Essays in Financial Economics:
Risk and Return of Private Equity

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der Johann Wolfgang Goethe Universität

Frankfurt am Main

vorgelegt von

Dipl.-Kfm. Philipp Krohmer

Lindwurmstrasse 139a

80337 München

+49 (0)179 1358219

philipp.krohmer@cepres.de

Matrikelnummer: 2473635

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Erstgutachter:

Prof. Dr. Mark Wahrenburg

Zweitgutachter:

Prof. Dr. Uwe Walz

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Einleitung

Bei der vorliegenden Arbeit handelt es sich um eine kumulative Dissertation. Sie besteht aus vier separaten wissenschaftlichen Arbeiten, die in einem inhaltlichen Zusammenhang stehen. Alle Artikel befassen sich mit der Analyse von Rendite- und Risikoaspekten von Private Equity Investitionen. Bevor die Inhalte der einzelnen Arbeiten näher beschrieben werden, soll im Folgenden zunächst die allen Artikeln übergeordnete Thematik vorgestellt werden. Dies umfasst begriffliche Abgrenzungen, die Darstellung aktueller Entwicklungen des Private Equity Marktes und die Einordnung der Arbeiten in den Gesamtkontext der bisherigen wissenschaftlichen Forschung.

Nach der Definition der European Private Equity and Venture Capital Association (EVCA) ist Private Equity der Überbegriff für den gesamten Markt der privaten Unternehmensfinanzierungen und umfasst damit Buyout, Venture Capital und Mezzanine- Investitionen. Im Gegensatz zum Public Equity handelt es sich bei Private Equity Investitionen um Eigenkapitalbeteiligungen an nicht börsennotierten Unternehmen. Die Kapitalanlage in Private Equity erfolgt in den meisten Fällen durch Beteiligung an einem geschlossenen nicht gehandelten Fonds in der Rechtsform einer „Limited Partnership" (LP), vergleichbar mit einer deutschen KG. Geldgeber sind in der Regel institutionelle Investoren wie etwa Banken oder Versicherungen, aber auch vereinzelt sehr vermögende Privatleute. Der Private Equity Markt hat nicht nur für die Finanzierung von innovativen Unternehmen und dem Wirtschaftswachstum[1] an Bedeutung gewonnen, er hat sich mittlerweile auch zu einem eigenständigen Kapitalmarktsegment entwickelt. Das Engagement in Private Equity hat sich weltweit aufgrund des überzeugenden Ertragspotentials und der Diversifikationsmöglichkeiten als Alternative zu den klassischen Kapitalanlagemöglichkeiten etabliert. Dies zeigt sich am kontinuierlich steigenden Kapitalzufluss. Auch wenn das Interesse zu Beginn des neuen Jahrtausends durch das Platzen der Dotcom- Blase zurückging, hat die Private

[1] Zahlreiche Studien untersuchen die Bedeutung von Private Equity für das Wirtschaftswachstum, wie z.B. kürzlich NVCA(2007a).

Equity Industrie nach den Konsolidierungsjahren 2002 bis 2004 einen enormen Aufschwung erfahren. Das Fundraising der Beteiligungsgesellschaften erreichte 2006 weltweit ein Volumen von über 350 Mrd. USD, in Europa stieg es um 25% gegenüber dem Rekord-Jahr 2005 auf 90 Mrd. Euro und selbst in Deutschland wurde mit knapp 3Mrd. Euro das Niveau der Boomjahre fast wieder erreicht.[2] Ein Abbruch dieses Trends ist nicht in Sicht und alles deutet darauf hin, dass auch im Jahr 2007 wieder Rekordsummen eingeworben werden.[3] Die alternative Anlageklasse lockt durch überdurchschnittliche Ertragsmöglichkeiten im Vergleich zu den klassischen Anlagemöglichkeiten.[4] Die höheren Renditen sind durch eine Illiquiditätsprämie[5] aber auch dem hohen Risikogehalt dieser Anlageklasse zu erklären. Kaum eine Anlageklasse weist derart hohe Bandbreiten der tatsächlich erwirtschafteten Renditen auf. Historische Renditen zeigen erhebliche Unterschiede zwischen erfolgreichen und weniger erfolgreichen Private Equity Gesellschaften, unabhängig davon, ob die Fonds in denselben oder in unterschiedlichen Jahren aufgelegt wurden.[6] Insbesondere Venture Capital ist durch sehr hohe Ausfallraten um 30% geprägt.[7] Dies verdeutlicht, dass neben Monitoring und Managementunterstützung auch die Fähigkeit des Investment Managers, die richtigen Deals zu selektieren eine fundamentale Rolle für den Investitionserfolg spielt.[8] Die stetig steigende Nachfrage nach dieser Asset- Klasse lockt jedoch auch unerfahrene Anbieter auf den Markt[9] und stellt Investoren vor eine besondere Herausforderung bei der Selektion der richtigen Management Firmen bzw. Fonds. Gegenüber anderen Anlageklassen gilt ein Engagement in Private Equity durch den privaten Charakter des Marktes darüber hinaus als spekulativ und intransparent. Informationen unterliegen strengen Geheimhaltungsverpflichtungen und die Messung von Rendite und Risiko gestaltet sich weitaus

[2] Vgl. EVCA(2006) und BVK(2006).
[3] Erste vorläufige Zahlen bestätigen diesen Trend. So wurde beispielsweise laut einer Studie von Private Equity Intelligence 2007 weltweit ein Volumen von über 500 Mrd. USD erreicht, vgl. hierzu Preqin (2008).
[4] In der Vergangenheit lagen die durchschnittlichen Langzeitrenditen nach Abzug aller Kosten über 20 Jahre bei ca. 15% pro Jahr für Private Equity und damit in etwa 5% über den Ergebnissen, die Investitionen in vergleichbare börsennotierte Unternehmen an der NASDAQ oder S&P 500 erzielten. Vgl. NVCA (2007b).
[5] Vgl. Ljungquist und Richardson (2003).
[6] Vgl. beispielsweise EVCA (2006).
[7] Vgl. u.a. Mathonet und Weidig (2004).
[8] Für einen Überblick über bisherige Studien zu Monitoring, value add und selection vgl. Tykvová (2000).
[9] Vgl. Gompers (1995).

komplexer als bei börsengehandelten Anlageklassen mit täglichen Preisen. Zum Zeitpunkt der Investitionsentscheidung lässt sich der Risikogehalt der einzelnen Beteiligungen eines Fonds nicht feststellen, da es sich bei Private Equity- Fonds in der Regel um „blind pools“ handelt. Für Investoren stellt sich vor allem die Frage, wie das Risiko und die Rendite von Private Equity-Engagements eingeschätzt werden können und von welchen Determinanten diese Kennziffern getrieben werden. Veröffentlichte Befunde vorangegangener Studien geben bisher nur wenig Anhaltspunkte, welche Kriterien den Erfolg von Private Equity Investitionen erhöhen. Eine ausführliche Due Dilligence, eine professionelle Rendite- und Risikoeinschätzung und ein erfahrenes Anlagemanagement sind daher fundamentale Voraussetzungen für ein erfolgversprechendes Engagement in Private Equity.

Vor diesem Hintergrund verbindet alle vier Arbeiten dieser Dissertation die Herausforderung, zu einem besseren, differenzierteren Verständnis der Determinanten des Investitionserfolgs oder -misserfolgs beizutragen und Erkenntniszuwächse für die Optimierung von Investitionsentscheidungen und das Potfoliomanagement in der Praxis zu liefern. Die vorliegende Arbeit ist thematisch in zwei Abschnitte unterteilt. Während die ersten beiden Studien des ersten Teilabschnittes den Einfluss des Investitionsverhaltens von Fondsmanagern auf den Beteiligungserfolg untersuchen, liefern die beiden letzten Studien konkrete Lösungsansätze für die Praxis bezüglich der Messung und Schätzung des Risikos und der Rendite von Private Equity Engagements. Im Hinblick auf die Einführung der EU-Richtlinien CAD III (Third Capital Adequacy Directive) und Solvency II, welche die Umsetzung von Basel II für die Mitgliedstaaten der Europäischen Union beinhaltet und unter anderem die Eigenkapitalunterlegung von Private Equity Investitionen durch Banken und Versicherungen neu regeln, sind die im zweiten Abschnitt vorgestellten Modelle zur Rendite- und Risikobestimmung von besonderer Aktualität und Bedeutung.

Ein Schwerpunkt innerhalb der Private Equity Forschung liegt in der Untersuchung der Determinanten für den Beteiligungserfolg. Die Basis für eine verlässliche Analyse der Erfolgskriterien bildet eine möglichst exakte Messung der Investitionsrendite.[10] Aufgrund des angesprochenen privaten Charakters dieser Anlageklasse sind die notwendigen Beobachtungs-Daten generell schwierig zu erhalten. Während frühere Studien noch mit Näherungen für den Beteiligungserfolg wie beispielsweise den Exit- Kanal der Investition[11] oder aggregierten Performancezahlen kommerzieller Datenbanken arbeiteten, sind in den letzten Jahren durch die steigende Verfügbarkeit detaillierter Daten präzisere Studien entstanden. Die meisten Studien basieren ihre Renditekalkulationen auf Bewertungen der Beteiligungen oder Fonds, wie beispielsweise Cochrane (2004), Hege et al. (2003) oder Quigley et al. (2005). Diese Kennzahlen sind jedoch unpräzise aufgrund der Gestaltungsspielräume bei der Bewertung des Nettovermögens einer Beteiligung oder aufgrund des so genannten „milestone-bias“: Kaplan, Sensoy und Strömberg (2002) betonen, dass eine genaue Kalkulation der internen Verzinsung (IRR) nur auf Basis der exakten Zahlungsströme möglich ist und die Berechnung auf Basis der (Runden-) Bewertungen zu erheblichen Verzerrungen führt. Die Datenbank des Center of Private Equity Research (CEPRES) bietet präzise Informationen zu jedem Kapitaltransfer zwischen Fonds und Portfoliounternehmen für über 20.000 Investitionen und ist damit in Umfang und Qualität einzigartig. CEPRES wurde 2001 als ein public-private Joint Venture zwischen der VCM Capital Management GmbH[12] und der Goethe Universität Frankfurt gegründet. Die Gründungsidee war die Etablierung eines Forschungsinstituts, das mit der Praxis nahe zusammenarbeitet und deren Fragestellungen aufgreift.[13] CEPRES unterscheidet sich von anderen kommerziellen Datenbanken[14] insbesondere durch die Bereitstellung exakter Zahlungsströme zwischen Fonds und

[10] Die heute weltweit angewandte Standardmethode zur Berechnung der Performance ist die durchschnittliche jährliche interne Verzinsung (Internal Rate of Return, IRR).
[11] Beispielsweise Gompers (1995).
[12] Die VCM Capital Management GmbH ist der älteste europäische Private Equity Dachfondsmanager. Sie verwaltet momentan Investitionen in über 130 Private Equity Fonds.
[13] Seither sind zahlreiche empirische Forschungsarbeiten auf Basis von CEPRES- Daten entstanden, wie etwa Cumming und Walz (2004) oder Nowak et al. (2006).
[14] Wie beispielsweise VentureOne oder VentureXpert.

Portfoliounternehmen. Darüber hinaus zeichnet sich die Datenbank durch ein Höchstmaß an Datengüte aus, da die Informationen nicht nur auf freiwilligen Angaben der Fondsmanager basieren, sondern alle Eingaben an Hand von zum Teil geprüften Reports und Due Dilligence Unterlagen validiert werden. Die Anonymisierung aller Angaben wirkt zusätzlich dem Anreiz einer „Beschönigung" der Zahlen durch die Fondsmanager entgegen. Andere Datenbanken zeichnen sich jedoch durch ihren enormen Umfang an Beobachtungen und eine größere Vielfalt an Untersuchungsvariablen aus. Die Venture Economics Datenbank (www.venturexpert.com) beispielsweise, enthält einen der umfangreichsten Datensätze über die Private Equity Industrie und bildet die Grundlage zahlreicher empirischer Studien. Allerdings enthält sie keine Informationen über die Zahlungsströme zwischen Fonds und Unternehmen, wodurch eine präzise cashflow-bezogene Berechnung der Investitionsrendite nicht möglich ist. Um die positiven Aspekte der CEPRES- und der Venture Economics- Datenbank zu kombinieren und eine außergewöhnliche Basis für eine präzise Untersuchung der Erfolgsdeterminanten im Private Equity zu schaffen, wurde ein neuer Datensatz durch die Zusammenführung der kongruenten Informationen beider Datenbanken kreiert. Dabei wurden sämtliche Variablen aus VentureXpert mit den Cash Flow-Informationen und den Variablen aus CEPRES zusammengeführt, sofern die Namen der Beteiligungsgesellschaft, des Fonds, des Portfoliounternehmens und der Investitionszeitpunkt der Beobachtungen in beiden Datenbanken übereinstimmend enthalten waren. Um die Rendite-Kalkulationen nicht durch subjektive Bewertungen zu verzerren, wurden darüber hinaus alle nicht realisierten Investitionen aus dem Datensatz genommen. Das Resultat ist ein einzigartiger Datensatz mit exakten Zahlungsströmen zu 712 Private Equity Investitionen und über 120 Untersuchungsvariablen. Die ersten beiden Arbeiten dieser Dissertation, welche sich auf die Untersuchung des Investitionsverhaltens von Private Equity Fondsmanagern und den Einfluss auf den Beteiligungserfolg konzentrieren, nutzen diesen zusammengeführten Datensatz. Dieser Datensatz ermöglicht Sachverhalte exakt zu untersuchen, welche mit Informationen einzelner, verfügbarer Datenbanken bisher nicht erforscht werden konnten. Die erste Studie untersucht den

Zusammenhang zwischen der stufenweisen Kapitalzufuhr (Staging) einer Investition durch den Fondsmanager und der Beteiligungsrendite. Der zusammengeführte Datensatz erlaubt neben der exakten Kalkulation der Rendite die Berücksichtigung der „milestones“ einer Investition und damit eine differenzierte Analyse des Staging- Phänomens. Die zweite Studie beschäftigt sich mit dem Verhalten der Fondsmanager bei verlustbringenden Investitionen und differenziert dabei zwischen erfahrenen und weniger erfahrenen Fondsmanagern. Bei den beiden letzten Studien steht die Schätzung der Rendite und des Risikos von Private Equity Engagements auf Basis historischer Daten im Vordergrund und nicht explizit das Verhalten der Fondsmanager. Diese Studien beruhen auf dem gesamten CEPRES- Datensatz und nicht auf dem zusammengeführten Datensatz.

Die erste Studie dieser Dissertation „The Bright and Dark Side of Staging: Investment Performance and the Varying Motivations of Private Equity Firms” ist in Ko-Autorenschaft mit Dr. Victor Calanog von der Wharton Business School (Pennsylvania, USA) und Dr. Rainer Lauterbach, von der Abteilung Finanzen der Goethe Universität Frankfurt entstanden (Krohmer, Lauterbach und Calanog 2007)[15]. Eine Besonderheit von Private Equity Beteiligungen stellt die Möglichkeit für den Investor dar, das gesamte Investitionskapital nicht im Voraus – wie bei Darlehen üblich – sondern in einzelnen Schritten dem Beteiligungsunternehmen zur Verfügung zu stellen. Dieses schrittweise Investieren wird mit dem Begriff „Staging“ definiert. Die bisherige Forschung bestätigt, dass Staging ein sehr wichtiges Instrument des Investors ist, um die Entwicklung der Beteiligung zu verfolgen und zu beeinflussen (Monitoring). Die Erteilung einer Folgefinanzierung hängt in der Regel von der Erreichung vereinbarter Meilensteine durch das Unternehmen ab. Dadurch ist es dem Investor möglich, vor jeder Teilfinanzierung wichtige

[15] Der Artikel wurde auf folgenden Konferenzen und Seminaren vorgestellt: Brown Bag-Seminar der Goethe Universität Frankfurt; HVB Doktoranden-Seminar in Eltville; Global Finance Conference 2006 in Rio de Janeiro; Global Conference on Business & Economics 2006 der Harvard Universität in Boston; Annual Meeting der American Finance Association 2007 in Chicago; Ninth Conference of the ECB-CFS Research Network 2007 in Dublin. Die eingereichte Arbeit wurde im Jahre 2005 erstellt. In der vorgelegten Version wurden alle konstruktiven Anregungen der Diskussionen berücksichtigt. Derzeit wird der Artikel von Gutachtern der Zeitschrift Journal of Banking and Finance geprüft.

Informationen über die bisherige Unternehmensentwicklung und weitere Wachstumsperspektiven als Entscheidungsgrundlage zu generieren. Die Frage, ob das Staging der Investitionen in einem positiven oder negativen Zusammenhang mit dem Beteiligungserfolg steht, konnte bisher nicht einvernehmlich gelöst werden. Bisherige Studien belegen einerseits einen positiven Einfluss, so die theoretischen Modelle von Neher (1999), Hsu (2002) and Wang and Zhou (2004) oder die empirischen Ergebnisse von Gompers (1995). Diese Arbeiten stützen sich auf die Wirkung von Staging als Monitoring- Instrument, um Informations- Asymmetrien gegenüber dem Unternehmer auszugleichen und Unterstützung bei der Entwicklung des Unternehmens zu leisten. Andere Studien dagegen zeigen einen negativen Zusammenhang, beispielsweise Bergemann und Hege (1998), Cornelli und Yosha (2003) sowie empirisch Hege et al. (2003). Diese argumentieren unter anderem, das Staging insbesondere in kritischen Situationen angewandt werden muss, um wertvolle Informationen als Entscheidungsgrundlage für weitere Finanzierungsschritte zu gewinnen. Wir gehen von der Annahme aus, dass zum Zeitpunkt des Beginns der Investitionsbeziehung der Investor positive Erwartungen an jede Beteiligung hat, die sich dann im Verlauf der Beziehung gemäß der Unternehmensentwicklung anpassen. Folglich wird er auch sein Staging- Verhalten im Laufe der Investitionsbeziehung an die Umstände anpassen. Daraus folgern wir, dass sich der offene Widerspruch bisheriger Forschungsergebnisse durch die differenzierte Untersuchung, *wann* Staging während der Investitions-Beziehung angewendet wird, lösen lassen sollte. Dieser Ansatz erfordert Informationen über den präzisen Zeitpunkt und die exakte Höhe jedes Kapitaltransfers zwischen dem Fonds und dem Unternehmen, um einerseits eine Unterteilung in verschiedene Finanzierungsphasen während der Investitionsbeziehung zu realisieren und andererseits eine exakte Messung des Beteiligungserfolgs zu garantieren. Darüber hinaus werden detaillierte Informationen zur Messung des Staging- Verhaltens benötigt.[16] Diese

[16] Der Investor kann das schrittweise Investieren über verschiedene Parameter steuern. Sein Staging- Verhalten bestimmt die Anzahl der Finanzierungsrunden, die Anzahl der Auszahlungen je Finanzierungsrunde (genannt: Milestone oder Tranche), die Dauer zwischen jeder Finanzierung, die Häufigkeit (Frequenz) der Finanzierungen und die Höhe jeder Finanzierungrunde- und Tranche.

hohen Datenanforderungen erfüllt keine einzelne, verfügbare Datenbank.[17] Für diese Untersuchung wurde wie eingangs beschrieben ein neuer Datensatz durch die Zusammenführung der kongruenten Informationen der Datenbanken Venture Economics und CEPRES kreiert. Insgesamt werden 712 Beteiligungen von 51 Private Equity Gesellschaften und ihnen zugehörenden 122 Fonds untersucht über einen Zeitraum von 1979 bis 2003 in den Regionen Nord Amerika, Europa, Asien und Latein Amerika. Die Investoren stellen diesen Beteiligungen insgesamt 1.549 Finanzierungsrunden zur Verfügung, die in 2.329 einzelne Finanzierungsschritte aufgeteilt waren. Dieser neue Datensatz erfüllt die Datenerfordernisse für die intertemporale Betrachtung und ermöglicht eine differenziertere Analyse des Staging- Phänomens im Vergleich zu bisherigen Studien. Um die Motive und das daraus resultierende Staging- Verhalten im Verlauf der Investitions- Beziehung differenziert untersuchen zu können, unterteilen wir die gesamte Investitionsperiode von der ersten Kapitalzuführung vom Fonds zum Unternehmen bis zur letzten Rückzahlung vom Unternehmen an den Fonds in drei gleich lange Phasen (wir nennen diese die Investitionsphase, die Reifephase und die Exitphase).

Die Ergebnisse unserer Untersuchung zeigen einen positiven Zusammenhang zwischen Staging und Beteiligungsrendite, wenn es am Anfang der Investitionsbeziehung – der Investitionsphase – eingesetzt wird. Dies steht im Einklang mit der Agency-Theorie, die dem Staging als Instrument zum Monitoring und zur Unterstützung des Portfoliounternehmens einen wertsteigernden Einfluss zuschreibt. Dagegen beobachten wir einen negativen Zusammenhang zwischen Staging und Rendite, sofern es verstärkt am Ende der Investitionsbeziehung, in der Exitphase, eingesetzt wird. Dieses Ergebnis kann so erklärt werden, dass der Investor bei einer negativen Entwicklung der Beteiligung vor dem „Liquidation Dilemma“ steht. Dies bedeutet, dass er beim Abbruch der Beteiligung die Option auf eine zukünftige Verbesserung der Entwicklung

[17] Bisherige empirische Analysen bezüglich des Zusammenhangs von Staging- Aktivitäten und der Investitionsrendite beschränken sich auf Stichproben aus der Venture Economics Datenbank. Zwar liefern diese detaillierte Informationen zu jeder Investitionsrunde, die Performance-Messung basiert jedoch auf Unternehmensbewertungen und ist damit unpräzise. CEPRES ermöglicht eine exakte Performance- Kalkulation auf Basis der Investment- Cash Flows und gibt darüber hinaus einen detaillierten Einblick in das Staging- Verhalten „zwischen den Runden“ – dem sogenannten Milestone Financing.

und eine potentielle positive Rendite verliert. Aufgrund dieses Dilemmas verzögert der Investor durch Folgefinanzierungen bei kritischen Beteiligungen den Abbruch, um möglichst lange die Chance auf einen Turn-Around aufrecht zu erhalten. Im Falle von Totalverlusten, wo besonders intensives Staging beobachtet werden kann, handelt es sich um erfolglose Rettungsversuche. Der Fondsmanager „wirft gutes Geld Schlechten hinterher", statt rechtzeitig aus der Beteiligung auszusteigen. Wir nennen diesen Nachweis die „dunkle Seite" des Staging.

Die zweite Studie „The Liquidation Dilemma of Money Losing Investments – The Impact of Investment Experience and Window Dressing of Private Equity and Venture Capital Funds" (Krohmer 2007)[18], baut auf den Erkenntnissen der ersten Arbeit auf und untersucht das Verhalten der Fondsmanager bei Beteiligungen in finanzieller Notlage. Insbesondere soll die Fragestellung untersucht werden, ob die Erfahrung des Fondsmanagers von Bedeutung für die Lösung des „liquidation dilemma" ist. Bei einer negativen Entwicklung der Beteiligung steht der Fondsmanager vor der Entscheidung, das Unternehmen weiter zu unterstützen oder aus der Beteiligung auszusteigen, wodurch er jedoch die Option auf eine zukünftige Verbesserung der Entwicklung und eine potentiell positive Rendite verliert. Zahlreiche Studien bestätigen einvernehmlich die Bedeutung der Erfahrung von Private Equity Managern für den Erfolg der Beteiligungen, so beispielsweise Kaplan and Schoar (2005) oder Gottschalg et al. (2003). Boot (1992) fragt "Why hang on to Losers?" und zeigt im Zusammenhang mit Public Equity, dass unerfahrene Manager nicht nur schlechtere Investitionsentscheidungen treffen, sondern erfolglose Investitionen auch zu lange halten. Gompers (1996) zeigt in Bezug auf die Exit- Entscheidung erfolgreicher Beteiligungen, genauer gesagt bei der Entscheidung eine Beteiligung über die Börse zu veräußern, dass junge, unerfahrene Venture Capital Gesellschaften ihre erfolgreichen

[18] Der Artikel wurde auf folgenden Konferenzen vorgestellt: XVI International Conference on Banking and Finance 2007 in Rom; The Paris International Finance Meeting 2007 in Paris; Campus for Finance Research Conference 2008 in Vallendar. Desweiteren wurde der Artikel für zwei noch kommende Konferenzen angenommen: French Finance Association 2008 Annual Meeting in Lille; Conference on the Corporate Finance and Governance of Privately Held Firms 2008 in Oslo. Der Artikel wird derzeit von Gutachtern der Zeitschrift Journal of Business Finance and Accounting geprüft.

Beteiligungen schneller und zu niedrigeren Preisen veräußern. Im Unterschied zu Gompers (1996) untersucht diese Studie den Zusammenhang zwischen Manager Erfahrung und Exit- Verhalten bei *erfolglosen* Beteiligungen. Wir stellen die Vermutung an, dass erfahrene Fondsmanager aufgrund ihrer Fertigkeiten und ihres Know-how das „liquidation dilemma" effizienter lösen können. Diese Annahme wird auf Basis des neu erstellten Datensatzes, in dem die kongruenten Beobachtungen der Datenbanken Venture Economics und CEPRES zusammengeführt sind, analysiert. Aus dem gesamten zusammengeführten Datensatz von 712 Beteiligungen werden zwei Teil-Datensätze erfolgloser Beteiligungen betrachtet, zum einen alle 312 Beteiligungen mit einer negativen Rendite und zum anderen die Untergruppe aller Totalausfälle mit 153 Beobachtungen. Die Rendite wird auf den exakten Zahlungsströmen zwischen dem Fonds und dem Portfoliounternehmen kalkuliert. Die Ergebnisse für beide Teil- Datensätze zeigen, dass unerfahrene Fondsmanager (1) erfolglose Beteiligungen länger in ihrem Portfolio halten, (2) relativ mehr Kapital in diese Beteiligungen zuführen und (3) relativ mehr Folgefinanzierungen (Staging) vor der Liquidation der Verlierer bereitstellen. Analog zu Gompers (1996), der die Unterschiede im Verhalten zwischen erfahrenen und unerfahrenen Fondsmanagern darauf zurückführt, dass jüngere, unerfahrene Manager durch einen Börsengang den Investoren Qualität signalisieren um eine Folgefonds aufzulegen, kann auch für den Fall erfolgloser Beteiligungen argumentiert werden. Unerfahrene Fondsmanager mit geringerer Reputation könnten motiviert sein, die Verlierer so lange im Portfolio zu halten und damit keine Totalverluste in ihrem Track Record auszuweisen, bis sie ausreichend Kapital für einen Folgefonds eingesammelt haben. Diese Beschönigung der Zahlen, auch „window dressing" genannt, kann dem Fondsmanager zwar kurzfristig bei der Beschaffung neuen Kapitals helfen, dies geschieht jedoch auf Kosten der Investoren des gegenwärtigen Fonds. Dieser Aspekt wird in den Analysen der Studie berücksichtigt und es kann nachgewiesen werden, dass „window dressing" zwar eine Rolle spielt, die unterschiedlichen Fertigkeiten der Fondmanager aufgrund unterschiedlicher Private Equity Erfahrung dennoch ausschlaggebend für das Verhalten sind.

Der zweite Teilabschnitt dieser Dissertation befasst sich mit der Erforschung der Determinanten des Beteiligungserfolgs und -misserfolgs und liefert konkrete Lösungsansätze für die Praxis bezüglich der Messung und Schätzung des Risikos und der Rendite von Private Equity Engagements. Die erste Studie des zweiten Teilabschnittes „Venture Capital Performance Projection: A Simulation Approach“ ist in Zusammenarbeit mit der BHF Bank in Frankfurt und in Ko-Autorenschaft mit Prof. Dr. Mark Wahrenburg von der Abteilung Finanzen der Goethe Universität Frankfurt und Dr. Daniel Schmidt vom Center of Private Equity Research in München entstanden (Krohmer, Schmidt, Wahrenburg 2006). Das Ziel dieses gemeinschaftlichen Forschungsprojekts war es, ein Modell zur Schätzung von Renditeaussichten für Private Equity-Anlagen zu entwickeln. Das Modell orientiert sich dabei an Ansätzen aus dem Kreditbereich wie etwa CreditPortfolioView von Wilson (1997) und baut auf bisherigen Erkenntnissen aus der Erforschung der Erfolgsdeterminanten von Private Equity Beteiligungen auf. Als Inputparameter für das Projektionsmodell werden lediglich Erwartungen makroökonomischer Entwicklungen und Informationen über das Anlageprodukt, welche aus dem Platzierungsprospekt ersichtlich sind, benötigt. Der vorgestellte Ansatz besteht aus drei grundlegenden Ablaufschritten: (1) Schätzung der Renditen der einzelnen Beteiligungen im Portfolio über einen Regressionsansatz, (2) Schätzung der Gesamtportfoliorendite gemäß der im Prospekt beschriebenen Struktur, und (3) Simulation unterschiedlicher Szenarien der Einflussfaktoren über einen Monte Carlo Ansatz. Im Ergebnis kann eine Aussage über die Bandbreite der zu erwartenden Rendite gemacht werden. Im ersten Schritt werden zunächst Faktoren, die historisch Einfluss auf Private Equity Renditen ausübten über eine lineare Regression identifiziert. Der hierzu verwendete Datensatz muss dabei dem Fokus der betrachteten Anlage entsprechen. Diese Studie betrachtet Venture Capital Beteiligungen und verwendet daher einen Teildatensatz aus dem Gesamtbestand von CEPRES[19] mit Informationen zu 3.737 realisierten Venture Capital Transaktionen. Es werden nicht nur

[19] Zum Zeitpunkt der Durchführung der Studie umfasste der CEPRES Datensatz Informationen zu über 13.000 Private Equity Beteiligungen.

gesamtwirtschaftliche Einflüsse wie beispielsweise Zinsentwicklung, Bruttosozialprodukt oder Börsengänge betrachtet, sondern auch investorspezifische (Erfahrung), fondsspezifische (Fokussierung, Größe, Dauer) und beteiligungsspezifische (Branche, Herkunftsland, etc.) Faktoren in die Regressionsanalyse mit einbezogen. Eine Besonderheit des Modells besteht darin, dass die Regressionsanalysen nur für eine Teilgruppe der Beobachtungen durchgeführt werden. Dies wird folgendermaßen begründet: Private Equity und insbesondere Venture Capital Investitionen sind einerseits durch sehr hohe Ausfallraten geprägt, andererseits erwirtschaften einige wenige „Homeruns“ außergewöhnlich hohe Renditen. Dadurch weisen historische Renditen stark rechtsschiefe Verteilungen auf. Regressionen auf Basis aller Beobachtungen würden die Koeffizienten verzerren. Die Analysen werden nur auf Basis der sogenannten „Normal-Performer“ mit Renditen zwischen -99% und +99% durchgeführt. Dieser Ansatz basiert auf der Erkenntnis, dass die historischen Renditen für diese Teilgruppe annähernd normalverteilt sind. Die Ausreißer werden im nächsten Schritt bei der Schätzung der Gesamt- Portfoliorendite berücksichtigt. Die Anteile der Ausreißer am Portfolio werden auf Basis historischer Ausreißerraten unter Berücksichtigung der Branche und der Investitionsphase der Beteiligungen ermittelt.[20] Als Ergebnis des zweiten Schrittes erhält man eine Schätzung der Portfoliorendite. Im dritten Schritt werden verschiedene Szenarien der ungewissen Einflussfaktoren simuliert. Dabei werden auf Basis von historischen Verteilungen und zukünftigen Erwartungen Wahrscheinlichkeitsverteilungen und Korrelationen für die jeweiligen Einflussfaktoren definiert. Als Endergebnis dieses iterativen Prozesses erhält man eine Wahrscheinlichkeitsverteilung der geschätzten Portfoliorendite.

Die Risikocontrolling-Software PerFore™ wurde von CEPRES auf Basis dieser Studie entwickelt. Heute setzen es zahlreiche institutionelle Investoren im Portfoliomanagement ein,

[20] Soll beispielsweise die Rendite für ein Portfolio geschätzt werden, für das gemäß Fondsstruktur und historischen Ausreißerraten ein Anteil von 30% Totalausfällen und 10% sehr erfolgreichen Beteiligungen erwartet wird, so ergibt sich die Schätzung der Gesamtportfoliorendite für ein Portfolio aus 100 Beteiligungen folgendermaßen: 30 Beteiligungen werden mit -100% angesetzt, 10 Beteiligungen erwirtschaften eine Rendite über 100%, für die verbleibenden 60 „Normal-Performer“ werden die Renditen über die Regressionsgleichung geschätzt.

Private Equity Gesellschaften nutzen es zur Vermarktung ihrer Produkte und eine österreichische Förderbank verwendet es, um Garantien auf Private Equity Beteiligungen zu bewerten.

Die letzte Studie dieser Dissertation „Modeling Default Risk of Private Equity Funds – A Market-based Framework" (Krohmer und Man 2007) ist in Ko-Autorenschaft mit Kwok-Sing Man von der Abteilung Finanzen der Goethe Universität Frankfurt entstanden und stellt eine Erweiterung des Projektionsmodells der dritten Arbeit dar. Motiviert durch Erkenntnisse aus der praktischen Anwendung des Modells und Anregungen aus den Diskussionen mit Anwendern aus der Praxis, verfolgt diese Studie das Ziel, ein Modell zur Bestimmung der Ausfallraten von Private Equity Portfolios zu entwickeln. Während die Ausfallratenbestimmung bei dem im vorangegangenen Abschnitt vorgestellten Projektionsmodell aus Gründen der Praktikabilität rein statisch, auf Basis der historischen Ausfallraten erfolgt, gehen wir in dieser Studie davon aus, dass Ausfallraten von Private Equity Beteiligungen insbesondere von gesamtwirtschaftlichen Entwicklungen abhängen. Für den Kreditbereich konnten sehr deutliche Zusammenhänge zwischen Marktzyklen und Kreditausfällen nachgewiesen werden. Vor dem Hintergrund der Besonderheiten des Private Equity Marktes und inspiriert durch Modelle aus dem Kreditbereich, entwickeln wir ein fünfstufiges Modell zur Bestimmung der Ausfallratenverteilung von Private Equity Portfolios: (1) Über einen logistischen Regressionsansatz werden Faktoren bestimmt, die einen Einfluss auf die empirischen Ausfallwahrscheinlichkeiten von Private Equity Beteiligungen haben. Studien aus dem Kreditbereich haben gezeigt, dass unterschiedliche Branchen oder Regionen auch unterschiedlich stark von wirtschaftlichen Entwicklungen betroffen sind. Daher werden separate Regressionsanalysen für mehrere Gruppen, unterteilt nach Region, Branche und Entwicklungsphase der Beteiligung, durchgeführt. Die Untersuchungen dieser Studie basieren auf einem Auszug aus dem Gesamtdatenbestand von CEPRES[21]. Es werden 3.941 realisierte Beteiligungen aus den USA berücksichtigt und für die Analysen zunächst in Buyout und Venture

[21] Zum Zeitpunkt der Durchführung der Studie umfasste der CEPRES Datensatz Informationen zu über 16.000 Private Equity Beteiligungen.

Capital unterteilt. Innerhalb dieser beiden Stichproben, werden fünf Branchengruppen gebildet. (2) Im zweiten Schritt werden für die identifizierten makroökonomischen Faktoren aus Schritt 1 zukünftige Entwicklungen über das so genannte ARIMA- Verfahren modelliert. Diese Prognosen dienen als Inputfaktor für den nächsten Schritt. (3) Die ersten beiden Schritte bilden die Basis für die Simulation der jährlichen Ausfallwahrscheinlichkeiten für jede Untergruppe. Es werden Werte aus den in Schritt zwei generierten Prognoseverteilungen gezogen und in die logistischen Gleichungen aus Schritt eins eingesetzt. Man erhält die jährlichen Ausfallwahrscheinlichkeiten für jedes Jahr der gesamten Fondslaufzeit, für jede nach Region, Branche und Phase unterteilte Analysegruppe. (4) Um die jährlichen Ausfallwahrscheinlichkeiten für das gesamte Portfolio zu bestimmen, werden gemäß der im Fondprospekt definierten Fokussierungsstrategie (nach Region, Branche, Phase) gewichtete Mittel gebildet. (5) Ziel dieses Modells ist die Bestimmung der Ausfallratenwahrscheinlichkeit von Private Equity Portfolios am Ende der gesamten Fondslaufzeit. Daher müssen die geschätzten jährlichen Portfolio-Ausfallwahrscheinlichkeiten gemäß der im Prospekt festgelegten Gesamtlaufzeit über alle Jahre auf einen Endwert aggregiert werden. Hierfür werden die Werte aus Schritt vier auf Basis historischer Veräußerungsverteilungen vergleichbarer Fonds gewichtet und aufsummiert. Um verschiedene Entwicklungsszenarien der Einflussfaktoren zu berücksichtigen, werden die Schritte 3 bis 5 über eine Monte Carlo Simulation für eine festgelegte Anzahl an Iterationen wiederholt. Als Endergebnis des Modells erhält man eine Verteilung der geschätzten Ausfallrate des Gesamtportfolios am Ende der Fondslaufzeit.

Weitere Arbeiten, die während der Promotion erstellt wurden, sind aufgrund des begrenzten Umfanges dieser Dissertation nicht mit aufgenommen worden und werden im Curriculum Vitae aufgelistet.

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München, im April 2008

Philipp Krohmer

Contents

CHAPTER A (I)

The Bright and Dark Side of Staging: Investment Performance and the Varying Motivations of Private Equity Firms

The Bright and Dark Side of Staging:

Investment Performance and the Varying Motivations of Private Equity Firms

by

Philipp Krohmer*, Rainer Lauterbach* and Victor Calanog**

Abstract

Previous papers that examined investment decisions by private equity funds are divided on whether staging has a positive or negative effect on returns. We believe these opposing views can be reconciled by studying *when* staging is used during the life of the investment relationship: We find that staging is positively associated with investment returns in the beginning of the investment relationship, consistent with the notion that staging helps mitigate information asymmetry. However, staging appears to be negatively associated with returns when used prior to the exit decision. Our unique dataset allows us to measure these intertemporal effects precisely.

JEL classification: G24; G11; G33

Key words: Private Equity; Staging; Investment Decisions; Liquidation

* Goethe Universität Frankfurt, Finance Department
** Wharton Business School, University of Pennsylvania, Philadelphia

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Please address all questions or comments to corresponding author Philipp Krohmer, Department of Finance, Johann Wolfgang Goethe-University Frankfurt am Main, Germany and CEPRES Center of Private Equity Research, email-address for correspondence: philipp.krohmer@cepres.de We thank Venture Economics and CEPRES for generous access to data. Constructive comments were provided by Mark Wahrenburg as well as participants in seminars at the American Finance Association's 2007 meetings, the Global Conference on Business & Economics at the Harvard Graduate School of Education, the Global Finance Conference 2006, the HVB Doctoral Conference, the Ninth Conference of the ECB-CFS Research Network and the brown bag seminars in Goethe University. We also thank the staff at the Wharton School's Lippincott Library for research assistance. All errors are our own.

Introduction

Staging involves the sequential disbursement of capital from a private equity (PE) or venture capital (VC) fund to a portfolio company, often dependent on whether companies receiving funding have satisfied predetermined targets. Our objective is to study the relation of staging and investment performance. Previous theoretical and empirical studies have yielded mixed predictions and results. Neher (1999), Hsu (2002) and Wang and Zhou (2004) provide theoretical models that predict positive returns from the use of staging. Gompers (1995) asserts that companies that successfully go public (and that earn the highest returns for their PE/VC investors) receive more total financing over a greater number of rounds than companies that go bankrupt or are acquired, providing empirical support for the optimistic view. On the other hand, Bergemann and Hege (1998) and Cornelli and Yosha (2003) suggest that there may be a theoretical basis for expecting negative returns from the use of staging. Hege et al. (2003) provide supporting empirical evidence, finding that the number of financing rounds appears to result in negative IRR and inferring that "… [their results are] at odds with standard manager-shareholder agency theory that predicts that stage financing and monitoring are value increasing."

We believe these opposing views can be reconciled by examining *when* staging is used during the life of the investment relationship: We define the beginning of the investment relationship as that point when the PE/VC fund provides the initial cash injection into the portfolio company and becomes a shareholder in the portfolio company. The end of the investment relationship is marked by that point when the PE/VC fund liquidates its investment in a particular firm, whether by taking the company public, selling the company in the private markets, or writing off the bad investment as a loss. Note that the life of the investment relationship is independent of the age of the portfolio company: A PE/VC fund may invest money in a start-up company that has yet to launch its first product, or in a 20 year old privately owned firm looking for financing to enable its expansion into different product or geographical markets. Like any other investor, PE/VC funds are concerned with maximizing returns while minimizing risks. We speculate that investors disbursing capital at the beginning of an investment relationship may have different motivations and expectations compared to investors disbursing funds prior to making an exit decision. We test whether these different motivations and resulting behavior, manifested during the beginning and end of the investment relationship, explain the varying impacts of staging on investment returns. Given the intertemporal nature of our approach, it is necessary for us to measure the precise amount and timing of cash injections and withdrawals over the complete life of the investment relationship. No other study has been able to do this in the past because of data limitations. In order to address these difficulties, we rely on a unique database that we created using the combination of information on PE and VC deals from *Venture Economics* and CEPRES. Our results suggest that staging does appear to have a positive relation with investment returns when used at the beginning of the investment relationship. This is in line with standard agency theory, where investors apply staging as a monitoring instrument to mitigate agency problems and provide needed resources to the portfolio company. At the end of the investment relationship, however, we find that firms in distress receive more frequent rounds of cash injections as investors "gamble for resurrection," perhaps attempting various turnaround efforts in the hope of minimizing losses. We interpret this as the potentially "dark" side of staging, and offer a set of explanations as to why financing rounds may be inefficiently employed in this phase of the investment relationship, often not achieving goals of minimizing losses, and perhaps even as an attempt of window dressing.

The paper is organized as follows. Section 1 reviews the literature on staging behavior. In Section 2 we explain our empirical approach in defining various phases in the life of the investment relationship. Section 3 provides hypotheses regarding the influence of staging on investment performance, conditional on when staging is employed over the life of the investment relationship. We describe the data in Section 4 and present analyses in Section 5. Section 6 concludes the paper. Tables and figures are collected in Section 7.

1 Literature

Several theoretical models explore how staging may influence investment performance positively, increasing efficiency in financial contracting and leading to optimal investment decisions both on the part of the investor as well as the entrepreneur. Admati and Pfleiderer (1994) develop a model of robust financial contracting, showing how inside investors like a PE/VC fund help resolve various agency problems that arise in multistage financial contracting. Neher (1999) argues that upfront financing may be suboptimal since the entrepreneur has an incentive to lower outside investors' shares of the enterprise through renegotiation once the investment is sunk. In this view, staging helps mitigate the commitment problem since early rounds of investment generate collateral that support future rounds. Hsu (2002) analyzes VC investments using a real options framework, concluding that staging not only gives the investor a "wait and see option" but also provides disincentives against underinvestment by entrepreneurs. Wang and Zhou (2004) show how staging for companies with high growth potential is superior to upfront financing, but qualify that upfront financing may be better for projects that are not too promising.

Other theoretical models provide reasons why staging may result in poor investment returns. Lerner (1998) discusses the Bergemann and Hege (1998) model and how portfolio companies' control over information flow limits benefits that funds may receive from using staging to elicit information about the firm's performance, concluding that "this appears to contradict the critical evidence in Gompers' empirical examination of staged financing." Cornelli and Yosha (2003) explore how staged financing creates a conflict of interest between the investor and entrepreneur, inducing the entrepreneur to focus on meeting the immediate hurdle of the next stage instead of focusing on long-term returns. They develop a model showing that this type of window dressing by the entrepreneur reduces the investor's payoff because the refinancing/liquidation decision is based on lower quality information. Baker (2000) similarly concludes that managers have incentives to inflate interim returns, with career concerns reducing any efficiency benefits conferred by staging.

Empirical studies reflect these conflicting findings. Gompers (1995) provides evidence of the positive effects of staging, linking staging behavior with exit decisions. His paper studies investments from the perspective of portfolio companies, showing how companies that go public (his measure of “investment success”) receive more total financing and a greater number of financing rounds. In an approach analogous to ours, Sahlman (1990) differentiates different stages in the company’s development, including seed, startup, first to fourth stage, bridge and finally liquidity stage at the exit event. He finds that staging is a powerful instrument that influences the company’s development (with positive results for investment returns). Note however that his definition of the life of the investment relationship is directly linked to the age of a particular company: As we stated in the introduction, our approach defines the life of the investment relationship based on when the PE/VC fund enters as a shareholder and liquidates the investment. This is independent of the age of the company.

Hege et al. (2003) provide empirical evidence that suggest that staging may have a negative influence on investment performance. They calculate investment returns from reported valuations in the *Venture Economics* database, suggesting that negative returns are associated with a larger total number of financing rounds. They point out that this result is at odds with standard manager-shareholder agency theory that predicts that stage financing and monitoring are value-increasing.

2 Empirical Strategy

In contrast to several of the previous studies that focused on the performance of portfolio companies, this paper focuses on the investor’s concerns. Specifically, we measure particular PE/VC funds’ decision to inject capital into specific portfolio companies, capturing each capital injection from the fund to the portfolio company until the exit stage is reached and proceeds flow back into the PE/VC fund. From the investor's perspective the life of the investment relationship starts with the initial capital injection into the portfolio company. The investment relationship ends with the exit decision as capital is distributed back into the PE/VCfund. Investors can time their initial investment at any stage of a given portfolio company's development, whether in the early stages for seed financing, or in more mature stages (expansion or pre-IPO). Although PE and VC investments are frequently syndicated, implying that any one fund has only partial influence on the company's performance, each investor independently decides on whether to pull out and exit from the deal, or provide follow-on financing, implying specific influence on the return of individual fund investments.

PE/VC funds can use staging as an instrument that helps determine whether follow-on financing will be provided. Associated with this decision is the choice of what level of supervision and support to provide. At each round of financing, the fund decides on whether to exercise predetermined options like providing follow-on financing or abandoning the project and terminating the investment. Given the evolving nature of portfolio companies' performance, it is not unreasonable to assume that the investor's motivations to apply staging may change over time. This may lead to changes in the magnitude and frequency of cash injections, which implies variation in the impact of staging on investment performance. Our speculations about these different motivations and associated investment behavior will be introduced in detail in section 3 as we present our hypotheses.

As we focus on changes in staging behaviour and its relation with return on investment, we take a segmentation approach to enable us to measure changes in behavior. We segment the total life of every investment relationship into three time periods. A minimum of three phases is necessary and sufficient to allow us to observe changes in investment behavior within any given investment relationship. However, investment relationships have varying lifespans: For the investments identified in this study, lifespans range from 2 to 8 years**.** To standardize the three phases for all investments, we cut the total life of the investment relationship into three time periods of equal length. This segmentation in sections of relative length is appropriate for empirical analyses across multiple investments by different investors in varying companies. While the actual terms and actions for each investment may not be the same, the underlying challenges within each of the three time periods are similar across all investments. We perform detailed analyses on the investors' staging behavior and its impact on investment returns for each of the three time periods separately.

During the first third of the investment relationship the investor provides the initial cash injection. By revealed preference and the assumption of individual rationality, the beginning of any relationship between an investor and the company is marked by an expectation of positive returns from both parties: Otherwise the relationship wouldn't have been started. We name this first phase the initial phase (*i*-phase). In the second third of the investment relationship, the company must prove its abilities to meet milestones and progress as anticipated. The relationship has matured and the investor has gained information about the company's strengths and weaknesses. We call this second phase the maturity phase (*m*-phase). During the final third of the investment relationship, the outcome of the investment will be realized. The investor and the company decide on the type of exit, whether it be the initiation of a listing at a public stock exchange, the private sale of the company, or termination of the investment, an option which carries with it the risk of letting the project slip into insolvency. As exit plans are prepared during this stage of the investment relationship, we call it the pre-exit-phase (*p*-phase).

Measurement of Financing Rounds and Tranches

We measure staging behavior in very precise terms: First, we quantify the number of financing rounds for all three phases of the investment relationship. However, in practice each financing round is further broken down into cash injections or tranches. Information about financing rounds alone without considering the underlying tranches would present an incomplete picture of the complexities of staging behavior. Limiting the measurement of staging behavior to the level of financing rounds also implies a less precise measure of IRR given that cash flows occur *within* financing rounds. Having detailed information about *both* financing rounds *and* tranches allows us to examine the determinants of staging behavior and investigate how changes in staging behavior affect investment returns. Table 3 in the Section 7 presents summary statistics for the number of tranches for each financing round. The frequency of staging is clearly seen *across* financing rounds, but it is also evident that staging occurs *within* financing rounds. A company will receive several cash injections within a given financing round if it does not receive the complete amount of capital committed by the PE/VC fund upfront. Each financing round is an opportunity for the investor to make a decision whether or not to continue the relationship. Within each financing round, the investor can opt to cease any further cash injection if agreed milestones are not achieved; otherwise the investor is usually contractually obliged to finance all tranches until the current financing round is completed. Disaggregating the total amount of committed capital within each financing round into smaller cash injections gives the investor more control over how capital is allocated: An option to provide just enough cash to the company given its development needs is created, enforcing a more disciplined focus to reach goals that were mutually determined. Terms and conditions, which include estimates of company valuation, share and non-participation rights, are negotiated for each financing round but usually remain unchanged for each tranche. At the first glance, measuring staging on the tranche level might look superior to the measurement based on financing rounds. However, in some cases tranching can simply reflect capital management rather than staged financing[1]. Therefore, we consider both terms in our analysis to provide a precise picture.

Given the interrelated nature of tranches and financing rounds, we introduce a new measure in this study: The ratio of the number of tranches to the number of financing rounds from the fund to its portfolio company, which may provide an indication of what drives financing decisions for particular PE/VC funds. Suppose the total capital of the financing round is provided upfront rather than in several tranches: In this situation, the fund will have less control over

[1] E.g. imagine a financing round in which investors commit $20 million to build a factory. The builder of the factory requires a $10 million payment upon commencement of construction and $10 million when the building is completed.

portfolio company operations relative to when each tranche is payable upon completion of a milestone. We interpret a higher value of the tranche-to-round ratio as implying more management intervention. A lower tranche-to-round ratio may be interpreted as an expression of the investor's confidence that the company does not need as much oversight, and will make optimal use of committed capital given contract terms.

3 Hypotheses and Predictions about the Influence of Staging on Investment Performance

The staging decision is essentially a signal of the investor's preference for the level of control it wishes to exercise, as well as the amount of resources it chooses to allocate. These resources may come in the form of capital, managerial support, knowledge transfer, time or effort. We analyze this active role of the investor and staging behavior with respect to the number of investments made, as well as the frequency, duration, amount and timing for each portfolio company. Given the active role that PE and VC funds as investors play, the type of staging decision as well as the motivations behind its use presumably has a direct impact on investment performance. We present an overview of the variables we examine in this paper in Table 1.

Initial Investment Phase (*i*-phase) Predictions

While previous papers focused only on staging behavior over the total post-investment period (mostly due to data limitations), our approach allows us to examine possible variations in the use of staging for each of the three phases. Do investors allocate a different level of resources across the different phases? As outlined earlier, we expect the *i*-phase to be marked by expectations about positive returns by both the PE/VC fund and the portfolio company, given the uncertainty of whether the investment will succeed or not. Information asymmetry is perhaps the most significant concern for the investor during the *i*-phase: The investor needs time to learn about the management team, the company's strengths and weaknesses and several other factors to better assess future prospects, and staged financing helps the PE/VC fund elicit the information it needs from the portfolio company. Staged financing may also play a critical role in mitigating moral hazard, given that it may induce higher effort from the entrepreneur. One reason for relatively high agency costs during the *i*-phase is the possibility that the entrepreneur might divert capital to his private benefit given that he or she is now awash in cash. This is in line with Neher (1999), who argues that staging can reduce the hold-up problem.

Hellmann and Puri (2002) find that active investors play a part in a company's success, showing how VC-financed firms are more likely to professionalize in a shorter period of time by adopting stock option plans or by bringing outsider CEOs to run the company. Better information flow may also enable investors to react more quickly should things go awry (by enforcing changes to the management team, for example), and through this help to further improve the prospects of portfolio companies. During the *i*-phase, we argue that more staging mitigates agency costs and leads to higher investment performance.

Prediction 1 – We predict that a higher share of the number of financing rounds and tranches during the *i*-phase in relation to the total investment period is positively associated with investment returns.

There is some ambiguity as to whether capital investment and effort are complements or substitutes. It is quite possible for investors who shell out a large amount of cash to devote less time to a project, arguing that firms that receive less cash require more attention. This does not seem to be the case for the typical PE/VC fund, most of which tend to assume an active role in portfolio companies. For the purposes of this paper, we assume the complementary relationship, implying that the investment manager will align his allocation of effort and resources with his allocation of capital to the portfolio companies. Investors will inject a relatively higher amount of capital for the most promising firms during the *i*-phase and will provide relatively more support. We do not observe the investor's relative effort across every company in its portfolio, but we do observe relative amounts of capital investment for particular portfolio companies. This relatively higher amount of resource allocation, both in terms of capital investments and effort, during the *i*-phase augurs well for the company's growth prospects *ceteris paribus*. All of this implies a positive relation with investment returns

Prediction 2 – A higher relative share of investment amount during the *i*-phase is positively associated with investment returns.

Pre-Exit Phase (*p*-phase) Predictions

During the pre-exit phase the investor makes the final decision on how to exercise the exit or termination option in an optimal manner. For successful companies, the exit decision is primarily a question of the best time and way to sell valuable assets. For unsuccessful companies dependent on external financing, the investor's decision to terminate the investment relationship implies the possibility of having the portfolio firm become illiquid or insolvent. These investments are written off completely, appearing as a total loss in the investor's books, hurting reputations and possibly impeding future business and career prospects for both the investor and entrepreneur. Sunk cost fallacy aside, the entrepreneur and the investor put in tremendous effort to avoid a complete failure of invested capital and work. In critical situations, the survival of the company often depends on the willingness of the investment manager to inject further capital. The investment manager faces a significant agency problem in solving this *termination dilemma*: How to balance his own personal interest by seeking to avoid failure, against the limited partners' (LP) interest as principal to minimize losses in unsuccessful projects. Should the investment manager cut his losses or gamble for resurrection?

Technically, staging offers the investment manager the option to abandon poorly performing investments and minimize further associated expenses. However, an interesting dynamic arises during the *p*-phase. Given the passage of time and the application of staging and various mechanisms during the course of the investment relationship, the investor presumably has better information about the portfolio company's prospects relative to the *i*-phase. Between the *i*- and *p*-phases it is often when *information about negative performance* is received that investors' attentions are focused: Investors typically seek out detailed reasons behind negative deviations from predetermined milestones. This is related to the idea in Bergemann and Hege (1998), where monitoring occurs when more information is produced, but note the *simultaneity* of monitoring and information acquisition: More information is demanded, produced and acquired when investors scrutinize the company's performance more closely, and negative performance is what invites closer scrutiny.

Closer scrutiny in the context of staging implies the imposition of either (a) more financing rounds, and/or (b) more tranches within financing rounds. A higher share of tranches during the *p*-phase can be interpreted as the investor seeking more control relative to earlier phases. This is usually an indication of negative company performance results in previous periods: Additional cash injections during the *p*-phase may be a signal that the company is not meeting milestones. Similarly, a high tranche-round ratio during the *p*-phase splits the round in more tranches so that the investor can have greater control over milestone accomplishments. A higher tranche-round ratio also implies *more options or opportunities* to abandon the project relative to previous phases, and should perhaps be considered by the ailing portfolio company a warning signal.

We arrive at one of the key findings of our paper. In critical situations the investor faces the *termination dilemma*: If he decides to abandon the nonperforming project he avoids incurring further costs, but also forfeits the possibility of a turnaround, ending up with some better return relative to what is currently expected. In critical situations, with portfolio companies dependent on external financing, the follow-on financing arrangement gives the company and the investor a termination grace period, allowing the investor one last chance to observe developments and come up with a plan to perhaps stimulate some improvement. We interpret increased staging during the *p*-phase as the investor providing stepwise grace periods and attempting to address the termination dilemma by postponing his decision to abandon nonperforming projects. This is in line with the argument presented by Kahl (2002) where creditors – in our case investors – often lack the information that is needed to make a quick and correct liquidation decision. Kahl (2002) explains that the long-term nature of financial distress is the result of dynamic learning strategies of lenders and suggests that it may be an unavoidable byproduct of an efficient resolution of financial distress. While creditors may not see the negative impact of this postponement on performance due to the fixed nature of credit returns (assuming that default is in fact prevented or recovery upon default is 100%), the equity investor will suffer a reduction in IRRs due to the temporal dimension.

An increased amount of monitoring during the *p*-phase may therefore be associated with lower performance. An increased share of rounds during the *p*-phase may therefore indicate the distinct (and troubling) possibility that the investor was not willing to abandon the project in time.

Prediction 3 – During the *p*-phase, the relative share of financing rounds and tranches as well as the tranche-round ratio increases in critical situations.

This is related to several strands of literature in behavioral economics and finance. According Kahneman and Tversky (1979), people underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty. This implies a tendency towards risk seeking in choices involving sure losses. If this holds in situations where a company's survival is in danger, the investment manager will prefer to shell out more cash to preserve the turnaround option, versus the sure loss of terminating a non-performing project. The tendency for risk seeking in choices involving sure losses leads to a higher share of financing rounds as well as a higher share of committed capital during the *p*-phase in critical situations.

Prediction 4 – The share of the investment amount during the *p*-phase increases in critical situations.

4 Dataset Description

Given our need to measure the amount and frequency of financing rounds and tranches as well as investment performance, we required specific data points that were not available using conventional datasets used by previous papers that examined staging. To obtain the data we needed, we merged variables from *Venture Economics* (www.thomsonfinancial.com) - which is very comprehensive for each financing round but does not contain information about the separate tranches within each round - with variables from a database from the Center for Private Equity Research (*CEPRES*) (www.cepres.com), which provides details on each cash transaction using information collected from due diligence reports, including audited filings of investment firms. *CEPRES* is a private consulting firm affiliated with the University of Frankfurt, Germany, and was formed in 2001 specifically to gather detailed fund- and industry-specific information on private equity and venture capital deals across different countries. For these purposes, *CEPRES* has established the so-called "CEPRES data exchange community". Community members (mostly GPs) get in exchange for their very detailed data exclusive access to unique benchmarking services of their direct investments process and substantial discounts on all other CEPRES consulting services. Besides strict confidentiality agreements, all data are completely anonymized and for publications sufficiently aggregated to impede deciphering. *CEPRES* requests the data directly from the cooperating fund managers through standardized information request sheets and additionally validates all data with due diligence reports, including audited filings to guarantee high quality information. Though not as comprehensive as the *Venture Economics* database (as of November 2003 CEPRES had detailed information for 5,300 deals), its efforts at combing through specific investment filings for particular funds yields valuable insight unavailable to other researchers in the past. The empirical studies of Cumming and Walz (2004), Cumming et al. (2004a) and Schmidt (2004) also provide more detailed information about the CEPRES database.

Previous papers that examined related issues in staging and investment performance also used either Venture Economics or CEPRES as a data source. Gompers (1995) worked with Venture Economics data to examine VC investments and financing rounds. His analysis could not include tranches because information on tranches is not available from Venture Economics. He uses a proxy for measuring performance by classifying the exit type and considering an exit via IPO as success. This measurement approach is imprecise: A highly valued trade sale can provide a higher return on investment than a poorly priced IPO. With information on cash flows from the CEPRES database, we can calculate a precise measure of internal rate of return (IRR).

Hege et al. (2003) define investment performance using valuations based on Venture Economics information. This definition of "IRR" is spurious at best given the nature of financing rounds and tranches: IRR measurements based on Venture Economics valuation data alone can lead to what Kaplan et al. (2002) call "milestone bias," which can materially affect researchers' estimates of returns and valuation patterns over time. Kaplan, et. al. (2002) call tranches or cash injections within a given financing round as "milestone rounds," and point out that the IRR is only technically meaningful when two important data points are identified: The precise timing of cash injections which occur *within* financing rounds, and the exact time when the investor cashes out. One can obtain the dates of financing rounds from Venture Economics but not the dates for cash injections. The exit date provided in Venture Economics also does not always overlap with the exact date of the cash flow distribution back to the investor.

Given our need to measure the influence of staging on IRR, we use financing round data from Venture Economics and combine this with accurate cash flow information for each milestone round (tranche) provided in the CEPRES database. CEPRES data provides precise information about each cash injection from the investor to the portfolio company and each cash distribution from the company back to the investor.

In November 2003, the CEPRES database had detailed information for 5,308 investments in 4,476 portfolio companies by 229 PE and VC funds belonging to 74 different investment management firms. We match this data with associated information on financing rounds from the Venture Economics database, ensuring that the specifics of each investment is consistent: The name of the investment manager, PE/VC firm, fund, and dates of investment of a particular investment manager into a particular portfolio company. Given that we want to control for type of industry, location of portfolio company, location of investment management, etc., we drop any observations which had missing variable data. Since we are studying investment returns using a very specific definition of IRR (cash distributions, not just valuations), we drop all unrealized investments and focus only on those deals that were consummated (including both, successful investments and losses) and which involved a cash distribution back to the investor. For the partially realized investments, we perform a further selection step: we select only those investments where the residual net asset value (RNAV) is smaller than 20% of the sum of absolute cash flows (injections and distribution). This condition ensures that the valuation does not carry to much weight in the IRR calculation as we calculate the IRR for the partially realized investments by taking the RNAV as the last cash flow paid back to the investor.[2] We also drop any observations which involve cross fund investments since we want to study new investments for particular investment managers or funds to test our hypothesis about learning and monitoring especially during the *i*-phase. After ensuring that we had as complete a dataset as possible, we were left with **712** different investments made by **122** PE and VC funds belonging to **51** varying investment managers that we could use for our study. These investments include **1,549** financing rounds with **2,329** cash injections (tranches) spanning a period of **24** years from 1979 to 2003.

While **712** investment relationships are a small sample of the universe of PE and VC deals, we believe our sample is comparable to sample sizes examined by previous studies focusing on staging, exit decisions and investment manager behaviour. Gompers (1995) examined staging based on a sample of 794 venture capital-backed companies provided by Venture Economics. Lerner (1994a) analyzed 350 privately held venture-backed biotechnology firms in regards to the

[2] This selection method is following the approach of Kaserer and Diller (2004)

exit decision of venture capitalists. In a more recent paper, Kaplan and Strömberg (2004) study the investment analyses of 67 portfolio investments by 11 VC funds and find that greater VC control is associated with increased management intervention, which is in line with the results of our study. Our sample may also suffer from reporting bias, in that we observe only those deals where we have complete information about financing rounds and tranches, but given limitations of existing publicly available data and our objective of studying the effect of staging on investment returns we believe that this is a necessary sacrifice. Table 2 provides more detailed descriptive statistics about our sample, including some cross tabulations for industry, age and exit type.

5 Empirical Specifications and Analysis

5.1 Measuring Investment Performance

We measure investment performance by quantifying specific draw downs (cash injections) and distributions for each financial transaction. This detailed information about the complete chain of financing and the precisely dated cash flows enable us to perform exact IRR calculations. We perform the analyses from the investor's perspective from his initial cash injection through the final distribution to derive the IRR for each investment, which we then use to examine staging behavior. With our detailed data and our specific approach, we can then measure the influence of particular investor's staging activities on investment performance.

We calculate the natural logarithm of the IRR for the linear regression analyses to deal with asymmetric distribution of raw returns. Using ln(IRR+1.1) we can include the full spectrum of IRR results, from positive to negative figures as well as write-offs (IRR= - 100 %) analysis, the distributions of which we provide in Panel A of Table 2. We also see in Panel A that the mean absolute return of the PE and VC investments in our sample is 65.2%. If investors chose to place the same amount of cash injections at the same time periods into broad indices like the NASDAQ composite or the MSCI World Index, they would have earned 42.4% and 57.1%, respectively. Excess returns for PE and VC investments support the argument that the higher risk associated with these assets should be compensated by higher returns relative to broad indices composed of publicly traded securities.[3]

5.2 Descriptive Statistics and Analysis

Tables 4 to 6 provide descriptive statistics on staging behavior. We find that investing in tranches is a common strategy across all industry sectors, company stages, ages and types of exit. We find descriptive support for a higher number of financing rounds and tranches for companies at the early stage of development, as well as those that are less than one year old. We interpret this relation as a sign of investors needing to exercise more control and oversight for investments with higher uncertainty due to information asymmetry. Investors want to get to know more about how the firm operates and its future prospects, and uses staging as a tool to obtain more information and gauge performance. Once investors decide to exit, we also find that staging intensity is higher for investments with a negative IRR as well as write-offs. We interpret this support for the idea that tranches are used to control risk, perhaps to minimize losses or as turnaround attempts.

Table 5 gives descriptive statistics on the i-phase and the p-phase. Panel B of Table 5 shows the total tranche ratio (TTR), which is the ratio of the number of tranches by the number of financing rounds. A high TTR means that the investor sliced individual financing rounds into a relatively high number of small cash injections, injecting capital with tight control (a TTR of 1

[3] Our analyses show similar results for absolute and excess return figures. Analyses with excess return figures are available upon request. We compare the return on the PE and VC investments with that of publicly traded securities and calculate excess IRR in the following way: (1) we choose the NASDAQ Composite index and MSCI World Index as the two closest comparable public indices. (2) We replicate the amount and timing of cash injections and distributions we observed in the PE and VC investments for the public indices, mimicking cash flow patterns for the publicly traded securities. Following this method we are able to compare and calculate value and time weighted excess returns for the two selected benchmarks. (3) To deal with asymmetric distribution of raw returns, we calculate the natural logarithm of the excess IRR for the linear regression analyses. (4) We omit the top and bottom 5th percentile to address extreme cases.

implies a lump sum cash injection for a specific financing round). From the discussion above, we should expect higher TTRs in critical situations during the p-phase. The mean TTR of investments with negative returns is 2.26, which is (statistically) higher than the TTR of 1.75 of those with positive returns. The mean TTR is highest (2.27) for investments that were eventually written off. A high TTR can also be interpreted as a measure of the use of tranches to reduce information asymmetries. The mean TTR of high-tech sectors such as Healthcare/Life Sciences, IT, Internet and Media and Telecommunication as well for companies with an age of less than one year at the initial investment is relatively high. In those circumstances, a high ratio of tranches to rounds shows the effort of the investor to both mitigate information asymmetries as well as to frequently interact with the company to more quickly react to information that might lead to closer management or even abandonment of a losing project.

We find little correlation between staging behavior in the *m*-phase (the second or middle stage of the investment relationship) and investment performance. The most material differences which appear to affect investment performance are found in staging behavior during the *i*-phase and *p*-phase, which we explore further in Table 6. We find that companies with positive returns (IRR > 0) received on average about 82% of all tranches during the i-phase and only 7% during the p-phase. Positive IRR firms also received 78% of all financing rounds during the i-phase and just 6% in the p-phase, and obtained 89% of the invested capital during the initial investment phase as opposed to only 3% during the p-phase.

How does this compare to negative IRR investments, or write-offs? During the i-phase these losers receive almost similar relative levels of tranches, rounds and capital than the winners (see the bottom panel of Table 6). We find the most striking differences in the p-phase: Negative IRR investments receive almost three times more tranches (20%), and about three times the number of rounds (17%) than positive IRR investments. Negative IRR investments also receive about four times more of their share of total capital during the p-phase relative to positive IRR investments. Write-offs receive four to five times more tranches, rounds and capital during the p-phase than investments leading to any other type of exit. The most significant difference in the staging behavior during the i-phase versus the p-phase is shown in the mean relative tranche round ratio (RTR) figure: Winners (IRR > 0%) receive 1.19 during the i-phase and only 0.24 during the p-phase, meaning that the winners receive a very high relative number of tranche to round ratio during the i-phase and a low number of tranches and rounds during the p-phase. The losers (IRR <= 0%) receive with a mean RTR of 1.07 an almost equal level of RTR during the i-phase. On a relative scale, losers are associated with a tranche-to-round ratio that is almost three times higher than that associated with winners during the p-phase. In other words, winners and losers appear to receive an equal amount of capital, financial support and oversight at the beginning of an investment relationship. However, winners receive (or require) relatively little support towards the end of the investment relationship, but losers require much more handholding (only to generate negative returns).

5.3 Control Variables and Empirical Analysis

With information about specific details of each investment relationship, we run empirical specifications that control for various observed heterogeneous factors. In particular, we specify control variables for the following:

Experience and regional focus of the specific investment management firm

The PE or VC firm acts as the investment manager for various funds. Several papers (Boot (1992), Gompers (1996), Kaplan and Schoar (2005)) argue that the investment experience of an investment manager affects the investment behaviour and the performance of the funds managed by him. We include two control variables for the PE or VC firm's experience: number of years in business (age) and number of funds raised (fund sequence) until the observed investment. Further we include an interaction term for where the PE/VC investment management firms are located (most of 51 firms we examined were located in the United States and Europe), given that other studies emphasize the relevance of local regulations and macroeconomic conditions on investment managers' choice of assets (Jeng and Wells (2000), Cumming (2002), Keuschnigg (2004), Bottazzi, et al. (2005)).

Type/identity of fund

We control whether the fund is a VC fund or not. Several studies have reflected on the special role of VC funds in terms of adding value to their portfolio company or managing their growth and innovation (MacMillan et al. (1989), Hellmann and Puri (2000), Jain and Kini (2000)). We also control for the impact of the fund size (Lerner and Schoar (2002), Cumming (2002)) and do not find any significant effect on investment performance.

Choice, type and timing of investments

We include six different control variables for specific investments.

1. Syndication may be a relevant factor that positively impacts investment returns (Lerner (1994b), Brandner et. al. (2002), Lockett and Wright (2003), Fluck et. al. (2005)). We control for syndication in our specifications by considering the number of investors in the initial round.
2. We control for the exit of the company via an IPO. Previous studies using Venture Economics data suggest that firms that go public yield the highest return on average and Gompers (1995) shows that these firms receive more total financing and a greater number of financing rounds.
3. We also consider the age of the company at the initial investment of the fund. Amit and Thornhill (2002) suggest that firms are at the greatest risk of failure when they are young and small.

4. We consider whether the portfolio company is active in the high technology industries where informational asymmetries are significant and monitoring is valuable as shown by Gompers (1995).
5. The particular stage of a portfolio company's development may impact information asymmetry and return on investment. We control for the stage of the company at the initial investment of the fund.
6. We also control for the use of convertible securities. Cornelli and Yosha (2003) illustrate an advantage of convertible debt over a mixture of debt and equity in stage financing situations. They argue that when the investor retains the option to abandon the project, the entrepreneur has an incentive to engage in window dressing and positively bias the short-term performance of the project, reducing the probability that it will be liquidated. They further explain that an appropriately designed convertible debt contract prevents such short-term focused behavior since window dressing also increases the probability that the VC will convert debt into equity. Further support of the idea that the optimal financing of investment projects include convertible securities is provided in several previous studies, including Kaplan and Stromberg (2003), Biais and Casamatta (1999), and others.

Overall market conditions at the time of entry and exit

We consider the influence of total committed capital in the overall market at the time of initial investment by particular PE and VC funds in our sample. Several studies suggest that investing in "hot" markets affects the probability of success of specific portfolio companies. Inderst and Mueller (2004) as well as Gompers and Lerner (2000) suggest that "hot markets" increase the valuation of PE and VC funds' new investments, positively influencing the ultimate success of the portfolio company. Gompers (1995) argued that growth of the investment pool may measure entry by inexperienced investors. These new entrants may overinvest and may not monitor companies as effectively as experienced investors. We also consider overall market conditions at the time of exit. Cumming et al. (2004b) show that investors adjust their exit decisions based on liquidity conditions in IPO exit markets, most rushing to exist when markets are liquid, which can have a negative effect on performance.

Table 7 shows the results of our specifications with various control variables. The absolute performance of a specific investment [ln(IRR+1.1)] is our dependent variable. Below we discuss our main results and whether they are consistent with the predictions we presented in Section 3.

Confirmation of Prediction 1: The results shown in table 7 confirm that the relative share of financing rounds and tranches during the i-phase is positively associated with investment returns. The underlying intuition is that more financing rounds as well as tranches enable the investor to monitor portfolio companies more closely, helping reduce agency problems. Staged financing may also induce higher effort from entrepreneurs (Wang and Zhou, 2004). Hellman and Puri (2002) also argue that active efforts by investors help engender more professionalism in company management. A higher share of financing rounds and tranches would enable investors to react quickly to new information, helping boost performance. If investors use cash injections as interactions for adding value to the company by providing advice and support, then we can infer that a higher share of tranches during the i-phase has positive impact on performance. Cuny and Talmor (2003) compare staged capital infusions in the form of milestones (tranches) versus rounds and found positive effects of staged financing in regards to the entrepreneurial effort and the VC's.

Confirmation of Prediction 2: Table 7's results also confirm that the relative share of investment amount during the i-phase (Pi Amount-share) has significant positive influence on investment return. This finding is consistent with Kaplan and Strömberg (2000), who provide evidence that the investor's initial appraisal of the management team is important. We also examine the influence of the initial investment amount both on an absolute level, and relative to the total investment amount. Both measures influence performance positively, consistent with empirical evidence presented by Hege, Palomino and Schwienbacher (2003).

Confirmation of Prediction 3: In various regression models we show that the relative share of financing rounds (Pp Round-share) and tranches (Pp Tranche-Share) as well as the tranche-round-ratio (Pp RTR) during the p-phase is negatively associated with investment performance. Sahlman (1990), Gompers (1995) and Wang and Zhou (2004) argue that staging is a powerful instrument for control, arguing that investors can use staging to abandon nonperforming projects. However, we appear to have found evidence that investors may not be using staging rigorously enough (or at least within a sufficient time frame) to abandon unsuccessful projects. The most pessimistic perspective would posit that fund managers may be "window dressing" their portfolio to impress sponsors, injecting just enough cash to keep losing projects afloat. Lakonishok et al. (1991) show that fund managers tend to oversell stocks that have performed poorly right before their performance evaluations are conducted. Cornelli and Yosha (2003) show in a theoretical model how agents (in this case, the PE or VC fund) have an incentive to positively bias the short-term performance of a project, reducing the probability of liquidation. While holding on to bad investments hurts overall results, a "window dressing" approach may work in the interim, concealing poor performers from appearing in the track record and helping the fund manager maintain the good reputation required to raise the next fund (but reducing existing fund investors' returns).

Confirmation of Prediction 4: The results in Table 7 confirm that an increase of the share of the investment amount during the p-phase (Pp Amount-share) is negatively associated with investment returns. This result appears consistent with a sunk cost effect (Johnstone, 2003), where investors have a bias to commit to further financing and less of an inclination to terminate nonperforming projects. If this effect is operative, the share of financing rounds and of the amount during the p-phase might increase in critical situations. Brockner (1992) also explains that escalating commitment (in our case, more capital injections) refers to the tendency for decision makers to persist with a failing course of action. He argues that escalation is determined, at least in part, by decision makers' unwillingness to admit that their prior allocation of resources to the chosen course of action was in vain.

Our results are extremely robust to several modifications of the empirical set-up. For example, concerning the relevance of local regulations and macroeconomic conditions discussed above, we test the regression models for the subsamples of investments made by investment management firms located in the US and outside the US. Furhtermore, we test the regression models with a data sample selecting only those investments made by VC funds (497 observations) leaving out all observations which were made by funds with no pure VC-focus. With regards to the discussion on only partial influence of the fund manager if the deal is syndicated, we limit the analyses to those deals, where the fund manager holds a boardseat. In addition to the absolute return measure IRR as dependent variable, we test all models with the excess return figures described above. The results are as robust as the analyses presented in this paper and available upon request. All of the specifications pass various tests for linearity, Gaussian distribution of residuals and minimal collinearity and heteroskedasticity.

6 Conclusions

Our findings shed light on the bright and dark side of staging. Staging is a widely used tool in VC and PE financing to deal with information asymmetries, agency problems and the decision to terminate a nonperforming project. Previous studies have shown different directions of the influence of staging on performance. We merge data from Venture Economics and CEPRES to create a comprehensive, objective and accurate sample of 712 matched investments including 1,549 financing rounds and 2,329 precisely dated cash injections. We analyze the data for financing rounds and tranches and examine their influence on investment return measured using a precise IRR specification based on cash flows.

We segment the total investment relationship into three equal phases, examining the influence of staging on investment returns in each phase. We find a positive relation of staging and returns during the initial phase (i-phase). Our results suggest investors successfully use staging to mitigate agency problems and take an active hand in company management that may help boost the probability of success. We call this the “bright” side of staging. We find no evidence that staging behavior affects investment performance during the second phase (*m*-phase) of the investment relationship.

We find increased staging intensity during critical situations in the *p*-phase or pre-exit phase. We also find that staging intensity is associated with negative investment returns. We call this the “dark” side of staging and illuminate a critical dilemma that investors face, which we call the *termination dilemma*: If a portfolio company is struggling and the investor chooses to terminate, he or she avoids throwing good money after bad, but also forfeits the option of a potential turnaround or perhaps a better (less negative) return at the moment of termination. We believe that investors may postpone their termination decision to learn more about the projects viability and name this postponement the grace period particular investors give to companies in which they have invested. However, we also believe that the investment manager faces a double-sided moral hazard if he or she decides to provide follow-on financing: The investment manager needs to cater to both the community of entrepreneurs in which he will find future investment opportunities, but also worry about providing good returns for fund investors. We argue that one way of balancing both needs is to “window dress” nonperforming projects in the interim, to avoid showing a loss in the track record. This aspect is perhaps the most pessimistic view of what investment managers tend to do when faced with nonperforming projects. Convincing empirical proof of window dressing needs to show, using an acceptable counterfactual, that investment returns would in fact have been higher had staging intensity not increased, or had termination occurred sooner, than it actually did. Although we can not clearly answer the question whether staging has a positive or negative impact on investment perfomance due to data limitations, we can solve the puzzle of previous conflicting findings.

Our results suggest that investment managers may need to be more disciplined in using staging to abandon negative NPV projects. The best investment that PE and VC funds can make may well be to allocate more time and effort in the beginning of an investment relationship: Assuming they can identify potential winners well, investment relationships appear to benefit much from close oversight and management in the *i*-phase. Should things take a turn for the worse for particular portfolio companies, investment managers may want to disburse follow-on financing more carefully.

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7 Tables and Figures

Table 1 Variable Names and Descriptions

		Variable Name	Variable Description
Dependant variables	Performance Measures	IRR [Log(IRR+1.1)]	The exact IRR (Internal Rate of Return) based on the investment cashflows [For the regression analysis we take logs of (IRR+1.1)]
		EXIRRnasdaq [Log(EXIRRnasdaq+6)]	Excess IRR of the Private Equity- investment over a simultaneous investment in the NASDAQ Composite Index [For the regression analysis we take logs of (EXIRRnasdaq+6)]
		EXIRRmsci [Log(EXIRRmsci+3)]	Excess IRR of the Private Equity- investment over a simultaneous investment in the MSCI World Index [For the regression analysis we take logs of (EXIRRmsci+3)]
Staging - related variables	Total Staging	Total Duration	Total Duration between the initial investment and the exit date in years (if not fully realised we consider the valuation date instead of the exit date)
		No.of Rounds	Total Number of Financing Rounds the company received
		No.of Tranches	Total Number of Tranches (cash injections) the company received
		Staging-Intensity (Rounds)	The Staging-Intensity (Rounds) is the ratio No.ofRounds/TotalDuration
		Staging- Intensity (Tranches)	The Staging-Intensity (Tranches) is the ratio No.ofTranches/TotalDuration
		Average Duration (Rounds)	Average Duration between Rounds (which is the ratio TotalDurarion/No.ofRounds)
		Average Duration (Tranches)	Average Duration betweenTranches (which is the ratio TotalDuration/No.ofTranches)
		Average Round- Investment [log]	The average Round- Investment is the total investment amount (in real 2003 U.S. Dollars)* divided by the No.of Rounds [for the regression analysis we take logs]
		Average Tranche- Investment [log]	The average Round- Investment is the total investment amount (in real 2003 U.S. Dollars)* divided by the No.of Tranches
	Initial Round	Initial Round amount [log]	The amount of this fund in its initial investment round in this company (in real 2003 U.S. Dollars)* [for the regression analysis we take logs]
		Initial Round amount/Total Investment	Relative Initial Round amount (The amount of this fund in its initial investment round in this company divided by the total amount the fund invested in this company)
		Initial Round No.of Investors	The Number of Investors which participated in the Initial financing round by this fund
		Initial Tranche amount/Initial Round amount	The ratio of the Initial Tranche and the Initial Round
	Investment Phases	TTR	Total Tranche Ratio (TTR) which is the ratio of No.ofTranches/No.ofRounds
		Pi Tranche-share	The share of the No.of Phase i (investment phase) tranches of the total No. of tranches (Pi Tranches / All Tranches)
		Pm Tranche-share	The share of the No.of Phase m (maturing phase) tranches of the total No. of tranches (Pm Tranches / All Tranches)
		Pp Tranche-share	The share of the No.of Phase p (pre-exit phase) tranches of the total No. of tranches (Pp Tranches / All Tranches)
		Pi Amount-share	The share of the Phase i (investment phase) amount of the total amount (Pi amount / Total amount) [all amounts in real 2003 U.S. Dollars]*
		Pm Amount-share	The share of the Phase m (maturing phase) amount of the total amount (Pm amount / Total amount) [all amounts in real 2003 U.S. Dollars]*
		Pp Amount-share	The share of the Phase p (pre -exit phase) amount of the total amount (Pp amount / Total amount) [all amounts in real 2003 U.S. Dollars]*
		Pi Round-share	The share of the No.of Phase i (investment phase) rounds of the total No. of rounds (Pi rounds / All rounds)
		Pm Round-share	The share of the No.of Phase m (maturing phase) rounds of the total No. of rounds (Pm rounds / All rounds)
		Pp Round-share	The share of the No.of Phase p (pre-exit phase) rounds of the total No. of rounds (Pp rounds / All rounds)
		Pi RTR	Phase i (investment phase) Relative Tranche Ratio.**
		Pm RTR	Phase m (maturing phase) Relative Tranche Ratio.**
		Pp RTR	Phase p (pre-exit phase) Relative Tranche Ratio.**
Other Control- variables	IM	IM Age	The age (years in business) of the Investment Manager at time of Initial Investment
		US-IM	A dummy variable equal to 1 for Investment Managers with the main office in the United States
	Fund	VC-Fund	A dummy variable equal to 1 for Funds specialized on Venture Capital
		Fundsize	Fundsize (in real 2003 U.S. Dollars)*
	Investment	No.of IM	Total No. of Investment Managers invested in the Company
		IPO	A dummy variable equal to 1 for Investments in private Companies that had an IPO (initial public offering) as exit
		Age of Company	Age of the Portfolio Company (in years since founding date) at date of Initial Investment by the Fund
		High Tech	A dummy variable equal to 1 for Companies of the High Tech - Sector [The Company was classified as High Tech, when belonging to one of the following CEPRES Sector categories: healthCare/LifeScience, IT, High Tech, Semiconductor, Software, Internet, Telecommunications]
		Later Stage	A dummy variable equal to 1 for Later Stage Companies [The Company was classified as Later Stage (early stage), when belonging to one of the following CEPRES Stage categories: Later, MBO/MBI, LBO, public to private, Mezzanine, turnaround, recapitalisation (seed, startup, early, expansion)]
		Use of Convertibles	A dummy variable equal to 1 if the investor held a convertible security [the use of convertibles was assumed, when more than 3 periodic disrtibutions occured to the Investor prior to exit/valuation]
	Market	No. Of IPOs	Number of (PE-backed) IPOs at date of exit/valuation
		Comitted Capital	Comitted Capital on the Overall Market at Date of Investment (in real 2003 U.S. Dollars)*

* The inflation adjustment is based on Consumer Price Index (CPI) data for all urban households and all items. Data is derived from the records of U.S. Department of labor (www.bls.gov)

** The Relative Tranche Ratio (RTR) for the Phase n (n = i, m, p) is calculated as follows: RTRn=PTRn/TTR with PhaseTrancheRatio(n) [PTR(n)] = No.ofTranches Phase n/No.of Rounds Phase n

Table 2 Descriptive IRR Statistics for the Total Sample and various Subsets

The two tables summarize performance (IRR) figures for the complete sample of 697 PE and VC investments. The IRR calculation is based on the precise cashflows between the fund and the portfolio company from the initial cash injection from the fund to the portfolio company until the final cash distribution from the company back to the fund. One observation is per company and not per financing round. **Panel A** shows in the left column percentile characteristics and in the right column the mean, median and other statistics. Skewness and Kurtosis values reveal non-normal distributions of the IRRs. In **Panel B**, several subclusters are considered for the analyses of structural differences. Variable description at table I.

Industry Cluster:
The 25 industry classifications provided by CEPRES were aggregated in the following 10 subclusters (comprising CEPRES categories in brackets): 1) Consumer discretionary (Consumer industry/food, Hotel. Leisure, Retail, Textile); 2) Financial Services (Financial Services, Fund of Fund Investments) 3) healthCare/LifeScience 4) Industrial Production (Industrial/Manufacturing, Construction, Traditional Products,) 5) IT (IT, High Tech, Semiconductor, Software) 6) Internet&Media 7) Materials (Materials, Natural Resources/Energy), 8) Services (Environment, Logistics, Waste/Recycling) 9) Telecommunication 10) Others (others, other Services).

Stage Cluster:
The 15 stage Classifications provided by CEPRES were aggregated in the following 4 subclusters comprising CEPRES categories in brackets): 1) Early (seed, start up, early) 2) expansion (expansion, acquisition financing) 3) Later (Later, MBO/MBI, LBO, public to private, Mezzanine), 4) turnaround (turnaround, recapitalisation). The CEPRES categories Spimoff, public and secondary trading do not appear in our sample and therefore no cluster-classification was needed.

Panel A

Internal Rate of Return (IRR)			
	Percentiles	Valid	697
1%	-1.000	Missing	15
5%	-1.000	Mean	0.652
10%	-1.000	Minimum	-1.000
25%	-0.879	Maximum	90.743
50%	0.095	Median	0.095
75%	0.471	Std. Deviation	4.544
90%	1.562	Variance	20.651
95%	3.862	Skewness	13.073
99%	15.754	Kurtosis	231.834

Panel B

	IRR of Investment			
	N	Mean	Median	Std. Dev.
All Investments	697	0.65	0.09	4.54
Industry Cluster				
Consumer Discretionary	47	0.11	0.17	0.88
Financial Services	12	0.46	0.37	0.36
HC/LS	117	0.67	0.09	3.43
Industrial Production	65	0.06	0.20	0.65
IT	178	1.60	0.05	8.00
Internet & Media	78	0.26	0.12	1.57
Materials	14	-0.01	-0.03	0.68
Services	5	0.02	0.28	0.79
Telecommunication	63	1.01	-0.27	4.05
Others	91	-0.03	0.03	1.01
Stage Cluster				
early	224	0.28	-0.42	3.37
Expansion	110	0.48	0.22	1.89
Later	128	1.52	0.21	8.46
Turnaround	13	0.02	0.31	0.63
Age Cluster				
<=1 year	218	0.59	-0.03	3.91
2 to 5 years	169	0.70	0.06	3.25
6 to 20 years	91	1.67	0.08	9.78
older than 20 years	35	0.27	0.29	0.74
Exit Type Cluster				
IPO	80	1.88	0.62	3.64
Sale/Merger	359	0.66	0.16	2.90
Write Off	153	-1.00	-1.00	0.00
else/not specified	105	2.09	0.33	9.58

Table 3 Tranches by Financing Rounds and Return on Investment

The table presents summary statistics for the number of tranches by the number of financing rounds. PE and VC funds can provide the financing of their portfolio companies not only in a single upfront investment, but rather in several financing rounds (between round financing), which can be partitioned further into several cash injections (within round financing), called tranches. Rows 4-8 show various summary statistics for 5 subsets differentiated by the number of rounds. Figure are given for the entire sample of 697 VC and PE investments (columns 2-7), and for the subsets of investments with IRR<=0 (columns 8-13) and IRR >0 (columns 14-19). For explanation: 65 companies out of the data sample have received three rounds of financing during the entire investment period from the initial cash injection by the fund to the portfolio company until the final cash distribution back from the company to the fund. These three rounds were on average (mean) partitioned into 4.12 tranches. The IRR is measured on the precisely dated cashflows between the fund and the portfolio company.

	No.of Tranches					
	N	**Mean**	**Median**	**Std. Dev.**	**Max.**	**% of Total N**
No. of Rounds	*Total Sample*					
1 Round	370	2.05	1	1.71	12	53.10%
2 Rounds	141	3.11	3	1.82	9	20.20%
3 Rounds	65	4.12	4	2.44	18	9.30%
4 Rounds	48	5.04	5	2.46	14	6.90%
5 or more Rounds	73	7.77	7	3.58	18	10.50%
Total	697	3.26	2	2.77	18	100.00%
	Subsample: IRR<=0					
1 Round	147	2.50	2	2.04	12	21.10%
2 Rounds	65	3.48	3	1.98	9	9.30%
3 Rounds	35	4.43	3	2.80	18	5.00%
4 Rounds	30	5.57	5	2.79	14	4.30%
5 or more Rounds	38	7.45	6.5	3.46	17	5.50%
Total	315	3.80	3	2.91	18	45.20%
	Subsample: IRR> 0					
1 Round	223	1.76	1	1.37	9	32.00%
2 Rounds	76	2.79	2	1.63	8	10.90%
3 Rounds	30	3.77	4	1.92	9	4.30%
4 Rounds	18	4.17	4	1.47	6	2.60%
5 or more Rounds	35	8.11	8	3.72	18	5.00%
Total	382	2.82	2	2.57	18	54.80%

Table 4 Tranche and financing round characteristics by various sub-samples for the entire investment period

The tables present summary statistics for several staging related variables for the total data sample of 712 investments. One observation is per company and not per financing round. **Panel A** shows tranche-specific details, **Panel B** provides round-specific information. PE and VC funds can provide the financing of their portfolio companies not only in a single upfront investment, but rather in several financing rounds, which can be split-up further into several cash injections so called tranches. Several subsets are considered for the analyses of structural differences. Variables are as defined in Table I. Details on the subset classifications by Sector and Stage are provided in Table II.

The IRR is measured on the precisely dated cashflows between the fund and the portfolio company. The investment duration is the period of time measured in years between the initial cash injection from the fund to the portfolio company and the final distribition from the company to the fund. The average duration is defined as the investment duration divided by the number of rounds or tranches during this time. The average round investment is the total investment amount from the fund to the portfolio company divided by the total number of financing rounds during the investment duration.

				Tranches				Rounds					
	Total Investment Duration			Number		Avg. Duration		Number		Avg. Duration		Avg. Investment	
	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
All Investments	712	3,98	3,42	3,28	2,00	1,79	1,24	2,18	1,00	2,47	1,89	9916,45	3896,67
Sector Cluster													
Consumer Discretionary	52	4,30	3,89	2,42	2,00	2,67	2,12	1,77	1,00	3,08	2,42	17041,22	10744,65
Financial Services	11	5,71	6,76	2,82	2,00	2,90	3,00	2,83	2,00	2,72	2,38	22821,54	14230,36
HC/LS	117	4,41	3,97	3,83	3,00	1,59	1,17	2,22	1,00	2,75	2,02	6412,14	2702,87
Industrial Production	68	4,46	4,50	2,41	1,50	2,76	2,25	1,75	1,00	3,23	3,05	9702,30	7311,77
IT	180	3,56	3,03	3,19	3,00	1,48	1,08	2,16	1,00	2,21	1,77	7477,21	1726,21
Internet & Media	80	3,64	3,08	3,06	2,00	1,72	1,16	1,99	1,00	2,20	1,55	14998,33	7893,26
Materials	14	5,48	5,99	5,21	3,50	1,53	1,19	4,71	3,50	1,60	1,51	6977,07	2147,87
Services	5	3,81	4,74	2,00	1,00	2,78	2,52	1,80	1,00	2,82	2,52	18667,09	21196,78
Telecommunication	65	2,94	2,28	3,74	3,00	1,07	0,86	2,34	2,00	1,59	1,35	7964,18	3292,51
Others	92	4,39	3,80	3,73	2,00	1,81	1,15	2,42	1,00	2,69	2,14	10887,57	5703,86
Stage Cluster													
early	226	3,74	3,30	3,99	3,00	1,20	0,84	2,69	2,00	1,85	1,28	3821,72	1961,96
Expansion	113	4,53	3,97	3,93	3,00	1,75	1,27	2,33	1,00	2,71	1,78	15097,25	8878,06
Later	132	3,32	2,50	2,18	2,00	1,99	1,47	1,54	1,00	2,53	2,00	16135,14	6819,70
Turnaround	14	3,54	3,13	2,71	2,00	1,83	1,65	1,57	1,00	2,52	2,54	9346,29	5008,92
Age Cluster													
<=1 year	224	4,17	3,71	3,67	3,00	1,68	1,17	2,50	2,00	2,22	1,65	9554,74	3584,59
2 to 5 years	170	3,47	3,08	2,89	2,00	1,63	1,14	2,16	1,00	2,06	1,74	4416,20	1965,50
6 to 20 years	91	4,12	3,29	3,64	2,00	1,75	1,00	2,22	1,00	2,66	1,91	8968,81	4682,98
older than 20 years	36	4,93	4,79	2,28	1,50	3,10	2,73	1,97	1,00	3,44	3,20	36195,28	10814,84
Exit Type Cluster													
IPO	82	3,84	3,17	2,54	2,00	2,02	1,49	1,57	1,00	2,88	2,25	9118,57	2248,18
Sale/Merger	370	4,51	4,03	3,29	2,00	2,10	1,55	2,29	1,00	2,73	2,19	10085,70	4516,41
Write Off	153	1,99	1,57	3,84	3,00	0,47	0,44	2,33	2,00	0,99	0,71	5978,19	2824,33
else/not specified	106	5,10	4,33	2,98	2,00	2,47	1,84	2,05	1,00	3,37	3,00	15742,09	6903,41
IRR Cluster													
IRR<=0	315	3,45	2,67	3,80	3,00	1,15	0,78	2,36	2,00	1,93	1,25	6787,95	2732,17
IRR> 0	381	4,43	3,93	2,79	2,00	2,36	1,75	2,01	1,00	2,93	2,50	12474,76	5678,13

Table 5 Tranche and financing round characteristics by various sub-samples for the i-Phase and p-Phase - in absolute terms

The table presents summary statistics for several phase-specific variables for the total sample of 712 investments. One observation is per company and not per financing round. PE and VC funds can provide the financing of their portfolio companies not only in a single upfront investment, but rather in several financing rounds, which can be split-up further into several cash injections so called tranches. Several subsets are considered for the analyses of structural differences. Variables are as defined in Table I. Details on the subset classifications by Sector and Stage are provided in Table II. We define the total investment relationship period of each investment starting from the initial cash injection from the PE or VC fund to the portfolio company and ending with the final cash distribution from the company to the fund.

We segment the total investment period into three fractional periods of time, each one third of the total period: the first as the initial investment phase, or i-phase; the second as the maturity phase, or m-phase; and the final third as the pre-exit phase, or p-phase. The table shows summary statistics for the following i- phase and p-phase- related staging variables: the number of tranches, the number of rounds and the total investment amount for each phase separately. For illustration: Pp-Amount is the sum of capital injected from the fund into the portfolio company during the p-phase. The last column provides details for the Total Tranche-to-Round-Ratio (TTR). The TTR is the ratio of the number of tranches to the number of financing rounds.

		Tranches				Rounds				Investment Amount					
		i-Phase		p-Phase		i-Phase		p-Phase		i-Phase		p-Phase		TTR	
	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
All Investments	712	1.96	1.00	0.57	0.00	1.23	1.00	0.27	0.00	13329.96	4514.39	1338.68	0.00	1.99	1.33
Sector Cluster															
Consumer Discretionary	52	1.38	1.00	0.52	0.00	1.19	1.00	0.27	0.00	20561.46	10744.65	4270.64	0.00	1.60	1.00
Financial Services	12	2.50	2.00	0.33	0.00	1.67	1.00	0.25	0.00	44124.82	14102.68	1196.72	0.00	1.48	1.21
HC/LS	117	2.10	2.00	0.65	0.00	1.15	1.00	0.26	0.00	8301.58	2771.54	481.71	0.00	2.23	1.50
Industrial Production	68	1.75	1.00	0.35	0.00	1.25	1.00	0.12	0.00	11122.75	8453.37	1177.68	0.00	1.78	1.00
IT	180	1.79	1.00	0.66	0.00	1.17	1.00	0.34	0.00	8947.15	2163.49	1357.89	0.00	1.94	1.45
Internet & Media	80	1.89	1.00	0.57	0.00	1.17	1.00	0.16	0.00	20594.11	11275.39	1289.34	0.00	2.01	1.50
Materials	14	2.29	2.00	0.71	0.50	1.64	1.00	0.29	0.00	17933.44	4381.51	1860.35	39.07	1.90	1.17
Services	5	2.00	1.00	0.00	0.00	1.80	1.00	0.00	0.00	18890.40	21196.78	0.00	0.00	1.04	1.00
Telecommunication	65	2.18	2.00	0.51	0.00	1.22	1.00	0.22	0.00	11734.91	3528.15	711.16	0.00	2.22	1.33
Others	92	2.53	2.00	0.53	0.00	1.46	1.00	0.33	0.00	17143.92	5835.00	1054.03	0.00	2.17	1.34
Stage Cluster															
early	226	2.14	2.00	0.83	1.00	1.29	1.00	0.42	0.00	5925.05	2226.23	954.57	1.77	2.14	1.50
Expansion	113	2.41	2.00	0.56	0.00	1.35	1.00	0.19	0.00	22687.74	12445.19	1123.37	0.00	2.25	1.60
Later	132	1.49	1.00	0.35	0.00	1.07	1.00	0.12	0.00	20136.20	6417.86	2057.14	0.00	1.68	1.00
Turnaround	14	1.57	1.00	0.36	0.00	1.21	1.00	0.07	0.00	11065.95	6620.40	321.80	0.00	1.62	1.50
Age Cluster															
<=1 year	224	2.22	2.00	0.59	0.00	1.35	1.00	0.30	0.00	15341.26	5011.69	1027.47	0.00	1.99	1.33
2 to 5 years	170	1.68	1.00	0.55	0.00	1.17	1.00	0.28	0.00	6301.38	2668.36	305.64	0.00	1.77	1.00
6 to 20 years	91	2.05	1.00	0.62	0.00	1.21	1.00	0.29	0.00	11670.34	6018.22	1297.13	0.00	2.07	1.50
older than 20 years	36	1.61	1.00	0.22	0.00	1.36	1.00	0.14	0.00	35006.32	10800.18	6009.90	0.00	1.38	1.00
Exit Type Cluster															
IPO	82	1.76	1.00	0.21	0.00	1.10	1.00	0.17	0.00	10219.73	2751.34	158.21	0.00	1.81	1.00
Sale/Merger	370	2.06	1.00	0.41	0.00	1.32	1.00	0.19	0.00	14676.33	5928.64	1132.06	0.00	1.94	1.14
Write Off	153	1.58	1.00	1.41	1.00	1.01	1.00	0.63	0.00	6773.09	2639.09	2245.64	614.98	2.27	1.50
else/not specified	107	2.30	2.00	0.21	0.00	1.36	1.00	0.10	0.00	20433.53	6663.69	1660.95	0.00	1.91	1.50
IRR Cluster															
IRR<=0	315	1.95	1.00	0.92	1.00	1.18	1.00	0.41	0.00	9097.68	3119.70	1408.38	54.29	2.26	1.50
IRR> 0	382	1.97	1.00	0.25	0.00	1.27	1.00	0.15	0.00	16978.71	5797.86	1249.83	0.00	1.75	1.00

Table 6 Tranche and financing round characteristics by various sub-samples for the i-Phase and p-Phase - in relative terms

The table presents summary statistics for several phase-specific variables for the total sample of 712 investments. One observation is per company and not per financing round. PE and VC funds can provide the financing of their portfolio companies not only in a single upfront investment, but rather in several financing rounds, which can be split-up further into several cash injections so called tranches. Several subsets are considered for the analyses of structural differences. Variables are as defined in Table I. Details on the subset classifications by Sector and Stage are provided in Table II. We define the total investment relationship period of each investment starting from the initial cash injection from the PE or VC fund to the portfolio company and ending with the final cash distribution from the company to the fund.

Columns 2-9 focus on analyses of the i-phase (columns 10-17 focus on the p-Phase) and provide summary statistics (mean and median) for the following staging variables: Tranche-share, Amount-Share, Round-share and the relative tranche-ratio (RTR). The tranche share of one phase is defined as the ratio of the number of tranches during this phase to the total number of tranches during the total investment period. This ratio works analogous for the investment amount and number of financing rounds. The RTR for phase n (n=i, m, p) is calculated as follows: RTRn = PTRn/TTR with PTRn (PhaseTrancheRatio)n = number of tranches in phase n divided by the number of rounds in phase n. The TTR is the ratio of the number of tranches to the number of financing rounds during the total investment period.

		i-Phase								p-Phase							
		Tranche-share		Amount-share		Round-share		RTR		Tranche-share		Amount-share		Round-share		RTR	
	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
All Investments	712	0.73	0.75	0.83	0.96	0.73	1.00	1.13	1.00	0.14	0.00	0.07	0.00	0.11	0.00	0.47	0.00
Sector Cluster																	
Consumer Discretionary	52	0.76	1.00	0.89	1.00	0.79	1.00	0.93	1.00	0.13	0.00	0.04	0.00	0.11	0.00	0.39	0.00
Financial Services	12	0.79	1.00	0.90	1.00	0.78	1.00	1.05	1.00	0.12	0.00	0.05	0.00	0.12	0.00	0.29	0.00
HC/LS	117	0.70	0.67	0.82	0.91	0.70	1.00	1.17	1.00	0.11	0.00	0.05	0.00	0.09	0.00	0.46	0.00
Industrial Production	68	0.84	1.00	0.92	1.00	0.86	1.00	1.01	1.00	0.09	0.00	0.04	0.00	0.05	0.00	0.33	0.00
IT	180	0.66	0.60	0.80	0.89	0.68	1.00	1.15	1.00	0.19	0.00	0.09	0.00	0.14	0.00	0.58	0.00
Internet & Media	80	0.75	0.78	0.79	0.98	0.78	1.00	1.12	1.00	0.14	0.00	0.09	0.00	0.08	0.00	0.50	0.00
Materials	14	0.54	0.46	0.69	0.70	0.54	0.50	1.22	1.00	0.13	0.04	0.06	0.01	0.04	0.00	0.64	0.27
Services	5	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Telecommunication	65	0.69	0.67	0.78	0.87	0.69	0.75	1.16	1.00	0.13	0.00	0.09	0.00	0.09	0.00	0.50	0.00
Others	92	0.79	1.00	0.87	1.00	0.79	1.00	1.14	1.00	0.11	0.00	0.05	0.00	0.11	0.00	0.36	0.00
Stage Cluster																	
early	226	0.63	0.57	0.74	0.79	0.66	0.67	1.13	1.00	0.18	0.09	0.11	0.00	0.15	0.00	0.60	0.21
Expansion	113	0.72	0.80	0.84	0.98	0.74	1.00	1.11	1.00	0.11	0.00	0.06	0.00	0.09	0.00	0.43	0.00
Later	132	0.81	1.00	0.91	1.00	0.84	1.00	1.09	1.00	0.10	0.00	0.05	0.00	0.05	0.00	0.38	0.00
Turnaround	14	0.77	1.00	0.92	1.00	0.89	1.00	0.89	1.00	0.07	0.00	0.01	0.00	0.04	0.00	0.31	0.00
Age Cluster																	
<=1 year	224	0.72	0.75	0.79	0.89	0.71	1.00	1.11	1.00	0.12	0.00	0.08	0.00	0.11	0.00	0.44	0.00
2 to 5 years	170	0.72	0.73	0.84	0.98	0.73	1.00	1.08	1.00	0.16	0.00	0.07	0.00	0.11	0.00	0.48	0.00
6 to 20 years	91	0.71	0.75	0.84	0.96	0.72	1.00	1.16	1.00	0.13	0.00	0.06	0.00	0.11	0.00	0.45	0.00
older than 20 years	36	0.85	1.00	0.92	1.00	0.81	1.00	1.11	1.00	0.07	0.00	0.04	0.00	0.09	0.00	0.30	0.00
Exit Type Cluster																	
IPO	82	0.78	1.00	0.88	1.00	0.75	1.00	1.26	1.00	0.08	0.00	0.04	0.00	0.09	0.00	0.29	0.00
Sale/Merger	370	0.76	1.00	0.87	1.00	0.76	1.00	1.13	1.00	0.09	0.00	0.04	0.00	0.08	0.00	0.36	0.00
Write Off	153	0.52	0.50	0.67	0.69	0.61	0.50	1.01	1.00	0.32	0.33	0.20	0.16	0.25	0.00	1.04	1.00
else/not specified	107	0.86	1.00	0.89	1.00	0.80	1.00	1.18	1.00	0.08	0.00	0.01	0.00	0.03	0.00	0.17	0.00
IRR Cluster																	
IRR<=0	315	0.62	0.50	0.76	0.84	0.67	1.00	1.07	1.00	0.20	0.17	0.12	0.01	0.17	0.00	0.70	0.40
IRR> 0	382	0.82	1.00	0.89	1.00	0.78	1.00	1.19	1.00	0.07	0.00	0.03	0.00	0.06	0.00	0.24	0.00

Table 7 Regression on the determinants of the return on PE and VC investments – Phase Approach

The sample is 712 Investments (one observation is per company, not per investment round) during the period from January 1979 till November 2003 merged from the Venture Economics and Cepres databases. The dependent variable is the logarithm of (IRR+1.1). The IRR is measured based on the precise cashflows between the fund and the portfolio company. The different regression models are grouped by four categories (see row one). PE and VC funds can provide the financing of their portfolio companies not only in a single upfront investment, but rather in several financing rounds, which can be split-up further into several cash injections, so called tranches. We define the total investment relationship period of each investment starting from the initial cash injection from the PE or VC fund to the portfolio company and ending with the final cash distribution from the company to the fund.

We segment the total investment period into three fractional periods of time, each one third of the total period: the first as the initial investment phase, or i-phase; the second as the maturity phase, or m-phase; and the final third as the pre-exit phase, or p-phase. Models (1) and (2) focus on the i-phase, models (3) and (4) on the m-phase, models (5) and (6) on the p-phase. Model (7) combines independent variables from both phases. The first column defines the categories of the independent variables, the second column presents the variables. Independent vairables include besides Investment Manger-, Fund-, Company- and market-specific variables, also variables concerning the staging behaviour within each phase. Variables are as defined in table I.

The last three rows present the model diagnostics (R square, Adjusted R square and the F- statistic). The coefficients (only) of the OLS regression are illustrated in the third to ninth column. *, **, *** Significant at the 10%, 5%, 1% levels, respectively.

		Dependent Variable: Logarithm of (IRR+1.1)						
		i- Phase		m-Phase		p- Phase		Mixed
Independent variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Constant	-0.737***	-0.764***	-0.013	-0.155	0.090	0.008	0.052
Investment Phases	TTR	-0.012	0.015	-0.036***	-0.020	-0.023**	-0.014	0.001
	Pi Tranche-share		0627***					
	Pm Tranche-share				-0.138			
	Pp Tranche-share						-0.507***	
	Pi Amount-share	0.665***						
	Pm Amount-share			-0.409***				
	Pp Amount-share					-1.095***		
	Pi Round-share	0.139**	0.141*					
	Pm Round-share			0.127	0.009			
	Pp Round-share					-0.438***	-0.501***	
	Pi RTR							-0.033
	Pm RTR							-0.063*
	Pp RTR							-0.314***
IM	IM Age		-0.002		-0.002		-0.002	-0.002
	Fund Sequence	0.017***		0.021***		0.017***		
	US-IM	0.038	0.050	0.056	0.067	2.25E-04	0.007	-0.026
Fund	VC-Fund	0.083		0.014		0.036		
	Fundsize	-2.29E-11	1.23E-11	-2.81E-11	-4.79E-12	-3.66E-11**	-6.10E-12	3.87E-12
Investment	No.of IM	-0.002	-7.32E-04	- 0.003	-0.002	-0.004	-0.003	-6.96E-04
	IPO	0.423***	0.363***	0.455***	0.406***	0.419***	0.350***	0.316***
	Age of Company		-1.53E-04		-9.51E-04		-7.97E-04	-1.90E-04
	High Tech		0.175***		0.130**		0.136**	0.150***
	Later Stage		0.132**		0.208***		0.159***	0.146***
	Use of Convertibles	0.243***	0.231***	0.269***	0.264***	0.211***	0.201***	0.213***
Market	No. Of IPOs	-5.17E-04**	-3.81E-04	-5.24E-04**	-2.96E-04	-2.56E-04	-1.26E-04	-2.40E-04
	Comitted Capital	-1.43E-06***	-1.48E-06***	-1.29E-06***	-1.22E-06***	-1.24E-06***	-1.38E-06***	-1.16E-06***
Model Diagnostics	Rsquare	0.267	0.284	0.193	0.182	0.321	0.286	0.308
	Adjusted Rsquare	0.254	0.263	0.179	0.158	0.309	0.265	0.287
	F - Statistic	20.652***	13.522***	13.610***	7.598***	26.769***	13.673***	14.096***

CHAPTER A (II)

The Liquidation Dilemma of Money Losing Investments – The Impact of Investment Experience and Window Dressing of Private Equity and Venture Capital Funds

The Liquidation Dilemma of Money Losing Investments –
The Impact of Investment Experience and Window Dressing
of Private Equity and Venture Capital Funds

by

Philipp Krohmer*

Goethe University Frankfurt, Germany and

CEPRES Centre of Private Equity Research

Abstract

This study examines the investor's decision on the exit of loss making projects. The investor faces a liquidation dilemma: follow-on financing versus terminating a loss making investment, and thereby giving up the turn-around option. I examine the role of investment experience on solving this liquidation dilemma. Evidence from a sample of 712 realized Private Equity and Venture Capital investments confirms that young and inexperienced fund managers (i) hold loss-making investments longer, (ii) invest a higher share of the fund's portfolio capital into these losers, and (iii) provide relatively more financing rounds to these deals before the exit compared to more experienced funds. The results are robust to controlling for potential reputational concerns.

JEL classification: G24; G33; E51

Keywords: Private Equity; Venture Capital; Staging; Risk; Losses

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* Please address all questions or comments to corresponding author Philipp Krohmer, Department of Finance, Johann Wolfgang Goethe-University Frankfurt am Main, Germany and CEPRES Center of Private Equity Research, email-address for correspondence: Philipp.krohmer@cepres.de.
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Introduction

When companies perform below plan and decrease in value, they often come into financial distress and depend on further financing to survive and potentially turn-around. In this critical situation, investors are faced with the liquidation dilemma of money losing investments: is it better to cut losses by terminating the investment or better to attempt a turn-around by follow-on financing the company?

This study is the first to empirically analyze the investment behaviour of Private Equity (PE) and Venture Capital (VC) Funds in regards to this liquidation dilemma. It focuses on the question, whether investment experience has an impact on the liquidation decision. Do less experienced managers lack the skills to terminate an investment efficiently or is their liquidation behaviour a consequence of less reputation potentially leading to window dressing behaviour?

Previous research has provided evidence that investment experience is an important factor for the exit decision. Boot (1992) argues in a theoretical framework that unskilled investment managers delay loss generating divestitures. Gompers (1996) shows in the context of successful investments, specifically VC backed IPOs, that young VC firms exit their winners faster and more underpriced than more established VC funds in order to signal quality. While Gompers' study has focused on the exit of winners (IRR > 0%), this study concentrates on the investment behaviour associated with the exit of losers (IRR < 0%). When the development of loss generating investments erodes into financial distress, the investment manager faces the liquidation dilemma of cutting losses versus injection of fresh capital to attempt a turn-around. Phalippou (2007a) points out that "Managing private equity investments requires skills…" and explains that "…it is reasonable to expect learning to play an important role in performance". I believe that investment experience plays a key role in solving the liquidation dilemma successfully. Consequently, this study examines the role of investment experience for the decision between follow-on financing versus termination.

Younger investment managers have been found more prone to reputation concerns as confirmed by Gompers (1996). Disclosure of losers can impede raising the next fund (Musto 1999; Gompers et al., 1998). Follow-on financing of losers postpones the surfacing of a potential down-valuation or even write-off in the track record and thereby window dress the reported performance of a PE/VC fund (Lakonishok et al., 1991; Morey et al., 2006). This behaviour might help the fund managers in the short-term, especially during periods of raising the next PE/VC fund, however at the expense of current investors by possibly throwing good money after bad. Therefore, this paper analyzes the role of window dressing at the liquidation dilemma.

The data is merged from the Venture Economics and CEPRES databases. It comprises of 712 realized investments spanning a period of 24 years from January 1979 until October 2003. The results confirm that investment experience plays a key role for solving the liquidation dilemma. Specifically, the findings show that investment experience has the following influence on investments with negative returns: (1) reduction of the share of the fund's capital invested into "loser" deals, (2) shorter holding periods of investments with negative returns, and (3) fewer add-on financings before the termination of non-performing deals compared to PE/VC funds with less investment experience. These findings can be explained by the learning effect: more experienced fund managers have improved skills to distinguish between an efficient and an inefficient attempt to turn-around a distressed situation. They have learned to avoid inefficient attempts by terminating losers more rigorously. Further, the results are robust controlling for potential window dressing behaviour. Both, window dressing motives as well as investment experience play a role in the liquidation dilemma.

The remainder of the paper is organized as follows: The next section reviews the literature and develops the hypotheses. Following the data and methodology section, the empirical results are presented and interpretation is offered. The final section concludes with a discussion and suggestions for future research.

1 Literature and Hypotheses

The exit decision for loss making investments is based on the question of the viability of the project to either provide further financing or terminate the investment. The decision whether to further support or abandon a loss making investment, and thereby giving up the option to turn-around the project, is called the liquidation dilemma.

When loss making investments depend on further cash injection to survive, they can erode into financial distress. Kahl (2002) argues that the long-term nature of financial distress can solely be explained as the result of dynamic learning strategies of creditors and suggests that it may be an unavoidable byproduct of an efficient resolution of financial distress. He introduces a model of dynamic liquidation and emphasizes that creditors – in my case PE/VC equity investors – "…lack the information that is needed to make quick and correct liquidation decisions." Odean (1998) finds that individual public equity investors demonstrate a significant preference for realizing winners rather than losers. This tendency to hold losers too long and sell winners too soon has been labelled as the disposition effect by Shefrin and Statman (1985), which is one implication of extending Kahneman and Tversky's (1979) prospect theory to investments. A dynamic agency model for the provision of venture capital is provided by Bergemann and Hege (1998). They argue that the "…value of the venture project is initially uncertain and more information arrives by developing the project. The allocation of the funds and the learning process are subject to moral hazard." In line with these theoretical predictions, Krohmer et al. (2007) show empirically that loss making investments of PE/VC funds have longer investment relationships, receive a higher share of financing rounds and capital before exit than successful investments.

Boot (1992) asks "Why hang on to Losers?" and explains in a theoretical framework the relation between the divestiture decision and the manager's investment experience. In the context of public equity investments, the key result of his study is that "…skilled managers generally make firm value-maximizing divestiture decisions, whereas bad (that is, unskilled) managers delay divestitures. This result indicates that bad managers are not only less able to select projects but also less willing to correct their mistakes." Several studies looked at the aspects of performance and investment management experience in regards to VC/PE investments. Kaplan and Schoar (2005) find significant persistence in the VC's returns and conclude that the most likely explanation is the heterogeneity in the skills of these investors. Gottschalg et al. (2003) find that investment managers who outperform their peers are often more experienced. Sapienza et al (1996) conclude that more experienced funds are in a position to support their portfolio companies better, thereby adding more value and generating higher returns. Gompers (1996) empirically examines the relation between the divestiture behaviour and the VC fund managers' experience. He shows in the context of successful investments, specifically VC backed IPOs, that young VC firms exit their winners faster and more underpriced than more established VC funds in order to signal quality. He denominates this behaviour as grandstanding. While Gompers' study has focused on investment behaviour and experience related to the exit of winners (IRR > 0%), this study concentrates on the investment behaviour associated with the exit of losers (IRR < 0%). I argue that investment experience plays a key role in solving the liquidation dilemma of bad performing investments.

I measure *experience* twofold: (a) the number of years the PE/VC investment management firm is in business from its founding year until the initial cash-injection date of the observed investment, and (b) the number of funds the PE/VC firm has managed until the observed investment. *Investment behaviour* is measured by three characteristics: (a) investment duration, (b) investment amount, and (c) staging. I believe that the dynamic liquidation introduced by Kahl (2002) and the learning process around loss making projects explained by Bergemann and Hege (1998) have common patterns, which PE/VC fund managers are able to recognize and to manage better with increasing experience. More experienced investment managers have improved skills and know-how to assess the viability and to decide about the termination of a loss making project. Based on the theoretical models of Boot (1992), Bergemann and Hege (1998) and Kahl (2002) I derive the first hypothesis:

Hypothesis 1: Less experienced investment managers hold their loss making investments longer than more experienced investment managers.

In a general context to the theories of Boot (1992) and Kahl (2002), experience will enable the investment manager to better assess the viability of a non-performing project and to be willing to terminate a loser. According to the disposition effect studied by Shefrin and Statman (1985) and the prospect theory of Kahneman and Tversky's (1979), investors underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty. This means that an investor faced with the liquidation dilemma may prefer to further finance the company to keep the option of improvement instead of terminating a nonperforming project, which would involve sure losses. These studies provide the foundation for the argument that especially less experienced managers will have problems to terminate losers rigorously in time and therefore inject relatively higher amounts of capital in bad performing companies compared to more experienced fund managers. Therefore, the second hypothesis is as follows:

Hypothesis 2: Less experienced investment managers invest relatively higher amounts of capital in loss making investments compared to more experienced investment managers.

According to the theory of Bergemann and Hege (1998), the staged provision of capital allows the PE/VC fund to elicit information from the developing project. With each financing round, the investor obtains further information. In distressed situations, which are analyzed by Kahl (2002), the need for information and a follow-on financing round occurs most prior to the exit. To be able to empirically analyze the pre-exit staging behaviour, I build on the approach of Krohmer et al. (2007). By this approach, the total investment period from the first capital injection from the fund to the company until the final distribution from the company back to the fund is segmented into three periods of equal length, each one third of the total duration. The period before the exit is named pre-exit phase. To differentiate in detail for the staging behaviour during the pre-exit phase, the numbers of financing rounds during this phase are divided by the total number of financing rounds during the entire investment period. Technically, staging offers the investment manager the option to abandon poorly performing investments and minimize further associated expenses. I believe that more experienced fund managers will be able to apply their learning from previous investments and therefore need less follow-on financing rounds in order come to a termination decision about a loss making investment. This leads to the third hypothesis:

Hypothesis 3: Less experienced investment managers provide a relatively lower share of financing rounds prior to exit at loss making investments compared to more experienced investors.

The presented hypotheses argue that less experience is analogous to fewer skills in identifying and dealing with loss making projects. As an alternative explanation, it is further possible that less experienced managers lack the willingness to exit losers due to reputational concerns. According to the theory of Boot (1992), investment managers who care about their reputation try to present good results to their investors and hide losers longer than their future payoff distribution would justify. Less experienced VC/PE fund managers are more interested in building a strong reputation than already established funds, which is confirmed by the Grandstanding findings of Gompers (1996). Theoretical and empirical research on investment funds show the importance of reputation in raising capital, e.g. Lakonishok et al. (1991) as well as specifically for VC funds Gompers et al. (1998). Lakonishok et al. (1991) find that fund managers are overselling stocks that have performed poorly in the period before their performance measurement, with the objective to "window dress" the portfolio to impress their sponsors. While a money manager can delete such poor performers from portfolios, the VC/PE fund manager has to disclose the complete investment history. Phalippou (2007b), however, explains that private equity funds are not subject to strict reporting regulations and therefore have "…more room to inflate track records or behave in a sub-optimal manner". He observes that IRR figures are often "shrouded" in fundraising prospectus and that managers have clear incentives to keep at cost poorly performing investments. Woodward (2005) shows on the basis of a large dataset of syndicated venture deals that some partners write down failing companies as soon as the probability of failure is high enough whereas others wait until the very last moment. Thus, in order to "window dress" his portfolio, the VC/PE fund manager can follow-on finance losers and thereby keep their valuation artificially higher than justified by their pay-off perspectives. As shown by Gompers (1996), younger funds can grandstand to signal quality. I argue that young funds can hide incapability by postponing liquidation of losers. There may also be a positive reputation effect from a fund manager's willingness to provide funding to companies in critical situations, acting as the "white knight" that will save the portfolio company from bankruptcy. Hsu (2004) shows that a better reputation of a VC/PE fund may result in a higher probability to be invited by entrepreneurs to highly attractive deals at reduced entry prices. These alternative explanations in regards to reputational concerns could further support the hypotheses. In the analyses section, I strive to separate the experience and the reputation rationale by controlling for fundraising of a follow-up fund.

2 Data and Methodology

Current research concerning investors' behaviour and investment performance may be divided into two categories. The first category focuses on analysing the influence of specific investment behaviour on performance. The second category (which is the focus of this paper) investigates the specific behaviour of fund managers, taking the outcome as exogenous (e.g. Gompers Grandstanding). The objective is to analyze the investment behaviour of PE/VC fund managers at bad performing investments. In contrast to the first category, which analyse the performance of *portfolio companies*, this paper focuses on the *investors' concerns*. Specifically, I strive to measure particular PE/VC funds' decision at bad performing investments. *From the investors' perspective*, the life of the investment relationship starts with the initial capital injection from the observed fund into the portfolio company. The investment relationship ends with the exit decision as capital is distributed back from the given portfolio company into the observed fund. Investors can time their initial investment at any stage of a given portfolio company's development, whether in the early stages for seed financing, or in more mature stages (expansion or pre-IPO). Although PE and VC investments are frequently syndicated, implying that any one fund has only partial influence on the company's performance, each investor independently decides on whether to pull out and exit from the deal, or to provide follow-on financing. PE/VC funds can use staging as an instrument that helps determine whether follow-on financing will be provided. Associated with this decision is the choice of what level of supervision and support to provide. At each round of financing, the fund decides on whether to exercise predetermined options like providing follow-on financing or abandoning the project and terminating the investment.

As described in the last section, I strive to analyse the investment behaviour in regards to three measures, the duration of the investment relationship, the amount of capital invested and the number of financing rounds. Given the need to compute these specific measures as well as accurately calculate investment performance to clearly identify the bad performing investments, I required specific data points that were not available using conventional datasets. The dataset used in this study is closely related to the one used by Krohmer et al. (2007) due to similarity of data requirements.

To obtain the data I need to test my predictions, I generate a unique dataset by merging congruent data from Venture Economics (www.thomsonfinancial.com) with the content from the CEPRES database (www.cepres.de). Both datasets combined provide congruent and complementing details for each investment.

To measure investment behaviour in terms of staging, I use Venture Economics data, which is very comprehensive for each financing round. Venture Economics gathers data voluntarily provided by investment firms. Several studies have used this database, including Gompers (1995) and Hege et al. (2003).

CEPRES is a private consulting firm affiliated with the University of Frankfurt, and was formed in 2001 specifically to gather detailed fund- and industry-specific information on private equity deals across different countries. For these purposes, CEPRES has established the so-called "CEPRES data exchange community". Community members (mostly GPs) get in exchange for their very detailed data exclusive access to unique benchmarking services of their direct investments process and substantial discounts on all other CEPRES consulting services. Besides strict confidentiality agreements, all data are completely anonymized and for publications sufficiently aggregated to impede deciphering. CEPRES requests the data directly from the cooperating fund managers through standardized information request sheets and additionally validates all data with due diligence reports, including audited filings to guarantee high quality information. The empirical studies of Cumming and Walz (2004), Cumming et al. (2004) and Schmidt (2004) also provide more detailed information about the CEPRES database.

Though not as comprehensive as the Venture Economics database (as of November 2003 CEPRES had detailed information for 5,300 deals)[1], CEPRES data provides precise information about each cash injection from the investor to the portfolio company and each cash distribution from the company back to the investor. The accurate cash flow information provided in the CEPRES database enables me to *perform exact IRR calculations for the definition of the performance-subsets required for the tests*. This is distinct from other papers, which appear to proxy returns based on the exit type (e.g. Gompers, 1995), on valuations (e.g. Hege et al. 2003) or on initial cash flows and final cash flows (e.g., Cochrane, 2001). IRR measurements based on Venture Economics data alone can lead to a milestone bias, which can materially affect

[1] However, CEPRES is growing steadily since its inception. As of April 2007, the database has detailed cash flow information on more than 18,000 investments.

researchers' estimates of returns and valuation patterns over time. This aspect is pointed out by Kaplan et al. (2002). They stress the incapacity of Venture Economics in accurately measuring the precise milestone round information. The IRR is only meaningful when calculated on the exact date of the investment, but Venture Economics only provides dates of financing rounds, not the exact date of the cash injection which can differ from the round date due to the tranching of rounds into several cash injections also known as milestone rounds.

The same aspect applies to the exit date provided in Venture Economics, which does not always overlap with the precise date of the distribution cash flow back to the investor. This enables me to measure the *duration* of the investment relationship very accurately. The combined dataset comprises more than 120 variables. Table 1 shows a selection of variables analysed in this study.

In November 2003, the CEPRES database had detailed information for 5,308 investments in 4,476 portfolio companies by 229 PE and VC funds belonging to 74 different investment management firms. I match this dataset with the information from the Venture Economics database as of November 2003[2], ensuring that the specifics of each investment was consistent on the following four levels of identification: the PE/VC firm, the fund, the portfolio company and the date of the initial investment from the fund into the company. The merged dataset contains information on 1,747 investments, which is further reduced along the following steps: I first exclude all unrealized investments and focus on the fully and partially realised investments. For the partially realized investments, I perform a further selection step: I select only those investments where the residual net asset value (RNAV) is smaller than 20% of the sum of absolute cash flows (injections and distribution). This condition ensures that the valuation does not carry to much weight in the IRR calculation as I calculate the IRR for the partially realized investments by taking the RNAV as the last cash flow paid back to the investor.[3]

[2] For this purpose, CEPRES provided me with an "unanonymized" dataset. Due to strict confidentiality agreements with the CEPRES data exchange community members, this matching project had to be conducted in the CEPRES premises. After matching, the dataset was anonymized again.
[3] This selection method is following the approach of Kaserer and Diller (2004)

The complete dataset after these reductions comprises of 712 different investments made by 122 PE and VC funds belonging to 51 varying investment managers. These investments include 1,549 financing rounds with 2,329 cash injections (tranches) – spanning a period of 24 years, from 1979 till 2003. The dataset can be considered as representative of the general pool of PE and VC deals, as it corresponds with the frequency distributions of key aspects of the PE and VC market. The frequency distribution over time of the beginning and exit of investments in this sample is in line with the market evolution from 1979 till 2003. The frequency distribution with respect to countries of origin is comparable with the size of regional PE and VC markets and as well comparable with respect to the industry distribution. Details on all frequency distributions are available upon request. While 712 investment relationships are a small sample of the universe of PE and VC deals, I believe the volume of data is comparable to sample sizes examined in previous studies (e.g. Gompers 1996).

As I strive to explore the specific investment behaviour in critical situations, I concentrate in this study on bad performing portfolio companies, specifically all investments with an IRR below 0%. I present two sub-sets of the complete sample to test the predictions: (1) all negatively performing investments with an IRR below 0% p.a.. This subset includes 315 investments, where the capital paid back to the investors was equal or below the invested capital. The mean IRR of investments within this sample is –71.19% p.a. (2) As second sub-set, I present the lower bound of the bad-performer-sample, the total write-offs with an IRR of -100% p.a.. This subset consists of 153 investments, where all of the invested capital was sunk. The reason why I additionally analyse the subset of total write-offs is, that I expect to observe slightly different patterns in these "extreme circumstances". Considering the alternative explanation of reputational concerns for example, there is a big difference between a total loss with an IRR of -100% and a bad performer with an IRR of -5% showing up in the record. Additional negative-IRR subsets were tested. The results are not sensitive to alternative cut-offs. The frequency distribution of the two subsets with respect to countries of origin is comparable with the distribution of the entire dataset, comprising around 60% of investments in US-American Portfolio companies, specifically 57.5% within the write-off subset and 63.5% within the bad-performers subset. With regard to the stage of development and the industry sector, I observe strong distinctions between the "loser"-subsets and the entire sample. The share of high technology investments within the negative IRR-sample is 59.7% and even higher among the total write-offs with 68.6%, compared to only 54.6% within the entire sample. The differences are even more significant with respect to the stage. The entire sample comprises of 47.6% early stage investments (seed, start-up, early and expansion), the "losers" of 63.5% and the write-offs even of 73.2%. Because early stage and high technology investments are riskier, their more frequent occurrence in the loser-subsets is plausible.

3 Empirical Results and Interpretation

3.1 Descriptive Statistics

To test the hypothesis presented in section 1, I first have to determine how to measure (1) the *experience of PE/VC-Fund management firms* (hereinafter referred to as *Fund managers*) and (2) their *investment behaviour*.

I employ two different characteristics to measure the *experience of PE/VC-Fund managers*. The fund sequence number, which indicates whether the observed fund was the first fund of the manager, the second fund, etc., and the PE/VC-Fund managers age (years in business since foundation) at time of initial investment in the observed portfolio company. This measurement is in line with previous studies concerning experience of management firms, e.g. Gompers (1996) and Cumming et al. (2005). Gompers (1996) points out, that these variables are imperfect measures of experience "[…] because experienced partners sometimes leave to start new venture capital firms, which effect would tend to bias the results away from seeing any difference between new and old venture capital firms". Other studies measure the experience for example in terms of number of investment rounds the VC firm has participated in (Sorensen, 2007) or the number of investments made by the VC firm (Gompers et al. 2005). As I strive to capture both effects, experience and reputation, I think that the fund sequence number and the VC/PE-fund manager's age are more appropriate for my purposes, because they are directly observable for potential investors. Out of the sample of 122 PE/VC-funds, 29 (24%) are first-time funds, 27 (22%) second-timers and 66 (54%) the third or later fund of the manager. The reduced dataset (unrealised investments excluded) consists of 154 (21.6%) investments by first-time-funds (thereof 64 negative performers with 26 total write-offs), 144 (20.2%) investments from second-time funds (64 losers with 26 write offs) and 414 (58.1%) investments of the third or a later fund of the manager (188 loser with 101 total write offs). Table 2 presents summary information for the comparison of young versus old PE/VC-Fund managers in the sample. I classify all PE/VC-fund managers to be young if the fund was the first or the second fund of the manager and those with the third or higher fund as old. The results are similar to alternative cut-offs. Table 2 shows that more experienced VC/PE-firms raise a new fund on average around 2.5 years after the closing of the prior fund, younger VCs on average not until after more than 4 years. Younger VC/PE-fund managers show on average a lower percentage of total losses within their funds, 14.6% versus 17.8% for more experienced fund managers. The sample does not contain unrealized investments, which might bias these proportions. A possible explanation for the higher write-off-ratio of the more experienced managers could be a higher disposition of risk-taking and a higher specialization of the funds (e.g. on risky early stage investments), discussed for example in Gompers et al. (2005). The mean IRR for all bad performing investments is also slightly higher for more experienced VC/PE-managers. The same does not hold true when excluding the total write-offs out of the negative-performer-subset. More experienced VC/PE-managers obtain on average an IRR of -41.01% p.a., whereas younger managers only a mean IRR of -49.68% p.a.

I measure the *investment behaviour* of PE/VC-fund managers at bad performing investments at three levels. First I look at the time horizon of the investment. The *duration of the investment* is defined as the time period between initial investment and the final cash flow in years. Previous studies examining various aspects of the investment duration include Gompers (1995), Cumming and MacIntosh (2001) or Megginson and Weiss (1991). There is no empirical study examining the investment behaviour in terms of duration specifically for bad performing companies. Table 3 presents summary statistics for investment behaviour characteristics for young versus old PE/VC-fund managers, Panel A for the subset of total write-offs, Panel B for all negatively performing investments. Analogous to Table 2, I classify all PE/VC-fund managers to be young if the fund was the first or the second fund of the manager and those with the third or higher fund as old. The statistics are consistent with the hypothesized differences of the investment duration in regards to the PE/VC-fund manager's experience. Younger VC firms hold total losses on average (median) 10 (8) months longer than older VC firms. The differences are even more significant with respect to the subset of all negatively performing investments. First- or second-time funds hold their bad-performing investments on average 51 months in their portfolio and thus 16 months longer than third-or-later funds. As one way to test if the dataset is viable, I draw a comparison to the results on the holding period of IPO's backed by young versus old VC-managers performed by Gompers (1996). He defines PE/VC-fund managers to be young if below six years old at date of IPO and those that are six years old and more as old and finds out that young VC-firms sit on the board of directors 8 months less than old VC-firms. For the IPO's within the sample, I observe a difference of 7 months between young and old VC-firms and therefore the dataset supports Gompers' grandstanding hypothesis.

Furthermore, I analyse the amount invested in the bad performing company. I define two measures for the amount: the *absolute investment share*, which is the total amount invested by the fund in this portfolio company divided by the total amount invested by the fund in all portfolio companies and the *relative investment share*, which describes the total amount invested by the fund in this portfolio company divided by the average amount invested by the fund in all portfolio companies. I choose ratios rather than absolute amounts to measure investment size because there might be substantial differences between the absolute invested amounts by young, un-experienced and older, more experienced fund managers. Theoretical and empirical research, e.g. Gompers and Lerner (1999), demonstrate the importance of reputation in raising new capital. Gompers (1996) points out that this relation "[…] is consistent with industry wisdom. Established venture capital firms with long track records raise large funds quickly and with little effort". If more experienced fund managers raise larger funds, the investment amount per portfolio company will also most probably be larger and a comparison of absolute values would make no sense. Therefore, I consider ratios to analyse differences in investment behaviour concerning the investment amount between experienced and un-experienced fund managers. Summary statistics in Table 3 for the investment amount also support the predictions for the differences in regards to the PE/VC-fund manager's experience. Younger PE/VC-fund managers invest on average around 90% of the average invested capital per portfolio company, corresponding to around 4.5% of the total fund commitments. More experienced fund managers invest only about 80% of the average invested capital per portfolio company and around 3% of the total fund commitments. These differences become even more apparent, when looking at three fund-number-categories: first-time-funds invest on average more in losers than in winners (almost 110%, 5% of the total fund commitments), fund managers with their second, third or fourth fund invest on average 80% (4% of total capital) and fund managers with their fifth or later fund invest on average only around 70% (less than 2% of the total invested capital). These results are not shown in table 3, but available upon request.

The third variable refers to the *staging* behaviour in critical situations. The investor can use staging as an instrument to decide about the level of control he wishes to exercise as well as the amount of resources he chooses to allocate. These resources may come in the form of capital, managerial support, knowledge transfer, time or effort. I analyze this active role of the investor with respect to the number of financing rounds he participates. I build on Krohmer et al. (2007), who find out that staging has a positive influence on performance during the initial investment phase and is negatively associated with performance during the pre-exit phase. To analyse the changes in behaviour within the investment relationship, they segment the total investment period of each investment into three phases of equal length, each one third of the total investment duration. They name the first third the initial phase (i-phase), the second third the maturity phase (m-phase) and the final third the pre-exit phase (p-phase). The relative share of staging during each of these phases is calculated as the number of rounds during a specific phase divided by the total number of rounds in all three phases. They interpret the increased staging during the p-phase as an attempt of the investor to address the termination dilemma by postponing his decision to abandon nonperforming projects. As I want to analyse the investment behaviour of PE/VC-fund managers with nonperforming projects, I concentrate on the p-phase and define the measure for staging in line with Krohmer et al. (2007) as the share of the number of rounds during the pre-exit phase to the total number of rounds during the entire investment duration. The summary statistics for the staging behaviour in table 3 are consistent with the predictions. The p-phase-round-ratio of inexperienced fund managers in total losses is on average 35.7%, whereas for experienced fund managers only 19.6%. The differences in staging behaviour between less and more experienced fund managers are smaller but still significant for the subset of bad-performers (IRR<=0%).

In the literature section, I discussed an alternative explanation to experience for differences in investment behaviour between young and old fund managers, namely *reputational concerns* of showing bad performers in the track record and its negative impact on raising capital for new funds. Postponing the liquidation of an investment in order to not show them in the track record unless a follow-up-fund is raised can be interpreted as window dressing. After the next fund has been raised, the pressure to window dress the results is greatly reduced. Gompers (1996) describes "positive signalling" by young funds. He shows that young VC firms are more likely to exit their better investments earlier than that which would otherwise be optimal for the entrepreneurial firm, in order to signal quality ('grandstand') to institutional investors for the purpose of raising capital for a new fund. In order to separate the experience and reputation rationale, I introduce the variable "follow-up-fund raised": a dummy variable equal to 1, if the fund manager raised a follow-up-fund already at time of investment in the portfolio company, and zero otherwise. As cut-off point for the starting date of the new fund, I take the exact date of the first cash flow in a portfolio company. Gompers (1996) states, that "[…] it takes approximately one year to solicit money and close a new fund". I tested the fundraising-dummy with a time lag of one year. The results were qualitatively similar using this definition for the dummy. All funds within the sample managed to raise a follow-up-fund, which indicates some type of survivorship bias, looking only at the behaviour of successful managers, but this would affect to bias the results away from seeing any differences between young and old fund managers. Table 4 presents summary statistics for the investment behaviour before and after a follow-up-fund is raised by the fund manager for three data-subsets. Panel A shows the results for the subset of complete write-offs and Panel B for all negatively performing investments. As the change of investment behaviour with regards to fundraising could be in addition to the window dressing rationale related to re-deployment of managerial resources to new investments, I show in Panel C the results for the subset of all positively performing investments. For the subset of total write-offs, which is the most important group with regards to window dressing, I observe high significant differences for all variables. The holding period of investments made *before* fundraising of a follow-up-fund is on average 16 months longer than for those investments, made *after* the closing of the follow-up-fund, supporting the hypothesis that fund managers tend to postpone the liquidation of weak investments in order to not show them in the track record until the follow-up-fund is raised. To keep the "losers" alive, fund managers have to continue to cover their financing needs with further capital injections. This aspect is reflected by the significantly higher investment share and a three times higher pre-exit-round-share for those investments made before fundraising of the follow-up-fund. After having secured the capital for his next fund, the fund manager has less incentive to window dress and can stop these abortive follow-on investments in the existing fund with the effect that at the end the losers crop up in the records. Except for the investment duration, I do not observe these explicit differences regarding the subgroup of all negatively performing investments. For the subset of positively performing investments, the duration is only somewhat longer for those before fundraising of the follow-up-fund. For the sub-samples of "out-performers" with an IRR above 50% p.a. or all venture-backed IPO's (not shown in this table), the differences disappear completely and the duration is even slightly shorter for investments before fundraising of the follow-up-fund, supporting the theory of signalling quality by taking companies public and discarding the alternative explanation of re-deployment of managerial resources.

Gompers and Lerner (1996) show that venture capital funds have predefined lifetimes, usually ten years with an option to extend the fund for up to three years. Therefore, it is arguable that the later the initial investment of a portfolio company occurs within the total fund-lifetime, the shorter will be its duration due to the predefined fund lifetime. This argument is also applicable to the investment amount. The results of the analyses for the winner-subsets and analyses with the lagged follow-up-fund-raised variable do not support this pattern, especially concerning more experienced fund managers, which raise funds shortly after the previous fund and may have several overlapping funds. To ensure that differences in investment behaviour are not simply caused by usual fund investment patterns, I additionally control in the regression analyses for the time between fund closing and initial investment in the portfolio company and the company investment sequence within the fund, which is calculated as the number of portfolio companies the fund has invested in since its closing date to date of initial investment of the portfolio company, divided by the total number of portfolio companies the fund invested in during the entire lifetime of the fund.

I further control for variables on four different levels: (1) the fund manager, (2) the fund, (3) the investment and (4) the market. (1) On the fund manager level, I examine, whether a fund manager is based in the United States. Studies reflecting on the relevance of the location for example in regards of legal regulations, macroeconomic conditions, or investment pattern include for example Bottazzi et al. (2005); Keuschnigg (2004); Cumming (2002); Jeng and Wells (2000); and others. (2) On the fund level, I control whether the fund is focused on Venture Capital investments or rather on later stage investments like management buyouts. (3) Alternatively to this variable, I test on the investment level whether the investment was made in an early development stage of the portfolio company where informational asymmetries are highest. Analogous to the stage of development, the degree of information asymmetries can vary strongly among different sectors. I control, whether the portfolio company is active in the high tech sector. (4) At the market level, I control for several parameters: most importantly I analyse the level of committed capital on the overall private equity market in two ways: I observe the committed capital at date of initial investment of a fund into a portfolio company, as well as the growth over the entire investment period of the company. Poterba (1989) argues that changes in fundraising can arise from changes in the supply of venture capital. High supply of capital could make fundraising more easy and therefore affect fundraising-driven investment behaviour like window dressing or grandstanding. Free cash flow agency costs have been studied by Blanchard et al. (1994), who found that cash windfalls adversely affect companies' investment behavior. Gompers (1995) argues that growth of the investment pool may measure entry by inexperienced investors. I also account for business cycles, changes in the capital market and public market conditions by including the average variation of the real U.S. GDP growth per annum over the entire investment period, the short term interest rate at date of investment and the variation of the NASDAQ Composite Index over the entire investment period. Nowak et al. (2006) document the investment and divestment timing of PE/VC fund managers using the NASDAQ Composite as main market valuation index. Lastly, I want to take into account whether the investment happened during a period of abnormal market conditions, leading to exaggerated valuations and returns. Therefore, I create a dummy variable which is equal to 1 if the initial investment took place during the so-called "internet bubble", i.e. between September 1998 and March 2000 and equal to 0 otherwise.

3.2 Regression Results and Interpretation

In this section I report the regression results for the predictions developed before. Table 1 provides a description of all variables used in the regression models. Tables 5-7 report the results of the regression analyses. Regressions are performed on the following dependent variables: (1) the duration of the investment, (2) the absolute investment share, (3) the relative investment share and (4) the pre-exit-phase round-share. Panel A of each table shows all regression models for the subset of negatively performing investments (IRR<=0% p.a.), Panel B for the subset of write-offs (IRR=-100% p.a.). All results are also robust for varying cut-offs for the IRR-subsets. All of the presented and additionally performed OLS and Poisson regressions meet the model restrictions, linearity, normal distribution of the residuals, multi-colinearity and heteroscedasticity.

Predictions regarding the investment duration

The regression results in Table 5, Panel A confirm the prediction and show that less experienced VC/PE fund managers - measured either by the fund sequence-number or by the fund managers' years in business - hold negatively performing investments longer than more experienced investment managers. The regressions for the write-off subset shown in Panel B of Table 5 generally confirm the results presented in Panel A, albeit less significant. This finding confirms the theory of Boot (1992) that unskilled managers delay divestitures of losers. The results of all regression models are robust for a variety of investment specific and macroeconomic control variables, including the stage of the company's development, industry sector, as well as NASDAQ composite and industry cycles. All regression models express high quality with an adjusted r-square around 50 per cent.

Investment experience or window dressing

Younger investment management firms apparently have more difficulties to solve the liquidation dilemma of bad performing companies than older firms. As discussed in Section 2, part of the increased difficulties of younger investment firms in solving the dilemma could be related to their inferior skills and abilities. However, reputational concerns could be a further factor. Postponing the write-off of bad performers in order to whitewash the track record until the follow-on fund is raised, namely window dressing, could be a motivation to prolong the holding period of bad performers. This incentive is particularly strong for young investment management firms with higher reputational needs. Old VC/PE investment management firms with already established good reputations do not need as much to signal as young firms, because investors have evaluated their performance over many years and trust in their strong skills.

In order to differentiate between investment skills and window dressing influence on the investment duration of a portfolio company, I control for window dressing in the following way: a dummy variable is set equal to one in case the investment management firm already has raised a follow-up fund at time of initial investment of the current fund in the observed portfolio company, or equal to zero otherwise. The raising of the follow-up fund can motivate especially the less experienced investment managers to window dress their portfolio by follow-on financing bad performing companies and keeping them alive longer than their prospects alone would justify. The regression results in Table 5 show in all models that the holding period is longer for those bad performing investments initiated before the follow-up fund is completely raised. When controlling for the committed capital to new VC/PE funds in the market at date of the initial investment, the impact of the follow-up fund raising variable on the holding period becomes insignificant. This result can be explained by the general interpretation that funds hold their loss making companies longer during "dry seasons", during which it is generally more difficult to raise a new fund.

On the contrary, additional analyses on the holding periods of the investments with positive return on investment (IRR >0% p.a.) do not show any significant differences in the holding period before or after the follow-up fund has been raised. This result confirms that the differences before and after the follow-up fund raising cannot be related to redeployment of managerial resources from the old to the new fund, but rather to window dressing. This finding can be interpreted in the way that fund managers do not rigorously abandon loss making projects until the follow-up fund has been raised – with the effect that good money might be thrown after bad for window dressing purposes. Controlling for this window dressing influence, the impact of experience on the holding period is still significant in all regression models. These results establish that a portion of this impact on the investment duration is explained by the investment experience supporting the prediction on the importance of investment skills for solving the liquidation dilemma.

Predictions regarding the investment amount

Table 6 presents the results for the regressions on the amount invested by the fund into the bad performing portfolio company. The first two regression models of Panel A and Panel B show the results for the absolute investment share as dependent variable, the last two models in each panel provide the results for the relative investment share. Variables are described in Table 1. These results strongly confirm the predictions. Younger fund managers inject relatively more capital in loss making deals than more experienced fund managers. These results are robust controlling for all of the previously introduced control variables, including potential window dressing behaviour. Until the follow-up fund has been raised, the fund managers inject more capital in loss making deals and after the follow-up fund has been raised, the investment amount decreases for loss making investments. This result can be interpreted as potential window dressing, as fund managers might feed their losers with further cash injections until the follow-up fund has been raised.

Predictions regarding the staging behaviour prior to exit

Table 7 show the results for the count data regressions (Poisson) and the determinants of pre-exit phase round share of loss making investments. I further performed OLS regressions and obtained similar results, which are available upon request. The Poisson regressions seem more adequate due to the distribution of the dependent variable. The results confirm the predictions of hypothesis 3. Younger investment managers need a higher share of financing rounds prior to the exit of nonperforming projects compared to more experienced fund managers. More experienced investors have learned from previous investments to better assess the viability of the future prospects of a loss making company and apply the option to abandon those losers more rigorously.

In summary, the results confirm the importance of investment management experience in solving the liquidation dilemma more efficiently. I find that more experienced investment managers (1) provide less financing rounds prior to exit, (2) inject less capital to loss making deals and (3) hold these deals for a shorter period of time than un-experienced investment managers. These results are in line with the findings of Lauterbach et al. (2007) who show empirically that more experienced VC/PE fund managers have a positive influence on reducing the losses of poorly performing companies (IRR < 0% p.a.). Sapienza et al. (1996) argue that investment managers add relatively more value when uncertainty is high, which also supports the given interpretations.

In regards to window dressing, the holding period is the most important criterion in order to postpone the disclosure of complete write-offs. Younger investment managers do not show significantly longer holding periods of complete write-offs compared to older investment managers. But younger investment managers inject significantly more capital through significantly more financing rounds to their complete write-offs. In summary, these results can be interpreted as follows: the investment skills (expressed by investment amount and financing rounds) have a stronger impact on the liquidation dilemma than window dressing (expressed most importantly by the holding period).

4 Conclusion

Investment managers of PE and VC funds face a liquidation dilemma at portfolio companies with eroding developments. When a loss generating company comes into financial distress, the investor has to decide to either cut further losses by abandoning the loser, or to attempt a turn-around by follow-on financing. The follow-on financing decision into a loss making investment is one of the most difficult decisions of an investment manager next to the initial investment decision. Several studies confirm investment experience as an important factor for successful investment decisions. This study offers new answers to the research question: what impact does investment experience have on the follow-on investment decision into loss making portfolio companies? The empirical analysis is based on 712 investments between 1979 and 2003, which are congruently provided by the Venture Economics and CEPRES databases. The merged dataset allows a precise analysis of the investment cash flow and more than 120 different variables for each of the observed investment.

The results show that investment experience plays a key role in solving the liquidation dilemma. Specifically, more experienced PE/VC fund managers (1) invest a lower share of the fund's capital into non-performing companies, (2) hold investments with negative returns for a shorter period of time, and (3) inject less often follow-on capital into a loss making deal before its termination. This result can be interpreted as a learning effect, so that more experienced PE/VC funds are less prone to throwing good money after bad in distressed situations.

Further, the examination separates between the role of investment experience and the reputation rationale in regards to the liquidation dilemma. Less experience is analogous to fewer skills in identifying and dealing with loss making projects. As an alternative explanation, it is possible that less experienced managers lack the willingness to exit losers due to reputational concerns. According to the theory of Boot (1992), investment managers who care about their reputation try to present good results to their investors and hide losers longer than their future payoff distribution would justify. The findings show that during periods of time, when fund managers raise their next PE/VC fund, they postpone the termination of loss-making deals. This result can be interpreted as follows: fund managers window dress their current portfolio's reported performance by delaying the termination and reporting of losers in order to improve the perceived track record for higher chances to raise capital from the potential new investor. This window dressing is confirmed for experienced and inexperienced PE/VC funds. In case this window dressing includes throwing good money after bad, it occurs at the expense of the current fund's investors. Controlling for this window dressing influence, the impact of experience on the holding period is still significant in all regression models. These results establish that a portion of this impact on the investment duration is explained by the investment experience supporting the prediction on the importance of investment skills for solving the liquidation dilemma.

In summary, this study provides for the first time evidence that investment experience has a positive impact on the investment behaviour of PE/VC fund managers in non-performing companies. They have learned how to successfully deal with the liquidation dilemma of loss making investments. On the more critical side, the findings confirm that fund managers window dress their portfolio and investors providing capital to the fund should be aware of this aspect, both in their due diligence, as well as in adjusting the incentive scheme and restrictions in order to mitigate potential window dressing behaviour.

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Table 1 Variable Description

Variable Name	Variable Description
Investment Duration	Total Duration between the initial investment of the fund in the portfolio company and the exit date [in years] (if not fully realised we consider the valuation date instead of the exit date)
Absolute Investment Share	The Absolute Investment Share is the total amount invested by the fund in this portfolio company divided by the total amount invested by the fund in all portfolio companies (all amounts in real 2003 U.S. Dollars)* [for the regression analysis we take logs]
Relative Investment Share	The Relative Investment Share is the total amount invested by the fund in this portfolio company divided by the average amount invested by the fund in all portfolio companies (all amounts in real 2003 U.S. Dollars)*
Pp Round-share	The share of the No.of Phase p (pre-exit phase) rounds of the total No. of rounds (Pp rounds / All rounds)
Pp Tranche-share	The share of the No.of Phase p (pre-exit phase) tranches of the total No. of tranches (Pp Tranches / All Tranches)
Fund Sequence Number	The number of funds managed by the investment manager (this fund and all predecessor funds)
Fund-Number: first or second?	A dummy variable equal to 1 for first-or-second-fund investments and equal to 0 for third-or-later-fund investments
IM Age	The age (years in business) of the Investment Manager at time of the initial investment in the portfolio company
Follow-up-fund raised	A dummy variable equal to 1 if the investment manager raised a follow-up-fund already at time of investment in the portfolio company, 0 otherwise
Time since closing	Maturity of the Fund (in years since its closing date, which marks the end of its fund raising) at date of initial investment of portfolio company i
Fraction of Companies since closing	The fraction of companies is the number of portfolio companies the Fund has invested in since its closing date to date of initial investment of portfolio company i, divided by the total number of portfolio companies the Fund invested in during the lifetime of the fund.
High Tech	A dummy variable equal to 1 for Companies of the High Tech - Sector [The Company was classified as High Tech, when belonging to one of the following CEPRES Sector categories: healthCare/LifeScience, IT, High Tech, Semiconductor, Software, Internet, Telecommunications]
Later Stage	A dummy variable equal to 1 for Later Stage Companies [The Company was classified as Later Stage (early stage), when belonging to one of the following CEPRES Stage categories: Later, MBO/MBI, LBO, public to private, Mezzanine, turnaround, recapitalisation (seed, startup, early, expansion)]
NASDAQ	NASDAQ Development is the variation of the NASDAQ Composite Index [p.a.] over the entire investment period
GDP	GDP is the average variation of Real US Gross Domestic Product [p.a.] over the entire investment period
Growth Committed Capital	Comitted Capital is the average variation of the committed capital on the overall market [p.a.] over the entire investment period of the portfolio company
Committed Capital	Comitted capital on the overall market during the year of the observed investment (in real 2003 U.S. Dollars, in millions)*
Investment in Bubble	A dummy variable equal to 1 for portolio companies with the initial investment date during the so-called "bubble period" (1998-2000), 0 otherwise
Short-term interest rate	The short-term interest rate at investment date (For U.S. investments:The Federal Reserve Bank 1-month treasury bills; for EU investments: the BBA Libor rate)
US-IM	A dummy variable equal to 1 for Investment Managers with the main office in the United States, 0 otherwise
VC-Fund	A dummy variable equal to 1 for Funds specialized on Venture Capital, 0 otherwise

The inflation adjustment is based on Consumer Price Index (CPI) data for all urban households and all items. Data is derived from the records of the U.S. Department of Labor (www.bls.gov)

Table 2 Comparison of Fundraising and Fund-Performance characteristics of young and old PE/VC Fund Managers

The total sample comprises of 712 PE/VC- investments made by 122 PE and VC funds belonging to 51 varying investment managers. For the IRR statistics we use the subset of (a) all negative performing portfolio companies and (b) all negative performing portfolio companies excluding the total losses (IRR=-100%).

	First-or-second-Fund of the Investment Manager	Third-or-later-Fund of the Investment Manager
Time from fund vintage date till fundraising follow-up-fund	4.10	2.47
Percentage of total losses (IRR=-100%) of all fully and partly realised portfolio companies in fund	14.6%	17.8%
IRR of negative performing portfolio companies (including total losses)	-65.96%	-74.88%
IRR of negative performing portfolio companies (excluding total losses)	-49.68%	-41.01%

Table 3 Comparison of the investment behaviour of young and old PE/VC Fund Managers

The total sample comprises of 712 PE/VC- investments. **Panel A** shows the results for the subsample of total losses (IRR=-100%), **Panel B** for the subsample of negatively performing investments (IRR<0%). Medians are in brackets. Significance tests in the third column are t-statistics of difference in averages (two-sided). *, **, *** Significant at the 10%, 5%, 1% levels, respectively. Variables are as defined in table 1.

Panel A	Subsample: write-offs (IRR=-100%)		
	First-or-second-Fund of the Investment Manager	Third-or-later-Fund of the Investment Manager	t-statistics
N	52	101	
Investment Duration	2.550 [2.043]	1.704 [1.333]	2.628***
Absolute Investment Share	0.043 [0.036]	0.031 [0.019]	1.715*
Relative Investment Share	0.895 [0.858]	0.798 [0.665]	0.853
Pp Round-share	0.357 [0.333]	0.196 [0.000]	2.661***
Pp Tranche-share	0.356 [0.333]	0.299 [0.333]	1.755*
Panel B	Subsample: Negative Performing (IRR< 0%)		
N	127	188	
Investment Duration	4.252 [3.808]	2.914 [2.293]	4.099***
Absolute Investment Share	0.044 [0.036]	0.032 [0.021]	2.802***
Relative Investment Share	0.932 [0.873]	0.835 [0.716]	1,304
Pp Round-share	0.208 [0.000]	0.137 [0.000]	1.977*
Pp Tranche-share	0.195 [0.056]	0.211 [0.200]	-0.650

Table 4 Comparison of the investment behaviour before and after fundraising follow-up-fund

The total sample comprises of 712 PE/VC- investments. **Panel A** shows the results for the subsample of total losses (IRR=-100%), **Panel B** for the subsample of negatively performing investments (IRR<0%) and **Panel C** for the subsample of positively performing investments (IRR>0%). Medians are in brackets. Significance tests in the third column are t-statistics of difference in averages (two-sided). *, **, *** Significant at the 10%, 5%, 1% levels, respectively. Variables are as defined in table 1.

	follow-up-fund NOT raised at time of investment in the portfolio company	follow-up-fund already raised at time of investment in the portfolio company	t-statistics
Panel A	Subsample: write-offs (IRR=-100%)		
Investment Duration	2.083 [1.619]	0.680 [0.254]	5.009***
Relative Investment Share	0.856 [0.727]	0.473 [0.295]	1.780*
Pp Round-share	0.262 [0.000]	0.100 [0.000]	2.233**
Panel B	Subsample: Negative Performing (IRR< 0%)		
Investment Duration	3.548 [2.854]	1.796 [1.450]	3.592***
Relative Investment Share	0.886 [0.821]	0.660 [0.458]	1.441
Pp Round-share	0.169 [0.000]	0.108 [0.000]	0.820
Panel C	Subsample: Positive Performing (IRR> 0%)		
Investment Duration	4.491 [3.933]	3.816 [3.739]	2.077*
Relative Investment Share	1.049 [0.895]	0.963 [0.951]	0.722
Pp Round-share	0.066 [0.000]	0.015 [0.000]	2.705***

Table 5 Regression Analysis on the Determinants of the Duration of bad performing investments

The total sample comprises of 712 PE/VC- investments merged from the Venture Economics and Cepres databases. **Panel A** shows the results for the subsample of negatively performing investments (IRR<=0%), **Panel B** for the subsample of total losses (IRR=-100%). The dependent variable is the investment duration. We define the total investment relationship period of each investment starting from the initial cash injection from the PE or VC fund to the portfolio company and ending with the final cash distribution from the company to the fund. The first column defines the categories of the independent variables, the second column presents the variables. Independent variables include three measures for fund experience, the fund sequence number, the investment manager's age at date of in initial investment into the portfolio company and a dummy variable equal to one for first-or-second-fund investments and equal to 0 for third-or-later-fund investments. A dummy variable equal to one if the investment manager raised a follow-up-fund already at time of investment in the portfolio company controls for window dressing behaviour. Variables are as defined in table I. The last three rows present the model summary (N, R squared, Adjusted R squared and the F- statistic).
The coefficients (only) of the OLS regression are illustrated in the third to tenth column. *, **, *** Significant at the 10%, 5%, 1% levels, respectively.

		Dependent variable: Duration of investment							
		Panel A: Subsample: Negative Performing (IRR< 0%)				**Panel B**:Subsample: write-offs (IRR=-100%)			
	Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Constant	1.099**	1.717***	2.639***	3.497***	0.236	0.371	1.414*	2.304***
Repuation/ Experience	Fund Sequence Number	-0.140***				-0.076*			
	Fund-Number: first or second?			0.789***	0.478*			0.263	0.074
	IM Age		-0.025**				-0.005		
Manager	US-IM	0.124	0.181	0.105	-0.052	0.148	0.135	-0.161	-0.277
Fundraising	Follow-up-fund raised	-0.882*	-1.270***	-1.148**	-0.802	-0.937**	-1.034**	-0.997*	-0.634
Investment	High Tech		-0.449*	-0.344			-0.097	0.167	
	Later Stage	0.590***	0.425*	0.382	0.396	0.588**	0.664**	0.363	0.335
Macro-economic Variables	Investment in Bubble			-2.893***				-1.986***	
	NASDAQ Development	1.382***	1.336***			1.149***	1.178***		
	GDP	-0.680**	-0.778**	-0.533		-0.475**	-0.508**	-0.335	-0.498*
	Growth Committed Capital	-0.044	-0.085	0.154		0.005	-0.009	0.082	
	Committed Capital				-1.62E-05***				-1.01E-05***
	Short-term interest rate	0.210***	0.151**	0.290***	0.309***	0.204***	0.155*	0.263***	0.255***
Model Summary	Number	312	295	295	312	153	144	144	153
	Rsquare	0.590	0.573	0.408	0.450	0.561	0.558	0.415	0.447
	Adjusted Rsquare	0.580	0.560	0.389	0.437	0.537	0.528	0.375	0.42
	F Statistic	54.603***	42.554***	21.814***	35.509***	23.019***	18.790***	10.541***	16.732***

Table 6 Regression Analysis on the Determinants of the Investment Amount Share of bad performing investments

The total sample comprises of 712 PE/VC- investments merged from the Venture Economics and Cepres databases. **Panel A** shows the results for the subsample of negatively performing investments (IRR<=0%), **Panel B** for the subsample of total losses (IRR=-100%). The dependent variables are the logarithem of the absolute investment share and the relative investment share. The absolute (relative) investment share is the total amount invested by the fund in this portfolio company divided by the total (average) amount invested by the fund in all portfolio companies. The first column defines the categories of the independent variables, the second column presents the variables. Independent variables include three measures for fund experience, the fund sequence number, the investment manager's age at date of in initial investment into the portfolio company and a dummy variable equal to one for first-or-second-fund investments and equal to 0 for third-or-later-fund investments. A dummy variable equal to one if the investment manager raised a follow-up-fund already at time of investment in the portfolio company controls for window dressing behaviour. Variables are as defined in table I. The last three rows present the model summary (N, R squared, Adjusted R squared and the F- statistic).
The coefficients (only) of the OLS regression are illustrated in the third to tenth column. *, **, *** Significant at the 10%, 5%, 1% levels, respectively.

	Dependent Variable:	Absolute Investment Share		Relative Investment Share		Absolute Investment Share		Relative Investment Share	
		Panel A: Subsample: Negative Performing (IRR< 0%)				**Panel B**:Subsample: write-offs (IRR=-100%)			
	Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Constant	-1.880***	-1.597***	1.048***	0.941***	-2.159***	-1.626***	1.153***	1.070***
Repuation/ Experience	Fund Sequence Number				-0.029**				
	Fund-Number: first or second?	0.259***				0.272***			
	IM Age		-0.021***	-0.011***			-0.023***	-0.010*	-0.048**
Manager	US-IM	0.141*	0.168**	0.216**	0.206**	0.170	0.224**	0.293**	0.288**
Fundraising	Follow-up-fund raised	-0.300**	-0.236**	-0.179	-0.138	-0.521***	-0.410***	-0.341	-0.340
Investment	High Tech	-0.032		-0.139*	-0.137	0:187*		-0.013	-0.001
	Later Stage	0.192***	0.170***	0.044	0.068	0.301***	0.160*	0.118	0.139
Macro-economic Variables	Investment in Bubble	0.115*			0.034	0.104			0.053
	NASDAQ Development			-0.006				-0.026	
	GDP	-0.043	-0.067	-0.126	-0.110	-0.025	-0.067	-0.133	-0.107
	Growth Committed Capital	-0.029		-0.004	0.005	-0.030		-0.008	-0.005
	Committed Capital		4.77E-07*				4.51E-07		
	Short-term interest rate	-0.013	-0.002	-0.018	-0.013	-0.002	0.005	-0.064	-0.057
Model Summary	Number	295	312	295	295	144	153	144	144
	Rsquare	0.139	0.245	0.075	0.057	0.181	0.272	0.102	0.112
	Adjusted Rsquare	0.112	0.228	0.046	0.027	0.127	0.237	0.042	0.053
	F Statistic	5.110***	14.089***	2.572***	1.910**	3.302***	7.743***	1.688*	1.887**

Table 7 Regression Analysis on the Determinants of the Pre-Exit-Phase Round-share of bad performing investments

The total sample comprises of 712 PE/VC- investments merged from the Venture Economics and Cepres databases. Panel A shows the results for the subsample of negatively performing investments (IRR<=0%), Panel B for the subsample of total losses (IRR=-100%). The dependent variable is Pre-exit-phase round-share. We segment the total investment period into three fractional periods of time, each one third of the total period: the first as the initial investment phase, or i-phase; the second as the maturity phase, or m-phase; and the final third as the pre-exit phase, or p-phase. The Pp-round-share is defined as the share of the No.of Phase p (pre-exit phase) rounds of the total No. of rounds (Pp rounds / All rounds). The first column defines the categories of the independent variables, the second column presents the variables.

Independent variables include three measures for fund experience, the fund sequence number, the investment manager's age at date of in initial investment into the portfolio company and a dummy variable equal to one for first-or-second-fund investments and equal to 0 for third-or-later-fund investments. A dummy variable equal to one if the investment manager raised a follow-up-fund already at time of investment in the portfolio company controls for window dressing behaviour. Variables are as defined in table I. The last three rows present the model summary (N and Pseudo R squared). The coefficients (only) of the poisson-regression are illustrated in the third to tenth column. *, **, *** Significant at the 10%, 5%, 1% levels, respectively.

		Dependent variable: Pre-exit-phase round-share							
		Panel A: Subsample: Negative Performing (IRR< 0%)				**Panel B**:Subsample: write-offs (IRR=-100%)			
	Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Constant	2.469***	3.029***	3.555***	3.016***	3.392***	3.998***	4.639***	4.014***
Repuation/ Experience	Fund Sequence Number	-0.067***				-0.088***			
	Fund-Number: first or second?		0.092***		0.092***		0.256***		0.255***
	IM Age			0.005***				-0.001	
Manager	US-IM	-0.318***	-0.334***	-0.251***	-0.334***	-0.279***	-0.234***	-0.371***	-0.233***
Fundraising	Follow-up-fund raised	-0.317***	-0.099	-0.012	-0.103	-0.787***	-0.403***	-0.368***	-0.391***
Investment	High Tech			0.127***				-0.043	
	Later Stage	-0.586***	-0.573***	-0.671***	-0.574***	-0.239***	-0.143***	-0.428***	-0.140***
Macro-economic Variables	Investment in Bubble				-0.059				0.079
	NASDAQ Development	-0.223***		-0.441***		-0.135***		-0.269***	
	GDP	0.156***	0.196***	0.171***	0.200***	-0.040	0.013	-0.003	0.006
	Growth Committed Capital	0.232***				0.125***			
	Committed Capital		-3.90E-06***	-7.38E-06***	-3.640E-06***		-4.98E-06***	-6.62E-06***	-5.34E-06***
	Short-term interest rate	0.185***	0.095***	0.099***	0.096***	0.083***	-0.002	-0.005	-0.002
Model Summary	Number	312	312	295	312	153	153	144	153
	Pseudo Rsquared	0.104	0.117	0.181	0.117	0.069	0.169	0.201	0.168

CHAPTER B (I)

Venture Capital Performance Projection: A Simulation Approach

Projection of Venture Capital Fund Performance:

A Simulation Approach

by

Philipp Krohmer*, Daniel Schmidt**, Mark Wahrenburg***

Abstract

In this paper, we propose a comprehensive and conceptually clear simulation approach for performance projection and risk management of venture capital investments. Our approach can be used for a single venture capital transaction and for funds of different size and focus. At the core of our model is a new methodology that comprises of two consecutive steps: first, an econometric analysis and modelling of individual venture capital investment returns; second, a Monte Carlo simulation of the returns of a venture capital fund, where the results from the econometric analysis are interpreted as data-generating processes for the returns of the individual investments in the fund. For the first step, we draw upon comprehensive cash flow information from 2,721 venture capital investments taken from the records of CEPRES to develop and estimate a simple multi-factor model of the return distribution of individual venture capital investments. This multi-factor model is then used to simulate returns of a venture capital fund portfolio. The final outcome of this iterative approach is a probability distribution of the portfolio returns, showing, for example, the likelihood of achieving a prespecified outcome. Furthermore, our approach is capable of illustrating the effects of diversification on the return distribution of a fund portfolio.

* CEPRES Center of Private Equity Research and Goethe-University of Frankfurt
** CEPRES Center of Private Equity Research, Managing Director
*** Goethe-University of Frankfurt, Professor Chair of banking and finance, CEPRES Center of Private Equity Research

Introduction

Despite the increasing importance of private equity as an asset class, there is only a limited understanding of the economic characteristics of this industry. Especially after the boom period of the late nineties, followed by the aftermath of the "Internet bubble" collapse that lead to wide variations in the success of venture capitalists, it requires a better understanding of performance characteristics and risk management. As data has gradually become available, several empirical papers have recently documented the risk and return of private equity investments, albeit research on this special issue is still scarce compared to the volume of literature on private equity.

The contribution of this paper is to shed light on the following two questions: First, how should the risk and return of private equity investments be estimated and what determines the performance of individual investments in a venture capitalist's portfolio? Second, how should the risk and return patterns of a venture capital portfolio be projected and reliably communicated to the potential investors? To answer this second question, we present a comprehensive and conceptually clear methodology for venture capital performance projection and risk management.

Our unique performance projection and risk management approach is based on a Monte Carlo simulation of the Internal Rates of Return (IRRs) of individual venture capital investments. Our Monte Carlo methodology can be used for the performance projection of a single transaction and for funds of different size and focus. Monte Carlo methods have been introduced into the finance literature by Boyle (1977) and are now widespread among many areas of finance. The basic idea behind this technique is that the behaviour of a random variable, such as the IRR of a venture capital investment in our case, can be assessed by the process of actually drawing lots of samples from the underlying probability distribution and then observing the behaviour of the resulting artificial distribution. This technique is especially useful in our case, as the "true" distribution of IRRs of venture capital investments is analytically not tractable. If the true underlying probability distribution is unknown or not tractable, the common strategy is to first create a model of the probability distribution, which should, of course, resemble the true probability distribution as good as possible. This artificial distribution can then be used as a sampling distribution in the next step.

In order to model the probability distribution of the IRRs of individual venture capital investments, we draw on a comprehensive database provided by the Center of Private Equity Research (CEPRES) to formulate an econometric model of venture capital returns. More specifically, we propose a multi-factor model of the individual venture capital investments IRRs that is estimated via a simple OLS Regression. The results from this regression analysis are then used as a data-generating process for our subsequent simulation procedure. Therefore, our performance projection and risk management methodology involves two consecutive steps: first, an **Econometric Analysis and Modelling** of the individual venture capital investment returns; second, a **Monte Carlo Simulation** of the returns of a venture capital fund, where the regression results from our econometric analysis are interpreted as data-generating processes for the individual investment return IRRs.

For the regression analysis, we build upon the prior literature by investigating the determinants of venture capital investment performance based on a comprehensive venture capital data sample provided by CEPRES. We analyse the investment returns of 201 venture capital funds that are part of 96 investment managers with 2,721 portfolio companies over a period of 33 years (1971 – 2004). The geography spread covers 4 continents: North America, South America, Europe and Asia. As we have information on the exact timing and cash streams between the venture capitalists and the portfolio companies, we can precisely calculate the actual investment IRRs for each portfolio company, rather than having to rely on a return proxy. The dataset enables us to analyse the influence of various factors on the returns on a venture capital investment. In specific, our regression analysis accounts for the influence of the investment managers, the fund and the portfolio company levels, as well as differences in transaction structures. Furthermore, we include several macroeconomic factors in our regression analysis. As venture capital investments are typically investments in young innovative companies, characterized by substantial informational asymmetries and uncertainty, the outcome of an investment is to a high degree ”opportunity-driven”. The high risk and return potential of venture capital investments is depicted by a high number of write-offs on the one hand, and extraordinary returns of the top performing companies on the other. These positive and negative outliers are more the result of mere chance, i.e, they are usually less affected by factors such as the overall macroeconomic conditions. Therefore, leaving these outliers in our regression analysis of the investment performance determinants could substantially bias the regression coefficients. For this reason, we at first exclude the total losses with an IRR of -100% and out- performers, defined as investments with an IRR above +99%, and perform the analyses only with the remaining deals, which we denote in the following as “normal-performer-sample”. This also has the advantage that historical returns for the “normal-performer-sample” are in good approximation normally distributed. Overall, we are able to explain via an OLS Regression analysis a high degree (over 20%) of the total variation in the IRR for this specific data sample, while most of the papers on this topic have accounted for far less of the variations.

In the second step, we draw on the results from the previous econometric analysis to simulate the returns distribution of a venture capital fund. In specific, this is done by using the previous regression results as a data-generating process for a Monte Carlo simulation of the returns of the individual investments in the fund portfolio. For the purpose of our regression analysis, we only accounted for individual normal deal returns, while write-off and out-performer deal returns were systematically excluded from the analysis. For the fund portfolio simulation, write-off and out-performer deal returns are now re-integrated in the portfolio construction by the following approach. For the total losses, the projected IRR will always be set to -100%, for the normal performers, the projected IRR of each deal is determined by running the regression analysis with partly simulating the parameters, for the out-performers, a simulation process randomly assigns a return out of the defined range to each of the investments in this group. The weighting for each of these subsets in the fund portfolio is based on the historical ratios of write-offs, normal and out-performer deals in a venture capital fund portfolio. This calculation process is then repeated for a predetermined number of iterations defined in the simulation settings. The final outcome of this iterative approach is a frequency distribution of the portfolio IRR, showing the likelihood of achieving a prespecified outcome, which has a higher informational content compared to the single value results often proposed in other studies.

In the next section, we present a brief overview of previous studies on private equity performance determinants. In Section 3, we present our approach for the performance projection and risk management of a venture capital fund. In Section 4, the dynamics of our model are illustrated with simulation results for two artificial funds. In the last section we summarize the main results and draw some final conclusions.

1 Related Literature

Private equity, and especially venture capital, has been the subject of extensive academic research. Despite the volumes of literature on private equity, there are only a few empirical papers analyzing the performance characteristics of this asset class. Limited availability of return data has been the main obstacle for a long time. As data has gradually become available, several papers have recently documented both the gross performance of private equity investments at the single deal level and the net performance at the fund level. While earlier empirical studies on private equity were based on aggregate data from public databases, there is now a set of recently published working papers that examine the relation between risk and return of private equity investments more closely and with more detailed data.

Important research on private equity performance on the *fund level* has been presented, for example, by Kaplan and Schoar (2005), Ljungquist and Richardson (2003), Gottschalg et al. (2003) and Diller and Kaserer (2005). Kaplan and Schoar (2003) use in their analyses a data set from Thomson Venture Economics. For 746 funds, they investigate individual fund returns measured by the public market equivalent (PME) and find that performance increases with the fund manager's experience and is persistent. They also show that better performing funds are more likely to raise follow-on funds. Gottschalg et al. (2003) analyze returns of more than 500 private equity funds derived from the records of Venture Economics on the basis of a profitability index. They document that the performance of venture funds is more sensitive to business cycles, while buyout fund performance is more sensitive to the state of the bond and stock market. Diller and Kaserer (2005) analyze the return determinants generated by European private equity funds by using a dataset of 200 mature funds raised over the period 1980 to 2003 provided by Thomson Venture Economics. They show that apart from the importance of fund flows, market sentiment, the general partners' skills as well as the idiosyncratic risk of a fund have a significant impact on its returns.

Ljungquist and Richardson (2003) stress the inappropriateness of the Venture Economics data for investigating the performance of private equity funds due to limitations of self-reporting and accounting treatment. The cash flow data they use in two papers (2003a, 2003b) was provided by one of the largest institutional investors in U.S. private equity. They show that fund managers time their investment and exit decisions in response to competitive conditions in the private equity market. In particular, they find evidence that competition for deal flow with other private equity funds affects the investment timing. Furthermore, they show that improvements in investment opportunities increase performance.

The dataset used in our paper is, in terms of reliability and accurateness, closest to the one used by Ljungquist and Richardson (2003). Even though we perform projections of fund performance, our analyses rely on detailed transaction and performance information on a single deal level.

Important research on private equity performance on the *single deal level* include, for example, Cochrane (2004), Hege et al. (2003) and Cumming and Walz (2004). Cochrane (2004) analyzes the performance of venture capital investments based on a dataset from Venture One, which consists of data from the financing rounds of 7,765 companies using a maximum likelihood estimate that corrects for selection bias. Hege et al. (2003) based their performance measurement first on a hand-collected questionnaire dataset and second on valuations based on Venture Economics data. For the hand-collected questionnaire dataset, they use a proxy for measuring performance by classifying the exit type and counting IPOs as success. Based on the Venture Economics data, they measure the performance as Internal Rate of Return (IRR) of the project between the first financing round and the last self-reported valuation of the project to quantify the impact of VCs' behavior on the profitability of their project. The IRR figures in their study again lack accuracy and reliability due to the measurements' basis on self-reported valuations.

The IRR-calculations in our study are based on exact monthly cash streams between the portfolio company and the fund. Thus, we do not have to rely on a return proxy based on the first inflow and last cash outflow or on valuation data. The cash flows are reported gross of fees and as such, are not biased by any externalities like management fees and carried interest. Our cash flow based IRR-calculations are extremely precise. The work closest to that presented in this paper in terms of data and performance measurement is that of Cumming and Walz (2004). They rely on the same database provided by the Center of Private Equity Research (CEPRES) and also perform precise cash-flow-based IRR calculations. They use a wide range of variables to proxy value-added activities which explain returns. Furthermore, they compare reported unrealized returns with predicted unrealized returns based on regression estimates of realized returns, and document significant systematic biases in the reporting of unrealized investments and their determinants.

In our paper, we aim to develop a comprehensive, accurate and easy-to-implement performance projection and risk management model for private equity and venture capital. The exact performance measurement and determinant analyses, as discussed in the aforementioned studies, serve as the starting-point of our approach. Recent academic literature on the modelling of private equity and venture capital funds include Takahashi and Alexander (2002), Malherbe (2004), Buchner et al. (2006) and Buchner (2008). However, the general approach of these papers differs from ours as they model cash flows and not the resulting Internal Rates of Return of a venture capital or private equity investment. The approach closest to ours is that presented by Weidig (2002). Weidig (2002) proposes a simple risk management scheme for performance and liquidity forecasting based on the reported interim IRR of an un-finished fund, but his approach does not work to predict the performance of the "future" market of funds, i.e. funds that not have started investing yet. Furthermore, in contrast to our model, the approach of Weidig (2002) does not capture diversification effects.

2 A Simulation Approach for Venture Capital Performance Projection and Risk Management

2.1 Description of the General Approach

In general, venture capital returns can vary significantly among different investments. Therefore, a merely deterministic forecast of the returns of an individual venture capital investment or fund will only provide an incomplete picture of the "true" return dynamics. In a more appropriate modelling setup, the return of an individual venture capital investment or of a venture capital fund must be a stochastic variable. In the following, let *IRR* denote the random return of an individual venture capital investment, where returns are measured by the Internal Rate of Return (IRR) of the investment. To model the dynamics of this random variable, we draw upon the existing empirical research on the determinants of venture capital investment performance. As already stated in the literature review above, the returns of venture capital investments are, in general, influenced by various factors such as the fund manager's experience or the overall macroeconomic conditions. Let $X_1,...,X_K$ denote a collection of k=1,…,K variables that influence the return of a specific venture capital investment. Thereby, any of these K variables can either be stochastic or deterministic, depending only on the nature of the specific factor. Under these assumptions, a model that relates these variables to the Internal Rate of Return *IRR* of a venture capital investment can be written as

$$IRR = L(X_1, X_2, ...X_K),$$

where $L(\cdot)$ is a function that relates the distribution of the K independent variables to the distribution of *IRR*. If this function and the deterministic values or probability distributions of the K independent variables are explicitly known, then this model specifies the probability distribution of the Internal Rate of Return. However, it would be very difficult to work out this relationship analytically. Therefore, we propose a simple multi-factor model of the form

$$IRR = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_K X_K + U, \quad (1)$$

where U is an error term for which $U \sim N(0, \sigma^2)$ is assumed. The constant coefficients $\alpha, \beta_1, ..., \beta_K$ of this model can be estimated by a simple OLS Regression analysis. In a second step, the results from this regression analysis can be used as a data-generating process for our subsequent simulation procedure of the performance of a venture capital fund portfolio. Therefore, our performance projection and risk management methodology involves two consecutive steps: first, an **Econometric Analysis and Modelling** of the individual venture capital investment returns; second, a **Monte Carlo Simulation** of the returns of a venture capital fund, where the regression results from our econometric analysis are interpreted as data-generating processes for the individual investment return IRRs.

The basic intuition behind our approach is to model the relationship between individual portfolio returns and investment-specific as well as macroeconomic factors by the simple multi-factor model given in equation (1) that can be estimated by an OLS Regression. For our regression analysis, we build upon the prior literature by investigating the determinants of venture capital investment performance based on a comprehensive venture capital data sample provided by CEPRES. The data provides precise information about each cash injection from the investor to the portfolio company and each cash distribution from the company back to the investor. Therefore, we can precisely calculate the actual investment IRRs for each portfolio company based on monthly cash flows. Furthermore, the dataset enables us to analyse the influence of various factors on the returns on a venture capital investment. In specific, our regression analysis accounts for the influence of the investment managers, the fund and the portfolio company characteristics, as well as differences in transaction structures. Furthermore, we include several macroeconomic factors in our regression analysis. As venture capital investments are typically investments in young innovative companies, characterized by substantial informational asymmetries and uncertainty, the outcome of an investment is to a high degree ”opportunity-driven”. The high risk and return potential of venture capital investments is depicted by a high number of write-offs on the one hand, and extraordinary returns of the top performing companies on the other. These positive and negative outliers are often more the result of mere chance, i.e, they are usually less affected by factors such as the overall macroeconomic conditions. Therefore, leaving these outliers in our regression analysis of the investment performance determinants could substantially bias the regression coefficients. For this reason, we at exclude total losses with an IRR of -100% and out-performers, defined as investments with an IRR above +99%, and perform the analysis only with the remaining deals, the so-called “normal-performer-sample”. This also has the advantage that historical returns for the “normal-performer-sample” are in good approximation normally distributed, as shown in the following section.

In the second step, we draw on the results from the previous econometric analysis to simulate the returns distribution of a venture capital fund. In specific, this is done by using the previous regression results as a data-generating process for a Monte Carlo simulation of the returns of the individual investments in the fund portfolio. Monte Carlo methods have been introduced into the finance literature by Boyle (1977) and are now widespread among many financial applications. For a comprehensive overview also see the classical textbook of Glasserman (2003). The basic idea behind this technique is that the behaviour of a random variable can be assessed by the process of actually drawing lots of samples from the underlying probability distribution and then observing the behaviour of the resulting artificial distribution. This is especially useful in our case, as the “true” distribution of the IRR is analytically not tractable. Using the estimated regression coefficients $\hat{\alpha}, \hat{\beta}_1, ..., \hat{\beta}_K$ from our multi-factor model, the IRR of an individual venture capital investment can be simulated by using the equation

$$IRR_j = \hat{\alpha} + \hat{\beta}_1 X_{1j} + \hat{\beta}_2 X_{2j} + ... + \hat{\beta}_K X_{Kj} + U_j, \tag{2}$$

where IRR_j denotes the Internal Rate of Return in the *j*th iteration of our simulation procedure, with $j = 1, ..., M$. In each simulation trial *j*, we must specify the values of the factors $X_{1j}, X_{2j} ... X_{Kj}$. This is done by either assigning a constant value to the factor in all simulation trials (*if the factor is deterministic*) or by drawing values from the corresponding specified probability distributions of that factor (*if the factor is stochastic*). The detailed procedure for this is explained in section 3.4. Furthermore, the values of U_j are drawn from a normal distribution with mean 0 and variance σ^2, where σ^2 is the variance of the residuals from the regression analysis. If the total number of simulation trials *M* is considerably large, then we get an empirical distribution of the investment IRRs that will converge towards the distribution of the IRR that is specified by the multi-factor model in equation (1). In order to form a venture capital fund portfolio, the simulation procedure of equation (2) can be repeated for different venture capital investments with different characteristics such as different industry backgrounds. However, for the purpose of our regression analysis, we only accounted for individual normal deal returns, while write-off and out-performer deal returns were systematically excluded from the analysis. For the fund portfolio simulation, write-off and out-performer deal returns must now be re-integrated. This can be achieved by the following approach. For the total losses, the projected IRR will always be set to -100%, for the normal performers, the projected IRR of each deal is determined by running the simulation according to equation (2), for the out-performers, a simulation process randomly assigns a return out of the empirical return distribution of the investments in this group. The weighting for each of these subsets in the fund portfolio is thereby based on the historical ratios of write-offs, normal and out-performer deals in a venture capital fund portfolio. This calculation process is then repeated for a predetermined number of *M* simulation iterations. The final outcome of this iterative approach is a frequency distribution of the portfolio IRR. Therefore, our model captures diversification effects or risk in the sense of having a variation of the expected values.

In order to illustrate the dynamics of our approach, simulation results for two fictitious venture capital funds are presented. At the core of this simulation study is a unique set of detailed cash flow data provided by CEPRES. Before the two consecutive steps of our performance projection and risk management model are illustrated in detail with real data, we start by giving a descriptive analysis of the data sample employed for the subsequent study.

2.2 Data Description

The unique dataset we use for this study originates from the database of CEPRES. CEPRES is a private consulting firm affiliated with the University of Frankfurt, and was formed in 2001 specifically to gather detailed information on private equity deals[1]. As of October 2005, the dataset provides detailed information on 171 private equity firms, 427 private equity funds, and their 9,950 investments in 8,063 different companies. These investments include more than 27,000 cash injections spanning over a period of 34 years (1971 – 2005) and cover 50 countries in North and South America, Europe and Asia. For reasons of confidentiality, names of firms, funds and portfolio companies are not disclosed. Although the database is completely anonymous, it provides us with high quality in-depth data.

The dataset is extraordinary with respect to the level of detail provided. The data consists of information on the investment manager, the fund and the portfolio companies. Together with detailed transaction specific data, the dataset also provides us with exact monthly cash flows between the portfolio company and the fund. The cash flows are reported as gross figures, and thus are not biased by any externalities like management fees and carried interest. Therefore, our cash flow based IRR-calculations are extremely precise.

[1] CEPRES requests the data directly from fund managers through standardized information request sheets. The fund managers get in exchange for their detailed data exclusive access to unique benchmarking services of their direct investments process and substantial discounts on all other CEPRES consulting services.

The dataset contains information on venture capital, private equity buyout and mezzanine funds. Although these three types of funds share similar characteristics such as the organizational structure, the underlying investments differ substantially and therefore, separate analyses should be performed. In this study, we focus on venture capital and exclude all buyout and mezzanine funds and investments where the development stage was not disclosed by the fund. Furthermore, as we strive to explore the determinants of venture capital returns, it is crucial to include only unbiased returns, i.e. the calculation of the returns must be based on objective values. Therefore, we include only partially and fully realized investments and eliminate all unrealized investments. In the case of partially realized investments the IRR is calculated by taking the Net Asset Value (NAV) at the valuation date as the last cash flow paid back to the investor.

The resulting dataset comprises of 2,721 (thereof 2,285 fully realized) investments, including 96 investment managers, 201 funds over a period of 33 years (1971 – 2004). The geography spread covers 4 continents: North America, South America, Europe and Asia, with 1,637 investments in the U.S., 813 in Europe (UK: 172, France: 200, Germany: 145). The remaining investments were pursued in 34 other countries.[2]

Table 2, Panel A provides detailed summary statistics for the performance dynamics, the Internal Rate of Return (IRR) for the complete venture capital sample, and several IRR-subclusters. Figures 1-3 illustrate the IRR-distributions graphically. For the entire venture capital dataset (Figure 1), we see that the curve has an asymmetric and positively skewed distribution of returns. This positive skewness and asymmetric shape is due to the high number of write-offs (failed deals with an IRR = -100%) and a small number of extreme out-performers. Taking the natural logarithm of the IRR, a common practice in empirical studies, could certainly smooth this distribution. This log-transformation works well when analysing whether a variable has a significant influence on performance. However, it is not feasible for our specific performance

[2] Argentina, Asia, Austria, Belgium, Brazil, Canada, China, Czech Republic, Denmark, Finland, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Luxemburg, Malaysia, Netherlands, Norway, Philippines, Poland, Portugal, Romania, Russia, Singapore, Spain, Sweden, Switzerland, Taiwan.

prediction model because the coefficients from our regression analysis would then be biased, due to the incorrect weighting of the outliers. Therefore, we perform the subsequent regression analysis without the extreme values, where extreme values or outliers are defined as follows. A complete loss is the worst outcome for an investment, we take the write-offs (IRR=-100%) as the lower bound to determine the outliers. As an upper bound, we define the out-performers as investments with an IRR > + 99%. The majority of the deals occur between these two limits, i.e. between -99% and +99%. We refer to deals in this range as "normal" deals. As Table 3 reveals this normal deals account for 60.50%, whereas outlier and write-off deals account for 9.80% and 29.70% of our entire venture capital data sample, respectively. Broad analyses of the return distributions of several sub samples for different types of private equity and single funds out of the entire CEPRES dataset show that these cut-off points lead in most cases to the best approximation of normally distributed returns. As can be inferred from Table 2, Panel A, for the resulting normal performing subset, skewness is close to 0 and the median and mode are very close to the mean IRR value. These descriptive statistics and additional tests (Kolmogorov-Smirnov and Q-Q-Plots) indicate that the IRR values for the normal subset are approximately normally distributed. This effect is also illustrated graphically by Figure 2, which shows the IRR distribution for the normal deals only. Therefore, it is this data sample which will be employed for our subsequent regression analysis.

Table 2, Panel A shows in detail the performance results measured by IRR for the entire VC dataset and the out-performer and normal deal subsets. We see the mean IRR for the complete VC dataset is 16%, for the outliers 480% and for the normal deals -2%. The dispersion of returns spans a wide range for all 3 types of data categories, as expressed by the high standard deviation, reflecting the high risk and return profiles of these investments.

The dataset is broadly diversified over more than 20 different industries. For our analyses, we create 5 sector classifications - Biotech, Telecom, Computer, Financial and Industrial[3]. Table 2, Panel B shows the dispersion of the sample across these sectors. Overall, 1,948 (71.6 %) investments of our venture capital sample are considered active in the high technology sectors (Biotech, Telecom and Computer). Out of these, 1,397 (51.5 % of the total sample) investments occurred during an early stage of company development, as depicted in Table 3.

We divide the dataset into sub-clusters to analyze possible trends based on structural differences (i.e. industry sector, stage of company development, exit type, country of origin, investment manager age, investment duration and fund size). The sub-cluster statistics are presented in Table 2, Panel B. We see that in the Sector Cluster, the highest standard deviations are in the high technology industries of biotech, computer and telecommunication. Besides for the standard deviation, the high risk and return potential in these sectors is reflected in Table 3 by a strong number of write-offs on the one hand, and extraordinary returns of the top performing companies on the other. In terms of mean IRRs, these three sectors clearly outperform the others, but at the same time, the median values are comparatively much lower. Most companies in the high technology sectors struggle to survive in an intensively competitive industry, but those that do succeed perform very well and counterbalance the failures.

The Stage Cluster of Table 2, Panel B shows that the majority of the deals were in the early stage and returned worse performance results in both the mean and median IRR, 6% and -44%, respectively, compared to later stage investments (34% and 5%). Companies in the later stage have a greater likelihood to continue to grow and expand, or to undergo a merger/acquisition, whereas an early stage company either survives the instabilities of birth to enter the growth phase or perishes. This is reflected in Table 3 by the high percentage of total losses for early stage

[3] The 26 industry classifications provided by CEPRES were aggregated into the following 5 sector clusters according to the FTSE Global Classification System (comprising CEPRES categories in brackets): 1) Industrials (Industrial/Manufacturing, Natural Resources/Energy, others, other Services, Media, Consumer industry/food, Construction, Materials, Waste/Recycling, Traditional Products, Hotel, Leisure, Retail, Textile, Environment, Transportation); 2) Financials (Financial Services, Fund of Fund Investments) 3) Biotechnology (Health Care/Life Sciences) 4) Computer (IT, Internet, Software, Semiconductor, High Tech) 5) Telecommunications (Telecom).

investments (36.5 %), which more than doubles the fraction of write offs for later stage investments (17.3 %).

In the Exit Type Cluster of Table 2, Panel B, we can observe performance patterns as expected. Companies that achieved IPO status returned the highest mean and median IRR (124%, 46%), followed by deals that resulted in a sale or merger (77%, 12%), and lastly, businesses that failed and were written-off (-100%, -100%).

A comparison of US to non-US investments shows only a slight difference in the mean IRR, 14% for US investments versus 18% for non-US investments, perhaps a bit of a surprise for some who expect or assume US deals to perform better.

The investment manager age (IM age) is the number of years the investment management firm has been in business at the time of initial investment into the observed portfolio company. We define three categories for IM age: young if it is 5 years old or less, medium between 6 and 19 years, and old if its age is 20 years or more. Considering the age as a proxy for experience, we see that more seasoned IMs achieve considerably higher returns in terms of mean IRR, while young IMs need time to learn the tricks-of-the-trade.

Table 2, Panel B also shows the performance results based on the investment duration cluster. We define investment duration as short if it spans 2 years or less, medium for durations between 2 and 5 years, and long for investments that last longer than 5 years. We see from the performance numbers that a short duration investment results in a poor median IRR, and this is sensible because it takes time for a company to utilize the investment capital for growth and it needs even more time before it begins to generate returns for the investors. Staging, the stepwise allocation of capital to the company as a mechanism to control an investment, could provide an alternative explanation. By staging the investment, the investor achieves an option to abandon underperforming companies in time, avoiding throwing good money after the bad. We assume that non-performing investments will derail some time after the initial investment and will not live as long as successful companies, even if the investor tries to bolster up its lifetime for a while by follow-on financings. Therefore, investments with a short duration might often be total write-offs leading to a median IRR for this group of -100%. For the same reason, there will be only few total losses within the long duration group. However, extraordinarily performing investments show very fast growth and are usually exited earlier, and therefore, will rarely be found in the long duration group. This is reflected by the similar mean and median IRR for this group (13% and 10%), and the low standard deviation and maximum value.

The last sub-cluster in the dataset breakdown is the fund size cluster. We use the total amount invested by the fund at the valuation date as a proxy for fund size, if the fund size was not disclosed. The size is expressed in US dollars valued in June 2005. We categorize a fund as small if the investment amount is less than $100 million, medium for amounts between $100 million and $500 million, and large if the investment amount exceeds $500 million. We see in Panel B that deals financed by small funds performed considerably better in terms of mean and median IRR, while deals in medium sized funds still returned a positive performance of 10% mean IRR. However, large funds performed poorly with a -6% mean IRR. A possible explanation for this pattern is that if a fund is too large, then it is unlikely to find enough good investment opportunities and may have to diversify (for example, invest in new industries) or invest in projects with poor perspectives. Smaller funds, however, can specialize in specific fields (sectors, stages) and develop exceptional expertise, resulting in better performance. Furthermore, for a given level of venture capital fund resources, tighter control and better value-added assistance to all portfolio companies decreases as portfolio size increases.

Our summary statistics in Table 2 indicate very distinct risk return profiles for the considered clusters and underline the importance of these variables for further analysis. We examine the dataset in further detail by combining the analysis shown in Table 2, Panels A and B. The venture capital data sample is depicted in Table 3 according to the three main categories (normal, outlier, write-off), stage and industry sector, relative to the entire dataset. We gain a deeper insight into the structure of the IRR samples by separately comparing the ratio of the outliers and write-offs for each sub-cluster. The highest failure rate occurs for early stage investments at 36.5%, and more specifically, early-stage computer and telecommunication sectors performed the worst considering the number of total losses, with 40.3% and 40.5% failure rates, respectively. Computer and telecom also have the highest loss rate overall, regardless of stage, at 36.7% and 35.9%, respectively. These two sectors also show the highest out- performer rates for later stage investments (Computer: 14.6%, Telecom: 16.2%) and for early stages (Computer: 10.5%, Telecom: 11.2%). It is evident that the failure or out-performer probabilities strongly depend on the development stage and industry sector of the portfolio company.

2.3 Econometric Analysis and Modeling

For the normal performing-sample defined above, we determine the factors influencing the outcome of the investment return via an Ordinary Least Square (OLS) regression analysis with the cash flow based IRR as the *dependant variable*. The regression model we estimate can be stated as

$$IRR_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_K X_{Ki} + U_i, \tag{3}$$

where:

IRR_i:	Internal Rate of Return of observation (investment) *i*,
α:	constant factor of the regression function,
β_k:	regression coefficient of explanatory variable k=1,…,K,
X_{ki}:	value of the explanatory variable k in observation i,
U_i:	residual value in observation i,
i:	i=1,…,I and I = total number of observations in the data sample.

In total, we consider a diverse collection of *K* explanatory variables on four different levels: (1) the investment manager, (2) the fund characteristics, (3) the portfolio company characteristics and (4) various market or macroeconomic variables. The variables are chosen with regard to prior academic literature. In addition to the variables presented in detail hereafter, which are the variables kept in the final model, we have tested alternative variables. Overall, more than 50 potential influencing factors have been analysed.[4] The resulting factors were selected according to their significance level, their contribution to the explanatory power of the model and multicollinearity restrictions. The final variables of our model variables are as defined in Table 1.

(1) Investment Manager: The investment manager is the PE or VC firm which manages the consecutive funds. The experience and reputation of the investment manager generally grows over time, because unsuccessful funds could cause the investment manager to not being able to raise the next fund. Maula and Seppä (2001) provide evidence that reputation strongly affects the IM's ability to select, certify and add value to investments, and to utilize negotiation power in the new investment's valuation. Therefore, we introduce the investment manager age in years since its foundation at the initial investment date of the fund into the company in our analyses. Contrary to this idea, Gompers and Lerner (1999) found that reputational concerns induce younger partnerships to work hard to achieve success. A further explanation for a possible negative influence is provided by Schmidt and Wahrenburg (2004). They argue that established fund managers older and closer to retirement, and therefore, put less weight on the effects of their actions on future business opportunities.

(2) Fund Characteristics: At the fund level, we test for the impact of the fund size on investment return. Several empirical studies have confirmed the importance of the fund size on success, for example Cumming (2003); Gottschalg et al. (2003); Diller and Kaserer (2004). Most studies argue that the performance decreases with increasing portfolio size due to less monitoring and value-added assistance.

(3) Portfolio Company Characteristics: At the portfolio company level, we test for 5 different characteristics: (3a) Our dataset includes companies from different nations. We control for the effects of geographic origin of the portfolio company by including a dummy variable,

[4] Additionally to alternative measures of the presented variables, time-lagged macroeconomic factors have been analysed. Furthermore, we test for linearity between dependent and explanatory variable using the "curve estimation" procedure offered in SPSS and include if necessary transformed variables in the analyses. For applied transformations see variable descriptions in Table 1.

indicating, whether the company is based in the United States. Studies reflecting on the relevance of the location for example in regards of legal regulations, macroeconomic conditions, or investment pattern include for example Bottazzi et al. (2005); Keuschnigg (2004); Cumming and MacIntosh (2002); Jeng and Wells (1998) and others. (3b) Further, we examine the portfolio company industry by introducing several sector-dummies in the analyses. Due to high information asymmetries we observe in Table 2, Panel B the highest IRR standard deviations for the high tech sectors: biotech, computer and telecom. This is also reflected by the high numbers of total losses and out- performers for high tech investments in Table 3. These sectors have the highest return dispersions even within the normal subset used for the regression analysis. (3c) Analogous to the sector, the degree of information asymmetries, as well as the return on investment, varies strongly depending on the stage of the company development. Therefore, we control for the influence of the stage of the company at the fund's initial investment. The last two portfolio company parameters are more related to the investment behaviour than to company characteristics. (3d) The investment duration is the total time (measured in years) between the initial investment and the exit date. If the deal is not fully realized, then we take the valuation date to be the exit date and determine the investment duration. As described before, the investment duration may be linked to the growth of the investment. We assume that non-performing investments will derail some time after the initial investment and will not live as long as successful companies. (3e)The second variable related to the investment behaviour is the total number of rounds, which is represented by a proxy as the total number of cash injections received by the company. The stepwise allocation of capital to a company in several financing rounds, instead of financing the venture upfront, is described as staging. The importance of staging as a mechanism to control an investment and to affect its success has been confirmed uniformly by several authors, e.g. Gompers (1995), Neher (1999) and Krohmer et al. (2007).

(4) Market and Macroeconomic Variables: Furthermore, we control for a variety of market and macroeconomic variables. (4a) First, we want to take into account whether the investment was exited during a period of abnormal market conditions, leading to exaggerated valuations and returns. Therefore, we create a dummy variable which is equal to 1 if the final exit or valuation took place during the so-called "internet bubble", i.e. between September 1998 and March 2000 and equal to 0 otherwise. (4b) Analogous to the exit period, we examine whether the investment was started during periods of poor average vintage year performance on the overall private equity market. We further account in our model for bank lending conditions, business cycles and stock market fluctuations by considering the (4c) short-term and (4d) long-term interest rates at investment date, (4e) the average variation of the real U.S.GDP growth per annum over the entire investment period and (4f) the average variation of the corresponding NASDAQ Sector Index during the investment period.[5] The short-term interest rate is defined to be The Federal Reserve Bank 1-month Treasury bill for U.S. investments and the BBA Libor rate for European investments[6], and for the long-term interest rate we set it as the 10-year US–Government Security. These macroeconomic variables have been recognized as relevant factors in several empirical studies, including for example Gottschalg et al. (2003), who can show empirically, that PE performance is positively related to public market performance and GDP and negatively related to interest rates. Moreover, to assess private equity market conditions, we test for two additional variables: (4g) the number of PE or VC backed IPOs at the date of exit or final valuation, this number is an equivalent for the liquidity conditions on the IPO exit market, and (4h) the average fund IRR per vintage year, one year before the investment date, classified for the US and EU venture capital submarkets. By including this IRR-market-benchmark in the analyses, we control for possible cyclical effects in the sample.

The last component to consider in the regression analysis formulation is the model residual. We analyse, whether the regression model residuals, which assemble the effects not captured by the explanatory variables, are independent and identically distributed or correlated with each other

[5] In order to measure the influence of the development of the public equity market on private equity investment performance as precise as possible, we assign each investment to a sector cluster defined above and consider it relative to the sector-specific public equity return rather than a broad benchmark.

[6] For the remaining countries, we apply the U.S. interest rate.

in some way. To do so, we perform a **bootstrap simulation** and estimate the empirical correlations between the residuals. We first create for our entire sample different subgroups of consecutive (2-3) investment years. For each subgroup we create 5,000 independent bootstrap samples of the residual values, each consisting of 2 data values, and calculate the correlation coefficients. As a result, we get for each subgroup and for the average over all subgroups, a correlation value very close to 0. Hence, our model does not face autocorrelation problems, and therefore, the correlations need not be considered further in our simulation analyses. Additionally, the regression model has been analysed and meets the regression model restrictions like multicollinearity and heteroscedastisity.

The results of the OLS regression analysis are presented in Table 4. We can observe that almost all of the included explanatory variables are highly significant and in line with our expectations with regards to the direction of influence. However, two parameters show different signs than expected. First, the “exit in bubble”-dummy, which controls for abnormal market conditions with exaggerated valuations and returns, shows a negative relation with performance. As most of the deals exited in this period fall into the out-performer subsample with extraordinarily high returns, it might be possible, that the remaining deals which are considered in the ‘normal’ regression might be the lemons of this market period, leading to a negative relation with returns. Furthermore, the number of cash injections is negatively related with investment performance. Krohmer et al. (2007) argue, that firms in distress receive more frequent rounds of cash injections as investors “gamble for resurrection,” perhaps attempting various turnaround efforts in the hope of minimizing losses.

In total, the *F*-statistic shows a high significance for the overall model at the 1 % level. The R^2 and the adjusted R^2 values are greater than 0.2 and indicate, that our regression model explains more than 20% of the variation of the investment performance.

2.4 Monte Carlo Simulation

In the second step of our approach, the regression results from the previous section are employed to implement a Monte Carlo simulation of the returns of a venture capital portfolio. Using the estimated regression coefficients $\hat{\alpha}, \hat{\beta}_1, ..., \hat{\beta}_K$ from the previous section, the IRR of an individual venture capital investment can be simulated by using equation (2) presented in section 3.1:

$$IRR_j = \hat{\alpha} + \hat{\beta}_1 X_{1j} + \hat{\beta}_2 X_{2j} + ... + \hat{\beta}_K X_{Kj} + U_j, \tag{2}$$

where:

IRR_j:	Internal Rate of Return of the investment in iteration j,
$\hat{\alpha}$:	regression estimate of the constant factor,
$\hat{\beta}_k$:	Estimated regression coefficient of explanatory variable k=1,…,K,
X_{kj}:	value of the explanatory variable k in iteration j,
U_j:	random draw in iteration j from a normally distributed variable with mean 0 and variance σ^2,
j:	j=1,…,M and M = total number of simulation trials.

If the total number of simulation trials M is considerably large, then we get an empirical distribution of the individual investment IRRs that will converge towards the distribution of the IRR that is specified by the multi-factor model in equation (1). In order to form a venture capital fund portfolio, the simulation procedure of equation (4) can be repeated for a prespecified number of different venture capital investments with different characteristics such as different industry backgrounds. However, for the purpose of our regression analysis, we only accounted for individual normal deal returns, while write-off and out-performer deal returns were systematically excluded from the analysis. For the fund portfolio simulation, write-off and out-performer deal returns must now be re-integrated into the model. This can be achieved by the following approach. For the total losses in the fund portfolio, the projected IRR will always be set to -100%, for the normal performers, the projected IRR of each deal is determined by running the simulation procedure according to equation (4), for the out-performers in the fund portfolio, the IRR is simulated according to the empirical IRR-distribution of our data sample. When making predictions, we have to determine the weighting for each of these subsets in the portfolio according to the considered fund structure. We identify the sector and the portfolio company development stage to be the characteristics with the strongest impact on IRR-categorization. The varying loss and out-performer ratios become particularly apparent, when comparing funds focused on early stage, high-technology investments with their counterparts active in later stages and more traditional industrial sectors. Although this approach solely based on historical sector and stage averages is quite simple, tests for the approximation of the real outlier ratios for funds out of the CEPRES dataset have shown good results. Additionally, this simple approach has the advantage that the necessary input information can directly be extracted from the fund prospectus of the target portfolio and no further assumptions and simulations have to be performed. Therefore, we determine the write off-, out- performer- and normal performer- rates according to the fund structure, based on the historical outlier- ratios for the entire venture capital sample presented in Table 3. The entire calculation process is then repeated for a predetermined number of *M* simulation iterations. To obtain the projected portfolio return, we then take the average of all projected deal IRRs.

For the simulation of the normal deals according to equation (4), we must specify the values of the *K* factors $X_{1j}, X_{2j} ... X_{Kj}$ in each simulation trial j=1,…,*M*. This is done by either assigning a constant value to the factor in all simulation trials (*if the factor is deterministic*) or by drawing values from the corresponding specified probability distributions of that factor (*if the factor is stochastic*). The detailed procedure for all employed variables is explained in the following.

At the **Investment Manager** and **Fund Level**, the two influencing determinants are the investment manager's years in business at initial investment and the total amount invested by the fund to date of exit or valuation, respectively. These values are both deterministic for a given fund and can be extracted from the private placement memorandum or other due diligence material of the fund. For our subsequent analysis, we did not determine specific values for these variables;

rather we simulated different compositions by randomly selecting the values out of the empirical observations.

For the **Portfolio Company Characteristics** most variables are deterministic and are represented by simple dummy variables. Namely the country-dummy, which specifically indicates whether or not the company is located in the U.S., the stage dummy, which identifies the deal as an early stage (categorized in CEPRES as seed, start-up and early) or late stage investment and the sector dummies. The industry sector is a collection of 5 categories, namely biotechnology, telecommunications, financial, industrial, and computer. Computer is the base case, meaning that if we do not declare a specific industry background for the simulation equation, then the investment is by default in the computer sector. These three abovementioned variables are simply dummy variables to indicate true (= 1) or false (= 0).[7] In contrast, the two remaining portfolio company variables can not be simply determined with one deterministic value, instead they have to be represented in our model with a probability distribution. For the portfolio company variables, "the total duration of the investment" and "the number of financing rounds", it is difficult to model a probability distribution analytically. Therefore, we account for the stochastic realizations of these variables by drawing values from the empirical distributions of these variables in our data sample. To deal with interaction effects, we further determine the correlation between these variables in our model. The distributions of the stochastic variables are presented in the Appendix.

On the **Macroeconomic Level**, there are two further dummy variables that have to be specified. We make the distinction for the exit period, namely, if the deal exited during the so called "Bubble Period" we defined as between September 1998 and March 2000. The major purpose of including this variable in the regression analysis is to control for this irrational market period with the result, that the coefficients of the other parameters are not biased by the extreme observations of this time. In the following analyses, we set this dummy to 0. Analogous to the exit

[7] For example, if a deal is an early-stage biotech company in the U.S., then these industry parameters of the regression equation would be: Early stage=1; Biotech=1, Financial=0, Industrial=0, Telecom=0 and U.S.=1

period, we indicate whether the investment is started during periods of poor average vintage year performance on the overall market with a true/false flag in the same way as we described above. We can choose both values, 0 if we have positive expectations for the market development, 1 otherwise. We can even choose the median value 0.5, if we expect a "medium" period of market performance**.** By running the model for all of the three cases separately, we can perform a scenario analysis for different market development. The analyses presented in the next section were performed with a value of 0.4667 (with 1 for strong and 0 for bad performing overall PE markets), which is the average in our sample over the last 33 years. Besides these dummy variables, we consider several other macroeconomic variables in our simulation approach. The influence of the short-term interest rates, the long-term interest rates, the GDP growth, the NASDAQ Sector Indices and the number of PE-backed IPOs is accounted for by assuming appropriate theoretical probability distributions for these variables. Another macroeconomic variable we identified in the regression analysis is the average fund IRR per vintage year one year before the investment date, classified for the U.S. and EU venture capital and buyout submarkets. Contrary to the other macroeconomic variables, we use the empirical probability distribution of our data sample to model the distribution of this variable for our simulation procedure.

Our approach combines the presented consecutive steps into *one comprehensive simulation procedure*. The final outcome of our iterative approach is then a frequency distribution of the portfolio IRR.

3 Simulation Results for Two Fictitious Venture Capital Funds

3.1 Structure of the Fictitious Venture Capital Funds

In this section, we illustrate the dynamics of our model by simulating two fictitious funds. In order to do so, we first have to determine the *structure of the two fund portfolios* – the number of investments in each portfolio, their geographic origin, industry, and development stage. If the model is applied to project the performance of a real fund, the fund structure can typically be extracted from the information given in the private placement memorandum. Our first fictitious fund should consist of 20 deals, and the second of 100 deals. The structures of both funds are assumed to be equal and correspond to the average fund structure of our entire venture capital sample with respect to geographical regions, sectors and stages of the investments. Furthermore, the distribution of the investments across the IRR-subgroups is also assumed to be equivalent to the average values of our total venture capital sample – 30% total losses, 10% out-performers and 60% normal performing deals. As stated above, we determine the write-off, out-performer and normal-performer rates according to the fund structure, based on the historical outlier- rates for the entire venture capital sample presented in Table 3. Then, by multiplying the total number of deals in the portfolio by the determined failure-, outperformer- and normal-rates, we obtain the number of total losses, out- performers and normal performers in our portfolio. Hence, the 20 (100) deal fund contains 6 (30) write offs, 2 (10) out- performers and 12 (60) normal- performers.

3.2 Simulation Results

In this section, we present the simulation results for two fictitious funds, where the first contains 20 deals and the second 100 deals. Tables 5 and 6 show the summary statistics for the projected performance of the two funds. As the funds' geographic-, sector- and stage- focuses are equal and the remaining input variables are exactly the same for both cases, we obviously obtain a very similar mean Fund IRR of 20.90% for the 20-deal case and 21.08% for the 100-deal case[8]. However, we can observe large differences for the median values, the standard deviations and the percentiles. For the 100-deal fund, the median value is 17.34% and more than 2 times higher than the median of the 20-deal case with a value of 7.56%. The standard deviation of the 20 deal case (44.08%) exceeds the standard deviation for the 100 deal fund (20.52%) by a factor of approximately 2. As both funds have exactly the same structure and only differ in the number of

[8] These numbers will converge to the same value with a growing number of iterations (law of large numbers).

deals, we can directly observe the diversification effects of the larger fund. This is also apparent when looking at the percentiles and probability distributions shown in Figures 4 through 7. The probability of obtaining a positive gross IRR for the 100-deal fund is approximately 90%, whereas for the 20-deal fund it is only about 60%. When comparing the two funds, which only differ by the number of deals, the advantage of producing a probability distribution rather than just one single prediction value becomes obvious.

4 Conclusions

In this paper, we propose a comprehensive and conceptually clear simulation approach for performance projection and risk management of venture capital investments. Our approach can be used for a single venture capital transaction and for funds of different size and focus. At the core of our model is a new methodology that comprises of two consecutive steps: first, an econometric analysis and modelling of individual venture capital investment returns; second, a Monte Carlo simulation of the returns of a venture capital fund, where the results from the econometric analysis are interpreted as data-generating processes for the returns of the individual investments in the fund. For the first step, we draw upon comprehensive cash flow information from 2,721 venture capital investments taken from the records of CEPRES to develop and estimate a simple multi-factor model of the return distribution of individual venture capital investments.

The richness of the dataset employed for this study enables us to develop and estimate a simple multi-factor model of the performance of venture capital investments that accounts for influencing factors on various levels: the investment manager, the fund and the portfolio company characteristics, as well as differences in transaction structures. Furthermore, the global nature of the dataset (50 countries) allows us to investigate the potential relevance of geography on the investment return, for example, with regards to legal regulations, macroeconomic conditions, or investment pattern. The data sample comprises of investments covering a period of 33 years (1971 – 2004). Therefore, we are able to avoid a focus on a specific market period like boom and bust years with specific investment characteristics. As part of our econometric analysis, we are able to explain via an OLS Regression a high degree (over 20%) of the total variation in the investment IRRs. In a second step, the estimated multi-factor model is used as a data-generating process to simulate the returns of the individual investments in a venture capital fund portfolio. This approach also allows us to illustrate the effects of diversification on the return distribution of a venture capital fund portfolio. The final outcome of our iterative approach is then a frequency distribution of the portfolio returns. The dynamics of our model are illustrated by comparing simulation results for two artificial funds with the same structure and focus, which only differ in portfolio size.

To the best of our knowledge, we are the first to propose a comprehensive and easy-to-implement simulation model for the prediction of venture capital future performance based on empirical data. Our approach is usable as a robust risk management tool for e.g. fund-of-fund managers, when evaluating potential investment opportunities in the due diligence process and assessing portfolio construction. Several robustness-tests (e.g. perfect foresight, back-testing etc.) show that our model allows to properly capture the specifics of private equity portfolios. However, despite the unique breadth of our dataset, we are still limited in constructing and evaluating the model. As the model strongly relies on private equity data, a further improvement and better validation will depend on the availability of more comprehensive data for this asset class. As a consequence of limited availability of private equity return data and our aim to keep the model practicable, there are several limitations of our approach which raise interesting questions for future research. For example, future work should examine additional determinants for the probability of default and outperforming or address the assessment of probability distributions and correlations of the endogenous factors. Furthermore, with an increasing supply of detailed data, we will be able to perform the analyses for more narrow market segments (e.g. clustered by country) than just venture capital and buyout, which should reveal new idiosyncrasies and enhance the explanation capability of our approach.

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Table 1 Variable Descriptions

Level	Variable Name	Description
Dependent	IRR	The exact IRR (Internal Rate of Return) based on the investment cashflows
IM	IM Age	The age (years in business) of the Investment Manager at time of initial investment in the portfolio company
Fund	Fundsize	As a proxy for Fundsize, we use the total amount invested by the fund to date of exit or valuation of the portfolio company (in 06/2005 US$)* [for the regression analysis we take logs]
Portfolio Company	US-PC	A dummy variable equal to 1 for portfolio companies from the United States, 0 otherwise
	Biotech- Sector	A dummy variable equal to 1 for companies of the Biotech - Sector [The company was classified according to the FTSE Global Classification System]**, 0 otherwise
	Telecom- Sector	A dummy variable equal to 1 for companies of the Telecom - Sector [The company was classified according to the FTSE Global Classification System]**, 0 otherwise
	Financial- Sector	A dummy variable equal to 1 for companies of the Financial - Sector [The company was classified according to the FTSE Global Classification System]**, 0 otherwise
	Industrial- Sector	A dummy variable equal to 1 for companies of the Industrial - Sector [The company was classified according to the FTSE Global Classification System]**, 0 otherwise
	Early Stage	A dummy variable equal to 1 for early stage companies [The company was classified as early stage, when belonging to one of the following CEPRES stage categories: seed, startup, early], 0 otherwise
	Investment Duration	Total Duration between the initial investment and the exit date in years (if not fully realised we consider the valuation date instead of the exit date) [for the regression analysis we take logs]
	No. of Rounds	As a proxy for the number of rounds, we use the total number of cash injections the company received [for the regression analysis we take logs]
Macroeconomic	Exit in Bubble [09/98 - 03/00]	A dummy variable equal to 1 for investments exited between September 1998 and March 2000, 0 otherwise (if the investment is not fully realised, we consider date of last valuation as exit date)
	Cold market	A dummy variable equal to 1 for investments with the initial investment date during periods of weak PE-market development (1980 - 1985 and 1998 to date), 0 otherwise
	Short-term interest rate	The short-term interest rate at investment date (For U.S. investments:The Federal Reserve Bank 1-month treasury bills; for EU investments: the BBA Libor rate)
	Long-term interest rate	The long-term interest rate at investment date (10-year US-Government Securities)
	No. of IPOs	Number of (PE-backed) IPOs at date of exit (if not fully realised at date of valuation)
	GDP	Average variation of Real US Gross Domestic Product p.a. over the entire investment period
	Sector Index	Average variation of the corresponding NASDAQ Sector Index (according to the FTSE Global Classification System)** p.a. over the entire investment period
	average Fund IRR	Average Fund IRR per vintage year one year before investment date (classified for the following submarkets: US-Venture Capital; EU-Venture Capital; US-Buyout; EU-Buyout) [for the regression analysis we take logs of the positive IRRs by first adding the lowest market performance to all values and then taking the logs of the sum]

* The inflation adjustment is based on Consumer Price Index (CPI) data for all urban households and all items. Data is derived from the records of the U.S. Department of Labor (www.bls.gov)

** The 26 industry classifications provided by CEPRES were aggregated into the following 5 subclusters according to the FTSE Global Classification System (comprising CEPRES categories in brackets): 1) Industrials (Industrial/Manufacturing, Natural Resources/Energy, others, other Services, Media, Consumer industry/food, Construction, Materials, Waste/Recycling, Traditional Products, Hotel, Leisure, Retail, Textile, Environment, Logistics); 2) Financials (Financial Services, Fund of Fund Investments) 3) Biotechnology (Health Care/Life Sciences) 4) Computer (IT, Internet, Software, Semiconductor, High Tech) 5) Telecommunications (Telecom) The Computer Cluster was taken as the reference class for the sector dummies.

Table 2 IRR Summary Statistics

Panel A

Internal Rate of Return (IRR)											
ALL VC Investments				**Outperformers (IRR>=100%)**				**Normal Performers (-100%<IRR<+100%)**			
	Percentiles	N	2721		Percentiles	N	266		Percentiles	N	1647
1%	-1.00	Mean	0.16	1%	1.01	Mean	4.80	1%	-0.99	Mean	-0.02
5%	-1.00	Mode	-1.00	5%	1.07	Mode	1.29	5%	-0.87	Mode	0.00
10%	-1.00	Minimum	-1.00	10%	1.17	Minimum	1.00	10%	-0.72	Minimum	-0.99
25%	-1.00	Maximum	42.14	25%	1.45	Maximum	42.14	25%	-0.34	Maximum	1.00
50%	-0.15	Median	-0.15	50%	2.27	Median	2.27	50%	0.03	Median	0.03
75%	0.29	Std. Deviation	2.56	75%	5.27	Std. Deviation	6.33	75%	0.29	Std. Deviation	0.47
90%	0.99	Variance	6.56	90%	10.57	Variance	40.03	90%	0.56	Variance	0.22
95%	2.22	Skewness	8.64	95%	16.29	Skewness	3.33	95%	0.74	Skewness	-0.21
99%	10.49	Kurtosis	102.70	99%	39.17	Kurtosis	13.17	99%	0.97	Kurtosis	-0.51

Panel B

Internal Rate of Return (IRR)							
Statistics	N	% of Total N	Mean	Median	Std. Dev.	Minimum	Maximum
Samples							
All VC Investments	2721	100.00%	0.16	-0.15	2.56	-1.00	42.14
Outperformers (IRR>=100%)	266	9.80%	4.80	2.27	6.33	1.00	42.14
Normal Performers (-100%<IRR<+100%)	1647	60.50%	-0.02	0.03	0.47	-0.99	1.00
Total Losses (IRR=-100%)	808	29.70%	-1.00	-1.00	0.00	-1.00	-1.00
Sector Cluster							
Biotech - Sector	469	17.20%	0.24	0.01	2.09	-1.00	29.62
Computer - Sector	1111	40.80%	0.13	-0.54	2.82	-1.00	39.96
Telecom - Sector	368	13.50%	0.48	-0.44	3.53	-1.00	30.58
Financial - Sector	50	1.80%	0.00	0.07	0.69	-1.00	2.25
Industrial - Sector	658	24.10%	0.02	0.00	1.86	-1.00	42.14
else/not specified	65	2.40%	-0.22	-0.34	0.97	-1.00	5.50
Stage Cluster							
Early Stage	1760	64.70%	0.06	-0.44	2.60	-1.00	39.96
Later stage	961	35.30%	0.34	0.05	2.48	-1.00	42.14
Exit Type Cluster							
IPO	319	11.70%	1.24	0.46	2.72	-1.00	29.21
Sale/Merger	758	27.90%	0.77	0.12	3.50	-1.00	42.14
Write Off	807	29.70%	-1.00	-1.00	0.00	-1.00	-1.00
else/not specified	837	30.80%	0.32	-0.01	2.31	-1.00	39.96
Country Cluster							
US Deal	1637	60.20%	0.14	-0.27	2.45	-1.00	39.96
Non - US Deal	981	36.10%	0.18	-0.04	2.73	-1.00	42.14
not specified	103	3.80%	0.23	-0.50	2.74	-1.00	20.28
IM- Age Cluster							
Young	848	31.30%	0.06	-0.24	2.67	-1.00	39.96
Medium	1238	45.60%	0.19	-0.11	2.31	-1.00	30.58
Old	627	23.10%	0.23	-0.16	2.87	-1.00	42.14
Investment Duration Cluster							
Short	882	32.40%	0.00	-1.00	3.03	-1.00	39.96
Medium	1148	42.20%	0.31	-0.10	2.86	-1.00	42.14
Long	691	25.40%	0.13	0.10	0.68	-1.00	7.96
Fundsize Cluster							
Small	943	34.70%	0.37	-0.07	3.03	-1.00	39.96
Medium	1280	47.00%	0.10	-0.20	2.46	-1.00	42.14
Large	498	18.30%	-0.06	-0.26	1.67	-1.00	16.95

The tables above summarize the Internal Rate of Return (IRR) figures for the entire sample. Panel A shows, besides mean, median and standard deviations, also the percentile characteristics in the left column (for All VC Investments, the Outperformer - and the Normal Performer- Subsamples separately). In Panel B, several subclusters are considered for the analyses of structural differences. Variables are as defined in Table 1.

Sector Cluster:	The 26 industry classifications provided by CEPRES were aggregated into the following 5 subclusters according to the FTSE Global Classification System (comprising CEPRES categories in brackets): 1) Industrials (Industrial/Manufacturing, Natural Resources/Energy, others, other Services, Media, Consumer industry/food, Construction, Materials, Waste/Recycling, Traditional Products, Hotel, Leisure, Retail, Textile, Environment, Logistics); 2) Financials (Financial Services, Fund of Fund Investments); 3) Biotechnology (Health Care/Life Sciences); 4) Computer (IT, Internet, Software, Semiconductor, High Tech); 5) Telecommunications (Telecom)
Stage Cluster:	The 6 stage classifications for venture capital investments provided by CEPRES were aggregated into 2 subclusters (CEPRES categories in brackets); 1) Early Stage (seed, start up, early) and 2) Later Stage (expansion, acquisition financing, later).
IM Age Cluster:	The IM age is the age (years in business) of the Investment Manager at time of initial investment. The IM is considered to be young if it has been in business 5 years or less, medium between 6 and 19 years, and old if 20 years or more.
Duration Cluster	Investment Durations are considered to be short if they span 2 years or less. Medium investment durations lie between more than 2 years and less than 5. Long Durations exceed 5 years.
Fundsize Cluster	As a proxy for the Fundsize, we take the total amount invested by the fund at date of valuation. The amounts are in terms of 06/2005 US Dollar. Investment amounts are considered small if they are below $100 mio., medium amounts are between $100 mio. and $500 mio. Large investment amounts exceed $500 mio.

Figure 1: IRR Distribution for the entire VC Sample

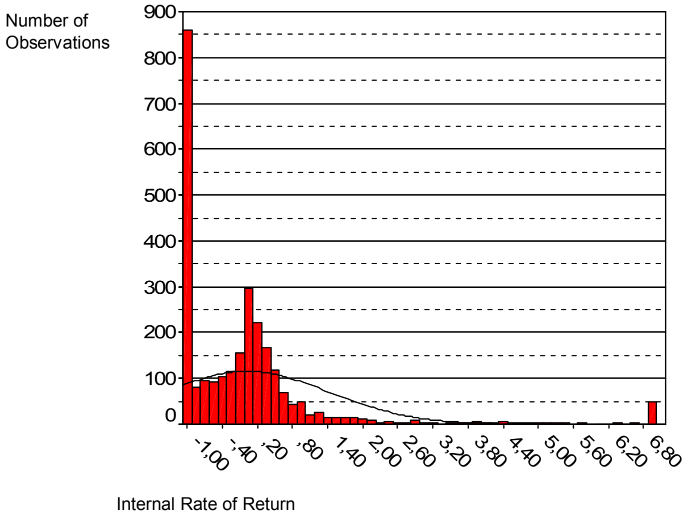


Figure 2: IRR Distribution for the Normal Performer Sample

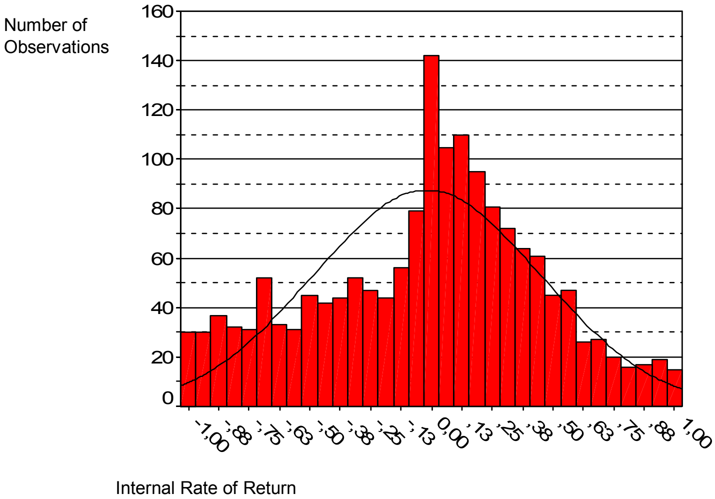


Figure 3: IRR Distribution for the Outperformer Sample

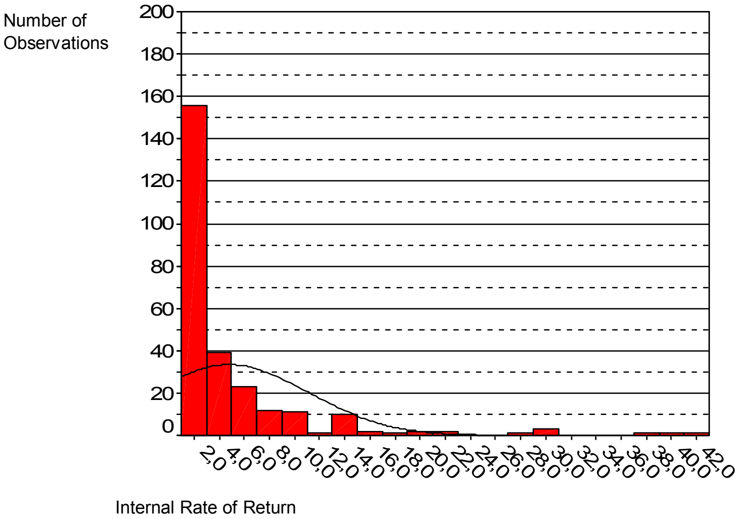


Table 3 Sample composition and average IRR by IRR-clusters and sector-stage-clusters

		ALL VC Investments			Total Losses (IRR=-100%)				Outperformers (IRR>=100%)				Normal Performers (-100%<IRR<+100%)			
Stage	**Sector**	N	% of Total N	Mean IRR	N	% of Total N	Mean IRR	% of Total Losses within Subclusters	N	% of Total N	Mean IRR	% of Outperformers within Subcluster	N	Mean IRR	% of Total N	% of Normal Performers within Subclusters
Later Stage	Biotechnology	150	5.50%	0.46	15	0.60%	-1.00	10.00%	17	0.60%	4.18	11.30%	118	0.10	4.30%	78.70%
	Computer	302	11.10%	0.38	82	3.00%	-1.00	27.20%	44	1.60%	4.80	14.60%	176	-0.07	6.50%	58.30%
	Telecom	99	3.60%	0.64	23	0.80%	-1.00	23.20%	16	0.60%	5.34	16.20%	60	0.01	2.20%	60.60%
	Financial	31	1.10%	-0.05	4	0.10%	-1.00	12.90%	2	0.10%	1.29	6.50%	25	-0.01	0.90%	80.60%
	Industrials	368	13.50%	0.23	41	1.50%	-1.00	11.10%	20	0.70%	4.43	5.40%	307	0.12	11.30%	83.40%
	Not Specified	11	0.40%	-0.11	1	0.00%	-1.00	9.10%					10	-0.02	0.40%	90.90%
	Total	961	35.30%	0.34	166	6.10%	-1.00	17.30%	99	3.60%	4.63	10.30%	696	0.05	25.60%	72.40%
Early Stage	Biotechnology	319	11.70%	0.14	78	2.90%	-1.00	24.50%	27	1.00%	4.21	8.50%	214	0.05	7.90%	67.10%
	Computer	809	29.70%	0.04	326	12.00%	-1.00	40.30%	85	3.10%	4.96	10.50%	398	-0.16	14.60%	49.20%
	Telecom	269	9.90%	0.42	109	4.00%	-1.00	40.50%	30	1.10%	7.75	11.20%	130	-0.08	4.80%	48.30%
	Financial	19	0.70%	0.08	2	0.10%	-1.00	10.50%	2	0.10%	2.03	10.50%	15	-0.04	0.60%	78.90%
	Industrials	290	10.60%	-0.23	106	3.90%	-1.00	36.70%	19	0.70%	1.95	6.60%	164	0.01	6.00%	56.70%
	Not Specified	54	2.00%	-0.24	21	0.80%	-1.00	38.90%	4	0.10%	2.30	7.40%	29	-0.05	1.10%	53.70%
	Total	1760	64.70%	0.06	642	23.60%	-1.00	36.50%	167	6.10%	4.90	9.50%	951	-0.07	35.00%	54.00%
Total	Biotechnology	469	17.20%	0.24	93	3.40%	-1.00	19.80%	44	1.60%	4.20	9.40%	332	0.07	12.20%	70.80%
	Computer	1111	40.80%	0.13	408	15.00%	-1.00	36.70%	129	4.70%	4.91	11.60%	574	-0.13	21.10%	51.70%
	Telecom	368	13.50%	0.48	132	4.90%	-1.00	35.90%	46	1.70%	6.91	12.50%	190	-0.05	7.00%	51.60%
	Financial	50	1.80%	0.00	6	0.20%	-1.00	12.00%	4	0.10%	1.66	8.00%	40	-0.02	1.50%	80.00%
	Industrials	657	24.10%	0.02	147	5.40%	-1.00	22.40%	39	1.40%	3.22	5.90%	471	0.08	17.30%	71.70%
	Transportation	1	0.00%	-0.60									1	-0.60	0.00%	100.00%
	Not Specified	65	2.40%	-0.22	22	0.80%	-1.00	33.80%	4	0.10%	2.30	6.20%	39	-0.04	1.40%	60.00%
	Total	2721	100.00%	0.16	808	29.70%	-1.00	29.70%	266	9.80%	4.80	9.80%	1647	-0.02	60.50%	60.50%

The table above gives an overview of the sample composition for the entire venture capital sample and the IRR- Subsamples: Total Losses, Outperformers and Normal Performers (see row 1). It shows the mean IRR and the proportion (number and percentage) of observations for several stage- and sector- subclusters (columns 1 and 2). Variables are as defined in Table 1.

Sector Cluster: The 26 industry classifications provided by CEPRES were aggregated into the following 5 subclusters according to the FTSE Global Classification System (comprising CEPRES categories in brackets): 1) Industrials (Industrial/Manufacturing, Natural Resources/Energy, others, other Services, Media, Consumer industry/food, Construction, Materials, Waste/Recycling, Traditional Products, Hotel, Leisure, Retail, Textile, Environment, Logistics); 2) Financials (Financial Services, Fund of Fund Investments); 3) Biotechnology (Health Care/Life Sciences); 4) Computer (IT, Internet, Software, Semiconductor, High Tech); 5) Telecommunications (Telecom)

Stage Cluster: The 6 stage classifications for venture capital investments provided by CEPRES were aggregated into 2 subclusters (CEPRES categories in brackets); 1) Early Stage (seed, start up, early) and 2) Later Stage (expansion, acquisition financing, later).

Table 4 Regression Results

Regression Analysis on the Performance Determinants of PE- Investments
Dependant Variable := Performance measured by the Internal Rate of Return (IRR)

The table presents the results of the OLS regression on the performance of venture capital investments; the entire venture capital dataset comprises of 2,721 fully and partially realised investments, and the "Normal-Performer" subset for the regression analysis includes 1,647 deals (one observation is per company, not per investment round). The first column defines the categories of the explanatory variables, the second column presents the variables for the regression equation, and the third column provides the variable names. The coefficients (unstandardised, standardised), the standard error and the *t*-statistics for the coefficients of the OLS regression are illustrated in the fourth through seventh column (*, **, *** significant at the 10%, 5%, 1% levels, respectively). The last two rows present the model diagnostics (Number of Observations, R-square, Adjusted R-square and the *F*-statistic). Observations with incomplete data for the transaction were skipped. Variables are as described in Table 1.

		Coefficients	**Unstandardized Coefficients**	**Standard Error**	**Standardized Coefficients**	**t statistics**
	α	Constant	0,43000*	0.221		1.947
IM	X_1	IM Age	0.00158	0.001	0.032	1.145
Fund	X_2	Fundsize	-0,04648**	0.022	-0.057	-2.074
Portfolio Company	X_3	US-PC	-0.04072	0.027	-0.043	-1.533
	X_4	Biotech- Sector	0,10100***	0.030	0.086	3.347
	X_5	Telecom- Sector	0,18000***	0.038	0.122	4.748
	X_6	Financial- Sector	-0.02919	0.075	-0.009	-0.388
	X_7	Industrial- Sector	0,07294**	0.030	0.070	2.440
	X_8	Early Stage	-0,08520***	0.023	-0.089	-3.646
	X_9	Investment Duration	0,27800***	0.047	0.174	5.876
	X_{10}	No. of Rounds	-0,23400***	0.035	-0.169	-6.651
Macroeconomic	X_{11}	Exit in Bubble [09/98 - 03/00]	-0,10600***	0.038	-0.073	-2.807
	X_{12}	Cold market	-0,12800***	0.027	-0.136	-4.734
	X_{13}	Short-term interest rate	0.00792	0.007	0.040	1.113
	X_{14}	Long-term interest rate	-0,36500**	0.168	-0.085	-2.178
	X_{15}	No. of IPOs	0,00038***	0.000	0.081	2.827
	X_{16}	GDP	4,89500***	1.482	0.105	3.304
	X_{17}	Sector Index	0,22300***	0.038	0.188	5.878
	X_{18}	average Fund IRR	-0.01421	0.043	-0.009	-0.329
Model Diagnostics			Number of Observations	R-square	Adjusted R-square	F-Statistic
			1560	0.218	0.209	23,834***

Table 5 Simulation Results (20-deal case): Statistics forecast values

	Percentiles:	Trials	10000
0%	-0,4049	Mean	0,2090
10%	-0,1490	Mode	---
20%	-0,0908	Minimum	-0,4049
30%	-0,0395	Maximum	5,5357
40%	0,0152	Range Width	5,9406
50%	0,0756	Median	0,0756
60%	0,1576	Variance	0,1943
70%	0,2619	Standard Deviation	0,4408
80%	0,4246	Mean Std. Error	0,0044
90%	0,7198	Skewness	2,7926
100%	5,5357	Kurtosis	16,8218

The table above summarizes the projected Internal Rate of Return (IRR) figures for the 20 deal case simulation (10,000 trials). It shows, besides standard statistics like mean, median and standard deviations, also the percentile characteristics in the left column.

Figure 4 Projected IRR probability distribution (20-deal case)

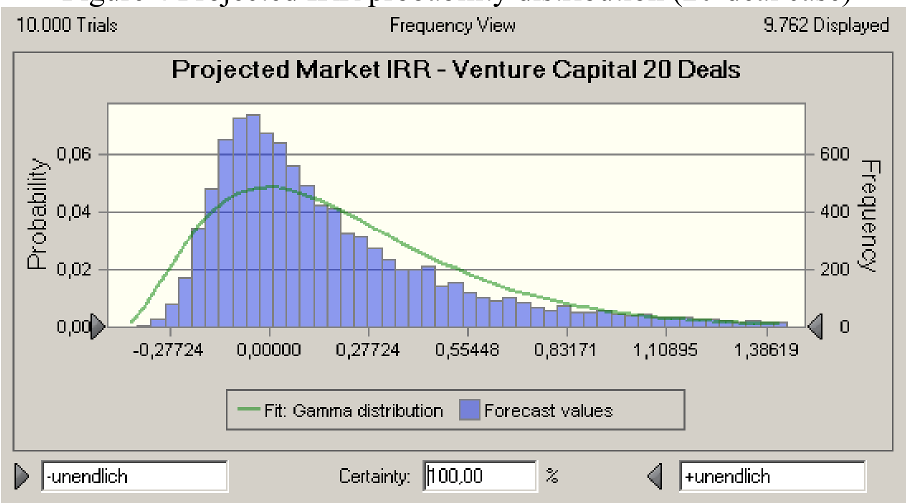


Figure 5 Projected IRR *cumulative* probability distribution (20-deal case)

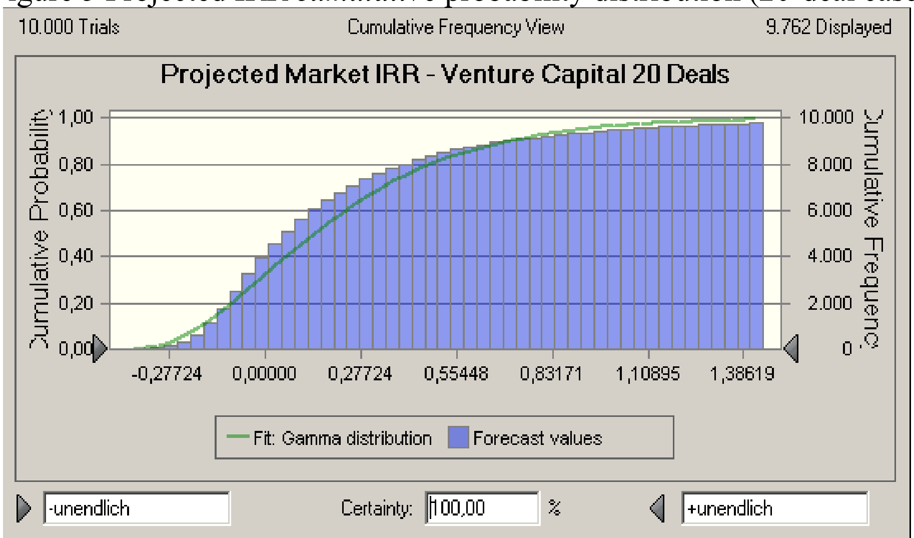


Table 6 Simulation Results (100-deal case): Statistics forecast values

	Percentiles:	Trials	10000
0%	-0,1854	Mean	0,2108
10%	-0,0086	Mode	---
20%	0,0422	Minimum	-0,1854
30%	0,0868	Maximum	1,6671
40%	0,1292	Range Width	1,8524
50%	0,1734	Median	0,1734
60%	0,2207	Variance	0,0421
70%	0,2785	Standard Deviation	0,2052
80%	0,3548	Mean Std. Error	0,0021
90%	0,4800	Skewness	1,3042
100%	1,6671	Kurtosis	5,9803

The table above summarizes the projected Internal Rate of Return (IRR) figures for the 100 deal case simulation (10,000 trials). It shows, besides standard statistics like mean, median and standard deviations, also the percentile characteristics in the left column.

Figure 6 Projected IRR probability distribution (100-deal case)

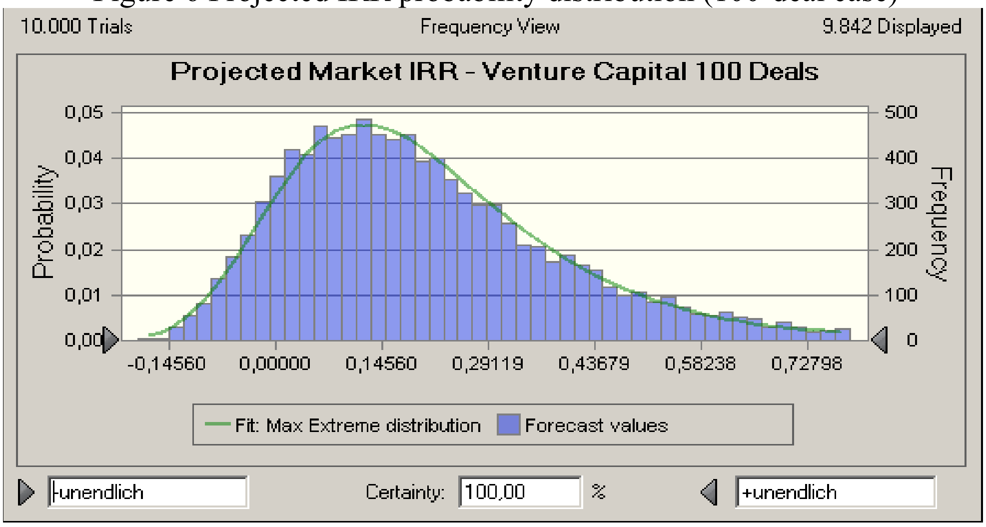
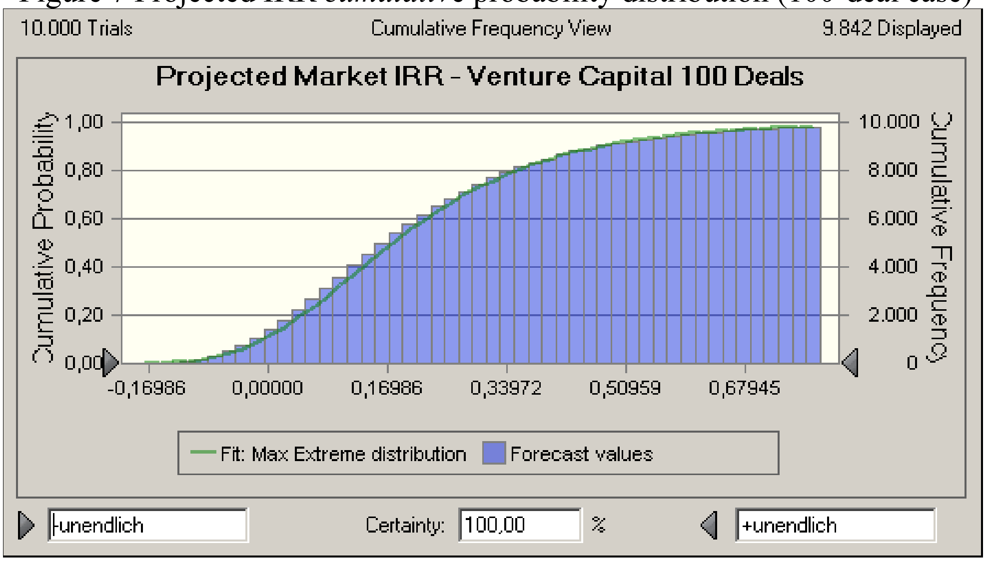


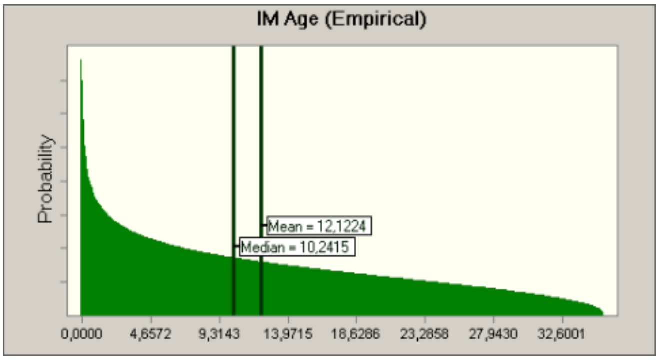
Figure 7 Projected IRR *cumulative* probability distribution (100-deal case)



Appendix Probability Distributions of the Input Factors

All distributions are fitted distributions (using the software Crystal Ball 5 – standard edition) based on historical observations. Distributions are truncated, if necessary, according to their possible value range.

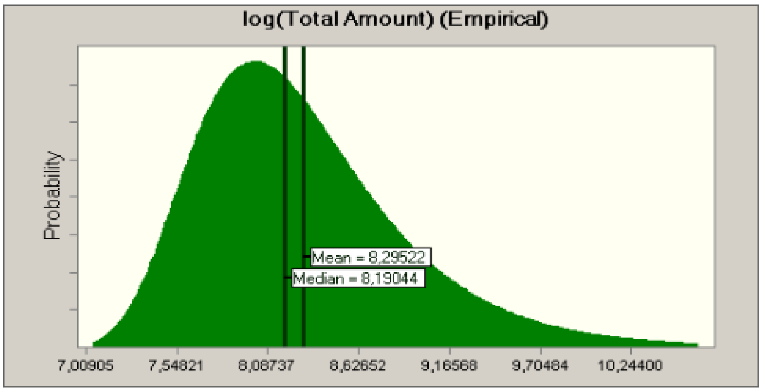
IM Age



Beta distribution with parameters:

Minimum	-0,126531043
Maximum	35,43006598
Alpha	0,753110638
Beta	1,433037107

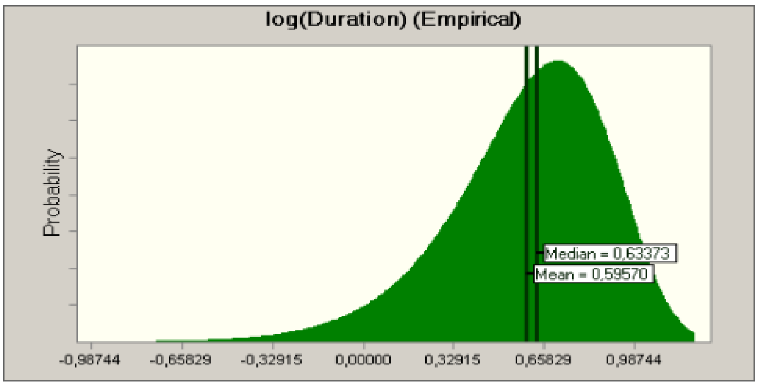
Log of Fundsize



Maximum Extreme distribution with parameters:

Likeliest	8,008192111
Scale	0,497254812

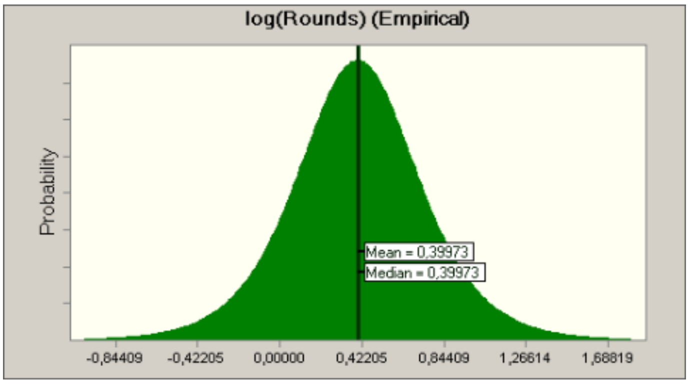
Log of Duration



Weibull distribution with parameters:

Location	-3,005836189
50%	0,633733574
95%	1,006788591

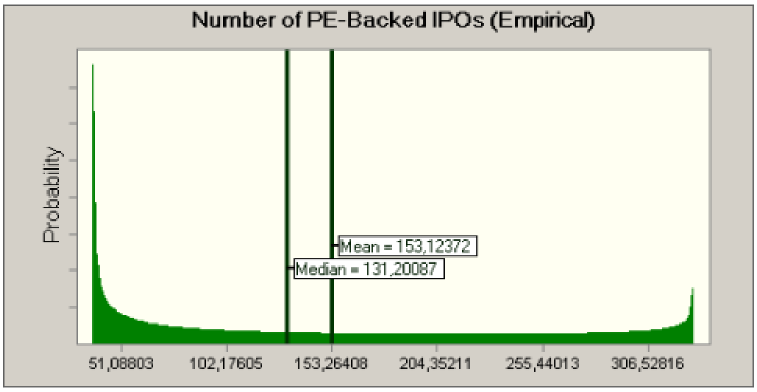
Log of No. of Rounds



Logistic distribution with parameters:

Mean	0,399725596
Scale	0,203688208

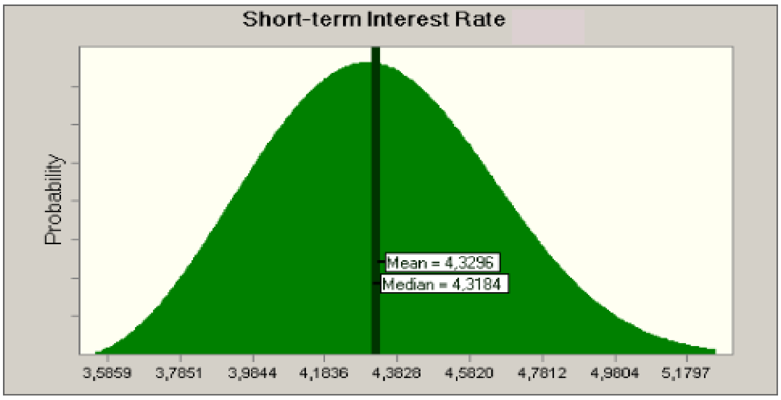
No. of IPOs



Beta distribution with parameters:

Minimum	36,82955874
Maximum	328,7617005
Alpha	0,430226819
Beta	0,649767547

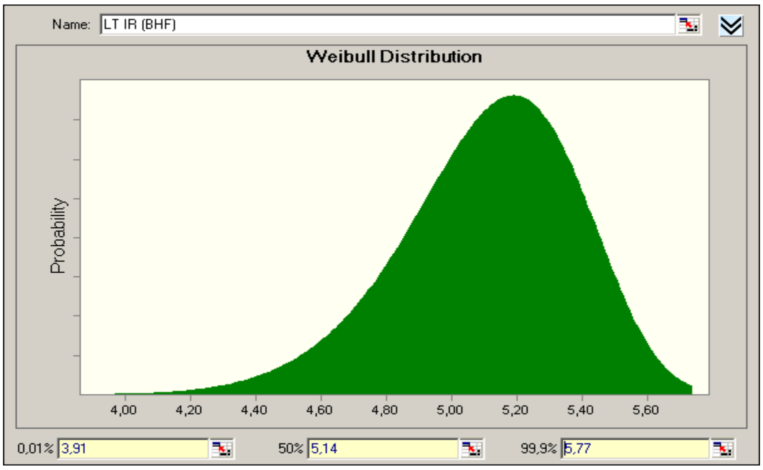
Short-term interest rate



Weibull distribution with parameters:

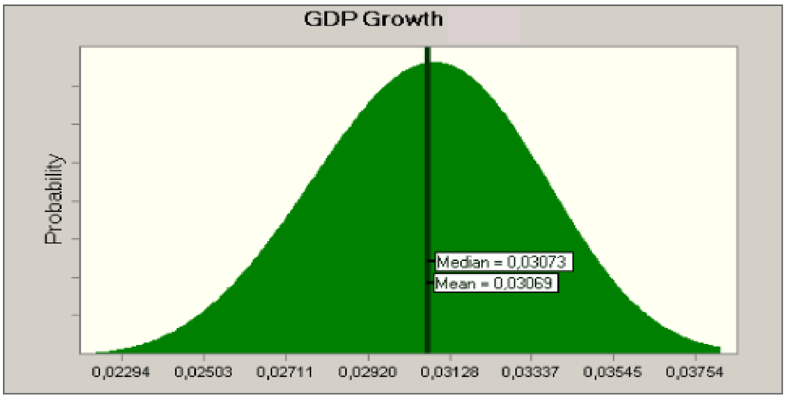
0,01%	3,5505
50%	4,3184
99,9%	5,3244

Long-term interest rate



Statistic	Weibull distribution
Trials	'---
Mean	5,1100
Median	5,1400
Mode	5,1900
Standard Deviation	0,2800
Variance	0,0800
Skewness	-0,4997
Kurtosis	3,2600
Coeff. of Variability	0,0539
Minimum	3,9091
Maximum	5,7727
Mean Std. Error	'---

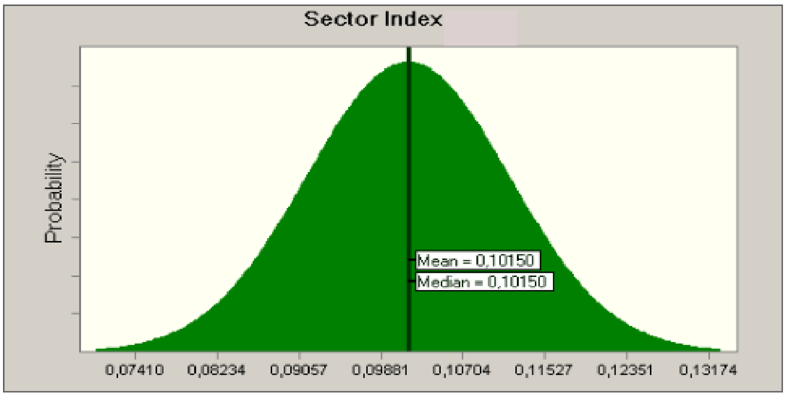
Real GDP growth p.a.



Weibull distribution with parameters:

0,01%	0,02227
50%	0,03073
99,9%	0,03864

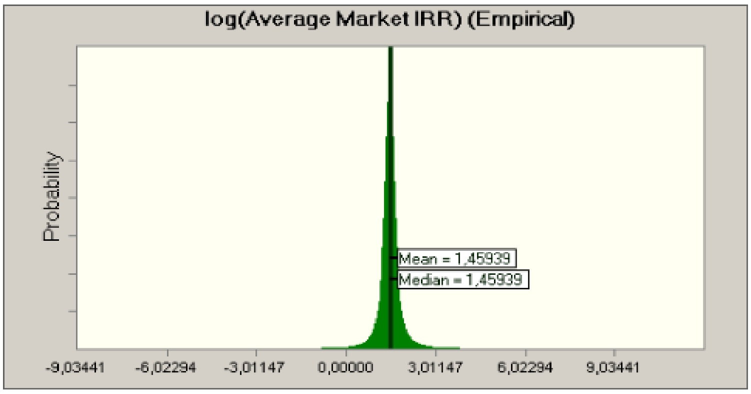
NASDAQ Index



Normal distribution with parameters:

Mean	0,101502818
Std. Dev.	0,010150282

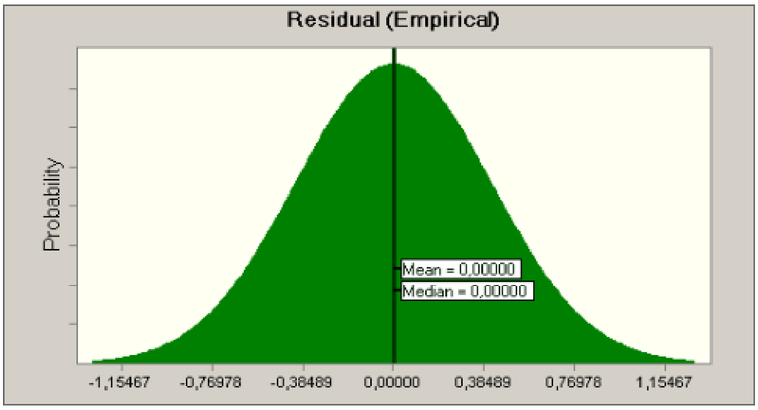
Log of average Fund IRR



Student's t distribution with parameters:

Midpoint	1,459392488
Scale	0,153630838
Deg. Freedom	1,409739142

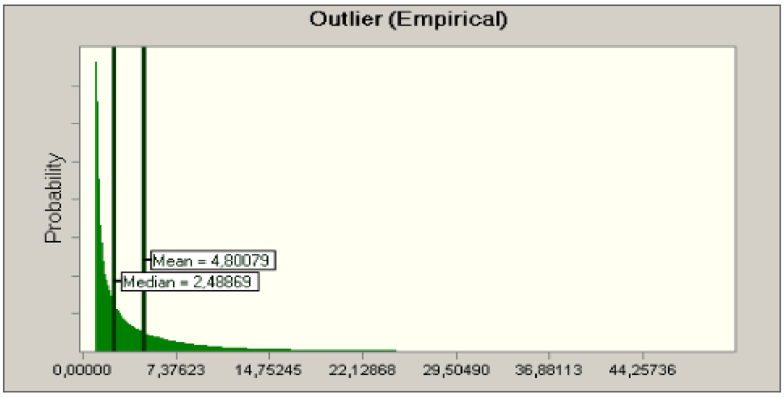
Residual values



Normal distribution with parameters:

Mean	7,05128E-08
Std. Dev.	0,4151685

Outlier Performance



Weibull distribution with parameters:

Location	1,006277497
Scale	2,661250827
Shape	0,626383977

CHAPTER B (II)

Modeling Default Risk of Private Equity Funds – A Market-based Framework

Modeling Default Risk of Private Equity Funds

– A Market-based Framework

by

Philipp Krohmer*, Kwok-Sing Man**

Abstract

With the rising importance of private equity as an alternative asset class and the introduction of the third Capital Adequacy Directive (CAD III), which will implement the recently published Basel II Accord in the EU at the beginning of 2007, there is a growing need for financial institutions to assess the risk and return of private equity investments. In a previous paper we proposed a framework for performance and risk forecasting. In the present paper, we strive to refine this approach concerning the calculation of the probability of default. We build on the basic idea of Wilson's CreditPortfolioView framework and develop a model to generate loss distributions for private equity portfolios. The proposed model is tested using a dataset of 3,941 U.S. venture capital and buyout investments taken from the records of CEPRES.

JEL classification: G24; G 32; E37

Keywords: Private Equity; Venture Capital; Risk; Losses; Risk Management;

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* Corresponding author Philipp Krohmer, Department of Finance, Johann Wolfgang Goethe-University Frankfurt am Main, Germany and CEPRES Center of Private Equity Research, email-address for correspondence: Philipp.krohmer@cepres.de.

** JP Morgan and Johann Wolfgang Goethe-University Frankfurt am Main, Germany

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Introduction

In the 1980s, the credit risk assessment was primarily dominated by subjective analysis or better known as expert systems. Credits were granted according to the borrower's character, capital, capacity, and collateral. This credit granting process was heavily biased by subjective judgment of the lender. However, in the mid 1990s, the focus of financial institutions and academics changed towards more quantitative-driven credit risk models. The reasons for this shift can be seen on the one hand by the fact that quantitative-driven credit risk models tend to outperform subjective analysis models, shown for example by Sommerville et al. (1995), and on the other hand in the introduction of internal market risk models for regulatory purposes by the Basel Committee on Banking Supervision, which allows banks to use their own internal models to estimate their regulatory capital and in general, leads to lower regulatory capital. As a response to the regulatory change and the associated growing demand for a practical solution for the internal models method, several methods for measuring credit portfolio risk have been developed and become accessible, including the four standard methods: CreditMetrics™ by J.P. Morgan, CreditRisk+™ by Credit Suisse Financial Products, CreditPortfolioView™ by Wilson and McKinsey, and PortfolioManager™ by KMV. A similar development like in the credit sector can now be seen in private equity. With the introduction of the new Basel Accord, the CAD III in 2004 and the associated regulations of the private equity sector, there is a rising need of an appropriate internal risk evaluation method for private equity. Furthermore, private equity has become one of the most important alternative asset classes. Despite the increasing importance of private equity as an asset class, there is only a limited understanding of the economic characteristics in this industry. The risk and return assessment poses a challenge since private equity investments are not continuous marked-to-market and there is generally a lack of good data. As data has gradually become more available, several empirical papers have documented the risk and return of private equity investments, albeit research on this issue is still scarce. Researchers and practitioners have only recently entered the field of private equity risk and return modeling, including Weidig (2002), Weidig and Meyer (2003) and Kemmerer (2006). The Center of Private Equity Research (CEPRES) has developed a risk model called PerFore. The model is based on the framework discussed in Krohmer et al. (2005) and is widely used by practitioners. PerFore consists of three basic elements: a regression estimate of the expected return for each individual investment within the portfolio, followed by an estimation of the overall portfolio return based on the individual deal return forecasts and lastly a Monte Carlo simulation to analyze the effect of varying inputs. As a special feature of PerFore, the linear regression analysis is performed only on the so-called “normal-performer-subset” (investments with an IRR above -100% and under +100%). This concept is based on the finding that historical private equity returns within the so-defined “normal” returns are in good approximation normally distributed. In the second step, the portfolio is constructed by inserting the individual normal deals mentioned above, plus the write-off and out-performer deals previously excluded from the normal deal regression analysis. Hereby, the weight and the performance data of the out-performers and write-offs are taken from historical averages. The write-off ratio of an individual portfolio, for instance, is derived by taking the weighted average of the historical sector default rates and the individual portfolio-sector allocations. This approach is very intuitive and easy to implement, however probably on the expense of accuracy.

The aim of this study is to mitigate the potential flaws of the calculation of the outlier-distribution, specifically the overall portfolio loss distribution applied within the PerFore approach. We develop a default rate model that is based on Wilson’s CreditPortfolioView. The newly developed model allows for the computation of yearly default probabilities conditional on the current macro factors and the simulation of the overall portfolio loss distribution dependent on the fund maturity. The iterative model consists of five basic steps: (1) a logistic regression analysis of a historical dataset to determine factors that influence the probability of default, including macroeconomic as well as investment-specific factors. Due to structural differences, we perform separate analyses for different clusters of country-sector-stage combinations; (2)

Modeling and estimation of the dynamics of the macroeconomic variables via a set of univariate autoregressive equations of order two; (3) Simulation of the yearly probability of default (PD) for each country-sector-stage group, separately for each year of the total fund lifetime; (4) calculation of the yearly portfolio-PD according to the fund structure (sector-/country-/stage- focus), separately for each year of the total fund lifetime; (5) calculation of the overall portfolio PD at the end of the total fund lifetime. For this purpose, we utilize the historical exit timing in terms of number of exited deals per year of comparable funds as the weighting-factor for each yearly PD. An integrated Monte Carlo simulation allows scenario analyses for uncertain input factors. The final outcome of our iterative approach is a frequency distribution of the expected portfolio loss rate at the time of exit. All analyses are based on a comprehensive dataset provided by CEPRES. As of December 2006, the dataset comprises of 252 private equity firms and 703 private equity funds with 16,097 investments in 12,088 different companies over a period of 35 years (1971 – 2006).

In the next section, we offer a brief overview of existing risk modeling approaches and discuss the special challenges of the private equity sector. In section 2, we describe in detail our five-step approach for the calculation of portfolio loss distributions. The empirical results are presented in section 3. Here, we first describe the dataset, then, we show the result of the regression model and finally we test the proposed methodology against the simple approach used in PerFore. In the last section, we summarize the main results and draw final conclusions.

1 Challenges and Approaches

Private equity and especially venture capital investments are characterized by substantial informational asymmetries and uncertainty with high risk and return potential, depicted by a high number of write-offs on the one hand, and extraordinary returns of the top performing companies on the other. Despite the high risk of this asset class and the rising demand for a practical answer, there are to date only few attempts to develop a risk model for private equity investments. The particular characteristics of private equity make risk modeling extremely challenging.

To assess the risk profile of an public equity portfolio, it is essential to know the standard deviation of each equity position within the portfolio and its correlation to other portfolio investments. To examine these two parameters, portfolio managers usually measure the fluctuations of market prices over time using historical datasets. However, in private equity there are no market prices since private equity investments are usually unlisted. In addition, private equity investments have a predetermined investment horizon and therefore are illiquid. Investors can only liquidate their position through the emerging secondary markets or by securitization. Furthermore, historical databases on private equity are rare and often possess certain downturns. Aside from the issue that information from most data providers is aggregated and thus, probably not accurate enough for using them in a risk model, there is also the question of data bias and consistency. For instance, private equity returns are often determined by the development of the net asset value (NAV). According to Cochrane (2004), this NAV can only be exactly measured "[…] when a company goes public, is acquired, or gets a new financing round". In other circumstances, the NAV is an appraisal of unrealized investments from funds by experts and does not necessarily reflect real market prices. Finally, a problem arises because of the bounded lifecycle of private equity funds. The cash inflows (capital draw downs) and cash outflows (capital distributions) of private equity funds are usually unscheduled. Thus, it is difficult to assess the amount and timing of these cash flows.

However, credits/debts and private equity investments possess certain comparable characteristics, e.g. since they are not traded, both asset classes have fixed maturities and are mostly illiquid. It is straightforward to think about a deduction from existing credit portfolio models towards an applicable private equity model. The common credit risk models can be classified into asset value models and models based on default rates.

The origins of asset value models (AVM) can be traced back to the work of Merton (1974) and Black and Scholes (1973). The AVM- approaches consider the fact that an equity holder has the choice between selling the firm's assets and refund the debt in case of default. A default occurs if the underlying asset value of the firm falls below the debt amount at termination. Two prominent representatives of this approach are PortfolioManager™ by KMV and CreditMetrics™ by J.P. Morgan.[1] The main difference between these two approaches is that the KMV model assigns company-specific default rates for each borrower by using company-specific asset values and asset volatilities, whereas CreditMetrics™ treats all borrowers having same rating classes within a portfolio equally by using identical unconditional default and transition probability from a historical migration matrix. A direct application of the AVM to private equity is not feasible since the models rely heavily on market data. Private equity investments are not marked-to-market everyday and there is no rating system for individual private equity investments, which can be explained by the lack of historical data.

Different from AVMs, default mode models (DMM) do not model the stochastic process of asset values to derive the probability of default but rather define the default process directly. In any discrete time period, only default and non-default is considered. According to Wahrenburg and Niethen (2000), CreditRisk+™ and CreditPortfolioView™ can be categorized into this classification.[2] CreditRisk+™ is a model that uses actuarial science methods to compute the probability of default and loss distribution of a credit portfolio. As a typical representative of DMMs, CreditRisk+™ only models default risk and does not take potential factors for a default into consideration. To account for the joint and correlated default behavior, credits are differentiated between country-industry level and exposure class and are assigned to different sub sectors. At first glance, CreditRisk+™ seems to be quite appropriate for private equity because it focuses on default and hence, implies relatively few estimates and inputs such as the expected

[1] For further details on CreditMetrics™ see J.P. Morgan (1997), for details on PortfolioManager™ see Kealhofer (1998).

[2] For details on CreditRisk+™ see Credit Suisse Financial Products (CSFP, 1997) and for CreditPortfolioView™ see Wilson (1997a, 1997b, 1997c, 1997d).

default rate, the volatility of default rate, and exposure. Nevertheless, it is not directly applicable to private equity, as the model requires rating classifications for the investments to determine a company's unconditional default probability for one period. Company-specific data needed for the rating is usually not available for private equity-backed companies.

CreditPortfolioView™ is a multifactor model that incorporates the basic observation that default and migration probabilities are not constant over time but rather cyclical depending on the state of the economy. To refine the observation, CreditPortfolioView™ divides a portfolio into different industry/country- combinations. The default rate of these clusters is modeled through a logit function of an economic index. This economic index is a function of economic factors such as the GDP growth rate, interest rates, and the aggregate savings rate. CreditPortfolioView™ uses the Monte Carlo technique to simulate different macroeconomic scenarios in order to generate default rate and migration rate distributions for portfolio segments. Comparable to CreditMetrics™, CreditPortfolioView™ considers transition matrices to produce transition and default probabilities for investment grade obligors. Until now, this kind of method is not applicable in private equity due to the lack of historical data, as mentioned above. On the other hand, CreditPortfolioView™ is more complex than CreditMetrics™ and provides a persuasive way to model default risk due to its economic intuition and its causality between the macroeconomic setting and the default manners of different sectors. Wilson (1997a) shows that over 90% of the variation in credit defaults can be explained by macroeconomic factors of most industrialized countries including USA, Germany, Japan, and France.

To summarize, none of these four credit risk portfolio models is directly applicable to private equity. However, we do not share the opinion of Weidig and Weber (2005) who claim that standard risk management does not work on private equity because of the absence of an efficient and transparent market. This might hold for the AVMs, which need actual market data to derive the probability of default. However, as highlighted above, DMMs are for the most part autonomous from current market prices and thus, provide at least a possible basis for a private equity risk management model.

In private equity, there are several models that were created with the aim to directly model the future cash flows of private equity investments for performance projections in portfolio management, including Takahashi and Alexander (2002), Weidig (2002), Weidig and Meyer (2003) and Malherbe (2004, 2005a, 2005b). Fitch Ratings (2006) developed a cash flow model with the objective of applying the method on private equity securitizations. Similar to Fitch Ratings, Standard & Poor's created a model for rating private equity collateralized fund obligations (CFOs). None of these models rely on current existing credit portfolio models. To our knowledge, there are only two private equity risk models that can be directly linked to existing credit risk approaches. Kemmerer (2006), for instance, applied an adjusted method of CreditRisk+™ to Venture Capital with the aim of deriving a loss distribution for Venture Capital portfolios to improve active portfolio management. To solve the abovementioned problem of computing rating classifications for the investments, he proposes a forward entry regression with macroeconomic factors as independent variables to extract systematic factors for the sector analysis. Under the assumption that macroeconomic factors are independent, he considers the improvement of the R^2 of each forward entry as the weight of the entered factor to explain the sector default rate and the remaining unexplained sample variance as the idiosyncratic risk. His approach is very intuitive and only little effort is required to implement the model. However, his assumptions are disputable and he claims that the model can only be used "to calculate the loss distribution for credits to venture capital-backed companies. If the model is used to calculate loss distributions for portfolios of venture capital investments, the results can be only considered as the worst case scenario because they do not take into account earnings."

PerFore, a risk and return model for private equity investments developed by the Center of Private Equity Research (CEPRES), is based on the study of Krohmer et al. (2005) and can be related to CreditPortfolioView™, albeit on a limited scale. PerFore is not primarily focused on computing default distributions, but rather on predicting performance distributions. The assessment of a portfolio's expected default rate is simply based on historical averages and separately embedded into the calculations to determine the overall portfolio performance. The final outcome of the iterative approach is a frequency distribution of the expected portfolio IRR, showing the likelihood of achieving this outcome. The model allows to assess the default rate indirectly by looking at the percentiles and probability distributions of achieving negative outcomes, comparable to the measure Value at risk. Contrary to Kemmerer (2006), PerFore does consider both, loss and earnings. Similar to CreditPortfolioView™, the PerFore approach considers, among others, macroeconomic factors as determinants of performance in the OLS regressions and uses the Monte Carlo technique to simulate different macroeconomic scenarios. As described above, the regression analysis is performed only on the so-called "normal-performer-subset" (investments with an IRR above -100% and under +100%) to avert a potential bias of the coefficients when including the outliers (total write offs with an IRR of -100% and out-performers with extreme IRRs above +100%) in the analyses. These outliers are considered separately in a second step. The return of the normal-performers is estimated based on expectation values for the determinants identified in the regression analysis. The weight and performance data of the out-performers and write-offs are taken from historical averages. The estimated return of the normal-performers, out-performers, and write–offs are then aggregated based on their exposure weight within the fund to calculate the overall portfolio return.

The historical outlier-ratios are determined separately for the three major types of private equity, venture capital, buyout and mezzanine. Within each group, the historical out-performer and write-off rates are tabulated dependent on the sector and stage of development of the portfolio company. The write-off rate of an individual portfolio, for instance, is derived by taking the weighted average of the historical default rates and the portfolio allocation (by sector and stage). This approach is very intuitive and easy to implement, however probably at the expense of accurateness, as the outlier and write-off deals are derived through historical averages and thus, are treated constant in every Monte Carlo simulation. It can be argued that this treatment is not realistic since default rates, for instance, are increasing or decreasing with time depending on the economic cycle as Wilson (1997a) observed for credit default risk and as shown in Figure 1 for private equity. In the following chapter, we will introduce a default rate model that is based on Wilson's CreditPortfolioView and aims to refine PerFore's determination of the fund's overall write off ratio at the end of the fund lifetime.

2 Theoretical Framework

CreditPortfolioView™ developed by Wilson (1997a, 1997b, 1997c and 1997d) provides a convincing way to model default risk due to its economic intuition and its causality between the macroeconomic setting as well as the default manners of different sectors. An application of the multifactor model of CreditPortfolioView™ to private equity, at least on the sector level, seems to be possible. The intuition is to model the relationship between default rates and macroeconomic factors. The model is fitted with historical data to simulate the evolution of future default rates conditional on the current macroeconomic conditions. The model basically consists of two elements: (i) an empirical model with a system of equations for default risk and macroeconomic dynamics, and (ii) a Monte Carlo simulation for producing a distribution of possible default. The basic framework of PerFore is characterized by the same fundamental elements with regards to performance projection. Even the determination of default within PerFore has similarities with CreditPortfolioView™. First, a default is a discrete and binomial variable in both approaches. In our case, a default is defined as a total loss with an IRR of minus 100% (write-off). Furthermore, both models follow the intuition that different industries behave differently and condition the computation of loss rates on the country and business sector of the observation. Thus far, PerFore determines the write-off ratios simply on the basis of historical averages of country-and sector-clusters and does not take economic cycles into account. In our model, we refine PerFore's determination of a fund's default rate. Analogous to CreditPortfolioView™, we model the relationship between default rates and macroeconomic factors via a logistic regression analysis and generate possible future loss distributions via a Monte Carlo simulation. However, contrary to CreditPortfolioView™, we do not consider rating classes and migration matrices due to the following reasons: (1) there is no rating system for individual private equity investments, which can be explained by the lack of historical data in this sector, (2) company-specific data needed to make a rating is usually not available for private equity-backed companies. Especially, venture capital- backed companies are usually very young and unprofitable with uncertain growth prospects and the explanatory power of the balance sheets is insufficient to perform a viable rating, (3) Private equity funds are usually "blind pools". When an investor decides to invest in a private equity fund, he generally does not know the individual portfolio companies. In the private placement memorandum of the fund, the fund managers solely specify the size and the focus of the fund, concerning the geographic origin, business sector and development stage of the target companies. As we strive to produce loss distributions for private equity funds, which have not yet started to invest, we build our model on the information usually given in the fund prospectus at date of closing of the fund. In addition to the abovementioned country-sector subgroups, we introduce the stage of development as an additional differentiator. Jones and Rhodes-Kropf (2003) for instance, found a significant correlation between stage and idiosyncratic risk in the venture capital industry. Stage can be used as an indicator for the company size and age, and serves as a "rating-class-proxy" in our model. Therefore, we build separate models for the three major types of private equity: venture capital, buyout and mezzanine. Each category is further split-up by country and business sector. For the computation of the overall portfolio loss distribution, the results will then be aggregated again in a later step of the model as described hereafter. Our iterative approach consists of the following five steps:

(1) A logistic regression analysis to determine factors that influence the probability of default
(2) An Auto Regressive Integrated Moving Average (ARIMA) time series to derive the economic factors

(3) Simulation of the yearly probability of default (PD) for each country-sector-stage group, separately for each year of the total fund lifetime
(4) Computation of the yearly portfolio-PD according to the fund structure, separately for each year of the total fund lifetime
(5) Calculation of the overall portfolio PD at the end of the fund lifetime, based on the historical exit-timing of comparable funds as the weighting-factor for each yearly PD

Our implementation combines the presented steps into one comprehensive simulation process. As a result of the iterative procedure, we obtain a frequency distribution of the expected portfolio default rate over the total fund lifetime.

Step 1: Logistic regression

Analogous to CreditPortfolioView™, we use a Logistic function to compute the average default rate of a certain industry sector:

$$p_{j,t} = \frac{1}{1+e^{-y_{j,t}}} \tag{1}$$

where $p_{j,t}$ denotes the default probability in industry *j* at time *t*, and $y_{j,t}$ the industry-specific macroeconomic index at time *t*. This index can be taken as an indicator of the overall state of the economy and is modeled as a linear function depending on the present and lagged values of macroeconomic variables:

$$y_{j,t} = \beta_{j,0} + \beta_{j,1}x_{j,1,t} + \beta_{j,2}x_{j,2,t} + \ldots + \beta_{j,n}x_{n,t} + \varepsilon_{j,t} \tag{2}$$

where $x_{i,t}$ (i = 1, 2, …, n) denotes the set of explanatory macroeconomic variables for the industrial sector *j* at time *t,* and $\beta_{j,n}$ denotes a set of regression coefficients, which show the direction and degree of the impact of these macroeconomic variables on the index and thus, on the default probability of the industry *j*. Wilson (1997a) proposes to use at least three macroeconomic variables to specify the macroeconomic index. To estimate the coefficient, a binary regression is used, where the error term $\varepsilon_{j,t}$ can be interpreted as a random shock to the index in the specific sector *j* at time *t* and understood to be independent and identically normally distributed as $N(0,\sigma_j)$. As we can expect that different industrial sectors and regions vary in their sensitivity to macroeconomic shocks and business cycles, individual functions should be estimated for each sector and region with different industry specific explanatory macroeconomic variables. As mentioned above, we further split-up the analyses by the types of private equity to consider structural differences of the transactions.

Step 2: Estimation of the macroeconomic variables

A second part of the equation system is the modeling and estimation of the dynamics of the macroeconomic variables. Similar to Wilson (1997a), Boss (2002), and Virolainen (2004), we use a set of univariate autoregressive equations of the second order (AR(2)) to describe the macroeconomic dynamics:

$$x_{i,t} = k_{i,0} + k_{i,1}x_{i,t-1} + k_{i,2}x_{i,t-2} + v_{i,t} \tag{3}$$

where k_i denotes a set of regression coefficients that has to be estimated for the *i*-th macroeconomic factor. The error term of the autoregressive process, $v_{i,t}$, is assumed to be identically normally distributed as $N(0,\sigma_i)$ and independent. The AR(2) process can be seen as a linear OLS regression function where the value of the dependent macroeconomic variable at time *t*, $x_{i,t}$, is described by its two previous values $x_{i,t-1}$ and $x_{i,t-2}$. The economic intuition behind this form is that it can be assumed that economic shocks – e.g. stock market crash – will last not only for one year but for several years. [3]

Just like Wilson (1997a), we assume that the error terms, or innovations, $\varepsilon_{j,t}$ and $v_{i,t}$ are correlated, with the variance-covariance matrix $\sum_{\varepsilon,v}$. Summarizing the structure of innovations for the whole system:

[3] Note that in practice, other macroeconomic prediction data from various other sources such as public or private economic forecast institutes can also be obtained instead of using the AR(2) process. However, by using forecasted values from other sources, an error term equal to $v_{i,t}$ should be applied and added to the forecasted value since the predicted values are uncertain.

$$Et = \begin{pmatrix} \varepsilon_t \\ \nu_t \end{pmatrix} \sim N(0, \Sigma), \quad \Sigma = \begin{pmatrix} \sum_{\varepsilon} & \sum_{\varepsilon,\nu} \\ \sum_{\nu,\varepsilon} & \sum_{\nu} \end{pmatrix} \tag{4}$$

The covariance matrix models the correlation of the shocks between the macroeconomic variables and their influence on the macroeconomic index. For instance, an oil price shock has an impact on the stock market and the inflation rate.

Step 3: Simulation of the probability of default (PD)

Based on step 1 and 2, we use a Monte Carlo simulation to automatically analyze the effect of varying inputs on outputs. A main advantage of Monte Carlo simulation is that it takes precisely the correlation structure of the portfolio into account instead of using large number of assumptions as for instance in an analytical approach. The process works as follows: First, a set of I macro factors are generated by simulating I correlated values of the error terms $\nu_{i,t+1}$.[4] Second, J segments of macroeconomic indices are produced by using the predicted macro factors and generating J random values of the residuals $\varepsilon_{j,t+1}$. Finally, the default probability for each segment j is determined by inserting the predicted value of the macroeconomic index into the Logit function (1). As this calculation process is performed for each year of the predetermined fund lifetime, we obtain as a result of step 3 the yearly probability of default $p_{j,t}$ for each country-sector-stage-group j for each year t over the whole expected fund lifetime.

Step 4: Computation of the yearly portfolio-PD

The default rate of the entire portfolio P_t at time t is the weighted sum of the estimated country-sector-stage-group default rates $p_{j,t}$. As weighting factor $w_{j,t}$, we apply the proportions allocated to each country-sector-stage-group within the portfolio (in terms of number of deals related to all deals or in terms of invested capital related to the fundsize):

[4] Correlated random values can be obtained for instance via a Cholesky decomposition of the correlation matrix $\sum_{\varepsilon,\nu}$. For details, see e.g. Fishman (1997).

$$P_t = \sum_j w_{j,t} \cdot p_{j,t} \tag{5}$$

As a result, we obtain the estimated portfolio default probability for each year of the entire fund lifetime according to the fund structure (type of private equity, stage focus, geographic focus, and sector focus).

Step 5: Calculation of the overall portfolio PD at the end of the total fund lifetime

Since our default rate calculation is based on all liquidated investments at each period, our portfolio default rate has to be adjusted by the ratio of liquidated deals at each period. The term *liquidated* refers to the exit of a deal from an investor's portfolio and therefore includes successful deals, generally exited via an IPO or an M&A, and unsuccessful ones which are written off. We use historical liquidation ratios in terms of number of deals of a sample of comparable funds for each period t as a weighting factor for P_t:[5]

$$Padj_t = l_t P_t \tag{6}$$

where $l_t = \dfrac{L_t}{\sum_{t=1}^{T} L_t}$

L_t denotes the number of liquidated deals in period t and T the planned total fund lifetime. Therefore, l_t denotes the ratio of liquidated deals in period t in terms of the number of liquidated deals in this period related to all deals made during the entire fund lifetime. To calculate the total fund PD at the end of the total fund lifetime, we simply take the sum of $Padj_{,t}$:[6]

$$Pend_T = \sum_{t=1}^{T} Padj_t \tag{7}$$

The end result of step 5 is an estimated probability of default for the total portfolio at the end of the total fund lifetime. However, this simple average does not accurately model the reality of the

[5] To consider historical liquidation schedules of comparable funds is a widely spread proceeding. Other approaches using e.g. historical cash flow patterns include for example Weidig and Meyer (2003) or Fitch Ratings (2006). The liquidation schedule applied in this study is illustrated in Figure 2.

[6] Note that the PD at each period relates to the liquidated deals only and not to all invested (not yet exited) deals of a portfolio. Therefore, the adjusted portfolio PD at each period $Padj_t$ is not contingent on the results of prior periods.

situation. What we really have is a collection of inputs, some of which have a corresponding probability distribution. As mentioned above, we use a simulation to automatically analyze the effect of varying inputs on outputs. Step 1 and step 2 build the basis of the calculation process, and steps 3 to 5 are then repeated for a predetermined number of iterations defined in the simulation settings. Our end result from the Monte Carlo simulation is an estimated probability of default for the total portfolio at the end of the total fund lifetime with a corresponding probability distribution showing the likelihood of achieving this outcome.

3 Empirical Results

3.1 Data Sample and Variables

Two categories of empirical data are required to develop the model presented in the last section: macroeconomic and private equity-specific data. Macroeconomic data is publicly available from the usual commercial databases. The private equity-specific dataset we use for this project originates from the database of CEPRES, The Center of Private Equity Research. As of December 2006, the dataset provides detailed information on 252 private equity firms, 703 private equity funds, and their 16,097 investments in 12,088 different companies. These investments include more than 44,000 cash injections spanning over a period of 35 years (1971 – 2006) and cover 50 countries in North and South America, Europe and Asia. For reasons of confidentiality, names of firms, funds and portfolio companies are not disclosed. Although the database is completely anonymous, it provides us with high quality in-depth data. Detailed information about the corresponding investment manager, the fund, and the portfolio companies as well as the exact monthly cash flows between the portfolio company and the fund is included. The cash flows are reported as gross figures, and thus are not biased by any externalities like management fees and carried interest. Therefore, our cash flow based IRR-calculations, which are the basis for the classification of the transactions into default and non-default, are extremely precise. Concerning the realization status, we have to exclude all unrealized investments from the sample, leaving all fully and partially realized investments in the data sample. For the unrealized investments, we can not yet identify the dependent variable of our analyses which is a dummy variable indicating if the investment was a default or not. We categorize all fully and partially realized investments with an IRR above -100% as non-defaults.

As described in the previous section, we can expect that different industrial sectors and regions, as well as different types of private equity vary in their sensitivity to macroeconomic shocks and business cycles. Therefore, we have to develop separate models for several sub-clusters. First, concerning the region, we focus on U.S.-transactions and exclude all transactions in South America, Europe and Asia. The reason for focusing on U.S.-transactions is dataset-driven. The U.S.-sample provides more observations over a longer time-period. Furthermore, we can expect greater heterogeneity within the other region-subgroups, especially within Europe, which would require a broader breakdown into several country specific models. Secondly, we further divide the dataset by the type of private equity. The dataset contains information on venture capital, buyout and mezzanine transactions. Venture capital investments are usually smaller investments in young and unprofitable companies, whereas buyout and mezzanine transactions are in most cases larger investments in already established companies. In this study, we focus on venture capital and buyout and exclude all mezzanine funds from the analyses. We develop two separate models, one for U.S. buyout and another for U.S. venture capital. The resulting sample contains 3,941 investments, 121 private equity firms, and 304 funds. The sample covers the years 1974 to 2005 as reported until the end of December 2006.

The *venture capital subset* encloses 2,794 investments by 224 funds, belonging to 89 investment managers, over a period of 34 years. The *buyout subset* comprises of 1,147 investments including 32 investment managers, 80 funds over a period of 29 years. Table 1 shows summary statistics for the default rates of our sample, Panel A for the venture capital subset and Panel B for the buyout subset. A default is defined as a total loss with an IRR of minus 100%

(write-off). The empirical default rate for a certain sector is measured by dividing the number of write-offs by the number of realized and partially-realized companies during the time period in question. The entire venture capital subset shows a significantly higher empirical default rate (30.0%) compared to the buyout subset (11.5%) reflecting the high risk profile of venture capital investments. Figure 1 shows the development of the overall default rate of the U.S. venture capital and buyout markets in the time period 1985 to 2005. Data is relatively sparse for the time period from 1971 to 1993 and thus, observed default rates could be incidental and not that meaningful. For the period after 1993, venture capital investments show consistently higher default rates than buyout investments. Furthermore, both investment classes show similar cyclical behaviors. Overall corporate default rates more than doubled from 10% (20%) to more than 20% (40%) for buyout investments (for venture capital investments) during the U.S. recession in early 2000.

The dataset is broadly diversified over more than 20 different industries. We divide the dataset into sector sub-clusters to accurately analyze industry-specific effects on default. We distinguish 5 sector classifications for our dataset - biotechnology, consumer, computer, industrial, and telecommunication[7]. Table 1 shows the sample allocation across these sectors. Overall, 2,250 (80.5%) investments of our venture capital sample are considered active in the high technology sectors (Biotech, Telecom and Computer), compared to only around 40% within the buyout sample. Out of the high tech venture capital investments, the computer and the telecom sector show the highest default rates with 34.3% and 35.3%, respectively. Surprisingly, the venture capital consumer sector shows the highest default rate of all sectors with 47.2%. This result seems questionable and could be due to the small number of observations. The sector default rates within

[7] The 26 industry classifications provided by CEPRES were aggregated into the following 5 sector clusters similar to the FTSE Global Classification System (comprising CEPRES categories in brackets): 1) industrials (industrial / manufacturing, natural resources / energy, business services, other services, financial services, media, construction, materials, waste/recycling, traditional products, textile, environment, transportation, logistics, others; 2) consumer (consumer industry/food, hotel, leisure, retail); 3) biotechnology (health care / life sciences); 4) computer (IT, internet, software, semiconductor, high tech); 5) telecommunications (telecom). Note that financials and transportation are added to industrials due to fewer observations. In addition, a consumer sector cluster is created by separating consumer industry/food, hotel, leisure, and retail from the industrials sector clusters.

the buyout subset are consistently lower than the comparable venture capital rates and range between 9.1% and 13.3%.

For the venture capital subset, we additionally differentiate among the development stage of the portfolio companies. The stage-variable for an individual investment can be either 1 to reflect a more mature company in the expansion or later stage of development, or 0 to indicate a seed, startup, or early venture. Table 1 shows that the majority of the deals are early stage investments (61%). The high risk associated with investments in young, innovative companies is depicted by the high default rate of the early stage deals of 36.0% compared to the default rate of 20.6% of more mature companies. Companies in the later stage have a greater likelihood to continue to grow and expand, whereas an early stage company either survives the instabilities of infancy to enter the growth phase or perishes.

Given the observed high correlation of the stage of development with default rates, we introduce this dummy variable as an explanatory factor in the regression model. In addition to the stage variable, we test two other investment-specific variables. On the investment management firm level, we consider the age of the investment manager (IM age), which is the number of years the investment manager has been in business at the time of initial investment in the portfolio company, as a proxy for experience and reputation. The experience and reputation of the investment manager generally grows over time because unsuccessful funds could impede the investment manager to raise the next fund. Maula and Seppä (2001) provide evidence that reputation strongly affects the investment manager's ability to select, certify and add value to investments, and to utilize negotiation power in the new investment's valuation. Contrary to this idea, Gompers et al. (1999) found that reputation concerns induce younger partnerships to work hard to achieve success. A further explanation for a possible negative influence of the investment manager's age on performance is provided by Schmidt and Wahrenburg (2004). They argue that established fund managers are older and closer to retirement, and therefore, put less weight on the effects of their actions on future business opportunities. As we can expect a concave relation between experience and reputation and investment success, we define three categories of the IM age: young (= 0) if she is five years old or less, medium (= 1) between 6 and 19 years, and old (= 2) if her age is 20 years or more.

At the fund level, we test for the impact of the fund size on the default probability. The fund size is defined as the total amount invested by the fund at the valuation date and is expressed in US dollar valued in June 2006. Several empirical studies have confirmed the importance of fund size on success, for example Cumming (2003), Gottschalg et al. (2003), and Diller and Kaserer (2004). While most studies argue that the performance decreases with increasing portfolio size due to less monitoring and value-added assistance, you can find empirical counterevidence. Therefore, we introduce analogous to the IM age, three fund size categories: (1) small (=0) for funds with less than \$100 million under management, (2) medium (=1) for funds with assets between \$100 million and \$500 million, and (3) large for funds with funds exceeding \$500 million. These two investment-specific variables are quite straightforward and are found in the private placement memorandum.

Concerning the macroeconomic inputs, we initially select a list of 9 variables for the prediction model.[8] All variables are referred to the date of exit of the observed investment and are converted to annual growth rates over the testing period of 1974 to 2005. Previous studies, including Knapp (2002) or Bär (2002), have shown empirically and theoretically that macroeconomic variables affect the default rate with time lags. Therefore, all variables are additionally tested with time lags of one and two years. The variables are chosen with regard to prior academic literature with the notion of covering the key characteristics, which have been found to be linked with business cycle, failure and financial distress. The variables can be divided into four categories: business cycle, bank lending conditions, financial market, and private equity specific variables. The business cycle category includes gross domestic product (GDP),

[8] Data sources: IMF, OECD, GPO, Thomson Financial.

unemployment rate, consumer price index (CPI), industry production, total manufacturing earnings, and level of research and development spending (R&D). Bangia et al. (2001) and Nickell et al. (2000), for instance, find evidence of macroeconomic effects on corporate defaults. They demonstrate that macro-economic factors are major drivers of systematic default risk. It can be assumed that the growth rates of real GDP, industry production, total manufacturing earnings, and R&D as indicators of current macroeconomic situations are negatively correlated with short-term default probabilities. Inflation measured by the change of the CPI tends to have a negative impact on business activity, and therefore, has a positive correlation with the default probability. The unemployment rate as a lagging business cycle indicator can be expected to contribute to the increase of business failure. Furthermore, we expect that the current bank lending conditions are a valuable signal for explaining default intensities. We differentiate between two variables: short-term and long-term interest rates are represented by the rates of the three-month and ten-year U.S. treasury securities, respectively. Duffie et al. (2003) and Fiorito and Kollintzas (1994), for example, show significant dependence of default probabilities on interest rates. Especially in buyout financing, where most of the investments are highly leveraged and are financed with borrowed capital, it can be anticipated that the default rate in this asset class is highly positively correlated with the development of the interest rates. The financial market variables are represented by the NASDAQ Composite and the NASDAQ Biotech Index. There are a number of papers, which show evidence that stock market returns are a good leading indicator of future business activities, and negative stock market performances are followed by severe down turn in industrial output, associated with a higher default probability. Finally, to assess private equity market conditions, we consider the amount of committed capital on the overall private equity market at the year of investment. Gompers et al. (1999) and Diller and Kaserer (2004) have shown that growth in venture capital commitments tend to increase the valuation of new investments. Ljungqvist and Richardson (2003) argue that increased money inflow leads to a tougher competition for deals. Moreover, Gompers (1995) argues that growth of the investment pool may measure entry by inexperienced investors. Therefore, we expect higher default intensities with a rising supply of capital.

3.2 Model Estimation

The starting point and basis for all following simulations of our approach is a logistic regression analysis to determine factors that influence the probability of default. We perform the analyses on the dataset presented in the previous section. We have two basic models, one for venture capital investments and the other for buyout investments. Within these two groups, we run five separate regression analyses, one for each of the previously described sector sub-clusters. All abovementioned macroeconomic and investment-specific factors are considered at first as potential explanatory variables within each model. In our approach, we utilize a forward likelihood-ratio change stepwise method to select the predictor variables and estimate the corresponding β values.[9]

Logit model results

The regression results for the five sector-clusters of the *buyout* sample are shown in Table 2. The Goodness-of-Fit tests (χ^2 and Hosmer and Lemeshow) for every sector specification suggest that the logit models present a good fit to the data and that the estimated variable coefficients are meaningful. The Nagelkerke R square varies between 0.503 and 0.849 depending on the sector, which means that in all sector-models over 50% of the variation in defaults can be explained by the proposed macroeconomic variables, for the computer-cluster even more than 80%. We observe that apart from the telecommunication sector, all industries are influenced by the interest rate indicators. These indicators show a positive sign supporting our expectations that buyout investments are sensitive to current banking lending conditions. Furthermore, most of the included

[9] We use an entry value of 0.05 and a removal value of 0.10, i.e. only variables with a score statistic significance (p-value) below 0.05 are included in the model. At each step, the effect with the largest significance level for the Likelihood ratio change is deleted, provided the significance level is larger than 0.10.

variables seem to have an impact on default with a time-lag of 1 or 2 years, which was previously confirmed by former studies, for instance Knapp (2002). All variables that are lagging for two periods meet our expectations and reveal an increase in default risk if their value increases. However, some parameters show different signs than expected. The current GDP and the current NASDAQ development reveal a positive contribution to the default rate, which does not correspond to our expectations. Furthermore, the private equity variables IM age and fund size do not show any significant impact on the default rate of buyout investments. The committed capital, however, contributes significantly to a higher default probability. Only the biotechnology and telecommunication sectors expose no impact from this indicator.

Table 3 shows the regression results for the five sector-clusters of the *venture capital* sample. Again, the goodness-of-fit tests demonstrate a good model fit and reasonable variable coefficients. Compared to the buyout models, the Nagelkerke R square values are lower and vary between 0.270 and 0.456. An explanation for the lower values can be the fact that venture capital funds usually invest in smaller and younger companies than buyout funds and that these companies do not depend as much on systematic factors as more mature companies. Comparable to buyout investments, banking lending indicators demonstrate a significant impact on all sectors with the expected sign over varying periods. Interestingly, once more, all variables, which are lagging for two periods, meet the previous stated expectations and show the expected sign. Contrary to the buyout sample, the annual NASDAQ change as a financial market indicator shows an influence on the biotechnology, computer and telecommunication sectors. Furthermore, the lagged GDP confirms the expected sign and decreases the default rate in the consumer sector. Finally, just like for buyout investments, the initial committed capital consistently shows a positive contribution to an increase of default probability. Moreover, the stage dummy has a positive impact on the biotechnology, computer, and telecommunication sectors, demonstrating that young companies are significantly more exposed to default risk than mature firms. As for the buyout case, IM age and fund size are insignificant.

Classification and prediction accuracies

To test the prediction accuracies of our models, we perform out-of-sample validations. The data set for each industry class of the buyout and the venture capital models is divided into two subsets. Three fourths of the industry data set, the training sample, is used to construct and determine models and parameters for the techniques, while the rest of the data set, the testing sample, serves the purpose of testing the model's accuracy and is randomly chosen from the full data set. Due to data limitations, we could not divide all industry data sets and only validate samples with more than 150 observations.

Two possible errors might occur when classifying a model. On the one hand, the model can point out low default risk when risk is actually high. This is also known as Type I error. On the other hand, the model can indicate a high default risk when, in fact, the risk is low. This is referred to as Type II error. To cross validate the models, we compare (1) the hit ratio of the model for predicting defaults and (2) the overall hit ratio for predicting correct default as well as non-default, of the training sample with the corresponding values of the testing sample. Similar values, which are above 50%, indicate the diagnostic suitability of the model.

Table 4 provides the prediction accuracies for each industry class of the *buyout* model. The observable data within the buyout sample is relatively small compared with the venture capital dataset. Only the computer and industrial sectors provide enough data to generate a second sample for validation purposes. The overall classification accuracy for the initial computer industry sample is 98.45%, which is extremely accurate. The model is able to differentiate bankruptcies with 75% correct assignment. The secondary sample confirms the positive results of the first sample with 92% overall classification accuracy and 66.67% correct default predictions. The higher accuracy ratio in the initial sample is known as upward bias and is, for instance, described by Altman (2000). Similarly, all other samples demonstrate high overall classification accuracies ranging from 86.64% up to 91.00%, as well as high default prediction rates with up to 87.50% for the telecom sample. The consumer industry model is less accurate than other models with a 54.55% default prediction rate.

Table 5 shows the default classification accuracies for the *venture capital* models. In contrast to the buyout sample, the venture capital sample is relatively large and except for the consumer sample, all other data sets could be divided into training and testing samples. Overall, the venture capital models reveal smaller overall accuracy and default rate ratios. Along with lower R squares, this result can be explained by the fact that venture capital funds invest more in small and young companies which are less sensitive to the macroeconomic environment and have higher idiosyncratic risk. The overall accuracy ratios range from only 69.34% to 83.96%, with default prediction accuracies between 60.32% and 76.92%.

3.3 Simulation results and comparison to the naïve approach applied in PerFore

In the previous section, we performed step 1 of our default model and obtained the logit regression equation for the country-sector-stage subgroups. In this section, we build on the logit results of step 1 and perform the remaining four steps of our prediction model to calculate the default distribution at the end of the fund lifetime for two reference portfolios constructed out of the entire dataset presented supra. To validate the results of our 5-step simulation approach, we compare the real empirical default rates of the two selected samples with the results of our new simulation approach and with the results of the naïve approach applied in PerFore. The determination of a suitable dataset for our purpose bears a challenge since data is limited. We focus on venture capital investments of two different time periods to test our venture capital model, which appears to be the weaker model. We decide to validate our model on the basis of a fictitious fund-of-funds composed of several funds from different investment management firms with varying experience and strategies, rather than for just one fund of a single investment management firm, to mitigate potential selection bias. We first select a portfolio of five U.S. venture capital funds within our entire dataset, which were all launched in 1997 and comprise of 124 investments, and evaluate the results of the adjusted CreditPortfolioView method and the PerFore method after a ten year period when the funds have finished their regular fund lifetime. The drawback of this sample selection is that the investment period of the funds falls into the boom period of the late nineties followed by the aftermath of the "internet bubble" collapse that lead to abnormal investment outcomes. However, this sample was the only possible combination of funds out of our entire sample, which had the specified geographic and stage focus, which were all launched in the same year and today have finished their regular fund lifetime. In a second attempt to validate the results, we construct a portfolio which is focused on early stage investments. We pick all U.S. early stage investments of our dataset starting in the vintage year 2001 jointly representing 75 investments to access the default rates of the two different methods over a 5 year period. The drawback of this selection is that contrary to the 1997-sample, we do not consider entire funds over the complete fund lifetime and therefore the default rate calculations of the sample might be less reliable.

1997 Sample Validation

The allocation in terms of sector and stage of the reference portfolio is depicted in Table 6. Overall, almost 90% of the investments are considered active in the high tech sectors: computer, biotech and telecom, 57.7% of the portfolio are investments in early stage companies. This structure clearly reflects the focus on young, innovative companies of the venture capital firms in the late 90s. Surprisingly, the 1997 sample only recorded a real default rate of 26.0% (27 defaults out of the 104 fully realized investments) until the last validation date as of June 30, 2006. This can be explained by the fact that most of the investments of this portfolio were exited before the bust of the so-called "internet-bubble" in March 2001, leading to less defaults and extraordinary overall pooled portfolio returns of over 80% gross IRR p.a. for this fictitious fund-of-fund construction.

In our simulation approach, we apply the same allocation structure of the portfolio shown in Table 6 to determine the sector and stage weights. If the model is applied to project the default distributions of future portfolios, the structure information is typically specified in the private placement memorandum. The necessary future macroeconomic values for the simulation are generated by the AR2 process by using historical macroeconomic data starting from 1974 up to the end of 1996. To deal with interaction effects, we further determine correlations in our model, which were calculated on the basis of historical observations. To calculate the probability of default for the total portfolio at the end of the total fund lifetime in step 5, we use the historical liquidation ratios in terms of number of exited deals of a sample of comparable funds illustrated in Figure 2. Figure 3 shows the end result from the Monte Carlo simulation, a frequency distribution of the default rate with an estimated median default rate of 39.56% and a standard deviation of 16.32%. Furthermore, the model provides the cumulated distribution of the portfolio default rate, which visualizes the loss percentiles. The calculation used in the PerFore-approach, which is based on the historical default rates described in Table 7 and simply multiplies the proportions of investments in specific sector-stage-groups according to the fund structure with the corresponding historical default rate, approximates a probability of default of 22.5%. This outcome represents a closer estimation to the real default rate than our proposed approach. While our result lies above the empirical value, the PerFore-result underestimates the real default rate. This can be explained by the fact that the PerFore- calculation is simply based on the historical default rates for the time before calculation, i.e. pre 1997, and therefore does not include the extreme market situation of the late nineties. Our approach should also be performed excluding these extreme observations for the period after 1997. However, this is not possible due to the limited number of observations for each country-sector-stage subgroup for the sample before 1997 and therefore leads to an overestimation of the probability of default.[10] Furthermore, as mentioned above, 20 out of the 124 investments of our validation sample were not exited yet at time of validation and all of those un-exited investments were made during the boom period where growth expectations and company valuations were exaggeratedly high. Therefore, we expect that there might be "living deads" remaining in the portfolio leading to higher final default rates of the overall portfolio after liquidating all investments.

2001 Sample Validation

Compared to the 1997 reference portfolio, this sample portfolio is even more focused on young and innovative companies. All investments of this fictitious fund-of-fund were made in the early stage of development of the portfolio companies, including seed, start-up and early stage, and 92.0% of the companies are considered active in the high tech sector. Expectedly, the 2001 sample has a higher real default rate of 45.33% (34 defaults out of 75 investments) until the last validation date as of June 30, 2006. Again, we apply the same portfolio allocation structure as the reference sample to determine the sector and stage weights. Historical macroeconomic data were taken up to the end of 2000 in order to generate the estimated future paths for the macroeconomic values. Contrary to the 1997 sample validation, we do not consider entire funds that have finished their regular fund lifetime, but rather investments that all started in the same year and are realized until the last validation date as of June 30, 2006. Therefore, we have to scale the historical distribution rates illustrated in Figure 2 to calculate the probability of default for the total portfolio at the end of the 5-year-period. As a result, the simulation model generates a mean default rate of 44.77%, which is very close to the actual default rate of 45.33%. Compared to the PerFore calculation, which approximates a probability of default of 34.85%, our model delivers a more exact result for the 2001 sample. Again, the PerFore-approach underestimates the probability of

[10] However, for "Perfect Foresight"-estimations, i.e. running our model using the real values for the endogenous factors, we obtain very close approximations.

default. The better fit of our model with this sample compared to the 1997 sample can be traced back to the fact that our logit analyses are based on the entire dataset, including the bubble period.

4 Conclusions

In this paper we construct and evaluate a comprehensive and conceptually clear simulation approach for the prediction of the probability of default of private equity portfolios based on CreditPortfolioView™, a widely used econometric default method in the credit risk sector. The newly developed model allows for the computation of yearly probabilities of default conditional on the current macro factors and the simulation of the overall portfolio loss distribution dependent on the fund maturity. The iterative model consists of five basic steps: in the first step, we determine factors that influence the probability of default, including macroeconomic as well as investment-specific factors via a logistic regression analysis. In a second step, the necessary future macroeconomic input values are generated by an AR2 process based on historical macroeconomic data. The first two steps build the basis for the simulation of the yearly probability of default performed in step three. As the first three steps are executed separately for several country-sector-stage groups to account for structural differences, we calculate in a forth step the yearly portfolio-PD according to the fund allocation structure, separately for each year of the total fund lifetime. To generate the overall portfolio-PD at the end of the total fund lifetime in the last step, we use the historical liquidation ratios (in terms of number of exited deals per year) of comparable funds as the weighting-factor for each year-PD. An integrated Monte Carlo simulation algorithm allows scenario analyses for uncertain input factors. The final outcome of our iterative approach is a frequency distribution of the expected portfolio loss rate at time of exit. All analyses are based on a comprehensive dataset provided by CEPRES. The richness of our dataset enables us to account for several investment-specific influencing factors and to perform separate analyses for different countries, sectors and private equity types. Furthermore, the data sample comprises of investments covering a period of 35 years (1971 – 2006) and therefore, we are able to avoid a focus on a specific market period like boom and bust years with specific investment characteristics. As part of our approach, we are able to explain via a Logit model up to 85% of variation in investment defaults. The practicability of the model was tested for two fictitious reference portfolios constructed from the entire dataset, dating back from 1997 and 2001, respectively. While the approximation for the 2001 sample comes very close to the empirical default rate, the model overestimates the probability of default for the 1997 sample. This result can be traced back to the fact that the logit analyses are based on the entire dataset, including the boom period of the late nineties followed by the aftermath of the “internet bubble” collapse that led to abnormal investment outcomes. Despite the unique breadth of our dataset, we are still limited in constructing and evaluating the model. As the model strongly relies on private equity data, a further improvement and better validation depends on the availability of data for this asset class. With an increasing supply of detailed data, we will be able to further refine the model by considering for example more subtle country and sector classifications or further segmentations for instance by exposure classes as proposed in the credit default model CreditMetrics™. Additional real sample validations have to be performed to evaluate the accuracy of the approach. Altogether, the descriptive analyses, the regressions for multiple subclusters, as well as the simulation analyses presented in this paper give valuable insights into the determinants and patterns of private equity defaults.

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Figure 1 Annual default rates for the venture capital and the buyout market

This figure shows the development of the overall default rate of the U.S. venture capital and buyout market in the time period 1985 to 2005. The venture capital dataset comprises of 2,794 realized U.S.- venture capital investments, the buyout dataset of 1,147 realized U.S.-buyout investments in the years 1974 - 2005. Both datasets are extracted from the records of CEPRES. Data are relatively sparse for the time period in 1971 to 1993 and thus, observed default rates could be less meaningful. A default is defined as a total loss with an IRR of minus 100 % (write-off). The empirical default rate is measured by dividing the number of write-offs by the total number of realized companies during the time period in question.

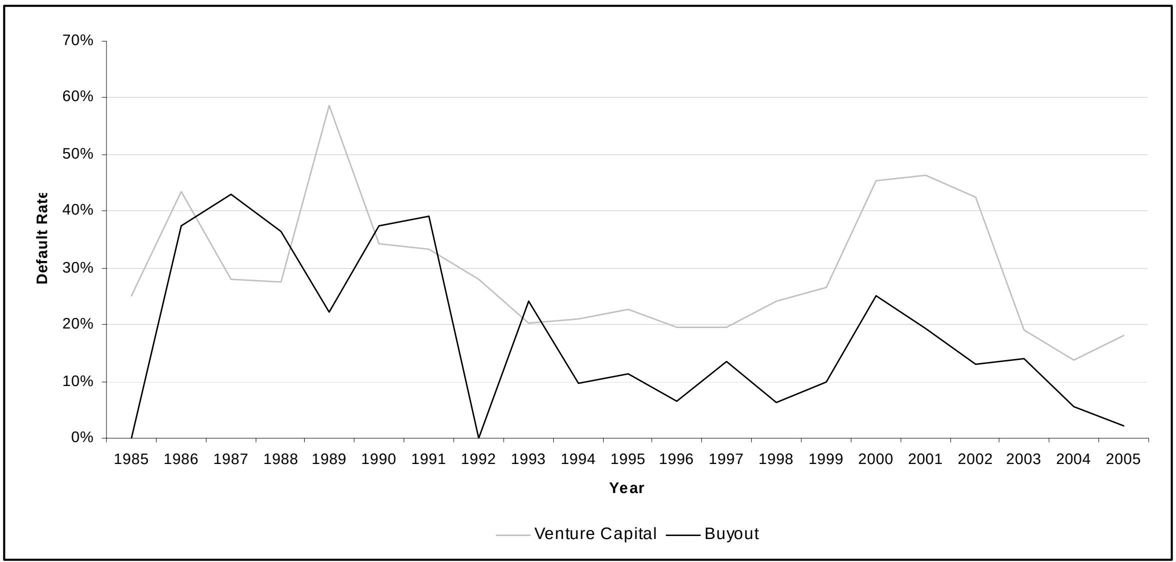


Table 1 Sector allocation and default rates

The table shows the sample allocation and empirical default rates by sectors, Panel A for the data subset of venture capital investments and Panel B for the data subset of buyout investments. The venture capital dataset comprises of 2,794 realized U.S. venture capital investments, the buyout dataset of 1,147 realized U.S. buyout investments in the years 1974 - 2005. Both datasets are extracted from the records of CEPRES. For the venture capital subset, we additionally differentiate among the stage of development of the portfolio companies. The 6 stage classifications for venture capital investments provided by CEPRES were aggregated into 2 subclusters (CEPRES categories in brackets); 1) Early Stage (seed, start up, early) and 2) Later Stage (expansion, acquisition financing, later). A default is defined as a total loss with an IRR of minus 100 % (write-off). The empirical default rate for a certain sector is measured by dividing the number of write-offs by the total number of realized companies within this subsample.

Panel A: Venture Capital	ALL VC Investments		Defaults (IRR=-100%)	
	N	% of Total N	N	% of Defaults within Subclusters
Full Sample	2794	100.00%	838	30.00%
Sector Cluster				
Biotech	565	20.20%	100	17.70%
Computer	1263	45.20%	433	34.30%
Telecom	422	15.10%	149	35.30%
Industrial	455	16.30%	114	25.10%
Consumer	89	3.20%	42	47.20%
Stage Cluster				
Early Stage	1705	61.00%	614	36.00%
Later Stage	1089	39.00%	224	20.60%

Panel B: Buyout	ALL Buyout Investments		Defaults (IRR=-100%)	
	N	% of Total N	N	% of Defaults within Subclusters
Full Sample	1147	100.00%	132	11.50%
Sector Cluster				
Biotech	120	10.50%	12	10.00%
Computer	286	24.90%	26	9.10%
Telecom	68	5.90%	8	11.80%
Industrial	532	46.40%	71	13.30%
Consumer	141	12.30%	15	10.60%

Table 2 Logit estimates for buyout investments

The table presents the results for the stepwise logit regression by sectors for the data subset of buyout investments (forward likelihood-ratio change stepwise method). The dataset comprises of 1,147 realized U.S.- buyout investments in the years 1974 - 2005, taken from the records of CEPRES. The dependent variable is a dummy variable equal to 1, if the investment was a default (with an IRR equal to -100% p.a.) and 0 otherwise. The first row indicates the business sector. The first column shows the explanatory variables. T-1 and t-2 indicate a time lag of the variable of one or two years, respectively. The last six rows present the model diagnostics. The coefficients (only) of the logit regressions are illustrated in the second to sixth column. All displayed coefficients are significant at the 5% level.

	Biotech	Consumer	Computer	Industrial	Telecom
Constant	-14.496	-65.052	-391.725	-60.751	5.756
LN(committed capital)		3.934	22.587	3.766	
GDP					326.378
Nasdaq	7.565				
Manufacturing earnings$_{t-1}$				-1.557	
Industry production$_{t-1}$					-249.007
CPI$_{t-2}$		239.742			
Unemployment rate$_{t-1}$					-225.403
Unemployment rate$_{t-2}$			854.945	78.613	
Long-term interest rate		213.787		81.469	
Long-term interest rate$_{t-1}$				140.387	
Long-term interest rate$_{t-2}$	149.911		1355.721		
Goodness-of-Fit Test: χ^2	39.201	31.971	89.905	113.711	27.411
p-Value	0.000	0.000	0.000	0.000	0.000
Cox & Snell R square	0.256	0.274	0.316	0.323	0.401
Nagelkerke R square	0.503	0.547	0.849	0.514	0.701
Hosmer and Lemeshow test	0.713	0.920	1.000	0.657	0.991
Number of observations	120	141	286	532	68

Table 3 Logit estimates for venture capital investments

The table presents the results for the stepwise logit regression by sectors for the data subset of venture capital investments (forward likelihood-ratio change stepwise method). The dataset comprises of 2,794 realized U.S.- venture capital investments in the years 1974 - 2005, taken from the records of CEPRES. The dependent variable is a dummy variable equal to 1, if the investment was a default (with an IRR equal to -100% p.a.) and 0 otherwise. The first row indicates the business sector. The first column shows the explanatory variables. T-1 and t-2 indicate a time lag of the variable of one or two years, respectively. The last six rows present the model diagnostics. The coefficients (only) of the logit regressions are illustrated in the second to sixth column. All displayed coefficients are significant at the 5% level.

	Biotech	Consumer	Computer	Industrial	Telecom
Constant	-20.855	-12.226	-22.858	-30.426	-34.145
LN(committed capital)	1.407	0.920	1.429	1.823	2.225
Short-term interest rate		94.698			
Short-term interest rate$_{t-2}$				32.294	
Long-term interest rate$_{t-1}$	66.653		70.487	120.114	144.685
Long-term interest rate$_{t-2}$	106.303		34.813		
Industry production				12.398	
GDP$_{t-1}$		-57.981			
Nasdaq$_{t-1}$			0.618		
Nasdaq$_{t-2}$	-1.524				-1.227
Unemployment rate$_{t-1}$	-121.891				
Manufacturing earnings$_{t-1}$	3.555				
Later stage dummy	-1.298		-0.713		-0.696
Goodness-of-Fit Test: χ^2	110.351	25.861	197.489	122.117	87.097
p-Value	0.000	0.000	0.000	0.000	0.000
Cox & Snell R square	0.242	0.252	0.198	0.231	0.336
Nagelkerke R square	0.415	0.337	0.270	0.343	0.456
Hosmer and Lemeshow test	0.517	0.132	0.470	0.899	0.107
Number of observations	565	89	1263	455	422

Table 4 Default classification accuracies for the buyout models

The table presents the out-of-sample prediction validation of the default predicition accuracies for the buyout models. The dataset comprises of 1,147 realized U.S.- buyout investments in the years 1974 - 2005, taken from the records of CEPRES. The data set for each industry class shown in the first column is divided into two subsets, the training sample comprising of three fourth of the industry subset, which is used to construct and determine the models, and the testing sample, which serves the purpose of testing the model's accuracy and is chosen completely randomly form the full data set. Due to data limitations, we could not divide all industry data sets and only validate samples with more than 150 observations. The first figure in the column "% correct" within each sector group indicates the percentages of correct predicting non-defaults, the second value the hit ratio of the model for predicting defaults and the third value the overall hit ratio for predicting correct default as well as non-default.

		Training Sample			Testing Sample		
Sector	Observed	non-default	default	% Correct	non-default	default	% Correct
Computer	non-default	181	0	100.00	42	2	95.45
	default	3	9	75.00	2	4	66.67
	Overall			98.45			92.00
Industrial	non-default	215	20	91.49	90	9	90.91
	default	19	38	66.67	1	5	83.33
	Overall			86.64			90.48
Biotech	non-default	76	9	89.41	-	-	-
	default	3	8	72.73	-	-	-
	Overall			87.50			-
Consumer	non-default	85	4	95.51	-	-	-
	default	5	6	54.55	-	-	-
	Overall			91.00			-
Telecom	non-default	41	4	91.11	-	-	-
	default	1	7	87.50	-	-	-
	Overall			90.57			-

Table 5 Default classification accuracies for the venture capital models

The table presents the out-of-sample prediction validation of the default predicition accuracies for the venture capital models. The dataset comprises of 2,794 realized U.S.- venture capital investments in the years 1974 - 2005, taken from the records of CEPRES. The data set for each industry class shown in the first column is divided into two subsets, the training sample comprising of three fourth of the industry subset, which is used to construct and determine the models, and the testing sample, which serves the purpose of testing the model's accuracy and is chosen completely randomly form the full data set. Due to data limitations, we could not divide all industry data sets and only validate samples with more than 150 observations. The first figure in the column "% correct" within each sector group indicates the percentages of correct predicting non-defaults, the second value the hit ratio of the model for predicting defaults and the third value the overall hit ratio for predicting correct default as well as non-default.

		Training Sample			Testing Sample		
Sector	Observed	non-default	default	% Correct	non-default	default	% Correct
Computer	non-default	404	159	71.76	214	73	74.56
	default	116	218	65.27	30	63	67.74
	Overall			69.34			72.89
Industrial	non-default	207	42	83.13	88	15	85.44
	default	28	54	65.85	8	22	73.33
	Overall			78.85			82.71
Biotech	non-default	297	39	88.39	101	35	74.26
	default	25	38	60.32	12	17	58.62
	Overall			83.96			71.52
Consumer	non-default	35	12	74.47	-	-	-
	default	14	28	66.67	-	-	-
	Overall			70.79			-
Telecom	non-default	134	47	74.03	66	29	69.47
	default	27	90	76.92	10	20	66.67
	Overall			75.17			68.80

Table 6 Reference Portfolio "1997"

This table gives an overview of the sample composition for the *1997 reference portfolio*. This sample comprises of five U.S. venture capital funds within our entire dataset, which were all launched in 1997 and enclose in total 104 fully realised investments. The table shows the total number of deals categorized by sectors and satge of development. The 6 stage classifications for venture capital investments provided by CEPRES were aggregated into 2 subclusters (CEPRES categories in brackets); 1) Early Stage (seed, start up, early) and 2) Later Stage (expansion, acquisition financing, later)

	Total	Biotech	Computer	Telecom	Industrial	Consumer
Later Stage	44	18	13	3	7	2
Early Stage	60	20	22	15	2	0

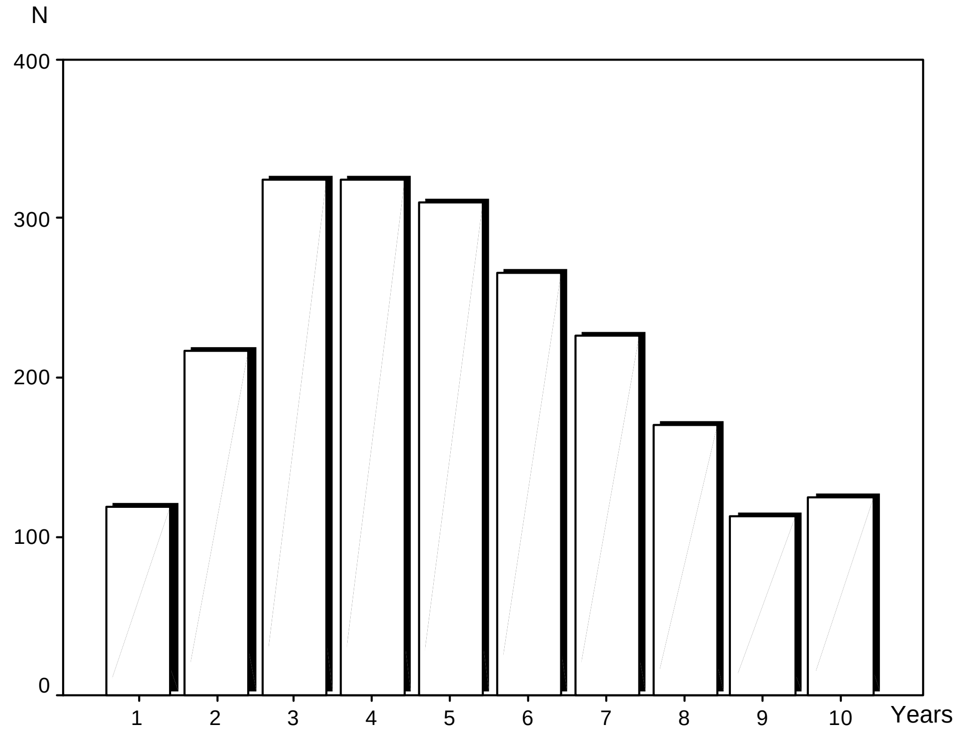
Table 7 Historical default rates for investments realised before 1997

This table shows the historical default rates by several sector-stage subclusters, which is applied within the PerFore-model for the estimation of the future default rates of the 1997-reference-portfolio. The calculations are based on a historical dataset of 632 U.S. venture capital investments which were realised before 1997. The numbers indicate the percentage of defaulted deals within the subcluster. A default is defined as a total loss with an IRR of minus 100 % (write-off). The 6 stage classifications for venture capital investments provided by CEPRES were aggregated into 2 subclusters (CEPRES categories in brackets); 1) Early Stage (seed, start up, early) and 2) Later Stage (expansion, acquisition financing, later)

	Total	Biotech	Computer	Telecom	Industrial	Consumer
Later Stage	16.2%	11.8%	10.4%	28.0%	16.1%	45.5%
Early Stage	34.5%	27.7%	29.6%	23.3%	44.3%	56.4%

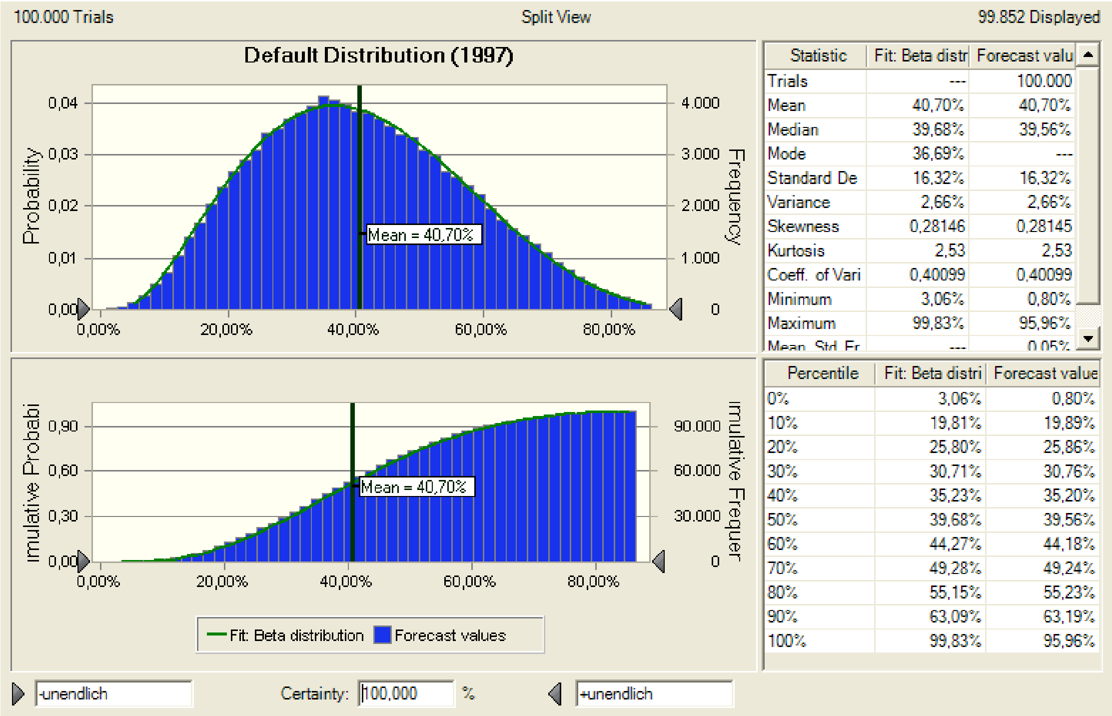
Figure 2 Historical fund liquidation schedule in terms of exited deals per year since fund closing

This figure shows the historical liquidation patterns for U.S. venture capital funds by years since closing of the fund in terms of number of exited portfolio companies. The dataset used for this analysis comprises of 2,195 investments for the period of 1971 to 2006. We show the first ten years since closing. All investments exited later than ten years since the closing of the fund are assigned to year ten.



Year	1	2	3	4	5	6	7	8	9	10	Total
N	118	217	325	325	310	266	226	170	113	125	2195
%	5%	10%	15%	15%	14%	12%	10%	8%	5%	6%	100%

Figure 3 Monte Carlo Simulation Results for the 1997 reference portfolio validation



Curriculum Vitae

A. Personal Data

Philipp Krohmer
Lindwurmstrasse 139a
80337 München
Germany
+49 (0)179 1358219
philipp.krohmer@cepres.de

B. Affiliation

Goethe Universität Frankfurt
Finance Department
Mertonstrasse 17
D-60054 Frankfurt

C. Education

2002 – 2008	Goethe Universität Frankfurt, Finance Department, Germany External Doctoral Student in Business Sciences within the Center for Financial Studies research- project "Venture Capital and the New Markets in Europe"
1995 – 2001	Universität Mannheim, Germany Business Studies Degree: Diplom Kaufmann
1998 – 1999	Universidad Autónoma de Barcelona, Spain 5th Year Course Scholarship of the Multiregional International Business Program (MIBP) and the Paul-Julius-Stiegler-Gedächtnis-Stiftung

D. Professional experience

2006 – present	Center of Private Equity Research, CEPRES GmbH, Munich, Germany Private Equity Consulting Investment Management Head of Data Center
2002 – 2005	VCM Venture Capital Management GmbH, Munich, Germany Project CEPRES – Center of Private Equity Research Establishment of the database PEA (Private Equity Analyzer)
Summer 1999	Andersen Consulting, S.A., Barcelona, Spain Business Process Reengineering Project
Spring 1998	Heidelberger Zement AG , Heidelberg, Germany Operative Controlling Department

E. Papers and Conferences

1. Philipp Krohmer, Rainer Lauterbach and Victor Calanog (2007): The Bright and Dark Side of Staging – Investment Performance & the Varying Motivations of Private Equity Firms, American Finance Association – Annual Meeting 2007, Chicago, Working Paper. Under Review at the *Journal of Banking and Finance*
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   - The Global Finance Conference, Rio de Janeiro, Brazil (2006)
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   - Brown Bag Ph.D. Seminar, Goethe University Frankfurt, Germany (2005)
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   - The Paris International Finance Meeting, Paris, France (2007)
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   Accepted at:
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8. Contribution in: *Encyclopedia of Alternative Investments edited by G.N. Gregoriou, 2008 Chapman Hall UK.*