CERGE
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Charles University Prague

Essays on Access to External Finance, Acquisitions and Productivity

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Dissertation

Prague, February 2013

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Acknowledgments

To my family and everybody who supported me:

I am deeply thankful to my advisor, Jan Bena, whose invaluable supervision, patience, enthusiasm and encouragement helped me to complete this dissertation. I would also like to thank Eva Vourvachaki, Štepán Jurajda and Jan Hanousek for their insightful comments, suggestions, questions and perfect guidance and the referees, Boyan Jovanovic and Hernan Ortiz-Molina, for their comments and suggestions.

This dissertation benefited from financial support from grant No. 69910 of the Grant Agency of the Charles University, grant No. 10-1491 of the Economics Education & Research Consortium and grant No. 403-111-2293 of the Grant Agency of the Czech Republic.

Last but not the least, I am grateful for the institutional support of CERGE-EI, Charles University and Czech Academy of Sciences. A very big thanks goes to all perfect people at CERGE-EI who made my time there unforgetable.

The Czech Republic, Prague Peter
February 2013

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Abstract

This thesis consists of three chapters that are empirical investigations of classical questions in the financial and industrial economics literature on the influence of institutions and industry conditions on the firm's access to finance, the propensity to merge, and productivity.

In the first chapter, coauthored with Jan Bena, we examine whether financial markets development facilitates the efficient allocation of resources. Using European micro-level data for 1996-2005, we show that firms in industries with high growth opportunities use more external finance in financially more developed countries. This result is particularly strong for firms that are more likely to be financially constrained and dependent on domestic financial markets, such as small and young firms. Our findings are robust to controlling for technological determinants of external finance needs and to using different proxies for growth opportunities.

In the second chapter, I investigate the role of productivity in the selection of firms into acquisitions and whether acquisitions lead to productivity gains. Using matching methodology and a large dataset of domestic acquisitions among public and private firms in Europe over the period 1998-2008, I find that first, targets are under-performing before engaging in horizontal acquisitions; second, there is positive assortative matching in revenue productivity for firms engaging in vertical acquisitions; and third, economically and statistically significant productivity gains exist only for targets acquired in horizontal acquisitions. Overall, the results for horizontal deals are consistent with the Q-theory of mergers, which assumes asset substitutability. The results for vertical deals, in which firms' assets are likely to be complements, are consistent with the search and matching model built on the property rights theory of the firm.

In the third chapter, coauthored with Jan Bena and Eva Vourvachaki, we examine the impact of market liberalization, e.g. the removal of state monopolies and entry barriers commanded by the European Commission as part of the Single Market Program, on the productivity of utilities, transport and telecommunication services in a set of European countries. Exploiting the variation in the timing and degree of liberalization efforts across countries and industries, we find that liberalization has increased firm-level productivity but has had no reallocation impact. Based on our estimates, the average firm-level productivity gain from liberalization amounts to 38 percent of the average within-firm productivity gain in network industries over 1998-2007. Our results underscore the growth-promoting role of liberalization efforts.

Abstrakt

Tato dizertace obsahuje tři kapitoly, ve kterých jsou empiricky zkoumány klasické otázky finanční a industriální ekonomie o vlivu institucí a odvětvových podmínek na schopnost firem získat financování, jejich sklon k akvizicím a jejich produktivitu.

V první kapitole, spolu s Janem Benou, zkoumáme, jestli rozvoj finančních trhů vede efektivnější alokaci zdrojů. S využitím dat o Evropských společnostech za období 1996-1995, jsme ukázali, že firmy v odvětvích s největšími růstovými příležitosti využívají více externích finančních zdrojů, pokud působí v krajinách s rozvinutými finančními trhy. Tento výsledek je obzvláště silný pro malé a mladé firmy, které mají vyšší šanci omezeného přístupu k financím a které jsou více závislé na domácích finančních trzích. Naše výsledky jsou robustné vůči zahrnutí technologických determinantů potřeb externího financování a vůči alternativním způsobům měření růstových příležitostí,

Ve druhé kapitole zkoumám roli produktivity v selekci firem do akvizic, a jestli akvizice vedou k růstu produktivity. S využitím empirické metodologie párování na základě pozorovatelných charakteristik a velké databáze domácích akvizic mezi veřejně obchodovanými, jako i privátními firmami v období 1998-2008 jsem ukázal, že za první, akviziční cíle v horizontálních akvizicích mají nižší produktivitu než porovnatelné firmy ve stejných sektorech; za druhé v případě vertikálních akvizic je mezi zúčastněnými firmami pozorovatelné pozitivně asortativní párování dle jejich produktivity; a za třetí, ekonomicky a statisticky významný nárůst produktivity existuje jenom u firem převzatých v horizontálních akvizicích. Celkově jsou výsledky pro horizontální akvizice konzistentní s Q-teorií akvizic, která předpokládá substitovatelnost aktiv. Výsledky pro vertikální akvizice, ve kterých jsou firmy spíš vzájemnými komplementy, jsou konzistentní s modelem hledání a párování založeném na teorii firmy.

Ve třetí kapitole, spolu s Janem Benou a Evou Vourvachaki, zkoumáme vliv tržní liberalizace, tj. odstranění státních monopolů a bariér vstupu dle požadavků Evropské Komise jako součást programu jednotného trhu, na produktivitu sektorů utilit, dopravních a telekomunikačních služeb ve vybraných Evropských krajinách. S využitím variace v časování a rozsahu liberalizačních snah přes krajiny a sektory, jsme zjistili, že liberalizace vedla k zvýšení produktivity jednotlivých firem, ale nevedla k zlepšení alokace zdrojů v dotčených sektorech. Na základě našich odhadů je průměrný nárůst firemní produktivity vyvolán liberalizací na úrovni 38 procent průměrného růstu firemní produktivity ve zkoumaných odvětvích v období 1998-2007. Naše výsledky tak podtrhují pro-růstovou roli liberalizačních snah.

Introduction

This thesis consists of three chapters that are empirical investigations of classical questions in the financial and industrial economics literature. The first chapter investigates whether more developed financial markets make it easier for firms to raise external finance when they need it. The second chapter studies the role of productivity in the firms' decision to participate in acquisitions, and whether acquisitions lead to productivity gains. Finally, the last chapter studies the impact of market liberalization on the productivity of network service industries in Europe.

In the first chapter, co-authored with Jan Bena, we study whether financial market development facilitates the efficient allocation of resources, one of the primary channels from finance to growth suggested by the theory. We assess that if more developed financial markets allocate capital more efficiently, it must be that they are able to identify firms with growth opportunities and to channel external finance towards these firms when they need it. The existing literature studies this question without observing the quantity of external finance raised by firms, resorting instead to aggregate industry-level data on investments. In this paper, we take a more direct approach and utilize cross-country firm-level balance sheet data to calculate an explicit firm-level measure of external finance use. We do so for a large sample of manufacturing firms operating in a set of European countries that differ in their level of financial market development.

Employing the identification approach developed by Rajan and Zingales (1998), we find that financial development improves the allocation of capital by channeling external finance to firms that operate in industries with better growth prospects. This result is obtained using two alternative proxies for the global industry-specific component of growth opportunities: (i) industry value-added growth in the U.S. and (ii) the change in the global industry price-to-earnings (PE) ratio. Both proxies rely on the assumption that a global component exists in industry-specific growth opportunities caused by demand and productivity shifts. For this reason, we focus our analysis on the manufacturing sector of a homogenous set of European countries with highly synchronized product markets and regulation, where the key underlying assumption of common shocks to industry growth is arguably most likely to hold. When we proxy growth opportunities by the growth of U.S. industries, the additional assumption is that firms in the U.S. are relatively financially unconstrained and are able to materialize the growth opportunities they encounter. When we proxy growth opportunities by the global industry PE ratio, we assume that financial markets are integrated to the extent that the common component of growth opportunities is priced into global industry portfolios.

Our results also suggest that it is especially the small and young firms — presumably more constrained in their access to public financial markets and more dependent on domestic financial markets — that benefit from financial development by being able to raise more external finance in response to growth opportunities.

In the second chapter, I examine the role of productivity in the firms' decision to participate in acquisitions and whether acquisitions lead to productivity gains. I reconcile conflicting results in the existing literature by showing that the role of productivity in the firms' selection into acquisitions and the post-acquisition productivity gains are very different in horizontal and vertical deals. The key insight that motivates the separation between horizontal and vertical deals is the different nature of synergies among potential acquisition participants. Firms that operate in the same industry, and thus are potential candidates for horizontal takeovers, are all familiar with the technology of that industry. Thus, within the industry, the firm-specific intangible capital of one firm is easily redeployable on the physical assets of the other firm, in line with the underlying assumptions of the standard Q-theory of mergers of Jovanovic and Rousseau (2002). The predictions of this theory that unproductive firms are acquired by the relatively productive ones in order to experience subsequent productivity gain, are thus most likely to hold for the horizontal acquisitions.

For the class of mergers between firms operating in industries tied by strong supplier-producer vertical linkages, however, the complementarity between intangible assets may be more relevant. Vertically related firms that choose to engage in productive relationship are facing the risk of a hold-up because either firm can threaten to quit and to search for another partner. According to the property rights theory of the firm, if the firms' intangible assets are complementary, so that both partners are essential for the realization of output, the possibility of hold-up mitigates incentives for ex-ante investments leading to output loss. The hold-up problem can be mitigated by vertical merger. The search and matching model of mergers and acquisitions developed by Rhodes-Kropf and Robinson (2008) incorporates these insights and predicts that under additional, reasonable assumptions, the equilibrium selection into vertical acquisitions can be characterized by the positive assortative matching in which firms merge with partners of similar productivity.

Based on these theoretical insights, I examine the role of productivity in vertical and horizontal acquisitions using a large sample of domestic acquisitions among public and private firms in Europe over the period 1998-2008. Using the approach based on matching on firm industry and size, I find that first, targets are under-performing before engaging in horizontal acquisitions; second, there is positive assortative matching in productivity for firms engaging in vertical acquisitions; and third, economically and statistically significant productivity gains exist only for targets acquired in horizontal acquisitions. Thus, the results for horizontal deals are consistent with the Q-theory of mergers which assumes asset substitutability. The results for vertical deals are consistent with the search and matching model built on the property rights theory of the firm, which assumes complementarity.

The third chapter, co-authored with Jan Bena and Evangelia Vourvachaki, is an empirical investigation of the impact of market liberalization, e.g. the removal of state monopolies and entry barriers, on the productivity of utilities, transport and telecommunication services in European countries. Specifically we ask: What is the impact of liberalization on the productivity of European network service firms? Has liberalization improved the allocation of resources across firms by bringing gains into the production scale of the relatively more productive firms?

Our main identifying assumption is that liberalization has been driven by EU-wide harmonization efforts as part of the EU Single Market Program rather than by the local industry-specific conditions. Exploiting the variation in the timing and degree of liberalization efforts across countries and industries, we find that liberalization has increased firm-level productivity but has had no reallocation impact. Based on our estimates, the average firm-level productivity gain from liberalization amounts to 38 percent of the average within-firm productivity gain in network industries over 1998-2007.

We also find that within-firm productivity gains attributable to liberalization are higher for firms with low pre-liberalization productivity. This result is in line with existing theories that stress the role of competition in the reduction of managerial slackness. This may be particularly relevant in our case given that at the beginning of the liberalization process, network service industries largely featured state monopolies where managerial slackness concerns are likely to be important. Overall, our findings suggest that the regulatory reforms for network services have been successful in increasing the threat of competition for incumbents and thus inducing them to become more productive.

Chapter 1

Financial Development and the Allocation of External Finance[1]

Abstract

We examine whether financial markets development facilitates the efficient allocation of resources. Using European micro-level data for 1996-2005, we show that firms in industries with growth opportunities use more external finance in financially more developed countries. This result is particularly strong for firms that are more likely to be financially constrained and dependent on domestic financial markets, such as small and young firms. Our findings are robust to controlling for technological determinants of external finance needs and to using different proxies for growth opportunities. Interestingly, the explanatory power of the measures of technological determinants identified in prior work decreases significantly once growth opportunities are controlled for.

JEL: F3, O16, G3
Keywords: Financial development, External finance, Allocative efficiency

[1] This paper has been published in Bena, J. and Ondko, P. (2012) Financial Development and the Allocation of External Finance, *Journal of Empirical Finance* 19(1):1-25. Earlier version of this paper has been published in Bena, J. and Ondko, P. (2009) Financial Development and the Allocation of External Finance, CERGE-EI Working Paper Series, 2009, No. 398. We thank Jan Hanousek, Štěpán Jurajda, Hernan Ortiz-Molina, Evangelia Vourvachaki, and seminar participants at CERGE-EI and UBC for helpful comments. This research was partly supported by a research center grant No. LC542 of the Ministry of Education of the Czech Republic implemented at CERGE-EI, the joint workplace of the Center for Economic Research and Graduate Education, Charles University, Prague, and the Economics Institute of the Academy of Sciences of the Czech Republic. We also acknowledge the financial support from the Social Sciences and Humanities Research Council of Canada (SSHRC). All errors remaining in this text are the responsibility of the authors.

1.1 Introduction

The key role of a financial system is to acquire information about investment opportunities and facilitate the allocation of resources into viable projects.[2] Recent empirical work uses aggregate data to present indirect evidence that more developed financial markets allocate capital more efficiently. Wurgler (2000) estimates the effect of financial development on the elasticity of aggregate investment with respect to growth opportunities. Fisman and Love (2004) measure the effect of financial development on the growth of industries with positive opportunities.[3] If more developed financial markets allocate capital more efficiently, it must be that they are able to identify firms with growth opportunities and to channel external finance towards these firms when they need it.

In this paper, we use micro-level data to examine whether financial markets development has a direct positive impact on individual firms by improving the allocation of capital. Specifically, we ask whether firms that operate in industries with positive growth shocks are more able to exploit the new opportunities by increasing their external financing in countries with higher levels of financial markets development. If external finance is more costly than internal finance, firms will turn to financial markets only after they have exhausted their internal funds. We show to what extent such firms' demand for external finance is satisfied by financial markets of different depth and institutional quality.

Using a large cross-section of manufacturing firms from European countries, we find that financial development improves the allocation of capital by channeling external finance to firms that operate in industries with better growth prospects. This result is obtained using two alternative proxies for the global component of industry growth opportunities: (i) industry value-added growth in the U.S. and (ii) the change in the global industry price-to-earnings (PE) ratio. Both proxies rely on the assumption that there exists a global component in the industry specific growth opportunities caused by demand and productivity shifts. For this reason, we focus our analysis on the manufacturing sector of a homogenous set of European countries with highly synchronized product markets and

[2]See the survey by Levine (2005) for a summary of financial systems' functions.
[3]We discuss how our study fits into this literature in detail in Section 1.2.

regulation, where the key underlying assumption of common shocks to industry growth is arguably most likely to hold. When we proxy growth opportunities by the growth of U.S. industries, the additional assumption is that firms in the U.S. are relatively financially unconstrained and are able to materialize the growth opportunities they encounter. When we proxy growth opportunities by the global industry PE ratio, we assume that financial markets are integrated to the extent that the common component of growth opportunities is priced in global industry portfolios.

Despite relying on different assumptions, both proxies yield estimates of similar economic magnitude. For example, the difference in external finance use between (otherwise comparable) firms that operate in an industry ranked at the 75th as opposed to the 25th percentile by the U.S. growth is 0.7 percentage points (on average per annum) larger in the Netherlands than it is in Bulgaria. When we approximate growth opportunities by global PE growth, we obtain the analogous estimate of 0.6 percentage points.[4] The effect is three to four times larger if we instrument to correct for measurement error in growth counterfactuals.

Our results also suggest that small and young firms—which are less likely to be able to access public financial markets and are also more likely to depend on domestic financial markets—are able to raise larger amounts of external finance in response to growth opportunities in financially more developed countries in comparison to large and old firms. This supports the view that domestic financial markets development alleviates the financial constraints of small and young firms by more. We also find that the degree of domestic financial markets development is a much more important determinant of the ability to raise external finance for firms with highly concentrated ownership structures, when compared to firms with dispersed ownership.

We contribute to the literature on the finance-growth nexus. This literature is founded on the argument that the technology used by firms in a given industry is the same across countries and it thus creates an industry-specific dependence on external finance (Rajan and Zingales, 1998). We show that the ability of more developed financial markets to

[4]The sample mean of external finance use is 0.4 percent and its standard deviation is 3.8 percent.

provide external finance to firms in industries with strong growth opportunities still holds when we control for technological determinants of external finance. Interestingly, we find that the estimated effect of the measures of technological determinants of external finance decreases by 10 to 50% once proxies for growth opportunities are included in our regressions. This is most pronounced when we include a proxy based on the value-added growth in the U.S. This suggests that the widely used measures of technological determinants of external finance are partly driven by growth opportunities that were financed and hence realized in countries with high financial development (such as the U.S.).

The structure of the paper is as follows: Section 1.2 relates our work to the literature; Section 1.3 presents the methodology; Section 1.4 contains the description of the data; Section 1.5 presents the results; Section 1.6 presents the robustness checks; and Section 1.7 concludes.

1.2 Related Literature

Theoretical models based on adverse selection or moral hazard imply that financial development improves screening of investment projects and/or enhances monitoring by external investors, which in turn leads to more efficient allocation of capital to investment projects.[5] This section summarizes the empirical literature that tests this broad prediction.

In his seminal paper, Wurgler (2000) estimates the country-specific elasticities of investment to value added in order to capture the country differences in the extent to which investment increases in growing industries and decreases in declining industries. He shows that the elasticity tends to be larger in countries with larger credit markets, more informative stock prices, less state-ownership of firms, and greater protection of minority investors. This important result suggests a causal link from financial development to more efficient reallocation of capital.

Wurgler (2000) uses industry-level gross fixed capital formation as the dependent vari-

[5] See for example Boyd and Prescott (1986) for adverse selection and Townsend (1979) for moral hazard arguments.

able as his focus is on the aggregate impact of financial system development. In our analysis, instead, we investigate the process of capital allocation at the micro-level which yields a direct test of the capital allocation efficiency hypothesis. There are two key differences. First, our dependent variable is the amount of dollars raised rather than investment, so we do not make any assumptions about how is a dollar of external finance utilized inside a firm. Second, we do not aim to explain the entire corporate investment, but only the part that is financed using external funds.

Wurgler (2000) uses realized industry-country level value added growth as a proxy for industry growth opportunities. He shows that this proxy can be justified as it is significantly positively correlated with more traditional measures of growth opportunities: average Tobin's Q, price-to-earnings ratio, and sales growth. Indeed, in a country with a perfectly developed financial market, realized growth is aligned with demand and productivity shocks and hence reflects growth opportunities. Also, if latent industry growth opportunities are positively autocorrelated, it is possible to use current realized growth to approximate future growth opportunities. However, it is less clear whether potential-to-realized growth correspondence holds in countries where opportunities anticipated in the past are not reflected in current growth due to financial or labor market frictions. Therefore, we digress from Wurgler (2000) and use realized growth in the U.S. (a country with high financial market development and low frictions) and price-to-earnings ratios of global industry portfolios as proxies for industry-level growth opportunities.

The reasons for choosing U.S. growth as a measure of latent global growth opportunities are similar to country-level studies of Fisman and Love (2007) and Ciccone and Papaioannou (2006), who test whether investment opportunities caused by global demand and productivity shifts lead to higher growth in financially more developed countries.[6] Unlike these two papers, we focus our analysis on manufacturing sectors of a homogenous set of European countries on a comparable level of economic development and with highly synchronized product markets where the key underlying assumption of global shocks to

[6]Ciccone and Papaioannou (2006) further recognize that relying on country-specific growth measures may lead to spurious conclusions due to measurement error and the possibility of systematic correlation of the country-specific component of growth opportunities with financial development.

industry growth is arguably most likely to hold.

Alternatively, to capture the global component of growth opportunities, we use price-to-earnings (PE) ratios of world-wide industry portfolios. In contrast to the realized U.S. industry growth, global industry PE ratio is forward-looking, based on ex-ante expectations of future growth. A high PE ratio means that investors are willing to pay a high multiple of current earnings for stocks in a given industry, which happens if they expect dividend growth.

Bekaert et al. (2007) show that under the stock market integration hypothesis, the global component of growth opportunities of a given industry should be competitively priced and reflected in the global industry's PE ratio. As a result, a country with a large share of industries with high global PE ratios should grow faster than the world economy. On the other hand, the local industry PE ratios would add information about the country's future growth only if markets are not fully integrated and the opportunities are priced locally rather than globally. The authors provide evidence in support of the hypothesis of market integration by showing that a country's industry-weighted global PE ratios predict future real GDP growth, while the industry-weighted difference of local and global PE ratios doesn't have any predictive power for relative economic growth. Importantly, their analysis suggests that the PE ratio of a global industry portfolio is a valid exogenous measure of growth opportunities as it does not use local price information that could be potentially contaminated by the local level of financial development.[7]

Our finding that firms with positive growth prospects receive more external finance in financially more developed countries directly verifies that financial development alleviates credit constraints. This result relates our work to firm-level structural investment model studies. Here, the optimal investment decision follows the Euler equation that trades off marginal benefits of investing today with discounted marginal costs of postponing investment to the next period. In the absence of financial constraints, the only relevant factor affecting a firm's investment decision is a project's growth potential. However, one

[7]As all European countries in our sample have their stock and banking sectors liberalized in our sample period, we do not formally test for market integration in our sample and rely on the result of Bekaert et al. (2007).

would observe positive elasticity of investments to cash-flow if firms experience difficulties in obtaining external finance. Love (2003) and Islam and Mozumdar (2007) show that this elasticity is decreasing with financial development, which indirectly suggests a positive role of financial development in alleviating credit constraints.

Alternative tests of the role of financial system in the improvement of allocative efficiency are based on the neoclassical argument that capital should be allocated such that its marginal product is equalized across projects. This insight underlies two studies that investigate the impact of financial liberalization on capital allocation. Galindo, Schiantarelli, and Weiss (2007) argue that a suitable approximation for marginal product of capital is either the sales to capital ratio (appropriate in the case of the Cobb-Douglas production function) or the ratio of operating profit to capital (valid under constant returns-to-scale production technology and perfect competition in output markets). They use firm-level panel data for 12 countries to create proxies for marginal product of capital and construct the efficiency index of capital allocation. Using the index, they show that efficiency increases in periods following financial liberalization. Abiad, Oomes, and Ueda (2008) approximates the expected marginal product of capital by the market-to-book ratio of publicly listed firms, the empirical equivalent of Tobin's Q. Next, he follows a difference-in-differences methodology to assess whether the dispersion in Qs decreases in the period following liberalization. The advantage of both studies is that they aim to test simple predictions of neoclassical theory. On the other hand, the assumptions needed to form empirical proxies for the theoretical concepts are rather strong. In this respect, we complement these neoclassical approaches by avoiding an empirical approximation of marginal product of capital and focusing instead on the degree of alignment between growth opportunities and external finance use.

1.3 Methodology

We test the hypothesis that financial development improves efficiency of capital allocation by channeling external finance towards firms in industries with the best growth opportunities. Our main regression specification is

$$EFU_{fic} = \alpha + \beta\ FD_c \times GO_i + \gamma\ GO_i + \sum_i \lambda_i D_i + \sum_c \lambda_c D_c + X'_{fic}\ \zeta + \varepsilon_{fic}, \tag{1.1}$$

where EFU_{fic} is the period-average external finance use of firm f from industry i and country c over the period 1996-2005. FD_c denotes the country-level indicator of financial development measured as of the beginning of our sample period. GO_i proxies global industry growth opportunities. D_i and D_c are industry and country fixed effects, respectively. X_{fic} is a vector of firm-level control variables.

External Finance Use (EFU) is computed as the net increase in the use of external finance in a given year divided by the total assets as of the beginning of the year (see equation (1.A.4) in Appendix 1.B).[8] A measure of external financing analogous to our EFU has been used in firm-level panel setting by Baker, Stein, and Wurgler (2003). The summary statistics for EFU are given in Table 1.1. The median and the mean EFU in the sample are close to zero. This is consistent with the fact that, at the firm-level over time, issuance and repayments of debt and equity should be balanced on average.

To proxy for growth opportunities GO_i, we use the period-average value-added growth rates of industries in the U.S. Alternatively, we use price-to-earnings (PE) ratios of global industry portfolios. As there are no clear predictions whether it is the level of PE ratio or the change in the level of PE ratio that capture growth opportunities better, we use the period-averages of both. Given that our dependent variable captures the average net additions to external finance, a change in the level of PE ratio seems more appropriate. In the case of a balanced panel, GO_i would be computed over the whole period and applied to all firm observations. However, as our panel is unbalanced, the period over which we

[8]In Appendix 1.B, we show that the numerator of EFU is the balance sheet approximation of the numerator of the external finance dependence measure used by Rajan and Zingales (1998). While Rajan and Zingales (1998) use capital expenditures in the denominator, we use total assets to scale the net flow of external finance. The reason is largely technical. Capital expenditure is a flow measure and as such it can take values very close to zero. For example, Nilsen and Schiantarelli (2003) show that around 30% of Norwegian plants and 6% of firms have zero capital expenditure in an average year. Rajan and Zingales (1998) use the value of external finance dependence of the industry median firm to characterize industry specific external finance dependence and, thus, they implicitly assume that capital expenditures of the median firm are positive. In the context of our firm-level regression with external finance use on the left-hand side, scaling by a variable that takes values close to zero would lead to excessive outliers.

compute EFU is different across firms. To mitigate the measurement error in capturing growth opportunities, for every firm, the period used to compute the growth opportunities counterfactual matches the period over which EFU is computed.

In all our specifications, we control for a set of firm-level variables, measured as of the first year a firm enters the sample. This is to eliminate the initial differences in the within-industry distributions of firms along characteristics that have potentially different effect on the use of external finance. Effectively, we are thus able to compare differences in EFU of highly comparable firms operating in environments with varying financial development and facing different growth opportunities. The set of firm-level characteristics included in our regression contains size, age, leverage, asset tangibility, the extent to which a firm's assets can be collateralized, and cash. Finally, we include industry and country dummies to control for time-invariant unobservable industry- and country-level factors affecting EFU.

Rajan and Zingales (1998) examine the impact of financial development on growth by investigating whether industries with higher need for external finance grow faster in financially more developed countries. Presumably, the underlying mechanism behind this result is that financial development relaxes financial constraints, which matters the most for those firms that are highly dependent on external finance due to specific technology used in their type of business. Using our measure of external finance use, we are ready to directly test this mechanism. We estimate

$$EFU_{fic} = \alpha + \beta\ FD_c \times Tech_i + \sum_i \lambda_i D_i + \sum_c \lambda_c D_c + X'_{fic}\ \zeta + \varepsilon_{fic}, \tag{1.2}$$

where $Tech_i$ denotes industry-specific technological determinants of external finance needs.

We consider three measures of the technological determinants. The first is the external finance dependence, measured as in Rajan and Zingales (1998). This is an all-encompassing measure of demand for external finance that is based on the assumption that in highly developed financial markets, such as the U.S., industry differences in the observed proportion of capital expenditures financed from external sources reflect underlying technological differences among industries.

In choosing the other two measures, we follow Ilyina and Samaniego (2008) who suggest R&D intensity and investment lumpiness as more explicit technological determinants of external finance need. The R&D Intensity is approximated by the average share of R&D expenditures on capital expenditures of a median firm in each U.S. industry. Firms operating in R&D intensive sectors may be in greater need for external finance, because R&D investments are often relatively large at the outset and may be associated with longer gestation periods, and it is likely that profits from R&D projects materialize over a long-term horizon.

Lastly, investment lumpiness is a proxy for the degree of mismatch between cash inflows and cash outflows. Firms that experience large cash-flow mismatches are more likely to seek outside financing due to a shortage of internal resources. One reason for the existence of cash-flow misalignment are investment 'spikes,' which are periods in which capital expenditures exceed their usual levels. Doms and Dunne (1998) show that more than one half of 12,000 U.S. manufacturing plants in their sample experience a year in which capital stock increases by over 35% and often the spikes occur in consecutive years. From the perspective of a structural investment model, this empirical pattern suggests the existence of important non-convexities in the adjustment costs. Assuming that these non-convexities are driven by industry-specific technological factors, we calculate Investment Lumpiness as the average number of investment spikes in relatively frictionless U.S. industries over a given period.

The proxies for technological determinants of external finance are calculated using U.S. data over the period under investigation, and thus they may as well be capturing underlying growth opportunity shocks specific to that period. To verify this, we estimate regressions where we interact financial development with growth opportunities as well as with technological determinants

$$EFU_{fic} = \alpha + \beta_1 \; FD_c \times GO_i + \beta_2 \; FD_c \times Tech_i + \gamma \; GO_i + \sum_i \lambda_i D_i + \sum_c \lambda_c D_c + X'_{fic} \; \zeta + \varepsilon_{fic}. \quad (1.3)$$

If measures of technological determinants are significantly contaminated by growth opportunity shocks, we would expect β_2 to be smaller than its counterpart in regression (1.2). The magnitude of this decrease should be larger when GO_i is approximated by value-added growth in the U.S., because it contains U.S.-specific growth shocks which are largely absent from the proxies based on the PE ratio.

1.4 Data

1.4.1 Sample

Firm-level panel data are obtained from Amadeus (Analyse MAjor Databases from EUropean Sources), which contains balance sheet and income statement information for a large set of private and public firms spanning all of Europe. We use the 'TOP 200 thousand' module of this database, which contains a subsample of the largest firms.[9] The coverage is incomplete before 1996 and we use data till 2005. We exclude Romania from the sample due to large inconsistencies in the accounting data of its firms. Denmark and Norway have only few firms in the final sample and have been dropped too. Since private firms are likely to rely more on domestic financial markets, while public firms are more likely to be in a position to raise external finance in international bond and equity markets, we include only private firms in our sample.

Our data-cleaning procedure is in line with the previous research utilizing this database. First, as in Bena and Jurajda (2011), in order to decrease the noise in average external finance use, we drop all firms for which less than 5 annual observations of external finance use is available. As Klapper, Laeven, and Rajan (2006), we use unconsolidated financial statements to avoid double counting and exclude firms that only report consolidated statements. Further, we exclude firm-years with very small total assets (less than EUR 1,000), very high leverage (long-term debt more than double the total assets), and very large profit/loss (absolute value more than ten times the total assets). Additionally, we drop the bottom and top percentile of year-on-year changes in total assets in order to

[9] Specifically, for a firm to be included in this module, at least one of the following criteria must be met: For UK, Germany, France and Italy, an operating revenue at least 15 million Euro, total assets at least 30 million Euro or number of employees at least 150. For all other countries, operating revenue at least 10 million Euro, total assets at least 20 million Euro, or the number of employees at least 100.

avoid the influence of extreme events such as mergers, acquisitions, or spinoffs. We deflate all financial variables by the producer price index defined over year-country-industry triple, where industry is defined by the ISIC 2-digit level. Lastly, to minimize the impact of long tails of firm size and age distributions, we exclude firms in the top percentile of the distribution by total assets, age, and employment measured as of the first year the firm appears in the sample.

1.4.2 Country-level Indicators of Financial Development

First, we use three traditional measures of depth of credit and stock markets: private credit by deposit banks and other financial institutions to GDP (Private Credit), stock market capitalization to GDP (Market Capitalization), and stock market total value traded to GDP (Market Value Traded). These data are taken from the 2006 version of World Bank's Financial Structure and Economic Development Database described in detail in Beck, Demirguc-Kunt, and Levine (2000). We complement measures of financial depth by a proxy for the institutional quality of financial markets as measured by the Accounting Standards index.[10]

For robustness, we use measures of the extent of bank ownership by governments (Government Bank Ownership and Government Bank Control) from La Porta, Lopez-De-Silanes, and Shleifer (2002), measures of efficiency and competition in the banking sector (Overhead Costs and Net Interest Margin) from Beck, Demirguc-Kunt, and Levine (2000), and Control Premium estimated by Dyck and Zingales (2004). Finally, we add two indexes constructed by Barth, Caprio, and Levine (2004) that capture regulatory environment in which the banking sector operates.

Table 1.2 presents summary statistics for financial development indicators and Panel B of Appendix Table 1.A.1 presents complete definitions and sources of these variables. The cross-country standard deviation is of the same order as the mean for all volume-of-

[10] Accounting Standards index is constructed based on rating annual reports of companies in 1990 according to the inclusion of 90 items in their balance sheets and as such it is an indicator of the quality of accounting standards. The index is produced by International Accounting and Auditing Trends (Center for International Financial Analysis and Research, Inc.) and it ranges from 0 to 90. We scale it down by 100 before using it in regressions.

financial-activity measures as well as for the measures of government ownership of banks and the measures of banking sector's efficiency, which suggests a substantial variation in financial development. The variation in Accounting Standards is smaller, which is most likely caused by the lack of data for Ireland and all countries of Central and Eastern Europe in our sample.

1.4.3 Industry-level Data

The value-added data for the U.S. used to compute our first proxy for growth opportunities are taken from OECD STAN database downloaded in 2009. We use the index of volume of value-added (VALK) for industries on the 2-digit level of ISIC rev 3.1. In some cases, the volume index of value added and corresponding value-added deflator is available only for a group of two or three industries.[11] In these instances we use the corresponding group deflator (VALP) to adjust nominal value-added (VALU), which is available for all industries.[12]

The data for the monthly series of global PE ratios are obtained from Datastream. As of March 2008, Datastream uses the Industry Classification Benchmark (ICB) created by FTSE Group and Dow Jones Indexes to classify companies into 114 sub-sectors. Following the approach of Bekaert et al. (2007), we link ICB sub-sectors into 22 manufacturing 2-digit ISIC industries.[13] Whenever more than one ICB sub-sector is linked to a given 2-digit ISIC industry, we calculate the weighted average of the PE ratios of entering sub-sectors using their market values as weights. Finally, for every industry, we compute yearly values of the PE ratios by taking the simple mean for all months in a given year.

Following Rajan and Zingales (1998) and Ilyina and Samaniego (2008), we use Compustat to compute industry-level technological determinants of the need and ability to raise external finance. Instead of using values tabulated in these papers, we re-calculate proxies using ISIC rev. 3.1 industry classification in order to be able to match them with the

[11] Specifically, these ISIC 2-digit categories are: 15-16, 17-19, 32-33.

[12] For categories '36 - Manufacturing n.e.c.' and '37 - Recycling,' neither volume nor nominal value-added data is available.

[13] We obtained the concordance table used in Bekaert et al. (2007) from the authors. We adjust their concordance table as the ICB classification has been expanded since their work, and also because Bekaert et al. (2007) link ICB sub-sectors to the SIC classification while we link them to the ISIC classification.

Amadeus data.[14] In line with Rajan and Zingales (1998), we compute External Finance Dependence (EFD) as the share of capital expenditures not financed by the cash-flow from operations. Capital expenditures is item 128 in Compustat and cash-flow from operations is defined as cash-flow from operations (item 110 or sum of items 123, 125, 126, 106, 213 and 217 if unavailable) plus change in payables (item 70 or 304 if unavailable) minus change in receivables (item 2 or 302 if unavailable) plus change in inventories (item 3 or 303 if unavailable). We sum both capital expenditures and cash-flows from operations over the 1996-2005 period for each firm and compute the firm-level dependence. The industry level external finance dependence is then dependence of the median firm.

Following Ilyina and Samaniego (2008), we compute R&D Intensity as the share of R&D expenditures (item 46) in capital expenditures. We sum both the nominator and denominator over the 1996-2005 period for each firm and compute firm-level R&D intensity. Again, each industry is characterized by a median firm. Investment Lumpiness is computed as the average number of investment spikes experienced by firms in a given industry over the 1996-2005 period, where an investment spike is defined as annual capital expenditure in excess of 30% of the firm's fixed assets (item 8).

The summary statistics for the industry-level proxies for growth opportunities and technological determinants of external finance are presented in Table 1.3. Complete definitions and sources of these variables are provided in Panel C of Appendix Table 1.A.1.

1.5 Results

1.5.1 Financial Development and External Finance Use

We present basic estimates of regression (1.1) in Table 1.4. In all specifications, we control for 3-digit ISIC industry and country dummies and firm-level control variables that are measured as of the first year a firm enters the sample (detailed definitions of these variables are provided in Panel A of Table 1.A.1). The estimates in Table 1.4 suggest that financial development improves allocation of external finance by channeling it to firms in industries

[14] We use the concordance table constructed by the U.S. Census Bureau to link the NAICS 2002 classification used in Compustat to 3-digit ISIC industries.

with strong growth prospects.

To inspect the economic magnitude of our estimates, we consider the effect of financial development in increasing the average use of external finance for firms operating in industries at the bottom and top quartile of the industry distribution by the real value-added growth in the U.S. Thus, using our estimated coefficients of the interaction terms $\hat{\beta}$, we compute

$$\hat{\beta} \times (FD_{max} - FD_{min}) \times (USGrowth_{75p} - USGrowth_{25p}), \tag{1.4}$$

where FD_{max} (FD_{min}) are the sample maximum (minimum) of the financial development indicator, and $USGrowth_{75p}$ ($USGrowth_{25p}$) are the sample top (bottom) quartiles of the real value-added growth in the U.S. (equal to 3.3 percentage points in the sample). The impact of the increase of Total Capitalization from its sample minimum to its sample maximum on EFU is then 0.38 percentage points. Thus, the difference in EFU between firms operating in the industries ranked at 75th and 25th percentiles of the U.S. real value-added growth is 0.38 percentage points higher in Netherlands than in Latvia, the countries with the highest and the lowest Total Capitalization in our sample, respectively. Using Private Credit, Market Capitalization, Market Value Traded, and Accounting Standards we obtain economic effects of 0.58, 0.16, 0.31, and 0.23 percentage points, respectively.[15] For the comparison, the sample mean and standard deviation of EFU are 0.4 percent and 3.8 percent, respectively.

In Panel A of Table 1.5, we complement estimates reported in Table 1.4 with the estimates obtained using the time-average of the level and growth of global PE ratios as alternative proxies for growth opportunities. We include both average level and growth in global PE ratios to investigate whether financial development improves channeling of external finances to industries with high expectations of future growth (high level of global PE ratio) or to industries in which the growth prospects increase over the investigated period (high growth of global PE ratio). Financial development makes no difference in allocating external finance to industries which differ in their average level of expected

[15] By approximating only for the industry-specific component of growth opportunities we are very restrictive. On the one hand, we alleviate endogeneity concerns, but on the other, we introduce measurement error which typically leads to an attenuation bias.

growth opportunities. On the other hand, our results suggest that financial development helps to facilitate financing of industries with growing market expectations as measured by the growth of global PE ratios. Thus, we choose Global PE Growth to be the alternative proxy for growth opportunities. The economic significance of estimates obtained with Global PE Growth is higher when compared to the case of US Growth. Specifically, the quantity (1.4) is calculated as 0.86, 0.90, 0.53, 0.42, and 0.39 percentage points if financial development is measured by Total Capitalization, Private Credit, Market Capitalization, Market Value Traded, and Accounting Standards, respectively.

The regression specifications in Panel A of Table 1.5 characterize each firm by the time-average of its external finance use. While this allows us to investigate the allocation of external finance across industries over a longer period, it creates the problem of averaging net external finance to zero. We would expect firms to obtain external finance in periods of positive shocks and pay it back when returns from investments are realized, which would show as a negative autocorrelation in time series of external finance use with the implication of the time average converging to zero with the length of time period. To bypass this issue, we consider a panel regression specification

$$EFU_{fict} = \alpha + \beta\ FD_c \times GO_{it} + \gamma\ GO_{it} + \sum_i \lambda_i D_i + \sum_c \lambda_c D_c + \sum_t \lambda_t D_t + X'_{fic}\ \zeta + \varepsilon_{fict}, \quad (1.5)$$

where EFU_{fict} is the external finance use of firm f from industry i and country c in year t. FD_c denotes the country-level indicator of financial development measured as of the beginning of our sample period. GO_{it} proxies global industry growth opportunities in year t. D_i, D_c, and D_c are industry, country, and year fixed effects, respectively. X_{fic} is a vector of firm-level control variables, which we measure as of the first year a firm enters the sample.

The estimates of regression (1.5) are reported in Panel B of Table 1.5.[16] We use all three proxies for growth opportunities. The estimated coefficients on the interaction terms 'FD × US Growth' and 'FD × Global PE Growth' reported in Panel B are positive and,

[16]We also use two alternative specifications of panel regression (1.5). First, we allow the firm-level control variables to vary over time. Second, we include firm fixed-effects instead of the firm-level control variables in the regression. With both approaches, we find similar results too those reported in Panel B of Table 1.5.

with the exception of the coefficient on 'Private Credit × US Growth,' are significant at conventional levels. Note that the estimated coefficients on the interaction terms 'Total Capitalization × Global PE Level' and 'Market Capitalization × Global PE Level' are significant in Panel B, while they were not significant in Panel A. The coefficients in Panel B are smaller in magnitude, which is likely due to the fact that our growth proxies measure year-on-year changes in growth opportunities with an error, which leads to an attenuation bias. Overall, our panel data analysis suggest that financial development improves the allocation of external finance by channeling it to industries with high growth prospects, and confirms our conclusions obtained using cross-sectional regression analysis.

1.5.2 Differences across Firms

To explore what mechanism underlies the positive link from financial development to external finance use in industries with strong growth opportunities, we check whether the degree of financial development matters more for those types of firms that are more likely to have limited access to public financial markets and/or those that cannot tap international bond and equity markets. We investigate this conjecture by focusing on subsamples of small/large and young/old firms.[17]

First, we estimate regression (1.1) on a subsample of 'small' and 'large' firms. These results are reported in Panels A and B of Table 1.6.[18] In Panel A (B) of Table 1.6, a firm is defined to be small (large) if its size, measured by total assets, is less or equal to (greater than) the median value of total assets taken across all firms in the same country–2-digit ISIC industry cell. In all specifications we consider, the estimated coefficients on the interaction terms 'FD × US Growth' and 'FD × Global PE Growth' reported in Panel A of Table 1.6 are always bigger when compared to the analogous estimates

[17] Small and young firms are likely to exhibit a higher degree of informational opaqueness and thus end up more financially constrained than their larger and older counterparts. In surveys, small and young companies report having less access to external finance than larger and older companies (Beck et al. (2006), Angelini and Generale (2008)). Beck et al. (2008) find that industries which are naturally composed of firms with small size are more likely to grow disproportionally faster than industries with high share of large companies in countries with high level of financial development.

[18] In order to keep Table 1.6 parsimonious, we do not report coefficients on the base effects of US Growth and Global PE Growth as well as on the firm-level controls, but they are included in all regression specifications.

reported in Panel B. Moreover, the estimates reported in Panel A of Table 1.6 are always significant, while those in Panel B of Table 1.6 are almost never significant. Finally, the estimated coefficients on the interaction terms reported in Panel A of Table 1.6 are bigger in magnitude in comparison to the estimates reported in Panel A of Table 1.5 that are based on the full sample. This evidence suggest that small firms in particular are able to raise more external finance in response to growth shocks in more developed financial systems. This supports the view that more developed financial systems alleviate the financial constraints of small firms more.

Second, we estimate regression (1.1) on a subsample of 'young' and 'old' firms. These results are reported in Panels C and D of Table 1.6. In Panel C (D) of Table 1.6, a firm is defined to be young (old) if its age, measured in years since incorporation as of the first year a firm enters the sample, is less or equal to (greater than) the median value of age taken across all firms in the same country–2-digit ISIC industry cell. We show that the estimated coefficients on the interaction terms 'FD $\times$ US Growth' and 'FD $\times$ Global PE Growth' reported in Panel C of Table 1.6 are always bigger (and are significant at the same or lower levels) in comparison to the analogous estimates reported in Panel D. This evidence confirms our findings obtained using subsamples of small/large firms. In sum, more developed financial systems are better able to allocate external finance as a response to growth shocks through alleviating financial constraints associated with small and young firms.

An important determinant of a firm's ability to raise external finance is its corporate governance. For example, Leuz, Lins, and Warnock (2009) find that U.S. investors do hold fewer shares in foreign firms where managers and their families have high levels of control, i.e., in firms with ownership structures that are more conductive to expropriation by controlling insiders. Motivated by these findings, we have collected data on ownership structures of the firms in our sample from the Amadeus ownership database.[19] Using

[19]For each firm, Amadeus identifies the shareholders and reports their ownership stakes. Each Amadeus update provides the ownership information as of the most recent date the data provider (Bureau van Dijk - BvD) was able to verify it. To cover as many firms as possible, we use seven Amadeus DVD updates: May 2001, May 2002, July 2003, May 2004, October 2005, September 2006, and May 2007. We supplement this data with more recent updates of Amadeus downloaded from WRDS in July 2007 and April 2008. Finally, we also use ownership data from Orbis, BvD's product with world-wide coverage, which was

the detailed data on firms' shareholders, we define firm-level variable 'Ownership Concentration' to be the sum of squares (Herfindahl-Hirschman index) of direct stakes of all reported shareholders in the year that is the closest to the first year a firm enters the sample, and it remains fixed over time. Concentrated ownership structures indicate the presence of controlling owners who might be in a position to expropriate minority shareholders. According to Leuz, Lins, and Warnock (2009), such firms should find it more difficult to raise external finance from outside investors in less developed financial systems as they may not be able to prevent expropriation.

We estimate regression (1.1) on a subsample of 'closely held firms' as well as on a subsample of 'firms with dispersed ownership.' These results are reported in Panels E and F, respectively, of Table 1.6. In Panel E (F), a firm is defined to be closely held (have dispersed ownership) if its Ownership Concentration is greater than (less or equal to) the median value of Ownership Concentration variable taken across all firms in the same country–2-digit ISIC industry cell.

The estimated coefficients on the interaction terms 'FD $\times$ US Growth' and 'FD $\times$ Global PE Growth' reported in Panel E of Table 1.6 are always more significant and in almost all cases they are also bigger in magnitude when compared to the analogous estimates reported in Panel F. This suggests that firms with dispersed ownership structures are better able to satisfy their external finance needs independently of the degree of domestic financial markets development. In contrast, for firms with highly concentrated ownership structures, the degree of domestic financial markets development is a much more important determinant of whether such firms are able to raise external finance in response to growth shocks. These results are consistent with the findings in Leuz, Lins, and Warnock (2009) that foreign investors avoid investing in firms with dominant owners and, as a result, such firms need to rely more on the domestic financial markets.

issued in November 2008. The resulting ownership dataset gives a unique breadth of cross-sectional coverage.

1.5.3 Growth Opportunities and Technological Characteristics

The extensive literature on finance-growth nexus uses the insight of Rajan and Zingales (1998) that the causal link from finance to growth can be identified by investigating the access to finance by industries differing in their natural external finance dependence (EFD). Ilyina and Samaniego (2008) further show that the strongest technological factors underlying cross-sectional variation in EFD are R&D Intensity and Investment Lumpiness. In line with these results, it is important to check whether industries dependent on external finance are actually using more of it in financially more developed countries. The results in Panel A of Table 1.7 suggest that this is indeed the case. The coefficient on the interaction of financial development and the technological measure is positive and significant with the exception of Accounting Standards. Interestingly, interactions with R&D Intensity and Investment Lumpiness are statistically more significant in explaining improvements in the allocation of external finance caused by financial development than EFD.

As discussed in Section 1.3, the differences in estimates of industrial technological determinants of dependence on external finance can be partially driven by the differences in growth opportunities over the period of their estimation. Specifically, the U.S. specific component of growth opportunities may be the common factor driving the differences in the estimates of R&D Intensity, Investment Lumpiness, EFD as well as realized value-added growth. This would empirically translate into higher correlation between real growth of U.S. industries and technological determinants of finance and the decrease in the coefficients on their interactions with financial development in the regressions on actual use of external finance. For the Global PE Growth proxy for growth opportunities, this should be less of a worry as the influence of the U.S. growth component should be limited.[20]

The results in Panel B of Table 1.7 are in line with the hypothesis of the existence of a common factor of U.S. growth opportunities in technological determinants.[21] The

[20]The spearman rank correlations between US Growth and technological determinants of finance are much higher than their counterparts for Global PE Growth. For example, the rank correlation of R&D Intensity and US growth is 0.42 with p-value 0.06 while the correlation of R&D Intensity and Global PE Growth is only 0.06 with p-value 0.80. A similar result is obtained for Investment Lumpiness and EFD, although in the case of the latter, the correlation with Global PE Growth rises to 0.29.

[21]In order to keep Table 1.7 parsimonious, we do not report coefficients on the base effects of US

estimated coefficients on interactions of financial development and R&D Intensity and EFD drops to almost half once interactions with US Growth are included. However, we actually observe a drop in the estimated coefficient on the interaction of financial development with US Growth once corresponding interaction with Investment Lumpiness is included in the specification.

The picture is different when we use Global PE Growth as a proxy for growth opportunities (Panel C of Table 1.7). The estimated coefficients on the interaction terms of financial development with Global PE Growth are statistically significant and very similar in magnitudes to their counterparts in specifications which exclude technological interactions (Panel A of Table 1.5). Overall, our evidence suggests that the role of financial development with respect to allocation of external financing is two-fold. On the one hand, it helps to channel external finance to industries which are presumably more dependent on it due to technological reasons. On the other hand, more developed financial markets are better in providing finance to industries with global growth opportunities.[22]

1.6 Additional Investigations and Robustness

1.6.1 Capital Expenditures Not Financed by Internal Funds

Our measure of net external finance use does not distinguish between external finance used for capital expenditures and external finance used for other purposes. As an alternative, we use capital expenditures not financed by internal funds (as in Rajan and Zingales (1998)), which is, in our case, given by equation (1.A.3) in Appendix 1.B. Table 1.8 is based on this alternative external finance use measure, while being otherwise (sample and regression specifications) identical to Table 1.5. The table shows that all estimated coefficients on the interaction terms of interest are bigger in magnitude and have the same significance (are often significant at lower thresholds) in comparison to the results reported in Table 1.5. This suggests that the conclusions of our analysis are robust to

Growth and Global PE Growth as well as on the firm-level controls, but they are included in all regression specifications.

[22]The results reported in Panels B and C of Table 1.7 are robust to using panel regression specifications similar to equation (1.5). See Table 1.OA.4 in Online Appendix 1.C.

changing the definition of the dependent variable.

1.6.2 Decomposing External Finance Use

In Appendix 1.B, we show that our EFU measure can be decomposed into the amount of equity raised/repurchased, the amount of long-term debt issued/repaid, and the change in other non-current liabilities. As there exist major contractual and institutional differences among these components of external finance, it is important to assess what is the role of financial development in the improvement of their allocation with respect to growth opportunities. To do so, we run a set of regressions equivalent to specification (1.1) separately using each component of external finance use as a dependent variable. We present the results of this exercise in Table 1.9.

Panels A and B document that financial development improves the allocation of both equity and long-term debt. When compared to the basic results in Panel A of Table 1.5, the estimated coefficients on the interaction terms suggest that around one third of the improvement in the allocation of external finance comes in the form of shareholder's equity, while the remaining two-thirds can be explained by long-term debt. This pattern is roughly consistent for both proxies for growth opportunities and all measures of financial development.

With respect to changes in other non-current liabilities, our results suggest that financial development makes no improvement in their alignment with growth opportunities. This result is in line with the expectations given that other non-current liabilities usually consists of items such as retirement benefit obligations, deferred tax liabilities, or long-term trade debts, and thus they are components of liabilities driven primarily by factors other than the need to finance growth opportunities.

1.6.3 Error in Measurement of Growth Opportunities

In our analysis, we use real US Growth and Global PE Growth in 2-digit ISIC industries as proxies for the global component of growth opportunities, which introduces measurement error to our analysis. The noise present in any proxy may lead us to underestimate the coefficient of interest due to classical measurement error bias. We investigate the magnitude of the bias in two ways. First, having two different proxies for growth opportunities allows us to use two-stage least-squares (2SLS) approach. Under the assumption of the orthogonality of measurement errors in the two proxies for growth opportunities, we can use one as the instrument for the other, which allows us to use only the variation common to both of them to estimate the coefficient of interest. We use the interaction of financial development with Global PE Growth (US Growth) and Global PE Growth (US Growth) as instruments for the interaction of financial development with US Growth (Global PE Growth) and US Growth (Global PE Growth). The results for both directions are presented in Table 1.10. Compared to the basic estimates, there is a significant increase in the estimated coefficients for all measures of financial development. In general, the order of increase of the estimates is between 1.7 to 7.2, which suggests that the impact of the measurement error may be large.[23]

Second, we use a simple version of simulation-extrapolation (SIMEX) method proposed by Cook and Stefanski (1994) to assess the magnitude of attenuation bias by comparing the estimates obtained by using the set of proxies created by adding white noise of varying precision to the base measure. Specifically, for each level of standard deviation ranging from 0.005 to 0.05, we simulate 100 draws from a multi-variate normal distribution and add them to a given proxy for growth opportunities. The newly created variable is then used as a proxy for growth opportunities in the interaction with the Total Capitalization in specification (1.1). Then, for each level of added noise, we compute the average of 100 obtained estimates and plot it against the standard deviation of added noise. The results obtained using US Growth are plotted in Figure 1.1.[24] The figure allows us to evaluate the magnitude of the attenuation bias caused by the random error. Extrapolating back the relationship between standard error of added noise and the average estimate provides a guess of how the estimate would look like if the measurement error was less

[23] Ciccone and Papaioannou (2006) carry out similar 2SLS exercise. In the industry-level growth regressions, they instrument growth opportunities approximated by the U.S. growth with the world-average value-added growth by industry controlling for the effects of financial underdevelopment. They obtain an increase in coefficients of the magnitude ranging between 3 to 6.

[24] Figure 1.1 is practically unchanged when we use Global PE Growth instead.

severe. For example, given that the standard deviation of the US Growth proxy is 0.041, then under the assumption that the measurement error is responsible for half of this variation, the quadratic extrapolation of the simulation results would suggest that the estimated coefficient would be approximately 0.035, which is about 25% larger than our basic estimate.

The results obtained from the 2SLS and SIMEX exercises suggest that there indeed is attenuation bias caused by measurement error and the two methods indicate somewhat different levels of the bias. Naturally, we don't have any estimate of the proportion of variance of US Growth or Global PE Growth caused by the measurement error. However, Figure 1.1 suggests that even if the measurement noise accounted for a very large proportion in the variation of US Growth, the resulting attenuation bias is not likely to be of larger magnitude than 2, which is low compared to the results obtained in the 2SLS exercise. A possible explanation for this discrepancy is a poor extrapolating performance of quadratic fit in the SIMEX exercise, or the existence of non-standard upward bias common to both proxies for growth opportunities, which would imply the violation of the assumption of the orthogonality of measurement errors in the 2SLS exercise.[25]

1.6.4 Alternative Measures of Financial Development

We check robustness of our results by investigating the effect of other dimensions of financial development on the allocation of external finance (Table 1.11). First, we test the hypothesis that the higher the involvement of government in the banking sector, the lower the efficiency of allocation of finance to firms in growing industries. To the extent that incentives of government as the owner of banks may not be fully in line with profit maximization, the government banks may be more distorted when allocating credit. Thus, we would expect that interaction of the government bank ownership and growth opportunities would be negative. We find that this is the case for both the level of Government Bank Ownership and the level of Government Bank Control in the top 10 banks in 1995 as calculated by La Porta, Lopez-De-Silanes, and Shleifer (2002).

[25] An upward bias common to both proxies may arise if they both approximate growth opportunities more precisely in more financially developed countries.

Second, we investigate whether the operational efficiency of the banks and the level of competition in the banking sector increase allocative efficiency. To the extent the competition among banks increases the quality of the financial sector, it may comparatively improve the chance of obtaining credit for firms operating in industries with potential growth prospects. In line with Demirguc-Kunt, Laeven, and Levine (2004), we approximate operational efficiency and competitiveness of banking sector by the Overhead Costs and the Net Interest Margin. The former reflects operational cost inefficiencies possibly associated with the market power while the later measures the mark-up between the interest received from borrowers and the interest paid to savers and thus it effectively approximates the degree of competition in traditional operations of the bank. Our findings suggest that higher mark-ups and cost inefficiencies are related to less efficient allocation of external finance.

Third, we use an all-encompassing market-based approximation of the country-level institutional quality, namely the control premium estimated by Dyck and Zingales (2004). The private control premiums correspond to the benefits enjoyed by the controlling shareholder and not shared by other shareholders. They arise as a consequence of the lack of limits to the extraction of private benefits, and they reflect the inverse of the level of investor protection in the country. Dyck and Zingales (2004) show that the control premiums are higher in countries with less deep financial markets, more concentrated ownership, less protected minority shareholders and weaker law enforcement. Our results are in line with the hypothesis that low quality of institutions is related to lower allocative efficiency.

Lastly, we use measures of bank regulation and supervisory practices which, as showed by Barth, Caprio, and Levine (2004), affect the development and performance of the banking sector. First, the banking sector development is significantly negatively associated with the restrictions on bank commercial activities, which we capture using the Restrictions on Bank Activities Index. Second, bank development and performance are positively associated with regulations that promote private monitoring of banks, which we capture using the Private Monitoring Index. Both indexes are constructed following methodology in Barth, Caprio, and Levine (2004). Our results suggest that firms raise more external finance in response to growth shocks in financial systems that feature fewer restrictions on the activities of banks.

1.6.5 Robustness Checks

We check for the robustness of our results across several dimensions.[26] First, as argued in Klapper, Laeven, and Rajan (2006), there exists substantial diversity in the legal forms of incorporation in Europe. The comparability of firms across countries can thus be increased by narrowing the sample to the forms of incorporation equivalent to limited liability companies. Our results hold for this subsample.

Second, in our difference-in-differences model, we regress firm-level external finance use on the industry-country group term that applies to all firms in the group. Effectively, we investigate conditional industry-country averages in external finance use and to the extent that the efficiency of this average is driven by the number of individual firms within each group, the potential concern is that our results may be affected by the industries with a small number of firms. The results are qualitatively unaffected and the investigated effect is economically stronger when we estimate our basic specification on the sample constrained to industry-country groups with at least 20 firms.

Third, we account more carefully for the unbalanced nature of our panel when estimating our cross-sectional regressions. If industry-specific factors affecting external finance use have been changing rapidly over time, controlling only for industry fixed effects can be insufficient. Thus, we amend our baseline specification (1.1), by interacting industry fixed effects with period fixed effects. A period dummy is equal to 1 for a given firm if its external finance use is computed as an average over a given period. Our results are not affected.

Fourth, we run median regressions which are robust to outliers and allow us to investigate industry-country median external finance use. The conditional median effects are economically smaller and in many cases statistically insignificant, but they always hold proper sign.

[26]The results presented in this section are available in Online Appendix 1.C.

Fifth, we also estimate regression (1.1) in which we, in addition to our standard set of firm-level control variables, control for Ownership Concentration and Ownership Concentration squared. The sample formation and regression specifications are otherwise identical to those in Table 1.4. The coefficients on the interaction term 'FD $\times$ US Growth' are bigger in magnitude and are more significant compared to those reported in Table 1.4.

Last, we check whether our results change if we use a sub-sample of EU-15 countries. Excluding countries from Central and East Europe (CEE) is justified by two reasons. First, CEE countries were still in the process of transition to a market economy and the resulting resource reallocation has been affected by their specific structure of growth opportunities. Second, EU-15 countries engaged in the single product market in 1993, which presumably brought higher degree of similarity in the growth opportunities of firms operating in the same industry across different countries. Our results show that leaving out CEE countries does not affect our findings.[27]

1.7 Conclusion

The most important role of a financial system is to provide external finance to viable firms so that they can exploit growth opportunities. The primary focus of this paper is to study whether the financial markets development improves the efficiency of the capital allocation. Using two alternative proxies for the global industry-specific component of growth opportunities, we show that comparable firms with growth opportunities obtain significantly more external finance in countries with more developed financial markets. We find the effect to be economically important. Given that our sample consists of relatively large and well-established firms, which are shown to be less affected by financial development, it is likely that the economic significance of our results in the overall population is even larger.

[27] Additionally, our results are robust to excluding Bulgaria and the Netherlands, which are countries with the lowest and highest levels of financial development in our sample.

1.8 Main Tables

Table 1.1: External Finance Use: Firm Data by Country, 1996-2005

				Percentile		
Country	N	Mean	S.D.	25th	50th	75th
Austria	129	-0.020	0.062	-0.060	-0.004	0.022
Belgium	1,630	0.000	0.037	-0.012	0.000	0.016
Bulgaria	113	0.023	0.057	-0.001	0.015	0.055
Czech Republic	1,033	-0.007	0.046	-0.027	-0.005	0.014
Estonia	119	0.009	0.046	-0.013	0.002	0.032
Finland	670	-0.007	0.037	-0.024	-0.005	0.011
France	4,629	0.002	0.032	-0.008	0.002	0.015
Germany	539	-0.008	0.059	-0.034	0.002	0.028
Greece	615	0.024	0.034	0.006	0.022	0.041
Hungary	104	-0.011	0.050	-0.039	-0.010	0.019
Ireland	168	0.002	0.044	-0.007	0.000	0.015
Italy	4,941	0.008	0.029	-0.004	0.008	0.022
Latvia	151	0.023	0.054	-0.005	0.014	0.054
Lithuania	54	0.053	0.054	0.022	0.054	0.087
Netherlands	425	-0.005	0.041	-0.019	-0.003	0.006
Poland	1,290	0.000	0.052	-0.024	-0.001	0.022
Portugal	510	0.008	0.039	-0.009	0.006	0.027
Slovakia	64	-0.013	0.049	-0.042	-0.012	0.007
Spain	3,026	0.007	0.033	-0.005	0.003	0.020
Sweden	1,351	-0.006	0.041	-0.023	-0.002	0.013
UK	3,177	0.006	0.038	-0.006	0.003	0.019
Total	24,738	0.004	0.038	-0.010	0.003	0.020

Note: The number of observations in the sample, N, corresponds to the number of firms with non-missing average External Finance Use (EFU) calculated based on at least 5 annual EFU values within the 1996-2005 period. Annual EFU is defined as change in shareholders' capital plus change in a firm's long-term debt plus change in a firm's other non-current liabilities divided by total assets. Before computing the statistics we remove EFU outliers (we use the 1-to-99 percentile range of annual EFU values). See Panel A of Appendix Table 1.A.1 for detailed definition of EFU.

Table 1.2: Financial Development: European Countries

	Mean	S.D.	Min	Max	Min Country	Max Country	N
Total Capitalization	1.05	0.94	0.08	4.21	Latvia	Netherlands	20
Private Credit	0.70	0.68	0.06	3.31	Latvia	Netherlands	21
Market Capitalization	0.32	0.34	0.00	1.33	Bulgaria	UK	20
Market Value Traded	0.19	0.21	0.00	0.82	Bulgaria	Netherlands	20
Accounting Standards	0.64	0.13	0.36	0.83	Portugal	Sweden	12
Government Bank Ownership	0.37	0.28	0.00	0.86	UK	Bulgaria	18
Government Bank Control	0.38	0.31	0.00	0.92	UK	Bulgaria	18
Overhead Costs	3.69	2.19	0.25	9.45	Ireland	Bulgaria	19
Net. Int. Margin	3.65	1.92	1.18	7.28	Netherlands	Latvia	19
Control Premium	0.17	0.19	0.01	0.58	Netherlands	Czech Republic	11
Private Monitoring Index	5.62	1.02	4.00	8.00	Slovakia	Finland	21
Restrictions on Bank Activities Index	7.90	1.67	5.00	10.00	UK	Bulgaria	21

Note: We present the Min, Max, Mean, and Standard Deviation of country-level financial development measures across Europe. Accounting Standards are as of 1990, Control Premium is estimated for the 1990-2000 period, Government Bank Ownership and Government Bank Control are as of 1995, Private Monitoring Index and Restrictions on Bank Activities Index are calculated using responses obtained over 1998-2000, and all remaining measures are as of 1996. Total Capitalization, Market Capitalization, and Market Value Traded are missing for Estonia. Accounting Standards are missing for Bulgaria, Czech Republic, Estonia, Hungary, Ireland, Lithuania, Latvia, Poland, and Slovakia. Government Bank Ownership and Government Bank Control are missing for Estonia, Lithuania, and Latvia. Overhead Costs and Net Interest Margin are missing for Finland and Sweden. Control Premium is missing for Belgium, Bulgaria, Estonia, Greece, Hungary, Ireland, Lithuania, Latvia, Poland, and Slovakia. See Panel B of Appendix Table 1.A.1 for complete definitions and sources of variables.

Table 1.3: Growth Opportunities and Technological Characteristics: Industry Data, 1996-2005

		US Growth	Global PE Level	Global PE Growth	R&D Intensity		Investment Lumpiness		External Finance Dependence	
	ISIC rev. 3.1	Mean	Mean	Mean	N	Median	N	Median	N	Median
15	Food products and beverages	-1.5%	23.87	2.3%	81	0.154	327	0.694	251	-0.117
16	Tobacco products	-2.0%	13.95	2.8%	10	0.245	23	1.043	16	-0.124
17	Textiles	-2.3%	19.41	0.8%	23	0.434	118	0.517	69	0.204
18	Wearing apparel	-7.7%	19.41	0.8%	5	0.000	58	1.759	50	-0.382
19	Leather	-4.9%	17.24	-2.1%	14	0.789	41	1.902	31	-1.548
20	Wood and cork	0.2%	20.52	3.1%	14	0.077	71	0.465	48	-0.061
21	Pulp and paper products	-0.2%	20.65	2.4%	59	0.146	143	0.476	120	-0.020
22	Publishing and printing	4.8%	24.67	1.5%	47	0.745	239	1.490	172	-0.217
23	Coke and refined petroleum	4.9%	18.92	1.2%	54	0.060	146	0.849	109	0.658
24	Chemical products	1.9%	19.56	1.9%	1,197	4.171	1,573	2.254	1,300	1.821
25	Rubber and plastic	2.3%	16.98	0.7%	90	0.257	212	0.675	138	-0.082
26	Other non-metallic mineral products	1.8%	13.87	0.4%	49	0.157	120	0.792	85	-0.101
27	Basic metals	0.7%	17.58	-0.8%	58	0.131	186	0.538	139	0.073
28	Fabricated metal products	0.4%	27.17	-0.1%	57	0.215	198	0.429	114	-0.320
29	Machinery and equipment	0.8%	23.27	0.0%	397	0.836	705	1.216	482	-0.117
30	Office machinery and computers	14.5%	38.45	1.5%	322	3.970	512	2.621	336	0.886
31	Electrical machinery and apparatus	-0.6%	31.29	2.2%	237	1.363	371	1.733	269	0.417
32	Radio, television and communication equipment	14.7%	41.13	1.2%	400	2.405	611	2.373	439	0.840
33	Medical, precision and optical instruments	17.7%	29.76	2.8%	673	2.933	1,008	2.144	711	0.665
34	Motor vehicles	2.1%	16.86	3.0%	65	0.392	115	1.200	90	0.170
35	Other transport equipment	2.3%	20.90	2.6%	94	0.617	174	0.954	129	-0.117
36	Manufacturing n.e.c.	NA	20.66	-0.3%	91	0.537	238	1.403	166	-0.141

Note: US Growth, Global PE Level, and Global PE Growth are the average growth rate of real value added in the U.S., the average world price-to-earnings ratio, and the average growth rate of the world price-to-earnings ratio, respectively, computed for each 2-digit ISIC industry over the 1996-2005 period. R&D Intensity is the time average of R&D to capital expenditure ratios of a median firm for each U.S. 3-digit ISIC industry over the 1996-2005 period. Investment Lumpiness is the number of investment spikes experienced by a median firm in each U.S. 3-digit ISIC industry over the 1996-2005 period. The investment spike is an event when annual capital expenditure exceeds 30 percent of the firm's stock of fixed assets. External Finance Dependence (EFD) is the share of capital expenditures not financed by cash flow from operations of a median firm for each U.S. 3-digit ISIC industry over the 1996-2005 period. N stands for the number of Compustat firms used to find the median values. All statistics are reported at 2-digit ISIC level, but we use 3-digit ISIC level industries for R&D Intensity, Investment Lumpiness, and External Finance Dependence in our regressions. See Panel C of Appendix Table 1.A.1 for complete definitions and sources of variables.

Table 1.4: Financial Development and External Finance Use: Basic Estimates

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
FD × US Growth	0.028**	0.055***	0.038*	0.115***	0.151*
	(0.011)	(0.016)	(0.021)	(0.041)	(0.085)
US Growth	-0.011	-0.019	0.007	-0.003	-0.074
	(0.043)	(0.043)	(0.042)	(0.042)	(0.071)
log(Total Assets)	-0.219***	-0.224***	-0.219***	-0.219***	-0.170***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
log(Total Assets) Squared	-2.463***	-2.420***	-2.456***	-2.459***	-3.901***
	(0.843)	(0.842)	(0.844)	(0.844)	(0.886)
log(Employees)	-0.455***	-0.451***	-0.454***	-0.455***	-0.583***
	(0.099)	(0.099)	(0.099)	(0.099)	(0.103)
log(Employees) Squared	4.374***	4.353***	4.367***	4.379***	6.447***
	(1.150)	(1.147)	(1.149)	(1.150)	(1.211)
Age	-0.006	-0.008	-0.006	-0.006	0.014
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
Age Squared	-0.032	-0.012	-0.038	-0.035	-0.133
	(0.373)	(0.373)	(0.373)	(0.373)	(0.390)
Leverage	-0.019***	-0.018***	-0.019***	-0.019***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tangibility	-0.013***	-0.013***	-0.013***	-0.013***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Collateral	0.004*	0.003	0.004*	0.004*	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cash	-0.008***	-0.009***	-0.008***	-0.008***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.023***	0.023***	0.023***	0.023***	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Country, Industry FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.081	0.081	0.081	0.081	0.080
N	24,619	24,738	24,619	24,619	21,642

Note: The table reports results of OLS regressions on the sample of European private firms. The dependent variable is the time average of annual firm-level External Finance Use (EFU) defined as change in shareholders' capital plus change in a firm's long-term debt plus change in a firm's other non-current liabilities divided by total assets. The average is taken over years in which a firm is present in the sample within the 1996-2005 period. US Growth is the time average of the real value-added growth of US 2-digit ISIC industries calculated, for each firm, over the same years for which EFU is computed. Country-level measures of Financial Development (FD) are predetermined. Firm-level control variables come from the first year a firm enters the sample and remain fixed over time. Logarithm of Total Assets (in EUR millions) is divided by 100. Logarithm of Employment is divided by 100. Age is the number of years since a firm's incorporation and it is divided by 1,000. Leverage is the ratio of long- plus short-term debt to total assets. Tangibility is the ratio of fixed assets to total assets. Collateral is measured as fixed assets plus inventories plus receivables divided by total assets. Cash is the ratio of cash holdings to total assets. See Appendix Table 1.A.1 for complete definitions and sources of variables. All specifications are linear regressions with outliers removed (we use the 1-to-99 percentile range of the dependent variable). We always control for country and 3-digit ISIC industry dummies. Robust standard errors (clustered at the industry-country level) are reported in parentheses; *, **, and *** denote significance at the 10%,5 %, and 1% levels, respectively.

Table 1.5: Financial Development and External Finance Use

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A: Cross-sectional Regressions		
FD × US Growth	0.028**	0.055***	0.038*	0.115***	0.151*
	(0.011)	(0.016)	(0.021)	(0.041)	(0.085)
US Growth	-0.011	-0.019	0.007	-0.003	-0.074
	(0.043)	(0.043)	(0.042)	(0.042)	(0.071)
Adjusted R^2	0.081	0.081	0.081	0.081	0.080
N	24,619	24,738	24,619	24,619	21,642
FD × Global PE Level	0.002	0.002	0.003	0.001	0.002
	(0.002)	(0.003)	(0.003)	(0.008)	(0.015)
Global PE Level	0.021*	0.021*	0.021*	0.022*	0.035**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)
Adjusted R^2	0.082	0.081	0.082	0.081	0.080
N	25,703	25,835	25,703	25,703	22,579
FD × Global PE Growth	0.054***	0.072***	0.104***	0.131**	0.216*
	(0.012)	(0.021)	(0.023)	(0.051)	(0.115)
Global PE Growth	-0.053***	-0.043**	-0.034**	-0.018	-0.117
	(0.020)	(0.020)	(0.017)	(0.018)	(0.079)
Adjusted R^2	0.082	0.082	0.082	0.082	0.080
N	25,703	25,835	25,703	25,703	22,579
			Panel B: Panel Regressions		
FD × US Growth	0.021**	0.019	0.048***	0.080**	0.127*
	(0.009)	(0.015)	(0.016)	(0.032)	(0.066)
US Growth	-0.026**	-0.015	-0.023**	-0.019*	-0.088*
	(0.013)	(0.013)	(0.011)	(0.011)	(0.045)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	181,070	181,838	181,070	181,070	161,593
FD × Global PE Level	0.006**	0.005	0.013**	0.014	0.017
	(0.003)	(0.004)	(0.005)	(0.010)	(0.020)
Global PE Level	-0.008**	-0.005	-0.007**	-0.004	-0.012
	(0.003)	(0.003)	(0.003)	(0.003)	(0.012)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	189,805	190,674	189,805	189,805	169,281
FD × Global PE Growth	0.011***	0.012**	0.023***	0.028**	0.047*
	(0.003)	(0.005)	(0.006)	(0.013)	(0.028)
Global PE Growth	-0.004	0.001	-0.001	0.003	-0.021
	(0.005)	(0.005)	(0.004)	(0.004)	(0.019)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	189,341	190,829	189,341	189,341	168,360

Note: The table reports results of OLS regressions on the sample of European private firms. Panel A reports results of cross-sectional regressions, where the dependent variable is the time average of annual firm-level External Finance Use, defined as in Table 1.4, and US Growth, Global PE Level, and Global PE Growth are time averages calculated, for each firm, over the same years for which EFU is computed. Panel B reports results of regressions on the panel of firm-year observations that corresponds to the sample used in Panel A. The dependent variable is the annual firm-level External Finance Use and growth opportunities proxies US Growth, Global PE Level, and Global PE Growth are allowed to vary over years. All specifications are linear regressions with outliers removed (observations outside the 1-to-99 percentile range of the dependent variable), include a constant and predetermined firm-level controls (see Table 1.4 notes for their definitions). Specifications in Panel A include country and 3-digit ISIC industry dummies, while specifications in Panel B include country, 3-digit ISIC industry, and year dummies. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on robust standard errors clustered at the industry-country level.

Table 1.6: Differences across Firms

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A: Small Firms		
FD × US Growth	0.037***	0.069***	0.057***	0.138***	0.243***
	(0.010)	(0.021)	(0.018)	(0.040)	(0.093)
Adjusted R^2	0.074	0.074	0.074	0.074	0.074
N	12,455	12,517	12,455	12,455	11,140
FD × Global PE Growth	0.072***	0.108***	0.126***	0.222***	0.294*
	(0.017)	(0.030)	(0.034)	(0.068)	(0.150)
Adjusted R^2	0.076	0.075	0.075	0.075	0.074
N	13,005	13,073	13,005	13,005	11,617
			Panel B: Large Firms		
FD × US Growth	0.022	0.043	0.026	0.111*	0.080
	(0.018)	(0.028)	(0.033)	(0.064)	(0.124)
Adjusted R^2	0.065	0.065	0.065	0.065	0.065
N	12,164	12,221	12,164	12,164	10,502
FD × Global PE Growth	0.030*	0.023	0.079**	0.021	0.114
	(0.018)	(0.026)	(0.037)	(0.074)	(0.165)
Adjusted R^2	0.066	0.065	0.066	0.066	0.065
N	12,698	12,762	12,698	12,698	10,962
			Panel C: Young Firms		
FD × US Growth	0.031**	0.058**	0.043*	0.124**	0.223*
	(0.013)	(0.024)	(0.024)	(0.051)	(0.120)
Adjusted R^2	0.099	0.099	0.099	0.099	0.100
N	11,974	12,036	11,974	11,974	10,306
FD × Global PE Growth	0.067***	0.087***	0.140***	0.164**	0.402**
	(0.019)	(0.029)	(0.041)	(0.078)	(0.181)
Adjusted R^2	0.101	0.100	0.101	0.100	0.100
N	12,515	12,583	12,515	12,515	10,756
			Panel D: Old Firms		
FD × US Growth	0.024*	0.050**	0.031	0.102**	0.063
	(0.013)	(0.021)	(0.025)	(0.052)	(0.100)
Adjusted R^2	0.069	0.069	0.069	0.069	0.065
N	12,645	12,702	12,645	12,645	11,336
FD × Global PE Growth	0.033**	0.046*	0.059*	0.073	-0.029
	(0.016)	(0.026)	(0.031)	(0.063)	(0.133)
Adjusted R^2	0.069	0.069	0.069	0.069	0.065
N	13,188	13,252	13,188	13,188	11,823

Table 1.6: Differences across Firms

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel E: Closely Held Firms		
FD × US Growth	0.044***	0.076***	0.061***	0.199***	0.325***
	(0.011)	(0.018)	(0.022)	(0.047)	(0.111)
Adjusted R^2	0.069	0.069	0.068	0.069	0.064
N	13,446	13,513	13,446	13,446	12,092
FD × Global PE Growth	0.058***	0.068***	0.118***	0.160***	0.365**
	(0.015)	(0.024)	(0.030)	(0.062)	(0.154)
Adjusted R^2	0.069	0.069	0.070	0.069	0.064
N	14,055	14,129	14,055	14,055	12,635
			Panel F: Firms with Dispersed Ownership		
FD × US Growth	0.007	0.022	0.006	0.002	-0.084
	(0.021)	(0.039)	(0.037)	(0.067)	(0.130)
Adjusted R^2	0.107	0.107	0.107	0.107	0.106
N	9,645	9,695	9,645	9,645	8,467
FD × Global PE Growth	0.065**	0.117**	0.106**	0.123	0.010
	(0.026)	(0.046)	(0.047)	(0.094)	(0.197)
Adjusted R^2	0.108	0.108	0.108	0.107	0.105
N	10,029	10,085	10,029	10,029	8,790

Note: The table reports results of OLS regressions analogous to those presented in Panel A of Table 1.5. The dependent variable is the time average of annual firm-level External Finance Use. Panel A uses the sample of small firms, where a firm is defined to be small if its size measured by Total Assets is less or equal to the median value taken across all firms in the same country and 2-digit ISIC industry cell (the country-industry median). Panel B uses the sample of large firms, where a firm is defined to be large if its Total Assets are greater than the corresponding country-industry median. Panel C uses the sample of young firms, where a firm is defined to be young if its age since incorporation as of the first year the firm enters the sample is less or equal to the country-industry median. Panel D uses the sample of old firms, where a firm is defined to be old if its age is greater than the country-industry median. Panel E uses the sample of closely held firms, where a firm is defined to be closely held if its Ownership Concentration, measured by Herfindahl-Hirschman Index of direct shareholders' stakes, is greater than the country-industry median. Panel F uses the sample of firms with dispersed ownership, where firm is defined to have dispersed ownership if its Ownership Concentration is less or equal to the country-industry median. All specifications are linear regressions with outliers removed (observations outside the 1-to-99 percentile range of the dependent variable), include a constant, the corresponding growth opportunity proxy as a base effect, firm-level controls (see Table 1.4 notes for their definitions), and country and 3-digit ISIC industry dummies. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on robust standard errors clustered at the industry-country level.

Table 1.7: Growth Opportunities and Technological Characteristics

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A: Technological Characteristics		
FD × R&D Intensity	0.083***	0.152***	0.107*	0.263**	0.161
	(0.028)	(0.055)	(0.060)	(0.121)	(0.278)
Adjusted R^2	0.081	0.081	0.081	0.081	0.079
N	23,756	23,862	23,756	23,756	20,921
FD × Investment Lumpiness	0.261***	0.490***	0.339***	0.796***	0.676
	(0.058)	(0.127)	(0.113)	(0.239)	(0.525)
Adjusted R^2	0.082	0.082	0.082	0.082	0.080
N	25,692	25,824	25,692	25,692	22,571
FD × EFD	0.096**	0.169**	0.140*	0.285	0.484
	(0.039)	(0.068)	(0.085)	(0.183)	(0.440)
Adjusted R^2	0.081	0.081	0.081	0.081	0.079
N	25,441	25,567	25,441	25,441	22,362

Table 1.7: Growth Opportunities and Technological Characteristics

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel B: US Growth		
FD × US Growth	0.025**	0.049***	0.033	0.109**	0.178*
	(0.012)	(0.018)	(0.024)	(0.047)	(0.104)
FD × R&D Intensity	0.054**	0.102**	0.062	0.125	-0.076
	(0.025)	(0.045)	(0.053)	(0.126)	(0.294)
Adjusted R^2	0.081	0.081	0.080	0.081	0.079
N	22,672	22,765	22,672	22,672	19,984
FD × US Growth	0.011	0.024	0.016	0.068	0.124
	(0.011)	(0.018)	(0.022)	(0.044)	(0.087)
FD × Investment Lumpiness	0.239***	0.435***	0.314***	0.648**	0.418
	(0.061)	(0.134)	(0.118)	(0.251)	(0.530)
Adjusted R^2	0.082	0.082	0.081	0.082	0.080
N	24,608	24,727	24,608	24,608	21,634
FD × US Growth	0.024**	0.047***	0.033	0.105**	0.136
	(0.011)	(0.017)	(0.022)	(0.044)	(0.090)
FD × EFD	0.062	0.106*	0.098	0.138	0.283
	(0.039)	(0.060)	(0.082)	(0.196)	(0.452)
Adjusted R^2	0.081	0.081	0.081	0.081	0.080
N	24,357	24,470	24,357	24,357	21,425
			Panel C: Global PE Growth		
FD × Global PE Growth	0.054***	0.068***	0.108***	0.138**	0.252*
	(0.013)	(0.022)	(0.025)	(0.056)	(0.133)
FD × R&D Intensity	0.050*	0.112**	0.034	0.175	-0.003
	(0.028)	(0.055)	(0.058)	(0.126)	(0.295)
Adjusted R^2	0.082	0.081	0.082	0.081	0.080
N	23,756	23,862	23,756	23,756	20,921
FD × Global PE Growth	0.043***	0.053***	0.092***	0.098*	0.195
	(0.012)	(0.020)	(0.025)	(0.051)	(0.118)
FD × Investment Lumpiness	0.201***	0.421***	0.204*	0.666***	0.435
	(0.060)	(0.131)	(0.114)	(0.244)	(0.543)
Adjusted R^2	0.083	0.083	0.083	0.082	0.080
N	25,692	25,824	25,692	25,692	22,571
FD × Global PE Growth	0.050***	0.065***	0.098***	0.123**	0.214*
	(0.013)	(0.022)	(0.025)	(0.055)	(0.126)
FD × EFD	0.059	0.117*	0.072	0.184	0.296
	(0.040)	(0.068)	(0.085)	(0.189)	(0.458)
Adjusted R^2	0.082	0.081	0.082	0.081	0.080
N	25,441	25,567	25,441	25,441	22,362

Note: The table reports results of OLS regressions on the sample of European private firms. The dependent variable is the time average of annual firm-level External Finance Use defined as in Table 1.4. Panel A reports estimates from specifications that include interactions of financial development proxies (FD) with technological characteristics. R&D Intensity is the time average of R&D to capital expenditure ratios of a median firm for each U.S. 3-digit ISIC industry over the 1996-2005 period. Investment Lumpiness is the number of investment spikes experienced by a median firm in each U.S. 3-digit ISIC industry over the 1996-2005 period. The investment spike is an event when annual capital expenditure exceeds 30 percent of the firm's stock of fixed assets. External Finance Dependence (EFD) is the share of capital expenditures not financed by cash flow from operations of a median firm for each U.S. 3-digit ISIC industry over the 1996-2005 period. Panel B reports estimates from specifications that include interactions of financial development proxies with US Growth as well as interactions of financial development proxies with technological characteristics presented in Panel A. Panel C reports estimates from specifications that include interactions of financial development proxies with Global PE Growth as well as interactions of financial development proxies with technological characteristics presented in Panel A. All specifications are linear regressions with outliers removed (observations outside the 1-to-99 percentile range of the dependent variable), include a constant, the corresponding growth opportunity proxy as a base effect, firm-level controls (see Table 1.4 notes for their definitions), and country and 3-digit ISIC industry dummies. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on robust standard errors clustered at the industry-country level.

Table 1.8: Capital Expenditures Not Financed by Internal Funds

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A: Cross-sectional Regressions		
FD × US Growth	0.062***	0.113**	0.088**	0.260***	0.600***
	(0.023)	(0.045)	(0.042)	(0.092)	(0.218)
US Growth	0.022	0.002	0.059	0.038	-0.226
	(0.090)	(0.092)	(0.088)	(0.088)	(0.171)
Adjusted R^2	0.078	0.078	0.078	0.078	0.077
N	24,489	24,609	24,489	24,489	21,493
FD × Global PE Level	0.008*	0.014*	0.010	0.023	0.053
	(0.004)	(0.008)	(0.008)	(0.018)	(0.038)
Global PE Level	0.006	0.003	0.011	0.009	0.022
	(0.023)	(0.023)	(0.023)	(0.023)	(0.035)
Adjusted R^2	0.077	0.077	0.077	0.077	0.075
N	25,566	25,700	25,566	25,566	22,422
FD × Global PE Growth	0.083***	0.134***	0.131***	0.304***	0.529**
	(0.024)	(0.040)	(0.048)	(0.105)	(0.249)
Global PE Growth	-0.119***	-0.119***	-0.075**	-0.088***	-0.333**
	(0.038)	(0.038)	(0.033)	(0.033)	(0.167)
Adjusted R^2	0.077	0.077	0.077	0.077	0.075
N	25,566	25,700	25,566	25,566	22,422
			Panel B: Panel Regressions		
FD × US Growth	0.064***	0.088***	0.118***	0.236***	0.385***
	(0.016)	(0.026)	(0.032)	(0.061)	(0.127)
US Growth	-0.076***	-0.066***	-0.052***	-0.053***	-0.256***
	(0.023)	(0.023)	(0.018)	(0.019)	(0.085)
Adjusted R^2	0.027	0.027	0.027	0.027	0.028
N	179,997	180,785	179,997	179,997	160,582
FD × Global PE Level	0.014***	0.016**	0.028***	0.039**	0.081**
	(0.004)	(0.007)	(0.008)	(0.016)	(0.032)
Global PE Level	-0.015***	-0.011*	-0.011***	-0.008*	-0.051**
	(0.005)	(0.006)	(0.004)	(0.005)	(0.020)
Adjusted R^2	0.027	0.027	0.027	0.027	0.028
N	188,670	189,564	188,670	188,670	168,202
FD × Global PE Growth	0.025***	0.027***	0.055***	0.092***	0.187***
	(0.006)	(0.009)	(0.010)	(0.022)	(0.047)
Global PE Growth	-0.012	-0.002	-0.007	-0.003	-0.106***
	(0.008)	(0.008)	(0.006)	(0.007)	(0.032)
Adjusted R^2	0.028	0.028	0.028	0.028	0.029
N	188,211	189,089	188,211	188,211	167,287

Note: The table uses the sample, variables, and specifications as Table 1.5 except that the firm-level External Finance Use variable is calculated as the time average of annual changes in shareholders' capital plus changes in a firm's long-term debt plus changes in a firm's other non-current liabilities minus profits/losses from operations plus changes in other shareholders' funds, all divided by total assets. The average is taken over years in which a firm is present in the sample within the 1996-2005 period.

Table 1.9: Decomposing External Finance Use

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A: Changes in Shareholders' Equity		
FD × US Growth	0.008**	0.010*	0.017**	0.028*	0.063**
	(0.004)	(0.006)	(0.008)	(0.015)	(0.031)
US Growth	0.015	0.018	0.018	0.019	-0.010
	(0.016)	(0.016)	(0.016)	(0.016)	(0.025)
Adjusted R^2	0.067	0.067	0.067	0.067	0.066
N	23,862	23,978	23,862	23,862	21,188
FD × Global PE Growth	0.010**	0.011*	0.022**	0.018	0.051
	(0.005)	(0.006)	(0.011)	(0.018)	(0.038)
Global PE Growth	-0.008	-0.005	-0.006	-0.000	-0.023
	(0.008)	(0.008)	(0.007)	(0.008)	(0.027)
Adjusted R^2	0.066	0.066	0.066	0.066	0.064
N	24,907	25,036	24,907	24,907	22,099
			Panel B: Changes in Long-term Debt		
FD × US Growth	0.015***	0.026**	0.026**	0.060***	0.096*
	(0.005)	(0.010)	(0.011)	(0.022)	(0.055)
US Growth	0.014	0.013	0.022	0.019	-0.030
	(0.030)	(0.031)	(0.031)	(0.031)	(0.047)
Adjusted R^2	0.095	0.095	0.095	0.095	0.089
N	23,862	23,978	23,862	23,862	21,188
FD × Global PE Growth	0.025***	0.033**	0.054***	0.042	0.049
	(0.009)	(0.013)	(0.018)	(0.037)	(0.085)
Global PE Growth	-0.021	-0.018	-0.014	-0.001	-0.018
	(0.013)	(0.013)	(0.012)	(0.011)	(0.058)
Adjusted R^2	0.095	0.095	0.095	0.094	0.088
N	24,907	25,036	24,907	24,907	22,099
			Panel C: Changes in Other Non-current Liabilities		
FD × US Growth	0.002	0.012	-0.009	0.010	-0.037
	(0.005)	(0.011)	(0.008)	(0.020)	(0.036)
US Growth	0.006	-0.001	0.011	0.006	0.026
	(0.024)	(0.024)	(0.023)	(0.023)	(0.036)
Adjusted R^2	0.039	0.039	0.039	0.039	0.035
N	23,859	23,975	23,859	23,859	21,187
FD × Global PE Growth	0.013*	0.022*	0.013	0.040	0.018
	(0.007)	(0.013)	(0.010)	(0.026)	(0.050)
Global PE Growth	-0.019*	-0.019*	-0.009	-0.013	-0.012
	(0.010)	(0.011)	(0.008)	(0.009)	(0.034)
Adjusted R^2	0.040	0.040	0.040	0.040	0.035
N	24,904	25,033	24,904	24,904	22,098

Note: The table uses the sample, variables, and specifications as Panel A of Table 1.5 except that the dependent variables are, one at a time, individual components of the External Finance Use measure. The dependent variable in Panel A, B, and C is the time average of annual firm-level changes in shareholders' capital, in a firm's long-term debt, and in a firm's other non-current liabilities, respectively. All variables are scaled by total assets and then averaged over years in which a firm is present in the sample within the 1996-2005 period.

Table 1.10: Error in Measurement of Growth Opportunities

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A : Instrumenting by Global PE Growth		
FD × US Growth	0.168***	0.260***	0.275***	0.438**	0.846*
	(0.050)	(0.094)	(0.102)	(0.179)	(0.432)
US Growth	-0.022	0.076	0.079	-0.022	-0.101
	(0.292)	(0.283)	(0.281)	(0.292)	(0.381)
Adjusted R^2	0.069	0.072	0.070	0.077	0.068
N	24,619	24,738	24,619	24,619	21,642
			First-stage Regression Statistics		
F-statistics	58.497	57.283	58.614	57.176	64.252
			Panel B : Instrumenting by US Growth		
FD × Global PE Growth	0.128**	0.240***	0.175*	0.547***	0.793*
	(0.050)	(0.079)	(0.096)	(0.203)	(0.457)
Global PE Growth	-0.142	-0.056	-0.095	-0.142	-0.496
	(0.113)	(0.103)	(0.101)	(0.113)	(0.326)
Adjusted R^2	0.080	0.077	0.082	0.077	0.078
N	24,619	24,738	24,619	24,619	21,642
			First-stage Regression Statistics		
F-statistics	66.947	66.44	67.124	65.554	75.511

Note: The table reports results of two-stage least-squares regressions. The sample, variables, and specifications are as in Panel A of Table 1.5. In Panel A, 'FD × US Growth' and 'US Growth' are instrumented using 'FD × Global PE Growth' and 'Global PE Growth.' In Panel B, 'FD × Global PE Growth' and 'Global PE Growth' are instrumented using 'FD × US Growth' and 'US Growth.' F-statistic we report for the first-stage regression is heteroskedasticity-robust Kleibergen-Paap rk Wald F-statistic for the test of weak instruments.

Table 1.11: Alternative Measures of Financial Development

	Gov. Bank Ownership	Gov. Bank Control	Overhead Costs	Net Interest Margin	Control Premium	Private Monitoring Index	Restrictions on Bank Activities Index
FD × US Growth	-0.029	-0.015	-0.013	-0.004	-0.096**	0.003	-0.012***
	(0.043)	(0.043)	(0.009)	(0.009)	(0.042)	(0.008)	(0.004)
US Growth	0.031	0.027	0.057	0.031	0.010	0.008	0.113**
	(0.044)	(0.044)	(0.051)	(0.053)	(0.046)	(0.061)	(0.052)
Adjusted R^2	0.077	0.077	0.078	0.078	0.072	0.081	0.081
N	24,414	24,414	22,717	22,717	20,430	24,738	24,738
FD × Global PE Growth	-0.165***	-0.153***	-0.043***	-0.029***	-0.130**	0.002	-0.017***
	(0.047)	(0.047)	(0.009)	(0.007)	(0.058)	(0.010)	(0.005)
Global PE Growth	0.063***	0.059***	0.157***	0.111***	0.046***	-0.002	0.143***
	(0.018)	(0.018)	(0.034)	(0.031)	(0.016)	(0.059)	(0.038)
Adjusted R^2	0.079	0.079	0.080	0.079	0.073	0.081	0.082
N	25,483	25,483	23,742	23,742	21,339	25,835	25,835

Note: The table uses the sample, variables, and specifications as Panel A of Table 1.5 except that we use alternative country-level measures of Financial Development (FD). See Panel B of Table 1.A.1 for their complete definitions and sources.

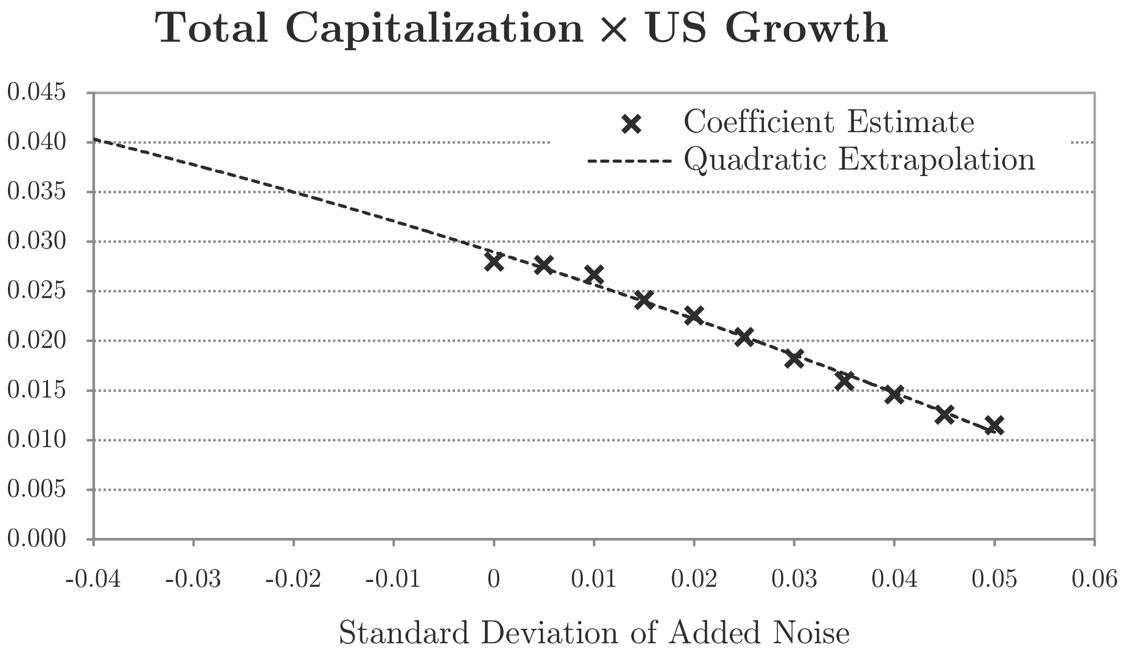


Figure 1.1: Sensitivity of estimates to added noise in GO_i

1.A Appendix Tables

Table 1.A.1: Definitions and Sources of Variables

Name	Definition and Source
	Panel A: Firm-level Variables
Total Assets	Firm's total assets (TOAS) in billions of Euro. We use the value from the first year a firm enters the sample within the 1996-2005 period. Source: Amadeus.
Employees	Number of employees (EMPL). We use the value from the first year a firm enters the sample within the 1996-2005 period. Source: Amadeus.
Age	The number of years since a firm's incorporation, scaled down by 1,000. We use the value from the first year a firm enters the sample within the 1996-2005 period. Source: Amadeus.
External Finance Use	First, we sum the year-on-year change in shareholders' capital ($CAPI_t - CAPI_{t-1}$), the year-on-year change in a firm's long-term debt ($LTDB_t - LTDB_{t-1}$), and the year-on-year change in a firm's other non-current liabilities ($ONCLI_t - ONCLI_{t-1}$). The result is divided by total assets from the beginning of each year ($TOAS_{t-1}$). Second, we compute the time average of annual measures from the first step over the years in which a firm is present in the sample within the 1996-2005 period. Source: Amadeus.
Leverage	Long-term debt (LTDB) plus current liabilities (CULI) divided by total assets (TOAS). We use the value from the first year a firm enters the sample within the 1996-2005 period. Source: Amadeus.
Tangibility	Fixed assets (FIAS) divided by total assets (TOAS). We use the value from the first year a firm enters the sample within the 1996-2005 period. Source: Amadeus.
Collateral	Fixed assets (FIAS) plus inventories (STOK) plus accounts receivables (DEBT) divided by total assets (TOAS). We use the value from the first year a firm enters the sample within the 1996-2005 period. Source: Amadeus.
Cash	Cash holdings (CASH) divided by total assets (TOAS). We use the value from the first year a firm enters the sample. Source: Amadeus.
Ownership Concentration	The sum of squares of direct stakes of all reported shareholders (Herfindahl-Hirschman index). We use the value from the the year that is the closest to the first year a firm enters the sample. Source: Amadeus.

Table 1.A.1: Definitions and Sources of Variables

Name	Definition and Source
	Panel B: Country-level Variables
Total Capitalization	Private credit by deposit money banks and other financial institutions plus stock market capitalization divided by GDP in 1996. Source: Beck, Demirguc-Kunt, and Levine (2000).
Private Credit	Private credit by deposit money banks and other financial institutions divided by GDP in 1996. Source: Beck, Demirguc-Kunt, and Levine (2000).
Market Capitalization	Stock market capitalization divided by GDP in 1996. Source: Beck, Demirguc-Kunt, and Levine (2000).
Market Value Traded	Stock market total value traded divided by GDP in 1996. Source: Beck, Demirguc-Kunt, and Levine (2000).
Accounting Standards	Index created by examining and rating companies' 1990 annual reports on their inclusion or omission of 90 items in balance sheets and income statements and published by the Center for International Financial Analysis & Research, Inc. The maximum is 90, the minimum 0, and we scaled it down by 100. Source: The Center for International Financial Analysis & Research.
Government Bank Ownership	Share of the top 10 banks' assets owned by a country's government in 1995. The percentage of the assets owned by the government in a given bank is calculated by multiplying the share of each shareholder in that bank by the share the government owns in that shareholder, and then summing the resulting ownership stakes. Source: La Porta, Lopez-De-Silanes, and Shleifer (2002).
Government Bank Control	Share of the top 10 banks' assets controlled by a country's government at the 50 percent level in 1995. The percentage of assets owned by the government in a given bank is calculated following the same methodology outlined for Government Bank Ownership. Source: La Porta, Lopez-De-Silanes, and Shleifer (2002).
Overhead Costs	Accounting value of banks' overhead costs as a share of their total assets. Scaled up by 100. Source: Beck, Demirguc-Kunt, and Levine (2000).
Net Interest Margin	Accounting value of banks' net interest revenue as a share of their interest-bearing assets. Scaled up by 100. Source: Beck, Demirguc-Kunt, and Levine (2000).
Control Premium	Control premium estimated by Dyck and Zingales (2004) using the sample of 393 controlling blocks sales in 1990-2000 period. We use the estimated country fixed effects from Table III, column (1).
Private Monitoring Index	Index of regulatory measures that promote private monitoring of banks constructed by Barth, Caprio, and Levine (2004) using information on: (a) whether an outside licensed audit is required of the financial statements issued by a bank; (b) The percentage of the top 10 banks that are rated by international credit-rating agencies; (c) whether there is an explicit deposit insurance scheme; (d) wether the income statement includes accrued or unpaid interest or principal on nonperforming loans and whether banks are required to produce consolidated financial statements; (e) wether off-balance sheet items are disclosed to the public; (f) wether banks must disclose risk management procedures to the public; and (g) wether subordinated debt is allowable (required) as a part of regulatory capital. Higher values indicate more private monitoring. See Barth, Caprio, and Levine (2004) for the exact formula for calculating the index.
Restrictions on Bank Activities Index	Index of regulatory measures that allow banks to engage in other than traditional interest-spread-based activities constructed by Barth, Caprio, and Levine (2004) using information on: (a) the ability of banks to own and control non-financial firms; (b) the ability of banks to engage in the business of securities underwriting, brokering, and dealing; (c) the ability of banks to engage in insurance underwriting and selling; and (d) the ability of banks to engage in real estate investment, development, and management. Higher values indicate more restrictions on non-traditional activities. See Barth, Caprio, and Levine (2004) for the exact formula for calculating the index.

Table 1.A.1: Definitions and Sources of Variables

Name	Definition and Source
	Panel C: Industry-level Variables
R&D Intensity	First, for each Compustat firm, we compute the time average of R&D expenditures and capital expenditures over the 1996-2005 period and take the ratio of the two averages. Second, we take the ratio from the first step of the median U.S. firm for each 3-digit ISIC industry. Source: Compustat.
Investment Lumpiness	First, for each Compustat firm, we compute the average number of investment spikes it experienced over the 1996-2005 period. An investment spike is defined as an event when annual capital expenditure exceeds 30 percent of the firm's stock of fixed assets. Second, we take the average of the statistic computed in the first step for each U.S. 3-digit ISIC industry Source: Compustat.
External Finance Dependence	First, for each Compustat firm, we sum capital expenditures and cash flows from operations over the 1996-2005 period. Second, for each Compustat firm, we compute the ratio of capital expenditures minus cash flows from operations over capital expenditures using the sums obtained in the first step. Third, we take the ratio from the second step of the median U.S. firm for each 3-digit ISIC industry. Source: Compustat.
US Growth	First, we compute year-on-year growth rates by taking the difference of natural logarithms of annual real value added for each U.S. 2-digit ISIC industry. Second, for each firm in our sample, we compute the time average of year-on-year growth rates over the same years for which External Finance Use is computed. Source: OECD STAN.
Global PE Level	First, we take the world price-to-earnings ratios of industry portfolios as they are defined in Datastream. Second, for each firm in our sample, we compute the time average of the world price-to-earnings ratios over the same years for which External Finance Use is computed. Finally, we match Datastream industries into 2-digit ISIC. Source: Datastream.
Global PE Growth	First, we compute year-on-year growth rates of the world price-to-earnings ratio of industry portfolios as they are defined in Datastream. Second, for each firm in our sample, we compute the time average of the year-on-year growth rates over the same years for which External Finance Use is computed. Finally, we match Datastream industries to 2-digit ISIC. Source: Datastream.

1.B Balance Sheet Definition of External Finance Use

Rajan and Zingales (1998) define external finance dependence (EFD) as the share of capital expenditure (CE) not financed by cash flow (CF)

$$EFD_t = \frac{CE_t - CF_t}{CE_t}.$$

To measure external finance use, we find an analogy to their definition using balance sheet data that are available for most firms in our sample. In a panel of annual firm balance sheet items, we can approximate capital expenditure by the change in fixed assets ($FIAS$) plus depreciation ($DEPRE$)

$$\begin{aligned} CE_t &= (FIAS_t - FIAS_{t-1}) + DEPRE_t \qquad (1.A.1) \\ &= \Delta FIAS_t + DEPRE_t. \end{aligned}$$

Cash flow is approximated by firm's operating profit (PL) increased by depreciation (depreciation is cost but not cash outflow) and adjusted for the change in the net working capital. An increase in current assets ($CUAS$, i.e., inventories and accounts receivables) uses cash, while an increase in current liabilities ($CULI$, i.e., short-term loans and accounts payables) releases cash

$$\begin{aligned} CF_t &= PL_t + DEPRE_t - (CUAS_t - CUAS_{t-1}) + (CULI_t - CULI_{t-1}) \qquad (1.A.2) \\ &= PL_t + DEPRE_t - \Delta CUAS_t + \Delta CULI_t. \end{aligned}$$

Next, we show how is difference $CE_t - CF_t$ related to the amount of external finance raised. The fundamental balance sheet identity necessitates that change in total assets equals change in equity plus change in liabilities. Decomposing total assets into fixed assets ($FIAS$), current assets ($CUAS$), and cash ($CASH$); and decomposing total liabilities into shareholders' equity ($CAPI$), other shareholders' funds ($OSFD$, i.e., reserves and retained earnings), long-term debt ($LTDB$), other non-current liabilities ($ONCLI$, i.e., provisions), and current liabilities ($CULI$), the balance sheet identity becomes

$$\Delta FIAS_t + \Delta CUAS_t + \Delta CASH_t = \Delta CAPI_t + \Delta OSFD_t + \Delta LTDB_t + \Delta ONCLI_t + \Delta CULI_t.$$

Using the above equations we can rewrite difference $CE_t - CF_t$ as

$$\begin{aligned} CE_t - CF_t &= \Delta FIAS_t + DEPRE_t - PL_t - DEPRE_t + \Delta CUAS_t - \Delta CULI_t \\ &= \Delta FIAS_t + \Delta CUAS_t - PL_t - \Delta CULI_t \\ &= \Delta CAPI_t + \Delta LTDB_t + \Delta ONCLI_t - \underbrace{(PL_t - \Delta OSFD_t)}_{=DIV_t(Dividends)} - \Delta CASH_t \end{aligned} \quad (1.A.3)$$

We define External Finance Use (EFU) as

$$EFU_t = \frac{\Delta CAPI_t + \Delta LTDB_t + \Delta ONCLI_t}{TOAS_{t-1}}. \quad (1.A.4)$$

The numerator of EFU_t stands for the amount of equity raised/repurchased ($\Delta CAPI_t$) plus the amount of long-term debt issued/repaid ($\Delta LTDB_t$) plus the change in other forms of long-term financing ($\Delta ONCLI_t$). (We verify that equation (1.A.3) holds in our data when we use (1.A.1) and (1.A.2) to compute the left-hand side.) We scale the net flow of external finance by total assets as of the beginning of each year ($TOAS_{t-1}$). The reason is that capital expenditure is close to zero for many firms, which makes division impossible. We scale by total assets because it proxies for firm size and it is a measure that is the most comparable across firms in our sample.[28]

[28]Note that if a firm pays a dividend (DIV_t), the corresponding change in other shareholders' funds is $OSFD_t - OSFD_{t-1} = PL_t - DIV_t$, and thus term $PL_t - \Delta OSFD_t$ in equation (1.A.3) is equal to a dividend paid to shareholders. If a firm does not pay any dividend, $DIV_t = 0$, and the stock of cash does not change, $\Delta CASH_t = 0$, the difference between capital expenditure and cash flow from operations is equal to the amount of equity and long-term financing raised $CE_t - CF_t = \Delta CAPI_t + \Delta LTDB_t + \Delta ONCLI_t$.

1.C Online Appendix Tables

Table 1.OA.1: Growth Opportunities and Technological Characteristics: Descriptive Statistics

	Panel A: Basic Statistics					
	US Growth	Global PE Level	Global PE Growth	R&D Intensity	Investment Lumpiness	EFD
Mean	2.4%	22.55	1.3%	0.928	1.226	0.051
S.D.	6.3%	7.16	1.4%	1.478	0.723	0.885
N	21	22	22	58	58	58
	Panel B: Rank Correlations					
	US Growth	Global PE Level	Global PE Growth	R&D Intensity	Investment Lumpiness	EFD
US Growth	1					
Global PE Level	0.335	1				
	(0.138)					
	21					
Global PE Growth	0.165	0.153	1			
	(0.475)	(0.509)				
	21	21				
R&D Intensity	0.416	0.480	0.060	1		
	(0.061*)	(0.028**)	(0.795)			
	21	21	21			
Investment Lumpiness	0.342	0.327	0.059	0.653	1	
	(0.130)	(0.147)	(0.801)	(0.000***)		
	21	21	21	58		
EFD	0.552	0.281	0.293	0.216	0.255	1
	(0.010***)	(0.217)	(0.198)	(0.104)	(0.054*)	
	21	21	21	58	58	

Note: In Panel A, we present descriptive statistics for US Growth, Global PE Level, and Global PE Growth on 2-digit ISIC industries and R&D Intensity, Investment Lumpiness, and EFD on 3-digit ISIC industries over the 1996-2005 period (see Table 1.3 and Panel C of Table 1.A.1 for definitions and sources of the variables). Panel B presents Spearman rank correlations with corresponding p-values in brackets and the number of observations used to estimate it.

Table 1.OA.2: Controlling for Ownership Concentration

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
FD × US Growth	0.032***	0.061***	0.043**	0.127***	0.165*
	(0.011)	(0.016)	(0.020)	(0.040)	(0.087)
US Growth	-0.002	-0.011	0.018	0.007	-0.069
	(0.044)	(0.044)	(0.043)	(0.043)	(0.072)
log(Total Assets)	-0.208***	-0.214***	-0.208***	-0.208***	-0.154***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
log(Total Assets) Squared	-2.556***	-2.507***	-2.546***	-2.553***	-3.908***
	(0.859)	(0.857)	(0.859)	(0.859)	(0.892)
log(Employees)	-0.426***	-0.422***	-0.424***	-0.426***	-0.557***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.106)
log(Employees) Squared	4.196***	4.166***	4.184***	4.199***	6.287***
	(1.190)	(1.187)	(1.189)	(1.189)	(1.235)
Age	-0.011	-0.012	-0.011	-0.010	-0.000
	(0.032)	(0.032)	(0.032)	(0.032)	(0.034)
Age Squared	0.104	0.125	0.096	0.099	-0.003
	(0.385)	(0.385)	(0.385)	(0.385)	(0.398)
Leverage	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tangibility	-0.012***	-0.012***	-0.012***	-0.012***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Collateral	0.003	0.003	0.003	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cash	-0.008***	-0.009***	-0.008***	-0.008***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Ownership Concentration	0.013***	0.012***	0.013***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ownership Concentration Squared	-0.012***	-0.012***	-0.012***	-0.012***	-0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.023***	0.023***	0.023***	0.023***	0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Country, Industry FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.082	0.082	0.082	0.082	0.081
N	23,091	23,208	23,091	23,091	20,559

Note: The table uses the sample, variables, and specifications as Table 1.4 except that we, in addition, control for Ownership Concentration and Ownership Concentration squared. Ownership Concentration is Herfindahl-Hirschman Index of direct shareholders' stakes. It is calculated as the sum of squares of direct stakes of all reported shareholders in the year that is the closest to the first year a firm enters the sample and it remains fixed over time.

Table 1.OA.3: Alternative Specifications of Panel Regressions

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A: Time-varying Firm-level Controls		
FD × US Growth	0.021***	0.024*	0.043***	0.079***	0.112*
	(0.007)	(0.012)	(0.014)	(0.028)	(0.065)
US Growth	-0.011	-0.004	-0.005	-0.004	-0.061
	(0.012)	(0.012)	(0.010)	(0.010)	(0.046)
Adjusted R^2	0.019	0.019	0.019	0.019	0.018
N	158,240	158,971	158,240	158,240	143,214
FD × Global PE Level	0.005**	0.005	0.013***	0.011	0.029
	(0.002)	(0.003)	(0.004)	(0.008)	(0.019)
Global PE Level	-0.008***	-0.006*	-0.008***	-0.005	-0.021*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.012)
Adjusted R^2	0.019	0.019	0.019	0.019	0.018
N	165,028	165,843	165,028	165,028	149,228
FD × Global PE Growth	0.006*	0.006	0.015**	0.013	-0.006
	(0.003)	(0.005)	(0.006)	(0.013)	(0.028)
Global PE Growth	-0.003	-0.000	-0.003	0.001	0.008
	(0.005)	(0.005)	(0.004)	(0.004)	(0.019)
Adjusted R^2	0.019	0.019	0.019	0.019	0.018
N	165,028	165,843	165,028	165,028	149,228
			Panel B: Controlling for Firm Fixed Effects		
FD × US Growth	0.018***	0.013	0.044***	0.070***	0.131**
	(0.006)	(0.012)	(0.012)	(0.025)	(0.057)
US Growth	-0.010	0.002	-0.009	-0.005	-0.078**
	(0.009)	(0.010)	(0.008)	(0.008)	(0.038)
Adjusted R^2	0.005	0.005	0.005	0.005	0.005
N	184,607	185,402	184,607	184,607	164,784
FD × Global PE Level	0.009***	0.007	0.024***	0.032***	0.061***
	(0.002)	(0.005)	(0.004)	(0.009)	(0.018)
Global PE Level	-0.012***	-0.006	-0.012***	-0.008***	-0.041***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.012)
Adjusted R^2	0.005	0.005	0.005	0.005	0.005
N	192,550	193,431	192,550	192,550	171,769
FD × Global PE Growth	0.006***	0.005	0.015***	0.012	0.006
	(0.002)	(0.004)	(0.004)	(0.008)	(0.017)
Global PE Growth	-0.001	0.002	-0.001	0.003	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.012)
Adjusted R^2	0.005	0.005	0.005	0.005	0.005
N	192,550	193,431	192,550	192,550	171,769

Note: The table uses the sample, variables, and specifications as Panel B of Table 1.5 with the following modifications: Panel A reports results obtained using specifications in which we allow the firm-level controls to vary over time. Panel B reports results obtained using specifications in which we include firm fixed effects.

Table 1.OA.4: Growth Opportunities and Technological Characteristics: Panel Regressions

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
			Panel A: US Growth		
FD × US Growth	0.015*	0.010	0.039**	0.061*	0.121*
	(0.009)	(0.015)	(0.017)	(0.034)	(0.072)
FD × R&D Intensity	0.051*	0.127**	0.027	0.095	-0.032
	(0.029)	(0.052)	(0.058)	(0.128)	(0.293)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	166,797	167,398	166,797	166,797	149,261
FD × US Growth	0.016*	0.009	0.042**	0.067**	0.113*
	(0.009)	(0.016)	(0.017)	(0.034)	(0.068)
FD × Investment Lumpiness	0.217***	0.461***	0.227*	0.549**	0.711
	(0.066)	(0.138)	(0.127)	(0.258)	(0.550)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	180,996	181,764	180,996	180,996	161,544
FD × US Growth	0.019**	0.016	0.045***	0.073**	0.116*
	(0.009)	(0.015)	(0.016)	(0.033)	(0.066)
FD × EFD	0.055	0.132**	0.046	0.139	0.215
	(0.042)	(0.064)	(0.084)	(0.191)	(0.431)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	179,123	179,855	179,123	179,123	160,081
			Panel B: Global PE Growth		
FD × Global PE Growth	0.011***	0.012**	0.025***	0.029**	0.054*
	(0.003)	(0.006)	(0.006)	(0.014)	(0.030)
FD × R&D Intensity	0.054*	0.122**	0.045	0.141	0.095
	(0.028)	(0.048)	(0.058)	(0.123)	(0.284)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	174,719	175,406	174,719	174,719	156,284
FD × Global PE Growth	0.010***	0.010**	0.022***	0.025**	0.044
	(0.003)	(0.005)	(0.006)	(0.013)	(0.028)
FD × Investment Lumpiness	0.218***	0.440***	0.263**	0.619**	0.969*
	(0.060)	(0.121)	(0.116)	(0.241)	(0.533)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	189,249	190,106	189,249	189,249	168,299
FD × Global PE Growth	0.010***	0.011**	0.023***	0.025*	0.044
	(0.003)	(0.005)	(0.006)	(0.013)	(0.029)
FD × EFD	0.066*	0.135**	0.081	0.202	0.437
	(0.040)	(0.063)	(0.082)	(0.183)	(0.427)
Adjusted R^2	0.016	0.016	0.016	0.016	0.015
N	187,306	188,129	187,306	187,306	167,219

Note: The table uses the sample, variables, and specifications as Panel B and Panel C of Table 1.7 except that we use the panel of firm-year observations. To proxy for growth opportunities, Panel A uses time-varying US Growth, while Panel B uses time-varying Global PE Growth. All specifications are linear regressions with outliers removed (observations outside the 1-to-99 percentile range of the dependent variable), include a constant, the corresponding growth opportunity proxy as a base effect, predetermined firm-level controls, and country, 3-digit ISIC industry, and year dummies.

Table 1.OA.5: Robustness Checks

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
	Panel A: Limited Liability Companies Only				
FD × US Growth	0.023**	0.047***	0.029	0.091**	0.109
	(0.011)	(0.017)	(0.020)	(0.044)	(0.083)
Adjusted R^2	0.075	0.074	0.075	0.075	0.072
N	16,398	16,516	16,398	16,398	14,629
FD × Global PE Growth	0.056***	0.070***	0.115***	0.190***	0.303**
	(0.013)	(0.021)	(0.025)	(0.054)	(0.125)
Adjusted R^2	0.076	0.075	0.076	0.075	0.072
N	17,158	17,289	17,158	17,158	15,303
	Panel B: Only Industries with at Least 20 Firms				
FD × US Growth	0.032**	0.096***	0.038*	0.121**	0.195**
	(0.014)	(0.030)	(0.023)	(0.047)	(0.096)
Adjusted R^2	0.065	0.065	0.065	0.065	0.065
N	23,284	23,284	23,284	23,284	20,900
FD × Global PE Growth	0.063***	0.109***	0.103***	0.134**	0.246*
	(0.014)	(0.026)	(0.024)	(0.057)	(0.128)
Adjusted R^2	0.066	0.066	0.066	0.065	0.065
N	24,288	24,288	24,288	24,288	21,780
	Panel C: Controlling for Industry-Period Fixed Effects				
FD × US Growth	0.025**	0.048**	0.036	0.103**	0.100
	(0.012)	(0.019)	(0.024)	(0.046)	(0.101)
Adjusted R^2	0.179	0.178	0.179	0.179	0.188
N	24,619	24,738	24,619	24,619	21,642
FD × Global PE Growth	0.119**	0.047***	0.056**	0.099***	0.231*
	(0.056)	(0.014)	(0.023)	(0.027)	(0.132)
Adjusted R^2	0.179	0.180	0.178	0.180	0.188
N	24,619	24,619	24,738	24,619	21,642
	Panel D: Median Regressions				
FD × US Growth	0.055*	0.006	0.015	0.01	0.043
	(0.031)	(0.007)	(0.014)	(0.015)	(0.072)
Adjusted R^2	0.038	0.038	0.037	0.038	0.036
N	24,619	24,619	24,738	24,619	21,642
FD × Global PE Growth	0.009	0.01**	0.017**	0.017	0.025**
	(0.0218)	(0.005)	(0.008)	(0.012)	(0.011)
Adjusted R^2	0.038	0.038	0.038	0.038	0.036
N	25,703	25,703	25,835	25,703	22,579

Note: The table reports results of OLS regressions in Panels A, B, and C and median regressions in Panel D. The sample, variables, and specifications are as in Panel A of Table 1.5 with the following modifications: In Panel A, we use the sub-sample of companies incorporated with limited liability legal form. In Panel B, we use the subsample of 2-digit ISIC industry-country pairs with at least 20 firms. Panel C reports estimates obtained while controlling for firm-specific industry-period dummies (instead of 3-digit ISIC industry dummies), where, for each firm, period is defined as a sequence of years for which the External Finance Use is available. Panel D reports estimates obtained using median regressions. Standard errors reported in Panel D are bootstrapped and clustered at the industry-country level.

Table 1.OA.6: Using 2-digit ISIC Industry Fixed Effects

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
FD × US Growth	0.028**	0.055***	0.039*	0.116***	0.148*
	(0.011)	(0.017)	(0.022)	(0.042)	(0.088)
US Growth	-0.014	-0.021	0.005	-0.005	-0.075
	(0.044)	(0.043)	(0.043)	(0.043)	(0.072)
log(Total Assets)	-0.219***	-0.225***	-0.219***	-0.219***	-0.169***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
log(Total Assets) Squared	-2.411***	-2.377***	-2.404***	-2.405***	-3.870***
	(0.839)	(0.837)	(0.840)	(0.840)	(0.883)
log(Employees)	-0.455***	-0.451***	-0.454***	-0.455***	-0.582***
	(0.099)	(0.099)	(0.099)	(0.099)	(0.104)
log(Employees) Squared	4.360***	4.348***	4.353***	4.365***	6.441***
	(1.150)	(1.147)	(1.149)	(1.150)	(1.215)
Age	-0.007	-0.008	-0.007	-0.007	0.013
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
Age Squared	-0.048	-0.032	-0.055	-0.051	-0.121
	(0.375)	(0.375)	(0.375)	(0.375)	(0.389)
Leverage	-0.019***	-0.018***	-0.019***	-0.018***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tangibility	-0.012***	-0.013***	-0.012***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Collateral	0.004*	0.003	0.004*	0.004*	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cash	-0.008***	-0.008***	-0.008***	-0.008***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.023***	0.023***	0.023***	0.023***	0.023***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Country, Industry FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.080	0.080	0.080	0.080	0.079
N	24,619	24,738	24,619	24,619	21,642

Note: The table uses the sample, variables, and specifications as Table 1.4 except that we include 2-digit ISIC industry dummies instead of 3-digit ISIC industry dummies in all specifications.

Table 1.OA.7: Subsample of EU-15 Countries

	Total Capitalization	Private Credit	Market Capitalization	Market Value Traded	Accounting Standards
	Panel A: Growth Opportunities				
FD × US Growth	0.037***	0.072***	0.046**	0.138***	0.151*
	(0.011)	(0.015)	(0.021)	(0.040)	(0.085)
US Growth	-0.023	-0.036	0.004	-0.009	-0.074
	(0.046)	(0.046)	(0.045)	(0.045)	(0.071)
Adjusted R^2	0.081	0.081	0.080	0.080	0.080
N	21,810	21,810	21,810	21,810	21,642
FD × Global PE Level	0.002	0.002	0.003	-0.001	0.002
	(0.002)	(0.004)	(0.004)	(0.009)	(0.015)
Global PE Level	0.034***	0.035***	0.035***	0.037***	0.035**
	(0.012)	(0.012)	(0.011)	(0.011)	(0.015)
Adjusted R^2	0.080	0.080	0.080	0.080	0.080
N	22,753	22,753	22,753	22,753	22,579
FD × Global PE Growth	0.046***	0.057***	0.086***	0.084	0.216*
	(0.013)	(0.022)	(0.024)	(0.053)	(0.115)
Global PE Growth	-0.030	-0.016	-0.011	0.010	-0.117
	(0.022)	(0.022)	(0.018)	(0.018)	(0.079)
Adjusted R^2	0.081	0.080	0.081	0.080	0.080
N	22,753	22,753	22,753	22,753	22,579
	Panel B: Technological Characteristics				
FD × R&D Intensity	0.082***	0.143***	0.100*	0.247*	0.161
	(0.028)	(0.054)	(0.059)	(0.127)	(0.278)
Adjusted R^2	0.079	0.079	0.079	0.079	0.079
N	21,081	21,081	21,081	21,081	20,921
FD × Investment Lumpiness	0.223***	0.417***	0.269**	0.634***	0.676
	(0.054)	(0.112)	(0.108)	(0.243)	(0.525)
Adjusted R^2	0.080	0.080	0.080	0.080	0.080
N	22,745	22,745	22,745	22,745	22,571
FD × EFD	0.125***	0.199**	0.183*	0.375*	0.484
	(0.043)	(0.081)	(0.094)	(0.192)	(0.440)
Adjusted R^2	0.080	0.080	0.079	0.079	0.079
N	22,536	22,536	22,536	22,536	22,362

Note: The table reports results of OLS regressions on the sub-sample of EU-15 countries. Panel A uses specifications and variables as Panel A of Table 1.5, while Panel B uses specifications and variables as Panel A of Table 1.7.

Chapter 2

Selection and Productivity Gains in Horizontal and Vertical Acquisitions[1]

Abstract

What is the role of firm productivity in the selection to acquisitions and do acquisitions lead to productivity gains? I investigate these questions using a large dataset of domestic acquisitions among public and private firms in Europe over the period 1998-2008. I found that first, targets are under-performing before engaging in horizontal acquisitions; second, there is positive assortative matching in revenue productivity for firms engaging in vertical acquisitions; and third, economically and statistically significant productivity gains exist only for targets acquired in horizontal acquisitions. Overall, the results for horizontal deals are consistent with the Q-theory of mergers, which assumes asset substitutability. The results for vertical deals, in which firms' assets are likely to be complements, are consistent with the search and matching model built on the property rights theory of the firm.

JEL: G34, D24
Keywords: Mergers and acquisitions, Selection, Productivity, Gains from acquisitions

[1] I thank Jan Bena, Randy Filler, Jan Hanousek, Štepán Jurajda and Evangelia Vourvachaki for helpful comments and suggestions. This research was supported by a grant No. 69910 of the Grant Agency of Charles University. An earlier version of the paper won the first prize in the competition Young Economist of the Year 2011 awarded by the Czech Economic Society. All errors remaining in this text are the responsibility of the author.

2.1 Introduction

There is a long standing debate about what drives firms to engage in acquisitions and whether they lead to efficiency gains. Although there is a range of explanations for the existence of mergers such as empire building (Jensen, 1986), the exploitation of stock misvaluation (Shleifer and Vishny, 2003) or the replacement of poorly performing managers (Manne, 1965; Jensen and Ruback, 1983), the empirical evidence on the fundamental question of who buys whom in mergers is mixed. Consistent with the inefficient management hypothesis, the standard neoclassical framework, formalized by Jovanovic and Rousseau (2002) in the Q-theory of mergers, states that unproductive firms are acquired by productive firms, and the subsequent transfer of the acquirer's superior technology to the target's capital results in a productivity gain. While there is evidence on the existence of abnormal stock returns following the announcement of an acquisition and of operating performance improvements following acquisition completion,[2] the evidence that acquisition targets under-perform before the deal is weak at best. Agrawal and Jaffe (2003) document that significant pre-acquisition stock return under-performance for the average target is found only in 2 out of 12 instances they reviewed, and the evidence on operating under-performance is mixed, too. In further contrast, recent studies by Rhodes-Kropf, Robinson, and Viswanathan (2005) and Rhodes-Kropf and Robinson (2008) report that market-to-book (M/B) valuation of targets is higher than that of an average firm, and that evidence exists for positive assortative matching in pre-acquisition M/B for merging firms.

In this paper, I reconcile conflicting results in the literature by showing that the selection of firms into acquisitions and post-acquisition productivity gains are very different in horizontal and vertical acquisitions. The key theoretical insight that motivates separate investigation of horizontal and vertical acquisitions is the different nature of synergies among potential acquisition participants. Firms that operate in the same industry, and

[2]Among others, Andrade, Mitchell, and Stafford (2001) show that shareholders of target firms experience on average three day abnormal returns of 16 % following the announcement of an acquisition. Maksimovic and Phillips (2001) report a 2% increase in industry-adjusted TFP of target plants in the three years following a takeover.

thus are potential candidates for horizontal takeovers, are all familiar with the technology of that industry, and all possess some level of know-how or skill on how to use this technology to deliver the industry-specific product. This implies that firm-specific intangible capital is easily redeployable on the physical assets of other firms operating within the same industry, which is the underlying assumption of the standard Q-theory of mergers of Jovanovic and Rousseau (2002). The predictions of this theory are thus most likely to hold for the horizontal acquisitions.

However, the assumption of the redeployability of intangible capital is not always relevant. It is less likely to hold in across-industry mergers as a firm operating in one industry is not necessarily familiar with the technology and physical assets of a firm operating in another. In mergers between firms operating in different industries, especially those tied by strong supplier-producer vertical linkages, the complementarity between intangible assets may be more relevant. Asset complementarity is particularly important in the property rights theory of the firm, where joint production requires the ex-ante relationship-specific investments of both parties, and the division of ex-post revenues is subject to contractual incompleteness. Vertically related firms that choose to contract with each other are facing the risk of hold-up as either firm can threaten to quit the relationship and to search for another partner. If firms' industry-specific intangible assets are highly complementary, so that both partners are essential for the realization of output, the possibility of hold-up mitigates incentives for ex-ante investments and leads to underinvestment and thus joint output loss. Based on these insights, Rhodes-Kropf and Robinson (2008) build a model of search and matching between firms operating in two distinct industries that are characterized by asset complementarity. Their model predicts that if the cost of searching for a merging partner is not very high, and the scarcity of firms in both industries is comparable, positive assortative matching occurs, in which firms merge with partners of similar quality.

Q-theory of mergers as well as the search and matching model, based on the property rights theory of the firm, offer a range of testable predictions, and the relevant empirical literature is summarized in section 2.2. However, quite surprisingly, predictions of these theories have not yet been investigated using the natural distinction of horizontal and vertical acquisitions. The sharp differences in assumptions and predictions of these theories motivate research questions asked in this paper: How do firms self-select into being a target or an acquirer in acquisitions, and do their incentives to participate differ in horizontal and vertical acquisitions? Do acquisitions improve operating performance of targets in general, or are these gains present only for targets acquired by companies with highly substitutable assets?

To investigate these questions, I use a sample of domestic acquisitions in the old-member states of the European Union (EU-15) over the period 1998-2008 that are drawn from a relatively under-utilized database of mergers and acquisitions — Zephyr, compiled by Bureau van Dijk (BvD). The advantage of this dataset over other sources is that it can be precisely linked with the detailed balance-sheet and income statement information for a large sample of private and public firms covered in Amadeus. This allows for a detailed investigation of acquisitions involving private firms and thus to ignore possible implications of theories based on stock market misvaluation.[3] Balance-sheet information in Amadeus allows for the calculating of a key firm-level operating performance measure used in this study: revenue total factor productivity.

I first show that the good-firms-buy-bad-firms pattern is a prominent feature of horizontal acquisitions. This result sheds light on the mixed evidence of a target's pre-acquisition under-performance summarized by Agrawal and Jaffe (2003). Only firms which can easily re-deploy their intangible capital to assets of poorly performing targets are willing to acquire them, which makes target under-performance a salient feature of horizontal acquisitions.

Second, I find evidence of positive assortative matching on pre-acquisition revenue productivity for vertical acquisitions. Further, using a sub-sample of acquisitions between

[3]Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) offer models in which mergers result from managerial timing of market mis-valuation of their firms. Shleifer and Vishny (2003) argue that bidders with overvalued stock use it to buy assets of undervalued targets through merger. Target managers with a short time horizon are willing to accept the bidder's temporarily overvalued stock. Rhodes-Kropf and Viswanathan (2004) argue that informationally constrained targets will rationally accept bids from overvalued acquirers because they over-estimate synergies, especially during periods of high market valuations.

firms operating in different industries, I show that this pattern increases with the strength of vertical linkages between industries. This evidence is in line with predictions of the search and matching model built on the assumption of asset complementarities.

Third, I find that economically large and statistically significant gains in targets revenue productivity are present only for horizontal acquisitions. My estimates of these gains are at least twice as large as those reported in previous studies, which lump all acquisitions together. This suggests that previous empirical tests of targets productivity gains suffered from low power. Looking at the sub-set of acquisitions where the Q-theory's assumption of redeployability is most likely to hold increases the power of the test considerably.

The rest of the paper proceeds as follows. In the next section, I summarize relevant literature and develop testable hypotheses. Section 2.3 presents the sample and construction of key variables, section 2.4 presents the empirical results of the developed hypotheses and section 3.7 concludes.

2.2 Literature Review and Hypothesis Development

2.2.1 Q-theory of Mergers

To build the Q-theory of mergers, Jovanovic and Rousseau (2002) extended the Q-theory of investment by allowing firms to adjust their capital stock not only by investing into new assets but also by participating in the market for used assets. The key assumption in their model is that there is one type of asset which is re-deployable across all firms in the economy. Firms differ in their productivity, and every firm can transfer its productivity, a form of intangible capital, to all new and used assets that it buys. In this model, as in Q-theory of investment, the optimal level of investment increases with Q, the value of capital inside the firm, proxied by M/B ratio. If a firm's productivity is positively autocorrelated, then firm's Q increases in its productivity and the level of its investments will depend on the level of productivity, too. Firms with low productivity will find it profitable to sell their assets, cash-in on the corresponding market price, and exit, while firms with productivity exceeding the endogenous threshold will invest. For the investing firms, the decision to invest into new or used assets is influenced by the assumption of the fixed costs of acquiring used capital. Firms with medium productivity, and thus lower investment needs, will avoid the fixed cost and invest only into new assets, while firms with high productivity will use both margins. Thus, if mergers are simply another form of investment, then firms with high growth opportunities, and thus high M/B ratios, should be buying assets from firms with low opportunities, and hence low M/B.

Yang (2008), extended the Q-theory of mergers into the dynamic setting by developing a dynamic structural model of an industry in which firms are heterogeneous in productivity, which changes subject to random shocks. In his model, due to decreasing returns to scale, it is the optimal firm size, not optimal growth, that is the monotonic function of the firm's productivity. If there is a positive aggregate shock, all firms have an incentive to increase their scale by investing, while no firm is willing to sell its assets. This makes new investments more attractive. If shocks are idiosyncratic, then firms with negative shocks find it optimal to downsize and sell their assets, while firms with positive shocks may find it optimal to invest by purchasing used assets. The main implication of this model is that changes in productivity, rather than their levels, should matter for the firms' decisions to engage in acquisitions.

The Q-theory of mergers offers several empirically testable predictions. One class of predictions focuses on relationships between the aggregate characteristics of an economy in time. First, the asset re-deployability assumption implies that aggregate merger activity, or merger waves, should be correlated with the volume of activity in the market for used capital. Jovanovic and Rousseau (2002) show that this seems to be the case in the U.S. in the 1971 - 2000 period.

Second, when cross-sectional dispersion in M/B ratios is high, and thus more opportunities exist for profitable asset reallocation, the amount of merger activity should increase. Jovanovic and Rousseau (2002) show that the dispersion in M/B ratios indeed leads movement in aggregate merger activity. Third, the reallocation of assets is likely to be the consequence of unexpexted economic shocks, such as shocks to the industry's technological, economical or regulatory environment, which affect the productivity of firms operating in the industry in an idiosyncratic way. Along these lines, Harford (2005) shows that merger waves tend to be preceded by clusters of industry shocks. He also finds that the actual spike in merger activity occurs only if the capital market is sufficiently liquid, which is a necessary condition for firms' access to cheap financing. In a related work, Jovanovic and Rousseau (2008) show that merger waves tend to be driven by the need for the reallocation of capital that is driven by the arrival of major technical change. In their model, the arrival of new general purpose technology requires firms to reorganize. If a firm fails to reorganize internally, by a re-adjustment of its workers or physiscal assets, it will be reorganized externally either by liguidating or by being taken over. Thus, exits and mergers should rise following major technological shocks, a fact supported by the data.

Lastly, Yang (2008) shows a positive cross-sectional relationship exists between the amount of asset reallocation and both the time persistence and the cross-sectional dispersion of firm-level productivities in the industry.

While the aggregate predictions of the Q-theory of mergers find support in the data, the evidence on the class of predictions that focus on micro-level characteristics of the firms' behavior is less clear. First, according to the inefficient management hypothesis, firms targeted in takeovers should have poor management, low operating performance and poor stock performance. Agrawal and Jaffe (2003) summarize the relevant literature and conclude that it does not provide strong evidence that targets, as a whole, are under-performing prior to acquisition. Out of the 12 studies they discuss, only 2 find evidence of stock returns under-performance prior to a merger offer. The evidence on operating under-performance is inconclusive, as well.

Second, the Q-theory of mergers predicts that firms with a high M/B ratio should be acquirers of firms with low M/B. Andrade, Mitchell, and Stafford (2001) find that an acquirer's M/B is higher than a target's M/B in more than two-thirds of mergers in the U.S. since 1973. Related, Jovanovic and Rousseau (2002) show that M&A investments are 2.6 times more sensitive to a firm's M/B than direct investment, indirectly supporting the idea that firms with high values of M/B, and thus a higher ability to increase the value of a target's assets, use M&As more intensively than purchases of new capital. Rousseau (2006) further shows that these results extend beyond the U.S. M&A market, applying to domestic and cross-border mergers among a set of seven European countries. Additionally, Servaes (1991) finds that the total abnormal stock returns following takeover are larger when the target has a low M/B, and the acquirer has a large M/B prior to the merger announcement.

However, Rhodes-Kropf, Robinson, and Viswanathan (2005) report that while the M/B of targets is on average lower than the M/B of acquirers, target valuations are often higher than the M/B of the average firm. This finding suggests that instead of "high q buys low q", the pattern "high q buys less high q" seems to describe the data better. Recently, Rhodes-Kropf and Robinson (2008) document even stronger empirical pattern: They find evidence of positive assortative matching between Acquirers and Targets with respect to their M/B ratios.

2.2.2 Property Rights Theory of the Firm and the Market for Mergers

The property rights theory of the firm was pioneered by Grossman and Hart (1986) and Hart and Moore (1990). Grossman and Hart (1986) note that in a world of incomplete contracts, it is impossible for the parties to negotiate ex-ante on all future contingencies. The impossibility of fully contingent contracts leads to ex-post bargaining over the division of surplus, with the possibility of a "hold-up", in states of the world which were not foreseen. Further, if the ex ante relationship-specific investments are required, the possibility of a "hold-up" leads to a misalignment between ex ante investments and ex post returns accruing to parties in a contract relationship. Grossman and Hart (1986) show that this misalignment has negative welfare consequences, which can be mitigated by integrating both parties into one firm.

Hart and Moore (1990) generalize the property rights theory as a theory of the optimal allocation of asset ownership. One of their main results is that if contracts are incomplete, the complementary assets should be placed under common ownership. In their model, the assets complementarity means that none of the assets are productive unless used together. This creates scope for mutual dependence between the managers of the complementary assets, which leads to opportunities for rent seeking. The managers' incentives to invest ex ante are strongest if the opportunities for rent seeking are minimized, which can be achieved by allocating decision rights over the use of assets to a single party. In contrast, for assets without any complementarities there are no benefits from joint ownership.

It was only recently that insights from the property rights theory motivated the literature on mergers and acquisitions. Rhodes-Kropf and Robinson (2008) build a model of search and matching between firms operating in two distinct industries. Each industry requires a different type of intangible or human capital for a firm to be productive. Further, in each industry, firms are heterogeneous in their productivity. A technology shock creates the potential for synergy benefits from the combined use of assets of both industries, and synergy gains are increasing in the product of productivities of both firms engaging in asset combination. Rhodes-Kropf and Robinson (2008) further assume that contractual incompleteness restricts firms from contracting on the benefits of synergies from asset combinations. The only way to realize such benefits is through common control and the joint surplus created by merging the firms split by bargaining. In this setting, the firms optimally search for a merger partner trading off their share of potential realized synergies with a reduced bargaining power and cost of a continued search. Due to supermodularity of synergy gains in the productivities of potential merging partners, every firm is interested in a more productive partner, but this demand increases the bargaining power of very productive partners, which in turn decreases the share of synergy gains accruing to the firm in the other industry. Rhodes-Kropf and Robinson (2008) show that if the costs of a search for a merging partner are low, and the scarcity of firms in both industries is similar, then supermodularity leads to a match of merger partners that is positively assortative in productivity as well as in the M/B ratio.[4]

[4] In a recent work, David (2011) extends the search and matching model of the M&A market along several dimensions. Most notably, the technology of transforming the productivities of merger participants to the productivity of a new entity is assumed to be, more general, the CES production function. This assumption allows him to embed into the model substitutability as well as complementarity considerations and thus to explain the mixed patterns in the data. This paper differs from his by showing the particular margins, the horizontal or vertical relationship between merger candidates, along which substitutability

The search and matching model with asset complementarities thus provides an explanation for the "high buys high and low buys low" pattern in the M/B ratios of merger participants observed by Rhodes-Kropf and Robinson (2008). A further prediction of their model is that positive assortative matching should be stronger in markets in which the search costs are low. Using liquidity of the financial market as a proxy for search costs, the authors show that the assortative pattern is stronger in periods of high liquidity.

The relationship between asset complementarities and mergers is explored in two other recent studies. Hoberg and Phillips (2010) provide direct evidence that product market synergies are important drivers of mergers. They measure the similarity of products offered by every pair of publicly traded firms in the U.S. using a common vocabulary in their product description in 10-K statements filed with the Security and Exchange Commission. They show that acquirers are willing to merge with partners that have complementary assets in order to achieve product range expansions, and thus to differentiate their product line from main rivals. However, at the same time, acquirers pick target firms that are related enough so that they can manage the new assets.

Bena and Li (2010) focus on the complementarity stemming from technological overlaps between potential merger partners. Using cross-citations between the patents of potential merger partners, they directly identify whether their innovation activities are related. They show that more innovative companies are more likely to engage in acquisition activities, the technological overlap between the innovation activities of two firms has a positive impact on the probability of their merger pairing, and innovation-driven acquisitions lead to more innovation and improved operating and stock performance.

The relevance of asset complementarities for acquisitions can be illustrated using the example of Nokia and its recent fight to keep up its position as the world leader in cellphone market. A recent rise in microprocessor computing power has led to the rise of smart-phones, a new class of cell-phones in which software and data services play a much more important role. This has led Nokia to reconsider its market strategy:

> Historically, Nokia has been a highly efficient manufacturing and logistics ma-

or complementarity assumptions gain importance.

chine capable of churning out a dozen handsets a second and selling them all over the world. Planning was long-term, and new devices were developed by separate teams, sometimes competing with each other—the opposite of what is needed in software, where there is a premium on collaborating and doing things quickly.

Olli-Pekka Kallasvuo, Nokia's boss from 2006 until September 2010, was keenly aware of the difficulty. To get an infusion of fresh blood, Nokia bought several start-ups and was reorganized to strengthen its software and services.[5]

In line with the predictions of property rights theory, it was complementarity between hardware and software and the lack of know-how in software development that led Nokia into acquisitions of software companies.

2.2.3 Hypotheses

The evidence from both streams of the literature suggests that both explanations have some merit in the data. However, their predictions hinge on widely different assumptions. The Q-theory assumes that assets of all firms are perfect substitutes, and they can be re-deployed at very little cost. In contrast, the search and matching model of Rhodes-Kropf and Robinson (2008), which builds on the insights of the property rights theory of the firm, uses the assumption of the existence of two classes of complementary assets managed by perfectly specialized parties. The predictions of the Q-theory should apply to settings when assets are highly substitutable, while the predictions of the search and matching model are likely to be relevant in cases when assets are complementary.

In this paper, I use the industry affiliation of firms and information on the between-industry flow of commodities to distinguish three classes of mergers. First, the high substitutability of capital embedded in firms is more likely to be present among firms operating in the same industries. Thus, micro-level predictions of the Q-theory of mergers are likely to be relevant in horizontal mergers, which are defined as mergers in which both merging parties come from the same industry. Second, building on the property

[5]"Blazing platforms: Nokia at the crossroads", The Economist, London, February 10, 2011.

rights theory of the firm, the complementarities between physical and more importantly, intangible assets are likely to be economically most relevant among firms operating in industries with tight supplier-producer linkages. Indeed, the property rights theory of the firm has been developed to understand structural choices of organization that form between vertically related firms. The micro-level predictions of Rhodes-Kropf and Robinson's search and matching model are thus likely to be relevant in vertical mergers, which will be defined as those involving firms operating firms in different industries that are characterized by a high level of intermediate flows.

The predictions of Q-theory regarding the selection into acquisition status lead to:

Hypothesis 1: If the assets of the firms engaging in acquisitions are close substitutes, the productivity of the target firm should be low, or recently declining, while the productivity of the acquirer should be high and recently increasing.

In other words the "high buys low" pattern is expected to be present in horizontal acquisitions. This question is of high interest given the lack of clear evidence connected to the inefficient management hypothesis, even though this implication is present in all neoclassical models of mergers. In Q-theory, the incentives that drive acquisitions are driven by the re-deployment of assets to productive uses. If significant portion of mergers is due to other incentives such as synergy motivations, this prediction is likely to be muted in the data.

Regarding the self-selection of acquirers and targets, the prediction of the model of mergers based on the property rights theory is more nuanced. The model essentially predicts positive assortative matching in performance between firm pairs participating in acquisition:

Hypothesis 2: The firms that participate in vertical mergers should be of a similar pre-acquisition industry adjusted productivity. The wedge in productivity between targets and acquirers should be decreasing with increasing complementarity of their assets.

While Rhodes-Kropf and Robinson (2008) offer evidence on positive assortative matching in M/B ratios in a full sample of US acquisitions, they don't investigate productivity. More importantly the strength of their model should depend on the degree of asset complementarity between acquirers and targets. While Hoberg and Phillips (2010) and Bena and Li (2010) investigate asset complementarities as a motive for mergers, neither of these papera investigate the performance differences between parties engaging in merger.

Regarding the performance gains in mergers, only Q-theory offers a clear prediction:

Hypothesis 3: The targets acquired by firms with assets that are close substitutes should experience productivity gains.

There is evidence that productivity of targets increases in acquisitions, e.g.Lichtenberg (1992), McGuckin and Nguyen (1995), Maksimovic, Phillips, and Prabhala (2008) and Maksimovic and Phillips (2001). However in this study, I argue that most of the productivity gains for targets will be observed among horizontal acquisitions, in which the re-deployability of the acquirer's human capital to the target's physical assets is the easiest.

The model of mergers based on the property rights theory predicts that mergers are motivated by synergy gains. It has no prediction regarding the performance gains of targets as the division of surplus between acquirer and target created by synergies is not clear. However, the model does predict that the firm that arises as a combination of acquirer and target should be more efficient in providing incentives for relationship-specific investments compared to the situation prior acquisition. The test of this prediction would require a reasonable proxy for relationship-specific investments, which is not possible with the data in this study.

2.3 Data Sample and Variable Construction

2.3.1 Data Sources

The sample of acquisition events is obtained from Zephyr, a new international dataset of ownership changes compiled by Bureau van Dijk. Compared to other databases of M&As, the primary advantage of Zephyr is the use of a unique company identification number (BvD ID) which allows precise linking with Amadeus, a database of detailed balance-sheet and income statement information for a comprehensive sample of private and public firms across all industries in Europe. The merged dataset allows me to compare the performance of acquiring and targeted firms to similar firms which were not involved in any ownership transaction. It also allows me to track the performance of companies for several years before and after the date of deal completion, and as such, it is suitable for investigating questions posed in this paper. Although Zephyr has been tapped in the ownership change literature, most of the papers focus on narrow topics and thus utilize only small sub-samples of Zephyr.[6] To my knowledge, this is the first paper that attempts to use the broad category of mergers and acquisition deals in Zephyr and link them with Amadeus. For a thorough description of Zephyr's coverage and structure, as well as the adjustments necessary for matching the dataset with Amadeus, see Bena, Fons-Rosen, and Ondko (2009).

The Amadeus dataset is constructed by combining several updates that add information over time: DVD updates from May 2002 and May 2004 together with updates downloaded from WRDS in July 2007, April 2008, August 2009 and February 2010. Every update contains up to the 10 most recent years of firms' financial data (if available). Also, a given firm is present in Amadeus as long as it provides its financial statements; however, it is kept in the database only for four extra years after its last filing.[7] Combining several updates, obtained in different points in time, allows me to add back the observations for firms that are not present in more recent updates. The key advantages of this procedure are first, it eliminates survivorship bias inherent in the single update of the database, and second, it extends firms' historical accounting data beyond the most recent 10 years.

[6] Among others, Grimpe (2007) uses a sample of 179 mergers obtained from Zephyr and Thompson Deals to study the post-merger integration of firms' R&D units and its effect on innovation activity; Pasiouras, Tanna, and Zopounidis (2007) study the performance of multi-criteria decision aid prediction models in identifying acquisition targets in the banking industry on a sample of 168 acquired and 168 non-acquired banks from the EU-15; Grimpe and Hussinger (2008) investigate the motives for pre-empting technology competition through mergers and acquisition on a sample of 657 horizontal deals from Europe; Michaely and Roberts (2006) use Zephyr jointly with SDC Platinum to extract information on IPOs and going-private transactions to study differences in the dividend policies of public and private firms.

[7] For example, a firm that files a financial statement in 2002 but stops filing in 2003, remains in the database until 2006. In 2007, the firm is dropped from the sample, and all year entries of the firm are taken out of Amadeus.

To classify acquisitions into Unrelated, Vertical and Horizontal categories, I utilize the UK Analytical Use Table for the year 1995.[8] In the UK Input-Output Tables, the industries are classified by the UK SIC 2003 standard, which recognizes 129 industries out of which 76 are in the Manufacturing sector. However, both Amadeus and Zephyr provide the industry affiliation of firms in the 4-digit level of the NACE rev. 1.1 classification. In order to match merger data from Zephyr to the UK SIC industries, I follow the correspondence table between NACE rev 1.1 and UK SIC 2003 classifications that is provided by the UK Statistical Office together with the Input-Output tables. In general, the UK SIC industries correspond to 3-digit level NACE rev 1.1 industries, but in some cases, the correspondence is finer (4-digit) or rougher (2-digit). Given that the relationship between 4-digit NACE rev. 1.1 and UK SIC 2003 is always n-to-1, the definition of an industry in the analysis will follow the UK SIC 2003 classification.

2.3.2 The Sample

The sample of acquisitions is constructed by constraining the Zephyr dataset to transactions completed between the beginning of January 1998 and the end of May 2008. The set of countries is constrained to the EU-15 except Luxembourg, which is dropped due to too few observations. I include only transactions in which both acquirer and target operate in the same country as cross-country acquisitions are often motivated by reasons that are not in the focus of this analysis.[9] Next, I drop industries with specific regulations and those with very rough correspondence between NACE rev. 1.1 and UK SIC: Farming (UK SIC 1, 2 and 3), Utilities (UK SIC 85, 86 and 87), Transportation (UK SIC 95 and 96), Finance (UK SIC 100, 101 and 102), Other business activities (UK SIC 109 to 114), Public sector (UK SIC 115 to 118 and 124 to 129) and Other non-business activities (UK SIC 120 to 123). Further, I retain only those acquisitions in which the acquiring firm obtains a majority directly by the means of an acquisition event, that is, the acquired stake is greater than 50%. Next, I include only acquisitions between firms

[8]Downloaded from http://www.statistics.gov.uk/

[9] For example, cross-border acquisitions are often considered to be a form of foreign direct investment, where the acquirer is seeking to gain access to a new market or cheap input by utilizing the local country-specific capability of a target (e.g. Nocke and Yeaple, 2007).

that are either Public Limited companies, which are private limited-liability companies that are allowed to issue shares that can be listed or Private Limited companies, which are private limited-liability companies whose shares cannot be listed. Finally, I keep only the transactions in which both acquirer and target has a BvD ID non-missing, which is necessary for obtaining accounting information from Amadeus.

Given the sample of acquisitions obtained from Zephyr, I define three samples that will be used to investigate the stated hypotheses. First, the *Acquirers Sample* consists of all firms that were participating in acquisition as an acquirer during the sample period. This sample is used to test hypotheses about the relative performance of Acquirers relative to the firms that did not participate in M&As. Second, the *Targets Sample* includes all firms that were participating in acquisition as a target during the sample period. This sample is utilized for the performance comparisons of targets and non-participating firms. Third, the *Acquirer-Target Pairing Sample* consists of transactions in which both the acquirer and the target firm were participating in acquisition during the sample period. This sample is used to test hypothesis 2 on the effect of acquirer-target relative performance on the probability of acquirer-target pairing.

To examine the effect of performance on decisions to participate in acquisitions and to investigate post-acquisition targets' performance gains, I use Amadeus to form samples of pseudo-acquirers, pseudo-targets and pseudo-deals which are then, respectively, appended to the *Acquirers Sample*, the *Targets Sample* and the *Acquirer-Target Pairing Sample.* These pseudo-samples are formed in two ways: either by exact matching on country/industry/year, or by exact matching on country/industry/year combined with the nearest neighbor matching on size.

First, the *Random Acquirers Sample* (the *Random Targets Sample)* is formed by taking each acquirer (target) from the *Acquirers Sample* (the *Targets Sample)* and randomly selecting up to five firms that satisfy the following: 1) they were neither an acquirer nor a target firm in the *Acquirer Sample* or in the *Target Sample;* and 2) they operate in the same country and industry in the year preceding the acquisition as a given acquirer (target). This procedure is equivalent to exact matching on country/industry/year, where year corresponds to year preceding the completion of an acquisition. It yields a set of matches, one for each acquisition deal, which contains up to 6 firms: 1 actual acquirer (target) and 5 pseudo-acquirers (targets). As pseudo-acquirers (targets) in the *Random Acquirers Sample* (the *Random Targets Sample)* are selected by conditioning only on country/industry/year, these samples allow for a preliminary investigation of the role of size on the participation in acquisitions.

Second, the *Matched Acquirers Sample* (the *Matched Targets Sample*) is formed by taking each acquirer (target) from the *Acquirers Sample* (the *Targets Sample*) and selecting up to five matching firms that satisfy the following: 1) they were neither acquirer nor a target firm in the *Acquirer Sample* or in the *Target Sample*; 2) they operate in the same country and industry in the year preceding the acquisition as a given acquirer (target); 3) their Total Assets are closest to the actual acquirer's (target's) Total Assets as of the year preceding the completion of the acquisition; and 4) their Total Assets differ from the Total Assets of the actual acquirer (target) at most by 10%. This procedure is equivalent to the exact matching on country/industry/year combined with the 5-nearest neighbor matching in Total Assets with caliper set to 10%. Caliper 5-nearest neighbor matching non-parametrically controls for firm size, as approximated by Total Assets.

In addition, the *Matched Acquirer-Target Pairing Sample* is formed by taking each actual deal from the *Acquirer-Target Pairing Sample* and selecting up to five pseudo-deals formed by pairing pseudo-acquirers and pseudo-targets that are selected to satisfy the same criteria as those used to construct the *Matched Acquirers Sample* and the *Matched Targets Sample.* This procedure yields a dataset of firm-pairs which are organized in the set of matches, one for each actual acquisition deal. Each match can contain up to 6 firm-pairs: 1 actual acquirer-target pair and 5 pseudo acquirers-target pairs. This is equivalent to the *two-sided* exact matching on country/industry/year combined with the 5-nearest neighbor matching in Total Assets with caliper set to 10%, both for the acquirer's and the target's side of a deal.

2.3.3 Classification of Acquisitions

To categorize acquisitions into Horizontal, Vertical and Unrelated, I follow the methodology used in Fan and Goyal (2006), Becker and Thomas (2010) and Ahern and Harford (2010). First, Horizontal transactions are defined as those in which both acquirer and target operates in the same UK SIC industry. Next, to distinguish Vertical and Unrelated acquisitions, I use the measure of Vertical Dependence defined for each industry pair, which is calculated using the UK Analytical Use table for the year 1995. First, for industry pair ij, I calculate the dependence of the producing industry i on the supplier industry j as the share of input flows from j to i on the total output of industry i. However, it is common that industries in a given pair have non-zero intermediates supply in both directions. Thus for industry pair ij, I also calculate the reverse index of dependence of producing industry j on the supplier industry i. With these two quantities in hand, I define the index of Vertical Dependence of industries i and j as their maximum.

$$Vertical\, Dependence_{ij} = max\,(\,\frac{Input\, Flows_{j\rightarrow i}}{Total\, Output_i}\,,\,\frac{Input\, Flows_{i\rightarrow j}}{Total\, Output_j}\,).$$

Finally, I split all between-industry transactions into two groups. Those with the value of Vertical Dependence of acquirer's and target's industry pair above the median value[10] are classified as Vertical and those below as Unrelated.

2.3.4 Productivity Measure

In order to evaluate firms' performance, I will rely on the logarithm of revenue total factor productivity (TFPR) calculated at the firm level. Revenue total factor productivity measures the efficiency of a given firm in generating sales. Conditional on a vector of inputs, a given firm can have higher sales either because it is more efficient in transforming inputs to output, as reflected by its high physical productivity, or because it can govern a higher price for its products, for example as a result of its market power. As noted by Foster, Haltiwanger, and Syverson (2008), dis-entangling these two effects requires

[10] Median Vertical Dependence is 1.1% in the *Matched Acquirers Sample,* 1.0% in the *Matched Targets Sample,* and 1.2% in the *Matched Acquirer-Target Pairing Sample.*

detailed data on firm-level input and output prices, which are unfortunately not available in Amadeus. Estimating physical productivity is important for evaluating the impact of various industry policies on the firm and aggregate productivity. However, the firm entry, survival and the selection into acquisition status are also likely to be driven by revenue not physical productivity as the ability to secure revenues by charging a premium price for the product is important too. Nevertheless, to stress the fact that the performance of the firms is evaluated using revenue total factor productivity, it is labeled TFPR.

The TFPR is calculated as a difference between the actual sales of a given firm and the predicted sales that the firm would generate if it used its actual amount of inputs and the prevailing technology in the industry. I assume that the transformation of inputs to output Y in a firm is governed by the Cobb-Douglas production function

$$Y = AK^{\alpha}L^{\beta}M^{\gamma}, \tag{2.1}$$

where Y is physical output, A is a constant term measuring physical productivity of the firm, K denotes capital, L denotes labor and M denotes material cost. Multiplying equation (2.1) with the output price P yields revenues $R = PY$ on the left-hand side, and further logarithmic transformation gives a familiar specification that can be used to estimate the parameters of the "revenue" production function and to estimate the TFPR of the firm as the estimation residual term:

$$r_{it} = c + \alpha k_{it} + \beta l_{it} + \gamma m_{it} + \varepsilon_{it}, \tag{2.2}$$

where small letters denote logarithms of actual values, c is a constant and ε_{it} is the error term. When estimating TFPR, the capital K_{it} is approximated by the book value of fixed assets. As Amadeus doesn't provide information on the skill level of labor at the firm level, the labor services L_{it} are measured using a total wage bill. Given that wages reflect the different skill level of workers within the firm, the total wage bill given by the sum of wage bills for individual workers reflects the value of human capital embodied in labor services, e.g. Hsieh and Klenow (2010), Bloom, Draca, and Van Reenen (2011).

Finally, material inputs M_{it} are approximated by the total cost of materials.

Specifically, equation (2.2) is estimated using ordinary least squares separately for each UK SIC industry, while controlling for country and year fixed effects. Given the estimated parameters, firm level TFPR is calculated as $TFPR_{it} = r_{it} - (\hat{\alpha}k_{it} + \hat{\beta}l_{it} + \hat{\gamma}m_{it})$. This estimation method also makes this paper comparable with other studies in the acquisitions literature that rely on the estimates of firm productivity such as Maksimovic and Phillips (2001), Yang (2008) and Li (2011). Appendix 2.B discusses other concerns and methodological issues that may arise when estimating TFPR.

2.3.5 Sample Overview

Table 2.1 presents the distribution of the within-country transactions in the *Acquirers Sample*, the *Targets Sample* and the *Acquirers-Targets Pairing Sample* over time and the type of transaction. There is a total of 2509 targets in the *Targets Sample*, 2161 acquirers in the *Acquirers Sample* and 1015 acquisition deals in the *Acquirer-Target Pairing Sample*. From the 2509 domestic acquisitions in the *Targets Sample*, 1524 are between firms that operate within same UK SIC industry and are thus classified as horizontal. The share of horizontal acquisitions is similar in *Acquirers* and *Acquirer-Target Pairing Samples*. Given that across industry deals are classified to Unrelated and Vertical based on the median Vertical Dependence between industries of acquirer and target, their total number is similar in all three samples.

The number of transactions is increasing over the 1998 - 2008 period. The trend until 2003 corresponds mostly to an improvement in the coverage of the European transactions in Zephyr, which coincided with the merger wave that finished in 2002 as reported by Bartholdy, Blunck, and Poulsen (2009). The second increase after 2005 corresponds to the M&A wave that was finished just before the financial crisis of 2008. Importantly, all three samples show similar temporal trends.

Table 2.2 presents the descriptive statistics for the main variables in all three *Matched* samples. In both, the *Matched Targets Sample* and the *Matched Acquirers Sample*, pseudo-targets (pseudo-acquirers) label descriptive statistics for the observations corresponding to matched firms that are not participating in acquisition during the sample period. Comparing the size of actual targets as measured by Total Assets (TOAS) with the average size in the population of all non-participating firms, shown in Panel D, reveals that actual targets are about 6 times larger. This implies that the selection of targets on size is not random and that in order to participate on the acquisition market as targets, firms often have to reach some critical size. When compared to the pseudo-targets selected by matching on size, which are described in panel A, the actual targets are still about 24% larger. This implies that caliper matching doesn't remove all the differences in size, and in the econometric analysis, all specifications should control for firm size in order to remove the residual imbalance.[11] In terms of TFPR, the targets are on average 4% less productive than the pseudo-targets matched by size, and a similar difference holds for the comparison of the medians.

Panel B of Table 2.2 presents similar summary statistics for the *Matched Acquirers Sample*. The acquirers are about 31 times as large as the average non-participating firm, about five times as large as the average target and about 84% larger than a matched pseudo-acquirer. Acquirers don't appear to be more productive than their industry peers of similar size as their average TFPR is about 4 percentage points lower than the TFPR of matched pseudo-acquirers.

Panel C of Table 2.2 presents descriptive statistics for the acquirer-target pairs in actual acquisition deals and in matched pseudo-deals in the *Matched Acquirer-Target Pairing Sample*. In order to provide meaningful comparisons of TFPR for acquirers and targets coming from different industries, rTFPR is calculated as a firm's TFPR z-score, obtained by subtracting the mean TFPR of its industry and dividing by the industry standard deviation. The normalization effectively removes across-industry differences in the mean and dispersion of productivity. Measuring performance in units that correspond to standard deviations from the industry average allows me to compare firms operating

[11] That the difference between the average size of actual targets (actual acquirers) and the average size of matched pseudo-targets (matched pseudo-acquirers) is larger than 10%, the value of caliper in the matching procedure, is explained by the fact that larger firms are more difficult to match. The size distribution of matched pseudo-targets (matched pseudo-acquirers) is thus more representative of deals with smaller actual targets (actual acquirers).

in different industries. The proximity of acquirer and target performance measured by the absolute value of the difference between Acquirer's and Target's rTFPR appears to be significantly lower for actual deals, on average about 11% of the standard deviation of TFPR. This suggests that acquisitions are pairing firms that are more similar in terms of their TFPR rank in their respective industries than pseudo-pairs formed by matching on the industry affiliation and size. The average value of Vertical Dependence between the industries of targets and acquirers in the *Matched Acquirer-Target Pairing Sample* is 5%, and its distribution is skewed to the left as the median is 2%. The median value 2% is somehow higher than the cutoff value of 1.2% used to split between-industry acquisitions into Unrelated and Vertical because the descriptive statistics in panel C include targets in within-industry acquisitions, as well. The 90 to 10th percentile difference in Vertical Dependence is 20 percentage points suggesting large variation in the vertical relationship between targets and acquirers.[12]

Table 2.3 decomposes the *Matched Targets Sample* in panel A, the *Matched Acquirers Sample* in panel B and the *Matched Acquirer-Target Pairing Sample* in panel C into Unrelated, Vertical and Horizontal deals. Panels A and B show that the number of actual acquisition participants quoted on the stock exchange is very small: It is almost negligible in the *Matched Targets Sample* and about 17% in the *Matched Acquirers Sample.* Comparing actual targets with matched pseudo-targets in panel A shows that the TFPR under-performance of actual targets is 4% in Horizontal acquisitions, which is in line with Hypothesis 1. There is evidence of the TFPR under-performance of targets in Unrelated acquisitions, too. Actual targets in vertical deals have similar TFPR to their matched pseudo-targets.

In panel B, actual acquirers seem to under-perform matched pseudo-acquirers by about 7% in Unrelated deals and by 3% in Vertical and Horizontal deals. Finally, the absolute value of the difference between the acquirer's and target's rTFPR is 15 percentage points lower for actual vertical deals than for vertical pseudo-deals and similar comparison holds for horizontal deals. This suggests that vertical relatedness is a factor that drives the

[12]The distribution of Vertical Dependence in the *Matched Targets Sample*and the *Matched Acquirers Sample* is similar, but not reported.

acquisition pairing of firms of similar performance.

2.4 Results

2.4.1 The selection of Acquirers and Targets

What is the role of TFPR and its recent trends in the selection of companies into the role of acquirers or targets in acquisitions? In order to answer this question, I start with an investigation of a selection of targets and acquirers in the *Random Target Sample* and in the *Random Acquirers Sample.* As counterfactual pseudo-targets (pseudo-acquirers) in these samples are selected randomly by matching only on country/industry/year, an analysis on these samples enables me to investigate the potential confounding effects of firm size. This step is important as it is well known that more productive firms tend to be larger than less productive ones (e.g. Syverson (2011)). Yet, large firms have presumably a greater scope to participate in acquisitions either due to financial or informational frictions. Not controlling appropriately for firm size would thus bias the estimate of the importance of firm TFPR on the decision to engage in acquisitions.

In order to investigate the role of firm size, I estimate a set of simple logit models using the *Random Target Sample* and the *Random Acquirers Sample,* both of which have a cross-sectional structure: For each match m, there is 1 actual target (actual acquirer) and up to 5 pseudo-targets (pseudo-acquirers) with the explanatory variables measured as of the year preceding the acquisition deal. For both targets and acquirers, the logit models are estimated first jointly and second separately for three categories of acquisitions> Unrelated, Vertical and Horizontal, indexed by superscript $X \in \{U,V,H\}$ respectively. The models take the form:

$$\begin{aligned} Target^X_{fm} &= \alpha + \beta\, TFPR_{fm} + \gamma\, log(TOAS)_{fm} \\ &+ Year\, FE_m + \varepsilon_{fm}. \end{aligned} \tag{2.3}$$

The dependent indicator variable $Target^X_{fm}$ equals 1 if firm f is the actual target in match m and 0 otherwise. $TFPR_{fm}$ denotes the TFPR level in the year preceding the acquisition. Specifications estimated on the *Random Acquirers Sample* replace $Target^{X}_{fm}$ by the equivalent variable defined for acquirers, $Acquirer^{X}_{fm}$. [13]

Table 2.4 presents the estimates of average marginal effects from the logit model specified in equation 2.3 for the *Random Targets Sample* in panel A and for the *Random Acquirers Sample* in panel B. Columns 1-3 present estimates obtained without controlling for the firm size. Unconditionally on firm size, Targets and Acquirers in all types of acquisitions are more productive than randomly selected firms operating in their respective industries in a year preceding the acquisition. However, controlling for firm size, by including $log(TOAS)_{fm}$, columns 4-6 reveal that the productivity advantage of targets and acquirers appears to be merely driven by their large firm size.

This implies that the careful investigation of the role of productivity on the selection into acquisitions has to be based on the comparisons of participating firms with firms operating in the same industry that are of comparable size. For this, I employ the *Matched Targets Sample* and the *Matched Acquirers Sample,* in which pseudo-targets and pseudo-acquirers are selected by matching on industry as well as size. Non-parametrically controlling for firm size in this way is superior to a simple linear model. To investigate the selection of targets, I estimate a set of fixed-effects (i.e., conditional) logit models, which take advantage of the logistic specification of the likelihood function that allows me to partial out unobserved match-specific characteristics. In a similar fashion as fixed effects panel models, this approach allows for a controlling of unobserved country/industry/year factors that are common to all firms within the match. The disadvantage of this approach is that it is not possible to calculate the marginal effects on the response probabilities as match fixed effects, which should be plugged into the calculation, are not estimated in the process. For this reason, I will present estimated coefficients, which can be interpreted as the effect of the explanatory variables on the log of the odds-ratio $log(p_i/(1-p_i))$, where p_i is the probability of participating in an acquisition. The models take the form:

[13] The standard errors are estimated by clustering on the match level under the assumption of intraclass correlation of error terms within matches. This assumption is maintained through all specifications that follow.

$$
\begin{aligned}
Target^{X}_{fm} &= \alpha + \beta\, TFPR_{fm} + \gamma\, log(TOAS)_{fm} \\
&+ \; Target\, Characteristics_{fm} \\
&+ \; Match\, FE_{m} + \varepsilon_{fm}.
\end{aligned}
\tag{2.4}
$$

where $X \in \{U,V,H\}$ indexes the type of acquisition; $TFPR_{fm}$ is a measure of firm TFPR, entered either as a level or a change in the year preceding the acquisition; $Target\ Characteristics_{fm}$ is a set of control variables measured as of the year preceding the completion of an acquisition. An equivalent set of fixed-effects logit models is estimated to investigate the selection of acquirers.

Table 2.5 presents the estimates of average marginal effects from the logit model specified in equation 2.4 for the selection of Targets. Columns 1-3 in panel A show that, using the *Matched Targets Sample,* less productive firms are more likely to become targets in horizontal and unrelated acquisitions, but there is no significant role of productivity in the selection of vertical targets. Columns 4-6 add additional controls for the firms' cash flow, revenue growth, cash balances, leverage, form of incorporation and publicly quoted status. While, the estimated coefficients are reduced considerably becoming insignificant for unrelated acquisitions in column 4, the result for horizontal acquisitions is confirmed in column 6. The estimated coefficient -0.24 on TFPR in column 6 suggests that decreasing TFPR by 1 standard deviation, about 0.4, increases the log of the odds-ratio by about 0.096. This magnitude is almost one-tenth of the unconditional within-sample log of the odds-ratio of being a horizontal target, -1.14. Note that controlling for firm size by means of matching removes most of the unbalancedness as coefficient on $log(TOAS)$ is insignificant, except of column 5.

In panel B, TFPR level is replaced by TFPR growth in the last year preceding the acquisition. Columns 3 and 6 show that firms with declining productivity and low cash stock are more likely to be targeted in horizontal acquisitions, but this is not the case for targets in other types of acquisitions. In addition, low cash flow increases the likelihood of being targeted in all types of acquisition. This suggests that financial or liquidity reasons are important determinants of being targeted by a horizontally or vertically related as well as an unrelated acquirer. Lastly, being incorporated as a Public Limited Company increases the chance of being a target in all types of deals, as well. In Public Limited Companies, the shareholders' equity is explicitly divided into stakes that can be easily sold, which makes this type of incorporation form easier to acquire.

Table 2.6 presents the estimates for the selection of acquirers in the *Matched Acquirers Sample*. In panel A, in columns 1 and 4 the estimated coefficient of the TFPR level is significant and negative, while the coefficient on cash flow in column 4 is positive. This implies that diversifying acquirers in unrelated acquisitions are firms that are under-performing in productivity but have significant positive cash flow shocks.

In panel B, TFPR growth is statistically insignificant in all columns. In column 6 for horizontal deals, the coefficient on Sales Growth is estimated to be positive in both panels A and B. This suggests that even though horizontal acquirers are not over-performing their industry peers of similar size in terms of TFPR, they are experiencing significantly faster growth in sales, which is the reason for their acquisition choices. The other significant factor that is driving the selection of acquirers in all types of deals is their publicly quoted status.

Overall, conditional on firm size, these results do not directly confirm the prediction of Q-theory of mergers that acquirers are firms with superior productivity or recent productivity growth. This holds even in the sub-set of horizontal acquisitions, where the key assumption of asset substitutability is more likely to be satisfied. On the other hand other variables that are related to firm performance, such as high sales growth for horizontal deals and high cash flow for vertical and unrelated deals, are significant factors improving the likelihood of being an acquirer.

As a robustness check, I modify equation 2.4 to one which includes only industry and year fixed effects.

$$\begin{aligned} Target^X_{fm} &= \alpha + \beta \, TFPR_{fm} + \gamma \, log(TOAS)_{fm} \qquad (2.5) \\ &+ \; Target\, Characteristics_{fm} \\ &+ \; Industry\, FE_m + Year\, FE_m + \varepsilon_{fm}. \end{aligned}$$

Equation 2.5 is estimated using a standard logit regression. This approach allows me to calculate the marginal effects of explanatory variables, which are easier to interpret; however, not controlling for match fixed effects can potentially bias the estimates due to unobserved country/industry/year factors.

Appendix Table 2.A.1 presents coefficient estimates for equation 2.5 for the selection of Targets in the *Matched Targets Sample*, and appendix Table 2.A.2 presents results for the equivalent specification of the selection of acquirers in the *Matched Acquirers Sample.* Both tables confirm results presented in Tables 2.5 and 2.6.

Overall, the presented evidence partially supports Hypothesis 1. Firms with low and declining productivity are more likely to be targets in horizontal deals. This supports the inefficient management hypothesis that poorly managed firms are more likely to be acquired only by firms with similar assets, in line with the Q-theory of mergers. Predictions of Q-theory for the selection of acquirers are inconclusive. On the one hand, neither productivity nor its recent trend are significant factors in the selection of acquirers which is at odds with the predictions of the Q-theory of mergers. On the other hand, sales growth appears to affect the selection of horizontal acquirers positively. However importantly, it is stressed that this holds only after carefully conditioning on firm size. Without conditioning on size, productivity becomes the important factor in the selection of firms into acquirers in all types of acquisitions.

TFPR is not a significant factor in the selection of firms into vertical acquisitions, neither as acquirers nor as targets. Together with descriptive statistics provided in Table 2.3 these suggest that firms participating in vertical acquisitions are of similar productivity. A formal test of this hypothesis is presented in the next section.

2.4.2 Acquirer-Target Pairing

Observed productivity similarity of acquirers and targets in vertical acquisitions is in line with the predictions of the search and matching model of Rhodes-Kropf and Robinson (2008). The necessary assumption of asset complementarity is presumably more likely to be satisfied for vertical deals than for other types of acquisitions. However, instead of comparing vertical targets and acquirers to their peers, one should ask whether actual targets and actual acquirers participating in vertical acquisitions are closer to each other in terms of their productivity than pseudo-pairs of non-participating firms which operate in the same respective industries and are of comparable size.

To address this question, I use the *Matched Acquirer-Target Pairing Sample.* I test for the effect of the distance in normalized productivity rTFPR between firms in a given pair p on the probability of pairing in actual acquisition by running a fixed-effects logit regression of the form:

$$\begin{aligned} Actual\,Deal_{pm} &= \alpha + \beta Distance(rTFPR_{pm}) \\ &+ Acquirer\,Characteristics_{pm} + Target\,Characteristics_{pm} \\ &+ Match\,FE_m + \varepsilon_{pm}, \end{aligned} \tag{2.6}$$

where the dependent variable $Actual\,Deal_{pm}$ is one if firm pair p is the actual acquirer-target pair and zero otherwise. $Distance(rTFPR_{pm})$ is the absolute value of the difference in pre-acquisition normalized productivity rTFPR between firms in a given pair, where rTFPR is TFPR normalized to account for the industry average and dispersion as described in section 2.3.5. $Acquirer\,Characteristics_{pm}$ and $Target\,Characteristics_{pm}$ include other control characteristics of acquirers and targets measured as of the year preceding the completion of a deal.

The estimated coefficients from the logit regressions of specification 2.6 are presented in Table 2.7. Column 1 shows that in the sample of all types of acquisition deals, distance in rTFPR is negatively related to the probability of pairing in acquisition. Column 5 confirms that this result is robust controlling for the characteristics of individual firms in pairs. If the distance in firm productivities increase by 1 standard deviation of within industry TFPR distribution, the log of the odds-ratio of a firm-pair participating in actual acquisition decreases by 0.31. This is about one-third of -0.88, which is the within sample log of the odds-ratio of acquisition pairing.

Results for the sub-samples of unrelated, vertical and horizontal deals without included firm-level controls are presented in columns 2, 3, 4 and with included controls in columns 6, 7 and 8. Comparing columns 7 and 5, the effect of the distance rTFPR is almost two times as large in the sample of vertical acquisitions as in the full sample. Estimated marginal effects on the sub-sample of horizontal acquisitions in columns 4 and 8 are a little higher than the results obtained in the full sample, columns 1 and 5.

Two observations emerge from the results in Table 2.7. First, similarity in rTFPR is a significant factor in observed acquisition pairing. Second, the effect of the distance in rTFPR is strongest in the sample of vertical deals but still present, albeit with a lower magnitude, in the sample of horizontal deals. The second observation is consistent with the fact that supplier-producer vertical relationships, or other types of unobserved complementarities, exist also within UK SIC industries. This is an artifact of the coarseness of industry classification and the limitation of this empirical strategy. The only way to clearly alleviate this concern would be to observe actual producer-supplier relationships at the firm-level. To my knowledge, such a dataset hasn't been tapped in the economic literature yet.

One way to provide a check on the importance of supplier-producer industry links in the observed patterns of merger pairing is to use the sub-sample of matches corresponding to across-industry acquisitions and estimate the model where $Distance(rTFPR_{pm})$ is interacted with the actual measure of vertical dependence between industries of firms belonging to a given pair p as well as with the proxy for technological similarity of acquirer's and target's industries. Using the assumption that the technological similarity of two industries is revealed by the similarity of inputs used in the production, I approximate the technological similarity of two industries by the variable called $Supplier\,Similarity$, calculated as the simple correlation of their respective inputs vectors. These inputs vectors are defined in the space of supplying industries on the UK SIC level and their elements are calculated as a share of inputs from the supplying industry in the total output of the receiving industry. As in the case of the index of $Vertical\ Dependence$, they're calculated using the UK Analytical Use table for the year 1995. Including these two interaction terms allows me to investigate how the effect of distance in rTFPR on the likelihood of pairing varies with vertical dependence and technological similarity. Specifically, I run a fixed-effects logit regression:

$$
\begin{aligned}
Actual\ Deal_{pm} &= \alpha + \beta Distance(rTFPR_{pm}) * Vertical\ Dependence_{m} && (2.7)\\
&+ \gamma Distance(rTFPR_{pm}) * Supplier\ Similarity_{m} \\
&+ \delta Distance(rTFPR_{pm}) && (2.8)\\
&+ Acquirer\ Characteristics_{pm} + Target\ Characteristics_{pm} \\
&+ Match\ FE_{m} + \varepsilon_{pm}.
\end{aligned}
$$

The estimated relationship between vertical dependence and the average marginal effects of $Distance\ (rTFPR_{pm})$ as well as their estimated 95% confidence interval is reported in Table 2.8. As the degree of vertical relatedness of the industries corresponding to firm-pair increases, the effect of the distance in rTFPR on the probability of engaging in acquisition gets more negative. This holds in all specifications, whether they include additional firm-level control variables or the interaction of the distance in rTFPR with $Supplier\ Similarity$. This confirms the results obtained in columns 6 and 7 of Table 2.7. Thus, the presented evidence suggests an important role for vertical relatedness on the observed patterns in the positive sorting of firms into acquisition deals.

As a robustness check, I modify equation 2.6 to include only year and acquirers' and targets' industry fixed effects and estimate it using standard logit regression. The results, presented in Table 2.A.3, confirm the main findings presented in Table 2.7. Column 5, for the sample of all acquisitions, suggests that if the distance in firm productivities increases by 1 standard deviation of within-industry TFPR distribution, the probability of a firm-pair participating in an actual acquisition decreases by 5%. This is about one-sixth of 28%, which is the within-sample probability of acquisition pairing. The estimated marginal effect for the sub-sample of vertical acquisitions is more than twice as big. For the comparison, Rhodes-Kropf and Robinson (2008) estimate that increase in the distance in M/B by 1 standard deviation decreases the probability of acquisition pairing by 9%.

Overall, the evidence presented in this section suggests the existence of positive assortative matching in vertical acquisitions in line with the Hypothesis 2. The effect of the difference in productivities on the probability of acquisition pairing is negative, and this is most pronounced among firms operating in industry-pairs with a strong vertical relationship.

2.4.3 Productivity Gains in Acquisitions

The last part of the investigation concerns targets' productivity gains following acquisitions. The prediction of the Q-theory of mergers stated in Hypothesis 3 is: Targets acquired by firms with assets that are a close substitute should see gains in productivity. Before turning to the difference-in-differences econometric model, I explore the productivity dynamics of target firms relative to their industry peers of similar size in the 3-year window surrounding the year of acquisition. For this purpose, I will use the *Matched Targets Sample* with two modifications. First, in order to mitigate the potential truncation bias, I limit the investigation only to deals that are completed by the end of year 2005, at least 3 years before the end of the sample period. Second, I retain only firms for which TFPR is available at least in one year before and one year after the acquisition. Finally, I include only deals in which targets were targeted at most once during the sample period, which mitigates concerns about the effects of multiple acquisitions on firm's productivity.

In order to describe relative productivity, I perform a series of two-sided t-tests of equality in TFPR. These tests are performed separately for each category of acquisitions and for each of the 3 years before and after the year of acquisition. Each t-test performs a comparison of the average TFPR of actual targets with the average TFPR of pseudo-targets that operate in the same industry and are closest to the actual targets in terms of size in one year preceding the actual deal.

The results of this series of t-tests are summarized in Table 2.9. The TFPR of unrelated as well as vertical targets is very similar and not statistically different from the TFPR of their industry peers with similar size. In line with the evidence presented in Table 2.5, unrelated targets appear to be a bit less productive compared to their peers over the three-year period before acquisition. Productivity of vertical targets is on par with that of their peers before the acquisition. Lastly, the productivity of horizontal targets deteriorates in the 3-year period before their acquisition, and it is about 5% lower than the TFPR of their peers within 1 year preceding the deal, the difference being significant at the 1% level. Note that in the 1st year after the acquisition, the negative productivity gap of horizontal targets disappears, and in the 3rd year after the deal, the productivity of horizontal targets is 2% higher than productivity of corresponding pseudo-targets.

To investigate the TFPR gains of targets in acquisitions formally, I employ two sets of models: difference-in-differences model with firm-fixed effects (FEM) and lagged dependent variable model (LDVM). The key identifying assumption of FEM is that conditional on unobserved time invariant characteristics (and exogenous time varying factors), the selection of firms as acquisition targets is random. However, it is likely that this assumption may be inappropriate in the current context, as the productivity of actual horizontal targets declines before the acquisition (see evidence in Tables 2.5 and 2.A.1). This is reminiscent of the results from the literature evaluating the effects of training programs, which usually find that participants in these programs exhibit a drop in earnings just prior to joining the program — i.e. Ashenfelter's dip, Ashenfelter (1978). As shown in Angrist and Pischke (2008), among others, in the case when treatment (i.e. acquisition) is determined by the low pre-treatment value of the variable of interest (i.e. TFPR), the gain from treatment estimated using FEM will be biased upwards. As a remedy, Angrist and Pischke (2008) suggest to estimate gains from treatment using LDVM, which explicitly conditions for the dependent variable in the period just before the treatment, but does not control for fixed effects. However, if the identifying assumption of FEM is correct, but the gain from treatment is estimated using LDVM, it will be biased downwards.

Estimates obtained using FEM and LDVM thus provide bounds upon the causal effect of acquisition on TFPR.

In this setting, FEM can be specified as:

$$\begin{aligned} TFPR_{fmt} &= \alpha + \beta After_{ft} * Target^{X}_{fm} \\ &+ \gamma_1 After_{ft} + \gamma_2 Target^{X}_{fm} \\ &+ Firm\,FE_{fm} + Year\,FE_t + \varepsilon_{fmt}, \end{aligned} \tag{2.9}$$

where $Target^{X}_{fm}$ is an indicator variable equal one if the firm is an actual target, and zero otherwise; and $After_t$ is an indicator variable equal to 1 for the year after acquisition and zero otherwise. The coefficient on the interaction term $After_t * Target^{X}_{fm}$, captures the difference in the before-after change in the dependent variable between actual targets and pseudo-targets belonging to match m. For each type of acquisition indexed $X \in \{U, V, H\}$, this specification is estimated on three panel sub-samples, each of them having two time series observations: the pre-acquisition value and the post-acquisition value. In each subsample, the pre-acquisition year corresponds to 1 year before the actual deal, but the sub-samples differ in post-acquisition year, which corresponds to 1, 2 and 3 years after the deal, respectively for each subsample. Separately investigating the before-after change for each of the 3 years after acquisition allows me to capture the dynamics of the TFPR change.

The LDVM is specified as:

$$\begin{aligned} TFPR_{fmt+s} &= \alpha + \beta Target^{X}_{fm} + \gamma TFPR_{fmt-1} \\ &+ \mathit{log}(TOAS)_{fmt-1} + Year\,FE_t + \varepsilon_{fmt}, \end{aligned} \tag{2.10}$$

where $TFPR_{fmt+s}$ is TFPR s years after the deal, s taking values 1, 2, or 3. As in the case of FEM, equation 2.10 will be estimated jointly, as well as separately for each type of acquisition $X \in \{U, V, H\}$.

The estimates for specification 2.9 are presented in Table 2.10.a and for specification

2.10 in Table 2.10.b. Columns 1-4 (5-8, 9-12) present the estimates of TFPR gains between 1 year before and 1 year (2 years, 3 years) after the deal. If all acquisitions are considered as being of one type, the estimated average targets' TFPR gains over the 3-year period, which are reported in column 9 are between 1.7% for LDVM (Table 2.10.b) and 3.1% for FEM (Table 2.10.a). This is in line with existing evidence: For example, Maksimovic and Phillips (2001) report 2% increase in industry-adjusted revenue productivity three years following the acquisition.

However, once acquisition types are distinguished, the results change considerably. Estimates from both FEM and LDVM show that only horizontal targets experience statistically significant TFPR gains. Their TFPR rises by 4.5% (column 12 of Table 2.10.b) more compared to their matched peers by the third year after acquisition if estimated by LDVM and by 6.3% (column 12 of Table 2.10.a) if estimated by FEM.[14] Firms targeted in unrelated as well as vertical acquisitions don't experience any significant abnormal productivity gains, in fact their estimates are slightly negative for vertical deals.

From the reported numbers of targets in Tables 2.9 and 2.10.a it is clear that there is substantial attrition of all types of targets following acquisition. Due to the attrition, possible concern with the results can be that targets that remain in the sample after the deal are those which are better performing. While this is likely to be the case, there is no apparent reason why such a bias would appear only for the subset of horizontal targets and not for targets belonging to the other two groups. Maksimovic and Phillips (2001) and Maksimovic, Phillips, and Prabhala (2008) report significant restructuring in targeted firms following the acquisition. The observed attrition can thus be either due to simply the acquirer dismantling the targeted firm, re-incorporating it as a new organization or incorporating it into itself. Unfortunately, Amadeus data do not allow for a detailed investigation of reasons for the targets attrition.

Overall the presented finding that post-acquisition productivity increases significantly for targets acquired in horizontal acquisitions and not in other types of acquisitions is consistent with the prediction of the Q-theory of mergers stated in Hypothesis 3. Substi-

[14]In line with the discussion of the differences between FEM and LDVM, estimates obtained using LDVM tend to be lower.

tutability of assets appears to be the necessary condition for fast and successful transfer of acquirers' human and intangible capital and thus targets' productivity gains.

2.5 Conclusion

Using a comprehensive dataset of corporate acquisitions in Europe over the period 1998-2008, I show that while the good-firms-buy-bad-firms pattern is a prominent feature of horizontal acquisitions, there is positive assortative matching on firms' revenue productivity in vertical acquisitions. Furthermore, economically meaningful and statistically significant gains in revenue productivity and profitability are present only among targets acquired in horizontal deals. Overall, these findings are consistent with the Q-theory of mergers as well as the search and matching model of mergers based on asset complementarities. The results also suggest that to understand the sources of productivity gains, it is important to first understand the underlying incentives to merge and second, given the differing incentives, to investigate separately the different categories of mergers.

2.6 Main Tables

Table 2.1: Domestic Acquisitions over Time

	Targets Sample			Acquirers Sample			Acquirer-Target Pairing Sample		
Year	Unrelated #	Vertical #	Horizontal #	Unrelated #	Vertical #	Horizontal #	Unrelated #	Vertical #	Horizontal #
1998	21	20	75	10	11	43	6	4	4
1999	21	14	57	15	12	36	10	1	13
2000	37	17	43	23	8	40	11	6	8
2001	36	29	96	21	16	56	8	14	24
2002	49	66	179	41	56	149	32	27	66
2003	45	65	200	38	62	178	28	22	88
2004	50	47	173	37	51	162	37	17	52
2005	63	68	172	58	48	188	43	21	75
2006	66	84	239	56	68	239	41	35	106
2007	78	78	236	66	66	224	53	39	84
2008	18	13	54	14	8	61	7	8	25
Total	484	501	1524	379	406	1376	276	194	545

The table reports the number of within-country acquisitions by the year of the deal being completed. Transactions are categorized into Unrelated, Vertical and Horizontal based on the measure of Vertical Dependence between the primary industries of Acquirer and Target and their belonging to the same industry, see text. All Samples consist of within-country transactions that were completed between the beginning of 1998 and the end of May 2008, and the stake acquired in the transaction was at least 50%. Furthermore, both firms participating in a transaction must operate in the EU-15; they are either „Public" Limited companies, which are private limited-liability companies that are allowed to issue shares that can be listed or „Private" Limited companies, which are private limited-liability companies whose shares cannot be listed; they don't operate in the Farming, Utilities, Transportation, Finance, Other business activities, Public sector and Other non-business activities. The Targets Sample consists only of transactions in which both the target and the acquirer can be matched to Amadeus by BvD ID – year, where year corresponds to the year preceding the transaction; for the actual target, at least one pseudo-target can be found in Amadeus that operates in the same country/industry in the year preceding the transaction, and it's Total Assets differ from the Total Assets of the actual target at most by 10 %. The Acquirers Sample consists only of transactions in which both the acquirer and the target can be matched to Amadeus by BvD ID – year, where year corresponds to the year preceding the transaction; for the actual acquirer, at least one pseudo-acquirer can be found in Amadeus that operates in the same country/industry in the year preceding the transaction, and it's Total Assets differ from the Total Assets of the actual acquirer at most by 10 %. The Acquirer-Target Pairing Sample consists only of transactions in which both participants can be matched to Amadeus by BvD ID – year, where year corresponds to the year preceding the transaction; for both the actual acquirer and the actual target , at least one pseudo-acquirer and pseudo-target can be found in Amadeus that operate in the same country/industry in the year preceding the transaction, and it's Total Assets differ from the Total Assets of the actual acquirer (actual target) at most by 10 %.

Table 2.2: Sample Description

	Mean	S.D.	10th Percentile	Median	90th Percentile
	Panel A.: Matched Targets Sample				
Actual Targets:					
TOAS	25.28	95.78	0.85	5.63	44.78
TFPR	1.33	0.35	0.93	1.27	1.84
Pseudo Targets:					
TOAS	20.46	80.53	0.83	5.02	36.03
TFPR	1.37	0.36	0.95	1.31	1.92
	Panel B.: Matched Acquirers Sample				
Actual Acquirers:					
TOAS	129.76	1357.06	2.65	20.94	190.34
TFPR	1.43	0.41	0.96	1.35	2.06
Pseudo Acquirers:					
TOAS	70.68	789.77	1.96	15.61	120.62
TFPR	1.47	0.41	0.99	1.39	2.14
	Panel C.: Matched Acquirer-Target Pairing Sample				
Actual Deals:					
| Acq.(rTFPR) - Targ.(rTFPR) |	0.83	0.70	0.12	0.64	1.84
Vertical Dependence	0.05	0.07	0.00	0.02	0.20
Pseudo Deals:					
| Acq.(rTFPR) - Targ.(rTFPR) |	0.94	0.73	0.12	0.78	2.03
	Panel D.: Population of Non-Participating Firms				
Population:					
TOAS	4.12	531.07	0.015	0.22	2.46
TFPR	1.18	0.43	0.764	1.11	1.70

The table reports summary statistics in the year preceding the acquisition for actual targets and pseudo-targets in the Matched Targets Sample in Panel A; for actual acquirers and pseudo acquirers in the Matched Acquirers Sample in Panel B; for actual deals and pseudo deals in the Matched Acquirer-Target Pairing Sample in Panel C; and for the population of firms not participating in any acquisition in panel D. To form the Matched Targets Sample (Matched Acquirers Sample), for each actual target (actual acquirer) at most five pseudo-targets (pseudo-acquirers) are selected in Amadeus as firms that operate in the same country/industry in the year preceding the transaction and their Total Assets differ from the Total Assets of the actual target (actual acquirer) at most by 10 %. To form the Matched Acquirer-Target Pairing Sample, pseudo-deals are formed by pairing (without replacement) selected pseudo-acquirers and pseudo-targets that correspond to actual acquirer and actual target in a given actual deal. The population of firms considered in panel D corresponds to all firms not participating in an acquisition that are active in the year preceding the actual deal in all country/industries corresponding to actual deals that belong to the Acquirer-Target Pairing Sample. TOAS denotes Total Assets in millions of Euros. TFPR denotes normalized Total Factor Productivity which is calculated as a residual from a logarithmic Cobb-Douglas regression model estimated on the population of all firms in Amadeus separately for each industry by OLS while controlling for country/year fixed effects. rTFPR denotes a normalized TFPR, which is calculated as a deviation of the actual TFPR for a given firm/year from the mean value in a corresponding country/industry/year and scaled by the corresponding standard deviation. Vertical Dependence is a measure of vertical proximity between industries of Acquirer and Target. It is calculated as the higher of the intermediate flows from the Acquirer's industry to the Target's industry scaled by the Target's industry output and the intermediate flows from the Target's industry to the Acquirer's industry scaled by the Acquirer's industry output. Between-industry intermediate flows and industry outputs are calculated using the UK Input-Output Tables for 1995. Descriptions of the samples are provided in Table 2.1 and text.

Table 2.3: Descriptive Statistics by Type of Acquisition

	Acquisition: Unrelated	Vertical	Horizontal
	Panel A.: Matched Targets Sample		
Actual Targets:			
Observations #	484	501	1524
Quoted #	11	9	19
Mean TFPR	1.32	1.35	1.33
Pseudo Targets:			
Observations #	1699	1650	5241
Quoted #	10	13	35
Mean TFPR	1.36	1.35	1.36
	Panel B: Matched Acquirers Sample		
Actual Acquirers:			
Observations #	379	406	1376
Quoted #	74	70	235
Mean TFPR	1.40	1.43	1.44
Pseudo Acquirers:			
Observations #	1116	1200	4092
Quoted #	32	19	64
Mean TFPR	1.47	1.46	1.47
	Panel C.: Matched Acquirer-Target Pairing Sample		
Actual Deals:			
Observations #	276	194	545
Mean | Acq.(rTFPR) - Targ.(rTFPR) |	0.95	0.83	0.77
Pseudo Deals:			
Observations #	642	548	1591
Mean | Acq.(rTFPR) - Targ.(rTFPR) |	0.95	0.98	0.92

The table reports summary statistics by the type of acquisition in the year preceding the acquisition for actual targets and pseudo-targets in the Matched Targets Sample in Panel A; for actual acquirers and pseudo-acquirers in the Matched Acquirers Sample in Panel B; and for actual deals and pseudo-deals in the Matched Acquirer-Target Pairing Sample in Panel C. Descriptions of the samples are provided in Table 2.1 and text. The procedure to select pseudo-targets, pseudo-acquirers and pseudo-deals is described in Table 2.2 and text. The categorization of acquisitions into Unrelated, Vertical and Horizontal is described in the text. Observations # reports the number of observations. Quoted # reports the number of firms with publicly listed stock. Mean TFPR reports average Revenue Total Factor Productivity.

Table 2.4: The Role of Size in the Selection of Targets and Acquirers on Productivity

	Next Year Participation in Acquisition:					
	Unrelated	Vertical	Horizontal	Unrelated	Vertical	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Targets Selection					
TFPR	0.126***	0.177***	0.131***	-0.042	0.034	0.011
	(0.026)	(0.025)	(0.014)	(0.030)	(0.027)	(0.015)
Log (TOAS)				0.088***	0.085***	0.081***
				(0.008)	(0.008)	(0.004)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Targets #	442	413	1292	442	413	1292
Obs.	1979	1759	5558	1979	1759	5558
	Panel B: Acquirers Selection					
TFPR	0.194***	0.231***	0.231***	-0.019	0.024	0.001
	(0.026)	(0.027)	(0.013)	(0.018)	(0.022)	(0.011)
Log (TOAS)				0.062***	0.090***	0.077***
				(0.010)	(0.014)	(0.009)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Acquirers #	423	407	1374	423	407	1374
Obs.	1872	1708	5935	1872	1708	5935

The table reports average marginal effects from logit models on the Random Targets Sample in Panel A and the Random Acquirers Sample in Panel B. The Random Targets Sample (the Random Acquirers Sample) is constructed by randomly matching each actual target (actual acquirer) in the Targets Sample (Acquirers Sample) with at most five pseudo-targets (pseudo-acquirers) in Amadeus that operate in the same country/industry in the year preceding the transaction. In each column, the comparison group consists only of pseudo-targets (pseudo-acquirers) that were matched to actual targets (actual acquirers) belonging to the sub-sample corresponding to the type of acquisition (Unrelated, Vertical, Horizontal) in a given column. Log (TOAS) is a natural logarithm of total assets in millions of Euros. All specifications include constant and year fixed effects; their estimates are not reported. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.5: The Selection of Targets on Productivity: Fixed Effects Logit Model

	Next Year Target in Acquisition:					
	Unrelated	Vertical	Horizontal	Unrelated	Vertical	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: TFPR Level					
TFPR	-0.382**	0.062	-0.307***	-0.134	0.169	-0.241**
	(0.171)	(0.164)	(0.091)	(0.219)	(0.196)	(0.113)
Log (TOAS)	-2.240	-1.074	0.605	-2.689	-2.628*	1.248
	(1.651)	(1.349)	(1.031)	(2.088)	(1.532)	(1.215)
Cash Flow				-1.223**	-1.108*	-1.246***
				(0.610)	(0.672)	(0.339)
Sales Growth				0.268	-0.285	-0.117
				(0.202)	(0.183)	(0.100)
Cash				0.537	0.351	-0.433*
				(0.403)	(0.445)	(0.244)
Leverage				0.070	0.073	-0.149
				(0.245)	(0.255)	(0.147)
Public Limited Company				0.763***	0.546***	0.612***
				(0.187)	(0.175)	(0.102)
Quoted				0.490	0.673	0.332
				(0.546)	(0.453)	(0.377)
Match Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Targets #	484	501	1524	375	391	1177
Obs.	2183	2151	6765	1587	1567	4875
	Panel B: TFPR Growth					
TFPR Growth	-0.040	-0.190	-0.397**	0.300	0.399	-0.427**
	(0.319)	(0.284)	(0.157)	(0.385)	(0.346)	(0.177)
Log (TOAS)	-2.950	-1.319	0.895	-2.163	-1.792	1.507
	(1.911)	(1.470)	(1.176)	(2.188)	(1.593)	(1.267)
Cash Flow				-1.197*	-1.202*	-1.189***
				(0.640)	(0.693)	(0.354)
Sales Growth				0.124	-0.383*	-0.073
				(0.214)	(0.222)	(0.111)
Cash				0.540	0.466	-0.508**
				(0.424)	(0.485)	(0.253)
Leverage				0.177	0.069	-0.105
				(0.257)	(0.284)	(0.153)
Public Limited Company				0.771***	0.475***	0.655***
				(0.190)	(0.181)	(0.105)
Quoted				0.486	0.865*	0.453
				(0.562)	(0.472)	(0.388)
Match Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Targets #	417	427	1310	356	364	1106
Obs.	1784	1749	5533	1479	1423	4485

The table reports average coefficient estimates from fixed-effects logit models on the Targets Sample that condition on the full set of match fixed effects. The dependent variable is an indicator variable equal to one if a given firm is a target in an acquisition during the following year and zero otherwise (that is, all covariates are lagged by one year). In each column, the comparison group is derived only from pseudo-targets that were matched by industry/country/year and size to actual targets belonging to the sub-sample corresponding to the given column. The selection of pseudo-targets is described in Table 2.2 and text. Panel A reports results for the level of TFPR in a given year. Panel B reports results for the TFPR Growth between the current and previous year. Log (TOAS) is a natural logarithm of total assets in millions of euros. Cash Flow denotes cash flow in the year before the transaction scaled by total assets. Sales Growth denotes change in log sales in the year before the transaction. Cash is cash balance scaled by total assets. Leverage is total debt excluding accounts payables scaled by total assets. Public Limited Company is an indicator variable equal to one if a given firm is a private limited-liability company that is allowed to issue shares that can be listed. Quoted is an indicator variable equal to one if a given firm has publicly listed stock. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.6: The Selection of Acquirers on Productivity: Fixed Effects Logit Model

	Next Year Acquirer in Acquisition:					
	Unrelated	Vertical	Horizontal	Unrelated	Vertical	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: TFPR Level					
TFPR	-0.844***	-0.222	-0.368***	-0.939***	-0.127	-0.133
	(0.207)	(0.168)	(0.090)	(0.310)	(0.198)	(0.113)
Log (TOAS)	-1.237	0.330	0.337	0.034	2.899	1.440
	(1.589)	(1.632)	(0.847)	(2.349)	(1.893)	(1.118)
Cash Flow				2.414**	2.178**	-0.203
				(1.071)	(1.000)	(0.420)
Sales Growth				0.161	-0.022	0.412***
				(0.217)	(0.245)	(0.116)
Cash				0.278	-0.843	-0.243
				(0.610)	(0.538)	(0.278)
Leverage				-0.252	0.373	-0.448***
				(0.350)	(0.300)	(0.173)
Public Limited Company				0.595**	0.202	0.312***
				(0.261)	(0.230)	(0.121)
Quoted				1.837***	3.467***	2.209***
				(0.432)	(0.543)	(0.234)
Match Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Acquirers #	379	406	1376	276	328	1044
Obs.	1495	1606	5468	1026	1216	3884
	Panel B: TFPR Growth					
TFPR Growth	-0.522	-0.007	0.061	-0.613	-0.058	-0.080
	(0.340)	(0.351)	(0.162)	(0.506)	(0.423)	(0.217)
Log (TOAS)	-0.036	1.568	1.476	1.134	2.835	0.629
	(1.880)	(1.794)	(0.932)	(2.418)	(1.969)	(1.137)
Cash Flow				2.008*	1.488	-0.084
				(1.037)	(0.956)	(0.419)
Sales Growth				0.235	-0.028	0.443***
				(0.259)	(0.278)	(0.131)
Cash				0.139	-0.774	-0.290
				(0.600)	(0.540)	(0.288)
Leverage				-0.322	0.414	-0.480***
				(0.339)	(0.296)	(0.177)
Public Limited Company				0.692**	0.094	0.305**
				(0.278)	(0.229)	(0.125)
Quoted				2.043***	3.414***	2.486***
				(0.390)	(0.538)	(0.242)
Match Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Acquirers #	327	362	1187	294	328	1066
Obs.	1224	1330	4496	1050	1173	3874

The table reports coefficient estimates from fixed-effects logit models on the Acquirers Sample. The dependent variable is an indicator variable equal to one if a given firm is an acquirer in an acquisition during the following year and zero otherwise. In each column, the comparison group consits only of pseudo-acquirers that were matched by industry/country/year and size to actual acquirers belonging to the sub-sample corresponding to the given column. The selection of pseudo-acquirers is described in Table 2.2 and text. Panel A reports results for the level of TFPR in a given year. Panel B reports results for the TFPR Growth between the current and previous year. Explanatory variables are described in Table 2.5 and text. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.7: Acquirer-Target Pairing: Fixed Effects Logit Model

	Acquisition:							
	All	Unrelated	Vertical	Horizontal	All	Unrelated	Vertical	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
| Acq.(rTFPR) - Targ.(rTFPR) |	-0.265***	0.008	-0.301**	-0.405***	-0.314***	-0.087	-0.598***	-0.425***
	(0.057)	(0.103)	(0.129)	(0.082)	(0.077)	(0.156)	(0.185)	(0.109)
Target Log (TOAS)					-0.845	-3.860	0.830	2.453
					(2.494)	(4.816)	(4.926)	(4.399)
Target Cash Flow					-2.405***	-0.809	-5.822***	-2.355***
					(0.529)	(0.788)	(1.646)	(0.721)
Target Sales Growth					-0.390***	-0.748**	0.047	-0.426**
					(0.144)	(0.298)	(0.333)	(0.202)
Target Cash					0.210	1.036	-0.104	-0.123
					(0.375)	(0.717)	(1.155)	(0.517)
Target Leverage					0.365*	0.454	0.310	0.391
					(0.206)	(0.443)	(0.581)	(0.266)
Target Public Limited Company					0.524***	0.552**	0.139	0.629***
					(0.137)	(0.270)	(0.309)	(0.199)
Target Quoted					-0.177	0.067	1.521*	-0.957
					(0.660)	(0.982)	(0.791)	(0.863)
Acquirer Log (TOAS)					-0.242	-0.797	0.433	-0.104
					(1.469)	(2.924)	(3.778)	(2.204)
Acquirer Cash Flow					0.817	0.005	-1.029	2.605***
					(0.647)	(1.031)	(1.584)	(0.973)
Acquirer Sales Growth					0.230*	0.124	0.060	0.315*
					(0.126)	(0.256)	(0.253)	(0.189)
Acquirer Cash					-0.335	1.009	-2.270**	-0.780
					(0.372)	(0.712)	(1.094)	(0.504)
Acquirer Leverage					-0.478**	-0.268	0.247	-1.014***
					(0.227)	(0.472)	(0.533)	(0.350)
Acquirer Public Limited Company					0.101	-0.374	-0.127	0.487**
					(0.136)	(0.307)	(0.275)	(0.190)
Acquirer Quoted					2.765***	3.419***	3.338***	2.470***
					(0.299)	(0.619)	(0.940)	(0.391)
Match Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deals #	1015	276	194	545	745	194	154	397
Observations #	3796	918	742	2136	2547	597	533	1417

The table reports coefficient estimates from fixed-effects logit models on a cross-section corresponding to the year before an acquisition event in the Matched Acquirer-Target Pairing Sample described in Table 1 and the text. The dependent variable is equal to one if a given firm pair is participating in actual acquisition during the following year and zero otherwise. In each column, the comparison group consists only of pseudo-pairs in which both firms were matched by industry/country/year and size to actual participants in the acquisition belonging to the sub-sample corresponding to the given column. Columns 1 and 5 report results obtained on a full sample; columns 2, 3, 4, 6, 7 and 8 report results obtained on the sub-samples of unrelated, vertical and horizontal acquisitions. Control variables are described in Table 2.5 and text. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.8: The Probability of Acquirer-Target Pairing in Between-Industry Acquisitions

	(1)	(2)	(3)	(4)
| Acq.(rTFPR) - Targ.(rTFPR) |	0.024	-0.049	-0.074	-0.257
	(0.112)	(0.178)	(0.168)	(0.267)
| Acq.(rTFPR) - Targ.(rTFPR) | * Vertical Dependence	-6.394*	-9.837*	-6.467*	-11.542**
	(3.708)	(5.346)	(3.659)	(5.181)
| Acq.(rTFPR) - Targ.(rTFPR) | * Supplier Similarity			0.292	0.817
			(0.340)	(0.527)
Match Fixed Effects	Yes	Yes	Yes	Yes
Additional Acquirer and Target Controls		Yes		Yes
Deals #	470	348	470	348
Observations #	1660	1130	1660	1130

The table reports coefficient estimates from fixed-effects logit models on a cross-section of across-industry acquisitions in the Matched Acquirer-Target Pairing Sample corresponding to the year before an acquisition event. The dependent variable is equal to one if a given firm pair is participating in an actual acquisition during the following year and zero otherwise. In each column, the comparison group consists only of pseudo-pairs in which both firms were matched by industry/country/year and size to actual participants in acquisition belonging to the sub-sample corresponding to the given column. Vertical Dependence is defined in Table 2 and text. Supplier Similarity is calculated as the simple correlation of the inputs vectors between the acquirer's and target's industry, where the input vector is defined in the space of supplying industries on the UK SIC level, and its elements are calculated as a share of inputs from the supplying industry in the total output of the receiving industry. Columns 2 and 4 include additional firm-level controls as in Tables 2.5 and 2.6 for both Target and Acquirer. Their estimates are not reported. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.9: Productivity Comparisons of Targets and Their Matches

	Unrelated Target			Vertical Target			Horizontal Target		
	Diff.	T-stat.	N.	Diff.	T-stat.	N.	Diff.	T-stat.	N.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
-3 Years	-0.038	-1.15	148	0.010	0.27	148	0.009	0.42	392
-2 Years	-0.034	-1.11	161	0.013	0.36	157	-0.029	-1.37	439
-1 Year	-0.019	-0.69	192	0.009	0.25	174	-0.050	-2.63***	507
+1 Year	-0.027	-0.93	192	0.021	0.60	174	-0.009	-0.44	507
+2 Years	-0.022	-0.72	166	0.023	0.63	138	0.018	0.80	415
+3 Years	-0.036	-1.01	126	-0.011	-0.28	103	0.024	0.97	305

The table reports within-match differences in performance between actual targets and their corresponding pseudo-targets in the Matched Targets Sample that is constrained to events completed before 2006; transactions in which the target was targeted in acquisition at most once during the sample period; and firms for which TFPR is observed at least in 1 year before and 1 year after the acquisition event. Each row corresponds to a comparison for a year relative to the year of an actual acquisition event. Columns 1-3, 4-6, and 7-9 report comparisons for unrelated, vertical, and horizontal targets, respectively. For each comparison, column Diff. reports the actual difference between the TFPR of an actual target and the mean performance of corresponding pseudo targets; column T-stat. reports t-statistics of the t-test of the equality of the means; and column N. reports the number of actual targets. ***, **, * denote significance of the t-statistics in the two-sided t-test of equal means at the 1%, 5% and 10% levels, respectively.

Table 2.10.a: Productivity Gains: Model with Firm Fixed Effects on Panel Data

	TFPR Level -1 and +1 year around event				TFPR Level -1 and +2 years around event				TFPR Level -1 and +3 years around event			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
After	-0.013	0.010	0.020	0.010	0.015	0.003	-0.005	0.007	-0.001	0.010	0.007	-0.010
	(0.008)	(0.015)	(0.023)	(0.009)	(0.010)	(0.019)	(0.022)	(0.015)	(0.013)	(0.027)	(0.034)	(0.020)
After * Target	0.025**				0.027**				0.031**			
	(0.011)				(0.013)				(0.015)			
After * Unrelated Target		-0.008				-0.011				0.009		
		(0.022)				(0.024)				(0.028)		
After * Vertical Target			0.011				-0.021				-0.036	
			(0.026)				(0.030)				(0.035)	
After * Horizontal Target				0.042***				0.057***				0.063***
				(0.015)				(0.018)				(0.021)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unrelated #	192	192			190	190			147	147		
Vertical #	174		174		160		160		126		126	
Horizontal #	507			507	478			478	359			359
Obs.	7078	1574	1378	4126	6442	1458	1215	3769	4896	1114	931	2851

The table reports estimates from the firm fixed-effects model estimated by OLS using a panel dataset that has two time series observations, before and after the acquisition event, for every actual and pseudo-target in the Matched Targets Sample that is constrained to events completed before 2006 and transactions in which the target was targeted in acquisition at most once during the sample period. Year before acquisition event corresponds to 1 year before the event. Year after the event corresponds to 1, 2, 3 years after the event in columns 1-4, 5-8, and 9-12, respectively. The dependent variable is TFPR. After is an indicator variable that is equal to one for the post-acquisition year, zero otherwise. Unrelated (Vertical, Horizontal) Target are indicator variables that equal one if a given firm is a target in an unrelated (vertical, horizontal) acquisition. Regressions with Unrelated (Vertical, Horizontal) Target indicator variables are run on sub-samples that include only Unrelated (Vertical, Horizontal) targets and corresponding matched pseudo targets. All specifications include constant, firm fixed effects and calendar year fixed effects; their estimates are not reported. Robust standard errors (clustered at the firm level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.10.b: Productivity Gains: Model with Lagged Dependent Variable on Cross-sectional Data

	TFPR Level +1 year after event				TFPR Level +2 years after event				TFPR Level +3 years after event			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Target	0.015				0.016				0.017			
	(0.011)				(0.012)				(0.014)			
Unrelated Target		-0.017				-0.022				-0.009		
		(0.022)				(0.021)				(0.024)		
Vertical Target			0.007				-0.019				-0.035	
			(0.025)				(0.027)				(0.029)	
Horizontal Target				0.029**				0.043**				0.045**
				(0.014)				(0.017)				(0.020)
TFPR Level	0.764***	0.741***	0.766***	0.772***	0.699***	0.720***	0.668***	0.700***	0.641***	0.649***	0.544***	0.668***
-1 year before event	(0.016)	(0.030)	(0.035)	(0.021)	(0.019)	(0.033)	(0.042)	(0.027)	(0.025)	(0.051)	(0.053)	(0.033)
Log (TOAS)	0.017***	0.010*	0.031***	0.016***	0.018***	0.016**	0.036***	0.014***	0.025***	0.027***	0.047***	0.019***
-1 year before event	(0.003)	(0.006)	(0.008)	(0.005)	(0.004)	(0.007)	(0.008)	(0.005)	(0.005)	(0.008)	(0.011)	(0.006)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unrelated #	192	192			190	190			147	147		
Vertical #	174		174		160		160		126		126	
Horizontal #	507			507	478			478	359			359
Obs.	3283	725	638	1920	2907	655	547	1705	2125	477	404	1244

The table reports estimates from the lagged dependent variable model estimated by OLS using a cross-sectional dataset that has one observation for each actual and pseudo-target in the Matched Targets Sample constrained to events completed before 2006 and transactions in which the target was targeted in acquisition at most once during the sample period. The dependent variable is TFPR in 1, 2, 3 years after the event in columns 1-4, 5-8, and 9-12, respectively. Target is an indicator variable that is equal to one if a given firm is a target in acquisition. Unrelated (Vertical, Horizontal) Target are indicator variables that equal one if a given firm is a target in an unrelated (vertical, horizontal) acquisition. Regressions with Unrelated (Vertical, Horizontal) Target indicator variables are run on subsamples that include only Unrelated (Vertical, Horizontal) targets and corresponding matched pseudo-targets. All specifications control for TFPR and the natural logarithm of total assets as of 1 year before the acquisition event. All specifications include constant, and calendar year fixed effects; their estimates are not reported. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

2.A Appendix Tables

Table 2.A.1: The Selection of Targets on Productivity

	Next Year Target in Acquisition:					
	Unrelated	Vertical	Horizontal	Unrelated	Vertical	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: TFPR Level					
TFPR	-0.116***	-0.018	-0.073***	-0.090*	-0.012	-0.072***
	(0.038)	(0.031)	(0.018)	(0.046)	(0.035)	(0.020)
Log (TOAS)	0.023***	0.008**	0.017***	0.008	0.007	0.007***
	(0.004)	(0.004)	(0.002)	(0.006)	(0.005)	(0.003)
Cash Flow				-0.233	-0.117	-0.203***
				(0.145)	(0.130)	(0.059)
Sales Growth				0.038	-0.055*	-0.020
				(0.050)	(0.033)	(0.018)
Cash Stock				-0.233	-0.117	-0.203***
				(0.145)	(0.130)	(0.059)
Leverage				0.038	-0.055*	-0.020
				(0.055)	(0.045)	(0.023)
Public Limited Company				0.043	-0.006	0.021**
				(0.026)	(0.020)	(0.011)
Quoted				0.189	0.144*	0.097
				(0.125)	(0.087)	(0.068)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Targets #	484	501	1524	375	391	1177
Obs.	2183	2151	6765	1587	1567	4875
	Panel B: TFPR Growth					
TFPR Growth	-0.007	-0.032	-0.084***	0.044	0.091	-0.086***
	(0.076)	(0.064)	(0.032)	(0.084)	(0.076)	(0.033)
Log (TOAS)	0.013***	0.007**	0.012***	0.001	0.007	0.003
	(0.004)	(0.003)	(0.002)	(0.005)	(0.005)	(0.002)
Cash Flow				-0.231	-0.154	-0.188***
				(0.150)	(0.150)	(0.057)
Sales Growth				-0.007	-0.094**	-0.013
				(0.050)	(0.048)	(0.019)
Cash				0.086	0.054	-0.082*
				(0.101)	(0.100)	(0.043)
Leverage				0.051	0.040	-0.001
				(0.058)	(0.054)	(0.022)
Public Limited Company				0.046*	-0.008	0.024**
				(0.027)	(0.024)	(0.010)
Quoted				0.217	0.199**	0.117*
				(0.133)	(0.097)	(0.066)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Targets #	417	427	1310	356	364	1106
Obs.	1784	1749	5533	1479	1423	4485

The table uses same sample, variables, and specifications as in Table 2.5, but reports average marginal effects from logit models. All specifications include constant, industry and year fixed effects; their estimates are not reported. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.2: The Selection of Acquirers on Productivity

	Next Year Acquirer in Acquisition:					
	Unrelated	Vertical	Horizontal	Unrelated	Vertical	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: TFPR Level					
TFPR	-0.144***	-0.068*	-0.093***	-0.139***	-0.058	-0.058**
	(0.037)	(0.036)	(0.019)	(0.050)	(0.044)	(0.023)
Log (TOAS)	0.034***	0.030***	0.034***	0.013**	-0.001	0.013***
	(0.004)	(0.005)	(0.002)	(0.006)	(0.007)	(0.003)
Cash Flow				0.397*	0.486**	0.005
				(0.227)	(0.242)	(0.095)
Sales Growth				0.018	-0.001	0.096***
				(0.041)	(0.052)	(0.026)
Cash				0.397*	0.486**	0.005
				(0.227)	(0.242)	(0.095)
Leverage				0.018	-0.001	0.096***
				(0.073)	(0.062)	(0.035)
Public Limited Company				0.050*	-0.043	-0.029*
				(0.029)	(0.030)	(0.015)
Quoted				0.404***	0.788***	0.600***
				(0.066)	(0.098)	(0.050)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Acquirers #	379	406	1376	313	348	1163
Obs.	1495	1606	5468	1140	1285	4297
	Panel B: TFPR Growth					
TFPR Growth	-0.086	0.003	0.009	-0.174*	0.012	-0.010
	(0.061)	(0.073)	(0.034)	(0.100)	(0.094)	(0.050)
Log (TOAS)	0.025***	0.021***	0.027***	0.003	-0.004	0.008**
	(0.003)	(0.004)	(0.002)	(0.006)	(0.007)	(0.003)
Cash Flow				0.446*	0.367	0.019
				(0.239)	(0.249)	(0.101)
Sales Growth				0.057	-0.014	0.103***
				(0.051)	(0.057)	(0.031)
Cash				-0.015	-0.182	-0.058
				(0.112)	(0.122)	(0.065)
Leverage				-0.081	0.098	-0.095**
				(0.071)	(0.062)	(0.038)
Public Limited Company				0.042	-0.062**	-0.022
				(0.029)	(0.031)	(0.016)
Quoted				0.421***	0.745***	0.621***
				(0.066)	(0.098)	(0.058)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Acquirers #	327	362	1187	294	328	1066
Obs.	1224	1330	4496	1050	1173	3874

The table uses same sample, variables, and specifications as in Table 2.6, except it reports average marginal effects from logit models. All specifications include constant, industry and year fixed effects; their estimates are not reported. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.3: Acquirer-Target Pairing

	Acquisition:							
	All	Unrelated	Vertical	Horizontal	All	Unrelated	Vertical	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
| Acq.(rTFPR) - Targ.(rTFPR) |	-0.042***	-0.000	-0.055**	-0.059***	-0.052***	-0.030	-0.107***	-0.056***
	(0.010)	(0.020)	(0.023)	(0.014)	(0.012)	(0.024)	(0.034)	(0.017)
Target Log (TOAS)					0.002	0.004	-0.004	-0.000
					(0.005)	(0.011)	(0.014)	(0.007)
Target Cash Flow					-0.398***	-0.165	-0.862***	-0.398***
					(0.089)	(0.155)	(0.270)	(0.117)
Target Sales Growth					-0.062***	-0.117**	-0.015	-0.054*
					(0.024)	(0.052)	(0.065)	(0.029)
Target Cash					0.031	0.048	0.099	0.029
					(0.060)	(0.118)	(0.197)	(0.076)
Target Leverage					0.040	0.017	0.074	0.045
					(0.030)	(0.071)	(0.092)	(0.037)
Target Public Limited Company					0.042**	0.068*	0.021	0.034
					(0.018)	(0.040)	(0.048)	(0.024)
Target Quoted					0.007	-0.020	0.221	0.004
					(0.105)	(0.238)	(0.262)	(0.113)
Acquirer Log (TOAS)					0.010**	-0.005	0.038***	0.013**
					(0.005)	(0.009)	(0.012)	(0.006)
Acquirer Cash Flow					0.220**	0.081	0.158	0.369***
					(0.107)	(0.190)	(0.339)	(0.141)
Acquirer Sales Growth					0.048**	-0.000	0.088	0.062**
					(0.024)	(0.048)	(0.060)	(0.031)
Acquirer Cash					-0.052	0.191	-0.365*	-0.089
					(0.059)	(0.122)	(0.204)	(0.069)
Acquirer Leverage					-0.056	-0.018	0.111	-0.114**
					(0.035)	(0.077)	(0.090)	(0.046)
Acquirer Public Limited Company					-0.041**	-0.093***	-0.061	-0.020
					(0.017)	(0.036)	(0.048)	(0.022)
Acquirer Quoted					0.511***	0.639***	0.777***	0.410***
					(0.047)	(0.090)	(0.185)	(0.056)
Target Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Acquirer Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deals #	1015	276	194	545	806	219	162	425
Observations #	3796	918	742	2136	2894	688	587	1619

The table uses same sample, variables, and specifications as in Table 2.7, except it reports average marginal effects from logit models without conditioning on the full set of match fixed effects. All specifications include constant, target industry fixed effects, acquirer industry fixed effects and calendar year fixed effects; their estimates are not reported. Robust standard errors (clustered at the match level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

2.B Issues Involved in the TFP Estimation

Apart from the difficulty to distinguish the physical TFP due to a lack of firm-level price data, there are other methodological issues that may arise when estimating the Cobb-Douglas production function. First, it is likely that productivity shocks unobserved to the econometrician but observed by the firm are correlated with input choices, which introduces a simultaneity problem. Additionally, using a balanced panel, as is often the case in previous productivity studies, results have a selection bias if no allowance is made for entry and exit. In response to these issues, several alternative estimators have been proposed in the literature (see Eberhardt and Helmers, 2010 and Van Beveren, 2012 for recent reviews). Among them are traditional approaches to overcome endogeneity issues such as fixed effects, instrumental variables and GMM estimators as well as semi-parametric approaches based on clearly specified structural assumptions about the timing of productivity shocks and their propagation into input choices by firms such as Olley and Pakes (1996) and Levinsohn and Petrin (2003) and their extensions in Ackerberg, Caves, and Frazer (2006) and De Loecker (2011).

However, as noted by Eberhardt and Helmers (2010), none of these approaches are without problems. Fixed-effect estimators can only tackle time-invariant endogeneity, and instrumental variables and GMM estimators are often based on instruments that are either weak or of questionable validity. Structural approaches are based on a control function approach, where unobserved productivity shocks are controlled for using functions of firm state and choice-level variables that are derived from the underlying choice problem of the. Olley and Pakes (1996) use the assumption that firm investment is strictly monotonic in its capital and productivity to back-out the unobserved productivity shock from the observed capital and investments. As such it requires data on capital expenditures which are often missing in large panels such as Amadeus. Levinsohn and Petrin (2003) try to avoid this by controlling for productivity shocks using the function of capital and intermediate inputs, which are often available in the firm-level data. Both these approaches achieve identification through specific structural assumptions on the timing of a firm's choices of inputs and their law of motion across periods. The failure of these assumptions can result in the coefficients of production function being non-identified. Eberhardt and Helmers (2010) compare various production function estimators and note that the coefficients on labor and capital vary significantly across approaches. For example, using the Levinsohn and Petrin (2003) approach, they estimate coefficient on labor to be 0.2, which is too far from the expected value of around 0.7, to reflect the observed share of income accrued to labor, which is usually about 0.6 to 0.8. In contrast, the Olley and Pakes (1996) procedure yields a too low capital coefficient. Given these concerns, I resort to the simplest estimator of the production function using ordinary least squares. This choice makes this study comparable with previous studies on the productivity effects of acquisitions, too.

Chapter 3

Productivity Gains from Services Liberalization in Europe[1]

Abstract

As part of the Single Market Program, the European Commission commanded the liberalization and regulatory harmonization of utilities, transport and telecommunication services. This paper investigates whether and how this process affected the productivity of European network firms. Exploiting the variation in the timing and degree of liberalization efforts across countries and industries, we find that liberalization increased firm-level productivity but had no reallocation impact. Based on our estimates, the average firm-level productivity gain from liberalization amounts to 38 percent of the average total within-firm productivity gain in network industries. The results underscore the growth-promoting role of liberalization efforts.

JEL: D24, K23, L11, L51
Keywords: Productivity, Liberalization, Allocative efficiency, Services, Firm-level data

[1]Earlier versions of this paper have been published in Bena, J., Ondko, P. and Vorvachaki, E. (2011) Productivity Gains from Services Liberalization in Europe, EERC Working Paper No. 11/15E. and Bena, J., Ondko, P. and Vorvachaki, E. (2011) Productivity Gains from Services Liberalization in Europe, CERGE-EI Working Paper Series, 2011, No. 452. Financial support from the Economics Education & Research Consortium (Grant No. 10-1491) and the Grant Agency of the Czech Republic (GrantNo. P403-111-2293) is greatly appreciated. We would like to thank Christos Genakos, Christian Fons-Rosen, Stepan Jurajda, Steve Rivkin, David G. Tarr, Vladimir Vakhitov, Diana Weinhold, all the panels of experts and participants of EERC workshops, and conference participants at the 2011 Econometric Society European Meeting for useful comments and suggestions. All errors remaining in this text are the responsibility of the authors.

3.1 Introduction

In advanced economies, services grow continuously in their importance as final goods and also as inputs in production.[2] In view of their potential to strongly affect economy-wide performance, the European Commission extended its Single Market Program to services. In this process, the Commission commanded the liberalization and harmonization of services regulation among the EU member countries. The reforms were first implemented in network service industries: telecommunications and post, transportation, and utilities. Such a policy priority stemmed from the fact that network services were highly regulated and often monopolized in the EU. As services provided by network industries are essential inputs to other industries, the European Commission envisaged a large scope for gains throughout the economy from increased competition. While a single market for services is currently incomplete and subject to active policy debates, the scope for productivity gains from such regulatory efforts remains largely unknown.

In this paper, we investigate the impact of the European network services liberalization on productivity. Specifically, we ask: What is the impact of liberalization on the productivity of European network services firms? Has liberalization improved the allocation of resources across firms by bringing gains to the production scale of the relatively more productive firms? What is the quantitative importance of these margins? While we address important policy questions, we make a relevant contribution to the literature that examines how competition affects aggregate productivity.

The building blocks of our identification strategy are the following: First, unlike for other services, the removal of state monopolies and entry barriers for network industries is mostly complete to date. Second, we rely on measures of liberalization that capture the compliance of member-country regulations with the European Commission liberalization commands. Third, we put forward an empirical framework, where we identify the impact of liberalization on within-industry productivity moments using cross-country variation

[2] As an illustration, market services in the Eurozone in 1970 accounted for 26% of intermediate production and 39% of value added. Their contribution increased to 36% and 50%, respectively, by 2007. This excludes the community, social and personal services (NACE codes L to Q) that alone account for 20% of total production.

in the extent and timing of liberalization.[3] Importantly, we exploit variation due to the EU-wide harmonization principle while controlling for latent factors that shape policy or productivity outcomes.

To address these questions, we use a European firm-level dataset, which spans the entire liberalization window (1998–2007). The main findings highlight that the liberalization induced an important increase in firm-level Total Factor Productivity (TFP). Namely, the within-firm gains from liberalization are quantitatively important as they amount to 38% of the actual within-firm productivity gains in our sample. Meanwhile, there is no evidence that the more productive firms grew disproportionately more in size due to liberalization.

Our findings show institutions that foster competition are important for achieving high productivity outcomes. They are consistent with the view that regulatory distortions, like product market regulations, can distort firm-level decisions concerning investment, employment and technology (adoption or innovation) and thereby negatively affect firm-level and aggregate performance. Moreover, our findings support the view that the presence of "bad" regulations across EU members is an impediment for Europe's competitiveness and future growth (e.g., see the Sapir, Aghion, Bertola, Hellwig, Pisani-Ferry, Rosati, Viñals, Wallace, Buti, Nava et al., 2004).

In fact, "bad" product market regulations can have particularly severe productivity implications in the presence of strong growth opportunities, as was the case with the rapid diffusion of the Information and Communication Technologies (ICT) in the 1990s (e.g., see Jorgenson, Ho, and Stiroh, 2005). Indeed, the emergence of the "new economy" triggered a persistent divergence in aggregate productivity between Europe and the United States (Van Ark, O'Mahony, and Timmer, 2008). Multiple studies (e.g., Oulton and Srinivasan, 2005; Inklaar, O'Mahony, and Timmer, 2005; Inklaar, Timmer, and Van Ark, 2008) show that the main driver of Europe's underperformance is the poor productivity growth of the European distribution, financial and business services. Importantly, these industries

[3] The observed variation in policy change is driven by the initial level of regulation in each country and the policies taken to meet the European command for harmonization of regulations. See also Section 3.4.1

are fully open to competition in the United States, but remain highly segmented and regulated in Europe (see Inklaar, Timmer, and Van Ark, 2008 and Arnold, Nicoletti, and Scarpetta, 2008 for a review).[4] In sharp contrast, Europe maintained its competitiveness in manufacturing and network services during the ICT episode (Inklaar, Timmer, and Van Ark, 2008). Given that manufacturing was already fully liberalized in Europe by the early 1990s, and in view of our evidence of strong productivity gains from network services liberalization in the 1990s, there is an important scope for productivity gains from extending the EU-wide liberalization program for services.[5]

Our findings are in line with the conclusions coming from earlier studies of the productivity implications of policy-induced liberalizations. In this stream of research, multiple studies concern a single country (e.g., for the case of trade liberalization in Columbia see Eslava, Haltiwanger, Kugler, and Kugler, 2009) or a single industry (e.g., for telecommunications in the United States see Olley and Pakes, 1996). As such, they are vulnerable to concerns regarding the endogeneity of the liberalization policy or the external validity of the results. Our approach that combines multiple industries and countries reduces these concerns and makes our evidence a valuable contribution.

Our evidence in support of the growth-promoting role of competition is also consistent with the insights from studies that look into the impact of competition on productivity without exploiting specific regulatory reforms. This is the case in Bloom, Draca, and Van Reenen (2011) who investigate the role of import competition from China for European firms. For a broader sample of countries, Bartelsman, Haltiwanger, and Scarpetta (2009) relate the cross-country productivity differences with market distortions that result in the misallocations of resources across firms.

Finally, it is worth noting that our empirical specification is very different from the one based on neo-Schumpeterian models that features in earlier studies of the within-industry

[4] In the United States, professional services industries took advantage of the growth opportunities associated with ICT. Specifically, the United States services exhibited strong labor productivity due to both strong capital deepening, particularly of ICT, and strong TFP growth (e.g., Triplett and Bosworth, 2003; Basu, Fernald, Oulton, and Srinivasan, 2003).

[5] That more competitive services can foster aggregate economic performance is further supported by Barone and Cingano (2011), who show for a sample of OECD countries that manufacturing industries which use services inputs grow faster and more intensively in countries with lower services regulatory burdens.

productivity impact of services liberalization in Europe. In this line of research, Nicoletti and Scarpetta (2003) use industry-level data to investigate the neo-Schumpeterian prediction that industries closer to their technological frontier grow faster in more liberalized markets. They find no support that the level of competition in services has a positive impact on their own productivity growth. In contrast, Inklaar, Timmer, and Van Ark (2008) find evidence of such a positive effect, when they restrict their sample to network services.[6] This underscores the limitation in Nicoletti and Scarpetta (2003) that captures services liberalization using an Input-Output weighted average of measures of restrictive regulations for all services, independently of whether they are liberalized or not.[7] Their approach introduces a downward bias in their estimate of the impact of liberalization. In addition, their measure of liberalization is hard to interpret as its variation does not come from removing regulatory barriers within each specific services industry and is confounded with the regulatory barriers of other industries.[8] To overcome such limitations, we focus on the productivity impact of industry-level regulatory barriers. We also highlight that the existence of within-industry differences in liberalization across countries provides the necessary variation that allows the identification of different sources of productivity gains.

This paper is organized as follows. Section 3.2 summarizes the related theoretical and empirical literature, Section 3.3 presents our data, Section 3.4 lays out our methodology, Section 3.5 presents our results and Section 3.6 concerns our robustness checks. Finally, Section 3.7 concludes.

3.2 Theoretical Considerations and Hypothesis Development

The removal of industry distortions, like regulatory entry costs or the abolition of state monopolies, are expected to increase competition among firms. Models of industry equilibrium with firm heterogeneity highlight that such a liberalization policy would affect

[6]See also Boylaud and Nicoletti (2000) for telecommunications alone.
[7]A similar argument is discussed in Inklaar, Timmer, and Van Ark (2008).
[8]Similar arguments apply to Arnold, Nicoletti, and Scarpetta (2008), who estimate the within-firm productivity gains from liberalization.

industry productivity through three distinct channels: first, the within-firm productivity growth for the continuing firms in the industry that corresponds to the intensive margin of aggregate productivity; second, the within-industry productivity growth across firms' reallocation of resources, e.g., labor and output shares; and third, the selection mechanism, meaning the entry and exit decisions of firms. The latter two channels correspond to the extensive margin of aggregate productivity growth. Even though theory is clear about the impact of the margins of competition on aggregate productivity, it bears mostly confounded predictions regarding their direction.

In particular, there are ambiguous theoretical predictions regarding the ultimate direction of the within-firm growth channel. This is because higher competition can affect firm-growth in a number of ways that can go in opposite directions. First, continuing firms decide to expand their production capacity via physical investment. Alesina, Ardagna, Nicoletti, and Schiantarelli (2005) show that high competition results in lower profit margins and thus lowers the shadow price of capital, which increases the firm's investment rate. However, this result is challenged in the presence of formerly government-backed monopolies that tend to have inefficiently large production capacity.[9]

Second, competition impacts the TFP of incumbents because it affects incentives to adopt new technologies or innovate. Acemoglu, Aghion, and Zilibotti (2006) show that for firms that are away from their industry's technological frontier, it is optimal not to innovate but instead adopt the best-practice technologies. For such technologically laggard firms, competition creates stronger incentives to invest in the adoption of frontier technologies (see Parente and Prescott, 1994). To the contrary, for firms that are close to their industry technology frontier, competition bears a non-linear effect on their innovation decisions and thereby growth (Aghion, Howitt, and García-Peñalosa, 1998; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005).

In particular, the neo-Schumpeterian models highlight that innovation incentives are driven by the difference between pre-innovation and post-innovation rents. If competition reduces pre-innovation rents, it increases the incremental payoff from innovation

[9]Similarly, theory does not provide clear guidance regarding what to expect from the impact of competition on the capital intensity (capital-labor ratios) of firms.

and encourages innovation as a means of "escaping competition". In contrast, if competition reduces post-innovation rents, it discourages innovation through the standard "Schumpeterian effect". These imply an inverse-U relationship between competition and innovation activity within an industry, i.e., increased competition would have a positive impact on industry innovation only for low levels of initial competition. The results further highlight that the peak of the inverse-U relationship will occur at a higher degree of competition level in more "neck-and-neck" industries, i.e., where firms already compete closely. Therefore, removing entry barriers in industries with very low or no competition is expected to cause higher innovation and thereby growth. The effect should be higher the more increased competition reduces pre-innovation rents.

An additional explanation why competition can foster within-firm productivity is provided by the "trapped factors" hypothesis of Bloom, Romer, and Van Reenen (2010). The "trapped factors" refer to inputs, like human capital skills, that are highly firm-specific. When a firm faces higher competition in producing low-tech products, then the opportunity cost of its trapped factors falls. As a result, when the incumbent firms can innovate more easily than their competitors, then they have an incentive to reallocate teir factors toward innovation and the production of high-tech goods.

Finally, firms can grow due to an improvement in their managerial quality.[10] The impact of competition on managerial incentives is ambiguous in environments featuring asymmetric information/moral hazard problems (see Nickell, 1996, for a review). On the one hand, competition can increase managerial effort and reduce slackness, either by increasing the threat of firm liquidation or by an improvement in the quality of the manager's monitoring. The latter is due to the fact that competitors' performances offer owners additional sources of information for aggregate productivity shocks. On the other hand, managerial incentives worsen if managerial compensation packages are aligned to firm profits that are eroded by competition (see Vickers, 1995). Schmidt (1997) consolidates these opposing effects of competition to show that starting from the state of monopoly, there is a U-shaped effect of higher competition on managerial slackness. If managerial

[10]See Bloom and Van Reenen (2007) regarding the importance of managerial practices for firm-level productivity.

slackness results in lower productivity, this suggests a nonlinear effect of liberalization on firms with initially different levels of productivity.

A heterogeneous effect of liberalization across firms could be also driven by regulations that are explicitly tied to firm size or by aggregate regulations that can have asymmetric effects across firms in the presence of additional market frictions, like those relating to capital or labor inputs (e.g., see Guner, Ventura, and Xu, 2008). For example Beck, Demirguc-Kunt, and Maksimovic (2005) provide evidence that industries with a higher share of very small firms in the United States grow faster in countries with more developed financial systems, suggesting that small firms face higher constraints in obtaining external financing.

Turning to the remaining margins of industry productivity, it is worth noting that in a frictionless environment, in the spirit of Lucas (1978), firm size should be perfectly correlated to firm productivity. Thus, any deviations from the optimal allocation of resources across productive units due to regulatory costs would distort aggregate productivity downwards.[11] Indeed, a reduction of entry costs in static models of industry equilibrium with heterogeneous firms implies a positive within-industry reallocation of resources across firms (see Melitz, 2003; Melitz and Ottaviano, 2008). This is because as a response to the lower entry costs there is increased firm entry, so that a higher number of firms compete in the market. This results in lower average markups and profits, so that the productivity cut-off for surviving in the industry increases in the long-run. In other words, increased competition induces the least productive firms to exit and shifts resources towards the most efficient firms in the market. As a result, industry productivity increases.

While the selection margin is clearly predicted to contribute positively to industry productivity in the long run, this is not necessarily the case in the short run. The transition dynamics of the Melitz (2003) model suggest that in the short run, the productivity of the entering firms is lower than before the removal of entry barriers as the firms that

[11] There is a large and growing literature that attributes low aggregate productivity to differences in the misallocation of resources within/across firms (see Banerjee and Duflo, 2005). This line of research highlights the role of aggregate or firm-specific, policy-driven distortions in creating the scope for such misallocations, particularly in environments with firm-heterogeneity in productivity (e.g., Hsieh and Klenow, 2010; Bartelsman, Haltiwanger, and Scarpetta, 2009; Guner, Ventura, and Xu, 2008; and Restuccia and Rogerson, 2008)

enter initially are the "marginal" ones that were previously deterred (a similar argument is featured in Branstetter, Lima, Taylor, and Venancio, 2010). At the same time, there are dynamic models of industry equilibrium, like vintage capital or neo-Schumpeterian models, where it is shown that entrants have the strongest incentives to be on the technological frontier. All this discussion suggests that the role of selection is open to empirical investigation.

To summarize the testable predictions derived from theory: Competition can affect within-firm productivity outcomes, but the predicted direction of its effect is not clear. Moreover, higher competition is predicted to induce the more productive firms to grow in size and enjoy higher market shares. The number of both entrants and firms in an industry are expected to go up while there are ambiguous predictions about their productivity identity compared to the average firm in the liberalized industry.

We are able to investigate the direction of the within-firm productivity impact of liberalization and test the hypothesis of the positive reallocation of resources. Due to our data limitations that are illustrated in the following section, we are not able to investigate selection through exit and entry at a reasonable level of precision.

3.3 Data and Sample

3.3.1 The OECD measure of product market regulation in network services: The "ETCR"

Starting from 2001, the OECD produces indicators of product market regulation — the "ETCR" indexes — for network services: telecommunications and post, railways, road freight, airlines, electricity and gas. The industry-level indicators are broadly available for 21 OECD countries and cover the period 1975–2007. Details about the construction of these indexes are in Conway and Nicoletti (2006).[12]

The ETCR index for each industry is a quantitative measure that ranges between 0

[12]For detailed documentation and recent data updates, see the OECD webpage: http://www.oecd.org/document/36/0,3343,en_2649_34323_35790244_1_1_1_1,00.html.

and 6, "reflecting increasing restrictiveness of regulatory provisions to competition". The construction of the industry-level ETCR indexes is based on two principles. First, the regulations in each industry-country are judged in terms of their restrictiveness only in areas where the regulation theory and technological features suggest that there is scope for market competition. Therefore, an industry ETCR index does not judge regulatory outcomes in cases of "natural monopolies", i.e., large economies of scale. This principle is particularly important for the network services that are the subject of our study. Second, the industry-level ETCR indices are constructed on the basis of qualitative information in the Regulatory Indicators Questionnaire provided by national governments (1998, 2003 and 2008) and complemented by the OECD and other international organizations data. Hence, these indicators are, in spirit, fully "objective measures" of competition that aim to capture the stance of the regulatory environment in a given country-industry with respect to promoting market competition. This makes the measures of restrictive regulations we use robust to any bias related to local market conditions and the stage of the business cycle.[13]

Finally, the ETCR indexes cover a number of regulatory areas summarized using more disaggregated indexes of product market regulation. The regulatory areas for network services are barriers to entry, public ownership, price controls, market structure and vertical integration. The industry-specific indicators differ in terms of which regulatory areas are covered, and they are summarized in Table 3.A.1 of the Appendix. This cross-industry variation reflects the relevance of each regulatory area for a particular industry. In this regard, it is worth noting that regulatory barriers to entry and public ownership are the two areas universally covered. The areas of market structure and vertical integration are meant to capture the enforcement or effectiveness of the regulations as they reflect the dimensions of the actual industry competition stance.

We summarize the information on product market liberalization for each industry-country at two levels. First, we use the "Index of Overall Liberalization" (IOL) that

[13]Such a bias is a concern in the case of "subjective" competition measures that are based on individual responses to surveys. For a detailed discussion of the relevant advantages of the "objective" measures see Nicoletti and Pryor (2006).

includes information on barriers to entry and public ownership only. We leave out the lower-level indexes that capture market structure and vertical integration because they are prone to be contaminated by factors that are endogenous to drivers of industry-performance. Second, we employ the "Index of Entry Liberalization" (IEL) that concerns entry regulation exclusively. We examine in isolation the role of entry regulations because they refer solely to the de jure elements of the regulatory environment. In contrast, the information in IOL regarding state ownership share is indicative of incumbent market power and effective barriers to entry, and as such it captures also de facto elements of the competition environment. To ease the interpretation of the results of our empirical investigation, we measure both indices on a scale of 0 to 6, where 6 corresponds to the most liberalized marked and 0 to the most regulated market.

To facilitate the intuition for how a unit-change in IOL maps onto changes in the regulatory environment of the industry, consider the following hypothetical scenario for the case of telecommunications. Assume that the industry started with the highest degree of regulatory barriers and presence of monopoly: IOL score 0. A one-unit improvement for such a telecommunications industry would require that "legal conditions of entry into the trunk, international and mobile telephony" changed from "franchised to 1 firm" to "franchised to 2 or more firms". A full removal of entry barriers, i.e., a change in such legal conditions to "free entry", would cause a six-unit change in IEL but a three-unit change in IOL. Thus, IOL can increase by more than three units only if the removal of entry barriers is accompanied by a reduction in the percentage of public ownership "of shares of the largest firm in the mobile telecommunications sector" and in the "public telecommunication operator" by at least 50% of their initial level on average.[14]

3.3.2 Firm-level data

In order to track the contributions of individual producers to the dynamics of the productivity of an industry, we use Amadeus, a European–wide, firm-level dataset. It is

[14]The average four-year change in IOL amounts to 0.66 points in our sample. The IOL is an equal-weights' average of public ownership and entry sub-indices, for which the average four-year change is 0.95 and 0.39, respectively. Thus, more than two-thirds of the observed change in IOL is driven by the change in the entry sub-index.

compiled by Bureau Van Dijk (BvD) by harmonizing companies' annual reports obtained from various European vendors. The key advantage of Amadeus for our purpose is that it covers both public and private companies of all size categories across all industries for most countries.

Amadeus is available in multiple updates that add information over time. Every update contains a snapshot of the currently active population of firms as well as up to the 10 most recent years of firms' financial data (if available). Also, a given firm is present in Amadeus as long as it provides its financial statements; however, it is kept in the database only for four years after its last filing. For example, a firm that files a financial statement in 2002 but stops filing in 2003 remains in the database until 2006. In 2007, the firm is dropped from the sample and all year entries of the firm are taken out of the Amadeus database. Given this feature of Amadeus, we construct our dataset by combining several updates, specifically DVD updates from May 2002 and May 2004 together with updates downloaded from WRDS in July 2007, April 2008, August 2009 and February 2010. This procedure allows us to add back observations for firms that are not present in more recent updates. The key advantages of this procedure are: it eliminates the survivor bias inherent in a single update of data and it extends firms' historical accounting data beyond the most recent 10 years.

We use also the EU KLEMS database in order to obtain country-sector specific output and intermediate input deflators with the base year being 1995. EU KLEMS uses the two/three digit NACE rev. 1.1., which is broader than the classification of industries in this study. For this reason, we need to use the same aggregate deflator for all industries within a given EU KLEMS two/three digit sector. The correspondence between the EU KLEMS sectors and the network industries for which the OECD reports ETCR indexes is summarized in Table 3.A.2 of the Appendix.

3.3.3 Final sample

To construct our final sample from Amadeus, we first select all firm-year observations in the industries of interest for which the values of revenues, fixed assets, material costs and employment variables are not missing. When the total wage bill is available, but employment is missing, we impute employment as the ratio of the total wage bill over the average wage of the corresponding industry. The latter is estimated as the simple average of wages calculated over firms in the same industry-year that report both the total wage bill and employment. Next, we drop all observations of firms with less than 20 employees since their reported information is often missing or likely unreliable. Then, we drop observations in the top percentile of employment and revenues distribution as it is likely that these correspond to conglomerates operating over many markets that could bias our results. Last, we drop the Netherlands, Luxemburg and Slovakia, countries for which there are too few observations.

Table 3.1 reports the descriptive statistics for value added per employee, employment and IOL for our final unbalanced sample that spans 6 network services industries over the period 1998–2007. There is substantial cross-sectional variation in labor productivity and employment for the median firm in our sample. Labor productivity is the highest for the median firms in France, Germany and Austria, with Sweden following closely. The bottom end of labor productivity features the former transition countries (the Czech Republic, Hungary and Poland). Countries differ also in terms of the level of restrictive regulations in their network industries in 1998: France and Italy, together with the group of former transition countries, are among those with the most restrictive regulations in 1998. By 2007, however, the regulatory environments of EU countries had converged. Indeed, Table 3.2 shows countries that started as the most restrictive are the ones that experienced stronger liberalization over the sample period. The group of highly liberalized industries involves telecommunications, gas and electricity services. In contrast, post and railways are among the least deregulated industries.

Table 3.3 reports the descriptive statistics across industries in our sample. Airlines, electricity and gas services have the highest median labor productivity presumably because of the high capital intensity of these industries. The median firm size appears to be more balanced across industries, and it is the highest in the transportation industries, airlines and railways. The electricity industry is the one most represented in our sample.

3.4 Methodology

3.4.1 Identification strategy: The European Union legal framework for services liberalization

The crucial assumption for the identification of the effect of liberalization on productivity is that the EU-wide regulations aimed at liberalization are not driven by local market and growth conditions. This is ensured by the EU legal structure. In particular, all liberalization policies that are part of the EU's Single Market Program are based on a series of Directives that are approved by majority voting in the European Parliament. Directives set out the objectives and the timeframe of reforms. Such reforms are based on the need to ensure European-level outcomes and are thus independent of country-specific circumstances. In response to the EU Directives, member countries design their own policies to fulfill the reform goals by the set deadline.

Services Directives concern reforms to liberalize and harmonize regulatory frameworks for services among European Union members. They timely followed the liberalization of manufacturing industries in the 1990s and were largely viewed as a further step towards the fulfillment of the goals of the 1993 Single Market Program for goods.[15] Services liberalization is consistent with the European Common Market key goal to establish "a single market for goods and services by the removal of physical and regulatory barriers". The ultimate goal is to ensure competitiveness and sound long-run growth prospects for Europe. In this process, the European Commission prioritized the liberalization of network services because of their key importance as inputs for manufacturing. An additional driver for the case of telecommunications was the strong growth opportunities envisaged in relation to ICT. It is worth highlighting that the removal of entry barriers for services is particularly important for ensuring competition in such markets. This is because they are largely non-tradable and, as such, there is a limited scope for increased competition via imports.

Therefore, in view of the features of EU-wide regulations outlined above, we can ar-

[15] This is because of evidence that performance in manufacturing can be constrained by services performance (see Raa and Wolff, 2001).

gue that industry-specific liberalization reforms during the liberalization windows of the Directives are not initiated based on industry-country specific conditions and productivity prospects. The increasing compliance of countries to the EU Directives for network services liberalization is summarized in Figure 3.1. In our data, there are both a positive IOL trend across EU member countries as well as indications of shrinking cross-sectional variance. The developments of the median IOL reflect market developments in the electricity industry, which is the median industry in our sample. There, the first and second EU Electricity Market Directives were issued in 1996 and 2003 respectively, with a transposition deadline in 2007. A detailed exposition by industry and country is offered by Figure 3.2 (complemented by Table 3.2).

Our approach is potentially vulnerable to skepticism regarding whether differences in the degree and timing of compliance across countries/industries are driven themselves by local market or growth conditions. For instance, related to the implementation of Electricity Directives, Jamasb and Pollitt (2005) explain the poor performance of Spain and Italy, arguing that regulators appeared "weak in the face of established incumbent company interests" (p. 17; see also benchmarking reports by the EU). We address such concerns in Section 3.5.2 appealing explicitly to the harmonization principle.

3.4.2 Measures of productivity

To investigate the impact of liberalization on productivity, we estimate firm-level Revenue Total Factor Productivity (TFPR) that captures the efficiency of a firm in generating sales using its inputs and the industry-specific technology. We recover three measures of TFPR: the logarithm of revenue total factor productivity estimated by ordinary least squares (TFPR OLS), the logarithm of revenue total factor productivity estimated by Levinson and Petrin (TFPR LP), and the Wooldridge-Levinsohn-Petrin (TFPR W-LP) estimator.

To estimate all measures of TFPR, we use deflated sales as a measure of output, material inputs measured as material costs deflated by the intermediate inputs deflator, capital approximated by the book value of fixed assets, and labor measured by the number of employees in a firm. Assuming an industry-specific logarithmic Cobb-Douglas production function in capital, labor and materials, TFPR is calculated as the residual of the estimated industry production function.

There are potential sources of bias when estimating the production function. The unobserved productivity shocks known to a firm are likely to contemporaneously affect its input choice, which introduces a "simultaneity bias" to the estimated parameters of the industry-specific production function.[16] This suggests that when the production function parameters are estimated using OLS, the estimates are subject to a positive bias. This is particularly the case for the estimated parameters on flexible inputs, such as materials. To deal with the simultaneity bias, a number of alternative estimators have been proposed in the literature (see Eberhardt and Helmers, 2010 for a recent review). The most popular estimators are those by Olley and Pakes (1996) and Levinsohn and Petrin (2003). The Olley and Pakes (1996) estimator is based on a set of structural assumptions about the timing of a firm's input choices and their law of motion over time, as well as on the assumption concerning the firm's productivity process. Specifically, this approach assumes that capital takes (a one-period) "time-to-build" and that productivity follows a first-order Markov process. In this setting, investment is strictly monotonic in the firm's capital and productivity. Inverting this relationship allows controlling for the unobserved productivity shock using a general function of the observed capital and investment of the firm. As such, this estimation method requires data on capital expenditures, which are not reported in Amadeus. The Levinsohn and Petrin (2003) estimator is based on similar structural assumptions but is less demanding on data information. Productivity shocks are controlled for using a function of capital and intermediate inputs, which are available in our firm-level data. Using intermediate inputs to proxy for unobserved productivity shocks avoids the imputation of capital expenditures series from the stock of capital.[17] Thus, as the second measure of TFPR, we use the one estimated using the Levinsohn and Petrin (2003) approach, and we label it 'TFPR LP'.

[16] Additionally, using a balanced panel can introduce selection bias if there is no allowance for entry and exit. As discussed earlier, our sample does not suffer from such a bias by construction.

[17] Moreover, compared to Olley and Pakes (1996), using the Levinsohn and Petrin (2003) method is a way to avoid dropping observations with zero investment and thus utilize the full sample.

To the extent that there is collinearity between labor and the non-parametric function of capital and materials that proxy for the unobserved productivity shock, the Levinsohn and Petrin (2003) estimator may fail to identify the production function parameters of the variable inputs.[18] For this reason, we also estimate firm productivity using the one-step GMM formulation of the Levinsohn and Petrin (2003) estimator proposed by Wooldridge (2009) that is robust to this potential bias. In addition, the GMM framework provides efficiency gains and allows us to recover robust standard errors. In our application, we use a formulation in which unobserved productivity shocks are approximated by a 3rd-order polynomial in material spending and capital. Following De Loecker (2011), we estimate an industry-specific, value-added production function in order to ensure the identification of the perfectly variable material input. The double-deflated value added is calculated as deflated revenues minus deflated materials, obtained using the appropriate industry deflators. The resulting productivity measure is labeled 'TFPR W-LP'.

As a final note, since Amadeus lacks firm-level information about prices, our estimates of production function parameters are potentially subject to an "omitted prices bias". If there is a correlation between inputs and the firm-level price deviation from the industry-level price index, Klette and Griliches (1996) show that the omitted prices translate into a negative bias of the estimated scale elasticity. This suggests that any TFPR measure would deviate from physical productivity due to price dispersion and the bias in the scale elasticity. This implies that, when we are interested in estimating the impact of liberalization on firm-level productivity, the estimates confound the impact of liberalization on the actual firm-level physical productivity with its impact on the dispersion of prices across firms and demand conditions.

The solution proposed by De Loecker (2011) for this bias is the structural estimation of the production function, while conditioning for shifts in the CES-based firm residual demand. His identification of the demand parameters relies on the differences in variation in aggregate-level (segment/industry) output and firm-level (product) demand shifts

[18]The collinearity is due to the fact that, as an optimally chosen input, labor is likely to also be a deterministic function of the unobserved productivity and capital (see Ackerberg, Caves, and Frazer, 2006, for a detailed discussion).

stemming from policy change, in his case tariff liberalization. To disentangle the effect of policy change on productivity from that on demand conditions, he further assumes that a policy change shifts the firm-level residual demand instantaneously, and it affects firm-level productivity only with a lag. His strategy is not applicable in our setting since our liberalization index (IOL or EOL) does not vary at the firm level but only at the country/industry level.

In this context, it is worth noting that if European network services liberalization was successful in increasing competition, then average prices (mark-ups) and their dispersion would fall over time. This, in turn, suggests that our estimates would tend to underestimate the productivity impact of liberalization (a similar argument is found in Syverson, 2011). In an attempt to explore the importance of this bias for our baseline regressions, we have examined the relation between liberalization and firm-level, price-cost margins in our sample.[19] We find no systematic relation between them, which is in line with the existing evidence regarding the absence of the impact of European networks liberalization on prices and their dispersion (see Fiorio and Florio, 2009 and the review therein).[20] Overall, this evidence suggests that there is no systematic bias coming from mark-up and price dynamics. Therefore, mark-up and price dynamics could only introduce pure noise in our TFPR measures, and our estimates could be, if anything, downward biased.

As a further way to check the robustness of our results to using alternative productivity measures, we also report results for labor productivity measured by the logarithm of value added per employee (ln(Va/Empl)). Table 3.A.3 shows the correlations between different measures of productivity in our sample. The correlations are reasonably high even though the ones between TFPR OLS and other productivity measures are lower.

[19]We approximate price-cost margins by the earnings before interest, taxes, depreciation and amortization divided by sales, following Aghion et al. (2005). The regressions of price-cost margins on IOL are available upon request.

[20]A number of European Commission evaluations are available at: http://ec.europa.eu/economy_finance/structural_reforms/product/network_industries/index_en.htm.

3.4.3 Within-firm productivity change of incumbents

To explore the within-firm productivity gains from the network services liberalization, we investigate the relationship between the firm-level productivity growth and liberalization in the firm's industry. We account for time-invariant unobserved heterogeneity at the country/industry level by means of controlling for country and industry fixed effects.

The fixed-effects and first-differences models can often lead to an attenuation bias. This is particularly the case in settings where the exogenous variable of interest is highly auto-correlated and where outcomes are expected to respond to changes in conditions over a longer period of time. This is because even when the exogenous variable of interest is precisely measured, its variation over short time periods may only poorly approximate the incentives of firms to adjust their productivity. Thus, first differencing eliminates most of the useful information about true incentives to adjust and results in inconsistent estimates (see McKinnish, 2008). This is a potential issue in our setting since we estimate the productivity response of firms to changes in regulatory policy that is highly correlated in time. In our sample, the autocorrelation of the liberalization index is 0.73.[21] We therefore follow the literature and use instead a long-differences estimator that tackles this source of bias.

Formally, our baseline regression model can be stated as:

$$\Delta p_{fcit} = \beta \Delta Lib_{cit} + X_{cit} + \varepsilon_{fcit}, \tag{3.1}$$

where Δ denotes the long-difference operator, which corresponds to four-year differences in our baseline specification;[22] $fcit$ is the index of observation for firm f in country c, industry i and year t; p_{fcit} is a firm-level productivity measure and Lib_{cit} is the index of liberalization in country-industry-year, IOL or IEL. Finally, the vector X_{cit} denotes a set of country/industry/year controls.[23]

[21] Calculated by regressing the liberalization index on firm fixed effects and applying the Baltagi and Wu (1999) procedure for testing for the autocorrelation of residuals in unbalanced panel data.

[22] The exact choice of the number of years is subject to a trade-off between the attenuation bias resulting from using a too-short period and a reduction in sample size resulting from a too-long period. We obtain similar results when using 3- or 5-year differences.

[23] The set of included controls X_{cit} corresponds to already differenced variables.

In order to control for country-specific aggregate trends and shocks, such as the catch-up process of the new member states or the different timing of country-specific reforms and financial conditions, X_{cit} includes the full set of country-year fixed effects λ_{ct}. Furthermore, including λ_{ct} mitigates worries that our estimates are affected by the spillovers from other reforms that are simultaneous to the network services liberalization of a given industry, which would be a concern if countries were implementing reforms in the form of reform packages.

Vector X_{cit} contains the full set of industry fixed effects λ_i capturing differences in industry-specific average trends. If the liberalization efforts were correlated with unobserved industry-specific global growth opportunities in the cross-section, our estimate of β would be biased upwards. Thus, in the model, which includes country-year and industry fixed effects, the coefficient of interest is identified from the different timing and magnitude of the liberalization across countries within the same industry.

In an alternative specification, we control for unobserved differences in country-industry specific trends by replacing industry fixed effects λ_i with the full set of country-industry fixed effects λ_{ci}. The country-industry fixed effects absorb all differences in the average trend of productivity at the country-industry level. Therefore, their inclusion considerably reduces the variation that can be used for the identification of β. Notably, if the pace of the liberalization were constant over the whole sample period in any given country-industry cluster, the coefficient β would not be identified.

Finally, we extend the specification by including industry-year fixed effects λ_{it}. Controlling for λ_{it} mitigates concerns that the timing and scope of the liberalization by local authorities might be affected by industry-wide global productivity shocks (common across all countries).

Taken together, in our preferred specification, we control for country-industry fixed effects λ_{ci}, country-year shocks λ_{ct} and industry-year shocks λ_{it}. Thus, given the use of the four-year differences estimator, β is identified only from differences in the dynamics of productivity change in periods of significant liberalization and periods of low liberalization while controlling for country-specific and industry-specific shocks.[24]

3.4.4 The reallocation of market share between incumbents

To explore the reallocation channel, we investigate the differences in the employment growth of firms in the same industry that differ in their lagged productivity.[25] As discussed in Section 3.2, the theory predicts liberalization that strengthens competition causes inefficient firms to shrink and allows the more efficient firms to increase in size relative to the average firm in the industry.

To test this prediction, we estimate the four-year-differences model of employment growth of the form:

$$\Delta empl_{fcit} = \alpha \Delta Lib_{cit} + \beta \Delta Lib_{cit} \times p_{fict-4} + \gamma p_{fict-4} + X_{cit} + \varepsilon_{fcit}, \tag{3.2}$$

where $\Delta empl_{fcit}$ stands for the change in employment between year t and year $t-4$. If the liberalization has a positive effect on aggregate productivity through the reallocation channel, we would expect coefficient β to be positive, indicating that the employment of productive firms is increasing disproportionally more than the employment of relatively less productive firms.

As in the case of specification (3.1), X_{cit} includes country-year, industry-year and country-industry fixed effects in order to control for country and industry shocks and country-industry average trends. The sources of identification are the same as in the case of specification (3.1).

[24] We assume an intra-class correlation of firm productivities within country/industry groups and thus, in all specifications, the standard errors are estimated by clustering on this level.

[25] We focus on reallocation in terms of variable inputs as output/revenues shares would become vaguely defined in increasingly integrated European markets. In this way, we also make our results directly comparable with earlier studies regarding the reallocation impact of increased competition (e.g., Bartelsman, Haltiwanger, and Scarpetta, 2009). Besides, employment growth features among the key policy objectives of the European Union and is pervasively used to evaluate the success of its Internal Market reforms.

3.5 Results

3.5.1 Main results

We present our main estimation results concerning the impact of liberalization on within-firm TFP productivity and cross-firm allocation of resources.

Table 3.4 presents the results on the impact of liberalization on the four-year average TFP change at the firm level. Panel A presents the results of regressions for the four-year change in IOL, and Panel B presents analogous results for the four-year change in IEL. As discussed in detail in Section 3.3.1, the former is expected to capture more features of the state of market competition that incumbents face. The dependent variable in columns (1)-(4) of both panels is our baseline LP-based estimate of TFPR. Columns (5)-(7) report the estimates using, respectively, the TFPR W-LP, the TFPR OLS, and real value added per employee (see Section 3.4.2 for details).

The within-firm specification in column (1) of Panel A regresses the average firm TFP-growth on the change of the liberalization index while using country-year fixed effects that capture country-level macro shocks. This points to a 6.3% increase in within-firm productivity due to a one-unit change in IOL. The regression in column (2) adds industry fixed-effects to control for potential bias driven by a positive correlation between industry-specific trend growth and liberalization. Indeed, the estimate reduces in magnitude and is estimated more precisely. Column (3) controls for country-industry trends instead of industry ones. In this case, the coefficient of interest is identified by the cross-country time variation in the liberalization of a given industry and firm productivity outcomes. This corrects for any positive bias from the differential long-term growth opportunities of the same industry across countries, due to, for example, differences in countries' industrial structure. Consistent with this intuition, the estimate reduces further in column (3).

In column (4), we add industry-year fixed effects that control for any policy and/or technology related shocks that are common across firms operating in the same industry. As a result, the coefficient of interest now increases to 6.4%, suggesting a negative bias in the estimates of columns (1)-(3) that only partially correct for industry-specific time-varying factors. The suggested negative correlation between our liberalization measure and industry-year fixed effects could be due to the fact that policy makers are more willing to carry out liberalization measures when the industry is hit by negative technological shocks. It may also capture increased foreign competition driven by overall European-wide liberalization. As a means of robustness checking, columns (5) through (7) repeat the regression of column (4) for our alternative measures of productivity.

Turning to Panel B of Table 3.4, the estimates overall confirm the presence of within-firm TFP gains from entry liberalization. In contrast to the results in Panel A for changes in IOL, the estimates are uniformly lower (on the order of 2.4% for a unit-change of the index; see column (4)) and broadly weaker in significance. The differences in estimates between the two panels across the same specifications are due to the difference in the source and degree of variation between IOL and IEL. As discussed in Section 3.3.1, this difference is arguably driven by different information that these indexes include and by the fact that IEL captures one particular aspect of competition that affects incumbent firms only indirectly.

The evidence of strong within-firm TFP gains in Table 3.4 raises the question whether the initially high-TFP firms also expanded in size in response to the liberalization. As discussed in Section 3.2, the theory predicts that liberalization should improve productivity by improving the allocation of resources across firms in the industry. This would show up as a stronger correlation between size and productivity across firms in the industry. However, the results we present in Table 3.5, across all specifications in columns (1)-(7), entail no compelling evidence that such a positive reallocation was underway.[26]

To summarize, the results support the presence of within-firm, four-year productivity gains from the liberalization that are on average 5.5%. Assuming that our linear specification is a valid description of all potential liberalization events, our results suggest that a

[26]We have also investigated the cross-sectional relationship between allocative efficiency and the liberalization index. Using the cross-sectional decomposition of Olley and Pakes (1996), the industry productivity at any point in time can be decomposed into two terms: 1) the simple average of firm-level productivity and 2) the covariance between market shares and productivity. The latter term is a simple proxy for allocative efficiency. Using our sample, we calculated the average OP covariance term for every country/industry and regressed it on the liberalization index while controlling for industry and country fixed effects. The results show no systematic relationship between IOL and the OP covariance term. These regressions are available upon request.

change in IOL score from 0 to 6, e.g., full liberalization in four years, would be associated with 33% within-firm productivity gains. To get more intuition about the quantitative importance of our estimates, we examine the percentage of total actual within-firm productivity change that is explained by the liberalization in our data. To this end, we treat each firm in our sample as part of an "aggregate network services industry", which is defined by all the firms in our sample. We predict the four-year, within-firm productivity change based on our estimated coefficient of interest and on the change in IOL in the respective country-industry where a firm operates. Then, we take a weighted average of the predicted within-firm productivity change, where each firm is weighted by its initial employment share out of total employment in our sample. The predicted within-firm productivity growth amounts to 5.2% on average over our sample period. In a similar way, we find that the weighted average of the actual realized within-firm productivity growth in our sample is on average 13.5%. Therefore, up to 38% of the within-firm productivity gains of European network services in our sample can be explained by liberalization. This calculation underscores that the EU-wide liberalization efforts can be important drivers of aggregate productivity outcomes.

3.5.2 Endogeneity of the liberalization

In this section, we address the concern that the European network services liberalization policies are not exogenous to productivity shocks of firms operating in the liberalized industries. This concern is relevant because the actual implementation of the reforms adopted at the EU-level is left to national governments. In our empirical framework, by taking long differences over the liberalization index and controlling for country-industry fixed effects, as well as for country- and industry-year fixed effects, we account for the role of any politico-economic factors with such sources of variation.

Therefore, we are left to correct for any remaining factors varying at the country-industry-year level that are related to local policy choices that determine the degree and timing of liberalization. As an example, national governments may prefer to minimize the political costs of liberalization and choose to liberalize more and/or earlier the industries with weaker expected growth prospects. In this case, due to the negative selection of industries into the liberalization, we would underestimate the effect of liberalization on firm-level TFP. Furthermore, the liberalization policy could be driven by time-varying local industry factors relevant for firm-level productivity such as monopoly power or strong labor unions that relate to the political costs/benefits from liberalization. To the extent that our baseline specification does not explicitly control for such factors, the resulting omitted-variables problem may bias our coefficient of interest.

For these reasons, we investigate whether the observed changes in IOL are correlated with initial industrial characteristics that relate to the political costs/benefits of the liberalization.[27] The characteristics we consider are the number of firms and the median firm size. These act as a proxy for monopoly power and industry concentration and thereby the scope for the existence of a strong business lobby. Total industry sales proxy for the importance of the industry in the economy. Total employment and the average wage in the industry proxy for the magnitude of political costs that arise from labor unions opposing competition due to the fear of job or wage losses. Finally, the average productivity of the industry proxies for the growth prospects, for example, due to catch-up.[28]

The results are presented in Table 3.6. In each cell of Panel A, we report the estimated coefficient from the regression of the average four-year change of the liberalization index (IOL) on the industry characteristic in the respective column. The value of industry characteristics is taken as of the beginning of the sample period. In all cases, we control for country and industry fixed effects. In a similar way, in Panel B, we check the correlation between the four-year change in the liberalization index and the four-years-lagged value of each industry characteristic while controlling for country-year and industry fixed effects. Overall, the results show no statistically significant correlation between the initial industrial characteristics and the subsequent change in IOL. The only exception is the initial total number of firms in the industry that is negatively correlated with subsequent change in IOL in the cross section (at the 10% significance level). Still, this correlation

[27] A similar approach is followed by Topalova and Khandelwal (2011).

[28] The total number of firms and total employment are taken from Eurostat. The median firm size (employment) and average wage are calculated using the Amadeus sample.

disappears in the respective panel regression as shown in Panel B.

Finally, in the last column, we investigate the correlation of the change in IOL with its initial level. The latter is the politico-economic outcome that is inherited from the past and summarizes the initial condition of regulation in the industry. We find that it is the only statistically significant and economically important determinant of the change in IOL. The relationship is even stronger in the panel data estimation, where the estimated t-statistic is close to 10. The negative correlation between the change in IOL and its initial level captures the fact that, for those industry-country pairs that started as more liberalized (high level of IOL), there was a smaller scope for liberalization and thereby, they could experience a smaller change in their IOL index than the change experienced by country-industry pairs in our sample on average.

The correlation between the change in the liberalization index and its lagged value is consistent with the harmonization objective of the EU Directives. To further support this insight, we investigate how the strength of this correlation over earlier periods, 1978–1987 and 1988–1997, compares to the one over our sample period, 1998–2007. For each of the three periods, Panel A of Table 3.7 presents estimates from regressions of the four-year change in IOL on the four-year lagged IOL and an intercept. The comparison of the estimated constant terms across the three time periods suggests that the 1998–2007 period was the one with the strongest liberalization efforts as the IOL of a fully regulated industry was expected to increase on average by 1.5 over the four years. The IOL of a fully regulated industry increased only by about 0.7 during the 1988–1997 period, and essentially remained constant during the 1978–1987 period. Furthermore, the 1998–2007 period experienced the highest convergence of IOL as the estimated coefficient on the lagged IOL in column (1) is negative and highly statistically significant. The convergence pattern is much weaker during the 1988–1997 period and virtually non-existent in the 1978–1987 period. Panel B of Table 3.7 repeats the same exercise while controlling for country-year and industry fixed effects. Even in this case, the strength of the convergence in IOL is almost twice as large in the 1998–2007 period than it is in the 1988–1997 period, while there is no evidence of convergence during the 1988–1997 period.

The strong harmonization pattern in IOL during 1998–2007 suggests that the initial IOL level serves as a good proxy for the EU command for the network industries' liberalization that is exogenous to local firms' TFP growth. Therefore, we can use the lagged level of IOL as an instrument for the change in IOL in each country-industry in our sample over time. By doing so, we seek to explain TFP growth by the change in liberalization as predicted by the initial liberalization state, given the need to reach common policy objectives as set by the EU-wide harmonization efforts. The identifying assumption is that the initial liberalization state affects firm-level TFP growth only through its effect on the scope for liberalization policy and is uncorrelated with unobserved productivity shocks or other latent factors affecting firm-level productivity.

The results from the two-step efficient GMM estimation, using the four-year-lagged IOL as an instrument, are presented in Panel A of Table 3.8, while Panel B of the table presents the results from the corresponding first-stage regressions.[29] The regressions in columns (1)-(3) of Table 3.8 follow, one by one, our baseline specifications in columns (4)-(6) of Table 3.4. The GMM estimates are uniformly higher by about one percentage point for all employed measures of TFPR compared to the OLS ones, suggesting a negative bias in the OLS estimates. Such a negative bias arises if local authorities are choosing the timing and the scope of liberalization in order to respond to the prospects of declining industry productivity. For instance, such declining productivity could take place in the face of increasing foreign competition, if the rest of the EU members completed liberalization earlier. Hence, if anything, our evidence suggests a negative selection of industries into liberalization.

3.5.3 Additional results

As discussed in Section 3.2, there are theoretical reasons to examine whether the positive impact of liberalization is different across firms of different productivity level or size.

To investigate the possibility of the heterogeneous impact of liberalization on firms of different productivities, we split firm-year observations into two categories based on their

[29] Any differences between the results between Panel B of Table 3.10 and column 8 of Table 3.8 are due to the unbalanced nature of our final firm-level sample.

position relative to the median of the productivity distribution. Specifically, we construct an indicator variable that takes value 1 if the productivity of a given firm is higher than the median productivity of its industry and is 0 otherwise. Then, we extend specification (3.1) by including the interaction of the lagged value of this dummy variable with the change in the liberalization index.

The resulting specification is

$$\Delta p_{fcit} = \beta \Delta Lib_{cit} + \beta_h \Delta Lib_{cit} \times p^{High}_{fcit-4} + \gamma p^{High}_{fcit-4} + X_{cit} + \varepsilon_{fcit}, \tag{3.3}$$

where p^{High}_{fcit-4} is an indicator variable equal to 1 if a firm's productivity is above the median productivity of its industry as of four years ago and is zero otherwise. If productivity gains from liberalization come mostly from the productivity improvements of firms with initially low productivity, we expect β to be positive and β_h to be negative. The term p^{High}_{fcit-4} controls for the possibility of different productivity trajectories of firms that differ in their lagged productivity, i.e., due to 'catch-up' effects. As in the case of specification (3.1), we include a set of country/industry/year control variables X_{cit}, which consists of country-year fixed effects λ_{ct}, industry-year fixed effects λ_{it} and country-industry fixed effects λ_{ci}.

Table 3.9 presents the estimates of specification (3.3). The results suggest that the TFP gains from the liberalization are decreasing in the initial productivity of firms. This is in line with the predictions of Schmidt (1997) that when initial competition is very low, then increased competition would decrease managerial slackness, which translates into higher productivity. It is also consistent with the fact that, at the beginning of the liberalization process, the network services industries largely featured state monopolies where managerial slackness concerns are likely to be important (e.g., due to the lack of threat of firing).

The other scope for the heterogeneity of the estimated effect we consider asks whether the liberalization asymmetrically affected firms of different initial size. This is investigated by estimating a model analogous to specification (3.3), where we replace indicator p^{High}_{fcit-4} by its analog for the firm's position relative to the median of the employment distribution,

$empl^{High}_{fcit-4}$:

$$\Delta p_{fcit} = \beta \Delta Lib_{cit} + \beta_h \Delta Lib_{cit} \times empl^{High}_{fcit-4} + \gamma empl^{High}_{fcit-4} + X_{cit} + \varepsilon_{fcit}. \tag{3.4}$$

The estimates of specification (4) presented in Table 3.10 do not provide support that the impact of liberalization is heterogeneous across size. This suggests that either the policies were in no way specific to firm size, or other firm-size-specific distortions did not affect firms' responses in productivity.

3.6 Robustness checks

We perform a series of robustness checks for our main results on the impact of liberalization on within-firm productivity growth and reallocation. First, in Panel A of Table 3.A.4, we show that our results are robust to dropping the countries that joined the European Union in 2004, the Czech Republic, Hungary and Poland. If EU accession had a positive impact on the productivity of network services industries due to reasons other than the liberalization of these industries, including these countries could bias our results. We thus exclude these three countries from the sample and re-estimate our main specifications that correspond to columns (4)-(6) in Table 3.4 and columns (4)-(6) in Table 3.5. For the reallocation equation, we report only the coefficient on the interaction term of the change in IOL and lagged productivity. The results are qualitatively similar to our main results.

Second, we investigate whether the countries that are the most represented in our sample drive our results. As Table 3.1 shows, the most represented countries are Germany, Italy and Spain, each of which accounts for more than 10% of the sample. In Panels B to D of Table 3.A.4, we remove each of these countries one by one and re-estimate our main specifications on the resulting sub-samples. Again, our results remain qualitatively unchanged.

Third, we investigate whether our results are sensitive to the differences in sample coverage across industries or to the inclusion of industries with very strong liberalization experiences. We repeat a similar exercise as before by checking the robustness of our results on the sub-samples that are created by dropping, one by one, each of the suspect industries. Tables 3.A.5.a and 3.A.5.b show that our results also survive this check.

Fourth, we investigate whether our results are robust to excluding country/industry clusters that have unbalanced firm size distribution relative to the one reported for the aggregate population of firms in Eurostat. In principle, combining several updates of Amadeus should result in a sample that covers most companies in Europe. However, due to differences in reporting requirements among the underlying vendors of BvD, the final sample can be under-sampled in some size categories in some countries/industries. To perform this robustness check, we follow a procedure used in Klapper, Laeven, and Rajan (2006). We use data from Eurostat Structural Business Statistics (SBS) on the true number of firms within a country and industry and three size categories defined by employment: 20–49, 50–249 and 250 or more employees. For each country/industry/size category, we calculate the average number of firms between 2004 and 2007 in both Eurostat and our Amadeus sample and then calculate the ratio $R_{ci,Size}$ of the Eurostat over the Amadeus number of firms to obtain a measure of the under-representation of our sample.[30] A high value of this ratio suggests that the number of firms in our sample is very low compared to the true number reported in SBS. Next, we compare the ratios between the biggest and smallest size categories in a given country/industry cluster. A large difference between the coverage of large and small firms would suggest that the firm size distribution is skewed relative to the population firm-size distribution. To investigate whether this has a significant effect on our results, we drop the industry/country clusters where the relative underrepresentation of small firms to the underrepresentation of large firms (i.e., the ratio of $R_{ci,Low}$ to $R_{ci,High}$) is higher than 5 or lower than 0.2. Table 3.A.6 shows that our main results are unaffected.

Fifth, Table 3.A.7 shows the estimates obtained using 3-year and 5-year differences specifications. As expected, the estimates for the 3-year differences model are smaller

[30] The Eurostat SBS data on the firm size distribution have the best coverage after 2004. Additionally, given our version of Amadeus takes care of the survivorship bias, it is reasonable to expect that any sample unbalancedness will be the most pronounced in the cross-section rather than over time.

in magnitude, while the estimates for the 5-year differences model are larger than those obtained using the baseline four-years differences specification.

Finally, Table 3.A.8 documents that our main results are robust to excluding observations with the imputed values of employment.

3.7 Conclusions

We examined the productivity impact of European-level network services liberalization. To do so, we built an empirical framework that isolates the source of variation in industry-specific liberalization that is exempt of variation in country/industry-specific politico-economic conditions and productivity prospects. Our findings show that, as a response to removing regulatory barriers to entry and reducing state ownership, network services firms experienced on average 5.5% productivity gains over a four-year period. In our sample, the within-firm average productivity gains due to liberalization account for more than one-third of the actual within-firm average productivity gains of all firms operating in network services industries.

The magnitude of our estimates of within-firm productivity gains is in line with earlier findings in the literature that examines the impact of trade liberalization on the productivity of firms operating in liberalized markets. In particular, since our study concerns eliminating regulatory barriers in output markets, our estimates can be compared to estimates of output tariff reduction in manufacturing. As an illustration, Amiti and Konings (2007) or Topalova and Khandelwal (2011), among others, suggest corresponding estimates on the order of 9.5% and 3.5%, respectively. To our advantage, since network services are mostly non-tradable, import competition has a limited scope to bias our results.

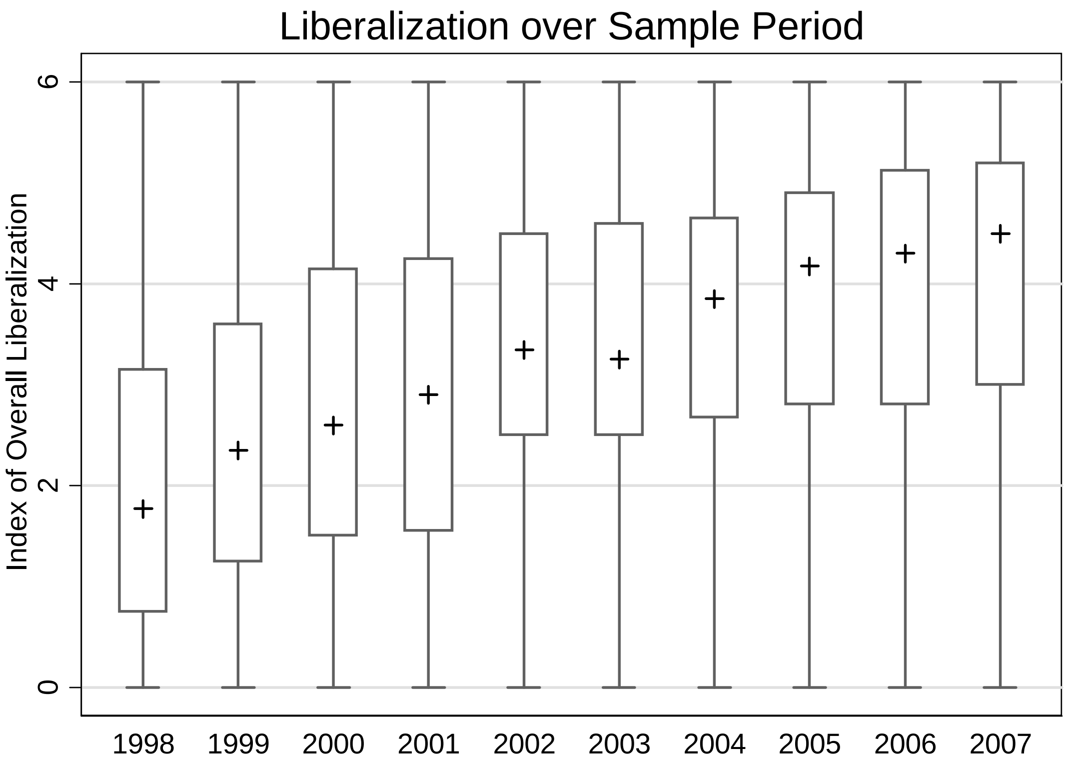
The distinction between the liberalization of output vs. input markets is an important one, because existing findings in the literature show that a reduction of input tariffs has a significantly stronger productivity impact on firms compared to a reduction of output tariffs. With this distinction in mind, our results are also consistent with Arnold, Nicoletti, and Scarpetta (2008), who find that one unit change in the OECD index of product market regulation implies within-firm productivity gains on the order of 10%. They study input liberalization, which suggests why their estimate is larger than ours. Also, they are interested in measuring the impact of liberalization in all services, both network and non-network ones, on the productivity of firms operating in any business activity. Our contribution is that we track down the initial source of these gains by focusing on network services that are the most important among all services inputs and the ones that are, to a large extent, liberalized by now.

Finally, we note that our finding that the gains from the liberalization came from the within-firm productivity improvements rather than from the reallocation of resources across firms is also in line with earlier studies of liberalization. In this regard, our conclusions regarding reallocation come with a caveat: We lack a full empirical model of entry and exit. Moreover, due to the length of our sample period, our results capture more short-term developments following the liberalization as opposed to long-term effects.

Turning to the policy implications, our findings suggest that the regulatory reforms for network services were successful in increasing the threat of competition for incumbents and thus inducing them to become more productive. Our results are in support of the European Commission's demand to extend liberalization to other market services.

3.8 Main Tables and Figures

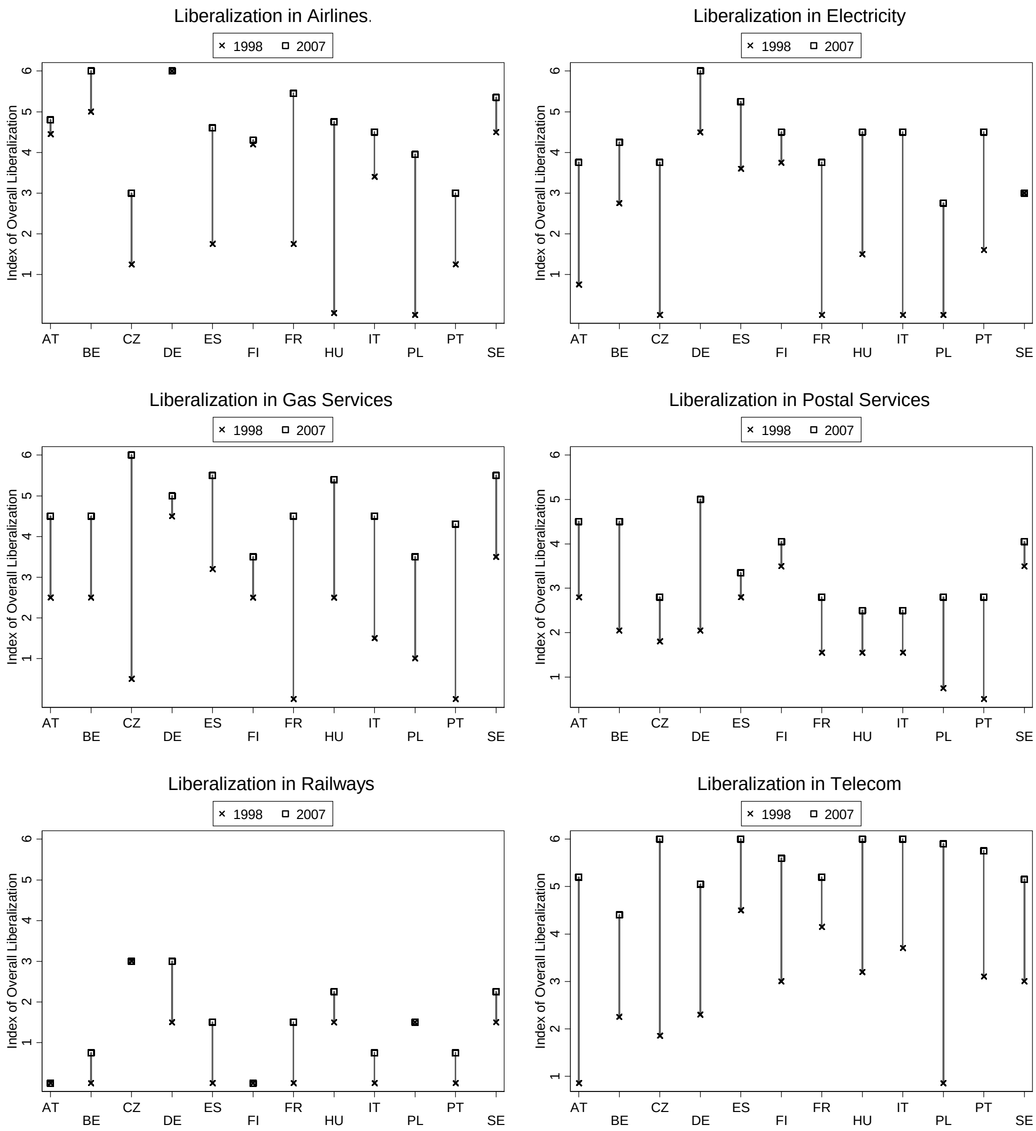
Figure 3.1: Liberalization in Services Industries – 1998 – 2007



Note: Box-plot of the distribution of the Index of Overall Liberalization over all countries and industries in the sample. Scale is 0–6 from the most to least restrictive of competition.

Source: OECD indicators of regulation in network industries, Conway and Nicoletti (2006).

Figure 3.2: Liberalization in Services Industries – 1998 – 2007



Note: Changes in the Index of Overall Liberalization (IOL). The scale is 0–6 from the most to least restrictive of competition.

Source: OECD indicators of regulation in network industries, Conway and Nicoletti (2006).

Table 3.1: Summary Statistics of Services Industries by Country

Country	# Obs.	(1) VA / Employee Pctile 10	(1) VA / Employee Median	(1) VA / Employee Pctile 90	(2) Employment Pctile 10	(2) Employment Median	(2) Employment Pctile 90	(3) IOL 1998	(3) IOL 2007
Austria (AT)	226	70.2	194.3	597.7	38	470	2396	1.6	4.0
Belgium (BE)	646	67.4	207.8	796.3	26	124	1159	2.9	4.4
The Czech Rep. (CZ)	501	12.1	49.0	202.3	33	150	1250	1.2	4.4
Germany (DE)	5070	91.6	197.2	416.3	30	98	972	4.3	5.6
Spain (ES)	4293	16.4	50.6	346.5	22	44	426	3.4	4.8
Finland (FI)	1537	29.1	127.2	347.7	25	64	374	3.4	4.7
France (FR)	1523	64.0	207.8	712.7	23	58	669	1.5	4.7
Hungary (HU)	802	3.8	12.6	49.4	24	157	1908	2.2	4.9
Italy (IT)	3227	44.5	120.8	483.7	24	56	549	1.6	4.4
Poland (PL)	1653	8.4	24.2	86.7	30	135	1694	0.3	3.9
Portugal (PT)	223	30.9	110.3	603.9	23	188	8649	1.6	4.3
Sweden (SE)	1461	68.7	159.5	552.0	23	44	361	3.2	3.5
Total Sample	21162	19.1	126.5	415.4	24	71	836	2.7	4.8

The table reports summary statistics for labor productivity (in 1995 EUR ths.) and employment for twelve countries in our sample. Labor productivity is calculated as the double-deflated value added over employment, where country/sector specific output and intermediate input deflators come from EU KLEMS. # Obs. corresponds to the number of observations in Amadeus. Column 3 reports the average value of the Index of Overall Liberalization (IOL) in the first and last year of our sample for each country.

Table 3.2: Change in the Index of Overall Liberalization over Sample Period

Country	Airlines	Electricity	Gas	Post	Railways	Telecom
AT	0.4	3.0	2.0	1.7	0.0	1.5
BE	1.0	1.5	2.0	2.5	0.8	2.2
CZ	1.8	3.8	5.5	1.0	0.0	4.2
DE	0.0	1.5	0.5	3.0	1.5	2.8
ES	2.9	1.7	2.3	0.6	1.5	1.5
FI	0.1	0.8	1.0	0.6	0.0	2.6
FR	3.7	3.8	4.5	1.3	1.5	1.1
HU	4.7	3.0	2.9	0.9	0.8	2.8
IT	1.1	4.5	3.0	0.9	0.8	2.3
PL	4.0	2.8	2.5	2.1	0.0	5.1
PT	1.8	2.9	4.3	2.3	0.8	2.7
SE	0.8	0.0	2.0	0.6	0.8	1.7
Mean	1.8	2.4	2.7	1.4	0.7	2.5

The table reports overall change in IOL between the first and last year of our sample for each Country/Industry cluster.

Table 3.3: Summary Statistics of Services Industries

Country	# Obs.	(1) VA / Employee Pctile 10	(1) VA / Employee Median	(1) VA / Employee Pctile 90	(2) Employment Pctile 10	(2) Employment Median	(2) Employment Pctile 90
Airlines	1350	53.3	152.7	325.9	26	122	1705
Electricity	8188	25.5	169.3	438.8	26	87	1140
Gas Services	2595	43.2	165.9	615.9	24	67	484
Postal Services	2664	10.5	36.4	206.5	22	46	430
Railways	1024	15.7	55.0	166.4	27	115	1815
Telecom	5341	19.5	90.3	449.0	23	60	650

The table reports summary statistics for labor productivity (in 1995 EUR ths.) and employment for six industries in our sample. # Obs. corresponds to the number of observations in Amadeus.

Table 3.4: Liberalization and Within-firm Productivity Change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Δ TFPR	Δ TFPR	Δ TFPR	Δ TFPR	Δ TFPR	Δ TFPR	Δ ln(Va/Empl)
	LP	LP	LP	LP	W-LP	OLS	
	4-year diff	4-year diff	4-year diff	4-year diff	4-year diff	4-year diff	4-year diff
	Panel A: Effects of Overall Liberalization						
Δ IOL	0.063***	0.056***	0.049***	0.064***	0.056***	0.046***	0.035**
4-year diff	(0.021)	(0.016)	(0.018)	(0.016)	(0.015)	(0.013)	(0.016)
Country * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes					
Country * Industry FE			Yes	Yes	Yes	Yes	Yes
Industry * Year FE				Yes	Yes	Yes	Yes
Adjusted R^2	0.059	0.093	0.119	0.124	0.203	0.157	0.175
Country / Industry clusters	70	70	70	70	70	70	70
Observations	6040	6040	6040	6040	6040	6040	6040
	Panel B: Effects of Entry Liberalization						
Δ IEL	0.018	0.028***	0.020	0.024*	0.027**	0.023**	0.014
4-year diff	(0.012)	(0.010)	(0.015)	(0.013)	(0.012)	(0.009)	(0.011)
Country * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes					
Country * Industry FE			Yes	Yes	Yes	Yes	Yes
Industry * Year FE				Yes	Yes	Yes	Yes
Adjusted R^2	0.053	0.090	0.117	0.121	0.202	0.156	0.175
Country / Industry clusters	70	70	70	70	70	70	70
Observations	6040	6040	6040	6040	6040	6040	6040

The table reports estimates from OLS regressions of 4-year differences in productivity on 4-year differences in the Index of Overall Liberalization (IOL) in Panel A and on 4-year differences in the Index of Entry Liberalization (IEL) in Panel B. TFPR LP is calculated as a residual from estimating a logarithmic Cobb-Douglas revenue production function using the Levinsohn-Petrin approach. TFPR W-LP is calculated by estimating a logarithmic Cobb-Douglas value added production function using the Wooldridge modification of the Levinsohn-Petrin approach with unobserved productivity shocks being approximated by 3rd-order polynomials in material costs and capital. TFPR OLS is calculated as a residual from a logarithmic regression model of revenue Cobb-Douglas production function estimated separately for each industry by OLS. All specifications include a constant, not reported. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.5: Liberalization and Change in Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff
Productivity in the Interaction Term	TFPR LP	TFPR LP	TFPR LP	TFPR LP	TFPR W-LP	TFPR OLS	ln(Va/Empl)
	Panel A: Effects of Overall Liberalization						
ΔIOL	0.034*	0.033**	0.040*	0.002	0.006	0.013	0.066*
4-year diff	(0.018)	(0.016)	(0.021)	(0.022)	(0.021)	(0.022)	(0.038)
ΔIOL* Lagged Productivity	-0.012	-0.007	-0.004	0.008	0.012	0.002	0.024*
4-year diff * 4-year lag	(0.011)	(0.012)	(0.013)	(0.013)	(0.009)	(0.022)	(0.013)
Lagged Productivity	-0.029***	0.005	0.003	-0.005	-0.025**	0.096***	0.093***
4-year lag	(0.009)	(0.016)	(0.017)	(0.016)	(0.012)	(0.029)	(0.020)
Country * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes					
Country * Industry FE			Yes	Yes	Yes	Yes	Yes
Industry * Year FE				Yes	Yes	Yes	Yes
Adjusted R^2	0.051	0.059	0.083	0.096	0.095	0.104	0.119
Country / Industry clusters	70	70	70	70	70	70	70
Observations	6040	6040	6040	6040	6040	6040	6040
	Panel B: Effects of Entry Liberalization						
ΔIEL	0.016	0.027**	0.027*	0.010	0.019	0.011	0.031
4-year diff	(0.011)	(0.011)	(0.014)	(0.014)	(0.015)	(0.012)	(0.016)
ΔIEL* Lagged Productivity	-0.008	-0.008	-0.009	-0.004	-0.010	-0.006	0.009
4-year diff * 4-year lag	(0.005)	(0.006)	(0.005)	(0.006)	(0.008)	(0.013)	(0.014)
Lagged Productivity	-0.035***	-0.004	-0.006	-0.012	0.010	0.103***	0.100***
4-year lag	(0.008)	(0.014)	(0.014)	(0.013)	(0.018)	(0.026)	(0.028)
Country * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes					
Country * Industry FE			Yes	Yes	Yes	Yes	Yes
Industry * Year FE				Yes	Yes	Yes	Yes
Adjusted R^2	0.051	0.060	0.084	0.096	0.095	0.104	0.118
Country / Industry clusters	70	70	70	70	70	70	70
Observations	6040	6040	6040	6040	6040	6040	6040

The table reports in Panel A the estimates from OLS regressions of 4-year logarithmic differences of firm employment (Empl) on 4-year differences in the Index of Overall Liberalization (IOL), with its interaction with the 4-year lagged productivity measure as given in the column header. Panel B presents the results for the equivalent specifications concerning the 4-year differences in the Index of Entry Liberalization (IEL). All specifications include a constant, not reported. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.6: Liberalization and Initial Industrial Characteristics

Liberalization and Initial Industrial Characteristics

	(1) Total # Firms in log	(2) Total # Employees in log	(3) Total Sales in log	(4) Mean Wage in log	(5) Median Employment in log	(6) Weighted Mean TFPR LP	(7) Weighted Mean TFPR W-LP	(8) Weighted Mean TFPR OLS	(9) IOL
Panel A: Cross-section									
Dependent Variable: Δ IOL (average 4-year change)									
Explanatory Variable in Column (as of the first year in the sample)									
	-0.238*	-0.038	-0.025	-0.016	0.051	-0.161	-0.045	-0.223	-0.299***
	(0.130)	(0.147)	(0.094)	(0.405)	(0.074)	(0.178)	(0.128)	(0.129)	(0.060)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.577	0.690	0.644	0.587	0.592	0.596	0.589	0.599	0.720
Observations	57	52	55	70	70	70	70	70	70
Panel B: Panel									
Dependent Variable: Δ IOL (4-year change)									
Explanatory Variable in Column (lagged 4 years)									
	-0.086	0.071	0.102	0.290	0.078	-0.173	0.103	-0.183	-0.483***
	(0.083)	(0.112)	(0.163)	(0.207)	(0.056)	(0.136)	(0.091)	(0.144)	(0.056)
Country * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.242	0.234	0.220	0.213	0.211	0.213	0.209	0.210	0.504
Observations	357	324	330	392	392	392	392	392	392

Each cell of the table reports estimates from a separate regression on the cross-section of industries (panel A) and the panel of industries (panel B) which comprise our firm-level sample. Panel A reports estimates of regressions of the time-average, 4-year change in the Index of Overall Liberalization (IOL) on the variable in the column heading, the value of which is taken as of the beginning of the sample period. Panel B reports estimates of regressions of the actual 4-year change in IOL on the 4-year lagged value of the variable in the column heading. Total # Firms is the number of firms in an industry as reported by Eurostat. Total # Employees is the number of employees in an industry as reported by Eurostat. Total Sales are the total industry sales as reported by Eurostat. Mean Wage is the industry average wage calculated using the Amadeus sample. Median Employment is the industry median employment calculated using Amadeus sample. Weighted mean TFPR LP, TFPR W-LP and TFPR OLS are weighted averages of corresponding (log) productivities with weights given by the revenue shares within the industry. Robust standard errors (clustered at the country level in panel A and the country/industry level in panel B) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.7: Convergence in Liberalization in Europe over Time

	(1)	(2)	(3)
Sample Period	1998-2007	1988-1997	1978-1987
Dependent Variable	Δ IOL	Δ IOL	Δ IOL
	4-year diff	4-year diff	4-year diff
	Panel A: Model without Controls		
IOL	-0.228***	-0.061	-0.002
4-year lag	(0.048)	(0.065)	(0.003)
Constant	1.514***	0.651***	0.013*
	(0.199)	(0.097)	(0.007)
Adjusted R^2	0.155	0.002	0.002
Observations	427	418	426
	Panel B: Model with Additional Controls		
IOL	-0.458***	-0.236***	0.005
4-year lag	(0.051)	(0.081)	(0.007)
Country * Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Adjusted R^2	0.474	0.303	0.002
Observations	427	418	426

The table reports estimates from industry-level OLS regressions of 4-year differences in the Index of Overall Liberalization (IOL) on the 4-year lagged value of IOL. The sample is comprised of 12 countries and 6 network industries that are included in the Amadeus firm-level sample. Regressions are estimated separately over 3 periods: 1978-1987, 1988-1997 and 1998-2007. Panel A presents results for a simple linear model with an included intercept. Panel B presents results for the model that includes additional controls: country/year fixed effects and industry fixed effects. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.8: Liberalization and Within-firm Productivity Change: IV Estimates

	(1)	(2)	(3)
Productivity Measure	Δ TFPR	Δ TFPR	Δ TFPR
Estimation Method	LP	W-LP	OLS
	4-year diff	4-year diff	4-year diff
	Panel A: Second-Stage Regression		
Δ IOL	0.079***	0.053***	0.052***
4-year diff	(0.017)	(0.017)	(0.015)
Country * Year FE	Yes	Yes	Yes
Country * Industry FE	Yes	Yes	Yes
Industry * Year FE	Yes	Yes	Yes
Country / Industry clusters	70	70	70
Observations	6040	6040	6040
	Panel B: First-Stage Regression		
Lagged IOL	-1.018***	-1.018***	-1.018***
4-year lag	(0.028)	(0.028)	(0.028)
Partial R^2	0.79	0.79	0.79
F-statistics	1307.75	1307.75	1307.75
p-value	0.000	0.000	0.000

The table reports estimates of 2-step GMM regressions of 4-year differences in productivity on 4-year differences in the Index of Overall Liberalization (IOL) instrumented by 4-year lagged IOL. All specifications include a constant, not reported. Robust standard errors (clustered at the country/industry level) are reported in parentheses. For the first stage regression, the bottom panel reports the estimated coefficient and the standard error of 4-year lagged IOL, its partial R2, F-statistics of the test of its significance and corresponding p-values. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.9: The Effects of Overall Liberalization on Firms of Different Productivity

	(1)	(2)	(3)
Productivity Measure	Δ TFPR	Δ TFPR	Δ TFPR
Estimation Method	LP	W-LP	OLS
	4-year diff	4-year diff	4-year diff
Δ IOL	0.076***	0.068***	0.055***
4-year diff	(0.020)	(0.019)	(0.018)
Δ IOL * Lagged High Productivity	-0.034	-0.037	-0.029
4-year diff * 4-year lag	(0.024)	(0.031)	(0.024)
Lagged High Productivity	-0.034	-0.156***	-0.156***
4-year lag	(0.024)	(0.051)	(0.047)
Country * Year FE	Yes	Yes	Yes
Country * Industry FE	Yes	Yes	Yes
Industry * Year FE	Yes	Yes	Yes
Adjusted R^2	0.146	0.229	0.199
Country / Industry clusters	70	70	70
Observations	6040	6040	6040

The table reports the estimates from OLS regressions of 4-year differences in productivity on 4-year differences in the Index of Overall Liberalization (IOL) interacted with the dummy variable, Lagged High Productivity, which takes the value one if the productivity of a given firm was above the median productivity of its respective industry as of 4 years ago and zero otherwise. All specifications include a constant, not reported. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.10: The Effects of Overall Liberalization on Firms of Different Size

	(1)	(2)	(3)
Productivity Measure	Δ TFPR	Δ TFPR	Δ TFPR
Estimation Method	LP	W-LP	OLS
	4-year diff	4-year diff	4-year diff
Δ IOL	0.066***	0.064***	0.052***
4-year diff	(0.021)	(0.016)	(0.018)
Δ IOL * Lagged High Employment	-0.003	-0.018	-0.013
4-year diff * 4-year lag	(0.024)	(0.019)	(0.020)
Lagged High Employment	-0.003	-0.001	0.036**
4-year lag	(0.024)	(0.020)	(0.016)
Country * Year FE	Yes	Yes	Yes
Country * Industry FE	Yes	Yes	Yes
Industry * Year FE	Yes	Yes	Yes
Adjusted R^2	0.125	0.203	0.158
Country / Industry clusters	70	70	70
Observations	6040	6040	6040

The table reports the estimates from OLS regressions of 4-year differences in productivity on 4-year differences in the Index of Overall Liberalization (IOL) interacted with the dummy variable, Lagged High Employment, which takes the value one if the employment of a given firm was above the median productivity of its respective industry as of 4 years ago and zero otherwise. All specifications include a constant, not reported. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

3.A Appendix Tables

Table 3.A.1: The ETCR Indicators: Regulatory Areas by Industry

	Regulatory areas				
	Barriers to entry	Public ownership	Market structure	Vertical integration	Price controls
Airlines	X	X			
Electricity	X	X		X	
Gas Services	X	X	X	X	
Postal Services	X	X			
Railways	X	X	X	X	
Telecom	X	X	X		

The table reports regulatory areas covered by the ETCR for individual industries. "X" denotes a regulatory area that is covered by the respective ETCR as a separate index. Source: Table 2 of Conway and Nicoletti (2006).

Table 3.A.2: The Correspondence among Industry Classifications

	NACE r. 1.1	NACE r. 1.1 2 digit	Eurostat	EU KLEMS
Airlines	621, 622	62	I62	60t63
Electricity	401	40	E401	E
Gas Services	402	40	E402	E
Postal Services	641	64	I641	64
Railways	601	60	I601	60t63
Telecom	642	64	I642	64

Table 3.A.3: Correlations of Firm-level Productivity Measures

Correlations of Firm-level Productivity Measures

	TFPR LP	TFPR W-LP	TFPR OLS
TFPR W-LP	0.88		
TFPR OLS	0.55	0.49	
ln (VA/Empl)	0.64	0.75	0.62

Table 3.A.4: Robustness to Removing Countries

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Δ TFPR LP 4-year diff	Δ TFPR W-LP 4-year diff	Δ TFPR OLS 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff
Productivity in the Interaction Term				TFPR LP	TFPR W-LP	TFPR OLS
	Panel A: Removing the Czech Republic, Hungary and Poland					
Δ IOL	0.077***	0.067***	0.056***			
4-year diff	(0.019)	(0.015)	(0.017)			
Δ IOL * Productivity				0.003	0.006	-0.008
4-year diff * 4-year lag				(0.016)	(0.011)	(0.029)
Observations	5371	5371	5371	5371	5371	5371
	Panel B: Removing Germany					
Δ IOL	0.044***	0.052***	0.034**			
4-year diff	(0.017)	(0.017)	(0.014)			
Δ IOL * Productivity				0.002	0.009	-0.001
4-year diff * 4-year lag				(0.014)	(0.010)	(0.023)
Observations	4341	4341	4341	4341	4341	4341
	Panel C: Removing Italy					
Δ IOL	0.060***	0.042*	0.036**			
4-year diff	(0.021)	(0.022)	(0.016)			
Δ IOL * Productivity				0.009	0.011	0.013
4-year diff * 4-year lag				(0.016)	(0.012)	(0.025)
Observations	5267	5267	5267	5267	5267	5267
	Panel D: Removing Spain					
Δ IOL	0.064***	0.052***	0.047***			
4-year diff	(0.018)	(0.018)	(0.015)			
Δ IOL * Productivity				0.008	0.013	0.000
4-year diff * 4-year lag				(0.014)	(0.010)	(0.021)
Observations	4887	4887	4887	4887	4887	4887

The table reports the estimates from OLS regressions for specifications corresponding to columns (4-6) of Table 3.4 and columns (4-6) of Table 3.5. For each panel, all specifications are estimated on a subsample obtained by removing a corresponding set of countries. For productivity regressions, we report the estimate of the coefficient on the (4-year) change in the IOL. For employment regressions, we report the estimate of the coefficient on the (4-year) change in the IOL interacted with a (4-year) lagged productivity measure specified in the column header. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.A.5.a: Robustness to Removing Industries

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Δ TFPR	Δ TFPR	Δ TFPR	ΔEmpl	ΔEmpl	ΔEmpl
	LP	W-LP	OLS			
	4-year diff	4-year diff	4-year diff	4-year diff	4-year diff	4-year diff
Productivity in the				TFPR	TFPR	TFPR
Interaction Term				LP	W-LP	OLS
			Removing Airlines			
Δ IOL	0.067***	0.054***	0.048***			
4-year diff	(0.018)	(0.015)	(0.014)			
Δ IOL * Productivity				0.003	0.010	0.007
4-year diff * 4-year lag				(0.014)	(0.010)	(0.021)
Observations			-0.006			0
			Removing Electricity			
Δ IOL	0.063***	0.067***	0.049***			
4-year diff	(0.016)	(0.015)	(0.014)			
Δ IOL * Productivity				0.018	0.018	0.008
4-year diff * 4-year lag				(0.019)	(0.011)	(0.028)
Observations	3290	3290	3290	3290	3290	3290
			Removing Gas			
Δ IOL	0.048**	0.057***	0.025*			
4-year diff	(0.020)	(0.019)	(0.015)			
Δ IOL * Productivity				0.014	0.020	-0.001
4-year diff * 4-year lag				(0.015)	(0.012)	(0.026)
Observations	5221	5221	5221	5221	5221	5221

The table reports estimates from OLS regressions for specifications corresponding to columns (4-6) of Table 3.4 and columns (4-6) of Table 3.5. For each panel, all specifications are estimated on a subsample obtained by removing a corresponding set of industries. For productivity regressions, we report the estimate of the coefficient on the (4-year) change in the IOL. For employment regressions, we report the estimate of the coefficient on the (4-year) change in the IOL interacted with a (4-year) lagged productivity measure specified in the column header. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.A.5.b: Robustness to Removing Industries

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Δ TFPR LP 4-year diff	Δ TFPR W-LP 4-year diff	Δ TFPR OLS 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff
Productivity in the Interaction Term				TFPR LP	TFPR W-LP	TFPR OLS
			Removing Post			
Δ IOL	0.072***	0.058***	0.049***			
4-year diff	(0.016)	(0.015)	(0.013)			
Δ IOL * Productivity				0.008	0.014	0.008
4-year diff * 4-year lag				(0.014)	(0.010)	(0.022)
Observations			-0.014			0
			Removing Railways			
Δ IOL	0.063***	0.053***	0.043***			
4-year diff	(0.016)	(0.015)	(0.013)			
Δ IOL * Productivity				0.007	0.012	0.003
4-year diff * 4-year lag				(0.014)	(0.010)	(0.022)
Observations	5826	5826	5826	5826	5826	5826
			Removing Telecom			
Δ IOL	0.068***	0.040*	0.059***			
4-year diff	(0.019)	(0.020)	(0.017)			
Δ IOL * Productivity				-0.002	-0.002	-0.025
4-year diff * 4-year lag				(0.015)	(0.010)	(0.021)
Observations	4753	4753	4753	4753	4753	4753

The table reports estimates from OLS regressions for specifications corresponding to columns (4-6) of Table 3.4 and columns (4-6) of Table 3.5. For each panel, all specifications are estimated on a sub-sample obtained by removing a corresponding set of industries. For productivity regressions, we report the estimate of the coefficient on the (4-year) change in the IOL. For employment regressions, we report the estimate of the coefficient on the (4-year) change in the IOL interacted with a (4-year) lagged productivity measure specified in the column header. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.A.6: Robustness to Removing Unbalanced Country/Industry Clusters

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Δ TFPR LP 4-year diff	Δ TFPR W-LP 4-year diff	Δ TFPR OLS 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff
Productivity in the Interaction Term				TFPR LP	TFPR W-LP	TFPR OLS
Δ IOL	0.066***	0.060***	0.050***			
4-year diff	(0.017)	(0.015)	(0.014)			
Δ IOL * Productivity				0.005	0.014	0.006
4-year diff * 4-year lag				(0.014)	(0.010)	(0.022)
Country / Industry clusters	60	60	60	60	60	60
Observations	5688	5688	5688	5688	5688	5688

The table reports estimates from OLS regressions for specifications corresponding to columns (4-6) of Table 3.4 and columns (4-6) of Table 3.5 on the subsample created by removing country/industry clusters for which the firm size distribution appears unbalanced relative to firms' size distribution reported in Eurostat. See section 6 for the description of the method used to indentify unbalanced clusters. For productivity regressions, we report the estimate of the coefficient on the (4-year) change in the IOL. For employment regressions, we report the estimate of the coefficient on the (4-year) change in the IOL interacted with a (4-year) lagged productivity measure specified in the column header. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.A.7: Robustness to Different Long Differences Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Δ TFPR LP	Δ TFPR W-LP	Δ TFPR OLS	ΔEmpl	ΔEmpl	ΔEmpl
Productivity in the Interaction Term				TFPR LP	TFPR W-LP	TFPR OLS
	Model in 3 year differences					
Δ IOL	0.056***	0.037*	0.041***			
3-year diff	(0.018)	(0.019)	(0.015)			
Δ IOL * Productivity				0.009	0.013	0.015
3-year diff * 3-year lag				(0.013)	(0.009)	(0.021)
Observations	8051	8051	8051	8051	8051	8051
	Model in 5 year differences					
Δ IOL	0.087***	0.062**	0.053***			
5-year diff	(0.023)	(0.026)	(0.016)			
Δ IOL * Productivity				0.003	0.007	0.015
5-year diff * 5-year lag				(0.016)	(0.013)	(0.031)
Observations	4455	4455	4455	4455	4455	4455

The table reports estimates from OLS regressions for 3-year and 5-year differences specifications corresponding to columns (4-6) of Table 3.4 and columns (4-6) of Table 3.5. For productivity regressions, we report the estimate of the coefficient on the change in the IOL. For employment regressions, we report the estimate of the coefficient on the change in the IOL interacted with a lagged productivity measure specified in the column header. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3.A.8: Robustness to Removing Observations with Imputed Employment

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Δ TFPR LP 4-year diff	Δ TFPR W-LP 4-year diff	Δ TFPR OLS 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff	ΔEmpl 4-year diff
Productivity in the Interaction Term				TFPR LP	TFPR W-LP	TFPR OLS
Δ IOL	0.064***	0.051***	0.044***			
4-year diff	(0.015)	(0.014)	(0.014)			
Δ IOL * Productivity				0.014	0.015	0.005
4-year diff * 4-year lag				(0.014)	(0.010)	(0.021)
Country / Industry clusters	60	60	60	60	60	60
Observations	5473	5473	5473	5473	5473	5473

The table reports estimates from OLS regressions for specifications corresponding to columns (4-6) of Table 3.4 and columns (4-6) of Table 3.5 on the subsample created by removing observations with imputed value of employment. For productivity regressions, we report the estimate of the coefficient on the (4-year) change in the IOL. For employment regressions, we report the estimate of the coefficient on the (4-year) change in the IOL interacted with a (4-year) lagged productivity measure specified in the column header. Robust standard errors (clustered at the country/industry level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

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