMED	IND&FIN	ALL AREAS
Obs.	[39]	[36]	[32]	[95]	[29]	[84]	[320]
Interval in days*							
5	76.9	77.8	71.9	83.2	79.3	72.6	79.7
10	12.8	13.9	18.8	7.4	17.2	19.0	13.1
15	7.7	8.3	3.1	3.2	0.0	4.8	3.1
20	0.0	0.0	0.0	6.3	0.0	2.4	0.6
25	0.0	0.0	6.3	0.0	0.0	0.0	0.6
30	0.0	0.0	0.0	0.0	0.0	1.2	0.9
35	0.0	0.0	0.0	0.0	0.0	0.0	0.3
40	0.0	0.0	0.0	0.0	0.0	0.0	0.3
45	2.6	0.0	0.0	0.0	3.4	0.0	0.3
50	0.0	0.0	0.0	0.0	0.0	0.0	0.0
55	0.0	0.0	0.0	0.0	0.0	0.0	0.0
60	0.0	0.0	0.0	0.0	0.0	0.0	0.3
>60 days	0.0	0.0	0.0	0.0	0.0	0.0	0.6
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Difference from overall shares in percentage points							
5	-2.8	-1.9	-7.8	3.5	-0.4	-7.1	0.0
10	-0.3	0.8	5.6	-5.8	4.1	5.9	0.0
15	4.6	5.2	0.0	0.0	-3.1	1.6	0.0
20	-0.6	-0.6	-0.6	5.7	-0.6	1.8	0.0
25	-0.6	-0.6	5.6	-0.6	-0.6	-0.6	0.0
30	-0.9	-0.9	-0.9	-0.9	-0.9	0.3	0.0
35	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	0.0
40	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	0.0
45	2.3	-0.3	-0.3	-0.3	3.1	-0.3	0.0
50	0.0	0.0	0.0	0.0	0.0	0.0	0.0
55	0.0	0.0	0.0	0.0	0.0	0.0	0.0
60	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	0.0
>60 days	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6	0.0

Table 6: Relative frequency of the lengths of time between two consecutive IPOs within fixed intervals (adjusted) in the Nouveau Marché

Percentage shares within each area of technology

	SOFTWARE	ITSERVIC	HRDW&TEL	INT&MEDIA	BIOMED	IND&FIN	ALL AREAS
Obs.	[28]	[24]	[19]	[20]	[11]	[21]	[128]
Interval in days*							
5	39.3	52.2	47.4	50.0	9.1	38.1	44.5
10	17.9	21.7	21.1	20.0	36.4	9.5	22.7
15	10.7	13.0	5.3	15.0	9.1	19.0	7.8
20	10.7	0.0	0.0	0.0	27.3	9.5	7.8
25	3.6	8.7	21.1	0.0	18.2	9.5	2.3
30	3.6	4.3	0.0	5.0	0.0	0.0	1.6
35	7.1	0.0	0.0	5.0	0.0	4.8	2.3
40	0.0	0.0	0.0	0.0	0.0	4.8	3.1
45	3.6	0.0	0.0	0.0	0.0	0.0	2.3
50	3.6	0.0	0.0	0.0	0.0	0.0	0.0
55	0.0	0.0	0.0	0.0	0.0	0.0	1.6
60	0.0	0.0	5.3	5.0	0.0	0.0	0.0
>60 days	0.0	0.0	0.0	0.0	0.0	4.8	3.9
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Difference from overall shares in percentage points							
5	-5.2	7.6	2.8	5.5	-35.4	-6.4	0.0
10	-4.8	-0.9	-1.6	-2.7	13.7	-13.1	0.0
15	2.9	5.2	-2.5	7.2	1.3	11.2	0.0
20	2.9	-7.8	-7.8	-7.8	19.5	1.7	0.0
25	1.2	6.4	18.7	-2.3	15.8	7.2	0.0
30	2.0	2.8	-1.6	3.4	-1.6	-1.6	0.0
35	4.8	-2.3	-2.3	2.7	-2.3	2.4	0.0
40	-3.1	-3.1	-3.1	-3.1	-3.1	1.6	0.0
45	1.2	-2.3	-2.3	-2.3	-2.3	-2.3	0.0
50	3.6	0.0	0.0	0.0	0.0	0.0	0.0
55	-1.6	-1.6	-1.6	-1.6	-1.6	-1.6	0.0
60	0.0	0.0	5.3	5.0	0.0	0.0	0.0
>60 days	-3.9	-3.9	-3.9	-3.9	-3.9	0.9	0.0

* Shows the upper bound of the interval.

Table 7: The distribution of IPOs within intervals of duration from the start of the Neuer Markt

Interval in days*	SOFTWARE [40 Obs.]	ITSERVICE [37]	HRDW&TEL [33]	INT&MEDIA [96]	BIOMED [30]	IND&FIN [85]	ALL AREAS [321]
Percentage shares within each area of technology							
100	0.0	0.0	3.0	0.0	0.0	0.0	0.3
200	5.0	0.0	0.0	0.0	3.3	2.4	1.6
300	0.0	0.0	3.0	0.0	0.0	3.5	1.2
400	0.0	2.7	0.0	1.0	0.0	2.4	1.2
500	2.5	2.7	12.1	3.1	0.0	11.8	5.9
600	5.0	8.1	3.0	1.0	0.0	4.7	3.4
700	2.5	5.4	3.0	5.2	3.3	4.7	4.4
800	15.0	10.8	15.2	6.3	16.7	11.8	11.2
900	22.5	21.6	6.1	12.5	6.7	12.9	13.7
1000	7.5	8.1	15.2	19.8	10.0	16.5	14.6
1100	10.0	8.1	9.1	9.4	6.7	4.7	7.8
1200	22.5	5.4	12.1	22.9	16.7	8.2	15.3
1300	5.0	21.6	6.1	13.5	23.3	12.9	13.4
1400	2.5	5.4	12.1	5.2	13.3	3.5	5.9
Cumulative Shares							
100	0.0	0.0	3.0	0.0	0.0	0.0	0.3
200	5.0	0.0	3.0	0.0	3.3	2.4	1.9
300	5.0	0.0	6.1	0.0	3.3	5.9	3.1
400	5.0	2.7	6.1	1.0	3.3	8.2	4.4
500	7.5	5.4	18.2	4.2	3.3	20.0	10.3
600	12.5	13.5	21.2	5.2	3.3	24.7	13.7
700	15.0	18.9	24.2	10.4	6.7	29.4	18.1
800	30.0	29.7	39.4	16.7	23.3	41.2	29.3
900	52.5	51.4	45.5	29.2	30.0	54.1	43.0
1000	60.0	59.5	60.6	49.0	40.0	70.6	57.6
1100	70.0	67.6	69.7	58.3	46.7	75.3	65.4
1200	92.5	73.0	81.8	81.3	63.3	83.5	80.7
1300	97.5	94.6	87.9	94.8	86.7	96.5	94.1
1400	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Difference from shares in all areas in percentage points							
100	0.3	0.3	-2.7	0.3	0.3	0.3	0.0
200	-3.4	1.6	1.6	1.6	-1.8	-0.8	0.0
300	1.2	1.2	-1.8	1.2	1.2	-2.3	0.0
400	1.2	-1.5	1.2	0.2	1.2	-1.1	0.0
500	3.4	3.2	-6.2	2.8	5.9	-5.8	0.0
600	-1.6	-4.7	0.4	2.4	3.4	-1.3	0.0
700	1.9	-1.0	1.3	-0.8	1.0	-0.3	0.0
800	-3.8	0.4	-3.9	5.0	-5.5	-0.5	0.0
900	-8.8	-7.9	7.6	1.2	7.0	0.8	0.0
1000	7.1	6.5	-0.5	-5.1	4.6	-1.8	0.0
1100	-2.2	-0.3	-1.3	-1.6	1.1	3.1	0.0
1200	-7.2	9.9	3.1	-7.7	-1.4	7.0	0.0
1300	8.4	-8.2	7.3	-0.1	-9.9	0.5	0.0
1400	3.4	0.5	-6.2	0.7	-7.4	2.4	0.0

Table 8: The distribution of IPOs within intervals of duration from the start of the Nouveau Marché

Percentage shares within each area of technology

	SOFTWARE	ITSERVICE	HRDW&TEL	INT&MEDIA	BIOMED	IND&FIN	ALL AREAS
Obs.	[29]	[25]	[20]	[21]	[12]	[22]	[129]
Interval in days*							
200	0.0	8.0	0.0	0.0	8.3	9.1	4.7
400	10.3	0.0	5.0	0.0	8.3	9.1	6.2
600	3.4	0.0	0.0	4.8	16.7	9.1	5.4
800	3.4	0.0	10.0	4.8	25.0	22.7	9.3
1000	20.7	12.0	30.0	9.5	8.3	18.2	17.1
1200	13.8	16.0	20.0	23.8	16.7	0.0	14.7
1400	6.9	20.0	5.0	0.0	8.3	4.5	5.4
1600	24.1	36.0	25.0	47.6	8.3	22.7	27.9
1800	17.2	8.0	5.0	9.5	0.0	4.5	9.3
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Cumulative Shares							
200	0.0	8.0	0.0	0.0	8.3	9.1	4.7
400	10.3	8.0	5.0	0.0	16.7	18.2	10.9
600	13.8	8.0	5.0	4.8	33.3	27.3	16.3
800	17.2	8.0	15.0	9.5	58.3	50.0	25.6
1000	37.9	20.0	45.0	19.0	66.7	68.2	42.6
1200	51.7	36.0	65.0	42.9	83.3	68.2	57.4
1400	58.6	56.0	70.0	42.9	91.7	72.7	62.8
1600	82.8	92.0	95.0	90.5	100.0	95.5	90.7
1800	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Difference from shares in all areas in percentage points							
200	4.7	-3.3	4.7	4.7	-3.7	-4.4	0.0
400	-4.1	6.2	1.2	6.2	-2.1	-2.9	0.0
600	2.0	5.4	5.4	0.7	-11.2	-3.7	0.0
800	5.9	9.3	-0.7	4.5	-15.7	-13.4	0.0
1000	-3.6	5.1	-12.9	7.5	8.7	-1.1	0.0
1200	0.9	-1.3	-5.3	-9.1	-1.9	14.7	0.0
1400	-1.5	-14.6	0.4	5.4	-2.9	0.9	0.0
1600	3.8	-8.1	2.9	-19.7	19.6	5.2	0.0
1800	-7.9	1.3	4.3	-0.2	9.3	4.8	0.0

* Shows the upper bound of the interval.

Table 9: Determinants of time intervals between arbitrary pairs of IPOs*

	(1)	(2)	(3)
Dependent variable is the number of days between IPOs	Neuer Markt		Nouveau Marché
	1998-99 sample	1999 sample	total sample
Observations	15172	11570	8765
Constant	182.44	223.75	516
	(1.32) [0.00]	(2.12) [0.00]	(4.50) [0.00]
Time interval between firms' founding dates	0.01	0.01	0.02
	(0.00) [0.00]	(0.00) [0.00]	(0.00) [0.00]
Equality of technology focus	10.58	11.45	-52.37
	(3.39) [0.00]	(5.02) [0.02]	(12.16) [0.00]
Equality of lead underwriter	10.13	23.36	-43.01
	(5.46) [0.06]	(8.65) [0.01]	(21.94) [0.05]
Equality of venture capitalist	2.92	21.24	-110.83
	(13.43) [0.82]	(22.36) [0.34]	(23.40) [0.00]
adj. R-squared	0.045	0.029	0.034
F-statistic	180.90	89.02	79.25
Prob. (F-statistic)	0.00	0.00	0.00

*OLS with White heteroskedasticity–consistent standard errors in parentheses, probabilities in brackets.

Table 10a: Detailed determinants of time intervals between arbitrary pairs of IPOs*

	(1)	(2)	(3)
Dependent variable is the number of days between IPOs	Neuer Markt	Neuer Markt	Neuer Markt
	1998-99 sample	1998–99 sample	1998–99 sample
Observations	15172	15172	15172
Constant	182.34	182.31	182.38
	(1.33) [0.00]	(1.32) [0.00]	(1.33) [0.00]
Time interval between firms' founding dates	0.01	0.01	0.01
	(0.00) [0.00]	(0.00) [0.00]	(0.00) [0.00]
Equality of technology focus	-95.32	-95.29	10.81
	(24.24) [0.00]	(24.24) [0.00]	(3.49) [0.00]
Internet	90.25	89.71	
	(25.13) [0.00]	(25.09) [0.00]	
Software	44.54	46.51	
	(25.47) [0.08]	(25.34) [0.07]	
ITServices	90.45	89.56	
	(26.10) [0.00]	(25.97) [0.00]	
Hardware	123.03	125.90	
	(35.53) [0.00]	(35.11) [0.00]	
Media	71.18	72.42	
	(28.02) [0.01]	(27.80) [0.00]	
Telecom	137.92	131.97	
	(35.18) [0.00]	(35.15) [0.00]	
Biomedical	15.75	19.31	
	(26.61) [0.55]	(26.67) [0.47]	
Industry & Financial Services	132.72	132.80	
	(24.67) [0.00]	(24.64) [0.00]	
Equality of lead underwriter	10.83	11.72	10.85
	(5.95) [0.07]	(5.45) [0.04]	(5.95) [0.07]
Interaction with Internet	-15.97		-31.91
	(30.51) [0.60]		(29.92) [0.29]
Interaction with Software	18.53		-42.95
	(24.45) [0.45]		(23.36) [0.07]
Interaction with ITServices	-8.38		-23.98
	(35.53) [0.81]		(34.31) [0.49]
Interaction with Hardware	103.65		120.50
	(26.68) [0.00]		(6.77) [0.00]
Interaction with Media	18.98		-15.98
	(56.59) [0.74]		(54.89) [0.77]
Interaction with Telecom	-213.29		-181.45
	(25.21) [0.00]		(6.89) [0.00]
Interaction with Biomedical	49.55		-40.83
	(58.78) [0.40]		(57.82) [0.48]
Interaction with Industry & Financial Services	2.05		28.57
	(22.92) [0.93]		(22.64) [0.21]
Equality of venture capitalist	6.01	6.09	3.60
	(13.55) [0.66]	(13.53) [0.65]	(13.46) [0.79]
adj. R-squared	0.05	0.05	0.05
F-statistic	42.51	70.57	61.01
Prob. (F-statistic)	0.00	0.00	0.00

* The table reports OLS coefficient estimates, White heteroskedacity-consistent standard errors (in parentheses) and p-values (in brackets).

Table 10b: Detailed determinants of time intervals between arbitrary pairs of IPOs

	(1)	(2)	(3)
Dependent variable is the number of days between IPOs	**Neuer Markt 1999 sample**	**Neuer Markt 1999 sample**	**Neuer Markt 1999 sample**
Observations	11570	11570	11570
Constant	223.75	223.72	223.67
	(2.13) [0.00]	(2.12) [0.00]	(2.13) [0.00]
Time interval between firms' founding dates	0.01	0.01	0.01
	(0.00) [0.00]	(0.00) [0.00]	(0.00) [0.00]
Equality of technology focus	-137.01	-136.98	11.76
	(31.90) [0.00]	(31.89) [0.00]	(5.16) [0.02]
Internet	85.14	85.42	
	(32.95) [0.01]	(32.90) [0.01]	
Software	116.07	119.49	
	(35.81) [0.00]	(35.45) [0.00]	
ITServices	91.40	89.21	
	(33.52) [0.01]	(33.44) [0.01]	
Hardware	198.76	199.10	
	(46.59) [0.00]	(45.99) [0.00]	
Media	69.80	71.86	
	(35.80) [0.05]	(35.56) [0.04]	
Telecom	197.82	182.08	
	(63.72) [0.00]	(62.96) [0.00]	
Biomedical	90.93	84.86	
	(47.94) [0.06]	(46.96) [0.07]	
Industry & Financial Services	195.21	195.54	
	(32.54) [0.00]	(32.49) [0.00]	
Equality of lead underwriter	24.22	24.77	24.23
	(9.56) [0.01]	(8.61) [0.00]	(9.56) [0.01]
Interaction with Internet	9.33		-54.24
	(47.83) [0.85]		(47.31) [0.25]
Interaction with Software	32.29		-0.57
	(52.86) [0.54]		(50.49) [0.99]
Interaction with ITServices	-23.12		-80.46
	(43.52) [0.60]		(42.47) [0.06]
Interaction with Hardware	14.86		64.90
	(35.36) [0.67]		(10.69) [0.00]
Interaction with Media	26.63		-52.50
	(63.73) [0.68]		(61.74) [0.40]
Interaction with Telecom	-283.01		-234.24
	(55.95) [0.00]		(10.76) [0.00]
Interaction with Biomedical	-133.13		-191.13
	(56.34) [0.02]		(43.67) [0.00]
Interaction with Industry & Financial Services	7.70		54.17
	(31.44) [0.81]		(31.07) [0.08]
Equality of venture capitalist	24.54	24.45	22.26
	(22.62) [0.28]	(22.56) [0.28]	(22.37) [0.32]
adj. R-squared	0.04	0.04	0.03
F-statistic	24.49	40.51	30.57
Prob. (F-statistic)	0.00	0.00	0.00

* The table reports OLS coefficient estimates, White heteroskedacity-consistent standard errors (in parentheses) and p-values (in brackets).

Table 10c: Detailed determinants of time intervals between arbitrary pairs of IPOs

	(1)	(2)	(3)
Dependent variable is the number of days between IPOs	Nouveau Marché total sample	Nouveau Marché total sample	Nouveau Marché total sample
Observations	8756	8756	8756
Constant	516.44	516.52	516.27
	(4.52) [0.00]	(4.51) [0.00]	(4.52) [0.00]
Time interval between firms' founding dates	0.02	0.02	0.02
	(0.00) [0.00]	(0.00) [0.00]	(0.00) [0.00]
Equality of technology focus	264.09	264.04	-51.49
	(179.16) [0.14]	(179.09) [0.14]	(12.36) [0.00]
Internet	-584.94	-578.02	
	(179.94) [0.00]	(179.94) [0.00]	
Software	-274.02	-273.31	
	(180.07) [0.13]	(179.97) [0.13]	
ITServices	-331.80	-329.23	
	(180.91) [0.07]	(180.80) [0.07]	
Hardware	-394.25	-399.12	
	(191.06) [0.04]	(188.85) [0.04]	
Media	-453.97	-428.61	
	(183.66) [0.01]	(184.18) [0.02]	
Telecom	-339.74	-346.88	
	(182.03) [0.06]	(181.70) [0.06]	
Biomedical	-288.90	-292.70	
	(183.65) [0.12]	(183.49) [0.11]	
Industry & Financial Services	-239.15	-249.92	
	(182.40) [0.19]	(182.20) [0.17]	
Equality of lead underwriter	-39.41	-41.09	-39.40
	(23.12) [0.09]	(22.04) [0.06]	(23.11) [0.09]
Interaction with Internet	266.78		-1.48
	(85.07) [0.00]		(83.96) [0.99]
Interaction with Software	33.72		74.46
	(126.45) [0.79]		(125.59) [0.55]
Interaction with ITServices	44.44		28.56
	(139.89) [0.75]		(138.00) [0.84]
Interaction with Hardware	-49.56		-127.07
	(70.48) [0.48]		(26.07) [0.00]
Interaction with Media	353.98		216.18
	(176.37) [0.05]		(170.65) [0.21]
Interaction with Telecom	-126.81		-150.94
	(71.72) [0.08]		(64.64) [0.02]
Interaction with Biomedical	-255.28		-227.91
	(46.86) [0.00]		(25.87) [0.00]
Interaction with Industry & Financial Services	-331.27		-255.74
	(87.23) [0.00]		(81.19) [0.00]
Equality of venture capitalist	-110.24	-109.99	-111.19
	(23.33) [0.00]	(23.29) [0.00]	(23.42) [0.00]
adj. R-squared	0.04	0.04	0.03
F-statistic	19.00	31.04	26.79
Prob. (F-statistic)	0.00	0.00	0.00

* The table reports OLS coefficient estimates, White heteroskedacity-consistent standard errors (in parentheses) and p-values (in brackets).

Table 11a: Transition probability matrix for the sequence of IPO events

Neuer Markt

Initial IPO area (observations)	Transition end state (consecutive IPO)					
	SOFTWARE	ITSERVIC	HARDWTEL	INTMEDIA	BIOMED	INDFSERV
SOFTWARE (39)	**0.23**	0.10	0.05	0.33	0.05	0.25
ITSERVIC (36)	0.08	**0.08**	0.08	0.32	0.08	0.35
HARDWTEL (32)	0.09	0.21	**0.06**	0.33	0.12	0.18
INTMEDIA (95)	0.13	0.09	0.10	**0.29**	0.09	0.29
BIOMED (23)	0.14	0.07	0.14	0.31	**0.10**	0.24
INDFSERV (84)	0.11	0.14	0.13	0.27	0.11	**0.25**
Sample Distribution	0.13	0.12	0.10	0.30	0.09	0.27
Stationary Distribution	0.13	0.12	0.10	0.30	0.09	0.27

Nouveau Marché

	SOFTWARE	ITSERVIC	HARDWTEL	INTMEDIA	BIOMED	INDFSERV
SOFTWARE (28)	**0.21**	0.32	0.14	0.04	0.07	0.21
ITSERVIC (24)	0.12	**0.12**	0.16	0.36	0.12	0.12
HARDWTEL (19)	0.35	0.25	**0.10**	0.10	0.15	0.05
INTMEDIA (20)	0.29	0.10	0.29	**0.24**	0.00	0.10
BIOMED (11)	0.25	0.08	0.17	0.08	**0.08**	0.33
INDFSERV (21)	0.18	0.18	0.09	0.14	0.14	**0.27**
Sample Distribution	0.22	0.20	0.16	0.16	0.09	0.17
Stationary Distribution	0.23	0.19	0.16	0.16	0.09	0.17

Table 11b: Transition probability matrix, after aggregation over monthly intervals

Neuer Markt

Initial IPO area	Transition end state (percentage shares in next month's IPOs)					
	SOFTWARE	ITSERVIC	HARDWTEL	INTMEDIA	BIOMED	INDFSERV
SOFTWARE	**0.29**	0.00	0.00	0.12	0.24	0.35
ITSERVIC	0.12	**0.08**	0.21	0.23	0.00	0.36
HARDWTEL	0.13	0.00	**0.18**	0.18	0.00	0.51
INTMEDIA	0.18	0.22	0.00	**0.51**	0.09	0.00
BIOMED	0.04	0.14	0.00	0.00	**0.00**	0.82
INDFSERV	0.03	0.19	0.21	0.11	0.17	**0.29**
Sample Distribution	0.13	0.13	0.10	0.21	0.09	0.33
Stationary Distribution	0.12	0.13	0.12	0.21	0.10	0.33

Nouveau Marché

	SOFTWARE	ITSERVIC	HARDWTEL	INTMEDIA	BIOMED	INDFSERV
SOFTWARE	**0.12**	0.14	0.24	0.13	0.00	0.37
ITSERVIC	0.00	**0.16**	0.21	0.20	0.43	0.00
HARDWTEL	0.49	0.31	**0.02**	0.18	0.00	0.00
INTMEDIA	0.23	0.27	0.27	**0.23**	0.00	0.00
BIOMED	0.21	0.00	0.11	0.00	**0.00**	0.68
INDFSERV	0.27	0.00	0.09	0.14	0.30	**0.20**
Sample Distribution	0.22	0.11	0.17	0.15	0.12	0.21
Stationary Distribution	0.22	0.14	0.16	0.15	0.12	0.21

Table 11c: Transition probability matrix for the three-state model

Neuer Markt – unconditional estimates

Initial IPO area (observations)	Transition end state (consecutive IPO)		
	COMPUTER	MEDIACOM	OTHER
COMPUTER (103)	**0.40**	0.27	0.33
MEDIACOM (120)	0.27	**0.35**	0.38
OTHER (105)	0.21	0.44	**0.35**
Sample Distribution	0.31	0.37	0.32
Stationary Distribution	0.29	0.36	0.35

Ex-post prediction, based on the observed initial states

COMPUTER	**0.30**	0.29	0.41
MEDIACOM	0.31	**0.28**	0.41
OTHER	0.31	0.29	**0.40**
Sample Distribution	0.28	0.36	0.36
Stationary Distribution	0.31	0.29	0.40

Recursive ex-post prediction, based on the predicted initial states

COMPUTER	**0.42**	0.39	0.19
MEDIACOM	0.42	**0.40**	0.18
OTHER	0.37	0.36	**0.27**
Sample Distribution	0.43	0.43	0.14
Stationary Distribution	0.41	0.39	0.20

Determinants of transition probabilities in the three-state model*

Initial state	Transition end state (consecutive IPO)			
	COMPUTER		MEDIACOM	
	Index	Underpricing	Index	Underpricing
COMPUTER	0.0002	0.3846	0.0002	0.2587
	(35.8)	(10.3)	(44.4)	(14.6)
	[0.0]	[0.0]	[0.0]	[0.0]
	adj. R-squared 0.89		adj. R-squared 0.98	
MEDIACOM	0.0002	0.1690	0.0002	0.2807
	(38.9)	(7.1)	(49.2)	(13.5)
	[0.0]	[0.0]	[0.0]	[0.0]
	adj. R-squared 0.86		adj. R-squared 0.92	
OTHER	0.0002	0.4699	0.0002	0.3781
	(37.3)	(14.3)	(42.7)	(14.4)
	[0.0]	[0.0]	[0.0]	[0.0]
	adj. R-squared 0.91		adj. R-squared 0.91	

* t-statistics in parantheses, probabilities in brackets.

Table 11d: Transition matrix for consecutive IPOs with the same lead underwriter in the Neuer Markt

Initial IPO area	Transition end state (consecutive IPO)		
	COMPUTER	MEDIACOM	OTHER
COMPUTER	**0.34**	0.07	0.59
MEDIACOM	0.79	**0.04**	0.17
OTHER	0.16	0.14	**0.70**
Sample Distribution	0.30	0.20	0.50
Stationary Distribution	0.28	0.11	0.61

Table 11e: Mobility indices for the estimated transition matrices

Transition matrix	Mobility indices		
	$(m - tr(\Pi))/(m-1)$	$\left(m - \sum_j \lvert\lambda_j\rvert\right)/(m-1)$	$1-\lvert\det(\Pi)\rvert$
ONE STEP IPO AREA TRANSITIONS (Table 11a)			
Neuer Markt	0.998	0.928	1.000
Nouveau Marché	0.996	0.842	1.000
MONTHLY INTERVAL TRANSITIONS (Table 11b)			
Neuer Markt	0.930	0.773	1.000
Nouveau Marché	1.054	0.760	1.000
THREE STATE UNCONDITIONAL (Table 11c)			
Neuer Markt	0.950	0.903	0.993
Nouveau Marché	n.a.	n.a.	n.a.
SIMPLE EX-POST PREDICTION (Table 11c)			
Neuer Markt	1.010	0.990	1.000
Nouveau Marché	n.a.	n.a.	n.a.
RECURSIVE EX-POST PREDICTION (Table 11c)			
Neuer Markt	0.955	0.955	0.999
Nouveau Marché	n.a.	n.a.	n.a.
UNDERWRITER-CONDITIONED TRANSITIONS (Table 11d)			
Neuer Markt	0.960	0.838	0.974
Nouveau Marché	n.a.	n.a.	n.a.

Table 12: Testing for the equality of the survivor functions across technology areas and across venture capital-backed and non-backed IPOs

	Log-rank		Wilcoxon (Breslow)		Stratified Wilcoxon for Venture capital-backing	
Neuer Markt	$\chi^2(1)$	$Pr>\chi^2$	$\chi^2(1)$	$Pr>\chi^2$	$\chi^2(1)$	$Pr>\chi^2$
Information and communications technology	0.02	0.88	2.10	0.15	–	–
Software	1.58	0.21	0.90	0.34	0.31	0.58
Hardwtel	0.01	0.91	0.73	0.39	1.49	0.22
Internet/Media	0.53	0.46	5.72	0.02	0.52	0.47
ITservice	0.09	0.77	0.00	0.95	0.26	0.61
Biomedical	4.80	0.03	4.46	0.03	0.09	0.77
Ind. & financial services	3.30	0.07	8.74	0.00	6.35	0.01
Venture capital-backing	3.04	0.08	6.97	0.01	4.06	0.04
Nouveau Marché						
Information and communications technology	1.61	0.20	4.33	0.04	–	–
Software	1.40	0.24	1.11	0.29	0.03	0.86
Hardwtel	0.27	0.60	0.03	0.86	0.42	0.52
Internet/Media	0.55	0.46	2.81	0.09	0.42	0.52
ITservice	1.28	0.26	3.66	0.06	0.01	0.90
Biomedical	3.57	0.06	13.04	0.00	2.35	0.13
Ind. & financial services	3.64	0.06	5.98	0.01	0.62	0.43
Venture capital-backing	0.34	0.56	0.10	0.76	0.03	0.87

Table 13a: Results from the Cox proportional hazards model with social interaction under rational expectations in the Neuer Markt*

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4
Age at IPO	1.012	1.011	1.013	1.014
	(1.48) [0.139]	(1.51) [0.132]	(1.61) [0.107]	(1.79) [0.073]
Employment	1.000	1.000	1.000	
	(0.89) [0.372]	(0.88) [0.380]	(0.84) [0.399]	
VC-backing	0.896	0.891	0.907	0.770
	(–0.91) [0.360]	(–0.96) [0.336]	(–0.81) [0.416]	(–1.56) [0.118]
VC stake before IPO				1.006
				(1.36) [0.173]
Debt-equity ratio	1.005			
	(0.46) [0.642]			
Sales growth over employment growth	0.994	0.994	0.994	
	(–0.55) [0.586]	(–0.49) [0.626]	(–0.49) [0.625]	
Software	0.488	2.800	1.861	1.876
	(–0.37) [0.708]	(1.54) [0.123]	(1.56) [0.118]	(1.59) [0.112]
ITservice	13.065	2.574	1.457	1.506
	(1.29) [0.198]	(1.41) [0.159]	(1.06) [0.298]	(1.16) [0.247]
Biomed	0.307	2.969	1.408	1.429
	(–0.60) [0.548]	(1.71) [0.086]	(0.90) [0.366]	(0.94) [0.346]
Hardwtel	0.000	0.000	0.000	0.000
	(–3.57) [0.000]	(–4.37) [0.000]	(–4.59) [0.000]	(–4.61) [0.000]
Intmedia	2.014	4.981	2.774	2.877
	(0.51) [0.613]	(2.66) [0.008]	(3.44) [0.001]	(3.58) [0.000]
Interaction with market price index:				
Biomed	1.000			
	(0.43) [0.664]			
Hardwtel	1.000			
	(–0.05) [0.958]			
ITservic	1.000			
	(–0.47) [0.640]			
Intmedia	1.000			
	(1.12) [0.261]			
Software	1.001			
	(1.85) [0.065]			
Interaction with the expected number of IPOs from the technology neighbourhood within 4 months:				
Biomed	1.030	1.019		
	(1.26) [0.206]	(0.86) [0.387]		
Hardwtel	1.031	1.025		
	(0.76) [0.445]	(0.65) [0.513]		
ITservic	1.028	1.034		
	(0.72) [0.470]	(0.95) [0.341]		
Intmedia	1.010	1.015		
	(0.47) [0.642]	(0.83) [0.405]		
Ind. & financial	1.056	1.046		
	(2.38) [0.017]	(2.37) [0.018]		
Software	0.984	1.041		
	(–0.28) [0.781]	(1.20) [0.228]		

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4
Interaction with the expected mean time distance of future IPOs in the technology neighbourhood:				
Biomed	1.081			
	(1.76) [0.078]			
Hardwtel	0.005			
	(–1.89) [0.059]			
ITservic	0.988			
	(–0.81) [0.416]			
Intmedia	0.997			
	(–0.27) [0.783]			
Ind. & financial	1.001			
	(0.09) [0.925]			
Software	0.992			
	(–0.41) [0.684]			
Interaction with the expected median time distance of future IPOs in the technology neighbourhood:				
Biomed	0.971	0.990	0.991	0.990
	(–2.65) [0.008]	(–4.97) [0.000]	(–5.05) [0.000]	(–5.10) [0.000]
Hardwtel	0.991	0.991	0.992	0.992
	(–3.58) [0.000]	(–4.24) [0.000]	(–4.46) [0.000]	(–4.50) [0.000]
ITservic	0.990	0.989	0.990	0.990
	(–2.59) [0.009]	(–4.58) [0.000]	(–4.89) [0.000]	(–4.90) [0.000]
Intmedia	0.988	0.987	0.988	0.988
	(–4.15) [0.000]	(–5.54) [0.000]	(–5.78) [0.000]	(–5.78) [0.000]
Ind. & financial	0.991	0.992	0.991	0.991
	(–3.19) [0.001]	(–4.29) [0.000]	(–4.57) [0.000]	(–4.58) [0.000]
Software	0.991	0.989	0.989	0.989
	(–1.84) [0.066]	(–4.97) [0.000]	(–5.00) [0.000]	(–5.00) [0.000]
No. of observations	39132	39132	39132	39269
No. of subjects	320	320	320	321
No. of failures	320	320	320	321
Time at risk	297555	297555	297555	298546
Log likelihood	–1487.9449	–1494.5419	–1498.0958	–1503.6527
LR χ^2	86.19	72.99	65.89	66.33
Prob > χ^2	[0.000]	[0.000]	[0.000]	[0.000]

*The table reports the estimated coefficient, the hazard ratio, the z-value (in parentheses) and the p-value (in brackets)

Table 13b: Testing for the area specificity of the expectations impact in the Neuer Markt*

The dependent variable is the hazard rate	Model 1: Biomed IPOs	Model 2: Hardwtel IPOs	Model 3: Itservice IPOs	Model 4: Intmedia IPOs	Model 5: Ind.& financial IPOs	Model 6: Software IPOs
Age at IPO	1.015	1.014	1.014	1.014	1.014	1.014
	(1.87) [0.061]	(1.79) [0.074]	(1.78) [0.075]	(1.81) [0.070]	(1.78) [0.075]	(1.82) [0.069]
VC-backing	0.757	0.768	0.767	0.764	0.768	0.769
	(–1.67) [0.096]	(–1.58) [0.113]	(–1.59) [0.112]	(–1.61) [0.107]	(–1.58) [0.114]	(–1.57) [0.116]
VC stake before IPO	1.007	1.006	1.006	1.006	1.006	1.006
	(1.51) [0.131]	(1.38) [0.168]	(1.38) [0.169]	(1.41) [0.158]	(1.36) [0.175]	(1.38) [0.167]
Software	1.855	1.907	1.858	1.823	0.0226	86977.29
	(1.59) [0.112]	(1.65) [0.099]	(1.56) [0.118]	(1.51) [0.132]	(–0.84) [0.401]	(1.52) [0.129]
ITservice	1.434	1.462	8.479	1.571	0.021	1.538
	(1.02) [0.308]	(1.07) [0.284]	(0.37) [0.711]	(1.28) [0.200]	(–0.89) [0.375]	(1.20) [0.229]
Biomed	6.786	1.424	1.436	1.444	0.020	1.454
	(0.23) [0.819]	(0.93) [0.350]	(0.96) [0.338]	(0.98) [0.327]	(–0.90) [0.370]	(0.97) [0.330]
Hardwtel	0.000	4.94e-11	0.000	2.18e-06	2.60e-08	7.57e-06
	(–3.62) [0.000]	(–3.66) [0.000]	(–4.23) [0.000]	(–4.99) [0.000]	(–3.51) [0.000]	(–4.30) [0.000]
Intmedia	2.734	2.840	2.895	0.511	0.041	2.986
	(3.42) [0.001]	(3.52) [0.000]	(3.59) [0.000]	(–0.15) [0.885]	(–0.73) [0.463]	(3.64) [0.000]
Interaction with the expected median time distance of future IPOs in the technology neighbourhood:						
Biomed	0.956	0.992	0.990	0.989	0.987	0.989
	(–3.98) [0.000]	(–4.21) [0.000]	(–4.69) [0.000]	(–5.37) [0.000]	(–4.91) [0.000]	(–4.78) [0.000]
Hardwtel	0.993	0.982	0.992	0.990	0.990	0.991
	(–3.54) [0.000]	(–3.68) [0.000]	(–4.15) [0.000]	(–4.89) [0.000]	(–4.36) [0.000]	(–4.22) [0.000]
ITservic	0.992	0.991	0.984	0.988	0.988	0.989
	(–3.90) [0.000]	(–3.93) [0.000]	(–2.98) [0.003]	(–5.13) [0.000]	(–4.79) [0.000]	(–4.60) [0.000]
Intmedia	0.990	0.989	0.988	0.992	0.986	0.987
	(–4.75) [0.000]	(–4.77) [0.000]	(–5.23) [0.000]	(–1.73) [0.084]	(–5.45) [0.000]	(–5.33) [0.000]
Ind. & financial	0.993	0.993	0.991	0.989	0.993	0.990
	(–3.57) [0.000]	(–3.58) [0.000]	(–4.19) [0.000]	(–4.97) [0.000]	(–1.67) [0.096]	(–4.27) [0.000]
Software	0.991	0.990	0.987	0.987	0.986	0.986
	(–4.08) [0.000]	(–4.09) [0.000]	(–4.64) [0.000]	(–5.32) [0.000]	(–4.75) [0.000]	(–2.76) [0.006]
Interaction with expectations for other technology areas:						
Biomed median		0.999	1.002	1.001	1.002	1.003
		(–0.47) [0.635]	(0.73) [0.466]	(0.36) [0.722]	(0.11) [0.913]	(0.96) [0.339]
Hardwtel median	1.001		1.002	0.999	1.003	1.008
	(0.21) [0.834]		(0.33) [0.743]	(–0.35) [0.726]	(0.95) [0.341]	(1.39) [0.164]
ITservic median	1.012	1.004		1.003	1.000	0.997
	(1.38) [0.167]	(0.59) [0.554]		(0.81) [0.418]	(–0.10) [0.922]	(–0.55) [0.581]
Intmedia median	1.011	0.997	1.009		0.994	0.988
	(1.29) [0.196]	(–0.44) [0.658]	(1.30) [0.195]		(–1.26) [0.208]	(–1.66) [0.097]
Ind. & fin. median	1.011	1.013	0.989	0.994		1.003
	(1.22) [0.223]	(1.66) [0.097]	(–1.80) [0.072]	(–1.16) [0.247]		(0.40) [0.691]
Software median	1.006	1.000	1.004	0.997	0.999	
	(0.90) [0.365]	(0.13) [0.896]	(1.38) [0.167]	(–1.08) [0.281]	(–0.46) [0.646]	
No. of observations	39269	39269	39269	39269	39269	39269
Subjects (failures)	321 (321)	321 (321)	321 (321)	321 (321)	321 (321)	321 (321)
Time at risk	298546	298546	298546	298546	298546	298546
Log likelihood	–1495.977	–1500.635	–1500.229	–1500.034	–1501.373	–1499.489
LR χ^2 [Prob > χ^2]	81.68 [0.00]	72.36 [0.00]	73.18 [0.00]	73.57 [0.00]	70.89 [0.00]	74.65 [0.00]

* The table reports the estimated coefficient, the hazard ratio, the z-value (in parentheses) and the p-value (in brackets).

Table 13c: The adaptive expectations model for the Neuer Markt*

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4	Model 5
Age at IPO	1.012	1.012	1.012	1.014	1.014
	(1.58) [0.115]	(1.57) [0.117]	(1.52) [0.128]	(1.74) [0.081]	(1.80) [0.071]
VC-backing	0.743	0.752	0.712	0.759	0.769
	(–1.76) [0.079]	(–1.69) [0.091]	(–2.01) [0.044]	(–1.64) [0.102]	(–1.57) [0.117]
VC stake before IPO	1.006	1.006	1.007	1.006	1.006
	(1.41) [0.159]	(1.36) [0.175]	(1.48) [0.138]	(1.35) [0.177]	(1.37) [0.171]
Sales growth over employment growth	0.990	0.991	0.988		
	(–0.85) [0.394]	(–0.82) [0.415]	(–1.01) [0.311]		
Biomed	0.511	0.537	0.618	1.943	1.584
	(–1.45) [0.146]	(–2.04) [0.042]	(–1.21) [0.226]	(1.25) [0.211]	(0.92) [0.350]
Hardwtel	0.883	0.618	1.334	0.000	0.000
	(–0.21) [0.830]	(–1.57) [0.116]	(0.64) [0.522]	(–4.66) [0.000]	(–4.57) [0.000]
ITservice	0.796	0.889	0.831	2.233	1.977
	(–0.51) [0.611]	(–0.43) [0.665]	(–0.44) [0.657]	(1.74) [0.081]	(1.20) [0.230]
Intmedia	0.867	1.103	0.874	3.849	2.803
	(–0.35) [0.727]	(0.40) [0.691]	(–0.37) [0.708]	(3.21) [0.001]	(2.30) [0.022]
Software	0.572	0.691	0.966	1.811	2.235
	(–1.25) [0.212]	(–1.27) [0.205]	(–0.09) [0.927]	(1.17) [0.243]	(1.55) [0.122]
Interaction with the median time distance of past IPOs in the technology neighbourhood:					
Biomed	0.999		0.999		1.001
	(–0.36) [0.717]		(–0.41) [0.685]		(0.22) [0.828]
Hardwtel	1.001		1.001		1.001
	(1.11) [0.268]		(1.55) [0.120]		(0.33) [0.738]
ITservic	1.000		0.999		0.999
	(–0.07) [0.940]		(–0.37) [0.714]		(–0.35) [0.728]
Intmedia	1.002		1.000		1.004
	(0.69) [0.501]		(–0.15) [0.879]		(1.43) [0.152]
Ind. & financial	0.999		1.000		1.001
	(–0.34) [0.734]		(–0.11) [0.914]		(0.50) [0.618]
Software	1.001		1.001		0.999
	(0.46) [0.647]		(0.32) [0.751]		(–0.37) [0.712]
Interaction with the average area-specific underpricing over 2 months lagged 1 month:					
Biomed	0.999	1.000		0.999	
	(–0.15) [0.883]	(–0.07) [0.945]		(–0.24) [0.807]	
Hardware	1.002	1.003		0.999	
	(0.57) [0.570]	(1.18) [0.237]		(–0.23) [0.822]	
ITservic	0.997	0.997		0.997	
	(–1.30) [0.193]	(–1.33) [0.185]		(–1.22) [0.221]	
Intmedia	0.996	0.996		0.999	
	(–1.99) [0.046]	(–2.03) [0.043]		(–0.67) [0.501]	
Ind. & financial	1.004	1.004		0.997	
	(1.66) [0.097]	(1.44) [0.151]		(–0.90) [0.368]	
Software	1.005	1.005		1.006	
	(1.59) [0.113]	(1.58) [0.115]		(1.65) [0.099]	

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4	Model 5
Interaction with the expected median time distance of future IPOs:					
Biomed				0.990	0.990
				(–5.07) [0.000]	(–5.16) [0.000]
Hardware				0.992	0.991
				(–4.59) [0.000]	(–3.17) [0.002]
ITservic				0.990	0.989
				(–4.82) [0.000]	(–4.89) [0.000]
Intmedia				0.988	0.987
				(–5.62) [0.000]	(–5.89) [0.000]
Ind. & financial				0.991	0.991
				(–4.50) [0.000]	(–4.65) [0.000]
Software				0.988	0.989
				(–5.06) [0.000]	(–5.08) [0.000]
No. of observations	39132	39132	39132	39269	39269
No. of subjects	320	320	320	321	321
No. of failures	320	320	320	321	321
Time at risk	297555	297555	297555	298546	298546
Log likelihood	–1514.463	–1515.504	–1521.367	–1500.421	–1502.408
LR χ^2	33.15	31.07	19.35	72.79	68.82
Prob > χ^2	0.045	0.009	0.199	0.000	0.000

*The table reports the estimated coefficient, the hazard ratio, the z-value (in parentheses) and the p-value (in brackets).

Table 14a: Results from the Cox proportional hazards model with social interaction under rational expectations for the Nouveau Marché*

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4	Model 5
Age of IPO	1.014	1.013	1.013	1.012	
	(0.98) [0.325]	(0.90) [0.366]	(0.92) [0.357]	(0.87) [0.387]	
Employment	1.000				
	(–0.66) [0.507]				
Debt-equity ratio	0.981				
	(–0.76) [0.445]				
Sales growth over employment growth	1.004	1.004	1.004	1.004	
	(0.74) [0.461]	(0.71) [0.480]	(0.70) [0.487]	(0.76) [0.447]	
VC-backing	1.371	1.371	1.351	1.309	1.581
	(1.15) [0.250]	(1.15) [0.252]	(1.09) [0.274]	(0.99) [0.322]	(1.72) [0.085]
VC stake before IPO	0.988	0.989	0.988	0.991	0.986
	(–1.19) [0.232]	(–1.06) [0.287]	(–1.17) [0.242]	(–0.93) [0.350]	(–1.45) [0.147]
Software	0.328	0.291	4.262	1.366	
	(–0.31) [0.757]	(–0.34) [0.731]	(1.34) [0.181]	(0.58) [0.559]	
Biomed	29.312	22.247	0.027	0.096	
	(0.71) [0.479]	(0.64) [0.521]	(–1.12) [0.264]	(–2.40) [0.016]	
Hardwtel	65.409	52.826	4.694	1.877	
	(1.31) [0.192]	(1.25) [0.212]	(1.46) [0.144]	(1.09) [0.276]	
Intmedia	119.714	99.309	20.915	2.489	
	(1.31) [0.190]	(1.27) [0.204]	(2.59) [0.010]	(1.69) [0.091]	
ITservice	128.787	108.616	3.660	1.180	
	(1.46) [0.143]	(1.42) [0.155]	(1.06) [0.287]	(0.31) [0.757]	
Interaction with the expected number of IPOs from the technology neighbourhood within the next 4 months:					
Software	1.186	1.185	1.032		
	(2.12) [0.034]	(2.10) [0.035]	(0.52) [0.606]		
Biomed	1.792	1.573	3.569		
	(0.52) [0.603]	(0.41) [0.683]	(0.80) [0.424]		
ITservice	0.983	0.983	1.043		
	(–0.16) [0.870]	(–0.16) [0.871]	(0.43) [0.667]		
Hardwtel	1.100	1.103	1.058		
	(1.19) [0.234]	(1.22) [0.224]	(0.82) [0.409]		
Intmedia	0.838	0.840	0.909		
	(–1.43) [0.154]	(–1.40) [0.161]	(–0.94) [0.350]		
Ind. & financial	1.553	1.536	1.227		
	(1.98) [0.048]	(1.94) [0.052]	(1.74) [0.082]		
Interaction with the expected mean time distance of future IPOs in the technology neighbourhood:					
Software	1.215	1.215			
	(3.82) [0.000]	(3.81) [0.000]			
Biomed	1.000	1.000			
	(–0.02) [0.981]	(0.01) [0.993]			
Hardwtel	1.055	1.054			
	(2.15) [0.032]	(2.13) [0.033]			
Intmedia	1.022	1.022			
	(1.13) [0.260]	(1.14) [0.254]			
ITservice	1.071	1.071			
	(1.95) [0.051]	(1.96) [0.050]			
Ind. & financial	1.040	1.038			
	(1.64) [0.100]	(1.59) [0.111]			

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4	Model 5
Interaction with the expected median time distance of future IPOs in the technology neighbourhood:					
Software	0.940	0.940	0.984	0.985	0.989
	(–4.81) [0.000]	(–4.81) [0.000]	(–6.04) [0.000]	(–6.33) [0.000]	(–6.88) [0.000]
Biomed	0.982	0.982	0.983	0.981	0.983
	(–3.37) [0.001]	(–3.44) [0.001]	(–4.15) [0.000]	(–5.77) [0.000]	(–5.97) [0.000]
Hardwtel	0.970	0.970	0.982	0.982	0.987
	(–4.22) [0.000]	(–4.22) [0.000]	(–6.39) [0.000]	(–6.42) [0.000]	(–6.70) [0.000]
Intmedia	0.980	0.979	0.983	0.983	0.988
	(–3.83) [0.000]	(–3.88) [0.000]	(–5.83) [0.000]	(–6.28) [0.000]	(–6.78) [0.000]
ITservice	0.961	0.960	0.978	0.980	0.986
	(–3.85) [0.000]	(–3.88) [0.000]	(–6.51) [0.000]	(–6.56) [0.000]	(–6.88) [0.000]
Ind. & financial	0.978	0.978	0.985	0.985	0.987
	(–3.91) [0.000]	(–3.89) [0.000]	(–5.63) [0.000]	(–6.10) [0.000]	(–6.36) [0.000]
No. of observations	8522	8522	8522	8522	8548
No. of subjects	133	133	133	133	134
No. of failures	133	133	133	133	134
Time at risk	146109	146109	146109	146109	146809
Log likelihood	–453.824	–454.404	–468.021	–471.221	–482.214
LR χ^2	143.90	133.74	106.51	100.11	87.92
Prob > χ^2	0.00	0.00	0.00	0.00	0.00

*The table reports the estimated coefficient, the hazard ratio, the z-value (in parentheses) and the p-value (in brackets).

Table 14b: Testing for the area-specificity of the expectations impact in the Nouveau Marché*

The dependent variable is the hazard rate	Model 1: Biomed IPOs	Model 2: Hardwtel IPOs	Model 3: Itservice IPOs	Model 4: Intmedia IPOs	Model 5: Ind.& fin. IPOs	Model 6: Software IPOs
Age of IPO	1.013	1.012	1.012	1.013	1.015	1.013
	(0.93) [0.351]	(0.88) [0.378]	(0.88) [0.381]	(0.96) [0.335]	(1.05) [0.295]	(0.91) [0.363]
VC-backing	1.289	1.288	1.296	1.289	1.349	1.304
	(0.93) [0.350]	(0.93) [0.354]	(0.95) [0.342]	(0.93) [0.353]	(1.10) [0.272]	(0.98) [0.329]
VC stake before IPO	0.991	0.991	0.991	0.991	0.988	0.991
	(–0.89) [0.376]	(–0.88) [0.376]	(–0.90) [0.370]	(–0.93) [0.351]	(–1.19) [0.236]	(–0.91) [0.365]
Sales growth over	1.004	1.004	1.004	1.004	1.004	1.004
employment growth	(0.79) [0.428]	(0.74) [0.462]	(0.77) [0.442]	(0.68) [0.498]	(0.76) [0.447]	(0.81) [0.421]
Biomed	0.244	0.102	0.103	0.099	1.477	0.117
	(–0.98) [0.326]	(–2.30) [0.022]	(–2.30) [0.021]	(–2.33) [0.020]	(0.26) [0.796]	(–2.19) [0.028]
Hardwtel	1.914	1.951	1.897	1.672	21.392	1.862
	(1.09) [0.276]	(0.94) [0.346]	(1.10) [0.271]	(0.91) [0.363]	(2.53) [0.011]	(1.09) [0.275]
ITservic	1.171	1.183	0.859	1.023	14.427	1.172
	(0.29) [0.774]	(0.31) [0.775]	(–0.20) [0.843]	(0.04) [0.965]	(2.24) [0.025]	(0.30) [0.766]
Intmedia	2.727	2.439	2.432	1.735	28.070	2.463
	(1.82) [0.069]	(1.64) [0.100]	(1.64) [0.100]	(0.79) [0.427]	(2.80) [0.005]	(1.68) [0.092]
Software	1.515	1.306	1.412	1.172	15.668	1.171
	(0.76) [0.450]	(0.49) [0.622]	(0.64) [0.522]	(0.30) [0.764]	(2.34) [0.019]	(0.25) [0.804]
Interaction with the expected median time distance of future IPOs in the technology neighbourhood:						
Intmedia	0.976	0.981	0.980	0.967	0.982	0.981
	(–6.27) [0.000]	(–5.82) [0.000]	(–6.21) [0.000]	(–3.84) [0.000]	(–5.61) [0.000]	(–5.86) [0.000]
Ind. & financial	0.981	0.985	0.985	0.985	0.964	0.985
	(–5.82) [0.000]	(–5.42) [0.000]	(–5.77) [0.000]	(–5.57) [0.000]	(–3.73) [0.000]	(–5.51) [0.000]
Hardwtel	0.979	0.975	0.983	0.983	0.984	0.983
	(–6.21) [0.000]	(–3.26) [0.001]	(–6.06) [0.000]	(–5.83) [0.000]	(–5.37) [0.000]	(–5.77) [0.000]
Biomed	0.985	0.982	0.982	0.981	0.984	0.982
	(–3.12) [0.002]	(–5.17) [0.000]	(–5.49) [0.000]	(–5.29) [0.000]	(–4.80) [0.000]	(–5.27) [0.000]
ITservic	0.980	0.984	0.978	0.984	0.985	0.984
	(–6.05) [0.000]	(–5.56) [0.000]	(–2.50) [0.012]	(–5.75) [0.000]	(–5.35) [0.000]	(–5.72) [0.000]
Software	0.981	0.985	0.985	0.985	0.987	0.982
	(–6.11) [0.000]	(–5.57) [0.000]	(–5.99) [0.000]	(–5.68) [0.000]	(–5.31) [0.000]	(–3.46) [0.001]
Interaction with expectations for other technology areas:						
Biomed median		1.001	1.004	0.989	1.026	0.998
		(0.38) [0.700]	(0.75) [0.452]	(–2.74) [0.006]	(2.88) [0.004]	(–0.67) [0.501]
Hardwtel median	0.996		0.999	1.014	1.003	1.005
	(–0.93) [0.350]		(–0.17) [0.863]	(1.77) [0.076]	(0.75) [0.456]	(1.21) [0.226]
ITservic median	1.000	1.003		1.002	0.995	0.998
	(0.14) [0.890]	(1.20) [0.232]		(0.58) [0.559]	(–1.73) [0.083]	(–0.48) [0.632]
Intmedia median	0.995	1.001	1.006		1.014	1.002
	(–0.89) [0.375]	(0.14) [0.890]	(0.75) [0.454]		(2.40) [0.016]	(0.32) [0.747]
Ind. & fin. median	01.000	1.003	1.003	0.995		1.001
	(–0.10) [0.917]	(0.60) [0.549]	(0.58) [0.562]	(–1.25) [0.211]		(0.23) [0.816]
Software median	1.002	1.000	0.998	01.009	0.999	
	(0.24) [0.810]	(–0.02) [0.988]	(–0.44) [0.657]	(1.52) [0.129]	(–0.25) [0.805]	
No. of observations	8522	8522	8522	8522	8522	8522
Subjects (failures)	133 (133)	133 (133)	133 (133)	133 (133)	133 (133)	133 (133)
Time at risk	146109	146109	146109	146109	146109	146109
Log likelihood	–467.649	–469.905	–470.497	–465.122	–463.760	–469.721
LR χ^2 [Prob > χ^2]	107.25 [0.00]	102.74 [0.00]	101.56 [0.00]	112.31 [0.00]	115.03 [0.00]	103.11 [0.00]

*The table reports the estimated coefficient, the hazard ratio, the z-value (in parentheses) and the p-value (in brackets).

Table 14c: The adaptive expectations model for the Nouveau Marché*

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4
Age of IPO	1.015	1.013	1.011	1.012
	(0.97) [0.332]	(0.92) [0.357]	(0.78) [0.435]	(0.84) [0.399]
Employment	1.000	1.000		
	(–0.79) [0.432]	(–0.85) [0.395]		
Debt-equity ratio	0.968	0.965	0.961	0.985
	(–1.21) [0.226]	(–1.31) [0.189]	(–1.50) [0.133]	(–0.60) [0.551]
VC-backing	1.297	1.310	1.353	1.320
	(0.97) [0.331]	(1.00) [0.316]	(1.13) [0.258]	(1.02) [0.309]
VC stake before IPO	0.991	0.990	0.991	0.989
	(–0.92) [0.356]	(–1.00) [0.316]	(–0.91) [0.362]	(–1.08) [0.278]
Sales growth over employment	1.003	1.003		1.004
growth	(0.57) [0.570]	(0.61) [0.545]		(0.76) [0.447]
Biomed	1.747	1.784	1.841	0.544
	(0.82) [0.410]	(0.89) [0.372]	(0.95) [0.340]	(–0.28) [0.779]
Hardwtel	0.558	0.728	0.701	2.141
	(–0.51) [0.612]	(–0.74) [0.456]	(–0.84) [0.402]	(0.72) [0.470]
ITservice	0.350	0.407	0.416	0.652
	(–2.24) [0.025]	(–2.07) [0.038]	(–2.04) [0.042]	(–0.43) [0.670]
Intmedia	0.480	0.660	0.639	5.556
	(–1.47) [0.140]	(–0.94) [0.345]	(–1.02) [0.305]	(1.68) [0.092]
Software	0.629	0.715	0.722	1.790
	(–0.90) [0.371]	(–0.76) [0.448]	(–0.74) [0.462]	(0.65) [0.514]
Interaction with the median time distance of past IPOs in the technology neighbourhood:				
Biomed	1.001	0.999	0.999	0.996
	(0.19) [0.846]	(–0.35) [0.723]	(–0.30) [0.766]	(–0.72) [0.469]
Hardwtel	0.998	0.998	0.997	1.000
	(–0.98) [0.326]	(–1.86) [0.063]	(–1.90) [0.058]	(–0.20) [0.839]
ITservice	0.998	0.998	0.998	0.998
	(–2.19) [0.028]	(–2.36) [0.018]	(–2.38) [0.017]	(–1.56) [0.118]
Intmedia	0.997	0.997	0.997	1.003
	(–2.27) [0.023]	(–2.59) [0.010]	(–2.61) [0.009]	(0.83) [0.407]
Ind. & financial	1.001	1.000	1.000	0.999
	(0.99) [0.323]	(0.10) [0.917]	(0.12) [0.903]	(–0.42) [0.672]
Software	0.998	0.997	0.997	1.000
	(–1.66) [0.096]	(–1.91) [0.056]	(–1.92) [0.055]	(0.07) [0.942]
Interaction with the average area-specific underpricing over 2 months, lagged 1 month:				
Biomed	0.928			
	(–1.12) [0.265]			
Hardwtel	1.013			
	(0.11) [0.914]			
ITservice	1.005			
	(0.60) [0.548]			
Intmedia	1.010			
	(1.52) [0.129]			
Ind. & financial	1.076			
	(2.17) [0.030]			
Software	0.996			
	(–0.23) [0.817]			

The dependent variable is the hazard rate	Model 1	Model 2	Model 3	Model 4
Interaction with the expected median time distance of future IPOs in the technology neighbourhood:				
Biomed				0.984
				(–6.26) [0.000]
Hardwtel				0.980
				(–5.39) [0.000]
ITservice				0.982
				(–5.74) [0.000]
Intmedia				0.985
				(–5.82) [0.000]
Ind. & financial				0.978
				(–6.06) [0.000]
Software				0.985
				(–5.88) [0.000]
No. of observations	8522	8522	8522	8522
No. of subjects	133	133	133	133
No. of failures	133	133	133	133
Time at risk	146109	146109	146109	146109
Log likelihood	–499.097	–504.033	–508.731	–469.045
LR χ^2	44.36	34.49	34.89	104.46
Prob > χ^2	0.001	0.007	0.003	0.000

*The table reports the estimated coefficient, the hazard ratio, the z-value (in parentheses) and the p-value (in brackets).

Table 15: Definitions of Symbols

	Definition
P_t	Observed stock price in the period t
P_t^f	Fundamental value
B_t	Bubble
E_tD_{t+I}	Divided payment in the period between t and t+i expected on the basis of information at time t
δ	Discount factor
$\overline{\kappa}$	Initial real capital endowment
C	A basket of conventional goods
X	High-tech goods
$\Pi(K_x)$	Rate of return in the high-tech sector
γ	The world market rate of interest
$\left\|\dot{K}_X\right\|/\gamma$	Set-up cost for each entrepreneur
γ	Inverse index of the adjustment cost that determines the speed of adjustment
g	The present value of a start-up located in the high-tech industry
$\dot{g}$	The rate of capital gains on g
β	The strength of the external economics in high-tech technology
$y_j^i(t)=1$	The ith firm listed in the stock market at time t
$y_j^i(t)=0$	Unlisted
$P_{jk}^i(t)$	Probability that the ith firm is in state j at time t given that it was in state k at time t–1 (transition probability)
$y_j^i(0)$	Initial condition
$P^i(t)$	Matrix of the non-negative transition probabilities (Markov matrix)
$k=\{1,2,...,m\}$	Areas of technology
$P_{x_0}^0$	The vector of initial probabilities
P_{jk}	The probabilities of transition from the jth to the kth area of technology between any two consecutive IPOs
n_{jk}	The frequency of the one-step transitions from state j to k in the sample x_{n+1}
P_k^s	The stationary distribution to which the Markov chain will converge after a sufficient number of iterations
m	The number of technology areas to which an IPO firm may belong
Y_t	NxM matrix with rows $y^i(t)'$
$\overline{Y}_t$	Nx(M–1) matrix made up of the first (M–1) columns of Y_t
$\widetilde{\Pi}$	Toikka's estimator
F(t)	Cumulative distribution function $(F(t)=\Pr(T\le t))$
S(t)	Survival function
h(t)	Hazard function, where h(t) is the hazard rate and Δt is the next short time interval

$h_i(t)$	Firm i's hazard function of going public
x_i	Time-invariant characteristics of firm i
$f(t)$	Time-varying variables
λ_i	The hazard function for firm i
Xi	The exogenous characteristics of the firm
$y_{n(i)}$	Neighbourhood characteristics of the firm
$m^e_{n(i)}$	The firm's subjective expectation of a neighbourhood behavioural measure (a vector)
n (i)	The neighbourhood of the firm (a firm's area of technology)
$E\left(t \middle\| X_i, Y_{n(i)}, m^e_{n(i)}\right)$	The expected duration for firm i, conditional on specific realizations of the covariants
Fx	The probability distribution of characteristics within neighbourhood $n(i)$ and $m^e_{n(i)}$
$W^e_{n(i)}$	The average duration among IPOs
$\Psi_{n(i)}$	The set of firms going public by duration τ in neighbourhood $n(i)$
V	The statistical test for the independence of the transition probabilities
$h_i(t \| xi)$	The hazard function of going public
$\eta_o(t)$	A baseline non-negative hazard function at time t
$h_o(t)$	The baseline hazard in the Cox proportional hazard model