Value Creation and Persistence in Private Equity [*] [†]

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Abstract

We study how private equity (PE) firms generate returns for their investors, by estimating the effects of PE funding on portfolio companies' operational efficiency and market power. We confirm prior findings that PE funding leads to operational efficiency: both labor productivity and total factor productivity improve as PE-backed companies ramp up investment, employment, and sales. We find no evidence that PE-backed companies increase their market power. In fact, the PE-backed companies in our sample reduce their price markups by 6%, which allows them to gain substantial market shares. Using detailed confidential information obtained from inside PE firms, we show that the PE firms in our sample push for operational improvements and that these improvements are the main drivers of the returns investors receive from PE funds. We find that the majority of the operational improvements instigated by PE firms persist even after they fully exit their investments. These findings are consistent with PE firms' ability to create long-lasting value as opposed to maximizing short-term returns at the expense of portfolio companies.

JEL Classification: D24, G24, G32, G34, L11, L25

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Do private equity funds increase operational efficiency at portfolio companies or are they more interested in generating returns by exploiting market power? If private equity funds do deliver efficiency improvements to their portfolio companies, do these improvements survive beyond the tenure of private equity ownership? The answers to these questions can both shed light on the sources of value creation for investors in private equity and have profound implications for assessing the overall impact private equity has on economic welfare. Yet there is limited evidence to date on whether the returns private equity funds generate for their investors result from efficiency improvements (a potential net positive for the economy) or increases in market power (a potential net negative).

Against this background, we investigate how private equity firms affect the real outcomes of their portfolio companies on the one hand and investor returns on the other. For the former, we draw on recent advances in the production-function literature to estimate changes in total factor productivity and company-level price markups. We also examine changes in investment in capital stock and inventory management as well as changes in financial performance. We relate these real outcomes to soft information about the value-creation strategies pursued by private equity firms in each of their portfolio companies. For the latter, we draw on proprietary deal-level cash flow data (which allow us to estimate returns to investors) and relate the variation in investor returns to company-level changes in operational efficiency and market power.

Our empirical approach allows us to examine when the economic and financial returns of private equity deals diverge. Existing evidence suggests that persistence of returns in private equity deals has declined over time (Braun et al. 2017), as the private equity industry has matured and competition for deal flow has increased. However, it is unclear whether there are also structural reasons behind this decline. For instance, greater product market competition due to increased import penetration may make it more difficult for portfolio companies to maintain high sales margins. More generally, it is unclear if investor returns derive mainly from cost efficiencies (i.e., the real effects of improved monitoring, which may, for example, lead to higher quality management and 'lean' production technologies) or changes in pricing policies and market power. Our empirical approach is designed to disentangle changes in efficiency from changes in market power and to relate each of these to investor returns.

Identifying the impact of private equity (PE) involvement on efficiency and market power is challenging. A key empirical challenge arises because PE firms endogenously select which companies to invest in. It is plausible that selection reflects, in part, a PE fund's expectations of the scope for changes in productivity and market power. For instance, PE firms may target industries undergoing consolidation or deregulatory changes – changes that may provide a boost to the efficiency or pricing power of companies operating in these industries regardless of the involvement of PE firms.

We combine a traditional difference-in-differences strategy with matching methods to address this selection challenge. To reduce selection bias, we form a set of control companies matched on country, industry, size, and the year of the PE transaction. These controls are similar in spirit to those used by Bharath et al. (2014) and Davis et al. (2014) in their studies of private equity, jobs, and productivity in the U.S.

A second empirical challenge relates to the measurement of productivity and market power. Disentangling productivity improvements from changes in market power is challenging when micro-level data on the prices companies charge for their products are unavailable. Absent micro-level price data, researchers need to rely on a set of assumptions about how companies compete in the product market to estimate market power, which is typically measured by price markups over production costs. We follow recent advances in the industrial organization literature on production function estimation suggested by De Loecker and Warzynski (2012) and

De Loecker and Eeckhout (2017), who impose minimal assumptions on market competition. This approach allows us to estimate time-varying company-level markups consistently so that we can track how a company's productivity and market power change while under PE ownership.

Our results provide evidence of a significant and positive impact of PE ownership on revenue growth, employment, investment, and operational efficiency at portfolio companies. Over the time companies spend in a PE firm's portfolio (an average of five years in our sample), their revenues increase by an average of 89%, employment by 44%, the capital stock per employee by 33%, labor productivity by 19%, and total factor productivity by 4%, over and above the corresponding changes at matched control companies. At the same time, we find that markups charged by portfolio companies fall by an average of 6%. This suggests that cost reductions achieved through operational improvements are passed on to consumers via lower prices.

Our results indicate that the majority of the effects documented survive beyond PE firms' tenure in portfolio companies. Notably, these companies continue to enjoy revenue growth and maintain higher levels of efficiency even after PE firms fully realize their investments. We also show that these operational improvements are behind the investor returns that PE funds generate for our sample of deals. In particular, improvements in efficiency and revenue growth are strongly associated with higher investor returns. As part of our analysis, we identify inorganic deals in which PE firms grow a portfolio company via mergers and acquisitions (M&A) and show that our results are not driven by this subset of deals.

Which value creation strategies are the main drivers of the relationship between operational improvements and returns? To answer this question, we hand-collect textual information from proprietary quarterly reports the PE firms supply to their investors. These reports provide information on the operational changes at each portfolio company and how instrumental PE firms have been in enacting them. To validate whether PE firms actually carry out the operational improvements that they say they do, we correlate the textual information with post-investment effects on debt, capital investment, inventories, and working capital management. We then relate detailed soft information on each portfolio company's operational changes – such as product introductions, market expansion, and pricing strategy – to changes in labor productivity, total factor productivity (TFP), and markups.

Our analyses are based on unique data for a 25-year panel of 1,444 deals in 20 transition economies in primarily Central and Eastern Europe, which were financed by 178 PE funds. This somewhat unusual setting has several advantages. First, as large shareholders, the PE funds have skin in the game and thus an incentive to engage in value creation and active monitoring of their investments. Second, as a first approximation, we know what the fund manager knows. We have access to quarterly summaries of the hard and soft information fund managers have about their portfolio companies and the conclusions they draw from it. Our data allow us to capture each fund's intended strategy to create value at the time of investment and how they achieve it over time. Third, we also know what actions fund managers take in response to the information they collect. Specifically, the quarterly reports that we have access to provide comments on how fund managers change their strategies when intended plans are not realized on time or at all.

We complement the soft information from quarterly reports with hard data from the annual balance sheets and income statements of each portfolio company. In order to do so, we manually match each deal to a company in Orbis, a global database provided by BvD. Orbis provides harmonized balance sheet information on a rich set of public and private companies. This allows us to calculate measures of efficiency and market power in a consistent manner across countries, and also to create comparable control groups for our econometric analysis.

We contribute to the literature in four ways. First, we add to the growing evidence on the real operational implications of private equity by providing direct estimates of key outcomes such as

TFP and market power. Existing literature shows that leveraged buyouts contribute to raising aggregate productivity by increasing capital expenditures (Boucly et al. 2011) and reallocating resources to more productive plants amid net job destruction (Davis et al. 2014, Bharath et al. 2014). Unlike previous studies, we emphasize the role of lowering price markups in driving value creation through organic growth. The only other study of market power and pricing that we are aware of is Fracassi et al. (2017), who draw on product-level price data to show that U.S. consumer-goods companies acquired by PE firms raise prices only marginally on their existing products and that PE ownership benefits consumer-goods customers through new product introductions and increased variety. Unlike Fracassi et al., our data encompass all industries PE firms have targeted (not just consumer goods). The drawback of our more comprehensive sample is that we do not observe product-level prices (though production-function estimation helps mitigate this drawback).

Our finding that PE-backed companies do not increase their markups generalizes Fracassi et al.'s (2017) conclusion that PE deals are not harmful to U.S. consumers to a wider range of industries and countries. More importantly, we add nuance to this conclusion by showing that consumers benefit as the gains of productivity improvements are passed on to consumers in the form of lower prices. We are able to pinpoint the exact operational changes that PE firms carry out in their portfolio companies to enable them to pass on cost savings to consumers.

Second, we provide the first evidence on whether operational improvements persist beyond PE ownership and how PE firms time their exits. Previous literature has documented that PE firms improve sales and operational efficiency at portfolio companies. But is this a temporary effect, deriving from relatively short-lived change in ownership that imposes high-powered incentives on senior management to improve efficiency? Or is it a more permanent effect, deriving from long-lasting changes in a company's corporate governance, managerial capital, or business strategy? Our findings are consistent with PE firms implementing structural changes, the effects of which persist beyond their investment horizon. In addition, we find evidence that PE exits coincide with industry-wide downturns in demand, which suggests that PE firms time their exits.

Third, we provide new evidence on how operational improvements are related to investor returns at the deal level. PE funds increasingly turn to generating returns through increasing growth and carrying out efficiency improvements (Gompers et al. 2016), such as using better cost control or realigning businesses into higher margin products. In line with this, Acharya et al. (2013) show that the improvements in financial performance of PE deals can be traced to improvements in sales and operating margins. We contribute to this literature by measuring which value creation strategies help explain returns to investors. Our findings suggest that increases in labor and TFP alongside sales growth are most strongly related to returns.

Fourth, in ongoing work, we use textual information from PE firms' quarterly reports to quantify the actions they take. This helps us open the black box of value creation by estimating whether the returns generated by PE firms really are the product of their actions. As such, it helps us achieve identification in a way that has been elusive to earlier researchers.

1. Sample and data

Our data come from the European Bank for Reconstruction and Development (EBRD). The EBRD is among the largest investors in PE funds that operate in emerging markets. Since it started operations in 1991, the EBRD has committed USD 5,165 million to PE funds (as of December 2017).[1] As part of its mandate, the EBRD seeks to contribute to the development of the PE industry in its region, which spans Central, Eastern, and Southern Europe, the Baltics, the Commonwealth of Independent States (CIS), and the Middle East and North Africa. Given the

[1] See http://www.ebrd.com/equity-funds.html for details.

coverage and the obligatory reporting demanded by the EBRD, our data do not suffer a survivor bias resulting from only the best or only the largest fund managers contributing data.

Our dataset extends the sample used in Cornelli et al. (2013). Our 178 sample funds were raised between 1992 and 2017 with an average (median) size of USD 163.2 million (USD 88.5 million). After excluding a small number of deals in countries not covered in Orbis, our sample contains 1,444 deals from 20 countries, with an average (median) of 9.9 (9) deals per fund.[2]

Table 1 provides a sample overview by country and time period. The top three countries are Russia, Poland, and the Czech Republic, which together account for just under half the sample. Deal activity has varied over time, with the busiest periods in 1997-2001 (433 deals) and 2012-2017 (389 deals). We follow each deal from inception to the earlier of exit (which may take place through a trade sale or an initial public offering on a stock market), write-off, or December 2017. As of the end of 2017, 953 deals have been exited (including 131 write-offs), while 491 deals remain in the funds' portfolios. The average (median) deal size is USD 13.9 million (USD 5.4 million), indicating that most portfolio companies are medium-sized enterprises.

For each portfolio company in our sample, we estimate returns to investors, measures of financial performance and value creation (including productivity and price-cost markups), as described in the remainder of this section. Summary statistics are provided in Section 2.

1.1 Returns to investors

For each portfolio company, we observe precisely dated cash flows between company and fund (i.e., initial and subsequent investments, dividends, and exit-related proceeds, if any).[3] Cash flows are gross of the fund's management fees and carried interest and thus reflect a portfolio company's actual performance. Using these data, we estimate three standard measures of returns

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[2] The excluded countries are Albania, Armenia, Azerbaijan, Belarus, Cyprus, Egypt, Georgia, Jordan, Kosovo, the Kyrgyz Republic, Moldova, Mongolia, Tunisia, and Turkmenistan, accounting for 105 deals over our sample period.
[3] For partially realized and unrealized portfolio companies, we also observe fair-value estimates as of year-end 2017.

to investors: the internal rate of return (IRR), the multiple on invested capital (MOIC), and the public market equivalent (PME). We construct the PME in the spirit of Kaplan and Schoar (2005), using the MSCI Emerging Markets Total Return Index as a public-market benchmark.

1.2 Financial performance and measures of value creation

Our company-level measures use BvD's Orbis database. Orbis provides consolidated accounting data taken from income statements and balance sheets as well as data on employment and industry for both stock market listed and privately held companies, covering the vast majority of companies operating in the EBRD's investment region. To the extent possible, Orbis reports data in a manner that is consistent and comparable across countries and years.

We manually link sample companies to Orbis by name (including historical ones where names have changed). Of the 1,444 companies in the full sample, we are able to link 1,228 to Orbis. For 330 of these matches, Orbis lacks data around the time of PE investment (i.e., the period starting three years before and ending three years after PE ownership). This leaves us with a sample of 898 portfolio companies in what we call the Orbis sample. (The number of observations used in our empirical specifications will vary depending on data availability.) Table IA.1 in the Online Appendix confirms that the Orbis sample is representative of the full sample in terms of investor returns, so that data gaps in Orbis are random at least in this sense.

Using Orbis, we construct a number of measures related to four sources of value creation. The first is "financial engineering", which includes a portfolio company's leverage, net debt to EBITDA, and the (implicit) interest rate it pays on its outstanding debt. The second is "operational improvements", which includes capital intensity, labor productivity, and TFP.[4] The

[4] TFP captures the efficiency with which all inputs into production (labor, materials, and capital) are used. There is a long established literature on TFP estimation, which carefully deals with the challenge that companies' input choices are correlated with the error term, given that companies likely choose their inputs based on their current and expected future productivity (which is observed to the company but not to the econometrician). We follow the

third is "cash management", which includes working capital. The fourth is "top line growth", which includes sales, price-cost markups, and market shares. We describe how we measure markups in the next subsection. We also construct measures of each company's profitability using data on cash flows, operating margins, and return on assets. Appendix A provides detailed definitions of all variables we use.

1.3 Price-cost markups

There is a long tradition in the industrial organization and international trade literatures to estimate markups from production data and test the assumption of perfect competition.[5] We follow De Loecker and Warzynski (2012) in deriving company-level markups from a production-function framework. Earlier methodologies require the availability of detailed price and quantity information and assumptions about market structure. This has often led researchers to focus on narrowly defined consumer markets. A key contribution of De Loecker and Warzynski is that their approach provides markup estimates without the need for data on prices and quantities and without specifying how companies compete in the product market.

De Loecker and Warzynski (2012) assume cost-minimizing firms with access to a variable input of production (e.g., materials or labor). Their approach relies on the insight that the output elasticity of this input equals its expenditure share in total revenue when price equals marginal cost, i.e., when markup = price/marginal cost = 1. With imperfect competition, firms can charge a price above their marginal cost, thereby introducing a wedge between the input's revenue share and its output elasticity. Given consistent estimates of any input's output elasticity, the ratio of this elasticity to the input's revenue share provides a consistent estimate of a company's markup. The details of the estimation approach can be found in Appendix C.

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production-function approach to TFP estimation pioneered by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006). The details of the estimation approach can be found in Appendix B.

[5] See Hall et al. (1986), Hall (1988), and Hall (1989) for earlier contributions. Klette (1999) provides a more recent example using dynamic panel estimation techniques.

Table IA.2 reports summary statistics of company-level markups for the *universe* of companies with data available in Orbis, broken down by country. Average markups typically range from 1.20 to 1.80, implying that the average company charges a price that is 20% to 80% percent higher than its marginal cost. Average markups are higher than medians, indicating that a number of companies are able to charge prices that significantly exceed their marginal cost.

2. Empirical strategy

2.1 Econometric specification

We document the effects of PE ownership on sources of value creation and profitability using a difference-in-differences strategy. Specifically, we estimate regressions of the following form:

$$y_{it} = \beta_0 + \beta_1 PE_i * postPE_{it} + \beta_2 postPE_{it} + \beta_3 PE_i * postPE_{it} * Exit_{it} + \beta_4 postPE_{it} * Exit_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

where y_{it} is an outcome for company *i* in year *t*, and PE_i is a treatment indicator equal to 1 for companies acquired by a PE firm and 0 for companies in the control group. For portfolio companies, $postPE_{it}$ equals 1 for years following the first PE funding round and 0 before. For control companies, $postPE_{it}$ equals 1 for years after their matched targets first received PE funding and 0 before. Our main coefficient of interest is β_1, which is identified from the interaction of the PE treatment indicator PE_i and $postPE_{it}$.

We track portfolio companies that are fully realized deals (meaning that the PE firms have exited completely) for up to three years post-exit. This allows us to isolate operational improvements that manifest themselves during the PE ownership and test whether these improvements persist or abate post-exit. To this end, equation (1) includes the interaction term $PE_i * postPE_{it} * Exit_{it}$, where $Exit_{it}$ equals 1 post-exit and 0 otherwise.[6] Given this

[6] Our database identifies the buyers when deals are exited. We code as exits only strategic sales, IPOs, or full write-off. In cases of secondary buyouts involving PE buyers, we define our $postPE_{it}$ variable such that it continues to equal 1; it equals 0 only after the last PE fund has exited the company.

specification, the β_3 coefficient on this additional interaction term captures any incremental post-exit effects, over and above the average impact of PE ownership captured by the β_1 coefficient (and relative to control companies). This setup allows us to test whether any effect realized under PE ownership persists post-exit: if the sign of β_3 disagrees with the sign of β_1, the effect does not persist and reverts toward the pre-investment level. To estimate the long-term effect of PE ownership relative to control companies, which compares the sum of the ownership effect and the post-exit effect to the pre-investment level of the outcome variable in question, we report the linear combination $\beta_1 + \beta_3$.

Naturally, equation (1) also includes the interaction term $postPE_{it} * Exit_{it}$, which captures the performance of target and control companies in the years following PE firms' exits relative to the earlier years.[7] Its coefficient, β_4, allows us to test whether PE firms time the market when exiting portfolio companies. Specifically, a negative sign on β_4 suggests an industry-wide downturn while a positive sign suggests an industry-wide expansion.

We estimate the model with a full set of company (γ_i) and year (δ_t) fixed effects and cluster standard errors at the company level, as disturbances to a company's operating performance are potentially correlated over time. To guard against the influence of outliers, we remove company-year observations with values at the bottom and top 3rd percentiles of the sample distribution.

2.2 Forming a counterfactual group

To ensure comparability between our treatment and control groups, we form a matched control group based on observables in the first PE transaction year. In particular, we select up to five matched control companies for each PE portfolio company using the following procedure. First, we divide all companies in Orbis into country-by-4-digit industry groups. Second, we sort by total assets within each country-industry pair and select the five nearest companies to the

[7] $Exit_{it}$ for control companies is defined such that it equals 1 for years after their matched targets are fully realized.

portfolio company as per the first year of PE funding. We require that control companies have received no PE investment in the past and during the period they serve as a control.[8]

Estimating equation (1) on a matched sample constructed in this way gives us the effect of receiving PE funding on portfolio companies relative to an average matched control company with similar characteristics at the time of investment. By construction, we are able to strip out the effects of PE firms targeting certain countries, industries, or companies of a certain size within those country-industry pairs. Our industry classification (which follows NACE Rev. 2) contains 615 groups at the 4-digit level, which provides a highly detailed breakdown of industries. Therefore, our control companies come from narrowly defined cells in which they are likely to experience the same industry shocks or expectations about future profitability as our portfolio companies. Constructing such tight control groups based on observables is similar to the strategy followed by Davis et al. (2014) and Bharath et al. (2014) to tackle concerns of selection and unobservable company attributes that may correlate with these control groups.

2.3 Summary statistics

Table 2 reports summary statistics for the key variables included in the empirical analysis. Panel A reports the characteristics of the portfolio companies targeted by PE firms, averaged over the three years prior to their first year under PE ownership, while Panel B reports the same characteristics for control companies.

By construction, the two groups share the same country and industry distributions and are similar in asset size. They differ somewhat in sales, employment, markups and market share. Specifically, the average (median) portfolio company had USD 21 million (USD 10 million) in annual sales averaged over the three years preceding a PE deal, employed on average 197 (100) employees, charged an average markup of 1.91 (1.14), and commanded a market share of 5%

[8] For robustness purposes, we also consider a control group that is propensity-score matched on a broader set of pre-investment characteristics such as sales, TFP, and markup in addition to country and industry.

(2%). In comparison, the average (median) control company had USD 18 million (USD 6 million) in annual sales averaged over the three years preceding its corresponding PE deal, employed on average 164 (70) employees, charged an average markup of 1.82 (1.14), and commanded a market share of 4% (1%). These numbers suggest that companies targeted by PE firms tend to command market-leading positions.

3. Empirical findings

We first document that portfolio companies in the Orbis sample deliver financial returns for their investors. Table 3 reports means and medians for our three measures of investor returns. The average portfolio company has an IRR of 9.12% and an MOIC of 1.74 and outperforms the benchmark emerging-markets index with a PME of 1.16. These figures are similar for both the fully realized and the unrealized portions of the sample.

How are PE firms in the sample able to generate these returns? In the remainder of this section, we study four value creation channels that PE firms pursue and discuss which of these channels persist even after PE firms exit their investments. We also discuss how profitability is affected during and after PE ownership.

3.1 Value creation channels

3.1.1. Financial engineering

We find evidence that portfolio companies engage in financial engineering during PE ownership. Table 4 shows that portfolio companies increase their leverage by 3.8 percentage points relative to their matched controls (p=0.001) and that the additional tax shields the increased borrowing gives rise to reduce their effective tax rates by 1.4 percentage points on average (p=0.046). These are economically large effects relative to the sample means of 19% leverage and a 14% tax rate. Portfolio companies manage to increase leverage without paying significantly higher interest rates,[9] perhaps because their net debt to EBITDA ratio remains stable (implying that EBITDA increases, as we will shortly confirm). While tax rates fall, total taxes paid rise by around 34% relative to control companies (p=0.030),[10] again implying that EBITDA increases.

3.1.2. Operational improvements

We find strong evidence that portfolio companies engage in a variety of operational changes during PE ownership. Table 5 shows that portfolio companies increase employment by 44% more than their control companies on average (p<0.001), wages by 15% (p=0.001), and labor productivity by 19% (p<0.001). These operational changes are economically large and likely related to each other. They imply, for example, that the average portfolio company increases its headcount from 197 before PE ownership to 282 after.[11] The attendant increase in average wages could either reflect a positive change in skill composition or the need to offer higher wages to attract labor (possibly from direct competitors).[12] Assuming a textbook model of labor demand, which argues that workers are paid the marginal revenue product of their labor, our estimates suggest that workers at portfolio companies may not fully share in the gains from the rise in scale (i.e., average wage growth of 15% < average labor productivity growth of 19%).

Does the improvement in labor productivity simply result from an increase in scale, which allows portfolio companies to move down their average cost curves? In the remainder of Table 5, we test potential changes in capital investment and TFP, both of which can impact efficiency over and above increasing scale. An important difference, however, is that while capital investment represents a source of efficiency improvement that is technology-driven (i.e., an

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[9] Since we can calculate interest only for companies that borrow, the sample used in this regression is smaller.
[10] Computed as exp(0.290) – 1 = 0.34.
[11] Computed as the sum of the suitably exponentiated coefficients on PE x $postPE_{it}$ and $postPE_{it}$ times the pre-investment mean of 197 from Table 2.
[12] In ongoing work, we are reading through quarterly reports by PE firms to their investors on each portfolio company to figure out which of the mechanisms is more likely behind the finding of higher wages.

increase in capital intensity mechanically raises the marginal product of labor), changes in TFP are isolated from both increases in scale and changes to the production technology.

We find no statistical difference between the rate of net investment at portfolio and control companies, while capital intensity increases strongly (by 33%) at portfolio companies under PE ownership. Note that net investment is calculated as a rate (the annual change in net assets scaled by beginning-of-year total assets), while capital intensity is measured as the book value of fixed assets to employment. This suggests that PE funds oversee a one-time injection of capital investment rather than continuous increases in capital expenditures. In light of our earlier finding that portfolio companies increase their leverage during the same period, this increase in capital intensity is likely funded by external debt. The last column of Table 5 shows that TFP increases by 4% (p=0.035). This point estimate is smaller than the increase in labor productivity, which suggests that part of the efficiency improvement is facilitated by capital investment.

3.1.3. Cash management

It is often argued that PE firms create value and generate free cash flow by renegotiating contracts with suppliers and customers, introducing lean-manufacturing techniques, and reducing working capital needs (Braguinsky et al. 2015). Table 6 provides evidence of such value-creation strategies in our sample. Compared to control companies, portfolio companies reduce their working capital as a share of total assets by 3.9 percentage points on average (p=0.003). This corresponds to around a 12% improvement in working capital management relative to an average portfolio company before PE ownership.

To understand where the working capital improvement comes from, we examine the number of days portfolio companies take to pay their suppliers, the number of days they wait to collect payments from customers, and stock turnover. While portfolio companies do not pay their suppliers any more slowly, they do collect payment from their customers 8.6 days sooner under

PE ownership (p=0.013), which is a 14% improvement over the pre-PE average of 61 days. Stock turnover rates, on the other hand, do not change significantly. These findings suggest that the improvement in working capital management is most likely driven by contract renegotiations with customers rather than better inventory management.[13]

3.1.4. Top-line growth

Portfolio companies experience strong growth in revenues while under PE ownership. Table 7 shows that their top line grows by around 89% on average compared to their matched controls (column 1). Given average (median) sales of USD 21 (10) million, the point estimate implies that by the time a PE fund exits its investment, annual sales will have risen to nearly USD 40 (19) million for the average (median) company.

Perhaps most interestingly, column 2 shows that company-level markups are on average 6% lower while under PE ownership (p=0.008). Taken together with the finding that portfolio companies improve their operational efficiency, lower markups imply that reductions in marginal costs (as captured by the increase in TFP) are at least partially passed on to customers in the form of lower relative prices. It also suggests that PE firms do not resort to increasing prices to service the higher indebtedness of their portfolio companies. Instead, they seem to follow a high-growth strategy by pricing their products and services competitively.

Reducing markups is expected to lead to market share gains. Column 3 confirms this conjecture: portfolio companies do indeed increase their market share, by 1.5 percentage points on average, a 30% increase from the 5% sample mean.

3.1.5. Organic vs. inorganic growth

Does the remarkable growth in the scale of portfolio companies reflect organic growth or

[13] In ongoing work, we draw on textual information from funds' quarterly reports to pinpoint whether the documented effects are indeed driven by portfolio companies in which PE funds have identified and taken action to improve working capital management.

buy-and-build strategies said to be popular among PE firms? We draw on two sources to classify sample deals into organic vs. inorganic. The first is BvD's Zephyr database, which tracks M&A transactions.[14] We code a company as following an inorganic-growth strategy if Zephyr lists it at least once as an acquirer while under PE ownership. The second is the EBRD archive of quarterly PE fund reports, which we use to verify and update the Zephyr classification. We classify 116 of the 898 portfolio companies (or 13%) as being engaged in M&A deals.

Columns 4 through 6 of Table 7 exclude these inorganic deals and their matched controls. This makes little difference to the magnitudes of the estimated effects of PE ownership on sales, markups, and market share. Portfolio companies that grow organically experience revenue growth of 84%, while lowering markups by 5%, and increasing their market share by one percentage point on average. None of these point estimates is significantly different from its counterpart in the full sample. In sum, we find no evidence that the effects we document are driven by the small number of portfolio companies that grow inorganically.[15]

3.1.6 Heterogeneity of PE treatment

The point estimates discussed so far are derived from a standard diff-in-diff framework, which captures the average effect of PE ownership but hides any underlying heterogeneous effects. Our sample includes companies with a large degree of variation in size; for instance, a portfolio company at the 25th percentile of the sample distribution employs 33 workers, while one at the 75th percentile employs 273 workers. To explore heterogeneity in the effects of PE ownership, we estimate quantile regressions on the sample of organic deals. These regressions are very similar to our main specification in equation (1), except that they do not admit company

[14] Zephyr screens news reports and company websites to track M&A activity. It provides information on acquirers, target companies, announcement dates, and transaction status, which can be either of "completed", "pending", "rumor", or "withdrawn".

[15] Removing inorganic deals similarly makes little difference to our findings regarding financial engineering, operational improvements, and cash management. See Tables IA.3, IA.4, and IA.5 in the Online Appendix.

fixed effects and provide estimates of β_1 at different points in the conditional distribution of the outcome variable.

Figure 1 displays the quantile regression estimates across deciles for three of our outcomes variables: revenues, market share, and labor productivity.[16] In the figure, q10 refers to the bottom decile and q90 refers to the top decile of a variable's conditional sample distribution. The quantile regression estimates are shown with a solid line, with dashed lines indicating 95% confidence intervals based on bootstrapped standard errors. We graph the baseline diff-in-diff estimates from earlier with a horizontal red line.

The top panel shows that while under PE ownership, portfolio companies experience strong revenue growth across the entire revenue distribution. As expected, the estimates are greatest in the lower deciles and decline uniformly as we move towards the higher deciles, ranging from 150% in the bottom decile to 25% in the top decile.

The middle panel reveals an interesting pattern: portfolio companies that experience the greatest market share gains are those at higher deciles of the distribution of market shares. For instance, the point estimate for the top decile is 10 percentage points, which is ten times greater than our baseline estimate. This suggests that PE firms target market-leading companies and then strengthen these companies' market positioning even further.

The last panel asks whether PE ownership helps already productive companies become even more productive, or if it helps companies that lag others to catch up. The estimates suggest the latter. Though not monotonic, PE ownership has a much larger impact on labor productivity among companies in the bottom three deciles than on the companies. In fact, for the already most productive companies, labor productivity does not improve significantly under PE ownership. In

[16] Quantile regression estimates for these three variables are representative of the other outcome variables that we study. For instance, estimates by decile on employment and capital intensity are similar to estimates for revenues. Likewise, quantile regression estimates for markups follow the same patterns as those for market shares (though with the opposite sign).

unreported results, we replicate this exercise for TFP. We do not find any heterogeneous effects in the case of TFP, which suggests that PE firms' ability to help portfolio companies catch up to the rest of the industry is likely driven by their switch to more capital intensive production technologies.

3.2 Persistence

Our empirical setting allows us to test the persistence of effects that companies experience under PE ownership. In particular, the coefficient on $PE_i * postPE_{it} * Exit_{it}$ captures whether gains in operational performance created under PE ownership survive beyond PE firms' tenure. A coefficient of the same sign as that on $PE_i * postPE_{it}$ suggests that the outcome in question continues to amplify in magnitude, while a coefficient of a different sign suggests reversion towards the pre-PE level (in each case relative to the control companies).

One particular way in which companies may be negatively affected following PE exit is a potential loss of access to external financing. Boucly et al. (2011) show that LBOs foster firm growth by alleviating credit constraints, presumably because lenders experience positive externalities from the monitoring PE firms engage in at their portfolio companies. When PE firms exit, lenders' willingness to lend may decline. The post-exit coefficients in Table 4 provide some support for this conjecture: after PE firms exit, interest rates increase by 3.9 percentage points more than at matched control firms (p=0.040). Debt falls, though not significantly, while effective tax rates rise by 2.3 percentage points (consistent with a reduction in tax shields), reversing the tax reduction experienced under PE ownership. Total taxes paid continue to rise.

With regards to operational improvements (Table 5), cash management (Table 6), and top-line growth (Table 7), we find no evidence that portfolio companies experience significant reversals post-exit. In a couple of cases, the improvements even continue post-exit: labor productivity continues to rise (by 12% relative to matched controls), and sales continue to grow (by a further 28% on average). Portfolio companies also continue to pay their workers higher wages (up a further 13%).

The long-term impact of PE ownership is captured by the linear combination $\beta_1 + \beta_3$ in equation (1). Looking across Tables 4 through 7, we see that PE ownership results in long-lasting changes. Over the period of PE ownership and the years that follow, portfolio companies employ significantly more people (by 64%), pay higher average wages (by 29%), enjoy greater labor productivity (by 34%) and higher TFP (by 6%), improve their collection times (by 14 days), grow their sales (by 144%) and market shares (by 1.2 percentage points), and reduce their price markups (by 7%), compared to before they were targeted by a PE firm (and relative to matched controls).

3.3 Exit timing

Our empirical design allows us to test whether PE firms time the market when exiting portfolio companies. Specifically, coefficient β_4 captures what happens to the portfolio company's industry (as represented by its control companies) in the years following exit, relative to the earlier years. Looking across Tables 5 through 7, we see that PE exits precede periods in which employment (by around 45%), average wages (by 8%), labor productivity (by 14%), capital intensity (by 18%), TFP (by 3%), and sales (by nearly 93%) all fall significantly. This suggests that PE firms exit their portfolio companies just before similar companies begin to experience significant stress, consistent either with industry-wide falls in demand or the possibility that control companies lost the battle with their PE-backed competitors.

3.4 Profitability

In addition to strong sales growth, there are two ways that the strategies that emerge from the previous sub-section can generate attractive returns to investors. First is EBITDA growth (EBITDA expansion): to the extent that PE firms keep the growth of operating costs below that of revenues, higher variable profits will translate into greater company value. Second, previously documented strategies may allow PE firms to exit portfolio companies at higher multiples (multiple expansion). While both are likely at play in generating returns, something that speaks for the multiple expansion channel is the fact that PE firms seem to exit just before industry-wide downturns. In this section, we look at changes in profitability: EBITDA as well as relative measures such as EBITDA margins and return on assets (ROA). (In ongoing work, we collect information on the EBITDA multiples at entry and exit to test the multiple expansion channel.)

Column 1 of Table 8 reports estimates of model (1) with EBITDA as the outcome variable. In line with previous literature, we find that profitability rises strongly under PE ownership. The point estimate indicates an increase of 52% relative to control companies on average (p=0.048). Portfolio companies continue to experience fast EBITDA growth even after PE funds exit – in fact, at twice the rate as during PE ownership. Notably, margins (column 2) and ROA (column 3) remain unchanged on average under PE ownership but then increase strongly following post-exit. We return to this pattern below, after we discuss the role of inorganic growth.

Columns 4 to 6 repeat the profitability analysis in the sample of organic deals. As before, EBITDA increases under PE ownership, but this effect is no longer statistically significant at conventional levels. This suggests that synergies from acquisitions can be a particularly important driver of profitability at portfolio companies. However, there could also be alternative mechanisms at play. For instance, our earlier results indicate that portfolio companies reduce markups while increasing scale and capital intensity, potentially at the expense of short-term profits. We therefore check how EBITDA, margins, and ROA evolve in each year following the first year of PE funding for the sample of organic deals. In particular, we estimate the following dynamic regression,

$$y_{it} = \beta_0 + \sum_{s=0}^{6+} \beta_s PE_i * postPE_{it}^s + \sum_{s=0}^{6+} \theta_s \, postPE_{it}^s + \gamma_i + \delta_t + \varepsilon_{it} \tag{2}$$

where $postPE_{it}^s$ equals 1 for year s after the first round of funding, with s=0, 1, 2, 3, 4, 5, and 6+. This specification allows us to decompose the main $PE_i * postPE_{it}$ effect documented earlier into year-by-year effects.

Figure 2 shows the results, with EBITDA in the top panel, margins in the middle panel, and ROA in the bottom panel. Profitability takes a considerable hit in the early years of PE ownership. As our sample mostly includes companies that can be classified as requiring expansion capital, this suggests that PE firms are willing to forgo profitability early on to focus on lowering prices relative to competitors and building market share. Over time, all three of EBITDA, margins, and ROA increase and significantly exceed pre-PE-ownership levels by year 5.

The long-term effect of PE ownership on profitability, as measured by $\beta_1 + \beta_3$ in equation (1), is significantly positive for both EBITDA and ROA, though not for margins. Finally, in line with our earlier observation that PE firms may be timing their exits, we find strong and significant downturns in profitability at control companies in the period following PE firm exits, whether we use EBITDA, margins, or ROA.

4. Which value creation strategies best explain returns?

We now turn to assess whether financial returns generated by PE funds go hand-in-hand with the value creation strategies studied in the previous section. We draw on proprietary deal-level cash flows, which allow us to relate the variation in returns to operational changes at the deal level. As our return measures, we use the three metrics introduced earlier: IRR, MOIC, and PME. We estimate cross-sectional company-level regressions of the form:

$$y_{it} = \alpha_0 + \alpha_1 [x_{i,exit} - x_{i,entry-1}] + \alpha_2 X_i + \delta_t^{entry} + \delta_t^{exit} + \varepsilon_{it} \quad (3)$$

where $[x_{i,exit} - x_{i,entry-1}]$ is a vector of company-level changes between the time of PE fund entry and exit, and X_i is a vector of controls including deal size and duration. We include a vector of company-level changes in our regressions that are chosen from variables that are most impacted by PE ownership as identified in the previous section.

It is possible that, in our sample, PE firms hold on to investments during a period of macroeconomic growth that coincides with ample liquidity and/or greater demand for PE assets. This can create a positive correlation between both operational improvements and investor returns. We therefore include time dummies for the years of entry and exit to capture the impact of market timing on returns.

We estimate equation (3) on a sample of fully realized investments and unrealized investments that have been held in a PE fund's portfolio for at least 5 years. (Excluding the latter category of unrealized investments does not change our results qualitatively, but reduces our sample size.) These regressions give us the relations between deal-level operational changes and investor returns. As these operational changes are highly correlated with each other – for instance, a high-growth firm sees its employment, revenues, productivity, and capital intensity all grow at the same time – we relate changes in each variable to returns one at a time.

Table 9 shows the results of model (3) when we relate portfolio company leverage and tax rates to deal-level returns for the full sample in Panel A and for organic deals only in Panel B. Across different specifications, we do not find strong evidence that changes in a portfolio company's debt position or tax rates while under PE ownership are associated with returns. Note that we construct leverage as the ratio of a portfolio company's debt to its total assets as reported on its balance sheet. As such, any debt raised by the PE fund for the financing of the deal – which is typically loaded on to a holding company for the target – does not appear in the accounts. We therefore interpret this result due to PE funds' ability to relieve portfolio companies' credit constraints, which does not seem associated with deal-level returns, as opposed to the more mechanical impact that deal leverage has on return on invested capital.

In Table 10, we relate changes in operational improvements in employment, labor productivity, capital intensity, and TFP to returns. Across the different specifications, we find very strong evidence that deals which experience higher growth in terms of labor productivity and TFP while under PE ownership also deliver higher returns for investors. For instance, the point estimate from column 4 suggests that a percentage point increase in TFP is associated with 17 percentage points higher IRR (p=0.018). Our point estimates (and R squareds) are typically larger when we focus on organic deals only in Panel B, suggesting that capital investment and efficiency improvements are especially important to explain returns for these deals. There is also some evidence that higher capital intensity and employment are associated with higher returns, but these relations are not always estimated with statistical precision.

Table 11 shows that improvements in working capital management are not associated with higher returns on average. What seems to matter instead, as Table 12 shows, is growth in the top line and market shares achieved by portfolio companies while under PE ownership. Column 1 suggests that each log point increase in the top line is associated with a 3.3 percentage points rise in IRR (p=0.003), 0.11 rise in the MOIC (p=0.008), and 0.07 rise in the PME on average (p=0.011). Interestingly, reductions in price markups are not directly relevant for explaining the variation in returns at the deal level. What seems to matter more for returns is that these markup reductions lead to gains in market share. Column 3 suggests that market share gains are strongly associated with returns. When we replicate our analysis for the sub-sample of organic deals only in Panel B, we find that the relations we identify are less strong. In other words, sales growth and market share gains seem to be especially important to generate financial returns for business strategies that involve growth through M&A.

Finally, in Table 13, we confirm the strong relation between changes in profitability while under PE ownership and returns. In both Panels A and B, changes in EBITDA, margins, and ROA are each strongly associated with our three financial return metrics. The coefficients are similar for the sub-sample of organic deals. These results indicate that investor returns are, to a significant degree, driven by operational improvements at portfolio companies, holding constant wider industry trends using the entry and exit year dummies.[17]

5. How do PE firms create value?

In ongoing work, we identify the channels through which fund managers realize operational efficiency improvements and changes in market power. To this end, we quantify soft information about value creation strategies as reported by the fund managers themselves and document how different strategies affect operational changes and returns at the company level.

The underlying information comes from the fund managers' quarterly reports and audited and internal financial statements. Of particular interest are fund managers' confidential comments regarding their value creation strategies and their ability to put their plans into action. Unlike accounting data, these comments are potentially difficult to verify (say, in the annual shareholders' meeting or in court) and thus constitute soft information.

Similar to the survey of Gompers et al. (2016), we design a template to collect soft information. We focus on changes at the portfolio company-level over the course of PE ownership and distinguish between (i) what the company would have done in any case and (ii) what the company did as a result of having accepted PE firm backing. We focus on those changes that can be objectively captured in a binary fashion and that two independent readers of

[17] This remains the case when we relate investor returns instead to company-level changes *relative* the contemporaneous changes experienced by the matched control companies. The results are report in the Online Appendix. They confirm the strong and positive relation between productivity growth and returns.

the monitoring reports could agree on.

Our soft information indicators capture the following categories: introduction of new products and services; expansion into new markets; capital investment; cost reductions; mergers, acquisitions and takeovers; introduction of new pricing strategies; quality management; customer service; customer loyalty; promotion and distribution; inventory turnover; working capital management; and debt. Each indicator equals 1 if in a given year the PE firm induced the change in question.

We use financial data from Orbis to validate the soft information reported by fund managers and test whether they have been successful in implementing their value creation strategies. For example, if a monitoring report states that a fund manager actively engages in upgrading physical assets in order to increase the company's output, then our Orbis data should indeed reflect an increase in property, plant, and equipment on the company's balance sheet.

6. Conclusions

We study how PE firms generate returns for their investors, focusing on four value-creation strategies: financial engineering, operational improvements, cash management, and top-line growth. Regarding the first strategy, we find that PE firms help portfolio companies increase their borrowing during their ownership. However, increased borrowing ability is not associated with investor returns. We confirm prior findings that PE ownership leads to operational efficiency and top-line growth: both labor productivity and TFP improve as PE-backed companies ramp up investment, employment, and sales. PE ownership also helps portfolio companies renegotiate faster payments from customers. Using detailed confidential information obtained from inside PE firms, we show that the PE firms in our sample push for operational improvements and that these improvements are the main drivers of the returns investors receive from PE funds. We find no evidence that PE-backed companies increase their market power. In fact, the PE-backed companies in our sample reduce their price markups by 6% on average.

We provide a first answer to the question, how persistent are the benefits of PE investment for portfolio companies? The answer matters greatly for both investors and target companies. If portfolio companies retain any competitive advantage they gain while under PE ownership, the value creation is more permanent in nature. Our results indicate that the majority of operational improvements that are instigated by PE firms remain beyond their investment period at a portfolio company. Finally, we find strong evidence that PE firms time their exits from portfolio companies to coincide with periods of industry downturns.

It is possible that the financial returns PE funds generate for their investors come from portfolio companies that they do not necessarily improve operationally. Likewise, there is no guarantee that operational improvements at a portfolio company will translate into higher returns for that deal. We show that this is not the case in our sample. To a great extent, the operational improvements instigated by PE funds go hand-in-hand with the investor returns they generate. In ongoing research, we quantify soft information gathered from quarterly reports of PE funds to their investors in order to pin down the exact mechanisms through which value creation takes place. Further research can shed light on whether PE firms specialize in certain value creation practices to generate returns.

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Appendix A. Variable definitions

Deal size is defined as the total cost of investment in a portfolio company by a fund; if there are multiple funds investing in a portfolio company, we sum up each fund's investment cost.

Fully realized is defined as a deal that been fully exited by a fund either through an initial public offering (IPO), a trade sale, or is written off.

Unrealized is defined as a deal that has not been fully exited.

<u>Financial engineering measures</u>

Leverage is defined as the ratio of short-term bank loans plus long-term debt (= total debt) to total assets.

Net debt to EBITDA is defined as the ratio of total debt minus cash to EBITDA.

Implicit interest rate is imputed as the ratio of interest expense to total debt.

Taxes paid is defined as the natural log of total taxes paid by the company.

Tax rate is imputed from 1 – earnings after tax / earnings before tax and winsorized at the bottom and top 5%.

<u>Operational measures</u>

Employment is defined as the natural log of the total number of full-time employees.

Average wage is defined as the natural log of the ratio of total staffing costs to employment.

Labor productivity is defined as the natural log of the value of company revenues per employee.

Net investment in fixed assets is the annual change in fixed assets net of depreciation and scaled by beginning-of-year nominal total assets.

Capital intensity is defined as the natural log of the ratio of fixed assets to employment.

Total factor productivity (TFP) captures the efficiency with which all inputs into production (labor, materials, and capital) are used. See Appendix B for details.

<u>Cash management measures</u>

Working capital is defined as the ratio of working capital to the sum of working capital and fixed assets.

Credit period is defined as the ratio of creditors account to operating revenue, multiplied by 360.

Collection period is defined as the ratio of debtors account to operating revenue, multiplied by 360.

Stock turnover is defined as the ratio of operating revenue to inventories.

Top line measures

Sales is defined as the natural log of annual operating revenue measured in USD.

Markup is defined as the natural log of the estimated ratio of price to marginal cost. See Appendix C for details of the estimation.

Market share is defined as the ratio of annual company sales to the total of annual sales by all companies in the same 4-digit NACE industry and country.

Profitability measures

EBITDA is defined as the natural log of a company's earnings before interest, taxes, depreciation, and amortization if it is positive, and minus the natural log of minus EBITDA if it is negative. Note that we replace EBITDA with EBIT whenever the former is missing.

EBITDA margin is defined as the ratio of EBITDA to sales.

Return on assets (*ROA*) is defined as the ratio of a company's net income to its total assets.

Appendix B. Estimating productivity

Assume production is given by $Y = L^{\beta_l} K^{\beta_k} M^{\beta_m} * \Omega$, where Ω is an unobserved technology parameter and *L*, *K,* and *M* are labor, capital, and materials, respectively. TFP is typically calculated as the residual in a Cobb-Douglas production function in logs:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} \tag{A.1}$$

where y_{it} denotes output, l_{it} denotes labor inputs, k_{it} denotes the capital stock, m_{it} denotes material inputs, and ω_{it} denotes unobserved productivity for company *i* at time *t*. The residual from a regression of output on the three inputs should therefore give us TFP. However, it is well known since Marschak and Andrews (1944) that such a regression suffers from endogeneity: input choices are correlated with the error term since companies are likely to choose their inputs based on their productivity, which is observed to the company but not to the econometrician. OLS estimates of the coefficients in equation (A.1) and the error term are then biased.

To address this endogeneity, researchers either follow the dynamic panel literature (as in Bharath et al. 2014) or use the more structural methods pioneered by Olley and Pakes (1994) and Levinsohn and Petrin (2003).[18] The latter use observed input decisions to control for unobserved productivity shocks. The two methods essentially differ in their assumptions about how unobserved productivity evolves to identify the coefficients in equation (A.1). In structural models, unobserved productivity follows an arbitrary first-order Markov process,

$$\omega_{i,t+1} = g(\omega_{it}) + \xi_{i,t+1}, \tag{A.2}$$

where $g(.)$ is any non-parametric function and $\xi_{i,t+1}$ is a shock to productivity. In contrast, dynamic panel models have to make the more restrictive assumption that the Markov process is parametric and linear.

Given their ability to accommodate arbitrary productivity processes, we estimate TFP using structural methods. We implement the methodology with a Cobb-Douglas production function as in equation (A.1), subject to the productivity process in equation (A.2). As companies may differ across countries or industries in the intensity with which they use each input, we estimate the production function separately for each country and industry pair.[19] This allows for differences in technology across industry-country pairs. We measure capital stock as the reported book value of fixed assets and labor inputs as total staffing costs.[20] We deflate all values by the appropriate country and industry level deflator, which transforms them into real values, stripped of the effect

[18] See Ackerberg et al. (2006) for a detailed discussion of problems encountered in the identification of production functions and how structural methods differ from the use of dynamic panel estimators.
[19] We use Rev. 2 of NACE as our industry grouping.
[20] We prefer using total staffing costs instead of number of employees. Staffing costs better capture the skill composition of a company's workforce assuming that more skilled employees get higher wages. Our TFP estimates are then less affected by the skill composition of a company's labor force.

of price changes.[21]

We closely follow Ackerberg et al. (2006) and De Loecker and Warzynski (2012) in obtaining estimates of the production function. Estimation proceeds in two stages. In a first stage, we obtain predicted output by estimating equation (A.1) via OLS and using the universe of companies available in the Orbis database. In a second stage, we compute the company's unobserved productivity ω_{it} using predicted output and regress it on a third-order polynomial approximation of past productivity (i.e., we approximate function $g(.)$ in equation (A.2) non-parametrically) to recover the productivity shocks $\xi_{i,t+1}$. The production-function coefficients are then identified by using standard GMM techniques on the following moment conditions:

$$E\left[\xi_{it}|l_{i,t-1}, k_{it}, m_{i,t-1}\right] = 0. \quad \text{(A.3)}$$

Once we obtain a consistent set of production-function coefficients, we calculate a company's time-varying (log) TFP as follows:

$$\widehat{\omega}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_m m_{it}. \quad \text{(A.4)}$$

We note that company-level expenditures on materials and staff costs are not always available in Orbis. In particular, some countries (Greece, Kazakhstan, Latvia, Lithuania, Russia, Turkey, and Ukraine) provide better coverage for total cost of goods sold than for materials and staff costs separately. In these cases, we follow De Loecker and Eeckhout (2017) and estimate a production function with two (rather than three) inputs. Specifically, for these subset of countries, we estimate the following production function by industry for this subset of countries:

$$y_{it} = \beta_k k_{it} + \beta_v v_{it} + \omega_{it} \quad \text{(A.5)}$$

[21] Deflators for capital goods and output are separately available for most of the countries in our sample at the 2-digit NACE Rev. 2 industry level either through Eurostat or the OECD. At its most detailed level, this corresponds to 64 industries, although deflators for capital goods are typically provided at a more aggregate level. Where Eurostat or the OECD does not provide deflators for sample countries, we rely on local sources such as national central banks and statistical institutes or the World Bank's World Development Indicators to obtain this information.

where v_{it} denotes total cost of goods sold, subject to the productivity process in equation (A.2). The two-step estimation procedure that uses the moment conditions in equation (A.3) and described above then yields consistent estimates of the coefficients on cost of goods sold alongside capital. We then calculate (log) TFP as:

$$\hat{\omega}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_v v_{it}. \quad \text{(A.6)}$$

Appendix C. Estimating price-cost markups

We follow De Loecker and Warzynski (2012) in deriving company-level markups from a production-function framework. De Loecker and Warzynski's approach assumes cost-minimizing producers who have access to a variable input of production (e.g., materials or labor) and relies on the insight that the output elasticity of this variable input equals its expenditure share in total revenue when price equals marginal production cost (i.e., when markup = price/marginal cost = 1). Under imperfect competition, companies can charge a price above marginal cost, thereby introducing a wedge between the input's revenue share and its output elasticity. The ratio of any input's output elasticity to the input's revenue share then provides a consistent estimate of a company's markup.

We obtain estimates of output elasticities for variable inputs from our production-function estimation as described in Appendix B. We choose materials as the variable input of production to calculate markups, since materials are more likely to respond to productivity shocks than labor, which is subject to potentially large hiring and firing costs. Using materials, we recover markups from:

$$\mu_{it} = \hat{\beta}_m / \alpha_{it}^M \quad \text{(A.7)}$$

where $\hat{\beta}_m$ is the estimated output elasticity of materials from equation (A.1) and α_{it}^M is the share of expenditures on materials in total company revenue. Following De Loecker and Warzynski (2012), we correct markup estimates for the presence of measurement error in revenues. That is, we calculate α_{it}^{M} as the ratio of reported expenditures on materials to predicted company revenues from equation (A.1).

As mentioned in Appendix B, countries vary in terms of their reporting of materials and staffing costs in the Orbis database. The methodology by De Loecker and Warzynski (2012) allows one to estimate markups consistently using the cost of goods sold alongside capital when a more detailed breakdown of variable input use – i.e., labor costs and material costs – is not available. We therefore follow De Loecker and Eeckhout (2017) in calculating markups based on estimates from a production function with two inputs for the set of countries listed in Appendix B. In particular, the price-cost markup in these countries is given by:

$$\mu_{it} = \hat{\beta}_v / \alpha_{it}^{V}$$

where $\hat{\beta}_v$ is the estimated output elasticity of cost of goods sold from equation (A.5) and α_{it}^{V} is the share of cost of goods sold in total company revenues. We again correct markup estimates for the presence of measurement error as in De Loecker and Eeckhout (2017).

Ideally, we would like to have quantity data on output and inputs so that price differences across companies (e.g., due to variation in quality or transfer pricing) do not distort estimation. De Loecker and Warzynski (2012) show that when relying on company revenue data, only the level of the markup is potentially affected by lack of data on physical output, but not the estimate of the correlation between markups and company-level characteristics or how markups change within a company over time. This means that we are fortunate: while we do not observe measures of physical output, our focus is on understanding how a portfolio company's markups change over time and how this change correlates with other company-level characteristics.

Table 1. Sample overview

The sample consists of 1,444 investments by 178 private equity funds investing in Central and Eastern Europe and the Central Asian republics of the former Soviet Union as well as North Africa. The private equity funds were raised and closed between 1992 and 2017 and made investments between 1992 and 2017. We track each investment through the earlier of the final outcome or December 2017 and record whether it has been "fully realized" (through an IPO or a trade sale, or written off) or "unrealized" as of December 2017. Tracking each investment over time gives us an unbalanced panel.

Country	1992-1996	1997-2001	2002-2006	2007-2011	2012-2017	Fully realized	Unreal-ized	All deals
Panel A. Number of Deals								
Bosnia & Herzegovina		4	5	1	2	10	2	12
Bulgaria	1	12	12	24	7	44	12	56
Croatia		9	5	4	6	15	9	24
Czech Republic	12	33	15	30	12	83	19	102
Estonia	2	22	16	8	19	44	23	67
FYR Macedonia		12	3		4	16	3	19
Greece			2	3	12	2	15	17
Hungary	11	40	13	10	4	74	4	78
Kazakhstan		12	1	5	14	18	14	32
Latvia		6	13	3	7	17	12	29
Lithuania	1	23	4	5	4	31	6	37
Morocco					22	3	19	22
Poland	49	91	31	53	53	201	76	277
Romania	3	32	17	27	21	69	31	100
Russia	35	99	46	62	82	207	117	324
Serbia			2	2	14	4	14	18
Slovak Republic		15	3	3	5	21	5	26
Slovenia	7	15	1	4	4	23	8	31
Turkey			3	12	75	15	75	90
Ukraine	26	12	9	14	22	56	27	83
All countries	151	433	203	268	389	953	491	1,444
Panel B. Deal size (USD millions)								
Mean	3.96	4.94	14.78	26.85	17.79	9.74	21.26	13.90
Median	2.02	2.22	5.58	13.85	9.21	3.27	10.68	5.40

Table 2. Pre-transaction characteristics of portfolio and control companies
This table reports summary statistics on company-level variables used in the baseline analysis. Panel A reports statistics for portfolio companies of PE firms, while Panel B reports statistics for the baseline matched control companies. For each company in the sample, each variable is averaged over the three years preceding the first year of PE funding. All dollar amounts are reported in thousands.

	Mean	p25	Median	p75	S.D.
Panel A. Portfolio companies					
Financial engineering measures					
Leverage (%)	0.19	0.01	0.14	0.32	0.19
Net debt to EBITDA	1.15	-0.45	0.43	2.49	3.10
Implicit interest rate (%)	0.12	0.05	0.09	0.14	0.12
Taxes paid (USD)	224.34	1.01	66.26	274.93	377.97
Tax rate (%)	0.14	0.00	0.14	0.22	0.13
Operational measures					
Employment	197	33	100	273	241
Average wages (USD)	13.39	6.21	10.23	19.93	9.87
Labor productivity (USD)	130.16	38.75	80.65	171.33	135.35
Net investment (%)	0.04	-0.01	0.01	0.07	0.10
Capital intensity (USD)	56.48	6.67	21.05	64.30	90.75
TFP	1.59	0.95	1.49	2.21	0.79
Cash management measures					
Working capital (%)	0.33	0.07	0.29	0.55	0.30
Credit period (days)	49.71	15.18	39.33	67.77	49.77
Collection period (days)	61.15	22.60	46.53	80.36	58.31
Stock turnover	57.94	6.73	14.86	57.68	102.27
Top line measures					
Sales (USD)	20,968	3,021	10,129	24,434	30,019
Markup	1.91	0.93	1.14	1.62	2.08
Market share (%)	0.05	0.00	0.02	0.08	0.07
Profitability measures					
EBITDA (USD)	1,863	65	738	2,531	2,863
EBITDA margin	0.10	0.03	0.08	0.15	0.11
Return on assets (%)	0.05	0.00	0.04	0.10	0.09

Table 2 (continued). Pre-transaction characteristics of portfolio and control companies

	Mean	p25	Median	p75	S.D.
Panel B. Baseline control companies					
Financial engineering measures					
Leverage (%)	0.13	0.00	0.03	0.20	0.18
Net debt to EBITDA	0.49	-0.80	-0.01	1.33	3.45
Implicit interest rate (%)	0.13	0.05	0.09	0.16	0.14
Taxes paid (USD)	161.19	0.39	24.90	155.47	320.96
Tax rate (%)	0.14	0.00	0.13	0.23	0.14
Operational measures					
Employment	164	18	70	197	239
Average wages (USD)	12.75	5.10	10.24	17.75	9.73
Labor productivity (USD)	131.28	34.32	78.58	171.75	142.07
Net investment (%)	0.03	-0.02	0.00	0.06	0.08
Capital intensity (USD)	63.35	7.86	23.69	66.79	102.18
TFP	1.52	0.91	1.47	2.02	0.75
Cash management measures					
Working capital (%)	0.37	0.08	0.31	0.63	0.33
Credit period (days)	48.04	8.21	32.22	63.30	55.69
Collection period (days)	63.59	20.13	45.37	83.63	63.47
Stock turnover	43.45	5.88	12.06	35.22	83.95
Top line measures					
Sales (USD)	17,784	1,301	6,171	19,634	29,427
Markup	1.82	0.93	1.14	1.64	1.91
Market share (%)	0.04	0.00	0.01	0.04	0.06
Profitability measures					
EBITDA (USD)	1,265	17	306	1,422	2,335
EBITDA margin	0.08	0.02	0.07	0.14	0.11
Return on assets (%)	0.05	0.00	0.03	0.09	0.09

Table 3. Returns in the Orbis sample

This table reports summary statistics on deal-level investor returns for the Orbis sample of companies with the necessary data to allow estimation of productivity and markups. IRR stands for internal rate of return, MOIC stands for money on invested capital, and PME stands for public market equivalent.

	Number of deals	IRR (%)		MOIC		PME	
		Mean	Median	Mean	Median	Mean	Median
All	898	9.12	7.83	1.74	1.27	1.16	0.90
Fully realized	523	7.27	8.74	2.00	1.49	1.19	0.89
Unrealized	375	11.44	6.97	1.41	1.12	1.11	0.91

Table 4. Value creation channels: Financial engineering

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Standard errors are clustered at the company level. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Leverage (1)	Net debt to EBITDA (2)	Implicit interest rate (3)	Taxes paid (4)	Tax rate (5)
β_1: *PE* x *postPE*	0.038***	0.342	0.011	0.290**	-0.014**
	0.011	*0.255*	*0.013*	*0.134*	*0.007*
β_2: *postPE*	0.006	0.159	0.002	-0.155***	-0.000
	0.005	*0.120*	*0.008*	*0.057*	*0.003*
β_3: *PE* x *postPE* x*exit*	-0.016	-0.324	0.039**	0.356*	0.023***
	0.015	*0.375*	*0.019*	*0.190*	*0.008*
β_4: *postPE* x*exit*	-0.021***	-0.250	0.006	-0.616***	-0.017***
	0.007	*0.187*	*0.010*	*0.079*	*0.004*
$\beta_1 + \beta_3$	0.022	0.018	0.050**	0.646***	0.009
	0.017	*0.400*	*0.022*	*0.200*	*0.010*
R-squared	0.010	0.003	0.036	0.037	0.020
Number of obs.	34,121	31,870	14,983	27,943	42,677

Table 5. Value creation channels: Operational improvements

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Standard errors are clustered at the company level. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Employment	Average wage	Labor productivity	Net investment	Capital intensity	TFP
	(1)	(2)	(3)	(4)	(5)	(6)
β_1: *PE* x *postPE*	0.371***	0.138***	0.172***	-0.002	0.287***	0.040**
	0.060	*0.040*	*0.044*	*0.007*	*0.066*	*0.019*
β_2: *postPE*	0.046*	0.013	-0.080***	-0.013***	-0.082**	-0.031***
	0.026	*0.020*	*0.022*	*0.003*	*0.034*	*0.009*
β_3: *PE* x *postPE* x *exit*	0.125	0.121**	0.118**	-0.006	-0.107	0.022
	0.090	*0.048*	*0.054*	*0.008*	*0.092*	*0.024*
β_4: *postPE* x *exit*	-0.373***	-0.076***	-0.129***	0.011***	-0.169***	-0.032**
	0.040	*0.023*	*0.029*	*0.004*	*0.044*	*0.013*
$\beta_1 + \beta_3$	0.496***	0.259***	0.290***	-0.008	0.180	0.062**
	0.108	*0.061*	*0.069*	*0.010*	*0.112*	*0.029*
R-squared	0.071	0.371	0.155	0.098	0.159	0.010
Number of obs.	33,417	19,883	30,993	20,649	30,278	31,615

Table 6. Value creation channels: Cash management

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Standard errors are clustered at the company level. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Working capital (1)	Credit period (2)	Collection period (3)	Stock turnover (4)
β_1: *PE* x *postPE*	-0.039***	-4.490	-8.602**	-1.018
	0.013	*2.888*	*3.466*	*6.269*
β_2: *postPE*	0.012*	0.467	2.095	-3.070
	0.007	*1.689*	*1.866*	*3.195*
β_3: *PE* x *postPE* x*exit*	0.012	-2.976	-5.555	5.502
	0.020	*4.030*	*4.419*	*9.128*
β_4: *postPE* x*exit*	0.018*	4.305*	2.332	-2.380
	0.010	*2.254*	*2.724*	*4.232*
$\beta_1 + \beta_3$	-0.027	-7.466	-14.157***	4.484
	0.023	*4.749*	*5.182*	*9.995*
R-squared	0.004	0.016	0.020	0.004
Number of obs.	35,908	37,842	39,492	34,194

Table 7. Value creation channels: Top line growth

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Standard errors are clustered at the company level. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

				Organic deals only		
	Sales (1)	Markup (2)	Market share (3)	Sales (4)	Markup (5)	Market share (6)
β_1: *PE* x *postPE*	0.644***	-0.056***	0.015***	0.614***	-0.053**	0.010***
	0.067	*0.021*	*0.003*	*0.073*	*0.023*	*0.003*
β_2: *postPE*	-0.019	0.012	-0.001	-0.011	0.014	-0.000
	0.034	*0.011*	*0.001*	*0.037*	*0.012*	*0.001*
β_3: *PE* x *postPE* x *exit*	0.252**	-0.012	-0.003	0.245**	0.009	-0.002
	0.111	*0.034*	*0.005*	*0.118*	*0.036*	*0.006*
β_4: *postPE* x *exit*	-0.666***	0.031*	-0.003	-0.625***	0.024	-0.004*
	0.052	*0.018*	*0.002*	*0.056*	*0.020*	*0.002*
$\beta_1 + \beta_3$	0.896***	-0.068*	0.012**	0.859***	-0.044	0.008
	0.127	*0.039*	*0.006*	*0.136*	*0.041*	*0.007*
R-squared	0.152	0.028	0.074	0.147	0.033	0.079
Number of obs.	40,988	33,021	40,989	34,373	27,519	34,099

Table 8. Profitability

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

				Organic deals only		
	EBITDA (1)	EBITDA margin (2)	Return on assets (3)	EBITDA (4)	EBITDA margin (5)	Return on assets (6)
β_1: *PE* x *postPE*	0.423**	-0.003	-0.005	0.293	-0.005	-0.005
	0.214	*0.007*	*0.005*	*0.232*	*0.007*	*0.006*
β_2: *postPE*	-0.211**	-0.007**	-0.008***	-0.231**	-0.008**	-0.007***
	0.093	*0.003*	*0.002*	*0.102*	*0.004*	*0.003*
β_3: *PE* x *postPE* x *exit*	0.944***	0.018*	0.029***	0.950***	0.019*	0.031***
	0.302	*0.009*	*0.007*	*0.330*	*0.010*	*0.007*
β_4: *postPE* x *exit*	-1.080***	-0.020***	-0.012***	-1.045***	-0.019***	-0.012***
	0.135	*0.005*	*0.003*	*0.146*	*0.005*	*0.004*
$\beta_1 + \beta_3$	1.367***	0.016	0.024***	1.243***	0.013	0.026***
	0.337	*0.010*	*0.008*	*0.363*	*0.011*	*0.009*
R-squared	0.023	0.015	0.018	0.022	0.016	0.019
Number of obs.	39,109	38,737	41,169	33,045	32,196	33,995

Table 9. Financial engineering and investor returns

This table reports regression results of equation (3) estimated on the cross-section of portfolio companies. For variable definitions and details of their construction see Appendix A. All regressions include (log) deal size, (log) deal duration, and entry and exit year fixed effects. Heteroskedasticity consistent standard errors are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	IRR (1)	IRR (2)	MOIC (3)	MOIC (4)	PME (5)	PME (6)
Panel A. All deals						
Leverage	0.012		-0.035		0.109	
	0.111		*0.329*		*0.218*	
Tax rate		0.170		1.153***		0.431
		0.129		*0.445*		*0.286*
R-squared	0.228	0.227	0.257	0.285	0.159	0.161
Number of obs.	342	396	342	396	342	396
Panel B. Organic deals only						
Leverage	-0.006		-0.209		0.002	
	0.129		*0.363*		*0.244*	
Tax rate		0.104		0.886*		0.162
		0.152		*0.503*		*0.316*
R-squared	0.268	0.251	0.276	0.310	0.203	0.194
Number of obs.	278	324	278	324	278	324

Table 10. Operational improvements and investor returns

This table reports regression results of equation (3) estimated on the cross-section of portfolio companies. For variable definitions and details of their construction see Appendix A. All regressions include (log) deal size, (log) deal duration, and entry and exit year fixed effects. Heteroskedasticity consistent standard errors are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	IRR (1)	IRR (2)	IRR (3)	IRR (4)	MOIC (5)	MOIC (6)	MOIC (7)	MOIC (8)	PME (9)	PME (10)	PME (11)	PME (12)
Panel A. All deals												
Employment	0.039				0.199***				0.105**			
	0.025				*0.076*				*0.050*			
Labor productivity		0.083***				0.259***				0.226***		
		0.031				*0.094*				*0.067*		
Capital intensity			0.043*				0.171**				0.091*	
			0.026				*0.068*				*0.047*	
TFP				0.166**				0.489**				0.320**
				0.070				*0.195*				*0.135*
R-squared	0.275	0.338	0.315	0.251	0.303	0.364	0.361	0.292	0.238	0.289	0.240	0.215
Number of obs.	278	260	256	286	278	260	256	286	278	260	256	286
Panel B. Organic deals only												
Employment	0.035				0.157*				0.088			
	0.031				*0.083*				*0.056*			
Labor productivity		0.097**				0.223**				0.226***		
		0.039				*0.101*				*0.076*		
Capital intensity			0.046				0.177**				0.119**	
			0.032				*0.078*				*0.055*	
TFP				0.266**				0.644**				0.403**
				0.103				*0.264*				*0.185*
R-squared	0.292	0.381	0.351	0.313	0.319	0.406	0.402	0.330	0.258	0.347	0.286	0.266
Number of obs.	233	211	206	227	233	211	206	227	233	211	206	227

Table 11. Cash management and investor returns

This table reports regression results of equation (3) estimated on the cross-section of portfolio companies. For variable definitions and details of their construction see Appendix A. All regressions include (log) deal size, (log) deal duration, and entry and exit year fixed effects. Heteroskedasticity consistent standard errors are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	IRR (1)	IRR (2)	MOIC (3)	MOIC (5)	PME (5)	PME (6)
Panel A. All deals						
Working capital	-0.046		-0.240		-0.236*	
	0.071		*0.224*		*0.139*	
Collection period		-0.000		-0.001		-0.001
		0.000		*0.001*		*0.001*
R-squared	0.210	0.252	0.264	0.278	0.186	0.179
Number of obs.	369	364	369	364	369	364
Panel B. Organic deals only						
Working capital	-0.018		0.065		-0.123	
	0.087		*0.241*		*0.157*	
Collection period		0.000		-0.000		0.000
		0.000		*0.001*		*0.001*
R-squared	0.232	0.294	0.283	0.310	0.210	0.228
Number of obs.	301	294	301	294	301	294

Table 12. Top line growth and investor returns

This table reports regression results of equation (3) estimated on the cross-section of portfolio companies. For variable definitions and details of their construction see Appendix A. All regressions include (log) deal size, (log) deal duration, and entry and exit year fixed effects. Heteroskedasticity consistent standard errors are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	IRR (1)	IRR (2)	IRR (3)	MOIC (4)	MOIC (5)	MOIC (6)	PME (7)	PME (8)	PME (9)
Panel A. All deals									
Sales	0.033***			0.112***			0.066**		
	0.011			*0.042*			*0.026*		
Markup		-0.055			-0.166			-0.119	
		0.042			*0.143*			*0.102*	
Market share			0.698***			3.472***			1.652***
			0.221			*0.839*			*0.545*
R-squared	0.244	0.262	0.237	0.297	0.300	0.311	0.224	0.230	0.227
Number of obs.	365	300	356	365	300	356	365	300	356
Panel B. Organic deals only									
Sales	0.031*			0.072			0.052		
	0.016			*0.048*			*0.033*		
Markup		-0.045			-0.133			-0.099	
		0.046			*0.154*			*0.118*	
Market share			0.630*			1.822*			0.815
			0.348			*1.086*			*0.781*
R-squared	0.258	0.315	0.246	0.312	0.353	0.309	0.244	0.285	0.231
Number of obs.	302	243	294	302	243	294	302	243	294

Table 13. Profitability and investor returns

This table reports regression results of equation (3) estimated on the cross-section of portfolio companies. For variable definitions and details of their construction see Appendix A. All regressions include (log) deal size, (log) deal duration, and entry and exit year fixed effects. Heteroskedasticity consistent standard errors are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	IRR (1)	IRR (2)	IRR (3)	MOIC (4)	MOIC (5)	MOIC (6)	PME (7)	PME (8)	PME (9)
Panel A. All deals									
EBITDA	0.015***			0.031***			0.026***		
	0.004			*0.011*			*0.008*		
EBITDA margin		0.382***			1.089***			0.762***	
		0.111			*0.316*			*0.192*	
Return on assets			0.702***			2.136***			1.598***
			0.165			*0.587*			*0.354*
R-squared	0.225	0.261	0.251	0.272	0.290	0.305	0.213	0.195	0.220
Number of obs.	367	362	388	367	362	388	367	362	388
Panel B. Organic deals only									
EBITDA	0.017***			0.042***			0.030***		
	0.005			*0.012*			*0.009*		
EBITDA margin		0.439***			1.306***			0.939***	
		0.134			*0.352*			*0.215*	
Return on assets			0.790***			2.421***			1.765***
			0.199			*0.612*			*0.369*
R-squared	0.246	0.302	0.271	0.297	0.324	0.332	0.234	0.258	0.266
Number of obs.	312	294	312	312	294	312	312	294	312

Figure 1. Quantile regression estimates

This figure reports quantile regression estimates from a sample of organic deals. The red line indicates the baseline OLS estimate. Dashed lines indicate the confidence interval at the 95% level. Standard errors are bootstrapped.

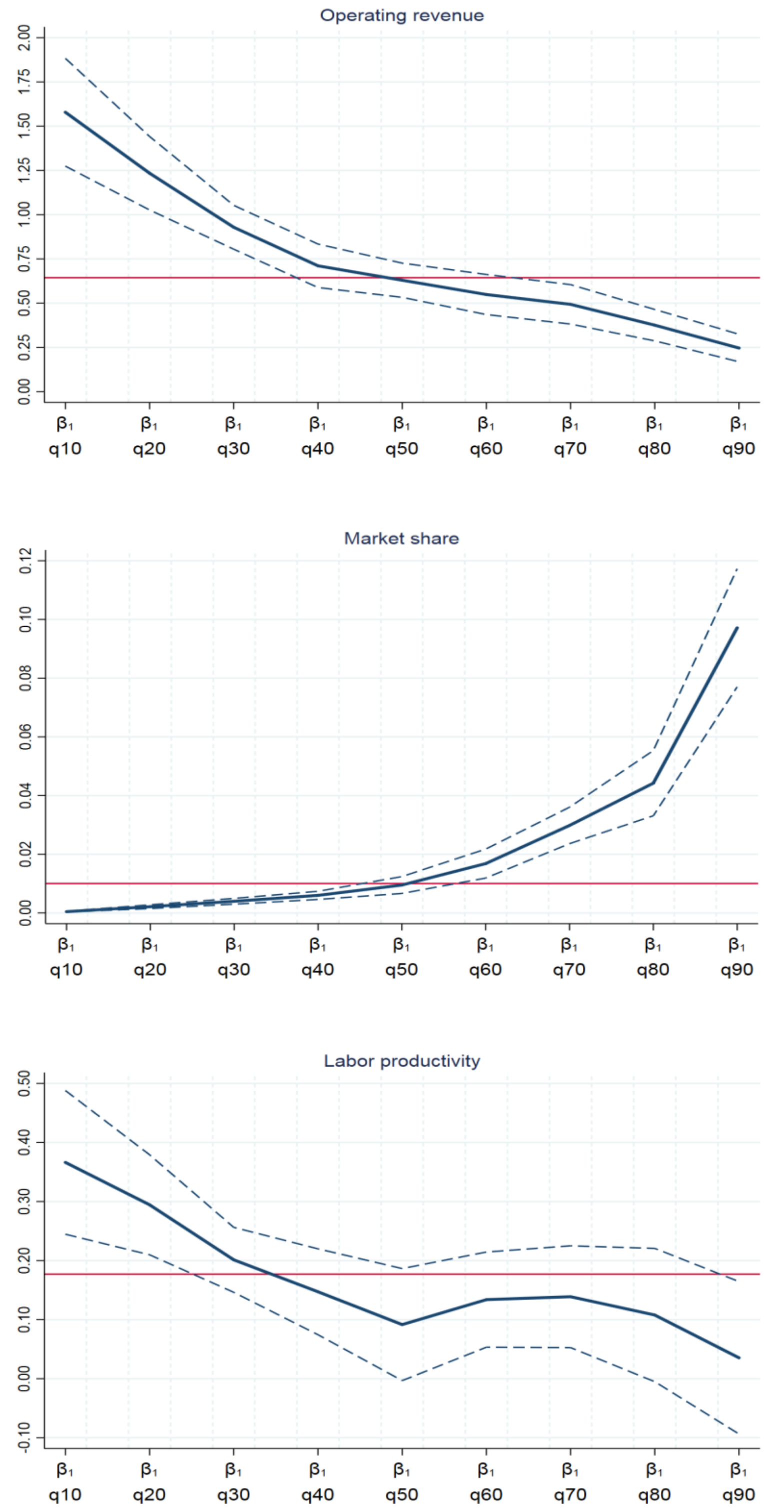
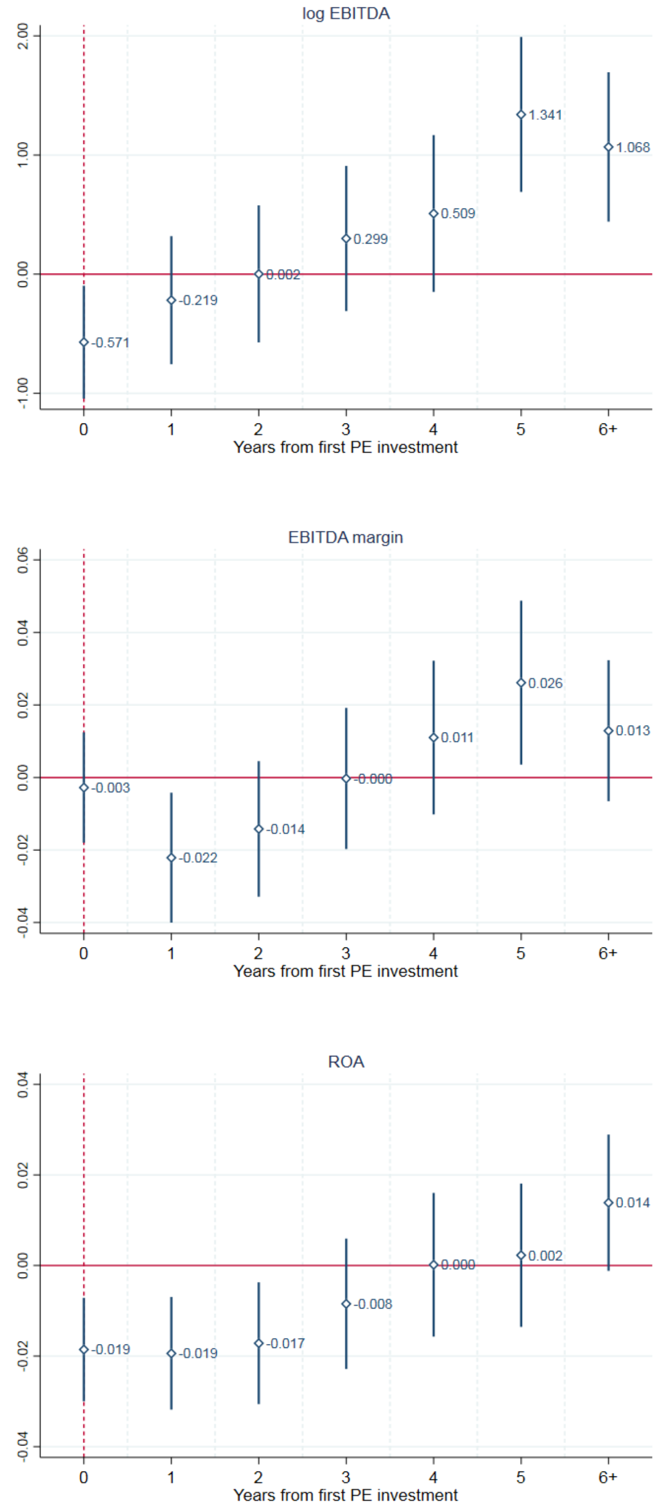


Figure 2. Dynamic regression estimates

This figure reports regression estimates from equation (2) estimated on a sample of organic deals only.



Value Creation and Persistence in Private Equity [†]

ONLINE APPENDIX
NOT INTENDED FOR PUBLICATION

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IA.1 Dataset construction

This appendix describes the details of our dataset. We first describe how we construct company-level datasets for each country from Orbis and checks we carry out to ensure that the resulting datasets are reliable. We then describe the details of the production function estimation and report summary statistics on our production function estimates.

IA.1.1 Sample selection

We apply some filters to our raw data. First, we remove investments that are based outside EBRD's region or investments in equities listed on a foreign exchange. Our raw dataset of portfolio companies contains entries from outside the EBRD's region in some rare cases. For instance, a private equity fund with a focus on Eastern Europe might have invested in a small start-up located in the US, which has back office functions in the region. Funds could also have invested in equities publicly listed on foreign exchanges. Such investments are removed from our analysis. Second, we eliminate all investments where we cannot identify a match in the Orbis database or the date of first private equity funding received.

IA.1.2 Estimating the production function

We first deflate all variables in Orbis using appropriate country-by-industry deflators in order to estimate the production function. We work with these deflated values in the rest of the analysis. We estimate a production function for each industry and country pair in which private equity funds in our sample have acquired at least one portfolio company. Because data observability affects number of companies included in the estimation for each industry-country pair, we pool together a few industries to ensure that estimation is done on at least 1,000 company-year observations.

Table IA.1. Comparing the full sample and the Orbis sample

This table reports summary statistics on deal-level investor returns for the full sample and the Orbis sample of companies with the necessary data to allow estimation of productivity and markups. IRR stands for internal rate of return, MOIC stands for money on invested capital, and PME stands for public market equivalent.

		IRR (%)		MOIC		PME	
	N	Mean	Median	Mean	Median	Mean	Median
Panel A: Full sample							
All	1,444	7.97	6.24	1.62	1.19	1.22	0.90
Fully realized	953	4.85	5.96	1.76	1.28	1.29	0.88
Unrealized	491	13.27	6.46	1.38	1.11	1.09	0.90
Panel B: Orbis sample							
All	898	9.12	7.83	1.74	1.27	1.16	0.90
Fully realized	523	7.27	8.74	2.00	1.49	1.19	0.89
Unrealized	375	11.44	6.97	1.41	1.12	1.11	0.91

Panel C: Two-sample *t*-tests of equality of means (full sample less Orbis sample)

	t-stat	*p*-value	*t*-stat	*p*-value	*t*-stat	*p*-value
All	-0.71	0.47	-1.36	0.17	0.93	0.35
Fully realized	-1.04	0.30	-1.81	0.07	0.97	0.33
Unrealized	0.73	0.47	-0.29	0.77	-0.24	0.81

Table IA.2. Summary statistics on markup estimation

This table reports summary statistics on company-level markups from the estimation of a Cobb-Douglas production function by industry and country in our sample. Observations indicate the number of company-year entries for which markups are calculated. Number of industries shows for each country how many industries the production function is separately estimated.

	Mean	Median	Std. Dev	Observations	Number of industries
Bosnia & Herzegovina	1.73	1.22	1.82	11,380	4
Bulgaria	5.96	4.01	5.63	470,124	14
Croatia	1.24	1.11	0.50	417,322	10
Czech Republic	1.75	1.13	2.00	658,647	33
Estonia	1.61	1.19	1.51	247,204	20
Greece	1.40	1.23	0.75	44,759	8
Hungary	2.66	1.26	3.35	114,072	15
Kazakhstan	1.17	1.12	0.87	5,222	3
Latvia	1.18	1.14	0.23	136,481	10
Lithuania	1.22	1.18	0.34	61,018	6
FYR Macedonia	7.93	5.07	8.64	59,441	8
Morocco	1.68	1.12	1.75	72,053	7
Poland	2.70	1.25	3.95	720,829	40
Romania	1.73	1.07	1.79	2,635,395	34
Russia	1.16	1.11	0.23	4,103,615	48
Serbia	1.40	1.07	1.04	236,603	8
Slovak Republic	2.15	1.32	2.25	294,958	13
Slovenia	2.08	1.21	2.21	146,356	13
Turkey	1.14	1.13	0.13	108,054	17
Ukraine	1.30	1.25	0.33	1,773,220	27

Table IA.3. Financial engineering – organic deals only

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Standard errors are clustered at the company level. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Leverage (1)	Net debt to EBITDA (2)	Implicit interest rate (3)	Taxes paid (4)	Tax rate (5)
β_1: *PE* x *postPE*	0.036***	0.358	0.018	0.278*	-0.017**
	0.012	*0.273*	*0.015*	*0.145*	*0.007*
β_2: *postPE*	0.006	0.165	0.002	-0.130**	0.000
	0.005	*0.132*	*0.008*	*0.061*	*0.003*
β_3: *PE* x *postPE* x*exit*	-0.026	-0.729*	0.035	0.382*	0.024**
	0.017	*0.404*	*0.022*	*0.206*	*0.009*
β_4: *postPE* x*exit*	-0.019**	-0.100	0.010	-0.626***	-0.016***
	0.008	*0.197*	*0.011*	*0.085*	*0.005*
$\beta_1 + \beta_3$	0.010	-0.370	0.053**	0.659***	0.006
	0.019	*0.428*	*0.025*	*0.221*	*0.011*
R-squared	0.009	0.002	0.024	0.032	0.018
Number of obs.	28,322	26,446	12,535	23,701	35,534

Table IA.4. Operational improvements – organic deals only

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Standard errors are clustered at the company level. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Employment (1)	Average wage (2)	Labor productivity (3)	Net investment (4)	Capital intensity (5)	TFP (6)
β_1: *PE* x *postPE*	0.322***	0.138***	0.177***	0.003	0.265***	0.040**
	0.061	*0.046*	*0.049*	*0.008*	*0.074*	*0.020*
β_2: *postPE*	0.059**	0.028	-0.078***	-0.013***	-0.088**	-0.038***
	0.028	*0.022*	*0.025*	*0.004*	*0.037*	*0.010*
β_3: *PE* x *postPE* x *exit*	0.159*	0.123**	0.087	-0.006	-0.157	0.026
	0.091	*0.055*	*0.059*	*0.009*	*0.103*	*0.026*
β_4: *postPE* x *exit*	-0.381***	-0.056**	-0.108***	0.013***	-0.138***	-0.038***
	0.044	*0.025*	*0.032*	*0.004*	*0.048*	*0.015*
$\beta_1 + \beta_3$	0.481***	0.261***	0.264***	-0.003	0.108	0.066**
	0.109	*0.070*	*0.076*	*0.011*	*0.124*	*0.029*
R-squared	0.065	0.362	0.154	0.092	0.153	0.012
Number of obs.	27,938	16,608	25,742	17,163	25,165	26,228

Table IA.5. Cash management – organic deals only

This table reports difference-in-differences regression results of the effect of receiving private equity funding on company-level outcomes. The sample includes both realized and unrealized deals and each deal's matched control group of companies. For variable definitions and details of their construction see Appendix A. All regressions include company and year fixed effects. Standard errors are clustered at the company level. Heteroskedasticity consistent standard errors clustered at the company level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Working capital (1)	Credit period (2)	Collection period (3)	Stock turnover (4)
β_1: *PE* x *postPE*	-0.040***	-4.773	-12.031***	-0.088
	0.014	*3.287*	*3.878*	*6.401*
β_2: *postPE*	0.017**	0.381	2.888	-5.188
	0.008	*1.861*	*2.085*	*3.350*
β_3: *PE* x *postPE* x *exit*	0.015	-5.706	-6.922	-1.030
	0.022	*4.465*	*4.818*	*8.400*
β_4: *postPE* x *exit*	0.019*	5.290**	3.553	-2.222
	0.011	*2.519*	*2.973*	*4.323*
$\beta_1 + \beta_3$	-0.025	-10.479**	-18.952***	-1.118
	0.026	*5.256*	*5.533*	*9.378*
R-squared	0.005	0.018	0.026	0.004
Number of obs.	29,820	31,390	32,822	28,535