An Analysis of the Economic Forces Driving Partial Exits in Private Equity Transactions

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Transactions

By

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Abstract

Private capital markets are rich with information asymmetries, including agency problems between General Partners (GPs) and entrepreneurs and between GPs and their respective Limited Partners (LPs). As such, this study investigates partial exits, or non 100% equity stake sales, as a mechanism by which private equity firms may mitigate inherent transactional (asset seller and buyer) and structural (GP and LP) agency challenges. Although their frequency of use by private equity firms has risen dramatically over recent decades, partial exits have drawn little academic attention in a buyout context. This thesis, thus, aims to provide explanatory detail behind private equity usage of partial exits. We propose three central hypotheses: frequency of partial exit usage will increase in (1) transaction contexts with significant information asymmetry between buyer and seller (2) situations that demand liquidity from GPs and (3) contexts in which GPs attempt to signal investment firm quality to LPs. We utilize a public dataset of over 13,000 private capital transactions, with asset, fund, and investment firm level detail per completed exit. Our results indicate that partial exit usage is indeed tied to information asymmetries faced by private equity firms; partial exit usage increases in transactions characterized by high information asymmetry and in macroeconomic and fund environments that pose liquidity constraints. Further, partial exits are demonstrated to strengthen GP fund quality signals by mitigating signaling costs associated with grandstanding and amplifying time-weighted return metrics.

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Section 1: Introduction

As discussed in seminal studies by Akerlof (1970) and Leland and Pyle (1977), information asymmetry lies at the foundation of financial markets, and equilibrium transaction values depend on levels of information transfer. As Leland and Pyle (1977) demonstrate, however, direct information transfer between transacting parties is oftentimes limited by moral hazard constraints; as a result, firms may utilize signaling effects as one mechanism of indicating the quality of the asset at hand (Riley, 1975; Spence 1978). Studies by Myers and Majluf (1984), Rothschild and Stiglitz (1978), and Ross (1977) show that this is especially pertinent in financial markets in which managers, investors, and lenders are constantly faced with informational imbalances when making financing and investing decisions.

One financial market in which information asymmetries are omnipresent is the private equity investment industry. In this market, summarily, private equity funds (acting as General Partners; GPs) are allocated funds by Limited Partners (LPs) such as pension funds, endowments, and other institutional investors; these funds are used to purchase and exit assets, typically with the use of leverage and within a 5-10 year period, in order to return capital to LPs. As such, private equity firms face information asymmetry in two contexts. First, at the forefront of academic study, is the inherent agency problem between GPs and portfolio company management teams, studied in detail by Gompers (1995); as detailed by Hart (2001) and Kaplan and Stromberg (2003), one means of resolving this agency challenge

is via screening prior to capital deployment by GPs. Evaluating the quality of an investment opportunity is made challenging, however, by the lack of mandated financial disclosures and significant barriers to dilligencing potential assets (cost, intangibility, etc.). Given that buyers in such scenarios are thus oftentimes at an informational disadvantage, sellers of the asset are incentivized to signal the quality of the asset for sale in order to facilitate the transaction (Boone and Mulherin, 2009).

Next, at a structural level, as discussed by Gompers and Lerner (1999), Prowse (2001), and Metrick and Yasuda (2010), there exists a significant principal-agent problem between GPs and their LPs, as GPs possess substantially more information as specialized investors operating the return-generating assets; LPs thus, in an environment with limited supervision and monitoring capacity, are challenged to allocate their capital optimally. Along with aligning incentives via compensation, signaling and reputation effects by GPs can help mitigate this asymmetry. Thus, the private capital markets are rich in informational differences that set the foundation for this study.

This analysis thus focuses on one potential mitigant of the inherent transactional and structural information asymmetries in the private equity industry: partial exits. A partial exit may be defined as a sale of less than 100% of an asset's equity by the current investor via any exit vehicle; despite their increasing frequency over the prior decade, making up 18% of all private equity exits in 2006 and 30% of all such transactions in 2018, little attention has been paid to the economic drivers and motivating factors behind this exit mechanism. As such, this study aims to initialize and significantly advance the current understanding

of partial exits as an information asymmetry mitigant in private equity contexts, utilizing recent advances in private equity data access to explore theoretical and empirical implications of their usage. Our key findings demonstrate that partial exit usage can be explained not only by transaction contexts with high information asymmetry but also by their capacity to generate liquidity in poor macroeconomic conditions and facilitate GP signaling quality to LPs.

We hypothesize that there exist three fundamentals drivers of partial exit usage by private equity firms. First, we argue that partial exits will be utilized most frequently in situations with significant information asymmetry between the buying and selling party; we propose four mechanisms (duration, asset industry, geographical distance, and investor resources) by which we proxy the information asymmetry in a given exit transaction. Second, we posit that partial exits will be advantageous to private equity firms in situations that pose liquidity constraints, including: (i) poor macroeconomic conditions, as measured by GDP growth (ii) investments exited near the end of a fund's lifecycle. Finally, we claim that partial exits may be used by GPs to signal investment capability. We evaluate this in two contexts. First, we claim that partial exits can mitigate signaling costs associated with grandstanding; second, we posit that partial exit usage may amplify fund-level IRR figures. As both grandstanding and increased IRR figures have been shown to be critical for GPs in reputation construction and fundraising, these contexts help us evaluate the role of partial exits in allowing GPs to signal investment ability to LPs.

Our first hypothesis centers around the capacity for partial exits to signal investment

quality and reduce transactional informational asymmetry between buyers and sellers; as detailed by Leland and Pyle (1977), Riley (1975) and Spence (1978), information asymmetry oftentimes cannot be measured directly. In this study, we utilize the following proxies to measure the information asymmetry present in a transaction: investment duration, asset industry, geographic distance, and investor resources. Given the granularity of our dataset, however, we are able to take a distinct approach in our examination of information asymmetry in equity stake sales; when studying industry and geographic distance, we incorporate posterior-transaction data regarding the acquirer in order to add explanatory power over pure predicative capacity. Results from this analysis demonstrate that partial exits are correlated with levels of the following proxies that represent heightened transactional information asymmetry (short investment durations, complex-industry assets, divergence in sector specialty between acquirer and portfolio company, and increased distance between seller and portfolio company).

Our second hypothesis focuses on partial exits in situations in which funds may desire liquidity. As demonstrated by Ljungqvist and Richardson (2003) and Blake et al. (2007), one such context is poor macroeconomic conditions (measured by quarter-over-quarter GDP growth). We investigate further by examining macroeconomic conditions near the end of a fund's lifecycle, when private equity firms must liquidate current investments and return capital to Limited Partners (LPs). We argue that in poor macroeconomic conditions, we should see increased partial exit usage; further, we posit that partial exit usage will be more frequent in strong macroeconomic conditions during the end of a fund's lifecycle vs.

poor macroeconomic conditions, per loss aversion behavioral theory. Our results confirm the presented hypotheses, demonstrating that partial exit usage is inversely correlated with macroeconomic conditions and that partial exits are used more frequently in strong macroeconomic conditions coupled with end of fund timelines.

Our final hypothesis claims that partial exits may facilitate signaling quality attempts by private equity firms (GPs) in mitigating GP-LP agency problems. We consider two contexts which reveal the utility of partial exits in GP-LP agency challenges: first, young investment firms tend to engage in grandstanding, or the process of exiting an investment early in order to signal quality and built reputation (Gompers, 1996; Lee and Wahal, 2004). However, this signal carries a significant cost, as that investment may have realized significant returns in the future. As such, we propose partial exits as a mechanism that may allow private equity firms to exit a large equity stake, thus signaling fund quality, while also retaining an equity stake, thus mitigating the signal cost. Second, LPs utilize time-weighted return metrics, such as the Internal Rate of Return (IRR), in order to evaluate the quality of a GP in order to decide capital allocations; we claim that partial exits may serve as a mechanism for private equity firms to amplify IRR metrics by generating cash flows early (Gompers and Lerner, 1998; Strömberg, 2008). As both grandstanding and time-weighted return metrics are used by GPs to signal their investment talent and performance to LPs, partial exits may thus be used to facilitate GP signaling. We conduct this analysis via both formal modelling and empirical analysis. Our theoretical results confirm mathematically that partial exits may reduce signaling costs associated with grandstanding and amplify fund-level IRR metrics;

the latter is confirmed via empirical testing.

We now briefly summarize our key findings from the above hypotheses. Our study first reveals that partial exits are indeed associated with transaction contexts high in information asymmetry, as proxied by duration, industry, and distance. We further demonstrate that partial exits are particularly useful in situations that place liquidity pressures on GPs. Finally, we find that partial exits may be utilized in signaling the quality of a GP's investment ability to LPs by mitigating grandstanding costs and amplifying time-weighted return figures.

With regards to data, this study benefits from leveraging the Preqin database of nearly 14,000 private capital transactions, which contains detailed information on entry (date, stage, investors), exit (partial/complete, date, type, buyer), and the portfolio company (sector, previous transactions). Further, the database contains fund level data (vintage date, IRR, cash multiple) as well as information on the private equity firms themselves. This level of granularity is recent to the private equity industry and bridges the historical tradeoff between detailed hand collected data with limited sample size and large datasets with little granularity (Sykes, 1990; Amit et al., 1998; Bruno and Tyebjee, 1985; Lockett and Wright, 2010; Fenn et al., 2001). The consequence of this is that we may introduce new variables to our econometric analysis and use higher sample sizes to generate more accurate distributions when modeling returns.

With regards to the structure of this thesis, we follow this introduction with a literature survey discussing foundational private equity and partial exit theory and contributions made

by this study. We then construct our core hypotheses in sections 3 through 5. Afterwards, we discuss our empirical regression specifications in section 6 and our model specifications for our third asymmetry hypothesis in section 7; we follow this with a discussion of our data in section 8. We then present our results in section 9 and conclusion in section 10. Our appendix section contains our tables and figures as well as additional model derivation components.

Section 2: Private Equity and Partial Exit Theory

The private equity industry is unique in that firms not only face individual investment value maximization problems but must also operate under a set of exogenously induced parameters by LPs. In this section, we first briefly review core facets of private equity transactions and incentive structures, emphasizing the inherent information asymmetry challenges present. Afterwards, we discuss the existing literature base and the manner in which this study builds upon and extends current published work. Finally, we conclude by introducing literature pertinent to each of our core hypotheses.

Section 2.1: Characterizing the private equity industry

We first examine firm incentives on an individual transaction and portfolio level: the staple private equity transaction is the leveraged buyout, characterized by concentrated equity stakes and relatively high levels of debt (Palepu, 1990; Kaplan, 2009; Kaplan, 1991). Not only must firms identify the proper entry price, but according to Ivashina and Kovner (2011), they must also take into account exogenous market conditions in order to take advantage of cheap debt. After entry, firms often have complete governance control, and, as identified by Kaplan and Stromberg (2009), engage in financial and operational engineering to increase the value of the firm by time of exit. Given that the mean private equity firm size is only 8 individuals, however, firms are challenged to allocate investment professionals optimally to maximize value-add per investment over the marginal cost of that investor;

further, as additional investments are added across the lifetime of the portfolio, resource allocation becomes even more critical (Cumming, 2003). Finally, upon exit, firms must consider exogenous market valuation levels while also signaling the quality of an investment to outside buyers.

In the transaction process, however, private equity firms must also contend with significant information asymmetry barriers between the seller and the acquirer at hand. This information asymmetry arises from a number of sources. First, as indicated by Leland and Pyle (1977), private assets are naturally associated with increased information asymmetry due to a lack of necessary mandated reporting or filing of financial and operational performance. Applying major results by Myers and Majluf (1984), Merton (1987), and Healy and Palepu (2000), the premium required on private asset equity stakes when put up for sale diminishes as the information asymmetry between buying and selling party decreases. While structured auction processes may have investment bankers facilitating such transfers, acquiring and selling parties are nonetheless incentivized to reduce information asymmetries within the relevant transaction. Such barriers can result from particularities of all three parties in the transaction: asset, seller, and buyer.

At the asset level, as detailed in our hypothesis section, assets belonging to highly niche, intangible-asset based industries or those located further from major geographic hubs are found to be associated with underpricing to alleviate information risk for acquirers in IPO processes (Lev, 2001; Barth, 2001; Barron et al., 2002; Gupta and Sapienza, 1992; Lerner 1995; Lerner 2010). Such assets often face higher financing costs for lenders, paying a pre-

mium for heightened diligence costs by financiers, referred to as the "church-tower principle" (Carling, 2002). The selling party, on the other hand, can alleviate information risk burdens for acquirers by signaling the quality of the investment opportunity: per Welch (1989), equity stake retention is one such mechanism. Sustained reputation and sector expertise by investors may also serve as quality signals in transaction processes. Finally, acquirers with little sector or asset expertise (comparable to retail investors in IPO transactions), are at a natural informational disadvantage. Such factors contribute significantly to the valuations of the asset proposed by potential acquirers and create opportunity within the private equity markets.

With regards to fund structure, limited partners contribute capital to a private equity firm over the lifetime of a given fund, which typically ranges between 7 to 10 years; these limited partners are oftentimes institutional investors, such as pension funds or university endowments. There exists significant heterogeneity in institutional investors and their ability to best allocate capital, as demonstrated by Lerner et al. (2007), coupled with varying degrees of agency problems with GPs (Shleifer and Vishny, 1997). As highlighted by Mehta (2004), one mechanism by which these agency issues may be mitigated is via compensation structures that align incentives: GPs are often paid both a management fee and a performance-based fee. Fund performance, as a result, is critical in signaling the quality of the GP and is measured traditionally both by a time-weighted IRR metric and a time-independent Multiple of Invested Capital (MOIC) figure. Once invested, LPs have access to inside information and returns metrics that govern their decision, often with priority, to reinvest capital in the

fund (Lerner et al., 2007). Studies published by Barber and Yasuda (2017) and Chung et al. (2010) reveal the importance of the IRR metric in particular, indicating that it can serve as a significant predictor of future fundraising success.

Section 2.2: Significance of this study

The above discusses the numerous parameters and constraints private equity funds must work under while attempting to optimize returns. Our investigation into partial exits is spurred by their seeming capacity to mitigate many of these challenges as related to (1) information asymmetry on a transaction level (2) liquidity generation and (3) returns optimization in the context of LP-GP agency problems. However, due to limited data availability and infrequent historic usage by private equity firms (Figure A1), this is the first study to provide an expansive investigation into partial exits within the late-stage buyout space. There exists one prior study into partial exits, focused on the early stage venture capital space, published by Cumming and MacIntosh in 2003; this study uses a hand-collected dataset of 248 venture capital transactions, examining the capacity of partial exits to signal quality and discussing distinctions in partial exit determinants between the United States and Canada. While Cumming and MacIntosh's 2003 study was foundational in introducing partial exit theory, this study expands the current understanding of partial exits in the following manners.

This study focuses on partial exits within the previously unexplored private equity industry, the unique structure of which contributes to the novel hypotheses and models proposed

in this study. We briefly introduce nuance between private equity and venture capital industries here and then explain their impact on hypothesis generation. On an asset level, private equity portfolio companies are significantly more mature, command larger absolute equity check sizes coupled with leverage, and extends into complex, capital intensive industries with little venture markets (Kaplan and Stromberg, 2009; Fenn et al., 1997; Ljungqvist and Richardson, 2003). Further, the investors selling equity stakes and engaging in the potential partial exit own majority or complete stakes in the asset up for sale. Private equity firm relations to LPs also cause distinctions in investment criteria and portfolio criteria from venture capital firms, resulting in lower failure rates of private equity portfolio companies (Robbie, 1998). Portfolio companies thus tend to be mature with significant cash flow generation, and fund level returns are significantly influenced by timing of cash flows.

These distinctions, coupled with access to a large, granular dataset of private equity transaction, allow us to (1) add significant nuance to the transactional information asymmetry hypothesis via detailed industry and geographic breakdowns of not only the asset and seller but also the buyer (2) construct a working theory regarding private equity behavior during poor macroeconomic conditions, particularly in scenarios that demand immediate liquidity, such as the end of a fund's lifecycle (3) take a mathematical approach in understanding partial exit usage in fund-level signaling context, namely grandstanding and optimizing cash flow timing. With regards to (3), this study not only investigates empirically whether fund level returns and grandstanding contexts are associated with partial exits, but also constructs explanatory economic models in an attempt to justify partial exit usage in such situations.

Section 2.3: Introductory theory per hypothesis

We conclude this section by briefly surveying prior literature relevant for each major hypothesis in our study. Our first hypothesis focuses on transactional information asymmetry between buyers and sellers, the theory of which was significantly advanced by Myers and Majluf (1984), who explored firm action when in the presence of a clear distinction in information between management and potential investors. This asymmetry has manifested itself in various forms throughout the private capital industry, including the variables used in this study to proxy information asymmetry. Megginson and Weiss, in a 1991 study examining IPO underpricing, relate information asymmetry to investment duration; numerous studies (including Barth et al., 2001; Kumar and Siddharthan, 1997) have also associated asset intangibility and complex-asset industries with increased information asymmetry between the firm and potential investors. Geographic distance, as examined by Gupta and Sapienza (1992) and Carling (2002), has similarly been associated with heightened diligence costs and information asymmetry. Exit Type (IPOs, GP to GP sales, Trade Sales, and Sales to Management) can also be directly related to information asymmetry, as the acquirers and sale process for each carry and convey distinct levels of information (Cumming and Johan, 2008; Eckermann, 2005); in our study, we utilize exit type as a control and a panel, but not as an independent variable, as the relationship between each exit mechanism and partial exits is definitionally implied by each exit vehicle.

With regards to the liquidity theory, private equity firms embody two forms of limited capital movement. First, LP's are investing in an inherently illiquid asset class based on fund structure, as distributions are made over the course of a 10-year private equity fund lifecycle. Second, the GPs themselves require liquid capital to be able to take advantage of investment opportunities. One core facet of such liquidity is access to the debt capital markets, as debt allows firms to invest in larger buyouts and drive returns (Loos, 2005; Folkman et al., 2009; Nielsen, 2008). A milestone study by Axelson et al. (2013) established that firms are more likely to take advantage of cheap debt when available in hot credit markets, linking leverage levels to market conditions. Published figures by *Pitchbook* showcase that private equity deal count drops significantly in periods of credit contractions, falling as low as 47% of 2018 transaction volume during the crisis (down 43% from '07 levels); on the other hand, similar industry data shows that average valuations also fall significantly during such periods; thus, low-liquidity periods for GPs may be proxied by poor macro conditions, in which multiples are cheap but with little opportunity to deploy capital (McKinsey, 2019).

Our third hypothesis examines the impact of partial exits on common quality signaling mechanisms by GPs; first, we consider the phenomenon of grandstanding. Grandstanding arises as a consequence of the accelerated nature of fundraising timelines when compared to capital deployment; in particular, as discussed by Gompers and Lerner (1995), fundraising typically occurs in three to five year cycles, whereas the funds themselves last around ten years. As a result, new investment firms are incentivized to exit investments early from their first fund in order to signal reputational quality to LPs with limited information on

performance when trying to raise a second fund. (Gompers and Lerner 1995; Gompers 1993). As Gompers (1993) finds, however, this signal comes at a significant cost, in which firms lose upside potential in their equity investments. In their 2003 study, Cumming and MacIntosh propose that partial exits may be utilized to mitigate these signaling costs by allowing for equity upside retention; in their study, however, they acknowledge that there is an inherent relationship between investment duration and partial exit usage as well due to information asymmetry; thus, it is challenging to establish grandstanding as a causal factor. In this study, we propose a similar hypothesis to Cumming and MacIntosh's; we explore it theoretically, however, by constructing a symbolic model and evaluating explicitly in which situations a partial exit actually mitigates signaling costs directly as a consequence of the financial structure of partial exits (thus providing explanatory justification).

The second aspect of this third hypotheses relates partial exits to the impact of time-weighted return metrics on fundraising and signaling GP quality; as shown by Shleifer and Vishny (1991) and Sirri and Tufano (1993), fundraising is dependent on GP performance. The IRR metric is critical in particular and can be used to overstate results; as such, firms are incentivized to maximize these return figures (Brown et al., 2013; Kaserer and Stucke, 2013). This hypotheses proposes that partial exits can improve signaling effects to LPs earlier in time by increasing IRR metrics via earlier cash flow generation. In evaluating private equity returns, studying timing of contributions by LPs and distributions by GPs is critical but oftentimes challenging due to limited granularity of industry data. Gompers and Lerner in 1997 were on the forefront of such analysis (in the venture capital space); fol-

lowing advances in data collection procedures, Ljungqvist and Richardson (2003) conducted a larger scale analysis in the private equity industry, taking into account cash flow timing in comparing private and public market returns. Recent studies have continued to examine contribution/distribution cycles while incorporating major public databases as used in this study.

Section 3: Transaction-based Information Asymmetry Hypothesis

Transactional information asymmetry between buyers and sellers may be reduced by a variety of methods, including signaling the quality of the given investment; one method of signaling quality is via a partial ownership stake (Folta and Janney, 2003; Cumming and Dai, 2010; Connelly et al., 2010). Examples of such activity in private equity are numerous, such as management's willingness to retain an equity stake post-transaction (rollover) or an investment firm's willingness to retain equity in a secondary sale to another buyout firm. Thus, our core hypothesis for this section is that partial exits may serve to reduce information asymmetry in private equity transactions. To investigate this, we develop a set of variables that indicate varying levels of information asymmetry and use regression analysis to understand the frequency of partial exits in relation to each of these. Within this section, we construct hypotheses for each of the following variables: investment duration, geographic distance, asset sector, and investor size. With regards to distance and industry, we incorporate data regarding the acquirer, adopting a posterior perspective on the transaction. Afterwards, we discuss our use of exit type as a control variable in our analysis

Section 3.1: Investment duration

Increased investment duration, as examined in studies by Tian (2011) and Cumming and

MacIntosh (2003), is associated with decreased information asymmetry; in the venture capital space, information asymmetry is lower in later stage investments as products have already been developed and investors have had time to resolve implicit agency issues. Further, public awareness of new technologies or products increases over time. When considering purely late stage buyouts, thus, we would expect that product development, agency issues resolution, and product awareness increases over time to justify decreased information asymmetry. As such, we predict that as the investment duration of a buyout increases, the frequency of partial exits will decrease.

Section 3.2: Asset industry

We utilize the industry of the asset as well as the sector-specialty of the acquirer in a given transaction to argue for two potential drivers of information asymmetry in private equity transactions. First, we focus solely on the industry of the asset. As demonstrated by Swheinbacher (2008), tech companies have a higher level of harder to diligence asset intangibility and as noted by Alves and Martins (2014), asset intangibility is associated with greater information asymmetry. Further, high levels of innovation render technology firms higher in information asymmetry, as it necessitates both sector expertise and periodic monitoring. As such, we would expect internet or software sector companies to have higher information asymmetry. We also expect niche sectors with highly complex assets to similarly be associated with increased information asymmetry; this includes assets in the healthcare, balance-sheet focused financial services, and heavy industrials sectors. We thus

expect portfolio companies in these industries to have increased association with partial exits. Our second argument takes into account the profile of the acquirer; if the acquirer and the portfolio company share specialty in the same sector, we expect decreased information asymmetry; as such, we expect increased overlap in specialty to be associated with fewer partial exits.

Section 3.3: Geographic distances between seller, portfolio company, and buyer

We now consider the pairwise distances between each of the three parties involved in a given transaction, forming distinct hypotheses for their various mechanisms of impacting information asymmetry. First, we consider the distance between the acquirer and the portfolio company. As discussed by Sufi (2007), the key challenges associated with investing in a company center around high diligence costs and lack of accessible information, especially in the context of geography. As such, we expect increased distance between the portfolio company and the acquirer to be associated with increased information asymmetry and thus greater use of partial exits (Lily et al., 2015; Usyal., 2008; Kang and Kim., 2008). Second, we examine the distance between portfolio company and seller; as this distance increases, monitoring capabilities of the original investor decrease (associated with increased information symmetry), thus increasing necessity for a quality signal. Finally, we consider distance between portfolio company and investor. There also exist significant information transfers between investors concentrated in a geographic area (on an asset and reputational level).

As such, we expect increased partial exit usage in transaction contexts in which buyer and seller are geographically close.

Section 3.4: Investor size

We finally construct an argument based on the information asymmetry between the seller and the portfolio company at the time of transaction based on investor resources. As discussed by Cumming and Macintosh (2003), private equity funds are limited in resources by investment professional headcount; in particular, increased investor size directly facilitates heightened monitoring capabilities by way of an increased presence on boards and exposure to operations. As such, we expect increased investor size to be associated with decreased information asymmetry and thus decreased usage of partial exits.

Section 3.5: Exit type

Unlike prior work conducted by Cumming and MacIntosh (2003) on partial exits, we choose not to utilize exit type as an independent variable in the context of information asymmetry. We do this because extracting a causal relationship between partial exits and exit vehicles is extremely challenging. We demonstrate this as follows. Prior literature indicates that we can construct a relative ranking of exit types by level of information asymmetry. IPOs are characterized by the most information asymmetry, given the preponderance of under-informed investors; private placements, involving non-specialized institutional investors, can be ranked second, followed by GP-to-GP transactions, trade sales, and finally sales back to management, who have perfect information on the asset at hand (Rock, 1986; Keasy

and Short, 1992; Ljungqvist, 2007; Mehta, 2004; Pindur, 2009). However, in practice and definitionally, IPOs are partial exits, and thus it is extremely challenging to decipher which direction the relationship between exit type and partial exits exists. However, the relative information asymmetries of each exit type will allow us to examine the results of the above hypotheses in the context of each exit vehicle.

Section 4: Liquidity Hypothesis

Our second central hypothesis is that in situations that incentivize liquidity for a given private equity firm, partial exit frequency will increase. We investigate this using two contexts: poor market conditions and timing in proximity to the end of a fund's lifecycle. With regards to the latter, we would tautologically expect an inverse relationship between the end of a fund's lifespan and use of partial exits (as liquidation is necessary); as such, we are more interested in private equity action during various macroeconomic conditions at the end of a fund's lifespan (the interaction between the two variables).

Section 4.1: Macroeconomic environment

There are two potential justifications for why a challenging macroeconomic environment may induce need for liquidity for private equity firms. First, as revealed by Axelson (2013), private equity firms utilize leverage most in credit expansions. In contractions, therefore, firms have inadequate access to the debt capital markets, limiting their ability to deploy capital. Further, as revealed by industry analyses conducted by McKinsey (2019), private equity exits occur less frequently during contractionary credit periods. As such, firms have less cash as distributions to return to LPs during these periods. Partial exits may mitigate these challenges by offering firms a chance to exit stakes in poor credit environments and generate liquidity which may be used as recallable distributions. A further benefit, external to liquidity challenges, is that partial exits open more investment opportunities to the market

that those with accumulated dry powder may take advantage of in contractions. Thus, we hypothesize that macroeconomic conditions are inversely related to frequency of partial exits.

Section 4.2: End of fund lifecycle

Private equity funds are structurally limited such that by a certain time the fund must liquidate investments and return capital to LPs. This poses a distinct exogenous problem for private equity firms: there may exist investments in the fund with significant future upside for both the GP and LPs, but fund structure dictates a liquidation. This is discussed in detail in an article written by Corelli (2018); the article provides insight into a complicated method by which firms may negotiate the opportunity to stay invested in high upside assets. Partial exits, however, can serve as another means for satisfying both GPs and LPs; via this mechanism private equity firms may take advantage of partial exits as a means of returning capital to LPs while still retaining equity in high-potential investments. Given the current practice of total liquidation, and the challenges discussed in the prior article, we believe that tautologically we should see preference for complete over partial exits when considering private equity action at the end of a fund's timeline in general. However, we also investigate the interaction between the macroeconomic variable and the indicator for the end of a fund's lifecycle; in particular, we hypothesize that when a firm reaches the end of a lifespan of a fund in poor macroeconomic conditions, private equity firms will prefer complete liquidation of assets, whereas in strong macroeconomic conditions, firms will exit partially and allow a remaining stake to accrue value. We attribute this to loss aversion behavioral theory, in

which investors follow the tendency lock in losses (or potentially unfavorable exit markets) to prevent further losses; given the low-risk appetite of private equity firms, as demonstrated by Braun et al. in 2011, we expect that such firms are less likely to hold assets through poor macroeconomic conditions.

Section 5: GP Quality Signaling Hypothesis

In this section, we detail our hypothesis regarding partial exits and their potential role in facilitating GPs signaling their investment abilities to LPs. In particular, we propose the following. As LPs make capital allocation decisions, GPs must indicate and signal their ability to generate returns early in a fund's lifespan. We claim that partial exits are one mechanism by which GPs can improve the strength of their quality signals to LPs. We study this by considering two contexts in which GPs signal performance to LPs. First, we examine grandstanding, in which new firms must pay significant opportunity costs in order to generate early returns from an asset and second, we consider fund-level IRR metrics utilized by LPs to evaluate GP quality. Respectively, we evaluate our hypothesis by studying whether partial exits can (i) mitigate signaling costs associated with grandstanding and (ii) amplify fund-level IRR figures.

Section 5.1: Grandstanding

For new or young private equity industries, grandstanding is the practice of exiting an investment early post-inception in order to generate returns early and establish a strong reputation (Gompers, 1996). While the early returns have been demonstrated to serve as a strong signal to current and potential LPs, this practice does result in sacrificed cash flows, deleveraging, and EBITDA accretion; these consequences can be thought of as the costs associated with signaling GP quality. As such, we hypothesize that partial exits may

serve as a unique mechanism that may mitigate theses signaling costs while still allowing for reputation construction. We develop a theoretical model to explore this theory symbolically, aiming to determine in which scenarios partial exits can mitigate signaling costs.

Section 5.2: Cash flow timing: IRR amplification

Private equity firms primarily utilize two means of reporting returns: the internal rate of return (IRR) and the Multiple of Invested Capital (MOIC); the former takes into account the timing of cash flows and is calculated by finding the discount rate that makes the net present value of a given investment opportunity equal zero. The MOIC, on the other hand, purely compares cash invested to cash generated, without accounting for time. The IRR serves in a critical signaling capacity, impacting both the ability to raise a subsequent fund and the size of the fund raised for a given GP (Phalippou, 2008; Robison and Sensoy, 2013). As such, private equity firms have a significant incentive to maximize their IRR figures; as noted by Phalippou (2008) a primary means of doing this is via the timing of cash flows.

Partial exits are unique in that they allow a firm to exit a partial stake from an investment, guaranteeing returns while still allowing the firm to retain an equity stake in the business to be fully exited at a future time. As the IRR figure takes into account timing, we propose the hypothesis that private equity firms may use partial exits to increase the end-of-fund IRR figures that are reported to LPs. On the other hand, we also hypothesize that partial exit usage will have no impact on fund level MOIC figures. We will examine this hypothesis by constructing a theoretical model, meant to provide causal evidence, that

explores and demonstrates the relationship between partial exits and IRR (and MOIC). We

then investigate whether empirical data reflects the outcome of this model.

Section 6: Regression Specifications

We now specify the regression models corresponding to and used to analyze our first two hypotheses: transactional information asymmetry and liquidity needs.

Section 6.1: Information asymmetry hypothesis

Our general hypothesis regarding transactional information asymmetry is that partial exits will have greater usage in transactions with significant information asymmetry present between buyers and sellers (as proxied by investment duration, asset industry, geographic distance, and investor size). We specify below the regressions utilized in conducting our analysis on each proxy for information asymmetry. The dependent variable used in all of these analyses is an indicator variable for Partial Exits (P_i) which takes the value of 1 if the exit is partial and 0 if the exit is complete (with no prior partial exit). Note that for many of the below regressions, we will also subset our data by exit type and generate additional regression models: we do not list the specific model forms here, but the empirical results are included in our results section and appendix. This is particularly apt for the asset industry and geographic distance variables; this is because our acquirer data is not applicable in IPOs (many acquirers involved). As such, for each of these two regressions, we will conduct a separate analysis analyzing only portfolio company to original investor relations, subset for IPO data specifically (and more broadly, we will subset our data by exit type for each

regression presented).

Regression 1: Investment duration

Our first regression relates partial exits to investment duration length as:

$$P_i = B_0 + B_1 * D + B_2 * ET + B_3 * ED + B_4 * M$$

Here, P_i refers to the partial exit binary dependent variable. D refers to investment duration and is a numerical variable measured in a unit of years: this is our independent variable in this regression. Our controls used are as follows: ET is a categorical variable referring to Exit Type with seven categories: IPOs, Private Placements, Sales to GPs, Sales to Strategics, Sales to Management, Recapitalizations, and Write-offs. ED is a time fixed effect, referring to exit date in terms of days. M refers to our macroeconomic condition variable, measured by change in GDP growth quarter over quarter. This regression is conducted as a logit-binomial regression.

Regression 2: Asset industry

Our logit regression analyzing our asset industry information asymmetry hypothesis is:

$$P_i = B_0 + B_1 * BI + B_2 * B * PA_{ind} + B_3 * (BI * PA_{ind}) + B_4 * D + B_5 * ED + B_6 * ET + B_7 * M$$

In this model, the new specifications that we include are: BI, a categorical variable referring to buyout industry; PA_{ind} which is a categorical variable that ranks the level of overlap in industry speciality between the portfolio company and acquirer. We also include an interaction variable between these two variables to study if the impact of sector specialty is magnified in certain industries.

Regression 3: Geographic distance

Our logit regression analyzing our distance information asymmetry hypothesis is:

$$\text{P}_i = B_0 + B_1 * PA_{dist} + B_2 * IA_{dist} + B_3 * PI_{dist} + B_4 * PA_{dist} * IA_{dist} + B_5 * PA_{dist} *$$

$$PI_{dist} + B_6 * IA_{dist} * PI_{dist} + B_7 * PA_{dist} * IA_{dist} * PI_{dist} + B_8 * D + B_9 * ED + B_{10} * ET$$

In this model, we include our pairwise geographic distance variables: PA_{dist} refers to distance in miles between portfolio company and acquirer; IA_{dist} refers to distance between original investor and acquirer; PI_{dist} refers to the distance between portfolio company and original investor. The remainder of the variables are interactions between these variables and previously defined terms.

Regression 4: Investor size

Our logit regression analyzing our investor size information asymmetry hypothesis is:

$$P_i = B_0 + B_1 * S + B_2 * D + B_3 * D + B_4 * ED + B_5 * ET$$

In this model, the new specification that we include is S, which is a numeric variable measuring the number of investment professionals.

In our results and appendix section, we will discuss the outcomes of the above regressions; we will also include the above regressions subset by each exit type to understand differential impact of each variable.

Section 6.2: Liquidity theory hypothesis

Our general hypothesis here is that private equity firms will make greater use of partial exits in situations that demand greater liquidity. We examine the two effects discussed in

the hypothesis section in this analysis by way of one multivariate regression:

Regression 5: Macroeconomic conditions and end of fund lifespan

$$\text{P}_i = B_0 + B_1 * M + B_2 * C_i + B_3 * M * C_i + B_4 * ED + B_5 * ET + B_6 * BI$$

In this regression, we define C as the end of fund lifespan variable. This is a binary variable that indicates 1 when the exit transaction occurs near the end of the fund's lifespan. In this analysis, we examine the impact of our macroeconomic variable in isolation and its differential impact near the end of a fund's lifespan.

Section 7: Model Development

In this section, we provide the specifications for the functional forms we will use to theoretically model our third hypothesis: GP signaling. First, we consider our grandstanding model, which we examine in both a levered and unlevered scenario. We next discuss our cash-flow timing model, which incorporates empirical data into model distributions.

Section 7.1: Grandstanding models

In our Grandstanding models, we will aim to determine under which conditions a partial exit is preferable to a complete exit in cases of grandstanding. To do so, we will consider an arbitrary investment; for this asset, we will calculate its valuation, measured using a present value calculation with a discount rate to be sensitized, in two scenarios: (1) the case of a complete exit, in which the entire investment is exited after the first year (2) the case of a partial exit, in which some portion of the investment is exited after the first year and the remainder is exited at a later date. We will then compare the valuations used in these two scenarios via an inequality and reduce into a functional form we can sensitize and analyze. We repeat this procedure for two models: first we consider a levered purchase and second an unlevered investment with excess cash generation. In this model development section, we will define our parameters, set up our inequality, and present the resulting simplified functional form for each model; we leave the mathematical reductions for the appendix section. We begin by defining our model parameters:

- M_t: Multiple (of EBITDA) that we value this company at a given time t. At $t = 0$, this represents the entry multiple and $t = T$ represents the exit multiple

- E_t: EBITDA value for the given investment at at time t

- L_0: Entry leverage multiple of EBITDA used by the investor

- f_t: Proportion of leverage that has been paid down by time t

- r: Discount rate for the given investment

- T: Length of investment until completely liquidated

- a: Proportion of investment exited at partial exit

- D: Entry Debt to Enterprise Value ratio (equal to $\frac{L_0}{M_0}$)

- CF_t: Free cash flows (detailed in appendix)

- J: Cash tax rate

Section 7.1.1: Grandstanding model (levered)

The equity purchase price of this asset can be defined as the enterprise value minus the leverage quantity: $M_0 E_0 - L_0 E_0 = (M_0 - L_0) E_0$. We assume that all excess cash generated by the business is used to deleverage the asset, going towards debt repayment. Further, we assume debt is paid off in a straight line fashion, meaning $f_t = \frac{t}{T}$. As such, the exit equity price can be defined as the enterprise value of the asset, or: $M_t E_t$. We now construct our two scenarios, the first being a complete exit at time $t = 1$ and the latter being a partial exit at time $t = 1$. We will introduce further assumptions to our model prior to the reduction step.

Scenario 1: Complete exit at time $t = 1$

The value of our asset at time $t = 1$ is thus, given the assumptions stated previously, just

the exit equity value of the asset, discounted. Thus, the value of the asset in this scenario,

denoted V_1:

$$V_1 = \frac{M_1 E_1 - (1 - f_1) L_0 E_1}{(1 + r)}$$

Scenario 2: Partial exit at time $t = t$

The value of our asset in this scenario can be defined as the value of the equity stake exited

partially at time $t = 1$ coupled with the value of the remaining equity stake upon exit at

$t = T$. We may define this as:

$$V_2 = a \left(\frac{M_1 E_1 - (1 - f_1) L_0 E_1}{(1 + r)} \right) + (1 - a) \left(\frac{M_T E_T}{(1 + r)^T} \right)$$

Scenario comparison and reduction

We thus now compare the two scenarios and examine what factors are necessary in order to

have: $V_2 > V_1$. This can be written as:

$$a \left(\frac{M_1 E_1 - (1 - f_1) L_0 E_1}{(1 + r)} \right) + (1 - a) \left(\frac{M_T E_T}{(1 + r)^T} \right) > \frac{M_1 E_1 - (1 - f_1) L_0 E_1}{(1 + r)}$$

We now introduce the following assumptions: as we take no view on operational improve-

ments or market variance in this model, we assume that the multiple value and EBITDA

generated stays constant for this business over time (i.e. $M_i = M$ and $E_i = E$ $\forall i$). We

leave the steps used in incorporating these assumptions and reducing this inequality for the appendix, and we find that we may rewrite this model inequality as:

$$GL(r, T, D) = \left((1+r)^{T-1}\right)\left(1 - \left(1 - \frac{1}{T}\right)D\right) - 1 < 0$$

Section 7.1.2: Grandstanding model (unlevered)

We now repeat the same analysis, except in this case we assume the asset is bought in all cash upon entry, which means that our equity purchase price is simply: $M_0 * E_0$. This further means that all excess cash generated by the business (unlevered free cash flow) will be allocated towards owners of the asset. As such, we present our two scenarios as:

Scenario 1: Complete exit at time $t = 1$

The value of our asset at time $t = 1$ is thus just the enterprise value of the asset:

$$V_1 = \frac{M_1 E_1}{1 + r}$$

Scenario 2: Partial exit at time $t = 1$

The value of this asset in this scenario can be defined as the value of the equity stake exited partially at time $t = 1$ coupled with the value of the remaining equity stake upon exit at $t = T$. We must also include the cash flows this asset generates over time since we assume no debt on the asset. We may define this as:

$$V_2 = a\left(\frac{M_1 E_1}{1 + r}\right) + (1 - a)\left(\frac{M_T E_T}{(1 + r)^T}\right) + \sum_{t=1}^{T}\frac{CF_t}{(1 + r)^t}$$

Now, we add the following assumption. Our formula for Unlevered Free Cash Flow is:

$EBIT * (1 - J) + D\&A - CAPEX - \Delta NWC$. We assume that our investment is in an asset-lite business coupled with a $\Delta NWC = 0$. Thus, we have that our $CF_t = EBIT_t(1 - J) = EBITDA_t(1 - J) = E_t(1 - J)$. Thus, we can rewrite our valuation for this scenario as:

$$V_2 = a\left(\frac{M_1 E_1}{1 + r}\right) + (1 - a)\left(\frac{M_T E_T}{(1 + r)^T}\right) + \sum_{t=1}^{T} \frac{E_t(1 - J)}{(1 + r)^t}$$

Scenario comparison and reduction

We thus now compare the two scenarios and examine what factors are necessary in order to have: $V_2 > V_1$. This can be written as:

$$a\left(\frac{M_1 E_1}{1 + r}\right) + (1 - a)\left(\frac{M_T E_T}{(1 + r)^T}\right) + \sum_{t=1}^{T} \frac{E_t(1 - J)}{(1 + r)^t} > \frac{M_1 E_1}{1 + r}$$

We again make the same simplifying assumption as in our levered scenario: we assume that the multiple value and EBITDA generated stays constant for this business over time (i.e. $M_i = M$ and $E_i = E$ $\forall i$). Thus, we can reduce our model to its functional form. We leave the steps used in incorporating these assumptions and reducing this inequality for the appendix, and we find that we may rewrite this model inequality as:

$$GU(r, T, J, a, M) = \left(\frac{(1 + r)^T - 1}{(1 + r)^{T-1} - 1}\right)\left(\frac{1 - J}{1 - a}\right)\left(\frac{1}{r}\right)\left(\frac{1}{M}\right) - 1 > 0$$

Section 7.2: Cash flow timing model

We now construct a model to investigate the impact of partial exits on cash flow timing in particular, making use of empirical data regarding when partial exits occur. This model

will be IRR based with the purpose of isolating the impact of the timing of the partial exits in particular. As such, we make the following simplifying assumptions: we assume that there are no changes in leverage levels on the investment and that all cash flows are reinvested into the business (this is as a consequence of lacking specific data on these metrics). We now provide a brief summary of the algorithm used in this model, including key parameters and distributions. The full specifications of this model are provided in the appendix section.

We consider an arbitrary investment with a fixed entry price; we assign a certain probability such that this investment may either follow the path of a partial exit or a complete exit. This probability is indicative of the proportion of fund exits that are partial. In the case of a partial exit, we construct a timeline of the cash flows generated or absorbed by this asset, including the initial equity check on entry, the partial liquidation, and the exit of the remaining stake. The time at which each of these events occurs is sampled based a proxied distribution derived from empirical data of partial exit timing. In the complete exit case, we construct a similar timeline of cash flows, except we only have an initial equity check followed by an exit; the timing of the complete exit is also based on a distribution constructed from empirical data. We then aggregate numerous iterations of this process in order to simulate a fund structure, and we combine these iterative series of cash flow timelines into one large fund level cash flow timeline. We then calculate the IRR and MOIC of this simulated fund; this entire process is repeated numerous times such that we can analyze the impact of the parameters used. We then adjust for the the proportion of partial exits in the fund as well as the stake exited in partial exit cases.

Empirical confirmation

In order to examine whether the theoretical results are reflected in empirical data, we construct the following two regressions. The dependent variable in this case is either IRR and MOIC, and the independent variable of interest is p, which refers to the proportion of partial exits of total exits in a given fund. The data that we use, both in this regression and in constructing the empirical distributions, derives from our *Preqin* dataset.

$$IRR = B_0 + B_1 * p + B_2 * ED + B_3 * BI + B_4 * M$$

$$MOIC = B_0 + B_1 * p + B_2 * ED + B_3 * BI + B_4 * M$$

Section 8: Data

Initial studies into the private equity industry made usage of survey data examining particular funds or collecting information from a limited number of firms. As such, sample size was limited, although granularity was quite high. A set of primary studies also utilized public information which was conversely limited in detail. As the number of exited deals has increased significantly over the past two decades, disclosure regulations and agencies focused on private data collection have similarly grown. As a result, resources such as Preqin and Pitchbook have facilitated the emergence of studies reexamining previous questions in greater detail and the construction of models grounded in empirical data. We follow a similar path in this study, using updated data to reflect the increased frequency of transactions in the prior two decades and using a model to provide causal justification for a core hypothesis.

There were several datasets that were integrated in order to conduct this analysis. The primary dataset of all exit transactions (13,975) was taken from Preqin, a public database that compiles and verifies private transaction data. Per exit, this dataset includes information on entry date, entry type, entry investor(s), exit date, exit type, investor exiting, geography, and industry. We verify the accuracy of this data by computing summary statistics and comparing to published studies as well as through manual validation of a random sample. There is significant precedent for using Preqin data in econometric studies, especially in those studying and modeling cash flow distributions (Larocque, 2019; Ang et al., 2018; Barber and

Yasu, 2017). From Preqin, we also extract fund-level data on geography, vintage date, and returns (IRR and MOIC). The only external data we introduce is GDP delta data as our macroeconomic environment indicator.

There are two primary characteristics we consider with regards to our data. First, there is naturally embedded missing data within our dataset. We expect that there are exits missing in Preqin data; this we cannot account for, but rather we compare frequency metrics with published studies to approximately validate our set of exits (Kaplan and Strombörg, 2008). Preqin also does not have complete firm level data, meaning that certain transactions for which we have investment level data do not necessarily have corresponding fund-level data (for variables such as grandstanding, end of fund lifecycle exits, and fund returns). Given that this missing data is concentrated in two variables, we choose not to run multiple imputation. This is supplemented by our expectation that there is no correlation between certain missing data on certain funds and metrics such as grandstanding. We also rule out issues of multicollinearity by constructing a correlation matrix and finding no significant correlation of note between independent variables. On the other hand, we do find a correlation between time (exit date) and variables of investment length, tech industry, and investments just prior to fund closing. We also find association between time and partial exit frequency per a regression analysis, justifying our use of time as a control. Finally, in our information asymmetry hypothesis, we incorporate data on particular acquirers per transaction; as such, this data is structurally only available for non-IPO acquirers. We account for this by adjusting our regression analysis to subset by exit type.

Section 9: Results and Discussion

We now consider the results generated by our empirical and theoretical analysis and interpret them in the context our proposed hypotheses and surveyed literature. In the following section, we will refer to Tables A1 through C7.

Section 9.1: Transaction-based information asymmetry hypothesis results

We begin with our first information asymmetry hypothesis, walking through each of our proposed proxy variables; overall, we find our results support our central hypothesis that partial exit usage is tied directly to transaction contexts with high information asymmetry, as studied via investment duration, asset industry, geographic distance, and investor size.

Information asymmetry proxy (1): Investment duration

Our hypothesis proposed that our binary partial exit usage dependent variable will be inversely related to investment duration, as increased duration is associated with mitigated information asymmetry. Model 1 in Table A1 presents the relevant regression for this hypothesis; in particular, we see that investment duration is indeed negatively associated with partial exit usage at the highest level of significance. As this is a logit regression, we exponentiate this coefficient to find that an increase in investment duration by one year is associated with a decreased chance of partial exit by 7%. We may also consider the impact of invest-

ment duration in various particular contexts: in Models 2-6 in Table A1, wee subset our data by exit type and run the same regression. We find that in IPOs, GP to GP transactions, and Trade Sales, the statistically significant inverse relation between investment duration and partial exit usage holds true. On the other hand, we find no significant relationship when examining sales to management; given that sales to management have the least amount of information asymmetry between the buyer and seller, the impact of duration may be largely mitigated. Interestingly, we find that duration is also not significant when subsetting our data by complex, intangible-asset industries in Model 6; this may perhaps be due to intrinsic reasons attributed to the industries chosen for this analysis. Thus, based on our results in Models 1-5, we find sufficient evidence to validate our hypothesis for investment duration.

Information asymmetry proxy (2): Buyout industry

With regards to buyout industry, we proposed a hypothesis with two effects: first, we argued that intangible-asset and niche industries with specialty requirements will induce higher information asymmetry and thus increased use of partial exits; second, we claimed that if the seller and portfolio company overlap in sector specialty, then the information asymmetry faced by the buyer would decrease and we would see decreased use of partial exits. Examining our results in Table A2, we list in Model 1 the industries that were found to be significant when running our regression, coupled with our overlap variable and controls. As predicted, niche industries such as Aerospace and Pharmaceuticals were found to be significant as well as intangible-asset industries such as Internet and IT Security. All of these had positive coefficients, indicating that they are related to increased partial exit usage.

On the other hand, we found similarly significant positive coefficients for the Hardware and Utilities industries, which requires further analysis We also find that our overlap variable is significant with a negative coefficient in Model 1, validating our hypothesis regarding its effect. When subsetting our data by IPO vs. GP to GP transactions, as done in Models 2 and 3, we find that it is within GP to GP sales that most of our complex asset information asymmetry is derived from; in the IPO subset, only financial services companies were found to be directly related significantly to partial exits. The overlap variable, not applicable in IPOs, was also found to be significant in GP to GP transactions. Thus, while our hypotheses were largely validated regarding industry, we are left with questions to explore regarding industries such as Utilities and Hardware as well as industry-driven information asymmetry in IPO contexts.

Information asymmetry proxy (3): Geographic distance

We hypothesized that there may be three mechanisms through which information asymmetry may be proxied with regards to geographic distance: increased (1) distance between portfolio company and acquirer (2) distance between portfolio company and seller and (3) distance between seller and buyer. In Model 1 in Table A3, we find that the distance between the portfolio company and the selling investor was found to be significant, directly related with partial exit usage. While this aligns with a portion of our hypothesis, we were surprised that this was the effect that generated a significant result of all three. While we provided justification for all three mechanisms, the most direct path to information asymmetry in the transaction is likely through distance between the buyer and the asset for sale. When

subsetting our data, we find that this significance is replicated only in GP to GP sales, with distance being a non-factor in transactions in which the buyer is a strategic acquirer. We note that the magnitude of our coefficient for our distance variables are small due to the large magnitude of the distances themselves, measured in miles. As such, we find support for one portion of our hypothesis regarding distance.

Information asymmetry proxy (4): Investor size

With regards to investor size, we hypothesized that investor size will be inversely associated with partial exit usage as each additional investor increases marginal capacity to monitor and diligence a current investment. However, per Model 1 in Table A4, we actually find that investor size is directly related to partial exit usage at the highest significance level. Examining our subset data models, we find that this effect is consistently true for GP to GP transactions, Trade Sales, and in our asset subset (as shown in Models 3,4, and 6). We posit how we may better understand this result in the conclusion section of this study.

Section 9.2: Liquidity generation hypothesis results

We now consider the results presented in Table B1, in which we investigate our hypotheses regarding liquidity. In particular, we had proposed two situations of interest: first, we claimed that partial exits would be used more frequently in poor macroeconomic conditions; second, we argued that in strong macroeconomic conditions near the end of a fund's lifecycle, private equity firms would be more likely to use partial exits and during poor conditions, they would tend towards complete exits. Examining Model 1 in Table B1, we see that our macro variable

is negatively related to partial exit usage at the highest level of significance; we also see that the coefficient of our interaction variable exploring macroeconomic conditions near the end of a fund's lifespan is positive, adding validity to our two hypothesized effects regarding liquidity. Note, we also see that in isolation, private equity firms tend to prefer complete exits near the end of a fund's timeline; this was expected based on common practice in the industry. Thus, we have provided justification for our information asymmetry and liquidity generation hypotheses; we revisit these results in our conclusion section, discussing their importance and avenues for further research. We now turn to the third major component of our study: understanding the mechanics by which partial exits may allow GPs to signal investment ability.

Section 9.3: GP quality signaling hypothesis results

We now present the results of our investigation into the ability of partial exits to facilitate signaling of private equity firm quality; we begin by discussing the theoretical results of our grandstanding models followed by an analysis of our empirical cash flow timing model. In the case of grandstanding, our goal is to evaluate in which scenarios a partial exit is preferable to a complete exit, thus mitigating costs associated with signaling and improving GP ability to demonstrate investment talent. In the cash flow timing model, we aim to demonstrate that firms can signal investment ability to LPs by amplifying IRR metrics via early cash flows from partial exit usage.

Grandstanding: Levered scenario

We first reiterate our model and the function we are interested in analyzing. In this model, we are comparing the value of an investment in which it is completely exited at $t = 1$ vs. the value of an investment which is exited partially at $t = 1$, with the remainder being exited at $t = T > 1$. In our previous analysis, we were able to reduce our comparison of when partial exit track value is greater than complete exit track value to the following inequality:

$$GL(r, T, D) = \left((1 + r)^{T-1}\right)\left(1 - \left(1 - \frac{1}{T}\right)D\right) - 1 < 0$$

The focus of our analysis thus becomes determining what factors make the function $GL < 0$, which is equivalent in our original inequality to a partial exit strategy holding more value than a complete exit. We proceed with our analysis as follows: first we examine the various partial first derivatives of GL in order to see how changing various parameters alters our function output. We next consider a three-way sensitivity analysis that allows us to determine under what leverage, timing, and discounting factors $GL < 0$.

Partial derivative analysis

Referencing the partial derivatives of our levered model in our appendix, we find first that $\frac{dGL}{dr} > 0$, which implies that increasing the discount rate decreases the benefit of a partial exit over a complete exit for a given asset. Taking a risk-based interpretation of r, the means that as we increase the riskiness of the asset at hand, purely based on equity cost of capital, the favorability of a partial exit decreases. This makes sense from both a mathematical and financial perspective; mathematically, our partial exit relies on the value

of the asset at some time $t = T > 1$, whereas our complete exit liquidates the entire business at $t = 1$. As such, partial exits have greater exposure to the decreased value of the asset at $t = T$ as the discount factor increases. Similarly, it is advantageous for a firm to exit and guarentee a return on a higher-risk asset early via a complete exit instead of leaving exposure to the asset at some later time, especially under our operative assumption of no EBITDA growth. Thus, we find that our partial exit becomes less preferable to a complete exit as our discount rate increases.

We next find that our function decreases strictly monotonically with D, our fraction of leverage used upon entry: $\frac{dGL}{dD} < 0$. This means that as we increase the amount of debt used to purchase the asset, the more preferable a partial exit becomes to a complete exit. This can explained, given our assumption of straight line debt paydown from $t \in [1, T]$, by the fact that a complete exit at $t = 1$ does not allow for a private equity firm to reap the benefits of deleveraging the asset on amplifying equity value. As a result, use of leverage increases favorability for a partial exit over a complete exit in the case of grandstanding.

We consider now the impact of changing T, the timing of liquidiation of the remaining equity stake in our asset. We find that $\frac{dGL}{dT}$ does not have a consistent sign, indicating that the impact of changing the value of T on GL will depend on the values of parameters (D, r). This finding also makes sense, as T impacts our consideration of partial vs. complete exit in two manners; first, increasing T will decrease the valuation of the partially exited investment, since a portion of the assets value will be recognized later in the future. On the other hand, increasing T will also decrease the valuation of the completely exited investment since it will

decrease the deleveraging of the asset completed by $t = 1$; this will disproportionatly impact the complete exit since a larger equity stake is exited at $t = 1$ relative to the partial exit. These two effects will conflict, resulting in the lack of consistent signage in our derivative.

Thus, in cases of grandstanding, we find that favorability of a partial exit to a complete exit will increase with a decrease of the discount rate and an increase in leverage used in onset. Finally, the impact of when the asset is completely liquidated has a multifacted impact on GL. We have also provided financial justification for each for each of these relative impacts.

Model sensitivity: Debt vs. Discount rate

We now want to examine situations in which partial exits are explicitly favorable to complete exits ($GL < 0$). We do this by examining the sign of GL as we sensitize this function. We create a three-way sensitivity by conducting a two-way sensitivity between debt level (D) and discount rate (r), and repeating this analysis for various levels of T. We will reference Tables C1.1 to C1.4 in this analysis, where each cell within this table represents an output of function GL. We sensitize our debt levels ($D \in [0\%, 100\%]$ in increments of 10%) and discount rate ($r \in [5\%, 20\%]$ in increments of 2.5%).

Examining Table C1.1, at $T = 4$, we see that $GL < 0$ and partial exits are favorable to complete exits at all values of r when leverage levels on entry are greater than 50%. Given that leverage levels up to 75% of the asset value are common in leveraged buyouts, this indicates that partial exits indeed have significant value adding capacity in grandstanding contexts. Evaluating the discount rates, we see that at a discount rate of 5%, a partial exit is favorable for all leverage values greater than 20%. As a result, we find that relatively low-

moderate risk assets with cost of capitals around market average result in partial exits being favorable. Thus, examining our results at $T = 4$, we see that the conditions for leverage and discount rates that favor partial exits in cases of grandstanding are those that match private equity investment profiles. Thus, at this given value of T, we have demonstrated the value-adding capacity of partial exits in grandstanding contexts.

We now consider the impact of altering T; examining Table C1.4, we find that at $T = 7$, there exists a significant decline in partial exit favorability; in particular, we find that at a 50% leverage level, only low-moderate risk assets are found to induce $GL < 0$. Note, however, that we can see the dual-effect impacts of changing T; at 50% leverage and discount rates less than 10%, increasing T from 4 to 7 decreases the favorability of partial exits; however, this same delta in T actually increases the favorability of partial exits in investments that are completely financed with extreme levels of debt greater than 80%; this is in accord with our previous examination of T in the derivative section. As such, private equity firms must take into account leverage levels and asset risk profiles when determining the optimal value of T. We find summarily that in parameters that resemble traditional private equity investment structures (discount rates around 7.5%, market average, and leverage levels greater than 50%), we may claim, given our assumptions, that partial exits are favorable in cases of grandstanding to complete exits; as such, in these cases, partial exits can help mitigate the signaling costs associated with grandstanding.

Grandstanding: Unlevered scenario

We now consider our unlevered grandstanding scenario in which the asset at hand is

purchased in all cash; the assumptions surrounding the grandstanding exit for partial and complete cases are the same as in our levered case. The functional form for the comparative model for this asset is:

$$GU(r, T, J, a, M) = \left(\frac{(1+r)^T - 1}{(1+r)^{T-1} - 1} \right) \left(\frac{1-J}{1-a} \right) \left(\frac{1}{r} \right) \left(\frac{1}{M} \right) - 1 > 0$$

Thus, in our analysis, we will again begin with an impact of each parameter via their respective partial derivatives and follow this with an explicit determination of when $GU > 0$. Note, unlike the previous scenario, we have that partial exits are favorable to complete exits in this model when GU is positive.

Partial derivative analysis

Our first finding that is that, as referenced in the appendix section, $\frac{dGU}{dJ} < 0$; this impact is relatively straightforward to explain. As the cash tax rate increases, then partial exits, which have significantly greater exposure to taxable cash flows until $t = T$, will bear the subsequent valuation burden, and thus decrease in favorability to complete exits. We also see that $\frac{dGU}{dM} < 0$, indicating that as we increase the entry and exit multiple for this asset, partial exits become less favorable; this is because increasing our exit value, again under the assumption of no EBITDA growth over time, allows the complete exit case to further accrue the early exit timing benefit at a fixed discount rate.

We now turn to our result that $\frac{dGU}{da} > 0$, indicating that as we increase the equity stake exited at $t = 1$ early in the partial exit case, the more we prefer partial exits to complete

exits. Financially, this makes sense as we are reducing the portion of the investment which has its valuation hampered by future discounting. Interestingly, we found in the previous section that $\frac{dGL}{da} = 0$, indicating that in the levered case, changing the stake exited partially is not deterministic in whether a partial exit is preferable, as in the unlevered case (note that this is distinct from the stake exited influencing the degree to which a partial exit is preferable, as a will clearly influence this factor).

In this scenario, unlike in the levered case, we can demonstrate that $\frac{dGU}{dT} < 0$ strictly, indicating that as our time value increases, the preferability of a partial exit decreases. This makes logical sense, as we have eliminated the relative deleveraging positive effect discussed in the prior section of increasing T. Further, we computationally demonstrate that $\frac{dGU}{dr} < 0$, indicating that as we increase our discount rate, partial exits become less favorable to complete exits in cases of grandstanding; the reasoning behind this result is equivalent to the one proposed in the levered grandstanding section.

Model sensitivity: Percentage stake partially exited vs. Discount rate

In Tables C2.1 to C2.4, we sensitize the proportion of our investment that is exited partially (a) vs. our discount rate (r); across these tables, we increase our valuation multiple from 5x to 14x in increments of 3x. We assume a constant time of liquidation of 6 years and a tax rate of 23%. Within each cell we calculate our function GU and highlight when it is greater than 0, indicating that a partial exit is preferable.

Examining Table C2.1, we find that at an entry and exit multiple of 5x, with a cash tax rate of 23%, partial exits are favorable to complete exits in all scenarios, regardless

of sensitivity to stake exited or discount rate; as the stake exited early increases, we find a dramatic increase in favorability. In particular, examining Tables C2.1 through C2.4, we see that at $a \geq 60\%$, we find that partial exits are always favorable to complete exits in grandstanding contexts, regardless of discount rate, even as increasing the valuation of the asset reduces the impact of the partial exit. Evaluating these results in the context of grandstanding, we consider that in order to realize a signaling benefit, firms must exit a substantial stake of the asset early ($> 50\%$). As such, our results corroborate that in such instances, in unlevered scenarios, partial exits will largely be favorable from a valuation perspective, thus further mitigating signaling costs associated with grandstanding. We note that increasing the percentage equity stake in the levered case will have a similar impact (can be trivially shown by considering the derivative of $\frac{dV_2}{da} > 0$ in the levered model). In the levered case, however, increasing the equity stake exited only serves to amplify the sign of the inequality resulting from parameters (D, r, T).

Thus, our results, operating under our stated assumptions, demonstrate that in both the levered and unlevered cases, under conditions in which private equity firms traditionally operate (moderate to high leverage levels, low to moderate costs of capital, and investment lengths of three to six years), private equity firms can mitigate the signaling costs associated with grandstanding by way of partial exits. We note, however, that this is not a blanket statement as has been previously claimed: there are distinct, and demonstrated, conditions in which a complete exit is favorable to a partial exit in a grandstanding context. This validates our hypothesis that casually, partial exits can be shown to facilitate GP investment ability

signaling by reducing costs associated with grandstanding.

Empirical cash flow timing model

Our goal in this model is to demonstrate that firms can signal GP investment ability by amplifying IRR metrics via. early cash flows from partial exit usage; given that this impact is predicted to be the result of timing in particular, we expect no distinction in MOIC metrics as we adjust fund level partial exits. The parameters and distributions used in this analysis were described in the model development section and in the appendix. The primary drivers of the IRR measured in this model are the timing of cash flows and the value of the investment exited partially. Our output for this model is a relationship between proportion of fund exits as partial exits (from 0 to 100%) and the calculated IRR of the fund. We also present a similar set of results for the proportion of fund exits as partial exits vs. MOIC (Figures C1-C5).

In Figure C1, we can see the distributions of time to complete exit from entry, time to partial exit from entry, and time between partial exit and complete exit. We already showed earlier that the time to partial exit is significantly lower than time to complete exit from entry; this is similarly visible in the graph referenced. As such, we expect that this distinction in timing will drive increases in IRR, as this metric is time sensitive. However, we must account for the value of the investment exited partially, on which we do not have data. To account for this, we sensitize each of our outputs at a distinct level of partial value exited; from this, we answer whether proportion of partial exits is driving IRR causally.

Considering the chart of graphs presented in Figure C2; we first note that the IRR values

graphed on the y-axes are irrelevant to this analysis as they are dependent purely on scale parameters. The focus on these graphs is whether the slope of partial exit proportion and fund IRR is positive (as predicted in our hypothesis). We find that when the value exited at partial exit is between 0% to 45%, the relationship between partial exit proportion and fund IRR is negative. On the other hand, it is clear that for partial exit values greater than 50%, there exists a positive relationship between partial exit proportion and fund IRR. We confirm this by examining the slope of each graph vs. partial value exited percentage, and we find a statistically significant ($p < 0.001$) positive relationship. This is presented in Figure C3.

With regards to our IRR results, we present the following explanation; for a given investment with a partial exit, there is a time period until partial exit, followed by a time period until complete exit. Given that the mean time until partial exit from entry is 4.16 years, the mean time from partial exit to complete exit is 2.50 years, and the mean time from entry to a complete exit (with no partial) is 5.08 years, it follows that oftentimes partial exits will generate cash early but potentially receive their final bullet exit payment later than a complete exit track investment. This additional nuance, irrelevant in our grandstanding models, adds significant nuance here: as such, the value exited at partial exit must be large enough to compensate for the potentially delayed bullet payment. From our results, it is clear that this payoff is achieved at significant stake reductions at partial exits (greater than 50%). On the other hand, for MOIC, timing has no influence on calculating returns and the model results confirm the consequential lack of impact of partial exits. Our analysis here

thus has demonstrated that partial exits, by way of timing, are a powerful tool for private equity firms to boost IRR values, taking into account the value exited in that partial exit. On the other hand, our model also demonstrates the relative irrelevance partial exits have on MOIC. We now consider the empirical results to examine how actual private equity conduct reflects this analysis.

Empirical regression results: IRR and MOIC vs. Partial exit usage

We now run a univariate regression, as shown in Table C6, using the standard fixed effects for time and sector to test whether (1) proportion of partial exits for a fund is significantly associated with IRR and (2) proportion of partial exits for a fund is not significantly associated with MOIC value. Our first regression in Table C6 indicates that the proportion of partial exits in a fund is significantly associated ($p < 0.05$) with IRR; the coefficient is 14.082 (in percentage), meaning that as the proportion of partial exits for a fund increases by 10%, the impact on IRR is 1.4%. On the other hand, regressing proportion of partial exits on MOIC shows no significant association, exemplifying the results of our theoretical model.

We now consider the implications of these results. We note there are likely numerous variables that may explain IRR that are excluded in this regression. We allow this because this model is not meant to be predictive or to measure effect size, but rather intended to establish a correlation that may be explained by the results of our theoretical model. Given that our theoretical model establishes a basis for partial exits driving IRR, via percentage equity stake invested, we are able to add causal support to our hypothesis that cash flow

timing and increasing IRR metrics is a core driver of partial exits. This is further bolstered by the fact that our empirical results demonstrate that the MOIC is not associated with partial exit proportion, indicating that the pathway by which partial exits impact returns is via cash flow timing in particular. Thus, we claim that partial exits, in conditions of significant early exit stakes, can be used to amplify IRR metrics in helping GPs signal the quality of their investment performance capacity.

Section 10: Conclusion

This study aims to examine partial exits in the context of the inherent information asymmetries intrinsic to the private equity industry. In particular, we present three hypotheses, examining partial exit's capacity to decrease transaction associated information asymmetry, generate liquidity, and amplify ability to signal performance. Here, we walk through our key findings and discuss their broader implications.

We begin with the transaction-based information asymmetry hypothesis. We had originally proposed four proxies for information asymmetry that exists between buyers and sellers in private equity transactions: investment duration, asset industry (individual industry and industry overlap with buyer), geographic distance (pairwise between all parties in transaction), and investor size; these proxies all derive from previous studies regarding asymmetry problems in the context of venture capital, lending, and IPO transactions. Our results indicated that the relationship between partial exit usage and investment duration, specific industries, industry overlap, and distance between asset and seller all aligned with and validated our proposed hypotheses; as such, we claim that partial exits may serve as an effective quality signal in transaction contexts with high information asymmetry in the private equity industry.

This result extends the current understanding of partial exits by considering three avenues by which information asymmetry can be induced in a transaction. Rather than focusing just

on asset-based information asymmetry, we account for investment and geographic profiles of both the seller and the buyer, allowing for a more nuanced perspective on where informational imbalances lie. This analysis is facilitated by our access to *Preqin's* substantial database of private equity transactions, including partial exit status. As a result, we are able to introduce the result that partial exits may be used to reduce information asymmetry inherent in private equity transactions.

We next examined partial exit usage by private equity firms in various macroeconomic conditions and at the end of a given fund's lifespan. The motivation behind this analysis was to understand the potential of partial exits to generate liquidity for GPs in contexts in which availability to capital is limited (poor macroeconomic conditions associated with expensive leverage) or liquidity is structurally demanded (end of a fund's lifespan). In the former, we find that GPs tend to utilize partial exits with greater frequency in poor macroeconomic conditions marked with low quarter-over-quarter GDP growth. We further find that at the end of a fund's lifespan, in strong macroeconomic conditions, firms tend to prefer partial exits. We explain this interesting latter phenomenon with loss-aversion theory. GPs with low risk-threshholds avoid further losses by exiting completely in poor macroeconomic conditions while drawing down some equity when conditions suggest a frothy valuation market. These results speak to and are supported by the behavior of private equity firms and reveal the multifaceted utility of partial exits.

Our final hypothesis is centered around the necessity for GPs to signal performance quality to LPs in order to improve future fundraising prospects. This particular hypothesis

is acutely interesting, as it allows us to take advantage of the mathematical structure of partial exits in order to model how partial exits may assist GPs in signaling investment capability. We first study grandstanding and demonstrate mathematically that, under our stated assumptions, private equity firms operating under standard risk and leverage profiles, as discussed in our results section, can significantly mitigate signaling costs associated with exiting an investment early to signal quality. We also show, however, that partial exits are not uniformly preferable, and in certain leverage, risk, and timing contexts, complete exits may still be preferable. As such, this study provides insight into strategies that may allow private equity to reduce the costs associated with grandstanding. Since grandstanding is a core mechanism by which young private equity firms signal investment capability to LP's, we treat our result as validation of our hypothesis. Our cash flow timing hypothesis, on the other hand, shows on a more straightforward basis that partial exits may be used to amplify time-weighted return metrics also used by GPs to signal performance quality. This result is both theoretically and empirically supported.

As such, our latter hypothesis completes our discussion of partial exits in an information asymmetry context. While we aim for this study to initialize the discussion of partial exits as a strategy in the private equity buyout context, there are significant avenues for expanded analysis. As *Preqin* and *Pitchbook* increase data access, both our transaction-based proxies of information asymmetry as well as our signaling modeling can be improved and enhanced. We thus look forward to continued formalization of partial exit theory across investment stages and vehicles.

Figure A1:
Partial exit frequency data in private equity transactions
This graphic highlights the frequency distribution of partial exits since 2000 both in terms of absolute quantity and proportion of overall exits to control for increased private equity action over time. In the table below, partial exit data is segmented approximately by macroeconomic condition. Exit data is taken from *Preqin* and verified with published *Preqin* reports.
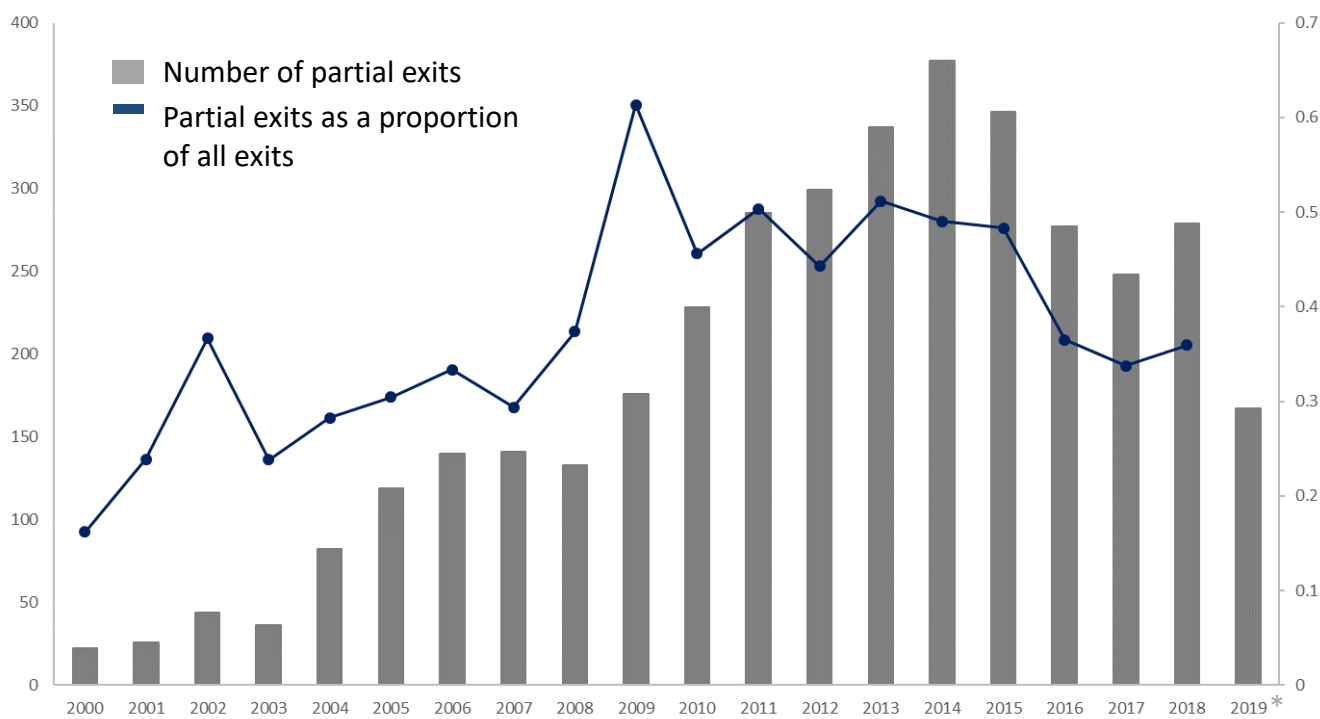
Timing	2000-2003	2004-2007	2008-2011	2012-2015	2016-2019
Partial exit count	128	482	822	1,359	971
Partial exit proportion	25%	30%	48%	48%	36%

*Note that 2019 data is complete only through Q3 and is not reflective of a full year

Table A1

Information asymmetry variable #1: Investment Duration vs. Partial Exits

This table highlights the impact of the duration of a given private equity investment on frequency of partial exit usage by private equity firms. This is a binomial-logit regression with a binary dependent variable, partial exit usage (1 for partial exit, 0 for complete exit with no prior partial exit). The investment duration variable is measured in years; exit date is a categorical control variable; Macro measures macroeconomic conditions as the quarter-over-quarter change in GDP growth at the time of transaction. Model (1) does not subset the data and controls for exit type. Models (2)-(5) subset the data by exit type and display the impact of investment duration in each subcase. Model (6) subsets the data for complex, niche, or intangible-assets.

Model	1	2	3	4	5	6
Panel	General	IPO	GP to GP	Trade Sale	Sale to Mgmt.	Asset
Dependent Variable	log(Partial)	log(Partial)	log(Partial)	log(Partial)	log(Partial)	log(Partial)
Regressors						
Constant	-148.30***	-263.74***	-169.42***	-132.41***	-100.48	-147.47***
	(1.18)	(32.59)	(29.63)	(21.31)	(117.23)	(28.32)
Investment duration	-0.07***	-0.10*	-0.19***	-0.05**	-0.16	-0.04
	(0.01)	(0.05)	(0.03)	(0.02)	(0.12)	(0.03)
Exit Date	0.08***	0.13***	0.08***	0.07***	0.05	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.06)	(0.01)
Exit Type: IPO	-0.33					0.12
	(0.19)					(0.50)
Exit Type: GP to GP Sale	-3.83***					-3.80***
	(0.17)					(0.45)
Exit Type: Trade Sale	-3.73***					-3.48***
	(0.16)					(0.43)
Exit Type: Sale to Mgmt.	-3.46***					-3.47***
	(0.36)					(0.89)
Macro	-0.20***	-0.03	-0.06	-0.40***	-0.58	-0.31*
	(0.05)	(0.24)	(0.13)	(0.09)	(0.59)	(0.12)

P-value significance: *p<0.05; **p<0.01; ***p<0.001. We report the coefficient first and the standard error in parentheses underneath. All data is drawn from *Preqin.*

Table A2
Information asymmetry variable #2: Buyout Industry vs. Partial Exits
This table highlights the impact of (i) the sector of a given private equity investment and (ii) overlap in sector specialty between portfolio company and acquirer on frequency of partial exit usage by private equity firms. This is a binomial-logit regression with a binary dependent variable, partial exit usage (1 for partial exit, 0 for complete exit with no prior partial exit). Model (1) does not subset the data and controls for exit type. Industry variables are binary indicators of portfolio company industry and the Industry Overlap variable indicates the extent to which the portfolio company and acquirer have sector specialties in common. Investment duration is measured in years and exit date is a categorical control. Models (2) and (3) subset the data by the two primary exit vehicles: IPOs and sales to GPs. We only show industries that were found to be significant in the below table; any industry not shown was not significant. The interactions between the overlap variable and each industry are not shown, as none were found to be significant. Other control variables utilized in the regression, such as exit type, are also not included in this table. Note that in Model (2) we do not include the industry overlap variable since there is not a defined, sole acquirer in an IPO transaction.

Model	1	2	3
Panel	General	IPO	GP to GP
Dependent Variable	log(Partial)	log(Partial)	log(Partial)
Regressors			
Constant	-185.50***	-273.70***	-206.60***
	(43.28)	(42.10)	(50.34)
Industry: Aerospace	3.61*	16.78	4.04*
	(1.75)	(1378.00)	(1.99)
Industry: Financial Services	-16.28	2.01*	-16.05
	(2368.00)	(1.00)	(10750.00)
Industry: Hardware	4.1*		5.98**
	(2.07)		(2.22)
Industry: Internet	4.35*	2.17	4.85*
	1.79	(1.43)	(2.01)
Industry: IT Security	5.60*		6.22**
	(2.16)		(2.33)
Industry: Pharmaceuticals	4.40*	1.07	5.81**
	(1.79)	(1.30)	(2.01)
Industry: Utilities	3.11*	0.76	4.07**
	(1.22)	(1.44)	(1.48)
Industry Overlap: portfolio company and acquiror	-3.01*		-2.86*
	(1.51)		(1.53)
Investment Duration	-0.19***	-0.12*	-0.21***
	(0.042)	(0.00)	(0.05)
Exit Date	0.092	0.14	0.10***
	(0.022)	(0.02)	(0.03)
Other variables:	All other industries, interaction between industries and overlap variable, Macro, Exit type control variable		

P-value significance: *p<0.05; **p<0.01; ***p<0.001. We report the coefficient first and the standard error in parentheses underneath. All data is drawn from *Preqin*.

Table A3

Information asymmetry variable #3: Geographic Distance vs. Partial Exits

This table highlights the impact of (i) the geographic distance between portfolio company and acquirer (ii) the geographic distance between portfolio company and seller and (iii) the geographic distance between seller and acquirer on frequency of partial exit usage by private equity firms (distances are measured in miles). This is a binomial-logit regression with a binary dependent variable, partial exit usage (1 for partial exit, 0 for complete exit with no prior partial exit). Investment duration and exit date are utilized as defined in the prior regressions. Model (1) does not subset the data and controls for exit type. Models (2)-(5) subset the data by exit type and display the impact of geographic distance in each subcase. Model (6) subsets the data for complex, niche, or intangible-assets. We do not show the pairwise interactions between distance variables and the exit type control in this table. Model (2) in particular does not include any regressors involving the distances including acquirers since a single acquirer cannot be identified in an IPO.

Model	1	2	3	4	5	6
Panel	General	IPO	GP to GP	Trade Sale	Sale to Mgmt.	Asset
Dependent Variable	log(Partial)	log(Partial)	log(Partial)	log(Partial)	log(Partial)	log(Partial)
Regressors						
Constant	-188.20***	-250.20***	-198.10***	-190.10	-82.38	-240.80
	(39.07)	(34.64)	(44.49)	(112.6)	(145.5)	(106.30)
Distance between Portfolio Company and Acquiror	-0.00		0.0001	-0.0003		-0.0001
	(0.00)		(0.00)	(0.00)		(0.00)
Distance between Portfolio Company and Seller	0.0003*	0.0004	0.0003*	0.0001	0.0003	0.0009
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Distance between Seller and Acquiror	-0.00		0.00	0.0001		0.00
	(0.00)		(0.00)	(0.00)		(0.00)
Investment Duration	-0.18***	-0.08	-0.23***	0.08	-0.20	-0.05
	(0.04)	(0.05)	(0.04)	(0.09)	(0.17)	(0.09)
Exit Date	0.09***	0.13***	0.10***	0.09***	0.04	0.10*
	(0.02)	(0.02)	(0.02)	(0.06)	(0.07)	(0.09)

Other variables: All interactions between distance variables, Exit type control variable

P-value significance: *p<0.05; **p<0.01; ***p<0.001. We report the coefficient first and the standard error in parentheses underneath. All data is drawn from *Preqin.* The small coefficients on the distance variables can be explained by the large magnitude of the distance independent variables (miles).

Table A4
Information asymmetry variable #4: Investor Size vs. Partial Exits
This table highlights the impact of original investor (seller) size on frequency of partial exit usage by private equity firms. This is a binomial-logit regression with a binary dependent variable, partial exit usage. Investor size is a numeric variable measuring investment team headcount. All other variables used are as defined in Tables A1 and A2. Model (1) does not subset the data and controls for exit type. Models (2)-(5) subset the data by exit type and display the impact of investor size in each subcase. Model (6) subsets the data for complex, niche, or intangible-assets. We do not show the numerous regression data for each buyout sector and exit type for these control variables.

Model	1	2	3	4	5	6
Panel	General	IPO	GP to GP	Trade Sale	Sale to Mgmt.	Asset
Dependent Variable	log(Partial)	log(Partial)	log(Partial)	log(Partial)	log(Partial)	log(Partial)
Regressors						
Constant	-145.3***	-260.90***	-173.33***	-157.00***	-90.27	-90.44***
	(13.43)	(34.57)	(35.62)	(24.60)	(147.24)	(24.38)
Investor Size	0.002***	0.001	0.003***	0.002***	0.002	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Investment Duration	0.07***	-0.08	-0.21***	-0.04***	-021	-0.08**
	(0.01)	(0.05)	(0.04)	(0.02)	(0.174)	(0.03)
Exit Date	0.07***	0.13***	0.09***	-0.08***	0.04	0.05***
	(0.00)	(0.02)	(0.02)	(0.01)	(0.07)	(0.01)

Other variables:	Buyout industries, Exit type control variable

P-value significance: *$p<0.05$; **$p<0.01$; ***$p<0.001$. We report the coefficient first and the standard error in parentheses underneath. All data is drawn from *Preqin*.

Table B1

Liquidity generation hypothesis variables #1 and #2: Macroeconomic conditions vs. Partial Exits

This table highlights the impact of (i) macroeconomic conditions solely and (ii) macroeconomic conditions near the end of a fund's lifespan on frequency of partial exit usage by private equity firms. This is a binomial-logit regression with a binary dependent variable, partial exit usage (1 for partial exit, 0 for complete exit with no prior partial exit). The Macro variable reflects macroeconomic conditions as is formulated as the quarter-over-quarter change in GDP growth. The End of Fund Binary variable indicates 1 if the investment is exited within a year of fund close. All other variables used are as defined in Tables A1 and A2. Model (1) does not subset the data and controls for exit type. Models (2)-(4) subset the data by exit type and display the impact of investor size in each subcase. Model (5) subsets the data for complex, niche, or intangible-assets. We do not show the regression data for each buyout sector as a control variable.

Model	1	2	3	4	5
Panel	General	IPO	GP to GP	Trade Sale	Asset
Dependent Variable	log(Partial)	log(Partial)	log(Partial)	log(Partial)	log(Partial)
Regressors					
Constant	-150.50***	-346.03***	-221.80***	-105.81**	-82.01*
	(20.08)	(70.69)	(52.20)	(33.68)	(35.43)
Macro	-0.47**	-0.28	-0.21	-0.97**	-0.25
	(0.15)	(0.91)	(0.43)	(0.36)	(0.32)
Binary variable indicating exit occurred within a year of fund close (End of Fund Binary)	-0.80***	-0.73	-0.89	-0.68	-0.00
	(0.19)	(1.49)	(0.57)	(0.39)	(0.39)
Macro * End of Fund Binary	0.32*	0.38	0.32	0.58	0.03
	(0.17)	(1.02)	(0.49)	(0.38)	(0.35)
Exit Date	0.08***	0.17***	0.11***	0.05**	0.04*
	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)
Other variables:	Buyout industries				

P-value significance: *p<0.05; **p<0.01; ***p<0.001. We report the coefficient first and the standard error in parentheses underneath. All data is drawn from *Preqin.*

Table C1.1
Grandstanding levered model sensitivity table: Debt to Enterprise Value vs. Discount Rate
Assumptions: **Time until liquidation = 4 years**
We run this sensitivity analysis on the symbolic variables (D: Debt as a percentage of enterprise value; r: Discount rate). This sensitivity is done under the following assumptions: time until liquidation of 4 years. The value that is output in the sensitivity table is our model $GL(r,T,D)$ as defined in Section 7.1.1. Per our model, we highlight in green output results when $GL(r,T,D) < 0$.

	Debt as a percentage of enterprise value (%)										
Discount rate (%)	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
5.00%	0.16	0.07	-0.02	-0.10	-0.19	-0.28	-0.36	-0.45	-0.54	-0.62	-0.71
7.50%	0.24	0.15	0.06	-0.04	-0.13	-0.22	-0.32	-0.41	-0.50	-0.60	-0.69
10.00%	0.33	0.23	0.13	0.03	-0.07	-0.17	-0.27	-0.37	-0.47	-0.57	-0.67
12.50%	0.42	0.32	0.21	0.10	0.00	-0.11	-0.22	-0.32	-0.43	-0.54	-0.64
15.00%	0.52	0.41	0.29	0.18	0.06	-0.05	-0.16	-0.28	-0.39	-0.51	-0.62
17.50%	0.62	0.50	0.38	0.26	0.14	0.01	-0.11	-0.23	-0.35	-0.47	-0.59
20.00%	0.73	0.60	0.47	0.34	0.21	0.08	-0.05	-0.18	-0.31	-0.44	-0.57

Table C1.2
Grandstanding levered model sensitivity table: Debt to Enterprise Value vs. Discount Rate
Assumptions: **Time until liquidation = 5 years**
We run this sensitivity analysis on the symbolic variables (D: Debt as a percentage of enterprise value; r: Discount rate). This sensitivity is done under the following assumptions: time until liquidation of 5 years. The value that is output in the sensitivity table is our model $GL(r,T,D)$ as defined in Section 7.1.1. Per our model, we highlight in green output results when $GL(r,T,D) < 0$.

	Debt as a percentage of enterprise value (%)										
Discount rate (%)	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
5.00%	0.22	0.12	0.02	-0.08	-0.17	-0.27	-0.37	-0.47	-0.56	-0.66	-0.76
7.50%	0.34	0.23	0.12	0.01	-0.09	-0.20	-0.31	-0.41	-0.52	-0.63	-0.73
10.00%	0.46	0.35	0.23	0.11	0.00	-0.12	-0.24	-0.36	-0.47	-0.59	-0.71
12.50%	0.60	0.47	0.35	0.22	0.09	-0.04	-0.17	-0.30	-0.42	-0.55	-0.68
15.00%	0.75	0.61	0.47	0.33	0.19	0.05	-0.09	-0.23	-0.37	-0.51	-0.65
17.50%	0.91	0.75	0.60	0.45	0.30	0.14	-0.01	-0.16	-0.31	-0.47	-0.62
20.00%	1.07	0.91	0.74	0.58	0.41	0.24	0.08	-0.09	-0.25	-0.42	-0.59

Table C1.3
Grandstanding levered model sensitivity table: Debt to Enterprise Value vs. Discount Rate
Assumptions: **Time until liquidation = 6 years**
We run this sensitivity analysis on the symbolic variables (D: Debt as a percentage of enterprise value; r: Discount rate). This sensitivity is done under the following assumptions: time until liquidation of 6 years. The value that is output in the sensitivity table is our model $GL(r,T,D)$ as defined in Section 7.1.1. Per our model, we highlight in green output results when $GL(r,T,D) < 0$.

Discount rate (%)	Debt as a percentage of enterprise value (%)										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
5.00%	0.28	0.17	0.06	-0.04	-0.15	-0.26	-0.36	-0.47	-0.57	-0.68	-0.79
7.50%	0.44	0.32	0.20	0.08	-0.04	-0.16	-0.28	-0.40	-0.52	-0.64	-0.76
10.00%	0.61	0.48	0.34	0.21	0.07	-0.06	-0.19	-0.33	-0.46	-0.60	-0.73
12.50%	0.80	0.65	0.50	0.35	0.20	0.05	-0.10	-0.25	-0.40	-0.55	-0.70
15.00%	1.01	0.84	0.68	0.51	0.34	0.17	0.01	-0.16	-0.33	-0.50	-0.66
17.50%	1.24	1.05	0.87	0.68	0.49	0.31	0.12	-0.07	-0.25	-0.44	-0.63
20.00%	1.49	1.28	1.07	0.87	0.66	0.45	0.24	0.04	-0.17	-0.38	-0.59

Table C1.4
Grandstanding levered model sensitivity table: Debt to Enterprise Value vs. Discount Rate
Assumptions: **Time until liquidation = 7 years**
We run this sensitivity analysis on the symbolic variables (D: Debt as a percentage of enterprise value; r: Discount rate). This sensitivity is done under the following assumptions: time until liquidation of 7 years. The value that is output in the sensitivity table is our model $GL(r,T,D)$ as defined in Section 7.1.1. Per our model, we highlight in green output results when $GL(r,T,D) < 0$.

Discount rate (%)	Debt as a percentage of enterprise value (%)										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
5.00%	0.34	0.23	0.11	0.00	-0.12	-0.23	-0.35	-0.46	-0.58	-0.69	-0.81
7.50%	0.54	0.41	0.28	0.15	0.01	-0.12	-0.25	-0.38	-0.51	-0.65	-0.78
10.00%	0.77	0.62	0.47	0.32	0.16	0.01	-0.14	-0.29	-0.44	-0.60	-0.75
12.50%	1.03	0.85	0.68	0.51	0.33	0.16	-0.02	-0.19	-0.36	-0.54	-0.71
15.00%	1.31	1.11	0.92	0.72	0.52	0.32	0.12	-0.07	-0.27	-0.47	-0.67
17.50%	1.63	1.41	1.18	0.95	0.73	0.50	0.28	0.05	-0.17	-0.40	-0.62
20.00%	1.99	1.73	1.47	1.22	0.96	0.71	0.45	0.19	-0.06	-0.32	-0.57

Table C2.1

Grandstanding unlevered model sensitivity table: Proportion of Investment Exited Early vs. Discount Rate

Assumptions: **Multiple of EBITDA value: 5x, time until liquidation = 6 years, tax rate = 23%**

We run this sensitivity analysis on the symbolic variables (a: Proportion of investment exited early; r: Discount rate). This sensitivity is done under the following assumptions: multiple of EBITDA value of 5x, time until liquidation of 6 years, and a tax rate of 23%. The value that is output in the sensitivity table is our model GU(M,r,T,D, J) as defined in Section 7.1.2. Per our model, we highlight in green output results when GU(M,r,T,D, J) > 0.

| Discount rate (%) | Proportion of investment exited partially early | | | | | | | | | |
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
2.50%	6.49	7.32	8.36	9.69	11.48	13.97	17.71	23.95	36.43	73.86
5.00%	2.79	3.21	3.74	4.42	5.32	6.58	8.48	11.64	17.96	36.91
7.50%	1.56	1.85	2.20	2.66	3.27	4.12	5.40	7.54	11.80	24.61
10.00%	0.95	1.16	1.43	1.78	2.24	2.89	3.87	5.49	8.73	18.46
12.50%	0.58	0.75	0.97	1.25	1.63	2.16	2.95	4.26	6.89	14.78
15.00%	0.33	0.48	0.67	0.90	1.22	1.67	2.33	3.44	5.66	12.33
17.50%	0.16	0.29	0.45	0.65	0.93	1.32	1.90	2.86	4.79	10.58

Table C2.2

Grandstanding unlevered model sensitivity table: Proportion of Investment Exited Early vs. Discount Rate

Assumptions: **Multiple of EBITDA value: 8x, time until liquidation = 6 years, tax rate = 23%**

We run this sensitivity analysis on the symbolic variables (a: Proportion of investment exited early; r: Discount rate). This sensitivity is done under the following assumptions: multiple of EBITDA value of 8x, time until liquidation of 6 years, and a tax rate of 23%. The value that is output in the sensitivity table is our model GU(M,r,T,D, J) as defined in Section 7.1.2. Per our model, we highlight in green output results when GU(M,r,T,D, J) > 0.

| Discount rate (%) | Proportion of investment exited partially early | | | | | | | | | |
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
2.50%	3.68	4.20	4.85	5.68	6.80	8.36	10.70	14.60	22.39	45.79
5.00%	1.37	1.63	1.96	2.39	2.95	3.74	4.92	6.90	10.85	22.70
7.50%	0.60	0.78	1.00	1.29	1.67	2.20	3.00	4.34	7.00	15.01
10.00%	0.22	0.35	0.52	0.74	1.03	1.43	2.04	3.05	5.08	11.16
12.50%	-0.01	0.10	0.23	0.41	0.64	0.97	1.47	2.29	3.93	8.86
15.00%	-0.17	-0.07	0.04	0.19	0.39	0.67	1.08	1.78	3.17	7.33
17.50%	-0.28	-0.20	-0.10	0.03	0.21	0.45	0.81	1.41	2.62	6.24

Table C2.3

Grandstanding unlevered model sensitivity table: Proportion of Investment Exited Early vs. Discount Rate

Assumptions: **Multiple of EBITDA value: 11x, time until liquidation = 6 years, tax rate = 23%**

We run this sensitivity analysis on the symbolic variables (a: Proportion of investment exited early; r: Discount rate). This sensitivity is done under the following assumptions: multiple of EBITDA value of 11x, time until liquidation of 6 years, and a tax rate of 23%. The value that is output in the sensitivity table is our model GU(M,r,T,D, J) as defined in Section 7.1.2. Per our model, we highlight in green output results when GU(M,r,T,D, J) > 0.

	Proportion of investment exited partially early									
Discount rate (%)	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
2.50%	2.40	2.78	3.25	3.86	4.67	5.81	7.51	10.34	16.01	33.03
5.00%	0.72	0.91	1.15	1.46	1.87	2.45	3.31	4.74	7.62	16.23
7.50%	0.16	0.29	0.46	0.66	0.94	1.33	1.91	2.88	4.82	10.64
10.00%	-0.12	-0.02	0.11	0.26	0.47	0.77	1.21	1.95	3.42	7.85
12.50%	-0.28	-0.20	-0.10	0.02	0.20	0.43	0.79	1.39	2.59	6.17
15.00%	-0.39	-0.33	-0.24	-0.13	0.01	0.21	0.51	1.02	2.03	5.06
17.50%	-0.47	-0.42	-0.34	-0.25	-0.12	0.05	0.32	0.75	1.63	4.26

Table C2.4

Grandstanding unlevered model sensitivity table: Proportion of Investment Exited Early vs. Discount Rate

Assumptions: **Multiple of EBITDA value: 14x, time until liquidation = 6 years, tax rate = 23%**

We run this sensitivity analysis on the symbolic variables (a: Proportion of investment exited early; r: Discount rate). This sensitivity is done under the following assumptions: multiple of EBITDA value of 14x, time until liquidation of 6 years, and a tax rate of 23%. The value that is output in the sensitivity table is our model GU(M,r,T,D, J) as defined in Section 7.1.2. Per our model, we highlight in green output results when GU(M,r,T,D, J) > 0.

	Proportion of investment exited partially early									
Discount rate (%)	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%
2.50%	1.67	1.97	2.34	2.82	3.46	4.35	5.68	7.91	12.37	25.74
5.00%	0.35	0.50	0.69	0.93	1.26	1.71	2.39	3.51	5.77	12.54
7.50%	-0.09	0.02	0.14	0.31	0.52	0.83	1.29	2.05	3.57	8.15
10.00%	-0.30	-0.23	-0.13	-0.01	0.16	0.39	0.74	1.32	2.48	5.95
12.50%	-0.44	-0.37	-0.30	-0.19	-0.06	0.13	0.41	0.88	1.82	4.64
15.00%	-0.52	-0.47	-0.40	-0.32	-0.21	-0.05	0.19	0.59	1.38	3.76
17.50%	-0.59	-0.54	-0.48	-0.41	-0.31	-0.17	0.03	0.38	1.07	3.14

Figure C1:

*Distributions of Exit Timing in Private Equity Investments*

This graphic is intended to showcase the distinctions in timing distributions between the following three elements: (1, in yellow): In the case of a complete exit with no partial exit involved, the length in time in years from initial entry to complete exit (2, in grey): In the case of a partial exit, the length in time in years from initial entry to partial exit (3, in green): In the case in which an investment had a partial exit, the length in time between the partial exit to complete liquidation.
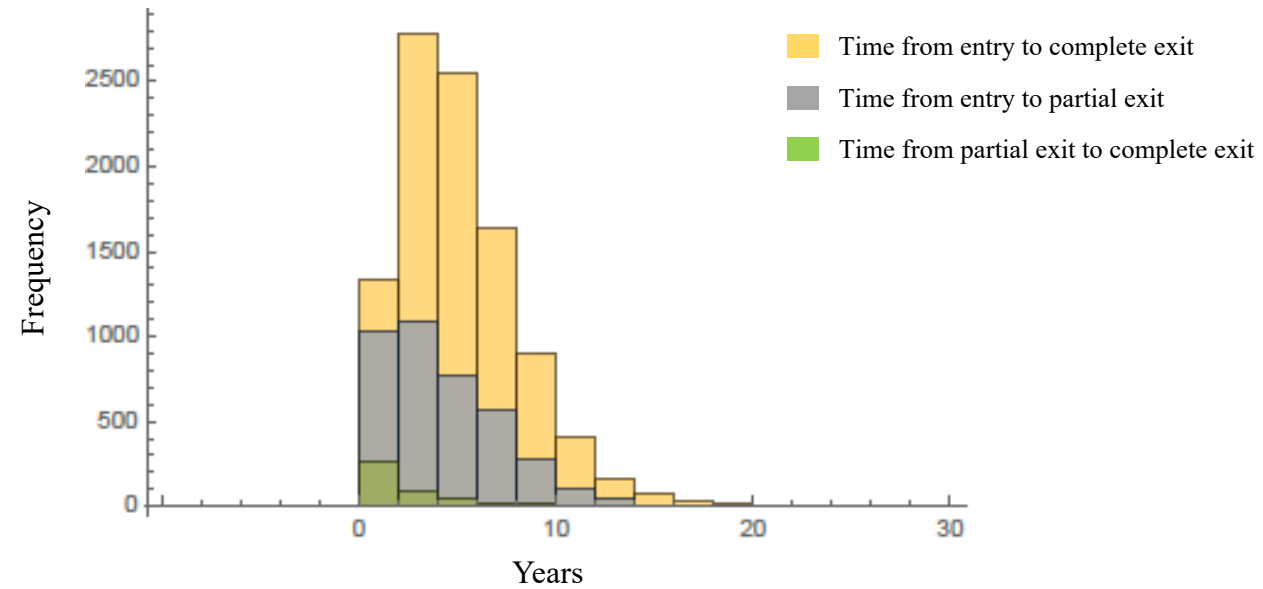
All data is drawn from *Preqin*, filtered only to include buyout transactions. The core distinction being identified in this graphic is the comparison between the yellow and grey distributions, which is reflected in Table A1

Figure C2
Cash Flow Timing empirical model: Fund-level IRR vs. Fund-level Partial Exit Usage
Assumptions: Model specifications are detailed in Section 7.2
The following set of graphs summarizes our output from our empirical model. First, per graph: the x-axis represents the variable (p), which is the proportion of investments in the lifetime of a given private equity fund in which a partial exit is utilized; the y-axis represents an IRR figure (as a decimal). The slope of the graph thus dictates how the IRR changes as we adjust the usage of partial exits per private equity firms. Now, we have sensitized our model to the parameter (a), which is the equity stake of the investment exited early in the case of a partial exit. We show how the slope of each graph (what we are interested in analyzing) varies as we vary our parameter (a) in the below model output.
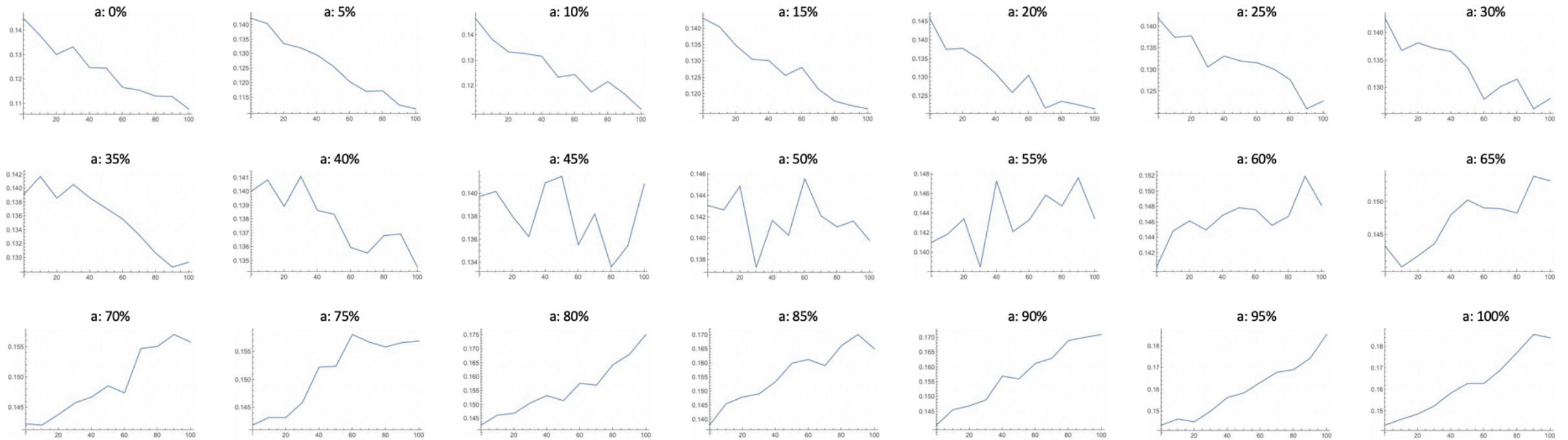
All data is drawn from *Preqin;* note that the y-axis in each graph is scaled in order to best showcase the slope of each graph. Figure C3 will standardize this as we examine the relationship between the slope and our parameter (a)

Figure C3:

Slope of (IRR vs. Partial exit relation) plotted against The equity stake of investments exited early in partial exits
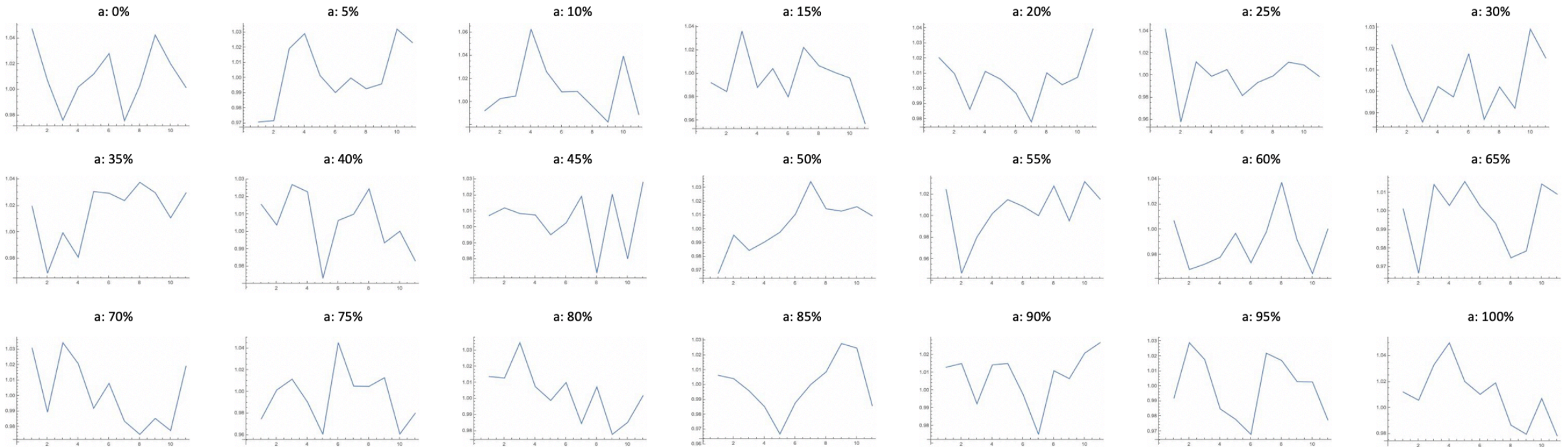
Simply put, this plots each of the slopes of each graph shown in Figure C2 vs. their respective (a) parameter value in order to understand the impact of the sensitivity directly. In detail, if we consider the IRR in our model to be a function of the parameters (a) and (p), where (a) is the percentage stake of an investment exited early in the case of a partial exit and (p) is the percentage of exits being partial for a fund, then this graph plots the derivative of the IRR function with respect to (p) as it varies with (a).
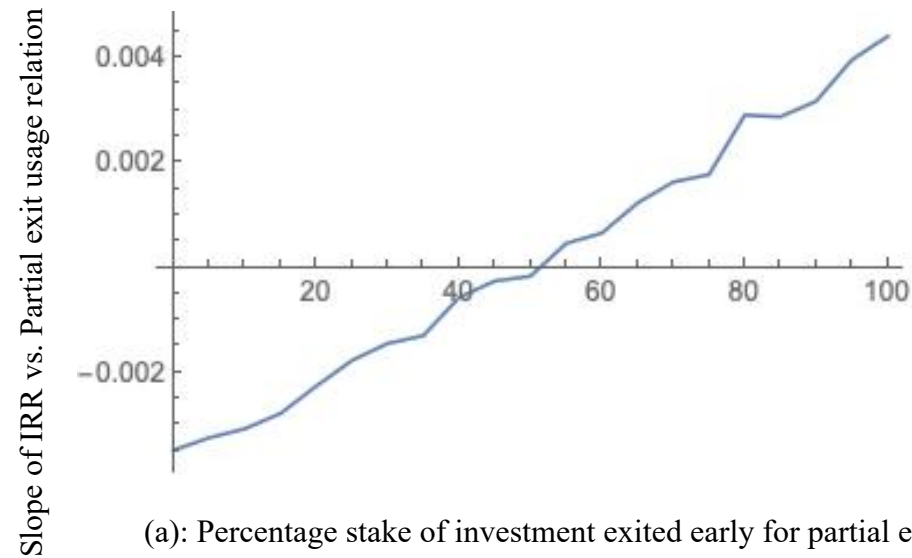
(a): Percentage stake of investment exited early for partial exits

All data is drawn from *Preqin,* filtered only to include buyout transactions. We statistically determine that this direct relationship is significant with $p < 0.001$

Figure C4
Cash Flow Timing empirical model: Fund-level MOIC vs. Fund-level Partial Exit Usage
Assumptions: Model specifications are detailed in Section 7.2

The following set of graphs summarizes our output from our empirical model. First, per graph: the x-axis represents the variable (p), which is the proportion of investments in the lifetime of a given private equity fund in which a partial exit is utilized; the y-axis represents an MOIC figure (as a multiple). The slope of the graph thus dictates how the MOIC changes as we adjust the usage of partial exits per private equity firms. Now, we have sensitized our model to the parameter (a), which is the equity stake of the investment exited early in the case of a partial exit. We show how the slope of each graph (what we are interested in analyzing) varies as we vary our parameter (a) in the below model output.
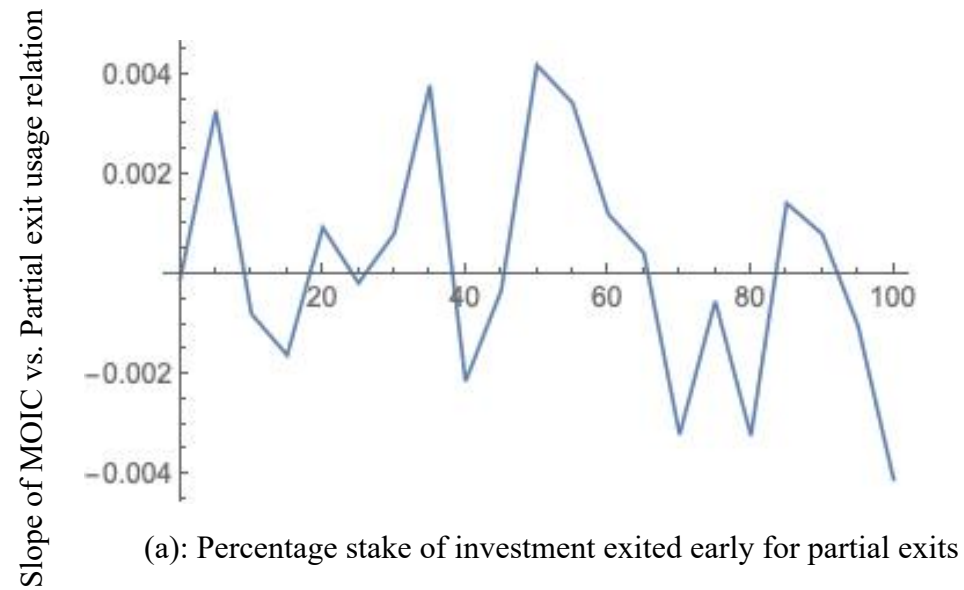

All data is drawn from *Preqin;* note that the y-axis in each graph is scaled in order to best showcase the slope of each graph. Figure C3 will standardize this as we examine the relationship between the slope and our parameter (a)

Figure C5:
Slope of (MOIC vs. Partial exit relation) plotted against The equity stake of investments exited early in partial exits
Simply put, this plots each of the slopes of each graph shown in Figure C2 vs. their respective (a) parameter value in order to understand the impact of the sensitivity directly. In detail, if we consider the MOIC in our model to be a function of the parameters (a) and (p), where (a) is the percentage stake of an investment exited early in the case of a partial exit and (p) is the percentage of exits being partial for a fund, then this graph plots the derivative of the MOIC function with respect to (p) as it varies with (a).

(a): Percentage stake of investment exited early for partial exits

All data is drawn from *Preqin*, filtered only to include buyout transactions. We statistically determine that there exists no relationship in the graphic shown above

Table C6

Cash Flow Timing hypothesis empirical regression: IRR and MOIC vs. Partial Exit Usage

These regressions presented are classical OLS regressions, not logit regressions as used previously, as our dependent variables are fund level non-binary return metrics: IRR and MOIC. We introduce one new variable here, which is the proportion of a fund's exits that are partial exits.

Model	1	2
Panel	General	General
Dependent Variable	IRR	MOIC
Regressors		
Constant	329.34	88.51***
	(365.06)	(17.37)
Proporion of fund exits as partial exits	14.08*	-0.07
	(5.97)	(0.28)
Exit Date	-0.16	-0.04***
	(0.18)	(0.01)
Macro	9.89***	0.31*
	(2.91)	(0.14)

P-value significance: *p<0.05; **p<0.01; ***p<0.001. We report the coefficient first and the standard error in parentheses underneath. All data is drawn from *Preqin.*

Table C7

Grandstanding confirmatory hypothesis: Grandstanding indicator variable vs. Partial Exit Usage

These regressions are logit binomial regressions with our binary partial exit variable as the dependent variable. Our only new variable is the grandstanding variable, which we define as a binary of whether the investment was exited in the first year of the firm post-inception. We do not include data on the numerous buyout industries and exit type, as they serve as control variables in this analysis.

Model	1	2
Panel	General	Trade Sale
Dependent Variable	log(Partial)	log(Partial)
Regressors		
Constant	-142.10***	-139.12***
	(13.90)	(24.31)
Binary of whether the investment was exited in first year post firm inception	-1.25**	0.42
	(0.43)	(0.66)
Investment Duration	-0.07***	-0.03
	(0.01)	(0.02)
Exit Date	0.07***	0.07***
	(0.01)	(0.01)
Other variables:	Buyout industries, Exit type control variable	

P-value significance: *p<0.05; **p<0.01; ***p<0.001. We report the coefficient first and the standard error in parentheses underneath. All data is drawn from *Preqin.*

Empirics based cash flow timing model

We discuss here the parameters, distributions, and algorithm utilized in constructing our cash-flow timing model.

Model parameters

- V: Entry equity purchase price

- p: Probability of partial exit for a given investment

- a: Percentage of asset exited partially

- t: We measure time in years

- t_e: Length of time from $t = 0$ until an investment is entered

- t_p: Length of time from $t = t_e$ (entry) until partial exit

- t_{pc}: Length of time from $t = t_p$ (partial exit) until the remainder of the asset is liquidated

- t_c: Length of time from $t = t_e$ until complete exit

- m: Multiple of V by which the asset value has increased

Now, each of the values $(t_e, t_p, t_{pc}, t_c, M)$ are recalculated each iteration as sampled from various empirical distributions. We now define the distributions used in this analysis:

Model distributions

- T_e: Timing distribution of entry: we model this as Uniform: $U[0, 10]$

- T_p: Timing distribution of length of time from entry until partial exit: we model this empirically using actual partial exit times from entry

- T_{pc}: Empirical distribution of length of time from partial exit to complete liquidation in partial exit instances

- T_c: Empirical distribution of length of time from entry to complete exit in cases of complete exits (without any prior partial exits)

- M: Uniform distribution $U[1,3]$ of multiple of V by which asset value increases

Model algorithm

We now present the process by which our model operates. The process we describe first is for a single iteration. For a given investment, we first assign a partial exit to it with probability p, predetermined as a parameter. We now discuss the two potential paths of this investment based on the results of this paramter p:

Partial Exit Path

If the partial exit trait is assigned to the investment, we then do the following. We randomly sample each of the following parameters (t_e, t_p, t_{pc}, m) from their respective probability distributions (T_e, T_p, T_{pc}, M). Then, we construct our timeline of cash flows. At $t = t_e$, we have a negative cashflow of $-V$. At $t = t_e + t_p$, we have a cash inflow of $aM * V$. At time $t_e + t_p + t_{pc}$, we have a cash inflow of $(1 - a) * M * V$. We save this series of cash flows (including their timing) as one iteration.

Complete Exit Path

If the complete exit trait is assigned to the investment, we then do the following. We randomly sample each of the following parameters (t_e, t_c, m) from their respective probability distributions (T_e, T_c, M). Then, we construct our timeline of cash flows. At $t = t_e$, we have a negative cashflow of $-V$. At $t = t_c$, we have a cash inflow of $M * V$. We save this series of cash flows (including their timing) as one iteration.

We run the above process 10 times to simulate a private equity fund portfolio, for fixed values of V, a, and p. Afterwards, we aggregate all the timed cash flow sets into one large cash flow timeline and calculate the IRR of this set. We then repeat this entire process 5000 times and calculate summary statistics on our resulting IRR values.

Holding a and V constant, we vary p from 0 to 100% and repeat the above, thus allowing us to see how the proportion of partial exits, p, impacts our IRR values. We further sensitize our analysis to a, running this entire analysis for each value of a in increments of 5% from 0 to 100%. We then study and examine the results of this model, which we present in the results section.

Grandstanding model derivation (levered)

We begin with our constructed $V_2 > V_1$ inequality as stated in our model development section and show the full reduction process to our final functional form.

$$a\left(\frac{M_1 E_1 - (1 - f_1)L_0 E_1}{(1+r)}\right) + (1-a)\left(\frac{M_T E_T}{(1+r)^T}\right) > \frac{M_1 E_1 - (1 - f_1)L_0 E_1}{(1+r)}$$

$$\iff (1-a)\left(\frac{M_T E_T}{(1+r)^T}\right) > (1-a)\left(\frac{M_1 E_1 - (1 - f_1)L_0 E_1}{(1+r)}\right)$$

$$\iff \frac{M_T E_T}{(1+r)^T} > \frac{M_1 E_1 - (1 - f_1)L_0 E_1}{(1+r)}$$

We now incorporate our assumption that the multiple value and EBITDA generated stays constant for this business over time (i.e. $M_i = M$ and $E_i = E \; \forall i$). Thus, we can reduce our model to:

$$\iff \frac{ME}{(1+r)^T} > \frac{ME - (1 - f_1)L_0 E}{(1+r)}$$

$$\iff \frac{M}{(1+r)^T} > \frac{M - (1 - f_1)L_0}{(1+r)}$$

Assuming straight line debt paydown, we may say that the final form for our grandstanding partial exit inquality is:

$$\left((1+r)^{T-1}\right)\left(1 - \left(1 - \frac{1}{T}\right)\frac{L_0}{M}\right) < 1$$

From this, we have our final functional form to be:

$$GL(r, T, D) = \left((1 + r)^{T-1}\right) \left(1 - \left(1 - \frac{1}{T}\right) D\right) - 1 < 0$$

Partial derivatives

We now state the partial derivatives that are utilized and referenced in our results section.

We have:

$$\frac{dGL}{dr} = (T - 1)(1 + r)^{T-2} \left(1 - \left(1 - \frac{1}{T}\right) D\right) > 0$$

$$\frac{dGL}{dD} = (T - 1) - (1 + r)^{T-1} \left(1 - \frac{1}{T}\right) < 0$$

$$\frac{dGL}{dT} = -\left(\frac{D(1 + r)^{T-1}}{T^2}\right) + (1 + r)^{T-1} \left(1 - \left(1 - \frac{1}{T}\right) D\right) Log(1 + r)$$

Grandstanding model derivation (unlevered)

We begin with our constructed $V_2 > V_1$ inequality as stated in our model development section and show the full reduction process to our final functional form.

$$a\left(\frac{M_1 E_1}{1+r}\right) + (1-a)\left(\frac{M_T E_T}{(1+r)^T}\right) + \sum_{t=1}^{T}\frac{E_t(1-J)}{(1+r)^t} > \frac{M_1 E_1}{1+r}$$

$$\iff (1-a)\left(\frac{M_T E_T}{(1+r)^T}\right) + \sum_{t=1}^{T}\frac{E_t(1-J)}{(1+r)^t} > (1-a)\left(\frac{M_1 E_1}{1+r}\right)$$

We now incorporate our assumption that the multiple value and EBITDA generated stays constant for this business over time (i.e. $M_i = M$ and $E_i = E \ \forall i$). Thus, we can reduce our model to:

$$\iff (1-a)\left(\frac{ME}{(1+r)^T}\right) + \sum_{t=1}^{T}\frac{E(1-J)}{(1+r)^t} > (1-a)\left(\frac{ME}{1+r}\right)$$

$$\iff (1-a)\left(\frac{M}{(1+r)^T}\right) + \sum_{t=1}^{T}\frac{1-J}{(1+r)^t} > (1-a)\left(\frac{M}{1+r}\right)$$

$$\iff \frac{M}{(1+r)^T} + \left(\frac{1-J}{1-a}\right)\sum_{t=1}^{T}\frac{1}{(1+r)^t} > \frac{M}{1+r}$$

$$\iff \frac{M}{(1+r)^T} + \left(\frac{1-J}{(1-a)(1+r)}\right)\left(\frac{1-\frac{1}{(1+r)^T}}{1-\frac{1}{1+r}}\right) > \frac{M}{1+r}$$

$$\iff \left(\frac{1}{r}\right)\left(\frac{1}{M}\right)\left(\frac{1-J}{1-a}\right)\left(1-\frac{1}{(1+r)^T}\right) > \frac{1}{1+r} - \frac{1}{(1+r)^T}$$

We reduce this to get the final form of our comparative model:

$$\left(\frac{(1+r)^T - 1}{(1+r)^{T-1} - 1}\right)\left(\frac{1-J}{1-a}\right)\left(\frac{1}{r}\right)\left(\frac{1}{M}\right) > 1$$

From this, we have our final functional form to be:

$$GU(r, T, J, a, M) = \left(\frac{(1+r)^T - 1}{(1+r)^{T-1} - 1}\right)\left(\frac{1-J}{1-a}\right)\left(\frac{1}{r}\right)\left(\frac{1}{M}\right) - 1 > 0$$

Partial derivatives

We now state the partial derivatives that are utilized and referenced in our results section.

We detail $\frac{dGU}{dJ}, \frac{dGU}{dM}, \frac{dGU}{da}$ here; we do not include formulations of $\frac{dGU}{dr}$ and $\frac{dGU}{dT}$ here as they do

not lend themselves to direct notational analysis. However, we computationally determine

that $\frac{dGU}{dr} < 0$ and $\frac{dGU}{dT} < 0$

$$\frac{dGU}{dJ} = -\left(\frac{(1+r)^T - 1}{(1+r)^{T-1} - 1}\right)\left(\frac{-1}{1-a}\right)\left(\frac{1}{r}\right)\left(\frac{1}{M}\right) < 0$$

$$\frac{dGU}{dM} = -\left(\frac{(1+r)^T - 1}{(1+r)^{T-1} - 1}\right)\left(\frac{1-J}{1-a}\right)\left(\frac{1}{r}\right)\left(\frac{1}{M^2}\right) < 0$$

$$\frac{dGU}{da} = \left(\frac{(1+r)^T - 1}{(1+r)^{T-1} - 1}\right)\left(\frac{1-J}{(1-a)^2}\right)\left(\frac{1}{r}\right)\left(\frac{1}{M}\right) > 0$$

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