Three Essays on Corporate Policies

Olga Kuzmina

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ABSTRACT

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Olga Kuzmina

Different fields of economics have historically tended to focus on firms' strategies in isolation. In contrast, a lot of the recent work explores how various aspects of firm behavior interact with each other. This dissertation contributes to this growing literature by studying the interdependences of organizational and financial policies within firms in different contexts.

The first essay studies the interactions between acquisition decisions of multinationals and innovation decisions in the subsidiaries they buy. My coauthors Maria Guadalupe and Catherine Thomas, and I use a rich panel dataset of Spanish manufacturing firms and a propensity score reweighting estimator to show that multinational firms acquire the most productive domestic firms, which, on acquisition, conduct more product and process innovation (simultaneously adopting new machines and organizational practices) and adopt foreign technologies, leading to higher productivity. The proposed model of endogenous selection and innovation in heterogeneous firms can explain both the observed selection patterns and the innovation decisions. The innovation upon acquisition is further shown in the data to be associated with the increased market scale provided by the parent firm, thereby highlighting the role of foreign ownership in increasing the benefits from innovation. This work has potentially important implications for the evolution of within-industry productivity distributions. Under the mechanism described in the paper, foreign entry may lead to divergence of productivity and contribute to the stylized fact of large and persistent productivity differences even within narrowly defined industries.

I further use this rich dataset in my second essay to establish a causal relationship between the use of flexible contractual arrangements with labor and capital structure of the firm. Using the exogenous inter-temporal variation from government subsidies, I find that hiring more temporary workers leads firms to have more debt. Since temporary workers, unlike permanent ones, can be fired at a much lower cost during their contract duration, or their contracts may be not extended upon expiration, a firm can more easily meet its interest payments and avoid bankruptcy when faced with a negative shock. I interpret this result as evidence of flexible workforce decreasing operating leverage which, in turn, promotes financial leverage. This study therefore contributes to the literature exploring the interactions between firm employment decisions and corporate policies by providing evidence for a new channel – the one of flexible employment contracts. Given the overwhelming extent of labor reforms in continental Europe in recent years that are aimed at offering more job security to workers, it is important to understand how such policies would affect firms, and for that it is necessary to model the interdependences of firms' strategies.

Finally, my third essay looks at a different type of firms – hedge funds. Although, they do not produce goods in a strict sense of the word, they provide valuable services to investors by smartly investing into large selections of assets. Hedge funds are a very interesting type of financial firms to study due to their lower regulation and reporting standards that enable them to use some know-how trading strategies and potentially outperform other investors. A part of such outperformance can be explained by higher risks born by certain hedge funds, which outlines the broad question we explore in this paper with my coauthor Sergiy Gorovyy. We use a proprietary dataset obtained from a fund of funds to study the risk premia associated with hedge fund transparency, liquidity, complexity, and concentration over the period from April 2006 to

March 2009. We are able to directly measure these qualitative characteristics by using the internal grades that the fund of funds attached to all the funds it invested in, and that represent the unique information that cannot be obtained from quantitative data alone. Consistent with factor models of risk premium, we find that during the normal times low-transparency, low-liquidity, low-complexity, and high-concentration funds delivered a return premium, with economic magnitudes of 5% to 10% per year, while during bad states of the economy, these funds experienced significantly lower returns. We also offer a novel explanation for why highly concentrated funds command a risk premium by revealing that it is mostly prevalent among the non-transparent funds where investors are unaware about the exact risks they are facing and hence cannot diversify them away. The large an significant return premium associated with more secretive, less transparent hedge funds has an important policy implication with respect to whether hedge funds should be required to disclose the information regarding their trades and positions, especially in the light of the recent regulatory changes, including the Dodd-Frank Wall Street Reform Act passed in July 2010, the consequences of which are yet to be evaluated.

TABLE OF CONTENTS

Table of Contents…… i

List of Charts, Graphs, Illustrations…… iii

Acknowledgements…… vi

Dedication…… vii

Essay 1: Innovation and Foreign Ownership…… **1**

Introduction…… 2

Acquisition and Innovation Decisions…… 7

Data Description…… 14

The Acquisition Decision…… 16

The Innovation Decision…… 21

Foreign Ownership and Productivity Evolution…… 30

Conclusion…… 32

Appendix…… 35

References…… 36

Figures and Tables…… 43

Essay 2: Capital Structure and Employment Contract Flexibility..... **62**

Introduction..... 63

Data Description and Variables Definition..... 70

Estimation Strategy and Main Results..... 72

Mechanisms and Robustness Tests..... 81

Conclusion..... 86

References..... 89

Figures and Tables..... 93

Essay 3: Hedge Fund Risk Premia: Transparency, Liquidity, Complexity, and Concentration..... **106**

Introduction..... 107

Data.....111

Empirical Strategy.....115

Results.....117

Conclusion.....124

References.....126

Tables.....128

LIST OF CHARTS, GRAPHS, ILLUSTRATIONS

Essay 1: Innovation and Foreign Ownership

LIST OF FIGURES

Productivity Growth as a Function of Initial Productivity

Distribution of Initial Productivity for Acquired and Non-Acquired Firms

Selection by Industry

Distribution of Productivity for Acquired Firms, Before and After the Foreign Acquisition

Distribution of Productivity for Non-Acquired Firms, Change over Four Years

LIST OF TABLES

Descriptive Statistics

The Selection Decision: Linear Probability Specification

Foreign Ownership and Innovation

Foreign Ownership and Innovation: New Machines and New Methods of Organizing Production

Access to Export Channel and Process Innovation: Evidence from Panel Data and Propensity Score Weighting

Access to Export Channel, Product Innovation and Assimilation of Foreign Technologies: Evidence from Panel Data and Propensity Score Weighting

Foreign Ownership and Exports

Foreign Ownership and Firm Productivity

Foreign Ownership and Innovation: First Differences Specification

Variable Definitions

The Selection Decision: Probit Specification

Productivity Regressions Including Innovation Variables

Probit model for propensity score estimation

Propensity score estimation when using only Lag Sales and Lag Labor Productivity in the score

Foreign Ownership and Innovation: Restricted Sample

Access to Export Channel and Innovation: Restricted Sample

Essay 2: Capital Structure and Employment Contract Flexibility

LIST OF FIGURES

Cross-European Relationship, 1997-2010 averages

Cross-Industry Relationship for Spain, 1994-2006 averages

Time-Series Relationship for Spain

Time-Series Evolution of Debt and Net Debt for Spain

LIST OF TABLES

Descriptive Statistics

Maximum Subsidies for Hiring Permanent Workers

Gender classification of employees in manufacturing industries

Capital Structure and Temporary Contracts: Panel Regressions

Capital Structure and Temporary Contracts: Instrumental Variable Approach

Capital Structure and Temporary Contracts: Liquidation Value Analysis

Capital Structure and Temporary Contracts: Pre- and Post-Subsidies

Capital Structure and Temporary Contracts: Exit Analysis

Capital Structure and Temporary Contracts: Ex Post Survival

Capital Structure and Subsidies: Reduced Form Analysis

Essay 3: Hedge Fund Risk Premia: Transparency, Liquidity, Complexity, and Concentration

LIST OF TABLES

Summary Statistics of Data

Hedge fund performance: Univariate regression results

Hedge fund performance: Multivariate regression results

Hedge fund performance: Balanced panel multivariate regression results

Hedge fund performance: Transparency and concentration interaction results

Hedge fund return volatility: Multivariate regression results

Hedge fund inflows: Multivariate regression results

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DEDICATION

This dissertation is dedicated to my husband, Alexander, and my parents, Elena and Konstantin, who, despite their own views on my future, have nevertheless supported me in choosing this path for myself.

Innovation and Foreign Ownership

Maria Guadalupe
Columbia University, NBER, CEPR

Olga Kuzmina
New Economic School

Catherine Thomas*
Columbia University

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Abstract

This paper uses a rich panel dataset of Spanish manufacturing firms (1990-2006) and a propensity score reweighting estimator to show that multinational firms acquire the most productive domestic firms, which, on acquisition, conduct more product and process innovation (simultaneously adopting new machines and organizational practices) and adopt foreign technologies, leading to higher productivity. We propose a model of endogenous selection and innovation in heterogeneous firms that explains both the observed selection patterns and the innovation decisions. Further, we show in the data that innovation upon acquisition is associated with the increased market scale provided by the parent firm.

Keywords: Foreign Ownership, Productivity, Multinational Production, Innovation.

JEL codes: D22, F23, O31.

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1 Introduction

The pervasiveness of large and persistent productivity differences across firms within narrowly-defined industries is a well-established fact that continues to intrigue researchers (see surveys by Syverson, 2011; Ichniowski and Shaw, 2010). One salient example that has attracted much attention in several different fields is that multinational subsidiaries generally outperform domestic firms.[1] Many have argued that this is because multinationals transfer superior technologies and organizational practices—in the form of new product and process innovation—to their foreign subsidiaries.[2] However, since the most prevalent form of multinational entry is through acquisition (89 percent of FDI flows in developed countries—Barba Navaretti and Venables, 2004), rather than through greenfield investment, their superior performance could be due to the selection of higher-performing domestic firms. To date, little is known about the economic determinants of which domestic firms are selected to become foreign subsidiaries and the extent to which newly acquired subsidiaries increase their productivity by innovating—introducing technologies that are new to that firm.

In this paper, we use a unique panel dataset to analyze both the selection and innovation decisions of multinational firms. We propose a new mechanism to explain how these decisions are jointly determined, highlighting how the market access provided by multinationals creates incentives for subsidiary innovation and, hence, acquisition. We argue that one cannot fully understand the relationship between foreign ownership and innovation without explicitly recognizing that the incentives for innovation—to increase firm productivity—and the incentives for foreign acquisition are inherently interdependent.

The data used in the paper contain information on an array of internal technological and organizational choices, as well as on foreign ownership and productivity, for approxi-

[1] Some examples in this literature are Caves (1974), Doms and Jensen (1998), Helpman, Melitz and Yeaple (2004), Baldwin and Gu (2005), Ramondo (2009), Criscuolo and Martin (2009), and Arnold and Javorcik (2009).

[2] Prominent examples include Teece (1977), Caves (1996), Bloom and Van Reenen (2010), and Branstetter, Fisman and Foley (2006). See the survey of recent empirical literature in Stiebale and Reize (2011).

mately 2,800 Spanish manufacturing firms between 1990 and 2006.[3] The main distinguishing feature of our data is that we can directly observe different productivity-enhancing actions taken within the firm and, hence, do not have to rely on arguably imperfect productivity estimates to show the impact of acquisition. We are able to study precisely what types of innovation the acquired firms implement, such as whether they undertake product or process innovation, assimilate foreign technologies, purchase new machinery or introduce new organizational practices. We identify our effects by looking at within-firm variation in innovation, using the panel structure of the dataset. In addition, to control for selection into acquisition based on time-varying observable characteristics, we implement a propensity score reweighting estimator to estimate the average treatment effect of foreign acquisition on innovation (Imbens, 2004; Busso, DiNardo and McCrary, 2009).

We first analyze which domestic firms are more likely to be the target of acquisition, a largely unexplored question in the international economics literature.[4] Empirically, our data reveal clear evidence of positive selection: Foreign firms buy the most productive firms within industries—i.e., they "cherry-pick."[5] Further, we find that accounting for the positive selection leads to a labor productivity premium associated with foreign acquisition that is one third of the cross-sectional estimate. Nonetheless, after accounting for selection, firm

[3]Spain has a substantial foreign multinationals presence. In 2005, 16.5 percent of the firms surveyed in our data were foreign-owned, representing 43 percent of total sales in Spanish manufacturing. The OECD reports that over 95 percent of FDI in Spain in 2005 originated in another OECD country (OECD.StatExtracts). This is consistent with Markusen (2002) who reports that over 75 percent of all worldwide foreign direct investment is between developed countries.

[4]Existing literature in international economics focuses on which parent firms will choose to engage in FDI (Helpman et al., 2004; Burstein and Monge-Naranjo, 2009), and the determinants of the extent of FDI activity (Blonigen, 2005). Nocke and Yeaple (2007, 2008) model FDI as the combination of complementary assets and inputs from firms located across different countries, and they evaluate empirical predictions about the parent firm's mode of foreign entry—greenfield or acquisition—as a function of parent firm characteristics. In contrast, we focus on the empirical question of which domestic firms are acquired.

[5]Relatedly, Criscuolo and Martin (2009) show that the observed U.S. multinational productivity advantage is driven mainly by positive selection. In contrast, the corporate finance literature on U.S. M&A activity has mixed evidence on the nature of selection, which reflects varying motives for acquisition. A strand of this literature asserts that low-performing firms are the most likely to be acquired (Lichtenberg and Siegel, 1987).

sales increase by 18 percent and labor productivity by 11 percent following acquisition.

Next, we analyze the type of productivity-enhancing innovations acquired firms implement following acquisition. After controlling for selection using a number of different strategies (including, among others, firm fixed effects and the propensity score reweighting estimator), we find that acquisition leads to improvements in a firm's technology: Acquired firms are more likely to innovate.[6] We also explore a distinction that has long been present in the literature about different types of process innovation. Teece (1977) distinguishes between two types of technology transfer in his seminal study of 26 U.S. multinational subsidiaries: The first is "hardware," such as tooling, equipment, and blue prints. The second is the information that must be acquired if this hardware is to be used effectively—the required methods of organization.[7] Our results indicate that firms do both simultaneously upon acquisition—i.e., they purchase new machines and adopt new methods of organizing production at the same time, rather than doing either on its own. This is consistent with the finding that it is optimal for firms to implement new information technology and organizational practices jointly, identified by a number of authors (Black and Lynch, 2001; Bresnahan, Brynjolfsson, and Hitt, 2002; Bartel, Ichniowski and Shaw, 2007), and also shown in the context of multinationals by Bloom, Sadun and Van Reenen (forthcoming).

The observed positive selection and technology upgrading upon acquisition are consistent with the predictions of a simple model in which the optimal amount of innovation upon acquisition depends on the costs and benefits of the innovation process and, hence, the

[6] These findings are consistent with Arnold and Javorcik (2009) who analyze the effects of foreign ownership on Indonesian firms, controlling for selection. They find that total investment and investment in new machinery increase under foreign ownership, along with employment, wages, productivity and sales. They also show that plants receiving foreign investment use more inputs from abroad and export a larger share of exports. Stiebale and Reise (2011), in contrast, find no evidence of an increase in innovation activity in foreign-acquired German firms.

[7] In the literature on the market for corporate control, Jensen and Ruback (1980) argue that the potential synergies prompting efficient mergers could occur through the adoption of more efficient production or organizational technology. More recently, Bloom and Van Reenen (2010) show that the subsidiaries of multinational firms exhibit more sophisticated managerial practices than do domestic firms across the U.S., Europe and Asia.

initial characteristics of the acquired subsidiary; in turn, the returns to innovation following acquisition determine which firms are acquired. We use the model to illustrate how the selection and innovation decisions are jointly determined. In showing empirical support for the model's predictions, we contribute to the existing literature by providing a new explanation for why some firms do not invest in technology and organizational upgrades (based on variation in the costs and benefits of innovation for heterogeneous firms), helping to explain the puzzle of persistent productivity heterogeneity.

In our model, there is a complementarity between the extent of innovation and the acquired firm's initial characteristics reflected in its initial productivity. This could arise for several reasons. For example, a product upgrade is more valuable when the acquired firm is able to sell more units of the good. Additionally, the benefits associated with a superior production process depend on the skill of the operators, and, more generally, on existing practices in the acquired subsidiary. We show in the model that the complementarity between innovation and the acquired firm's initial productivity is amplified when the foreign parent brings lower innovation costs or greater market access.[8] A foreign firm could bring with it lower innovation costs if it has a lower cost of capital (Desai, Foley and Hines, 2004; Desai, Foley and Forbes, 2008; Manova, Wei and Zhang, 2010) or access to proprietary technologies (Caves, 1996; Antras, 2003; Antras and Helpman, 2004), but it could also bring larger benefits from innovation. Multinational firms are known to provide acquired subsidiaries with access to export markets (as shown by Hanson, Mataloni and Slaughter (2005) for vertical and by Ekholm, Forslid and Markusen (2007) for horizontal foreign direct investment), thereby increasing firm scale. With either lower innovation costs or greater market access under foreign ownership, the surplus created by foreign acquisition is increasing

[8] The complementarity between innovation and market scale is a major theme of the international economics literature. For example, the promise of greater sales in export markets creates an incentive for a firm to invest in productivity-enhancing technologies (Verhoogen, 2008; Bustos, 2011; Lileeva and Trefler, 2010; Aw, Roberts, and Xu, 2011; Atkeson and Burstein, 2010).

in initial productivity. This explains both positive selection and increased innovation.

We empirically explore the relationship between the greater market scale granted by the foreign parent and subsidiaries' innovation decisions. We find that the higher levels of innovation by foreign subsidiaries are, in large part, driven by firms that export through a foreign parent. Process innovation, product innovation and assimilation of foreign technologies are each associated with increased market access through the foreign parent. This is consistent with foreign ownership facilitating access to larger markets and thereby creating incentives to invest in firm technology. We are able to determine the role of the export channel, as distinct from export status, because firms in our data are asked how they access export markets and, specifically, whether they export through a foreign parent—which could reflect either using the parent's distribution channels or selling directly to another entity within the multinational. Our findings provide strong evidence that multinational subsidiaries innovate more because they enjoy greater benefits from innovation due to their existing market scale and not just because their innovation costs are lower than domestic firms'. The fundamental link between foreign ownership—in particular, the increase in market access that comes with foreign ownership—and innovation is absent from the existing studies of trade and innovation, as well as from the literature on organizational structure and productivity.

Note that our empirical results about selection patterns rule out an alternative view of the process of technology transfer—namely, that multinational subsidiaries adopt the same technology level as the foreign parent independent of their initial productivity. If a multinational were able to transplant its own productivity to any acquired firm, the value added through acquisition would be largest for low-productivity firms, leading to negative selection; that is, multinationals would select to acquire the least productive firms.

Our results about positive selection and increased productivity upon acquisition have direct implications for the relationship between multinational activity and the evolution of the productivity distribution, and, hence, allocative efficiency. For firms that become foreign-owned, the productivity distribution shifts to the right. Since our results suggest

that multinationals do not purchase a random selection of firms, but are likely to acquire the initially most productive firms, the results illustrate one channel through which productivity differences across firms in the economy can be amplified over time.[9]

Finally, accounting for the links between the innovation and acquisition decisions can shed light on why foreign multinationals acquire larger firms and on why some firms innovate more than others. Thus, we provide one possible explanation for the persistent productivity differences that have long puzzled researchers. Our study suggests that both acquisition patterns and innovation decisions are determined by the variable costs and benefits of technology transfer. When this is the case, our key insight is that differences in market access alone, and not just foreign firms' innovation-cost advantages or their superior technologies, can explain these phenomena. More generally, the fact that firms within an industry may have differential access to markets provides a new rationale for why initial differences in productivity persist, a fundamental question in organizational economics, strategy, and in other fields (Bloom and Van Reenen, 2007; Syverson, 2011).

The rest of the paper proceeds as follows: Section 2 outlines a simple model illustrating the relationship between acquisition and investment to frame the empirical analysis. Section 3 describes the data. Section 4 presents the empirical strategy and results related to the acquisition decision. Section 5 focuses on the innovation decision and explores the role of the market access mechanism in driving our main results. Section 6 analyzes the effect of foreign acquisition on productivity, and Section 7 concludes.

2 Acquisition and Innovation Decisions

In this section, we set up a simple industry-level partial equilibrium model to illustrate 1) the endogenous choices of foreign acquisition and innovation when domestic firms differ in initial

[9] The presence of multinational subsidiaries in an economy is also likely to affect the overall productivity distribution through other channels—for example, by affecting the threshold level of productivity at which entering firms choose to remain in production. We have not examined these other channels in this paper.

productivity, and 2) the complementarities that can emerge among productivity, innovation and acquisition.[10]

A. Structure

Consider a model with heterogeneous domestic firms (Melitz, 2003) with a Constant Elasticity of Substitution (CES) demand structure and increasing returns to scale in a setting of monopolistic competition (Helpman and Krugman, 1985). The initial productivity of firm i is given by φ_i. Forward-looking foreign firms select which domestic firms to acquire, and all firms choose a level of innovation or other productivity-increasing investment, γ_i. Production and profits reflect post-innovation productivity levels, $\gamma_i\varphi_i$, and the firm's marginal cost is given by $\frac{1}{\gamma_i\varphi_i}$.

The price set by each firm is a constant markup over marginal cost, and each variety in an industry is produced by a single firm. Firm i sets a price $\frac{1}{\rho\gamma_i\varphi_i}$, where ρ is the parameter in the CES utility function that defines the elasticity of substitution between varieties $\sigma = \frac{1}{1-\rho} > 1$, assumed to be constant across all markets.[11] Each firm sells $A_i\rho^{\sigma}\left(\gamma_i\varphi_i\right)^{\sigma}$ units, generating revenues of $A_i\rho^{\sigma-1}\left(\gamma_i\varphi_i\right)^{\sigma-1}$, where A_i is a measure of market size for the markets relevant to firm i. The profits generated by each firm are given by:

$$\pi_i = A_i\left(\frac{1-\rho}{\rho}\right)\rho^{\sigma}\left(\gamma_i\varphi_i\right)^{\sigma-1}$$

To simplify, we denote $\chi = \left(\frac{1-\rho}{\rho}\right)\rho^{\sigma}$, and work with an increasing transformation of

[10] In the model, variation in investment levels across firms are optimal choices under complete information, so that persistent productivity differences are not based on any type of market failure, incomplete information or X-inefficiency.

[11] The representative consumer's utility function is given by $U = [\int_0^N q(i)^{\rho}di]^{\frac{1}{\rho}}$ where $\rho \in (0,1)$. The demand for a particular variety of the product sold by a given firm is $q(i) = \frac{E_i}{P_i}(\frac{p(i)}{P_i})^{-\sigma}$, where E_i is total expenditure in the relevant market for good i on all varieties in the industry, and P_i is a weighted average of variety prices in the relevant market. The subindex i on E_i and P_i captures the fact that firms can sell in different markets. We assume that doing so does not incur transport costs. We define $A_i = E_iP_i^{\sigma-1}$. See Dixit and Stiglitz (1977) for further details.

the innovation level $\lambda_i = \gamma_i^{\sigma-1}$ from now on. The value, V_i, of each firm operating in the domestic market (net of the fixed production cost) is equal to the variable profit it earns, π_i, less the total cost of innovations to increase productivity $C_i(\lambda_i)$:

$$V_i(\lambda_i) = A_i \chi \lambda_i \varphi_i^{\sigma-1} - C_i(\lambda_i) \tag{1}$$

B. The Innovation Decision

We allow the total cost of investment in productivity to be the sum of a fixed and a variable cost of innovation:

$$C_i(\lambda_i) = a_i + b_i f(\lambda_i)$$

where λ_i measures innovation—the improvement in the firm's productivity following the investment. We do not impose any specific functional form on $f(\lambda_i)$.[12]

The firm chooses a level of innovation λ_i^* that maximizes the value of the firm. When the optimal level of innovation is greater than zero, the firm innovates up to the level where the marginal benefit equals marginal cost:[13]

$$A_i \chi \varphi_i^{\sigma-1} = b_i f'(\lambda_i^*) \tag{2}$$

Equation (2) shows that, ceteris paribus, at an interior solution, innovation, $\lambda_i^* = \lambda^*(A_i, b_i, \varphi_i)$, is increasing in initial productivity level φ_i, greater market size A_i, and decreasing in the cost

[12] We require only that the technology total cost function $C_i(\lambda_i)$ has a continuous first derivative that is strictly positive whenever $\lambda_i > 1$. Note that we do not impose a technological complementarity between innovation and initial productivity, which could reflect an assumption that absorptive capacity (Cohen and Levinthal, 1990) is increasing in φ_i. One way to do this would be to specify b as a decreasing function of φ_i. The current specification can be extended to include this possibility.

[13] To ensure positive innovation, a_i must be sufficiently low so that firm value under the optimal investment level is larger than firm value under no investment. This is true when $a_i \leq b_i((\lambda^* - 1)f'(\lambda^*) - f(\lambda^*)$. In the interior optimum $\lambda^* > 1$, (since $V'_\lambda|_1 = A_i \chi \varphi^{\sigma-1} - b_i f'(1) > 0$ as $f'(1) = 0$ where we have imposed marginal cost continuity). λ^* is guaranteed to be a maximum as long as marginal cost (or, equivalently, f') is a continuous increasing function of λ. For λ^* to be unique, f' should also be strictly increasing for $\lambda > 1$.

of technology investment, b_i.[14] Figure 1 provides an illustration of the positive relationship between λ_i^* and φ_i for two possible values of $\left(\frac{A_i}{b_i}\right)$.[15] When $\left(\frac{A_i}{b_i}\right)$ is higher, the optimal level of innovation, λ_i^*, is greater for any level of φ_i. This illustrates two important economic mechanisms: the complementarity between innovation and initial productivity, as well as the complementarity between larger market size (or lower innovation costs) and innovation. $\underline{\varphi}_D$ ($\underline{\varphi}_F$) is the value of φ_i at which a firm with a low (high) value of $\left(\frac{A_i}{b_i}\right)$ would find it worthwhile to invest in innovation.

Insert Figure 1 around here

The optimal amount of innovation, λ^*, given by equation (2), and, hence, the firm's post-innovation productivity level, depend on the costs and benefits of innovation and the firm's initial productivity.[16] However, in contrast, a common assumption in the literature on multinational production is that subsidiaries operate at the same productivity level as their parent, independent of their initial characteristics.[17] This assumption about technology transfer within a multinational firm could be modeled in our setting by allowing any acquired firm to find it optimal to innovate up to the "state of the art" technology level, denoting

[14] It can be seen from the left hand side of equation (2) that the model's predictions are robust to specifying post-innovation productivity as an additive function of initial productivity and innovation ($\gamma_i + \varphi_i$) since the marginal benefit of innovation is also a positive function of φ_i in this case. The multiplicative setup used here is similar to the model in Bustos (2011), where the binary decision about technology investment is related to the export decision. In our case, firms choose whether to invest, but they also optimize over the level of investment as a function of innovation costs. Heterogeneous firm productivities could reflect variation in marginal costs or variation in the quality of output produced, allowing more productive firms to charge higher prices.

[15] The first order condition (2) does not separately identify A_i and b_i. Access to larger markets and lower marginal costs of investment in technology have similar effects on the choice of λ_i.

[16] In practice, this represents a world in which the innovation process is costly, and achieving a higher productivity level requires greater expenditure. For example, installing a technology with better machinery or more talented managers is likely to be more expensive; and we might think that there is an increasing opportunity cost of allocating scarce MNC resources to a particular acquired firm.

[17] This alternative view of technology transfer is consistent with an assumption made in McGrattan and Prescott (2010), Burstein and Monge-Naranjo (2009) and Ramondo and Rodriguez-Clare (2009) that all subsidiaries of a multinational firm operate with the same productivity (up to a discount factor, typically modeled as iceberg costs).

this technology as the productivity level $\Phi_{\max}$. This would imply that $\lambda_i = \left(\frac{\Phi_{\max}}{\varphi_i}\right)^{\sigma-1}$, so that innovation is a decreasing function of initial productivity.[18] In this case, the amount of innovation would, then, be independent of A_i.

C. The Acquisition Decision

We denote V_i^* as the value of the firm, given by equation (1), at the optimal investment level λ_i^* for firm i. We now turn to how foreign ownership affects innovation and firm value and, hence, how foreign firms select which firms to acquire.

We allow foreign acquisition to affect two model parameters. The trade literature has shown that foreign ownership often provides access to larger markets. If A_D measures the size of the market(s) a domestic firm can access, we allow foreign-acquired firms to have access to an additional market (denoted A^*), where access is granted via the parent firm's pre-existing trade contacts and distribution networks in foreign markets. The total market that a foreign-acquired firm can access is, then, $A_F = A_D + A^*$, where $A_F \geq A_D$. Foreign ownership may also bring with it lower innovation costs (access to proprietary technologies, lower costs of financing, etc.), such that $b_F \leq b_D$ or $a_F \leq a_D$. We assume throughout that $0 \leq b_F \leq b_D$ and, for simplicity, that the domestic firm is always at the solution given by the first-order condition in equation (2).

Given the parameter values relevant to the firm's ownership structure, the optimal level of innovation under domestic ownership is λ_i^{*D} and under foreign ownership is λ_i^{*F} (note that the interests of the parent and the subsidiary are aligned in this model.) Using equation (1) for firm value under each ownership structure, the incremental value of the firm under

[18] Once $\Phi_{\max}$ is included in the model, upgrading the subsidiary's productivity to $\Phi_{\max}$ would be optimal if productivity-enhancing innovation incurred only a fixed cost—i.e., $b_i = 0$. When $\Phi_{\max}$ gives the upper bound on the feasible technology, the first-order condition in equation (2) gives the optimal level of investment when b_i is sufficiently high that the firm does not find it optimal to innovate up to $\Phi_{\max}$. This is for $b_i > \frac{A_i \chi \varphi_i^{\sigma-1}}{f'((\frac{\Phi_{\max}}{\varphi_i})^{\sigma-1})}$).

foreign acquisition can be written as:

$$(3) \quad V_i^{*F} - V_i^{*D} = \left(A_F \lambda_i^{*F} - A_D \lambda_i^{*D}\right) \chi \varphi_i^{\sigma-1} - (a_F - a_D) - \left(b_F f\left(\lambda_i^{*F}\right) - b_D f\left(\lambda_i^{*D}\right)\right)$$

$\left(V_i^{*F} - V_i^{*D}\right)$ represents the value created by the acquisition. Under the assumptions that $A_F \geq A_D$, $b_F \leq b_D$ and $a_F \leq a_D$—and at least one of these inequalities is strictly true—expression (3) is positive.

We assume that the price a foreign firm would pay if it were to acquire firm i, R_i, divides the value created through the acquisition between the buyers and the sellers, where the buyer receives a share $\alpha_i \in [0, 1]$. The acquisitions market can be modeled as a game in which homogeneous foreign parents compete with each other to acquire a subsidiary.[19] We assume that there is a fixed cost to a foreign firm of making an acquisition, K, which could include fixed search and transactions costs. Imposing a free-entry zero-profit condition in the acquisitions market implies that firm i is acquired whenever the incremental value of the firm under foreign acquisition, $\left(V_i^{*F} - V_i^{*D}\right)$, exceeds K, so that there is a minimum threshold level of φ_i at which acquisition becomes efficient (Ravenscraft and Scherer, 1987). Competition among potential foreign parents means that α_i adjusts so that each parent is indifferent between acquiring any domestic firm with an initial productivity above this threshold level.[20] The price paid by the acquirer, $R_i = V_i^{*D} + (1 - \alpha_i)\left(V_i^{*F} - V_i^{*D}\right)$, varies with φ_i so that the share of the surplus generated going to the buyer, $\alpha_i\left(V_i^{*F} - V_i^{*D}\right)$, is always equal to K. That is, the following condition holds for all acquisitions:

$$(4) \quad \alpha_i\left(V_i^{*F} - V_i^{*D}\right) = K$$

[19] The model could easily be extended to include heterogeneity among foreign parents. This would not change the predictions regarding which domestic firms are acquired but would provide additional predictions related to sorting between parents and subsidiary firms.

[20] Note that this implies $\alpha_i = 1$ for the acquired firm with the lowest initial productivity level, at the minimum threshold φ_i. That is, the surplus generated by the acquisition of the least productive acquired firm is equal to K in equilibrium.

Now, we can investigate the relationship between acquisition incentives and initial firm productivity.

The optimal amount of innovation satisfies the first-order condition given in equation (2). Applying the envelope theorem to the value of the firm under foreign and domestic control yields $\frac{d(V_i^{*F}-V_i^{*D})}{d\varphi_i^{\sigma-1}} = \chi\left(A_F\lambda_i^{*F} - A_D\lambda_i^{*D}\right) > 0$. That is, the value created by foreign acquisition is increasing in initial productivity, and more productive domestic firms are more likely to be acquired. This result arises from the complementarity between foreign firms' characteristics (larger markets and/or lower costs of innovation), innovation and the acquired firm's productivity: A given innovation is more valuable in more productive firms; and this value is greater under foreign control due to, for instance, the access to the foreign firm's distribution networks, which means that the innovation can be leveraged in a larger market and, hence, is more profitable.

A very different scenario emerges under the alternative assumption that multinationals find it optimal to transplant their own superior level of technology, $\Phi_{\max}$, regardless of who they buy. Under this assumption, the value of the firm under foreign ownership, $V_i^{*F} = A_F\chi\Phi_{\max}^{\sigma-1} - a_F$, is independent of its initial characteristics and, in particular, independent of φ_i. This means that there are no sources of complementarity between the characteristics of the acquired firm and the implemented technology. Since the value of the firm, had it remained under domestic control, V_i^{*D}, is an increasing function of φ_i, the value added by acquisition is decreasing in φ_i, $\frac{d(V_i^{*F}-V_i^{*D})}{d\varphi_i^{\sigma-1}} = -A_D\chi\lambda_i^{*D} < 0$, and less productive domestic firms are more likely to be acquired. That is, the assumption of parent technology transfer generates the opposite prediction from the assumption that innovation is complementary to the acquired firm's initial productivity.

In our model, the identity of the acquiring firm is irrelevant to the optimal choice of innovation. We require only the possibility that the parent brings a lower cost of innovation and/or a larger market than the firm would have had under domestic control. Therefore, any heterogeneity among parents does not affect the model's predictions for innovation and

acquisition decisions.

Figure 1 illustrates the predicted relationship between λ_i^* and φ_i when innovation is complementary to the acquired firm's initial productivity. It highlights the role played by selective foreign acquisition. The bold line shows the predicted relationship between initial productivity and innovation within an industry for a given K. In the figure, firms above $\widetilde{\varphi}_1$ are acquired and innovate; firms between $\underline{\varphi}_D$ and $\widetilde{\varphi}_1$ remain domestic and innovate; and firms below $\underline{\varphi}_D$ remain domestic and do not make any investments.

3 Data Description

The results in this paper are based on the *Encuesta Sobre Estrategias Empresariales* (ESEE), a panel dataset of Spanish manufacturing firms collected by the Fundación SEPI (a non-government organization) and the Spanish Ministry of Industry every year since 1990. It is designed to be representative of the population of Spanish manufacturing firms and includes approximately 2,800 firms (with the intention of surveying all firms with more than 200 employees and a stratified sample of smaller firms). The response rate in the survey is 80 to 100 percent, and new firms are re-sampled over time to ensure that the panel remains representative.[21]

Our data span the years 1990 to 2006. 83.5 percent of the firms are domestic in the first year they appear in the data, while 16.5 percent are foreign-owned. We define a firm as foreign-owned if it reports that a foreign company owns at least 50 percent of its capital. 91 percent of firms report being either zero- or 100-percent foreign-owned. Markusen (2002) defines foreign direct investment through acquisition as an investment in which the firm acquires a substantial controlling interest in a foreign firm. Since 50 percent is a sufficient indicator for foreign control, we have favored this definition of "acquisition" (the results are

[21] Details on the survey characteristics and data access guidelines can be obtained at http://www.funep.es/esee/sp/sinfo_que_es.asp.

robust to specifying other thresholds). We restrict our sample to firms that are not owned by a foreign company in the first year they appear in the data, since the model generates predictions about which domestic firms will be acquired. The data do not record any further characteristics of the parent firm. However, our dataset is unique in that, in addition to recording ownership status, it reports a large number of variables that reflect each firm's productivity-enhancing innovation activity. The data include variables indicating whether the firm undertook process and/or product innovation and whether the firm made efforts to assimilate foreign technologies in a given year. These indicator variables reflect firm managers' answers to the survey questions.[22]

The variables recorded in our data allow us to distinguish between process innovation that introduces new machinery and process innovation that introduces new methods to organize production, reflecting the distinction in Teece (1977). The ESEE bases its survey questions on an OECD publication, the Oslo Manual, which was designed to formalize guidelines for collecting and using data on industrial innovation. It acknowledges the fine line between an organizational innovation and other types of process innovation by noting that "a starting point for distinguishing process and/or organizational innovations is the type of activity." In particular, "organizational innovations deal primarily with people and the organization of work." Accordingly, the ESEE asks respondents whether their firm has undertaken a process improvement that involves the use of new machines and/or the use of new methods to organize production. Some examples of the latter are "practices to improve knowledge sharing," "education and training systems," "new methods for distributing responsibilities and decision making" and "management systems for general production or supply operations." Although we do not have any further details on the nature of the technology implemented,

[22]Product innovation could mean upgrading the quality of existing products or, as in Dhingra (2010), developing new products. See Online Appendix Table S1 for the exact wording of the survey questions. Note that the questions do not ask whether the firm undertakes R&D activity but, rather, whether they implement an innovation. Salomon and Shaver (2005) and Salomon (2006) study the relationship among product innovation, patenting activity, and exporting activity.

when implementation coincides with acquisition, it is likely that some of these organizational practices, along with the assimilation of foreign technologies, reflect technology transfer from the parent.

The data contain other information on these firms' activities that allows us to shed light on the mechanisms at work in our model. In particular, we know whether a firm exports, as well as its volume of exports. We also observe whether the firm uses the foreign parent as a channel for its exports, or if it exports via other means (this information is available only every four years). We do not know of any other dataset that includes all these detailed variables for a large panel of firms over an extended period of time (17 years in our data).

We also use the ESEE data to define two different variables that measure firm productivity. The first is the natural log of the firm's real sales, relative to the industry mean (similar to Verhoogen, 2008). The second is labor productivity defined as the natural logarithm of real value added per worker, relative to the industry mean (similar to Lileeva and Trefler, 2010). The ESEE categorizes firms into 20 industries, based on the two-digit NACE classification. Summary statistics are given in Table 1, and variable definitions are included in the notes to the table.

Insert Table 1 around here

4 The Acquisition Decision

A. Estimation Strategy

The first set of predictions arising from the model reveals which domestic firms are likely to be the targets of foreign acquisitions. When there is a complementarity between a firm's initial productivity level and the amount of innovation, foreign firms acquire the most productive firms in the economy (those with higher φ_i), so that there is positive selection. In an alternative scenario, in which foreign firms transfer their own productivity level to the

domestic firm regardless of which firms they buy, negative selection emerges: Foreign firms acquire the least productive firms (those with lower φ_i).

We estimate the type of selection at work in the data in the following way: Equation (4) says that the share of the surplus generated by the acquisition going to the acquiring firm is equal to K for all acquired firms, and the free entry condition for foreign firms in the acquisition market implies that acquisition takes place whenever $\left(V_i^{*F} - V_i^{*D}\right) \geq K$. Rearranging this inequality, we denote $F_{it}^* = \left(V_i^{*F} - V_i^{*D}\right) - K$. The binary outcome of the acquisition decision F_{it} can be seen as reflecting a threshold rule for the underlying latent variable F_{it}^*, so that $F_{it} = 1$ (foreign ownership) if $F_{it}^* \geq 0$ and $F_{it} = 0$ (domestic ownership) if $F_{it}^* < 0$. We also allow the average probability of acquisition to vary by year and industry by including year (d_t) and industry (d_s) dummies. Given these assumptions, the probability that a given firm i in industry s is acquired in year t can be estimated using the following linear approximation:

$$F_{it} = \alpha + \beta\varphi_{it-1} + d_t + d_s + \nu_{it} \tag{5}$$

We first measure the productivity of firm i, φ_{i0}, in the base year (the first year the firm appears in the data, which we subsequently exclude from the analysis) and examine the probability in the data that a firm will ever be acquired (such that we use one observation per firm). We then allow for a time-varying measure of lagged productivity, φ_{it-1}, to examine the probability of being acquired in any given year, conditional on being domestically owned the year before. Empirically, lagged and initial productivity are highly positively correlated, but the ordering of firms based on lagged productivity may better reflect the attractiveness of any one firm at the time of potential purchase.

Under the assumptions of the model, $\widehat{\beta}$ is predicted to be positive. In contrast, with negative selection, $\widehat{\beta}$ is expected to be negative. Hence, the observed selection effect offers insight into the actual nature of the potential technology transfer from multinational parents

to domestic subsidiaries.

B. Foreign firms select the most productive domestic firms

Before turning to the analysis, we use our dataset to explore the patterns of selection graphically. Figure 2 plots the distribution of initial productivity for two groups of firms: those that are acquired by a foreign firm four years after our baseline productivity is computed and those that remain domestic. One can clearly see that the distribution of acquired firms (solid line) lies to the right of those that remain domestic. Since our measure of productivity is demeaned relative to the industry, this does not reflect differences in firm size by industry. Figure 3 reproduces Figure 2 by industry. A striking pattern emerges: Positive selection is present in every industry. These two figures provide prima facie evidence that the positive selection predicted in our model dominates in the Spanish data.

Insert Figures 2 and 3 around here

We now turn to a more systematic analysis and estimate equation (5) to establish this first fact. The estimated coefficients using a linear probability model are shown in Panels A and B of Table 2 (Online Appendix Table S2 shows that results are similar when using a probit specification). The dependent variable in all columns is the indicator for foreign ownership, and this is regressed on our two proxies for initial productivity. These are the logarithm of real firm sales (Columns 1 to 3) and the logarithm of labor productivity (Columns 4 to 6), each relative to its industry mean. The regressions in Panel A use baseline (initial) productivity measured by these two variables and one observation per firm to estimate the probability of ever being foreign-acquired (within the sample). Panel B uses (time-varying) lagged productivity as an independent variable to estimate the probability of being acquired in any given year, conditional on being domestic the year before. All regressions include industry dummies. Additionally, Panel B includes year dummies and industry trends, so the

results can be interpreted as within-industry differences in the probability of acquisition as a function of initial productivity, controlling for possible differential trends in acquisitions by industry.

Insert Table 2 around here

Regardless of the productivity measure used, we find that more productive firms are more likely to become foreign-owned. For example, the coefficient in Column 1a (0.0351) implies that, conditional on being domestic the year the firm enters the sample, a one standard deviation increase in initial productivity makes a firm six percentage points more likely to be acquired by the end of the sample. The same increase in lagged productivity is associated with a one-percent higher yearly probability of being acquired (Column 1b).[23]

Columns 2 and 5 replace the productivity variable with indicator variables for each productivity quartile. For example, in Column 2a, being in the second sales quartile increases the probability of becoming foreign-owned during the sample years by 3.3 percentage points relative to firms in the first quartile (corresponding to a yearly figure of 0.4 in Column 2b); being in the third quartile by 4.8 percentage points (1.1 yearly, in Column 2b); and being in the highest productivity quartile by as much as 14.8 percentage points (2.7 yearly, in Column 2b). A similar pattern emerges when using labor productivity as the productivity measure. Therefore, firms at the upper end of the productivity distribution are substantially more likely to become foreign-owned, and the effect is increasing in firm productivity, with firms in the upper quartile having a much higher probability of acquisition.

Finally, Columns 3 and 6 explore the possibility that foreign firms are selecting exporters (because, for example, exporting firms have less exchange rate exposure), and exporting is positively correlated with initial productivity. We introduce a dummy variable for exporting status and interact it with initial productivity. Initial productivity always remains positively

[23]Table 1 shows that 3.5 percent of our observations are firms under foreign ownership. This corresponds to 165 firms (or 4.6 percent) being acquired during the sample.

related to the probability of being acquired, regardless of export status. There is also some evidence that multinationals are more likely to target exporters, but we find no systematic evidence of differential positive selection among exporters. So, overall, even though some firms may be acquired because of their exporter status, positive selection persists, and multinationals are more likely to acquire the most productive firms among both exporters and non-exporters.

Table 2, therefore, reinforces the results from Figures 2 and 3 and shows that, within our cross-section of firms, the more productive domestic firms are more likely to become foreign-owned—evidence of positive selection and the presence of "cherry-picking." These selection patterns are inconsistent with a model in which foreign firms always find it optimal to transfer their superior technology across international (or firm) borders to any domestic firm, as is often assumed.

While the results in a number of papers point to the presence of positive selection by foreign firms in other countries (e.g., for Chile, Ramondo, 2009; for Indonesia, Arnold and Javorcik, 2009; for the U.K., Criscuolo and Martin, 2009), to the best of our knowledge, no prior studies have explained this empirical regularity. When viewed within the context of our model, our finding suggests that acquisition patterns reflect an underlying complementarity between the initial productivity of the acquired firm and the extent of innovation post-acquisition. As we will see later, this finding has significant implications for the relationship between multinational activity in a country and the evolution of the productivity distribution.

5 The Innovation Decision

A. Estimation Strategy: Fixed Effects and Propensity Score

Having established that foreign firms positively select domestic firms as targets, we now test the set of predictions relating productivity-enhancing investments to acquisition—namely, that upon being acquired, foreign subsidiaries invest more in innovation than they would have done had they remained domestic. Our model suggests that acquired firms undertake more investment activity, controlling for the initial productivity of the acquired firm. This can be seen in Figure 1 as the difference between λ_i^F and λ_i^D.

The optimal level of investment under each ownership structure is determined by the first-order condition given in equation (2). In this case, innovation can increase upon acquisition for several reasons. The foreign firm could provide access to a larger market and/or bring with it lower innovation costs, such that $(\frac{A_i}{b_i})^F > (\frac{A_i}{b_i})^D$.

Our innovation variables are based on the firm-level responses to the questions about whether the firm made specific types of innovation in that year, which we interpret as improvements to firm technology. We are interested in how the firm's technology, which is the result of successive innovations, changes with foreign ownership. Since, at any point in time, the firm's technology can be characterized as the sum of innovations made up to that point, we use the yearly variables on firm-level innovation described in Section 3 to measure the firm's technology at time t as: $I_{it} = \sum_{j=t_0}^{t} I_{ij}$, where t_0 is the year the firm entered the data.[24] Any differences in technology across firms in the year they enter the data will be captured by the firm fixed effects in our empirical specifications.[25] As a result, all the variation in a firm's innovative activity—and the resulting technology level—that we relate

[24] We have allowed the stock of innovation to depreciate at different rates over time. The results are qualitatively similar to the ones presented with this—the simplest—specification.

[25] First-differences specifications of the estimations with three different measures of the innovation stock (process innovation; product innovation; and process innovation that includes both new machines and new organizational practices) are presented as a robustness test in Appendix Table 1.

to changes in the firm's ownership structure occurs within the sample.[26]

Empirically, we first estimate the effect of acquisition on technology using the panel structure of the dataset and including year fixed effects as follows:

$$I_{it} = \alpha + \gamma F_{it-1} + \sum_j \beta^j X^j_{it-2} + d_t + \eta_i + \epsilon_{it} \tag{6}$$

where I_{it} is a proxy for productivity-enhancing innovation. The fact that the level of productivity φ_i affects investment directly for foreign-owned firms is absorbed by the firm fixed effects, η_i, along with any other permanent unobserved characteristics of firms. Including firm fixed effects implies that the estimated parameter $\widehat{\gamma}$ is a measure of the change in investment after being acquired, controlling for the fact that foreign firms choose to acquire higher initial-productivity firms, and this is predicted to be positive.

The fixed effects specification controls for selection based on time-invariant firm characteristics (e.g., initial productivity). However, it is important in the context of our 17-year panel to acknowledge that firm characteristics may evolve differently over time (for reasons outside the model) and impact multinational selection decisions differentially. In particular, selection may be driven by lagged firm characteristics and decisions that could be correlated with future innovation. To address this and ensure that the estimates of the parameter γ reflect changes in innovation activity associated with acquisition, we use three different strategies. First, we first include X^j_{it-2}, a set of j firm-level characteristics, lagged relative to the acquisition decision, that control for selection on time-varying observables.[27] Second,

[26] Online Appendix Table S3 shows that each measure of the stock of innovation I_{it}, enters the production function as a significant shifter of productivity.

[27] The variables that may be correlated both with being acquired and with subsequent innovation activity that are included as controls are: (1) the log of the level of firm sales; (2) the log of labor productivity (to control for time varying selection on firm size and productivity); (3) the log of sales growth (to control for time-varying selection on productivity growth); (4) export status (to control for time-varying selection on the international presence of these firms and potentially related productivity effects not captured by other variables); (5) average wage (to control for potential selection on changes in the skill mix of firms); (6) log capital per employee; and (7) log capital (to control for potential selection on the evolving level of capital and capital intensity of firms).

we include an indicator in equation (6) for whether the firm is acquired in the current period (F_{it}) and in the following period (F_{it+1}). This allows us to test directly in the data whether there was a change in the dependent variable that was already taking place prior to the acquisition (in which case, the coefficient on the lead variable should be different from zero).

Third, we use a propensity score estimator to reweight firms in equation (6) to reflect differences in the probability of being acquired based on prior characteristics. We calculate the propensity score for each firm in the following way. For each year, we consider firms acquired in that year as treated observations and firms that are never acquired as control observations. We pool treated and control observations across all years to estimate the probability that a firm is acquired as a function of a number of characteristics (see Lechner, 1999). This estimated probability is the propensity score, $\widehat{p}$. The characteristics used to obtain the propensity score are lagged productivity (measured by both log firm sales and log labor productivity), lagged log sales growth, lagged export status, lagged average wage, lag of the process innovation stock, innovation activity in the previous year, lagged log capital per employee, lagged log capital and a year trend. We also allow for this relationship to vary across industries by estimating the propensity score separately for each industry.[28]

One can transform the propensity score estimates into weights such that the propensity score reweighted regression yields a consistent estimate of a parameter of interest (Dehejia and Wahba, 1999; Busso, DiNardo and McCrary, 2009). Specifically, weighting each treated firm by $1/\widehat{p}$, and weighting each control firm by $1/(1-\widehat{p})$ provides an estimate of the Average Treatment Effect (ATE) of acquisition on innovation in a specification like equation (6).[29]

[28] We also performed the standard tests to check that the balancing hypothesis holds within each industry. We found that all covariates are balanced between treated and control observations for all blocks in all industries.

The relationships between each of these variables and the probability of being acquired are shown in Online Appendix Table S4. Lagged ln firm sales is the most significant predictor of acquisition, consistent with our model.

[29] Since never-acquired control firms may be used as controls more than once, we sum the control weights by firm to obtain the weight for the control firm (Lechner, 1999). We also winsorize the weights at one percent because of extreme outliers in the weights. The results are not sensitive to the exact outlier cut-off.

We restrict the analysis to firms that fall within the common support. Busso, DiNardo and McCrary (2009) show that the finite sample properties of this propensity score reweighting estimator are superior to the propensity score matching techniques (where each treated firm is matched to one or several controls).

The propensity score reweighting estimator obtained by reweighting observations in equation (6) allows us to control not only for selection into being acquired on time-invariant characteristics of firms (just like the equal-weighted fixed effects regression), but also for time-varying characteristics through the propensity score. The underlying assumption in the estimation is that, conditional on observable time-varying and any time-invariant characteristics that affect selection, treatment is random. Hence, outcomes for treated firms are attributable only to treatment status (this is typically referred to as the ignorability assumption, or selection on observables).

B. Acquired firms undertake more innovation

Since we have detailed information on the types of innovation domestic firms undertake upon foreign acquisition, our data allow us to shed light on the actual process of technology adoption by domestic firms, and on precisely what types of innovations are more likely to be adopted/transferred.

Our measures of innovation are specific actions related to the implementation of product and process innovation, as well as the assimilation of foreign technologies. All the columns in Table 3 reflect regressions of an innovation variable on the lagged foreign ownership variable. As we will see, we observe empirically that innovations take place mainly with a one-year lag, reflecting the fact that it takes some time for firm strategies to change after acquisition. Lagging this independent variable also reduces possible concerns about reverse causation.

Insert Table 3 around here

In Table 3, we report the results for each investment proxy variable: process innovation (Panel A), product innovation (Panel B) and assimilation of foreign technologies (Panel C). The first column in each panel includes only firm fixed effects; the second also includes industry-specific time trends; the third adds a large set of lagged controls (to control for possible differences in innovation related to previous firm characteristics); the fourth column also adds the lead and contemporaneous indicators of acquisition; the fifth column presents the propensity score reweighted estimates.[30]

The fixed effects specifications in Columns 1 to 3 of Panel A show that process innovation is positively and significantly associated with foreign ownership. Column 1a shows that a foreign-acquired firm is 57-percent more likely to have undertaken a process innovation while foreign-owned, relative to a firm that stays domestic. This estimate is robust to controlling for industry trends and lagged firm characteristics (Columns 2a and 3a). Column 4a shows that the coefficient estimate on the lead indicator for acquisition is not significantly different from zero. Furthermore, it is significantly smaller than the coefficient of interest (as shown by the p-value of 0.048). Column 5a presents the propensity score reweighted regressions that allow us to control for time-varying selection. The coefficient 0.611 is similar to earlier columns and also highly significant, implying that firms undertake more process innovation upon acquisition.[31]

Turning to the second and third panels of Table 3, the estimated coefficients in Column 1 reveal that product innovation and the assimilation of foreign technologies also increase after acquisition. However, the point estimates fall, and the standard errors are larger with further controls and in the propensity score estimation.[32] These results are the average over

[30] As we will see, the number of observations changes with the specification used, because of changes in the number of non-missing observations as we include more variables and their lags. Online Appendix Tables S6 and S7 repeat all the analysis that follows restricting the sample to only the non-missing observations of the most restrictive sample. The results are similar, so we chose to provide the estimates on the unrestricted sample in the main body of the paper.

[31] The results shown in the first differences specifications in Appendix Table 1 reveal that this increase occurs only one year after acquisition, with further increases in the second and third years.

[32] Note that the variable indicating the assimilation of foreign technologies is available only every four

all types of acquired firms, and as we will see in the next subsection, there is evidence that these two types of innovation increase significantly in firms that export through the foreign parent after acquisition.

Table 4 shows the effect of foreign ownership on the disaggregated measures of process innovation. We distinguish between firms that report to have invested only in new machines (Panel B), only in new methods of organizing production (Panel C), or in both simultaneously (Panel A). The results reveal some interesting contrasts. While foreign-acquired firms are not significantly more likely to only introduce new machinery or only introduce new ways of organizing production, the simultaneous introduction of new machinery and new organizational processes is significantly associated with foreign acquisition (Teece, 1977). Panel A shows this result. Both the fixed effects specifications of Columns 1a to 4a and the propensity score estimation of Column 5a show that upon acquisition, firms are more likely to introduce new machines and new organizational methods simultaneously. This is an interesting result since we might have expected that foreign firms would also be more likely to introduce either type of process innovation independently. The findings are consistent with the complementarities found by Black and Lynch (2001), Bresnahan et al. (2002), and Bartel et al. (2007) between different types of technology upgrading. Since firms appear to introduce both types of innovations jointly, it is important to allow for the effect of both actions when quantifying the multinational productivity advantage.[33]

Insert Table 4 around here

years, reducing the number of observations in these specifications and, thus, reducing the power of the fixed effects results since we have, at most, five observations within a firm for this variable.

[33] All of our results are robust to the analysis of firms that report no change in reporting unit throughout the time they are in the sample, as well as restricting the sample to firms that report no changes in the number of establishments. This rules out the concern that the definition of the reporting unit changes following acquisition.

C. The Role of Market Access Provided by the Foreign Parent

These findings on increased process innovation following acquisition, together with our positive selection results, are consistent with a world in which multinationals choose to acquire the most productive firms since that is where the returns to their investment are highest. One explanation for this is that—as proposed in the literature on the sources of multinational advantage—the foreign firm gives access to technology at a lower cost (b_i) than the acquired firm would have faced had it remained under domestic control. However, we highlight an alternative reason for our findings, based on a key feature of multinationals: They often grant their subsidiaries access to a larger global market.

Tables 5 and 6 explore whether innovation decisions are related to the fact that foreign ownership provides access to foreign markets. We regress the innovation variables on indicator variables for whether the firm exports, and for whether the firm exports through the foreign parent. Exporting through the foreign parent may mean that the firm is using the parent's distribution channels and networks to export, or that it sells its goods directly to the foreign parent (as part of a global production system). The base category includes all the channels that were always available to the domestic firms (exporting through its own means, using a Spanish specialized intermediary or cooperative export agreements with other firms).

Table 5 presents the results for overall process innovation (Panel A) and for process innovation that involves the simultaneous introduction of new machines and new methods of organizing production (Panel B). Column 1a reveals that exporting is positively associated with investment in process innovation, consistent with the findings of previous studies (Verhoogen, 2008; Bustos, 2011; Lileeva and Trefler, 2010; Aw et al., 2011). This result holds when controlling for foreign ownership (Column 2a), which is also significant, which suggests that the ownership mechanism outlined in this paper offers a separate explanation for acquired firms' increased process innovation.

Insert Table 5 around here

Columns 3a to 5a introduce our key variable of interest, showing fixed effects regressions using process innovation as a dependent variable, where we include the indicator variable for whether the firm exports via the foreign parent. Notably, we find that starting to export through a foreign parent has a large and significant coefficient. Since this specification also includes the interaction between exporting and being foreign owned, this suggests that it is not exporting while foreign-owned per se, but exporting through the foreign parent, that is associated with innovation.[34]

Since we can distinguish between different types of process innovation, we evaluate the type that exporters are more likely to undertake. Although exporting is, on average, not significantly associated with the simultaneous introduction of new machines and new forms of organizing production (Column 1b), foreign-owned firms are more likely to engage in this type of process innovation (Column 2b). Column 3b shows that, similar to the process innovation results in Column 3a, innovation is driven mainly by the foreign-owned exporters that export via the foreign parent. In contrast, we find that exporting is significantly associated with the introduction of new machines exclusively, while exporting through a foreign parent is not (unreported). This reinforces our findings in Table 4, which suggest that foreign ownership leads to a specific type of process innovation, involving both new machines and new methods of organizing production.[35]

Columns 6 through 8 in Table 5 present the propensity score results for the market access channel, allowing us to better control for time-varying selection. Here, we consider the treatment to be starting to export through the foreign parent, and we recalculate the propensity score and the associated weights for each firm as described in Section 5.B. Column 6 shows that exporting through a foreign parent is associated with more process innovation

[34] Consistent with the idea that foreign firms provide market access to exporting subsidiary firms in our data, Artopoulos, Friel and Hallak (2011) document that firms with knowledge of business practices in foreign markets are more successful exporters. We argue that foreign firms can provide that knowledge.

[35] We find no evidence that exporting through a foreign parent leads to the introduction of new machines or new organizational practices separately (results unreported).

(Column 6a) and, in particular, with innovation that involves the simultaneous introduction of new machines and new organizational practices (Column 6b). This result holds when controlling for lagged foreign ownership (Column 7), exporting status, and their interaction, and industry time trends (Column 8).

Table 6 shows the effect of market access through the foreign parent on product innovation and the assimilation of foreign technologies. Using both the fixed effects and the propensity score estimator, we find that exporting via a foreign parent leads to more product innovation and the assimilation of foreign technologies. These results shed light on those in Table 3, where we found a statistically weaker relationship between foreign ownership and these two variables. Once we distinguish between foreign-owned firms that export via a foreign parent and those that do not, we see that those that use the parent as an export channel also invest in new products and assimilate new foreign technologies.

Insert Table 6 around here

Taken together, these results imply that when firms are acquired by a foreign parent, they increase innovation, especially when the parent firm provides access to export markets. The observed relationship between market access and innovation activity offers further support for the mechanism outlined in the model, as it highlights the role for market access as a driver of innovation decisions. It also indicates that market access can be a sufficient reason for acquisition (even when foreign and domestic firms face similar variable innovation costs) when larger market access increases the potential benefits from investment activity. Furthermore, to the extent that there is persistence in market access, it provides a rationale for persistent productivity differences among firms.

D. Exports and Wages

Finally, in Table 7, we show other changes that take place within firms as a consequence of foreign ownership. We study how the share of exports in total sales (Panel A), the logarithm

of total exports for exporters (Panel B) and the logarithm of average firm wage (computed as the total wage bill divided by the number of employees, Panel C) change with foreign acquisition. Columns 1 through 4 show the equal-weighted fixed-effects specification, and Column 5 shows the propensity score reweighted results.

Insert Table 7 around here

We find that the proportion of exports in total sales increases significantly following foreign acquisition. The propensity score estimate in Column 5a shows that the share of exports is, on average, 6.7 percentage points higher in each year for acquired firms than for similar firms that are not acquired. The fact that the sales increase is disproportionately large in foreign markets is consistent with subsidiaries having increased access to these markets after acquisition. We also find that the volume of exports for exporters is 33-percent higher for exporters under foreign ownership (Column 5b). Finally, Panel C provides some suggestive evidence of average wages increasing upon acquisition, although this is not statistically significant. While this could mean that firms are increasing their wages and/or upgrading the skill of the workforce, we cannot distinguish between these possibilities with the available data.

6 Foreign Ownership and Productivity Evolution

Section 4.B showed that there is positive selection of target firms by foreign multinationals; and Section 5.B established that, upon acquisition, firms upgrade their technology by doing more process innovation and, in particular, by investing simultaneously in new machines and new methods to organize production. Now, we investigate the effect of acquisition on firm productivity directly, as well as its consequences for the evolution of the distribution of productivity within industries.

Under the assumption that the investment activities described above are, indeed, productivity-enhancing, we predict that the increased levels of these activities upon acquisition lead to higher productivity for acquired firms. Figures 4 and 5 illustrate our basic productivity results. Figure 4 shows the distribution of firm productivity in the base year, and four years after that, for firms that are domestic in that first year but will be foreign-owned four years later. The distribution is shifted to the right, indicating that productivity increased for acquired firms after acquisition over the whole distribution of firm initial productivity. Figure 5 shows the distribution of productivity in the base year and four years later for firms that remained domestic. While there is a slight increase in productivity, it is much less pronounced than for foreign-acquired firms.

Insert Figure 4 around here

Table 8 shows the results of estimating equation (6) with our measures of productivity as the dependent variable. Column 1 in Panels A and B (for each productivity measure) estimates equation (6) without firm fixed effects; Columns 2, 3, 4 and 5, progressively add firm fixed effects, industry trends, further selection controls, and lead and contemporaneous indicators of acquisition. Column 6 shows the propensity score reweighting estimates.

Insert Table 8 around here

The point estimates are much larger in the cross-sectional estimation of Column 1 relative to any of the other columns that include fixed effects and better control for selection using the propensity score. This reflects the fact that the positive selection identified earlier will lead to substantial over-estimation of the productivity advantage in cross-sectional analysis (as also demonstrated by Criscuolo and Martin, 2009)—by as much as three times in the case of labor productivity. However, we also find that acquisition is significantly positively associated with increased productivity, controlling for selection. The propensity score reweighted

specifications in Column 6 imply that, after acquisition, real sales increase by 18 percent and labor productivity by 11 percent, on average.[36]

Finally, we discuss the implications of our findings for the evolution of the distribution of productivity within industries. We show that foreign firms are more likely to acquire the most productive firms within industries (Table 2), and that, upon acquisition, firms innovate (Table 3), increasing productivity (Table 8). This set of results implies that acquisition activity can lead to an increase in the dispersion of the productivity distribution. This is an important consequence of our earlier findings since it has implications for the evolution of within-industry productivity distributions as more foreign firms enter an industry. Under this mechanism, foreign entry does not lead to productivity convergence, but, on the contrary, could lead to further divergence.[37] Of course, there could be other reasons (such as spillover effects or other externalities) why multinational entry may improve less productive firms' productivity. However, the direct effect of the foreign acquisition process is an increase in productivity heterogeneity.

7 Conclusion

In this paper, we use rich and detailed data on Spanish manufacturing firms to establish that foreign firms acquire the best firms within industries ("cherry-picking"), but also invest more in a number of innovation activities upon acquisition. In particular, controlling for the selection effect, firms increase their process innovation, with the simultaneous introduction

[36] Unlike the measures of innovation activity, the productivity measures are based on reported revenues. There may be incentives to change how revenues are reported within a multinational by adjusting transfer prices, affecting domestic firms once acquired. For example, reported revenues could reflect removal of double marginalization upon integration. This effect could lead to a decline in revenues, but this is not present in the data. The multinational may also face incentives to misreport the location of profits for tax purposes. We expect this problem to be small, given relative Spanish tax rates.

[37] If multinational entry also serves to raise the threshold level of productivity at which firms exit the domestic market (as in Helpman et al., 2004), the lowest-productivity surviving firm in the distribution will have a higher productivity level. This general equilibrium effect will serve to offset the increase in dispersion described above.

of new machines and organizational practices. Acquired firms that export through their parent firm also report that they increase their product innovation and start to assimilate more foreign technologies.

We develop a simple model that illustrates how these two facts can be fundamentally related. The model relies on standard assumptions about production, firm heterogeneity, consumer demand and market competition (Helpman and Krugman, 1985; Melitz, 2003) and incorporates two well-known characteristics of multinational firms: Multinationals grant access to larger markets and/or have lower technology-implementation costs. Since the incentives for innovation and acquisition are increasing in initial productivity, the surplus created by the acquisition is also increasing in initial productivity. Therefore, foreign firms find it more profitable to acquire the most productive firms and to innovate more on acquisition.

The observed positive selection suggests that there are complementarities between innovation activity and the initial characteristics of the acquired firm that could go beyond any possible technological complementarity between firms with similar productivity levels. Our results also suggest a complementarity between market access and innovation. Taken together, these findings can explain a number of important facts: first, why more productive firms innovate more; second, why foreign firms acquire the most productive firms within industries; and third, why foreign-owned firms increase their innovation upon acquisition.[38] Our contribution is to illustrate the drivers of the innovation process and to highlight that superior or proprietary technologies from the parent firm are not necessary to generate the prediction that a given firm finds it optimal to invest more under foreign control than under domestic control.

In addition, the observed complementarity between market scale and innovation offers

[38] The paper does not address why a foreign firm chooses to enter via acquisition rather than through an arm's length relationship, the subject of a large literature. As discussed in Blonigen (2005), this decision is thought to hinge on the value of internalizing firm-specific assets. Note that the model predictions evaluated in the data in this paper hold even without contractual incompleteness around the technology transfer between different parts of the firm.

one explanation for why all firms do not imitate the practices of high productivity firms in the market and why productivity differences persist. To the best of our knowledge, we are the first to link market scale to the jointly determined acquisition outcomes and innovation incentives. Finally, while we focus on the multinational firm's acquisition choice, the economic mechanism we emphasize should also be relevant for purely domestic integration decisions when the acquirer facilitates access to larger markets.

Appendix

Insert Appendix Table A1 around here

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Figures and Tables

Figure 1: Productivity Growth as a Function of Initial Productivity

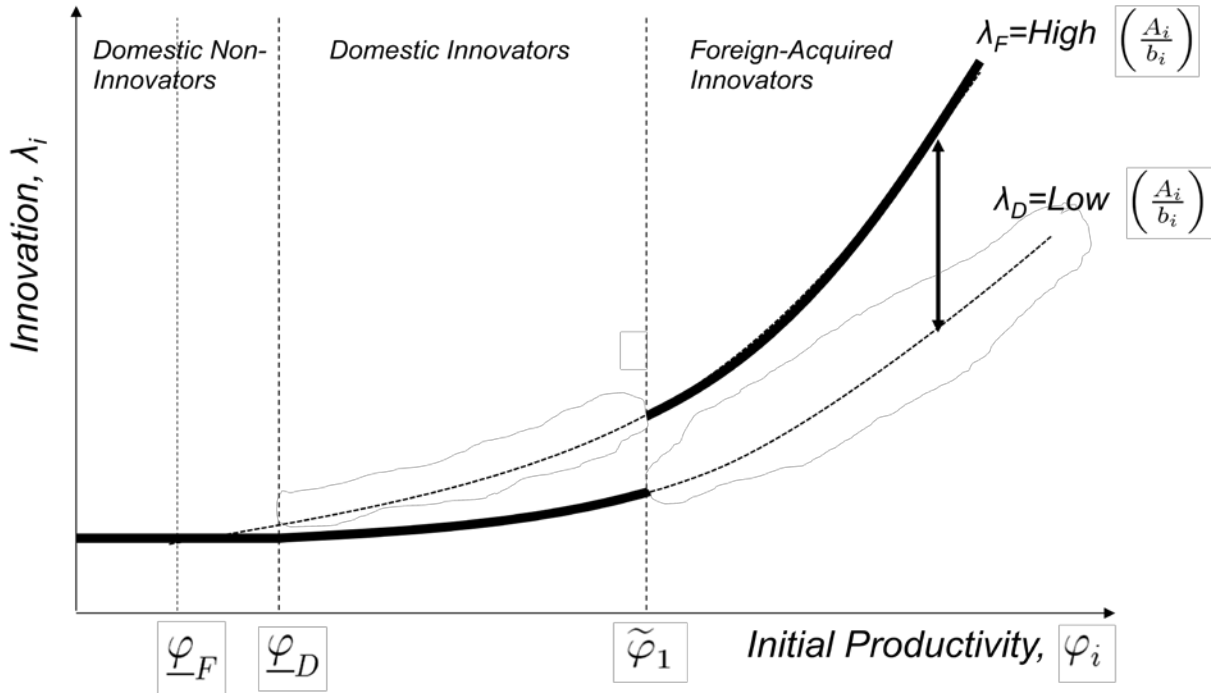
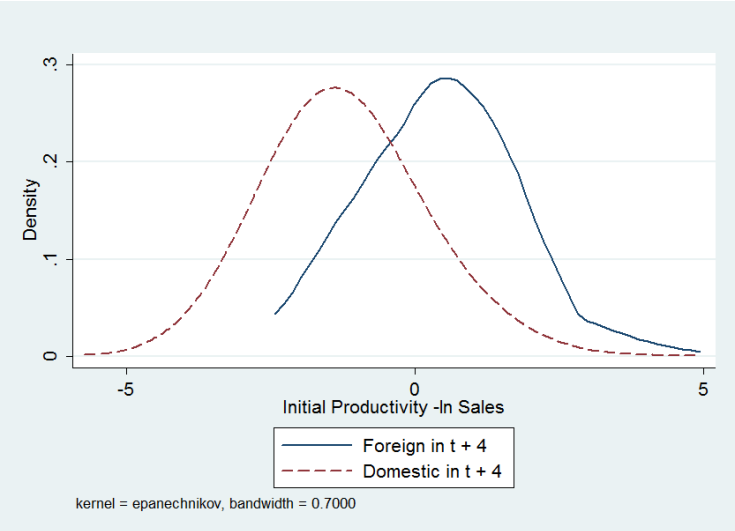
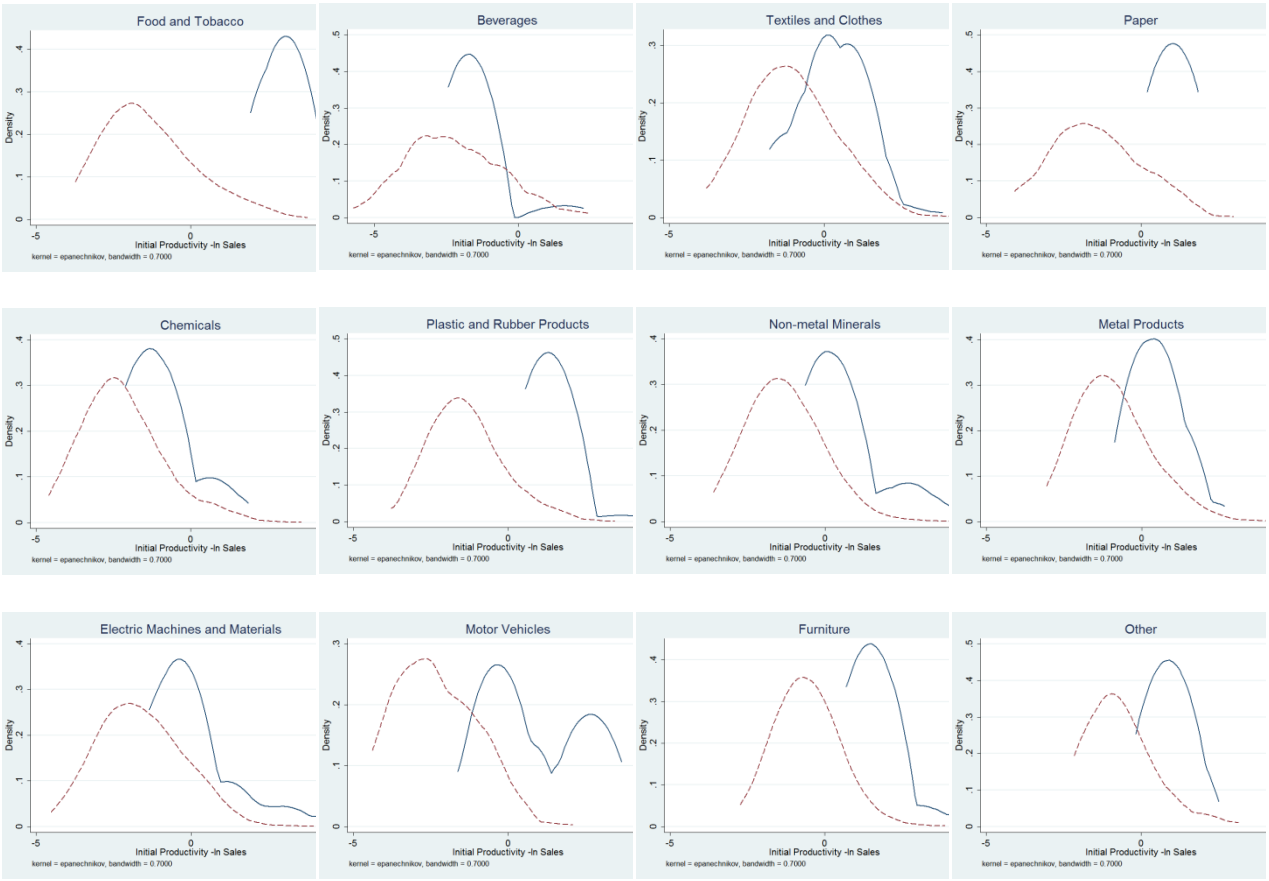


Figure 2: Distribution of Initial Productivity for Acquired and Non-Acquired Firms



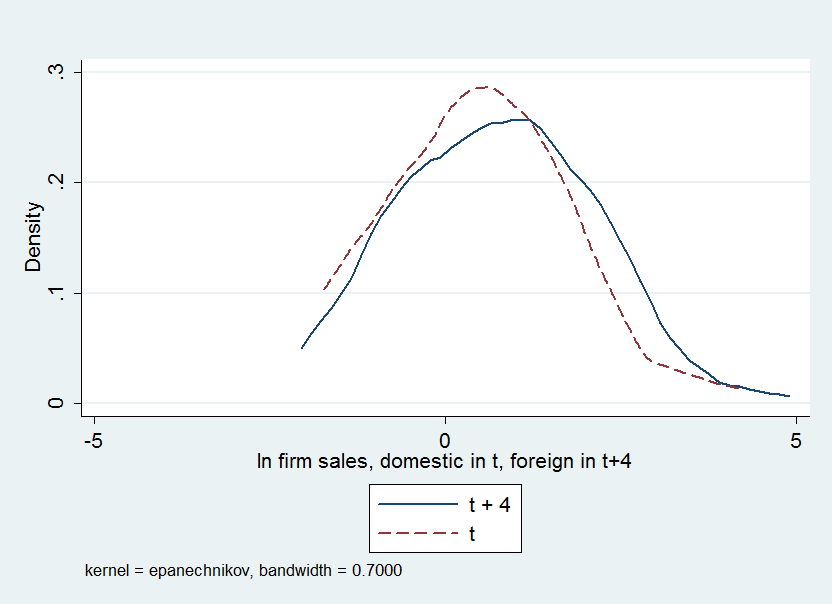
Note: The dashed line shows the empirical probability density function (pdf) of initial productivity (measured by ln sales demeaned by industry over the sample period) of firms that are domestic at time t and will stay domestic at time t+4. The bold line shows the empirical pdf of initial productivity of firms that are domestic at time t, but will become foreign-owned by time t+4.

Figure 3: Selection by Industry



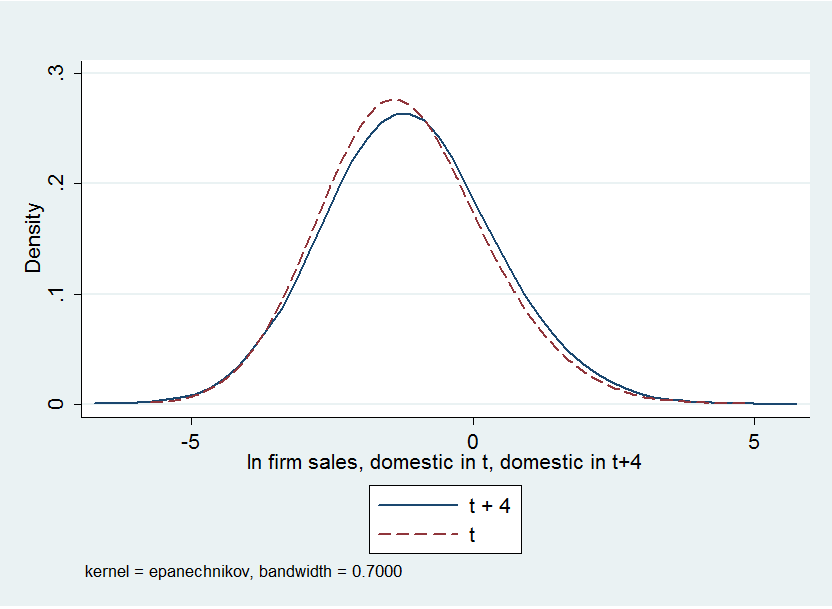
Note: This figure reproduces Figure 2 by industry.

Figure 4: Distribution of Productivity for Acquired Firms, Before and After the Foreign Acquisition



Note: The dashed line shows the empirical probability density function (pdf) of initial productivity (measured by log sales demeaned by industry) of firms that are domestic at time t, but will become foreign-owned by time t+4. The bold line shows the empirical pdf of productivity of these firms at time t+4 (i.e., after acquisition).

Figure 5: Distribution of Productivity for Non-Acquired Firms, Change over Four Years



Note: The dashed line shows the empirical probability density function (pdf) of initial productivity (measured by log sales demeaned by industry) of firms that are domestic at time t and will stay domestic at time t+4. The bold line shows the empirical pdf of productivity of these firms at time t+4.

Table 1. Descriptive Statistics

Variable	Mean	Std. deviation	N
Foreign	0.035	0.184	20896
Ln Sales	15.372	1.862	20845
Base year ln Sales (demeaned by industry)	-0.563	1.723	20845
Ln Labor productivity	10.399	0.680	20527
Base year ln Labor productivity (demeaned by industry)	-0.166	0.638	20203
Process Innovation	2.236	2.720	20896
Product Innovation	1.700	2.635	20896
Assimilation of Foreign Technologies	0.350	0.694	5555
New Machines	0.980	1.550	20896
New Methods of Organizing Production	0.305	0.773	20896
Both (new machines and new methods of organization)	0.837	1.677	20896
Export	0.530	0.499	20860
Export via foreign parent	0.016	0.125	5543
Exports/Sales	0.139	0.232	20803
Ln Exports	14.106	2.614	11024
Ln Average wage	10.029	0.447	20841

Notes: The sample includes the observations from all firms in the ESEE (1990-2006) that are not foreign-owned in their first year in the sample (potential acquisition targets). Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. Ln Sales is the natural logarithm of the firm's real sales. Base year Ln Sales is the natural logarithm of the firm's real sales, relative to the industry mean, in the first year the firm appears in the sample. Ln Labor productivity is the natural logarithm of real value added per worker (where valued added is calculated by ESEE as the sum of sales plus change in inventory, less purchases and costs of goods sold). Base year Ln Labor productivity is the natural logarithm of real value added per worker, relative to the industry mean, in the first year the firm appears in the sample. Process Innovation, Product Innovation, Assimilation of Foreign Technologies, New Machines, New Methods of Organizing Production, and Both are all defined in a similar way, and reflect the stock of reported innovations of each type the firm has done during the sample period (see Sections 3 and 5 for more details). Export is an indicator variable that equals one if the firm exports any goods. Export via foreign parent is an indicator variable that equals one if the firm declares that it exports through a foreign parent. Exports/Sales is the share of exports over total sales. Ln Exports is the natural logarithm of real exports. Ln Average wage is the natural logarithm of the real total wage bill per worker. All real variables are in 2006 euros (deflated using the equipment deflator for inputs into production function and the industry-level producer price index, Indice de Precios Industriales, for final goods).

Table 2. The Selection Decision: Linear Probability Specification

Productivity Measure			**Ln Sales**			**Ln Labor Productivity**
Panel A: The probability of being acquired during the sample period	1a	2a	3a	4a	5a	6a
Base year productivity	0.0351***		0.0279***	0.0300***		0.0222***
	(0.00303)		(0.00431)	(0.00548)		(0.00526)
2nd quartile Base year productivity		0.0331***			0.0282***	
		(0.00625)			(0.00873)	
3rd quartile Base year productivity		0.0478***			0.0323***	
		(0.00760)			(0.00894)	
4th quartile Base year productivity		0.148***			0.0577***	
		(0.0124)			(0.0104)	
Exporting firm in base year			0.00816			0.0542***
			(0.0103)			(0.00828)
Exporting in base year*Base year productivity			0.0136**			-0.00204
			(0.00615)			(0.0126)
Observations	3402	3402	3402	3313	3313	3313
R-squared	0.093	0.087	0.095	0.029	0.029	0.044
Panel B: The probability of being acquired in a given year	1b	2b	3b	4b	5b	6b
Lagged productivity	0.00630***		0.00502***	0.00772***		0.00513***
	(0.000651)		(0.000916)	(0.00146)		(0.00150)
2nd quartile Lagged productivity		0.00449***			0.00276**	
		(0.00112)			(0.00135)	
3rd quartile Lagged productivity		0.0109***			0.00786***	
		(0.00176)			(0.00179)	
4th quartile Lagged productivity		0.0267***			0.0147***	
		(0.00276)			(0.00237)	
Lag Exporting firm			0.000618			0.00883***
			(0.00205)			(0.00158)
Lag Exporting firm*Lagged productivity			0.00202			0.000960
			(0.00128)			(0.00276)
Observations	20075	20075	20037	19745	19745	19707
R-squared	0.019	0.017	0.019	0.009	0.010	0.011
Industry FEs (both Panels) and year FEs and industry trends (in Panel B)	yes	yes	yes	yes	yes	yes

Notes: Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. Base year (lagged) ln Sales is the natural logarithm of firm's real sales, relative to the industry mean, in the first year the firm appears in the sample (one year prior to the dependent variable). Base year (lagged) labor productivity is the natural logarithm of real value added per worker, relative to the industry mean, in the first year the firm appears in the sample (one year prior to the dependent variable). Exporting firm in base year equals one if the firm was an exporter in the first year it appears in the sample. Lag Exporting firm equals one if the firm was an exporter the previous year. The first year the firm appears in the sample is dropped from all regressions. Panel B regressions condition on the firm being not foreign-owned in the previous year. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 3. Foreign Ownership and Innovation

			Process Innovation		
Panel A	1a	2a	3a	4a	5a
Lag Foreign	0.574***	0.419**	0.388*	0.411**	0.611**
	(0.190)	(0.180)	(0.223)	(0.172)	(0.244)
Foreign				0.0459	
				(0.109)	
Forward Foreign				0.0663	
				(0.149)	
Observations	20722	20671	14656	12767	17578
R-squared	0.499	0.527	0.529	0.534	0.532
P-value of test Lag Foreign = Forward Foreign				0.0476	
			Product Innovation		
Panel B	1b	2b	3b	4b	5b
Lag Foreign	0.387*	0.293	0.0718	0.219	0.227
	(0.205)	(0.202)	(0.234)	(0.181)	(0.281)
Foreign				-0.0914	
				(0.113)	
Forward Foreign				-0.0416	
				(0.162)	
Observations	20722	20671	14656	12767	17578
R-squared	0.368	0.410	0.406	0.412	0.399
P-value of test Lag Foreign = Forward Foreign				0.150	
			Assimilation of Foreign Technologies		
Panel C	1c	2c	3c	4c	5c
Lag Foreign	0.144*	0.111	0.0565	-0.0318	0.123
	(0.0736)	(0.0705)	(0.0882)	(0.108)	(0.0817)
Foreign				0.151	
				(0.110)	
Forward Foreign				0.108	
				(0.0750)	
Observations	5434	5434	4100	2886	4348
R-squared	0.160	0.200	0.213	0.226	0.188
P-value of test Lag Foreign = Forward Foreign				0.258	
Firm FEs	yes	yes	yes	yes	yes
Industry trends		yes	yes	yes	
Selection controls			yes	yes	
Propensity score weighting					yes

Notes: Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. The dependent variables are our measures of innovation (see Section 3 for details). Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status, lagged average wage, lagged ln capital per employee, lagged ln capital. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 4. Foreign Ownership and Innovation: New Machines and New Methods of Organizing Production

	Both (new machines and new methods of organizing production)				
Panel A	1a	2a	3a	4a	5a
Lag Foreign	0.430***	0.360**	0.297*	0.321**	0.416**
	(0.156)	(0.144)	(0.159)	(0.136)	(0.209)
Foreign				0.0601	
				(0.0700)	
Forward Foreign				0.0591	
				(0.0968)	
Observations	20722	20671	14656	12767	17578
R-squared	0.244	0.296	0.298	0.299	0.272
P-value of test Lag Foreign = Forward Foreign				0.0541	
	New Machines				
Panel B	1b	2b	3b	4b	5b
Lag Foreign	0.0273	-0.0126	0.0429	0.0346	-0.0193
	(0.0871)	(0.0891)	(0.118)	(0.0882)	(0.132)
Foreign				-0.0225	
				(0.0600)	
Forward Foreign				-0.0187	
				(0.0919)	
Observations	20722	20671	14656	12767	17578
R-squared	0.346	0.368	0.368	0.370	0.382
P-value of test Lag Foreign = Forward Foreign				0.610	
	New Methods of Organizing Production				
Panel C	1c	2c	3c	4c	5c
Lag Foreign	0.117	0.0710	0.0481	0.0554	0.214**
	(0.0995)	(0.0929)	(0.118)	(0.0777)	(0.0914)
Foreign				0.00836	
				(0.0643)	
Forward Foreign				0.0259	
				(0.0884)	
Observations	20722	20671	14656	12767	17578
R-squared	0.146	0.186	0.178	0.178	0.163
P-value of test Lag Foreign = Forward Foreign				0.669	
Firm FEs	yes	yes	yes	yes	yes
Industry trends		yes	yes	yes	
Selection controls			yes	yes	
Propensity score weighting					yes

Notes: Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. The dependent variables are our measures of innovation (see Section 3 for details). Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status, lagged average wage, lagged log capital per employee, lagged log capital. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 5. Access to Export Channel and Process Innovation: Evidence from Panel Data and Propensity Score Weighting

	Process Innovation							
Panel A	1a	2a	3a	4a	5a	6a	7a	8a
Export via foreign parent			0.617**	0.526*	0.869***	0.611**	0.623*	0.647**
			(0.287)	(0.273)	(0.303)	(0.271)	(0.318)	(0.289)
Export	0.172**	0.160**	0.201*	0.181	0.160			0.0803
	(0.0711)	(0.0715)	(0.112)	(0.111)	(0.119)			(0.138)
Lag Foreign		0.579***	0.350	0.262	0.608		0.573	1.376*
		(0.193)	(0.510)	(0.441)	(1.038)		(0.482)	(0.779)
Export*Lag Foreign			0.183	0.0752	-0.248			-1.150
			(0.562)	(0.496)	(1.026)			(0.816)
Observations	20860	20686	5422	5422	4096	4913	4839	4839
R-squared	0.498	0.500	0.482	0.513	0.543	0.514	0.520	0.552
	Both (new machines and new methods of organizing production)							
Panel B	1b	2b	3b	4b	5b	6b	7b	8b
Export via foreign parent			0.520**	0.429*	0.759***	0.515**	0.536**	0.516**
			(0.254)	(0.234)	(0.255)	(0.220)	(0.256)	(0.205)
Export	0.0508	0.0444	0.0894	0.0707	0.0279			-0.0304
	(0.0491)	(0.0492)	(0.0734)	(0.0700)	(0.0765)			(0.0922)
Lag Foreign		0.441***	-0.127	-0.218	-0.169		0.309	0.559
		(0.158)	(0.314)	(0.285)	(0.566)		(0.296)	(0.609)
Export*Lag Foreign			0.360	0.398	0.360			-0.395
			(0.367)	(0.338)	(0.577)			(0.635)
Observations	20860	20686	5422	5422	4096	4913	4839	4839
R-squared	0.243	0.244	0.235	0.288	0.317	0.274	0.277	0.357
Firm FEs	yes	yes	yes	yes	yes	yes	yes	yes
Industry trends				yes	yes			yes
Selection controls					yes			
Propensity score weighting						yes	yes	yes

Notes: Export is an indicator variable that equals one if the firm exports any goods. Export via foreign parent is an indicator variable that equals one if the firm declares that it exports through a foreign parent. Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. The dependent variables are our measures of innovation (see Section 3 for details). Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status, lagged average wage, lagged log capital per employee, lagged log capital. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 6. Access to Export Channel, Product Innovation and Assimilation of Foreign Technologies: Evidence from Panel Data and Propensity Score Weighting

	Product Innovation						
Panel A	1a	2a	3a	4a	5a	6a	7a
Export via foreign parent	0.503**	0.477*	0.775***	0.463**	0.655***	0.655***	0.690***
	(0.242)	(0.250)	(0.275)	(0.227)	(0.242)	(0.249)	(0.242)
Export	0.0297	0.0506	0.0391			-0.0744	-0.0422
	(0.105)	(0.0982)	(0.112)			(0.126)	(0.117)
Lag Foreign	-0.181	-0.239	-0.179		-0.206	-0.309	-0.248
	(0.290)	(0.253)	(0.451)		(0.384)	(0.319)	(0.295)
Export*Lag Foreign	0.250	0.179	-0.153			0.106	-0.116
	(0.398)	(0.378)	(0.514)			(0.334)	(0.314)
Observations	5422	5422	4096	4913	4839	4839	4839
R-squared	0.346	0.390	0.418	0.377	0.380	0.380	0.430
	Assimilation of Foreign Technologies						
Panel B	1b	2b	3b	4b	5b	6b	7b
Export via foreign parent	0.259***	0.241**	0.277**	0.187**	0.197*	0.204*	0.187**
	(0.0993)	(0.0970)	(0.115)	(0.0936)	(0.102)	(0.104)	(0.0938)
Export	0.0103	0.00820	0.0319			-0.00653	-0.00705
	(0.0219)	(0.0217)	(0.0243)			(0.0304)	(0.0284)
Lag Foreign	0.0769	0.0655	0.132		0.0477	0.221**	0.217
	(0.0600)	(0.0595)	(0.103)		(0.0890)	(0.110)	(0.137)
Export*Lag Foreign	0.00849	-0.0108	-0.159			-0.182	-0.217
	(0.0906)	(0.0890)	(0.118)			(0.127)	(0.151)
Observations	5410	5410	4096	4913	4839	4839	4839
R-squared	0.167	0.207	0.221	0.227	0.226	0.226	0.271
Firm FEs	yes	yes	yes	yes	yes	yes	yes
Industry trends		yes	yes				yes
Selection controls			yes				
Propensity score weighting				yes	yes	yes	yes

Notes: Export is an indicator variable that equals one if the firm exports any goods. Export via foreign parent is an indicator variable that equals one if the firm declares that it exports through a foreign parent. Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. The dependent variables are our measures of innovation (see Section 3 for details). Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status, lagged average wage, lagged log capital per employee, lagged log capital. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 7. Foreign Ownership and Exports

			Exports/Sales		
Panel A	1a	2a	3a	4a	5a
Lag Foreign	0.0422***	0.0422***	0.0403**	0.0400**	0.0666***
	(0.0155)	(0.0155)	(0.0178)	(0.0159)	(0.0247)
Foreign				0.0121	
				(0.0187)	
Forward Foreign				0.0124	
				(0.0133)	
Observations	20630	20630	14658	12767	17550
R-squared	0.041	0.053	0.047	0.052	0.081
P-value of test Lag Foreign = Forward Foreign				0.0605	
			Ln Exports		
Panel B	1b	2b	3b	4b	5b
Lag Foreign	0.201*	0.204*	0.174	0.243*	0.333*
	(0.119)	(0.119)	(0.111)	(0.136)	(0.201)
Foreign				0.00395	
				(0.271)	
Forward Foreign				0.0840	
				(0.174)	
Observations	10907	10907	8020	7026	10058
R-squared	0.111	0.124	0.130	0.133	0.164
P-value of test Lag Foreign = Forward Foreign				0.266	
			Ln Average wage		
Panel C	1c	2c	3c	4c	5c
Lag Foreign	0.0238	0.0274*	0.0263	0.0312	0.0360
	(0.0152)	(0.0152)	(0.0189)	(0.0215)	(0.0251)
Foreign				-0.00502	
				(0.0170)	
Forward Foreign				-0.000806	
				(0.0180)	
Observations	20667	20667	14660	12771	17574
R-squared	0.211	0.215	0.209	0.204	0.245
P-value of test Lag Foreign = Forward Foreign				0.221	
Firm FEs	yes	yes	yes	yes	yes
Industry trends		yes	yes	yes	
Selection controls			yes	yes	
Propensity score weighting					yes

Notes: Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. Exports/Sales is the share of exports over total sales. Ln Exports is the natural logarithm of real exports. Ln Average wage is the natural logarithm of the real total wage bill per worker. Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status (dropped for Exports/Sales and Ln Exports), lagged average wage (dropped for Ln Average wage), lagged log capital per employee, lagged log capital. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 8. Foreign Ownership and Firm Productivity

			Ln Sales			
Panel A	1a	2a	3a	4a	5a	6a
Lag Foreign	2.042***	0.165***	0.120**	0.112*	0.0700*	0.182***
	(0.161)	(0.0621)	(0.0599)	(0.0582)	(0.0421)	(0.0540)
Foreign					0.0629	
					(0.0404)	
Forward Foreign					-0.0104	
					(0.0646)	
Observations	20671	20671	20671	16867	14760	17578
R-squared	0.169	0.100	0.147	0.275	0.284	0.130
P-value of test Lag Foreign = Forward Foreign					0.211	
			Ln Labor Productivity			
Panel B	1b	2b	3b	4b	5b	6b
Lag Foreign	0.367***	0.126***	0.109**	0.0877	0.109**	0.114**
	(0.0496)	(0.0466)	(0.0449)	(0.0538)	(0.0425)	(0.0487)
Foreign					0.0571	
					(0.0390)	
Forward Foreign					-0.0218	
					(0.0425)	
Observations	20359	20359	20359	16639	14567	17338
R-squared	0.185	0.014	0.031	0.029	0.035	0.016
P-value of test Lag Foreign = Forward Foreign					0.0119	
Firm FEs		yes	yes	yes	yes	yes
Industry FEs	yes					
Industry trends			yes	yes	yes	
Selection controls				yes	yes	
Propensity score weighting						yes

Notes: Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. Ln Sales is the natural logarithm of the firm's real sales. Ln Labor productivity is the natural logarithm of real value added per worker. Selection controls include lagged export status, lagged average wage, lagged log capital per employee, lagged log capital. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Appendix Table A1. Foreign Ownership and Innovation: First Differences Specification

	Process Innovation		Product Innovation		Both (new machines and new methods of organizing production)	
	1	2	3	4	5	6
Lag Foreign (t-1)	0.119***	0.195***	0.0363	0.0907	0.0731*	0.148***
	(0.0460)	(0.0638)	(0.0411)	(0.0632)	(0.0376)	(0.0504)
2 Lag Foreign (t-2)	0.124**	0.168***	0.0228	0.0355	0.103**	0.124**
	(0.0499)	(0.0617)	(0.0425)	(0.0566)	(0.0409)	(0.0507)
3 Lag Foreign (t-3)	0.0938**	0.0678	0.100**	0.0909*	0.0934**	0.0869*
	(0.0412)	(0.0524)	(0.0400)	(0.0521)	(0.0371)	(0.0489)
Foreign (t)		0.0703		-0.0129		0.0818*
		(0.0642)		(0.0589)		(0.0450)
Forward Foreign (t+1)		0.0659		0.0358		0.0732*
		(0.0585)		(0.0510)		(0.0421)
2 Forward Foreign (t+2)		0.0341		-0.0247		0.0484
		(0.0467)		(0.0475)		(0.0377)
Observations	12,555	9,292	12,555	9,292	12,555	9,292
R-squared	0.038	0.037	0.048	0.050	0.033	0.034
Industry trends	yes	yes	yes	yes	yes	yes
Selection controls	yes	yes	yes	yes	yes	yes

Notes: All specifications are in first-differences. Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership in that year. The lags and leads of Foreign reflect the ownership indicator in different time periods. The dependent variables are our measures of innovation (see Section 3 for details). Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status, lagged average wage, lagged ln capital per employee, lagged ln capital. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Innovation and Foreign Ownership

Maria Guadalupe, Olga Kuzmina and Catherine Thomas

WEB APPENDIX: NOT FOR PUBLICATION

Table S1: Variable Definitions

Variable	Survey Question number	Question wording (highlighted as in the original questionnaire)
Foreign	A11	State whether there was some **foreign participation** in the company's capital, directly or indirectly (through a company in which over 50 percent of the capital is in foreign hands), and its percentage.
Process Innovation, New Machines, New Methods of Organizing Production, Both	E8	State whether the company introduced some important modification in the production process (**process innovation**). If so, state whether it consisted of: 1. Introduction of new machinery 2. New methods for organizing production 3. Both
Product Innovation	E7	State whether the company has undertaken **product innovations** (completely new products, or with such modifications that they are different from those produced earlier).
Assimilation of Foreign Technologies	E3_3	State whether the company carried out or contracted efforts for assimilating imported technologies.
Export via foreign parent	F3_3	State whether the company used each one of the following mechanisms as a way of gaining access to international markets: 1. It has its own resources (agents' network, branch, delegation or affiliated company) 2. It uses a parent company established abroad (companies with foreign capital) 3. It uses a specialized intermediary established in Spain 4. It participates in some kind of collective action for exporting (industry-wide export agreement, exporters' association or export cooperatives) 5. Other (specify)

Notes: Variable definitions are given as in the 2002 questionnaire, which is available at ftp://ftp.funep.es/ESEE/pet_extr/c-esee02.pdf. Firms are asked the same questions in other years.

Table S2. The Selection Decision: Probit Specification

Productivity Measure	Ln Sales			Ln Labor Productivity		
Panel A: The probability of being acquired during the sample period	1a	2a	3a	4a	5a	6a
Base year productivity	0.363***		0.414***	0.374***		0.584***
	(0.0248)		(0.0469)	(0.0662)		(0.100)
2nd quartile Base year productivity		0.997***			0.410***	
		(0.255)			(0.127)	
3rd quartile Base year productivity		1.234***			0.473***	
		(0.247)			(0.126)	
4th quartile Base year productivity		2.011***			0.684***	
		(0.239)			(0.123)	
Exporting firm in base year			0.128			0.619***
			(0.0983)			(0.0863)
Exporting in base year*Base year productivity			-0.0977*			-0.428***
			(0.0551)			(0.128)
Observations	3354	3354	3354	3265	3265	3265
Pseudo R-squared	0.222	0.213	0.225	0.0732	0.0730	0.121
Panel B: The probability of being acquired in a given year	1b	2b	3b	4b	5b	6b
Lagged productivity	0.277***		0.330***	0.355***		0.481***
	(0.0205)		(0.0377)	(0.0659)		(0.126)
2nd quartile Lagged productivity		0.588***			0.181*	
		(0.193)			(0.108)	
3rd quartile Lagged productivity		1.017***			0.463***	
		(0.183)			(0.0998)	
4th quartile Lagged productivity		1.460***			0.677***	
		(0.179)			(0.101)	
Lag Exporting firm			0.104			0.493***
			(0.0856)			(0.0786)
Lag Exporting firm*Lagged productivity			-0.0903**			-0.280*
			(0.0444)			(0.146)
Observations	19786	19786	19750	19457	19457	19421
Pseudo R-squared	0.174	0.161	0.173	0.0831	0.0924	0.108
Industry FEs (both Panels) and year FEs and industry trends (in Panel B)	yes	yes	yes	yes	yes	yes

Notes: Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. Base year (lagged) ln Sales is the natural logarithm of the firm's real sales, relative to the industry mean, in the first year the firm appears in the sample (one year prior to the dependent variable). Base year (lagged) labor productivity is the natural logarithm of real value added per worker, relative to the industry mean, in the first year the firm appears in the sample (one year prior to the dependent variable). Exporting firm in base year equals one if the firm was an exporter in the first year it appears in the sample. Lag Exporting firm equals one if the firm was an exporter the previous year. The first year the firm appears in the sample is dropped from all regressions. Panel B regressions condition on the firm being not foreign-owned in the previous year. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table S3: Productivity Regressions Including Innovation Variables

	Ln Value Added (1)	Ln Value Added (2)	Ln Value Added (3)
Ln Capital	0.102***	0.116***	0.116***
	(0.0131)	(0.0127)	(0.0231)
Ln Labor	0.723***	0.730***	0.759***
	(0.0285)	(0.0282)	(0.0542)
Process Innovation	0.0247***		
	(0.00315)		
Product Innovation		0.0197***	
		(0.00317)	
Assimilation of Foreign Technologies			0.0975***
			(0.0270)
Firm FEs	yes	yes	yes
Observations	19529	19529	5170
R-squared	0.261	0.258	0.292

Column 1 presents univariate probit regressions of the Foreign ownership dummy on the set of lagged variables used in the propensity score estimation, on all industries pooled (for the results shown in the paper, we estimate the propensity score by industry, to allow for different coefficients on the included variables). Column 2 presents the multivariate probit regression using the same variables, on all industries pooled. All regressions include industry dummies. The right-hand side variables are highly correlated, so that when we run the multivariate regression, many of them become insignificant. Note that lagged firm sales is the most significant determinant, consistent with our model. In the paper, the propensity score weights are obtained by estimating the multivariate regression for each industry separately. All regressors are balanced in all industries using the set of covariates in Column 2. When we used a more parsimonious specification, with fewer variables, some of the regressors were not balanced across blocks in some industries. These results are shown in Table S5, for a simpler specification of the propensity score.

Table S4: Probit model for propensity score estimation

	Foreign Univariate	Foreign Multivariate
	1	2
Lag ln sales	0.240***	0.180**
	(0.0245)	(0.0906)
Lag labor productivity	0.260***	-0.0987
	(0.0619)	(0.0840)
Lag Sales growth	-0.0990	-0.185
	(0.117)	(0.149)
Lag export status	0.498***	0.109
	(0.0889)	(0.108)
Lag average wage	6.20e-07	1.27e-07
	(3.77e-07)	(6.06e-07)
Lag Innovation	0.221***	0.0717
	(0.0752)	(0.0953)
Lag Stock of Innovation	0.0171	-0.0336*
	(0.0132)	(0.0200)
Lag ln capital	0.215***	0.0537
	(0.0217)	(0.0938)
Lag ln capital per worker	0.284***	0.0945
	(0.0389)	(0.0938)
Year		-0.0188
		(0.0115)
Industry FEs	yes	yes
Observations	15417	15417
Pseudo R-squared		0.151

This table re-estimates the propensity score regressions in the paper, using a parsimonious specification for the propensity score that includes only Lagged firm sales, Lagged labor productivity and year as controls when calculating the score. The score is again calculated by industry, to allow for differences across industries in the coefficients. In this case, the covariates are not balanced in some industries and blocks, which is why we chose a richer specification for the paper, where all covariates are balanced. However, as the table shows, the results are fairly robust when using this simpler specification for the score.

Table S5: Propensity score estimation when using only Lag Sales and Lag Labor Productivity in the score

	Process Innovation	Product Innovation	Assimilation of Foreign Technologies
Corresponding Col in Paper	Table 3 Col 5a	Table 3 Col 5b	Table 3 Col 5c
Lag Foreign	0.473**	0.142	0.0867
	(0.194)	(0.207)	(0.0577)
Observations	20545	20545	5406
R-squared	0.523	0.392	0.177
	Both	New Machines	New Organization
	Table 4 Col 5a	Table 4 Col 5b	Table 4 Col 5c
Lag Foreign	0.353**	-0.105	0.225**
	(0.154)	(0.0927)	(0.104)
Observations	20545	20545	20545
R-squared	0.266	0.372	0.153
	Exports/Sales	ln Exports	ln Average wage
	Table 7 Col 5a	Table 7 Col 5b	Table 7 Col 5c
Lag Foreign	0.0356	0.162	0.0426*
	(0.0252)	(0.178)	(0.0250)
Observations	20506	10808	20541
R-squared	0.066	0.140	0.240
	ln Sales	ln Labor Productivity	
	Table 8 Col 6a	Table 8 Col 6b	
Lag Foreign	0.124**	0.0596	
	(0.0532)	(0.0572)	
Observations	20545	20245	
R-squared	0.104	0.017	
Firm FEs	yes	yes	yes
Propensity score weighting	yes	yes	yes

Table S6. Foreign Ownership and Innovation: Restricted Sample

	Process Innovation			Both		
Panel A	1a	2a	3a	1a	2a	3a
Lag Foreign	0.564**	0.452**	0.446**	0.408**	0.366**	0.361**
	(0.229)	(0.211)	(0.226)	(0.193)	(0.166)	(0.170)
Observations	12,767	12,767	12,767	12,767	12,767	12,767
R-squared	0.485	0.516	0.534	0.230	0.290	0.299
	Product Innovation			New Machines		
Panel B	1b	2b	3b	1b	2b	3b
Lag Foreign	0.261	0.164	0.167	0.0400	0.0232	0.0201
	(0.245)	(0.234)	(0.238)	(0.105)	(0.111)	(0.116)
Observations	12,767	12,767	12,767	12,767	12,767	12,767
R-squared	0.359	0.406	0.412	0.329	0.349	0.370
	Assimilation of Foreign Technologies			New Methods of Organizing Production		
Panel C	1c	2c	3c	1c	2c	3c
Lag Foreign	0.146	0.0867	0.0898	0.116	0.0630	0.0648
	(0.100)	(0.0987)	(0.101)	(0.132)	(0.117)	(0.117)
Observations	2,886	2,886	2,886	12,767	12,767	12,767
R-squared	0.160	0.207	0.221	0.128	0.176	0.178
Firm FEs	yes	yes	yes	yes	yes	yes
Industry trends		yes	yes		yes	yes
Selection controls			yes			yes

Notes: Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. The dependent variables are our measures of innovation (see Section 3 for details). Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status, lagged average wage, lagged ln capital per employee, lagged ln capital. The sample includes only observations when contemporaneous and forward Foreign as well as all selection controls are non-missing, and coincides with the sample in column 4 of Tables 3 and 4, respectively. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table S7. Access to Export Channel and Innovation: Restricted Sample

	Process Innovation		Product Innovation	
Panel A	3a	4a	1a	2a
Export via foreign parent	0.954***	0.853***	0.815***	0.792***
	(0.304)	(0.288)	(0.260)	(0.271)
Export	0.209	0.198	0.0261	0.0627
	(0.129)	(0.129)	(0.121)	(0.115)
Lag Foreign	0.828	0.612	-0.134	-0.186
	(0.648)	(0.584)	(0.434)	(0.379)
Export*Lag Foreign	-0.237	-0.249	0.0415	-0.146
	(0.672)	(0.611)	(0.513)	(0.455)
Observations	4,096	4,096	4,096	4,096
R-squared	0.485	0.517	0.359	0.409

	Both		Assimilation of Foreign Technologies	
Panel B	3b	4b	1b	2b
Export via foreign parent	0.848***	0.752***	0.297**	0.282**
	(0.281)	(0.251)	(0.116)	(0.114)
Export	0.0809	0.0683	0.0245	0.0253
	(0.0821)	(0.0800)	(0.0257)	(0.0254)
Lag Foreign	0.0183	-0.146	0.149**	0.117
	(0.451)	(0.419)	(0.0725)	(0.0738)
Export*Lag Foreign	0.241	0.345	-0.132	-0.143
	(0.475)	(0.444)	(0.0975)	(0.0972)
Observations	4,096	4,096	4,096	4,096
R-squared	0.238	0.301	0.172	0.210
Firm FEs	yes	yes	yes	yes
Industry trends		yes		yes

Notes: Export is an indicator variable that equals one if the firm exports any goods. Export via foreign parent is an indicator variable that equals one if the firm declares that it exports through a foreign parent. Foreign is an indicator variable that equals one if the firm has at least 50-percent foreign ownership. The dependent variables are our measures of innovation (see Section 3 for details). Selection controls include lagged ln firm sales, lagged ln labor productivity, lagged sales growth, lagged export status, lagged average wage, lagged log capital per employee, lagged log capital. The sample includes only observations when all selection controls are non-missing, and coincides with the sample in columns 5 and 3 of Tables 5 and 6, respectively. All columns include year fixed effects. Standard errors are clustered by firm. * indicates 10% significance; ** 5% significance; *** 1% significance.

Capital Structure and Employment Contract Flexibility

Olga Kuzmina*

New Economic School

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Abstract

This paper uses a unique panel dataset to establish a causal relationship between the use of flexible contractual arrangements with labor and capital structure of the firm. Using the exogenous inter-temporal variation from government subsidies, I find that hiring more temporary workers leads firms to have more debt. Since temporary workers, unlike permanent ones, can be fired at a much lower cost during their contract duration, or their contracts may be not extended upon expiration, a firm can more easily meet its interest payments and avoid bankruptcy when faced with a negative shock. I interpret this result as evidence of flexible workforce decreasing operating leverage which, in turn, promotes financial leverage. The economic magnitude of the effect is large. A thought experiment of completely prohibiting an average firm from offering temporary employment contracts would suggest that it should reduce its debt level by 4.9 percentage points, which is about 8% of the average debt level across firms. Given the overwhelming extent of labor reforms in continental Europe in recent years that touch upon the incentives to use different employment contracts and are aimed at offering more job security to workers, it is important to understand how such policies would affect firms.

Keywords: Capital Structure, Fixed-term Contracts, Operating Leverage.

JEL codes: G32, J47, M55.

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1 Introduction

This paper studies how a firm's composition of contractual arrangements with its factors of production affects its capital structure. In an uncertain environment the option to adjust input costs after shocks have realized has value. Therefore, when a firm uses more flexible contract arrangements with its capital and labor, it has a higher ability to convert some of its fixed operating costs into variable costs and decrease the operating leverage ex post. The optimal level of overall risk that a firm is willing to tolerate defines the total amount of fixed costs that its variable cash flow can potentially cover, so that operating and financial leverage are substitutes (Mandelker and Rhee, 1984). Since the use of flexible contracting with factors of production reduces operating leverage, it should also be positively related to financial leverage.

This paper uses a unique panel dataset of manufacturing firms to establish the causal effect of a firm's use of different types of employment contracts on its capital structure. Importantly, it builds the identification strategy on the exogenous inter-temporal variation in the introduction of government subsidies that promoted one type of contractual arrangement (permanent employment contracts) at the expense of the other, more flexible one (temporary employment contracts). The differential implementation of these subsidies across regions, years, and types of workers allows me to identify this causal relationship in a quasi-experimental setting. To the best of my knowledge this is the first paper that measures the composition of employment contracts at the firm level, as well as provides evidence of its causal effect on capital structure.

The economic magnitude of this causal effect is quite large. A thought experiment of completely prohibiting an average firm from offering temporary employment contracts would suggest that such a firm should reduce its debt level by 4.9 percentage points, which is about 8% of the average debt level across firms. Given the overwhelming extent of labor reforms in continental Europe in recent years that touch upon the incentives to use different employment

contracts and are aimed at offering more job security to workers, it is important to understand how such policies would affect firms. If firms cannot hire the optimal number of temporary employees, they may be forced to reduce the levels of debt financing to suboptimal ones, which can potentially affect their long-run growth and survival.[1]

The high levels of temporary employment may also explain why firms in some countries have higher levels of debt than in others. Figure 1 plots the relationship between average firm leverage ratio and the proportion of workers on temporary contracts for European countries.[2] Based on this preliminary motivating evidence, it can be seen, for example, that approximately one sixth of the difference in average debt financing between countries like Germany and the U.K or three quarters of the difference between Finland and Spain is associated with the difference in their employment practices.

Although the mechanism described in this paper can be applied to various factors of production, it is harder to find a source of exogeneous variation in the flexibility of capital or technology itself to provide a causal evidence. It is also more natural to illustrate it in terms of labor, because for this factor of production there naturally exist two types of employment contracts that differ dramatically in terms of the employment flexibilty they provide – temporary contracts and permanent contracts. The main distinct feature of a temporary contract, which is particularly relevant for capital structure decisions, is a much lower firing cost as compared to a permanent contract. In the context of this paper, it is exactly the difference in firing costs across the two classes of contracts that matters for the choice of capital structure. Hiring workers under temporary contracts, as opposed to

[1] A large literature has explored the impact of labor policies (typically related to unionization), on firms' real decisions and outcomes, such as profitability and market values (Ruback and Zimmerman, 1984, Abowd, 1989, and Hirsch, 1991), cost of equity (Chen, Kacperczyk and Ortiz-Molina, 2009), innovation (Acharya, Baghai and Subramanian, 2010). Besley and Burgess (2004) also investigate how pro-worker regulation is related to investment and economic growth. My paper, in constrast, looks at the effect of temporary employment per se, rather than that of the union-level bargaining.

[2] This figure is based on the firm-level data from Amadeus largest firms database and the country-level data from OECD.StatExtracts, for 1997-2010. The blue line plots the corresponding linear fit. The cross-country regression estimates are very similar to the causal IV estimates obtained in the main body of the paper.

permanent ones, allows firms to adjust their labor force, and hence labor costs, and profit or project returns faster and more cheaply when responding to idiosyncratic shocks. For example, upon a realization of an adverse shock to their cash flows or business conditions in general, firms may easily fire some of the workers on temporary contracts and still be able to meet their debt obligations.[3]

More precisely, when a negative shock occurs, workers become less productive in general, so that absent firing costs it may be optimal to reduce employment and save on fixed labor costs (wages). In the presence of large firing costs, however, firms may choose to hoard labor to save on the firing costs, instead. The two types of employment contract illustrate these two possibilities. When workers are hired under a temporary arrangement, they do not have to be kept in place when negative shocks realize, since there is practically no firing cost associated with this type of contract. The employment flexibility provided by temporary employment effectively reduces the ex post variability of firm's cash flow, and decreases the probability of bankruptcy for any given level of debt servicing obligations, which are a fixed expense. A lower bankruptcy probability enhances the debt capacity of firms and enables them to support a higher level of debt that may be otherwise advantageous due to different considerations, such as the tax shield it provides (DeAngelo and Masulis, 1980), a reduction in the free cash flow that is available for overinvestment by managers as in Stulz (1990), etc.

This mechanism may be further interpreted as a substitution between operating and financial leverage. Flexible temporary employment decreases the operating leverage of the firm by making the labor cost more variable, thereby increasing the capacity of the firm to bear fixed costs and promoting financial leverage, while sustaining the same level of risk.[4]

[3]Fired workers are still paid the wages for the work already accomplished. However, there is no obligation to keep them further employed and pay future wages.

[4]For the operating vs financial leverage story to work it must be the case that wages are senior to debt repayments, since otherwise they can be abandoned when bankruptcy becomes a concern, so that hiring temporary vs permanent workers does not make a difference in terms of shifting the bankruptcy threshold. Indeed, in Spain, which is the country which I study in my empirical analysis, wages are senior claims to non-collaterized debt.

Indeed, I find empirical evidence for such a substitution. When firm's employment structure is more flexible, i.e. it hires more temporary workers, it also uses more debt financing. This result is robust to accounting for unobserved time-invariant firm heterogeneity, firm-level controls, and macroeconomic effects. Furthermore, the use of an exogenous shock resulting from a government program promoting less flexible permanent employment at the expense of a more flexible temporary one, enables me to interpret the relationship between employment flexibility and capital structure as a causal one. To the best of my knowledge, this is the first paper to provide evidence of a causal relationship between employment flexibility and debt financing. In my empirical analysis I further discuss how my results are robust to alternative stories.

One may ask why firms can ever find it optimal to hire workers under permanent contracts, given the increased flexibility that comes with temporary employment and the observation that temporary employees (especially those hired under a particular type of temporary contract – fixed-term employment contract) often perform the same job within a firm as permanent employees (Jimeno and Toharia, 1994, for Spain – the country with one of the highest levels of temporary employment). The research on job security and worker productivity has shown that workers hired under temporary contracts may pose hidden costs on the firm, for example have more job accidents (Guadalupe, 2003) or be less productive in general (as modeled by Blanchard and Landier, 2002, and Caggese and Cu$\widetilde{n}$at, 2008). Hence, the benefit of a temporary employee in terms of giving firms the flexibility in bad states of the world may come at a cost of producing less in good states of the world.

In the light of a potentially lower productivity of temporary workers, it is interesting to explore for which firms the value of temporary employees is higher. One may think of temporary employment contract as embedding an option to fire workers, where the price of that option comes from their lower productivity. Intuitively, such option should be most valuable for firms for which bankruptcy cost is higher, for example for firms with a low liquidation value of assets. These firms can benefit most from temporary employees in terms

of relaxing the implicit borrowing constraint and enabling them to support a higher level of debt. Indeed, consistent with this logic my empirical results suggest that the positive relationship between flexible employment and debt financing is mostly pronounced within firms with low liquidation value of assets.

A dual labor market consisting of workers characterized by different degrees of job security exists in virtually all countries, either informally (with "under-the-table" payments) or formally (with differential legal contract arrangements with employees). One particular country that provides an excellent opportunity to study the effects of employment flexibility on financing decisions of firms, is Spain. Not only it has a formal dual market with an extraordinary level of temporary employment (24% of all salaried workers as of 2010[5]), which has been the highest among the OECD countries (OECD, 2002), but the difference in firing costs across the two types of contracts is quite dramatic.

When a temporary worker is dismissed (or when a fixed-term contract worker is not converted into a permanent one at the end of the three-year maximum tenure) a firm pays only up to 12 days' wages in severance payments as opposed to up to 45 days' wages for permanent workers (Jimeno and Toharia, 1994). Since both are per year of seniority, the effect is further amplified by the observation that a permanent worker is more likely to have worked for a longer time in the firm (given the three-year legal limit for workers on fixed-term and apprenticeship contracts and the short nature of contracts for temporary jobs), hence the cost differential in absolute terms is even bigger. Moreover, firing a permanent worker may involve a court procedure with substantial administrative costs, while a temporary worker does not have the right to sue her employer for dismissal. Finally, a firm may simply choose not to prolong the fixed-term contract upon expiration and anecdotal evidence suggests that fixed-term contracts with some employees are renewed every week. In this case employment and total wage bill for the next period can be adjusted at zero cost almost immediately.

[5] *Encuesta de Población Activa* 2010 (Economically Active Population Survey), conducted quarterly by the National Institute of Statistics (INE).

The origin of such a dual labor market in Spain lies in the 1984 reform which recognized the need for flexibility in the labor market by largely extending the applicability of temporary employment contracts. As a result, their use quickly rose up to 35% in 1995[6]. Empirical evidence for some of the European countries[7] suggests that such dualism in the labor market may have negative effects on the economy. Indeed in the late 1990s the Spanish government partially reversed the employment liberalization policy by introducing subsidies to firms for converting existing temporary workers into permanent employees and for hiring new workers on permanent contracts. Because these subsidies were implemented differentially across regions, years and had different eligibility criteria for workers, this institutional framework gives an opportunity to study the causal effect of a firm's composition of labor contracts on its financing decisions. At the same time I am able to use the panel structure of the dataset to control for any unobserved time-invariant characteristics of the firm that may influence its financing policy. The combination of these identification strategies allows me to evaluate the causal effect of a firm's use of temporary employment contracts on its capital structure in a quasi-experimental setting. This effect is economically large and suggests that labor policy has significant implications on capital structure of firms.

My paper also relates to the research on the interactions between corporate finance and labor economics that has recently attracted some attention (see a survey by Pagano and Volpin, 2008). Firms may choose more conservative financial policies in order to mitigate the workers' exposure to unemployment risk (Agrawal and Matsa, 2010), or in order to induce employees to invest more in firm-specific capital which would be lost in case of bankruptcy (Butt Jaggia and Thakor, 1994, and Berk, Stanton and Zechner, 2010). One particular question that has been explored in the labor-finance literature is the strategic effect of debt financing when workers are unionized (Perotti and Spier, 1993; Matsa, 2010; Simintzi, Vig

[6] *Encuesta de Población Activa* 1995.

[7] Blanchard and Landier (2002) for France; a survey by Dolado, García-Serrano and Jimeno (2002) for Spain.

and Volpin, 2010), suggesting that a firm may ex ante choose the level of debt in such a way as to preclude workers from bargaining over their wage ex post. In contrast to these bargaining models, in my model flexibility comes from the type of employment contract offered, rather than from firms facing less unionized labor. I believe that my empirical setup allows to illustrate the importance of labor contract type per se for capital structure decisions, by filtering out potential bargaining effects due to the special bargaining environment in Spain, and hence provides for a different causal relationship. The contribution of my paper is thus to give evidence of a new mechanism affecting capital structure decisions of firms – the use of more flexible contractual arrangements with the labor force, and potentially more generally with other factors of production.

Finally, my paper contributes to the empirical literature examining the relation between various real flexibilities and financial structure. Mauer and Triantis (1994) use numerical analysis to suggest that production flexibilities of firms can enhance their debt capacity. Petersen (1994) examines the role of operating leverage in the firm's pension choice. In particular, he finds that the probability of a firm choosing a more flexible defined contribution plan, rather than a less flexible defined benefit plan, is higher on average for firms with more variable cash flows. He interprets this result as firms effectively reducing their operating leverage by selecting a defined contribution plan, which can also be related to financial leverage. Hanka (1998) explores employment decisions in U.S. firms and finds that having more debt is correlated with reducing firm employment more heavily and relying more on part-time labor force. His conjecture is that this may be due to higher incentives of firms to make labor costs variable rather than fixed. MacKay (2003) shows that investment flexibility in workforce, estimated by the ratio of actual to shadow rents of the workforce input, is positively associated with leverage ratios. In contrast to these papers, I can directly observe the employment flexibilty at the firm level, as measured by the composition of different employment contracts, and use an exogenous shock to such a composition to establish a causal effect of firm employment flexibility on capital structure.

The rest of the paper proceeds as follows: Section 2 describes the data and defines the variables; Section 3 presents the empirical strategy and main results; Section 4 provides additional evidence and discusses the results of the paper in the light of other theories; Section 5 concludes.

2 Data Description and Variables Definition

The main results in this paper are based on three sets of data. I combine firm-level data with the regional data on subsidies to promote permanent employment contracts, with industry-level data on the composition of workforce.

The firm-level data come from the *Encuesta sobre Estrategias Empresariales* (ESEE), spanning the years from 1994 to 2006. This is a panel dataset of Spanish manufacturing firms collected by the Fundación SEPI (a non-government organization) and the Spanish Ministry of Industry. It is designed to be representative of the population of Spanish manufacturing firms and includes on average 1,700 firms per year. The response rate in the survey is 80% to 100% across years and, when firms disappear over time due to attrition, new firms are re-sampled to ensure the panel remains representative.[8]

This is also a unique dataset in that it contains information on both private and public firms. 14% of firms that enter the data with more than 200 employees will at some point trade on an exchange. Among smaller firms this percentage is less than 1%. Firms in the sample represent all 17 regions (autonomous communities) and 2-digit NACE industries.

Following the literature, I use Total Debt / Total Assets as a measure of leverage. Total Debt is defined as the sum of short-term and long-term liabilities, Total Assets is the book value of assets, also equal to the sum of Total Debt and Book Equity. As reported in Table 1, around 57% of firm financing comes from debt. Although the survey is anonymous and

[8]Details on the survey characteristics and data access guidelines can be obtained at http://www.funep.es/esee/sp/sinfo_que_es.asp.

the data cannot be matched to market values, this does not pose a problem given that the vast majority of firms are private and such data would not exist by definition.

These data also contain information on the total number of employees and, remarkably, on the proportion of workers on temporary contracts (both measured at the end of the year), which allows me to measure the flexibility of employment contracts at the firm level across years. 269 employees work in an average firm, and 24% of them have temporary contracts in the year the firm enters the data (this percentage is lower in later years, in particular due to the subsidies promoting permanent employment implemented by the government). Firm size, measured as the natural logarithm of firm's real sales, is equal to 16, which corresponds to approximately 8.8mln 2006 Euros. On average, 72% of firms assets are tangible, as measured by property, plant and equipment minus depreciation and amortization over property, plant and equipment plus intangible and financial assets minus depreciation and amortization.[9] Average profitability, measured by firm's operating profit margin (which is defined as the ratio of sales net of purchases and labor expenses to sales), is equal to 23%. To proxy for growth opportunities I also measure research and development intensity defined as the ratio of R&D expenditures over sales. These variables are typically found to be determinants of capital structure choice (Titman and Wessels, 1988) and will be used as firm control variables in the analysis.

All firms report the location of their industrial plants (85% of firms have just one plant; additional 6% of firms have two or more plants with the two main plants in the same region). Hence, I am able to merge the firm-level data with the data on regional subsidies promoting permanent employment. For firms with more than one plant I merge at the region of the main plant. These subsidies (García Pérez and Rebollo Sanz, 2009) were implemented differentially in various regions of the country. In particular, the time of implementation was different:

[9] Unfortunately, the data on the asset side of the balance sheet is not as detailed. The survey only records total value of depreciation and amortization. Given that fixed assets generally depreciate more, I have allocated total depreciation and amortization to property, plant and equipment. The results are robust to allocating it proportionally to gross tangible and intangible assets.

some regions introduced them in 1997 onwards, some only in certain years, while Catalonia did not introduce any regional-level subsidies during our sample period. Moreover, there is a considerable variation across regions and years in the amount of the subsidy (ranging from 1653 Euros per eligible employee in Baleares in 2000-2001 to more than 15000 Euros in Madrid in 2002), as well as the eligibility criteria by gender, age and other characteristics of employees. The maximum statutory amounts of subsidies introduced in different regions and years are summarized by gender in Table 2[10].

Finally, I use the data on intensities of the use of female and male employees in different manufacturing industries, as provided by the *Encuesta de Población Activa,* and merge them to the firm-level data. These gender intensities, measured as of the 4th quarter of 1993, are listed in Table 3.

3 Estimation Strategy and Main Results

In this section I provide the details of my estimation strategy and results. Before turning to the formal analysis, I first use the ESEE dataset to explore the relationship between the proportion of temporary employees and capital structure graphically. Figure 2 plots the averages of the two variables across different industries for the period from 1994 to 2006. As can be seen from this figure, the industries that employed larger proportions of temporary workers, such as Leather and Footwear or Timber, were also characterized by higher ratios of debt to assets than industries that employed relatively lower proportions of temporary labor force, such as Chemicals or Beverages.

Figure 3 plots the time-series relationship between the two variables and again a positive relationship can be deduced. One can notice a striking drop in the use of temporary labor

[10]Sometimes it was not clear what the maximum Euro value could be (e.g. Valencia in 1998-2000 offered subsidies as percentages of payroll tax). For these region-years I recorded a missing value. I also did a robustness check imputing values from total wage bill information that I have and the results were similar. Given that such imputation has to rely on additional assumptions, I opted to exclude such region-years from the main analysis.

force starting approximately in 1997. One of the possible explanations for this drop is the country-wide implementation of subsidies promoting permanent employment at the expense of the temporary one, which I further describe in Section 3.2 and use it to construct an instrumental variable. Interestingly, however, the drop in temporary employment was also accompanied by a fall in average debt to assets ratio.

Obviously, there may be various unobserved characteristics of industries or common macroeconomic factors that may show up as a positive relationship between temporary labor force and debt financing either across industries or across years. Therefore, I now turn to a more systematic firm-level analysis by employing the panel structure of the dataset and the exogenous variation arising from government labor programs to estimate the causal effect of the use of temporary employment contracts on capital structure, using fixed-effects and instrumental variable approaches.

3.1 Fixed-Effects Estimation

First, I estimate the effect of the use of temporary employment contracts on capital structure using the following specification:

$$D_{it} = \alpha_t + \gamma Temp_{it-1} + \beta X_{it-2} + \eta_i + \epsilon_{it} \tag{1}$$

where D_{it} is the ratio of total debt to assets, α_t are the year fixed-effects, $Temp_{it-1}$ is the proportion of temporary workers in the prior year[11], βX_{it-2} are firm-level control variables (size, tangibility, profitability and R&D expenditures, taken with a two-period lag[12]), and

[11] I have allowed for a one year lag in the independent variable, because it may take time for the firm to change its capital structure policy upon changes in employment policy, since these decisions are likely to be made by different divisions of the company. Empirically contemporaneous and lagged values of Temp are correlated, and the results are qualitatively similar to using contemporaneous values.

[12] For all my results I provide specifications with and without firm-level controls. In specifications with controls I lag all covariates by two years in order to avoid the "bad control" problem if the right-hand side variables are not truly exogenous and can themselves be outcome variables biasing the estimate of γ. I have also checked that results are robust to using contemporaneous values of these controls.

η_i are firm fixed-effects. Standard errors in all specifications are two-way clustered at the firm and region-year level (which provides conservative standard errors)[13].

The panel structure of the dataset allows me to control for any intrinsic unobservable differences firms may have with respect to their capital structure (for example, whether the firm has a more variable cash flow in general, whether it is a small business with a distrust in credit and banking, or whether its tasks generally require more human capital specificity), providing an opportunity to explore what drives within-firm changes in financing decisions. Including firm fixed effects allows me to control for any time-invariant observed and unobserved heterogeneity across firms. The results of fixed-effects estimation are reported in Table 4[14].

The coefficient in column 1 means that a one percentage point change in the proportion of workers on temporary contracts is associated with a 0.06 percentage points higher leverage ratio. I have also calculated the average within-firm standard deviation of proportion of temporary workers, which equals 0.11 in my data. Therefore, when a given firm changes its proportion of temporary workers by 1 standard deviation, it also increases its leverage by 0.62 percentage points.

I do a series of robustness checks to rule out concerns of spurious correlation. For example, column 2 reports results of a specification with region-year fixed effects. The results are similar and one can be sure that the differences in leverage ratios cannot be explained by firms potentially having differential access to credit over time driven by their location in more or less credit-abundant regions. Moreover, if there is generally more pressure from the society against firing workers in regions with higher unemployment rates and firms take more conservative debt policities there, region-year fixed effects will also capture such differences.

[13]The two-way clustered standard errors were obtained using the Schaffer (2010) xtivreg2 command in STATA.

[14]I provide the within R^2 coefficients in all specifications, so that the fit of the model can be interpreted on top of what can be accounted by the firm fixed effect. The corresponding adjusted R^2 (that include the explanatory power of firm fixed effects) are above 74% in all specifications.

It may also be the case that firms in certain industries in certain regions have been able to employ different proportions of temporary workers over time (due to e.g. trends in worker migration)

and at the same time raised debt at better terms. To refute such concerns and provide a more corroborative evidence, I include region-industry trend in column 3. Finally, to account for possible differences across industries in a flexible time-series framework, I have also added industry-year fixed effects to the specification (column 4). The identification becomes very tight in this case and rests on within-firm variation in temporary employment that cannot be explained by local region-year on industry-year attributes. The results are robust and significant at 1% significance level.

Columns 5 to 8 replicate the above specifications including firm-level control variables. Both the magnitude and the significance of the coefficient of interest stay similar, so that the observed differences in debt ratios cannot be explained by firms changing their tangibility or R&D expenditures over time, or growing and becoming more profitable.[15]

Although theoretically it may be possible that workers self-select into the type of contract depending on whether they are willing to invest in firm-specific capital which would be lost in case of bankruptcy (this would also show up as a positive correlation between the two variables of interest, consistent with the mechanisms outlined in Butt Jaggia and Thakor (1994) and Berk, Stanton and Zechner (2010)), practically it is not the case. Obtaining a permanent contract would be always preferred by the employee due to a higher wage and job security. Furthermore, the lag structure of the specification also mitigates such reverse causality concerns.

In general, however, firms may be subject to project substitution and risk-shifting problem. Given that temporary workers usually reflect non-specialized labor, firms with more

[15] I have also tried including accumulated profits during the previous 3 years, since firms are likely to pay out debt when they have had a positive shock to their cashflow. The results were similar and I opted to exclude this variable from the further analysis to keep more observations.

temporary workers may be able to alter the nature of their operations and specific tasks to be performed more easily. If firms employ temporary workers precisely in order to be able to take riskier projects, then firm creditors should rationally expect such project substitution and supply less debt. This unobserved risk-shifting behavior would show up as OLS coefficient being biased downwards.

In addition, as Caggese and Cuñat (2008) point out, firms that are financially constrained may generate a "demand for flexibility" and hire more temporary workers than firms that are not financially constrained. Then, if more financially contrained firms cannot get funding and are less levered, we may underestimate the true effect of temporary employment on capital structure. Therefore, it is important to use the exogenous variation in the proportion of temporary workers in order to uncover the magnitude of the causal effect of the use of flexible employment on debt financing of the firm, i.e. to make firms change their workforce compositions not due to potentially endogenous reasons, such as risk-shifting or financial constraints, but due to exogenous incentives, in my case provided by the government. Hence I proceed with the instrumental variable estimation.

3.2 Instrumental Variable Approach

Since I am able to directly observe the proportion of workers on temporary contracts, I do not have to rely on purely reduced form estimation (e.g. debt on employment laws), and can use government subsidies to construct an instrumental variable[16]. In this respect, Spain represents a unique opportunity to study the causal effect of temporary contracts on capital structure, because subsidies promoting permanent employment at the expense of temporary employment were introduced differentially in various regions of the country, depending on worker's exogenous characteristics (gender, age, etc). Hence, firms were affected differen-

[16]The reduced-form regression results (debt on subsidy), reported in Appendix Table 1, have predicted coefficient signs and are significant at conventional levels in most specifications. The estimates suggest that a 1000 Euro per-worker subsidy leads to 0.3-0.5 percentage point reduction in the debt to assets ratio.

tially depending on both the amount of subsidy in its region and on how many eligible temporary workers the firm had according to the region's criteria. To illustrate the source of identification, let's consider, for example, a firm located in the Baleares autonomous region. In 2000 such firm was eligible to get a one-time 1653 Euro subsidy for every female worker it converted from temporary to permanent contract. But if the firm did not employ women, this subsidy would not affect its proportion of temporary workers. Moreover, the more eligible workers a firm had (women in this case), the bigger was the overall benefit from the subsidy, and hence the incentive to substitute temporary workers with permanent employees. In other words, the more temporary workers the firm had originally, the lower would be the effect of a given level of subsidy on this firm and the lower the extent of the exogenous shift in firm's demand for temporary labor force. Hence, I can argue for the exogeneity of the following instrument: [17].

$$Subsidy_{it} = \sum_{g} w_{ig}^{T0} \cdot Subsidy_{grt} \tag{2}$$

where $Subsidy_{grt}$ is the maximum statutory subsidy allowed by the government in region r in year t for a worker of gender $g \in \{\text{female; male}\}$ (as summarized in Table 2 under "Maximum Subsidy"), and w_{ig}^{T0} is the firm-specific proportions of different types of temporary workers (which is held constant at the year the firm enters the data to avoid any endogenous gender substitution; that year is subsequently dropped from the estimation)[18].

Ideally I would like to observe the firm-specific workforce composition by gender, however the data allow me to see only the overall proportion of temporary workers (of both men and

[17] Autonomous regions introduced both subsidies for creating a new permanent contract and subsidies for converting an existing temporary contract into a permanent contract. However, the two types of subsidies were highly correlated and in many region-years identical. This makes me not differentiate across these two types of subsidies in my empirical analysis, so that I record one maximum subsidy value for each region-year-gender (the maximum across the two if they are different).

[18] I also tried to introduce one more layer of worker heterogeneity – age: $Subsidy_{it} = \sum_{ag} w_{iag}^{T0} \cdot Subsidy_{agrt}$, where workers are also characterized by their age cohort $a \in \{\text{less than 25; 25 to 30; 30 to 40; 40 to 45; 45 to 50; above 50}\}$. The results of the estimation were similar both qualitatively and quantitatively.

women), which is already an improvement upon many available datasets. In order to overcome this data limitation, I will use the industry-specific gender intensities (as summarized in Table 3) to proxy for firm-specific gender intensities in hiring temporary workers. As can be seen from Table 3, these industry-specific gender intensities provide a considerable variation. For example, more than three quarters of all employees in the "Apparel" industry are female, while only around 5% in the "Other transport equipment" industry. These ratios are quite stable over time at the industry level, but in order to mitigate any endogeneity concerns arising from the different eligibility criteria of subsidies and possible gender substitution within a firm, in the empirical analysis they are kept fixed at the pre-sample, 1993, year. Furthermore, the possible intrinsic differences in capital structures across industries, when industries happen to have different eligibility criteria due to their gender compositions, will be filtered out by the industry fixed effect (subsumed by the firm fixed effect in all specifications).

Hence I estimate equation (1), where I instrument the proportion of temporary workers with the lagged value of the following instrument[19]:

$$Subsidy_{it} = \sum_{g} w_i^{T0} w_{sg}^{0} \cdot Subsidy_{grt} \tag{3}$$

where w_{sg}^{0} is the industry-specific use of female and male employees, fixed at the pre-sample year (as summarized in Table 3), and w_i^{T0} is the firm-specific proportion of temporary workers at the year it enters the data (that year is subsequently dropped from the estimation). I have also deflated the subsidy amount using the industry-level producer price index to express it in real 2006 Euro amounts. This instrument hence calculates the actual total real Euro value of subsidies that a given firm would receive if it converted its temporary workers into permanent

[19] In some regions the subsidy is received in the year of the actual conversion, while in others it reduces the tax burden paid in the next year, hence there is no presumption on whether a lagged or contemporaneous value should be used. The lagged value is the one that is more significant in the reduced form estimation, however.

ones, per employee, and can be further described as an average wage bill reduction per employee (as summarized in Table 2 under "Maximum Subsidy per Employee" this average wage reduction on average amounted to 816 Euro). Although this variable implicitly assumes that all eligible workers would be converted this does not have to be true in reality for the instrument to work since we can also interpret it as as an intention-to-treat instrument. The regional level variable, $Subsidy_{grt}$, has been used in the literature on temporary employment in other contexts to instrument the worker's probability of being converted into a permanent employee on the worker-level data (Fernández-Kranz et al., 2010, Barceló and Villanueva, 2010). To the best of my knowledge my paper is the first one to construct the firm-specific subsidy from the regional data and use it as an instrument for the overall use of temporary contracts within a firm.

The results of the instrumental variable approach are presented in Table 5. It reports the same specifications as in the previous table and uses two-way clustering – by firm and by region-year – to account for both within-firm correlation and within-region-year correlation potentially arising from the same statutory subsidy amounts firms in general face in a given region-year. The results of the first stage are reported in Panel B. They suggest that a per-worker subsidy of 1000 Euro incentivizes a firm to reduce its proportion of temporary workers by 1.5 to 3.8 percentage points, depending on the specification. For each specification I also report the weak identification Kleibergen and Paap (2006) F-test statistic which exceeds the Stock and Yogo (2002) weak identification critical value for 5% maximal size distortion for 1 instrument and 1 endogenous regressor of 16.38 in all but one specifications, suggesting that my instrument is strong.[20] [21]

[20] The critical value for 10% maximal size distortion for 1 instrument and 1 endogenous regressor of 8.96, which is exceeded in all specifications. Stock and Yogo (2002) critical values are derived under the assumption of homoskedasticity and no autocorrelation, so that their comparison to Kleibergen and Paap (2006) F-statistic, which is robust to heteroskedasticity and within-cluster correlation, should be interpreted with caution, as suggested by Baum, Schaffer, and Stillman (2007).

[21] Adjusted R^2 has no statistical meaning for the IV specifications because a constant-only model of the dependent variable is not nested within the two-stage least-squares model, and the residual sum of squares is not constrained to be smaller than the total sum of squares. Hence, I do not report adjusted R^2 for IV

The coefficient in column 1 (0.207) means that a 1 standard deviation increase in the proportion of workers on temporary contracts leads to a 2.3 percentage points higher leverage ratio. This result is economically and statistically significant. In particular, such magnitude suggests that prohibiting an average firm from hiring temporary employees (i.e. reducing its proportion from 23.9% to 0%) would lead to a 4.9 percentage points reduction in debt level, i.e. about 8% of the average.

An important question to consider is why regions introduced subsidies in different years and in different amounts in the first place. It may be thought that in regions where firms had relatively more lobby power against converting cheaper temporary workers into more expensive permanent employees, the subsidies were introduced later and/or in bigger amounts. In order to address this concern I estimate a specification with region-year fixed effects (column 2). Such setup allows me to control for any potentially endogenous regional government choice based on the region characteristics in a given year. The coefficient magnitude becomes slightly smaller, but it is still statistically significant at 5% level.

A similar argument may apply to the industry lobbying in different regions. Hence, I saturate my specification by controlling for region-industry trends (column 3) as well as industry-year fixed effects (column 4). The coefficient of interest can still be identified because even within the same industry and region and year a firm with a higher original proportion of temporary workers can benefit relatively more from the same statutory level of subsidy per eligible temporary worker. Finally, I also include firm-level control variables. The results are very similar. Although, the coefficient in column 8 is only significant at 15% level, it can be mostly attributed to a relatively high standard error in the IV estimation, because its magnitude is the same as in the one without controls (column 4). [22]

specifications.

[22] The coefficient in column 8 is significant at 10% level when using the specification with contemporaneous instead of lagged2 controls (unreported).

4 Mechanisms and Robustness Tests

The results in this paper provide evidence of a positive causal relationship between the use of temporary employment contracts and financial leverage. In this section I will discuss these findings in the light of several existing theories of the interaction between labor characteristics and capital structure as well as provide additional results and robusness tests.

4.1 Liquidation Value Analysis

My intuition suggests that firms with higher bankruptcy costs should value the option to fire workers more and want to protect themselves from incurring these costs by hiring temporary workers. Therefore, I would like to empirically examine whether there are differential effects of having a flexible workforce on capital structure driven by the magnitude of potential bankruptcy costs. In order to do that I interact a measure of high liquidation value with the proportion of temporary workers, both in fixed-effects and IV frameworks. I classify a firm as having a high liquidation value if it has more buildings and land than the median industry firm in the year it enters the data. The results of these regressions are presented in Table 6.

Indeed, consistent with this intuition, the positive effect of having a flexible workforce is pronounced mostly within low liquidation value firms. The IV estimates in columns 5 to 8 suggest that for firms with low liquidation value a 1 standard deviation increase in the proportion of workers on temporary contracts leads to a 2.8 to 3.9 percentage points higher leverage ratio, depending on the specification. The difference between high and low liquidation value firms is statistically and economically significant. Although the point estimate for high liquidation value firms is still positive, it is not statistically different from zero (the 2-sided test statistics are reported for each specification). When bankruptcy is not a concern, and the firing option embedded into temporary employment contract has a low value, the relationship is supposed to be ambiguous, because of the counterbalancing effect of

a lower productivity. When flexibility is not valuable enough, hiring temporary workers may actually make firms take *less* debt because these workers are less productive and generate on average a lower cash flow.[23] Therefore, it is expected to find a positive relationship between employment flexibilty and debt financing only among the firms for which this flexibility matters, i.e. firms with a low liquidation value in my empirical setup.

It is also worth recalling that in a heterogeneous effects framework IV identifies a local average treatment effect which is a causal effect for a subpopulation of firms most affected by the instrument. In my setup it is likely that the most constrained firms in terms of the lower ability to convert temporary employees into permanent ones are those closest to bankruptcy, for which a low liquidation value is a potential measure. Given that I find a larger effect for these firms, this may provide for another reason why IV estimates are generally larger than those from panel specifications: the effect of interest is larger for the most constrained firms, i.e. those that convert temporary employees into permanent ones precisely because of the subsidy.

4.2 The Role of Bargaining

It has been argued that debt can serve as a strategic tool to preclude bargaining over wage in the context of unionized workers (Perotti and Spier, 1993; Matsa, 2010), so that a positive relation between bargaining power and debt financing is conjectured when debt is not renegotiable. Moreover, a recent paper by Simintzi, Vig, and Volpin (2010) suggests that when debt is renegotiable the opposite relation would obtain. I think the Spanish institutional environment allows me to claim that the results are robust to the collective bargaining story because its unique feature is that all workers irrespective of their contract type are covered by collective bargaining agreements, and the agreement a given firm faces does not discriminate

[23] Such a dichotomy is also consistent with the logic of Caggese and Cuñat (2008), who model the opposing effects of firm's "demand for flexibility" and "demand for productivity". They study the effect of financial constraints on flexible employment, while I explore the causal relationship of flexible employment on capital structure.

between workers based on their contract type.

Even if one thinks that the overall bargaining power of workers within a firm may be dependent on the proportion of temporary workers, the agreements for 85% of firms in manufacturing, and especially the smaller ones, are not at the firm level, but rather at a more aggregated level (such as industry provincial or industry national, as reported by Izquierdo et al., 2003). These agreements apply to all firms equally irrespective of whether they participated in the actual bargaining process or not, and given that smaller firms which I have in the sample are generally not in the core of the bargaining process, those agreements are arguably exogenous for them.

The above feature of the Spanish institutional environment makes for another reason why Spanish data are well-suited for studying the relationship between hiring temporary workers and debt levels controlling for possible collective bargaining effects. It does not, however, imply the two theories are at odds, but rather that my story outlines another important channel in the labor-finance relationship – the one of employment contracts flexibility. Simintzi, Vig, and Volpin (2010) use the employment protection legislation indicator to show in the reduced form estimation that in countries where it is more difficult to fire a worker firms take less debt. They interpret this result as more bargaining power of workers potentially arising from higher firing costs, is affecting capital structure. My setup allows to provide evidence that the difference in firing costs per se affects capital structure, where the mechanism works through higher firm's flexibility on the operating leverage side and not through workers demanding bigger concessions from the employer.

4.3 The Role of Cash

One important consideration to be analyzed is the observation that a subsidy promoting permanent employment does not only influence the composition of the labor force per se, but also provides the firm with a cash inflow. Firms may potentially use this cash to raise even

more debt or pay out existing debt. In this respect, the exclusion restriction of the instrument would not be satisfied. Given that the estimated effect of proportion of temporary workers on debt levels is positive, we should be concerned only if cash from the subsidy is used to pay out debt (this will bias the estimated effect upwards; if cash is used to raise more debt instead, then the estimated effect is biased downwards, which means that the actual result of the relationship between temporary workers and debt levels is even stronger).

Ideally, one could simply refute these concerns by looking at (Total Debt - Cash) / Total Assets as the dependent variable. In this case, had it been a purely cash story, net debt amount would not have changed in a situation when extra cash inflow from subsidies was used to pay out debt, and there would be no relationship between hiring temporary workers and net debt levels. If instead we find significant results in such a regression, then it means cash story cannot explain the findings.

Unfortunately, ESEE does not contain a separate entry for cash and cash equivalents. To mitigate this concern I do a back-of-the-envelope analysis of leverage ratios using Amadeus data for Spain, which can be used to calculate both the total debt to assets ratio, as well as the ratio of total debt less cash and cash equivalents to total assets.[24] Figure 4 plots the time-series evolution of these ratios for manufacturing firms in Spain. The firms in Amadeus are largely comparable to those in ESEE and as can be noticed from this graph the evolution of total debt to assets ratio closely resembles the one from Figure 3 which used ESEE data. The main results of my paper suggest that this drop if overall leverage can be attributed to the fall in temporary labor force across and within years, industries, and firms. Figure 4 also shows that the ratio of net debt to assets closely tracks the ratio of total debt to assets, and also declined during the period of temporary workers conversion. This provides some suggestive evidence for the robustness of the results of the paper to the cash story.

[24] The Amadeus data cannot be used for the main body of the analysis, since they lack the most important variable – percentage of temporary employees, which ESEE has. ESEE is an anonymous survey and the attempts to try merging it to other datasets are explicitly prohibited by teh data collecting agency.

Finally, I can also compare panel results in pre- and post-subsidies periods (given there is no variation in the instrument during the pre-subsidies period, one can only compare the fixed-effects specifications[25]). If the result is driven by cash considerations, then the coefficient in the post-subsidies period (from 1997 onwards) should be higher than that in the pre-subsidies period. Table 7 presents the results of such specifications. The coefficient of interest is generally not statistically different across periods, and if anything it is actually lower during the post-subsidies period (it is still positive and significant though: 2-sided p-values are reported for each specification). This provides additional corroborative evidence against cash effects[26].

4.4 Survival Analysis

Finally, there is some suggestive evidence that the ability to adjust debt levels according to the flexibility of workforce composition may be related to the survival of the firm. First, I explore the relationship between the probability of exiting the data in period $t+1$ (due to liquidation or switching to non-manufacturing activity), conditional on being alive in period t, and the composition of the labor force. The results of these specifications are reported in Table 8. Column 1 to 4 report the results of the panel specifications which suggest that hiring more temporary workers is associated with a higher probability of survival, controlling for any time-invariant firm-level characteristics. In particular, the magnitude of the coefficient suggests that a 1 standard deviation increase in the proportion of temporary workers is associated with a 0.5% higher probability of survival. This magnitude is economically large, given that the overall exit rate due to liquidation or switching to non-manufacturing activity

[25] I have also not included the lagged2 controls into this specification not to lose the data in the pre-subsidies period. The results are robust to including contemporaneous controls, and are reported in columns 3 and 4.

[26] Given that in my main specification proportion of temporary workers enters with a lag, I also performed a robustness check defining the post period from 1998 onwards. The results are qualitatively and quantitatively the same.

is about 7%. Columns 5 to 8 report the instrumental variable estimates. Their standard errors are very high, but the magnitudes are similar or even larger than those of panel estimates. The 2-sided p-values of these coefficients range from 11% to 28%, so unfortunately I may not convincingly say that there is a robust evidence with respect to the probability of survival, using these specifications.

Additionally, I can also examine some cross-sectional heterogeneity by comparing firms who will exit the data by the end of the sample with firms that will survive by the end of the sample. Columns 1 to 4 of Table 9 present panel results, while columns 5 to 8 employ the instrumental variable approach. I observe that the relationship between leverage and flexible employment contracts is stronger for surviving firms. Moreover, although both survivors and exiters did decrease their temporary labor force as a result of government subsidies[27], only survivors adjusted their leverage ratios according to the decreased labor force flexibility. However, these results should be interpreted with caution, since there can be unobserved factors that affect both the ability to adjust leverage and survival, so that it is harder to motivate the exclusion restriction in this case, which may also shed light why the IV results in Table 8 were not significant. [28] Therefore, this evidence on the importance of the ability of firms to accompany changes in employment contracts with corresponding changes in leverage for firm survival in the long run can only be interpreted as suggestive.

5 Conclusion

This paper considers how a firm's composition of contractual arrangements with its factors of production affects its capital structure. In particular, in the context of labor, the difference in firing costs across employment contracts provides for a different flexibility, upon realization

[27] The unreported first-stage results for IV specifications show negative and significant coefficients for both survivors and exiters.

[28] Notice, however, that if survival were related purely to higher liquidation value, then I should have observed a lower effect for surviving firms, rather than exiters. In contrast, the relationship is positive and significant only for survivors.

of firm-specific shocks, and firm's operating leverage. When firms face high potential bankruptcy costs, firms that use more flexible employment contracts are able to support higher levels of financial leverage, which can be beneficial from tax shield or other considerations. This mechanism provides an illustration of the substitution between operating and financial leverage when the overall amount of fixed costs, both operating and the debt-related, defines the overall risk of the firm given the variability of its cash flow.

I exploit the exogenous variation from government subsidies promoting the replacement of temporary employees by permanent ones to construct an instrument for the firm's use of more flexible, temporary, labor force. At the same time the panel structure of the dataset allows me to control for any unobserved time-invariant characteristics of the firm that may influence its financing policy. The combination of these identification strategies enables me to evaluate the causal effect of firm's use of temporary employment contracts on its capital structure in a quasi-experimental setting.

This effect is economically large and is more prevalent among the low liquidation value firms, for which bankruptcy is more of a concern. In particular, a thought experiment of completely prohibiting an average firm from offering temporary employment contracts would suggest that such a firm should reduce its debt level by 4.9 percentage points, which is about 8% of the average debt level across firms. These empirical results suggest that labor policy promoting more job security among workers and at the same time reducing the flexibility of firm's employment has significant implications for capital structure of firms, which is important in the light of the ongoing labor reforms across European countries.

I complement my main analysis by exploring the relationship between flexible employment and firm survival. There is some suggestive evidence that more flexible temporary employment is associated with a lower conditional probability of liquidation or switching to a non-manufacturing activity. Additionally, by examining the relationship between capital structure and temporary employment among firms that survive vs firms that exit by the end of the sample, I find that this relationship is ex post stronger for survivors. This evidence,

although suggestive, opens up the directions for future research on the channels through which temporary employment may affect firms' real decisions, long-run growth and survival, an interesting question from the academic point of view, that would be especially important from the policy perspective.

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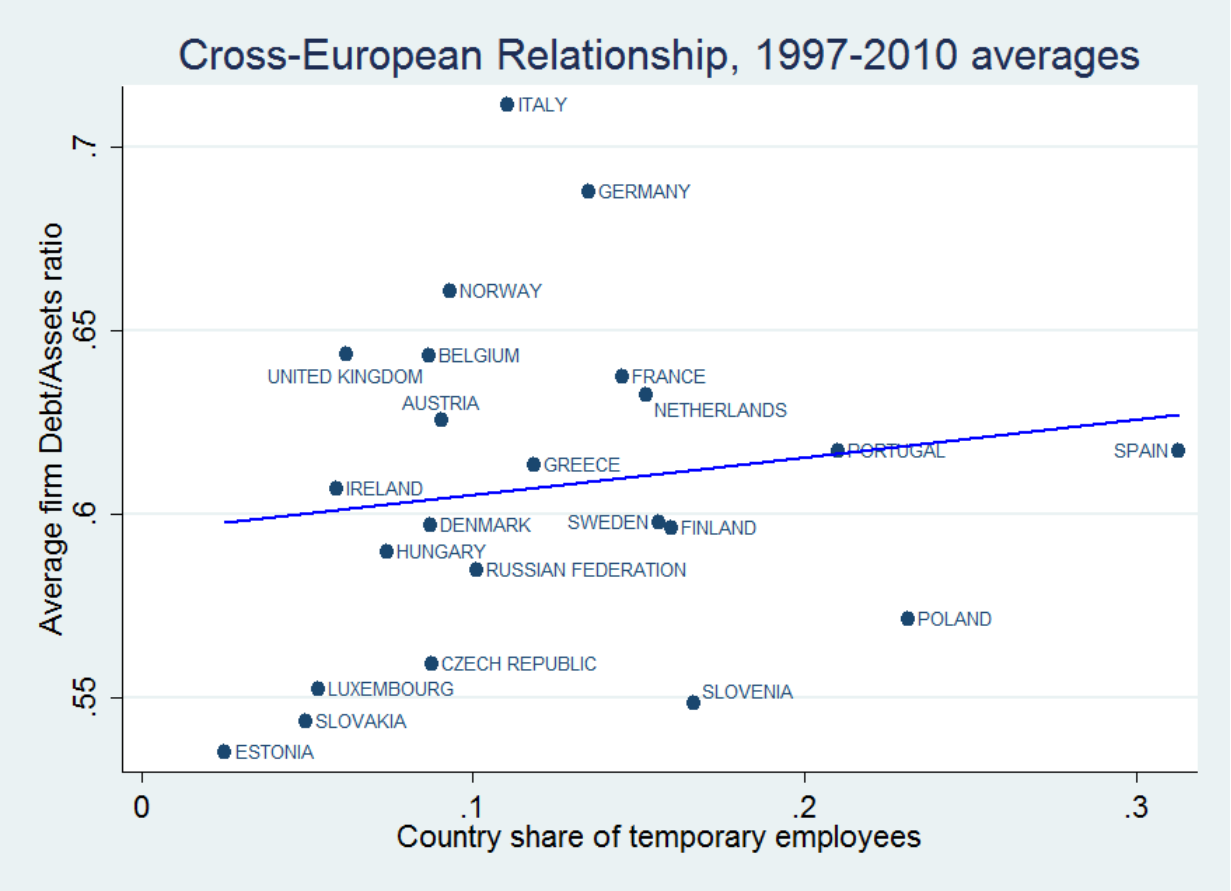
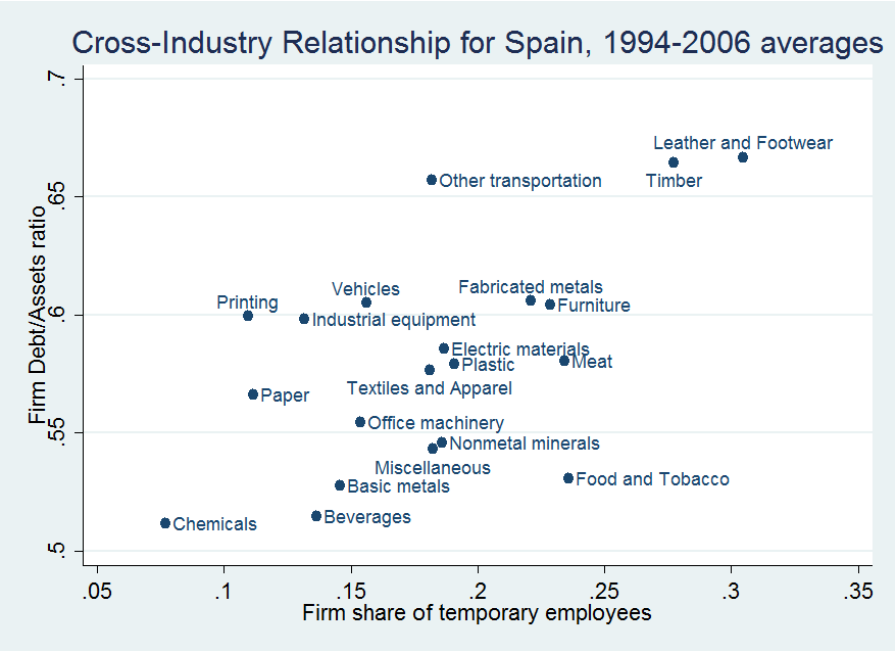
Figures and Tables

Figure 1



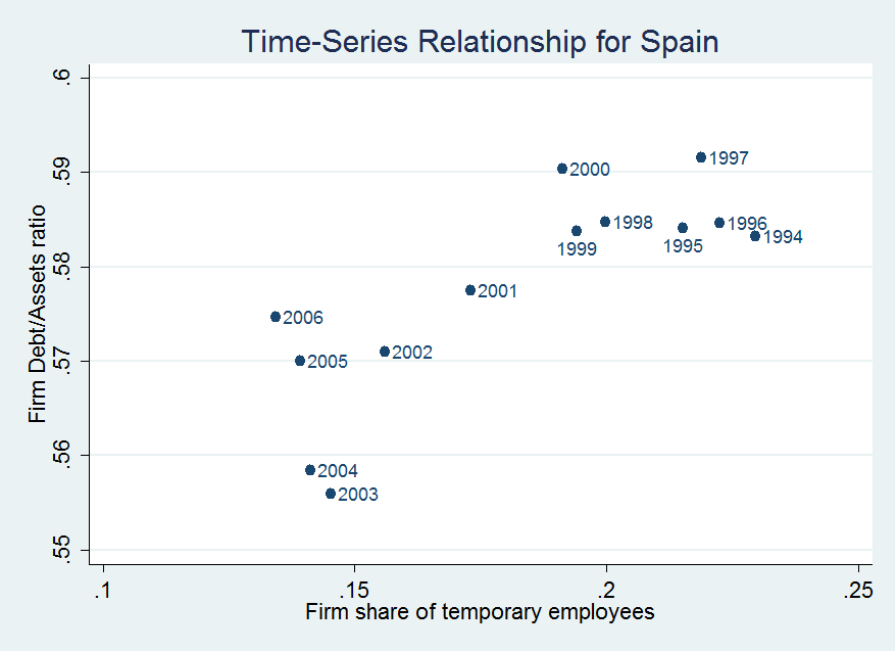
Note: This figure plots the relationship between leverage (defined as the average firm-level ratio of total debt to assets, computed across manufacturing firms from Amadeus largest firms database for each country-year pair) and the country share of temporary employees (averages across years at the country level; obtained from OECD Statistical Database). The time period covers 1997-2010 and excludes all country-year observations when fewer than 50 firms were used to compute the average. The blue line plots the corresponding linear fit.

Figure 2



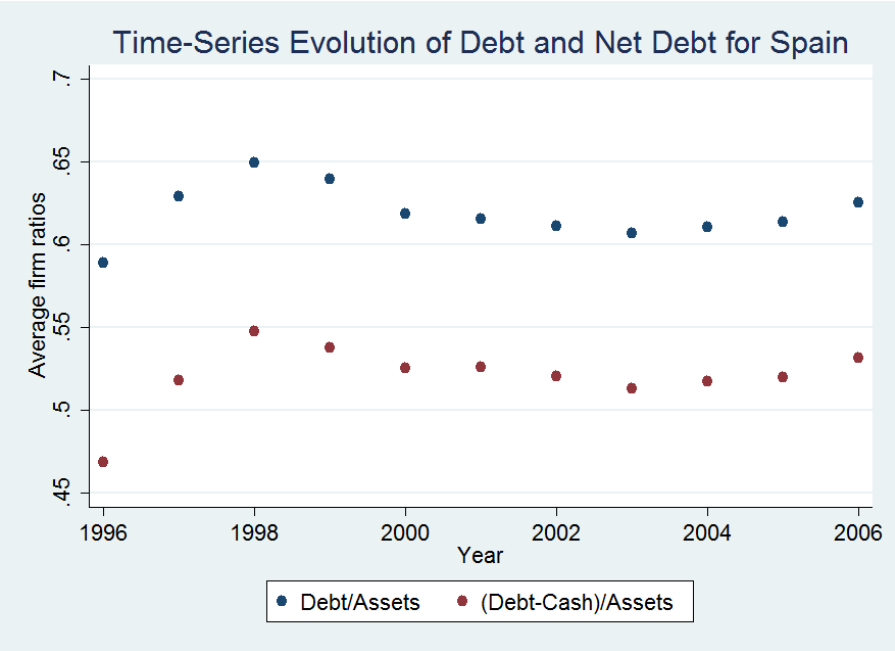
Note: This figure plots the relationship between firm-level leverage (defined as the ratio of total debt to assets) and firm-level share of temporary employees, computed for different industries across all firm-years in ESEE. The time period covers 1994-2006.

Figure 3



Note: This figure plots the relationship between firm-level leverage (defined as the ratio of total debt to assets) and firm-level share of temporary employees, computed for different years across all firms in ESEE.

Figure 4



Note: This figure plots the time-series evolution of leverage ratios (defined as the average firm-level ratio of total debt to assets and total debt less cash and cash equivalents to assets), computed across manufacturing firms from Amadeus largest firms database for Spain. The time period covers 1994-2006 to match the span of the ESEE data.

Table 1. Descriptive Statistics

Variable	Mean	Std. deviation	N
Capital Structure:			
Total Assets	57.7mln	255mln	18365
Total Debt / Total Assets	0.571	0.230	18365
Employment:			
Total Employment	269	783	18365
Temp	0.174	0.210	18365
$Temp_0$	0.237	0.250	18364
Subsidies:			
Maximum Subsidy	3523	4011	17488
Maximum Subsidy per Employee	816	1538	17488
Control Variables:			
Size	16.013	2.014	18347
Tangibility	0.718	0.355	18124
Profitability	0.225	0.134	18346
R&D	0.007	0.017	18246

Notes: The sample includes all firms in the ESEE (1994-2006). Total Assets is book value of total assets of the firm. Total Debt / Total Assets is the ratio of total debt (which is the sum of short-term and long-term liabilities) to total assets. Total Employment is firm's total employment at the end of the year. Temp is the ratio of workers on temporary contracts relative to total employment. $Temp_0$ is the ratio of workers on temporary contracts relative to total employment in the first year the firm is in the data. Maximum Subsidy and Maximum Subsidy per Employee are the maximum subsidy amounts a firm is eligible to receive (defined in Section 2), in 2006 Euros. Size is the natural logarithm of firm's real sales, in 2006 Euros. All amounts are deflated using the industry-level producer price index – Indice de Precios Industriales. Tangibility is the ratio of property, plant and equipment minus depreciation and amortization over property, plant and equipment plus intangible and financial assets minus depreaciation and amortization. Profitability is the operating profit margin of the firm, which is defined as the ratio of sales net of purchases and labor expenses to sales. R&D is the ratio of total expenses on research and development to sales. All firm-level controls are winsorized at 1% tails.

Table 2. Maximum Subsidies for Hiring Permanent Workers

Region \ Year		1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1	**Andalucia**	4200					6012			4750	
2	**Aragon**	None	4200	5280			5500		3750 if male, 5280 if female	5280 if male, 4500 if female	4000 if male, 5280 if female
3	**Asturias**	4350	4500	None	4200				4500 if male, 5400 if female		
4	**Baleares**	None			0 if male, 1653 if female		0 if male, 1800 if female	0 if male, 4808 if female		None	3000
5	**Canarias**	None	3600		None						
6	**Cantabria**	None	3900	None	4507	4207 if male, 4808 if female					
7	**Castilla-La Mancha**	None	3000 if male, 3600 if female	None	3000 if male, 3600 if female				3000 if male, 4200 if female		
8	**Castilla-Leon**	None	5112	5115	4508				4000 if male, 4500 if female		
9	**Catalonia**	None									
10	**Valencia**	None	.			1875 if male, 2000 if female	1875 if male, 2250 if female	4400	2500 if male, 5000 if female	2000 if male, 4600 if female	4000 if male, 5000 if female
11	**Exremadura**	13402	14027	14028	4296 if male, 5217 if female	4455 if male, 5410 if female	6010	.	4500		
12	**Galicia**	None	4200	4207 if male, 4808 if female	4200 if male, 4808 if female	6000		3600 if male, 4200 if female	5400 if male, 6000 if female	3300 if male, 3900 if female	5000 if male, 7500 if female
13	**Madrid**	None	6000	7800	6600 if male, 9000 if female	12000	13824 if male, 15027 if female	12000	0 if male, 3000 if female	9100 if male, 10000 if female	7000 if male, 7800 if female
14	**Murcia**	None	6000		6000 if male, 9000 if female		4800 if male, 6000 if female	5400 if male, 6000 if female	5400		
15	**Navarra**	None	3000	4800						.	
16	**Basque country**	None	3600	7512 if male, 9014 if female					6000 if male, 7500 if female		
17	**Rioja**	None	4500	4491	6011					4508 if male, 5109 if female	

Notes: This table lists the maximum available subsidies for hiring a permanent worker by region-year and gender criteria, in current Euro amounts, excluding the special treatment provinces and disabled workers.

Table 3. Gender classification of employees in manufacturing industries

	Total	Men	Women	% women
Total in manufacturing	2 105.4	1 638.4	466.9	**28.5%**
Food and beverages	331.1	242.7	88.4	**26.7%**
Tabacco	9.4	5	4.4	**46.8%**
Textiles	105.4	62.1	43.3	**41.1%**
Apparel	119.2	29.8	89.5	**75.1%**
Leather and Footwear	64	43.2	20.8	**32.5%**
Timber	59	54.1	4.9	**8.3%**
Paper	39.6	32.4	7.1	**17.9%**
Printing and publishing	113.4	82.7	30.7	**27.1%**
Petroleum refinery*	12.2	10.6	1.6	**13.1%**
Chemicals	128.4	93.9	34.5	**26.9%**
Plastic and rubber products	82.1	68.3	13.8	**16.8%**
Other nonmetal mineral products	140.6	124.5	16.1	**11.5%**
Basic metal products	99.4	92.1	7.3	**7.3%**
Fabricated metal products	169.8	156.2	13.6	**8.0%**
Industrial and agricultural equipment	130.8	120.2	10.6	**8.1%**
Office machinery	12.3	9.4	2.9	**23.6%**
Electric materials and equipment	59.7	44.6	15.1	**25.3%**
Radio and TV equipment	36.3	26.8	9.5	**26.2%**
Medical equipment and precision instruments	25.6	15.3	10.3	**40.2%**
Vehicles and accessories	178.1	162	16.2	**9.1%**
Other transport equipment	57.9	55.1	2.8	**4.8%**
Furniture and other manufacturing	126.3	102.7	23.6	**18.7%**
Recycling	4.8	4.6	0.2	**4.2%**

Note: This table lists total number of employees, in thousands of people, in different manufacturing industries and the corresponding proportion of women, measured as of the 4th quarter of 1993. The data come from Encuesta de Población Activa. *Petroleum refinery firms are not included in ESEE, but reported here for consistency.

Table 4. Capital Structure and Temporary Contracts: Panel Regressions

	Total Debt / Total Assets							
	1	2	3	4	5	6	7	8
Lagged Temp	0.0596***	0.0597***	0.0545***	0.0558***	0.0507***	0.0483***	0.0454***	0.0465***
	(0.0117)	(0.0118)	(0.0118)	(0.0119)	(0.0133)	(0.0133)	(0.0131)	(0.0132)
Observations	17679	17679	17679	17673	14795	14795	14795	14795
Within R-squared	0.0127	0.0273	0.0796	0.0992	0.0162	0.0320	0.0875	0.108
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y		Y	
Region*year FE		Y		Y		Y		Y
Industry*year FE				Y				Y
Region*industry year trends			Y	Y			Y	Y
Firm control variables					Y	Y	Y	Y

Notes: This table reports the results of regressing leverage (defined as the ratio of total debt to assets) on the proportion of workers on temporary contracts (one year prior to the dependent variable). Standard errors are two-way clustered at the region-year and firm level and are reported below the coefficients. Firm control variables include lagged2 values of size, tangibility, profitability, and R&D. The first year the firm appears in the sample is dropped from all regressions. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 5. Capital Structure and Temporary Contracts: Instrumental Variable Approach

Panel A: Second-stage results of regressing Total Debt / Total Assets on the instrumented variable

	1	2	3	4	5	6	7	8
Lagged Temp	0.207***	0.149**	0.163**	0.138**	0.205**	0.136*	0.170*	0.133
	(0.0713)	(0.0582)	(0.0681)	(0.0648)	(0.0945)	(0.0795)	(0.0971)	(0.0920)
Observations	16889	16889	16889	16889	14063	14063	14063	14063

Panel B: First-stage results of regressing the endogenous regressor on the instrument

	1	2	3	4	5	6	7	8
Lagged2 Subsidy	-0.0241***	-0.0377***	-0.0236***	-0.0343***	-0.0159***	-0.0254***	-0.0151***	-0.0224***
	(0.00427)	(0.00584)	(0.00496)	(0.00575)	(0.00346)	(0.00494)	(0.00398)	(0.00492)
F-statistic	31.80	41.06	22.11	33.98	20.94	26.03	14.06	19.84
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y		Y	
Region*year FE		Y		Y		Y		Y
Industry*year FE				Y				Y
Region*industry year trends			Y	Y			Y	Y
Firm control variables					Y	Y	Y	Y

Notes: This table reports the results of regressing leverage (defined as the ratio of total debt to assets) on the proportion of workers on temporary contracts (one year prior to the dependent variable), instrumented by the lagged subsidy amount (measured in thousand Euro). Standard errors are two-way clustered at the region-year and firm level and are reported below the coefficients. F-statistic is the Kleibergen and Paap (2006) test statistic for weak identification. Firm control variables include lagged2 values of size, tangibility, profitability, and R&D. The first year the firm appears in the sample is dropped from all regressions. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 6. Capital Structure and Temporary Contracts: Liquidation Value Analysis

	Total Debt / Total Assets							
	Fixed effects	**Fixed effects**	**Fixed effects**	**Fixed effects**	**IV**	**IV**	**IV**	**IV**
	1	2	3	4	5	6	7	8
Lagged Temp	0.0808***	0.0774***	0.0790***	0.0735***	0.315***	0.258***	0.353***	0.276**
	(0.0167)	(0.0166)	(0.0189)	(0.0189)	(0.104)	(0.0873)	(0.133)	(0.113)
Lagged Temp * High Liquidation Value	-0.0544**	-0.0487**	-0.0696***	-0.0641**	-0.207**	-0.208**	-0.258*	-0.258**
	(0.0234)	(0.0232)	(0.0270)	(0.0267)	(0.103)	(0.102)	(0.132)	(0.131)
P-value	0.112	0.088	0.614	0.606	0.185	0.494	0.369	0.846
Observations	17059	17059	14412	14412	16291	16291	13699	13699
Within R-squared	0.0133	0.0288	0.0177	0.0341	NA	NA	NA	NA
First-stage F-statistic	NA	NA	NA	NA	11.57	13.45	6.957	7.921
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y		Y	
Region*year FE		Y		Y		Y		Y
Firm control variables			Y	Y			Y	Y

Notes: This table reports the results of regressing leverage (defined as the ratio of total debt to assets) on the proportion of workers on temporary contracts (one year prior to the dependent variable) and its interaction with High Liquidation Value (defined as a binary variable that equals 1 if the firm has higher than industry median level of buildings and land in the year it enters the data, and 0 otherwise). Columns 1 to 4 use fixed-effects estimation, while columns 5 to 8 additionally instrument the dependent variables by the lagged subsidy amount and its interaction with High Liquidation Value. P-value reports the p-value of the 2-sided test that the sum of the coefficients at Lagged Temp and Lagged Temp*High Liquidation Value is equal to 0. Standard errors are two-way clustered at the region-year and firm level and are reported below the coefficients. First-stage F-statistic is the first-stage Kleibergen and Paap (2006) test statistic for weak identification for the IV specifications (the Stock and Yogo, 2002, critical value for 2 endogenous regressors with 2 instruments is 7.03 for 5% maximal size distortion, or 4.58 for 10% maximal size distortion). Firm control variables include lagged2 values of size, tangibility, profitability, and R&D. The first year the firm appears in the sample is dropped from all regressions. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 7. Capital Structure and Temporary Contracts: Pre- and Post-Subsidies

	Total Debt / Total Assets			
	Fixed effects	**Fixed effects**	**Fixed effects**	**Fixed effects**
	1	2	3	4
Lagged Temp	0.0811***	0.0796***	0.0739***	0.0733***
	(0.0179)	(0.0187)	(0.0168)	(0.0178)
Lagged Temp*Post	-0.0283*	-0.0261	-0.0293*	-0.0277
	(0.0169)	(0.0181)	(0.0158)	(0.0172)
P-value	0.000	0.000	0.001	0.000
Observations	17679	17679	17312	17312
Within R-squared	0.0130	0.0276	0.0163	0.0320
Firm FE	Y	Y	Y	Y
Year FE	Y		Y	
Region*year FE		Y		Y
Firm control variables			Y	Y

Notes: This table reports the results of regressing leverage (defined as the ratio of total debt to assets) on the proportion of workers on temporary contracts (one year prior to the dependent variable) and its interaction with Post dummy variable (which is equal to 1 for years from 1997 onwards, and 0 otherwise). P-value reports the p-value of the 2-sided test that the sum of the coefficients at Lagged Temp and Lagged Temp*Post is equal to 0. Standard errors are two-way clustered at the region*year and firm level and are reported below the coefficients. Firm control variables include size, tangibility, profitability, and R&D. The first year the firm appears in the sample is dropped from all regressions. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 8. Capital Structure and Temporary Contracts: Exit Analysis

	Exit							
	Fixed effects	**Fixed effects**	**Fixed effects**	**Fixed effects**	**IV**	**IV**	**IV**	**IV**
	1	2	3	4	5	6	7	8
Lagged Temp	-0.0375**	-0.0334*	-0.0458**	-0.0409**	-0.179	-0.0781	-0.329	-0.136
	(0.0180)	(0.0173)	(0.0204)	(0.0194)	(0.129)	(0.0723)	(0.211)	(0.116)
Observations	17065	17065	14075	14075	16291	16291	13699	13699
Within R-squared	0.0963	0.107	0.0975	0.108	NA	NA	NA	NA
First-stage F-statistic	NA	NA	NA	NA	50.36	72.03	38.22	65.12
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y		Y	
Region*year FE		Y		Y		Y		Y
Firm control variables			Y	Y			Y	Y

Notes: This table reports the results of regressing Exit (defined as the binary variable which equals 1 if the firm will exit the sample next period due to liquidation or switching to a non-manufacturing activity, and 0 otherwise) on the proportion of workers on temporary contracts (one year prior to the dependent variable). Columns 1 to 4 use fixed-effects estimation, while columns 5 to 8 additionally instrument the dependent variables by the lagged subsidy amount. Standard errors are two-way clustered at the region-year and firm level and are reported below the coefficients. First-stage F-statistic is the Kleibergen and Paap (2006) test statistic for weak identification. Firm control variables include lagged2 values of size, tangibility, profitability, and R&D. The first year the firm appears in the sample is dropped from all regressions. * indicates 10% significance; ** 5% significance; *** 1% significance.

Table 9. Capital Structure and Temporary Contracts: Ex Post Survival

	Total Debt / Total Assets							
	Fixed effects	**Fixed effects**	**Fixed effects**	**Fixed effects**	**IV**	**IV**	**IV**	**IV**
	1	2	3	4	5	6	7	8
Lagged Temp	0.0792***	0.0796***	0.0678***	0.0663***	0.257***	0.204***	0.252***	0.192**
	(0.0145)	(0.0145)	(0.0165)	(0.0164)	(0.0706)	(0.0589)	(0.0943)	(0.0827)
Lagged Temp*Ever Exit	-0.0646***	-0.0654***	-0.0613**	-0.0634**	-0.246**	-0.264**	-0.224	-0.249*
	(0.0245)	(0.0247)	(0.0281)	(0.0283)	(0.124)	(0.122)	(0.146)	(0.142)
P-value	0.451	0.474	0.766	0.900	0.935	0.620	0.862	0.683
Observations	17679	17679	14795	14795	16889	16889	14063	14063
Within R-squared	0.0136	0.0283	0.0170	0.0328	NA	NA	NA	NA
First-stage F-statistic	NA	NA	NA	NA	14.75	14.64	11.42	16.17
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y		Y	
Region*year FE		Y		Y		Y		Y
Firm control variables			Y	Y			Y	Y

Notes: This table reports the results of regressing leverage (defined as the ratio of total debt to assets) on the proportion of workers on temporary contracts (one year prior to the dependent variable) and its interaction with Ever Exit dummy (which equals 1 if the firm does not survive till the end of the sample, and 0 otherwise). Columns 1 to 4 use fixed-effects estimation, while columns 5 to 8 additionally instrument the dependent variables by the lagged subsidy amount and its interaction with High Liquidation Value. P-value reports the p-value of the 2-sided test that the sum of the coefficients at Lagged Temp and Lagged Temp*High Liquidation Value is equal to 0. Standard errors are two-way clustered at the region-year and firm level and are reported below the coefficients. First-stage F-statistic is the first-stage Kleibergen and Paap (2006) test statistic for weak identification for the IV specifications (the Stock and Yogo, 2002, critical value for 2 endogenous regressors with 2 instruments is 7.03 for 5% maximal size distortion, or 4.58 for 10% maximal size distortion). Firm control variables include lagged2 values of size, tangibility, profitability, and R&D. The first year the firm appears in the sample is dropped from all regressions. * indicates 10% significance; ** 5% significance; *** 1% significance.

Appendix Table 1. Capital Structure and Subsidies: Reduced Form Analysis

	1	2	3	4	5	6	7	8
Lagged2 Subsidy	-0.00498***	-0.00564**	-0.00377**	-0.00460*	-0.00322**	-0.00350	-0.00253	-0.00294
	(0.00178)	(0.00236)	(0.00174)	(0.00239)	(0.00155)	(0.00217)	(0.00160)	(0.00222)
Observations	16,987	16,987	16,987	16,987	14,117	14,117	14,117	14,117
Within R-squared	0.0103	0.0249	0.0806	0.100	0.0143	0.0303	0.0891	0.110
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y		Y	
Region*year FE		Y		Y		Y		Y
Industry*year FE				Y				Y
Region*industry year trends			Y	Y			Y	Y
Firm control variables					Y	Y	Y	Y

Notes: This table reports the results of regressing leverage (defined as the ratio of total debt to assets) on the lagged2 subsidy amount (measured in thousand Euro). Standard errors are two-way clustered at the region-year and firm level and are reported below the coefficients. Firm control variables include lagged2 values of size, tangibility, profitability, and R&D. The first year the firm appears in the sample is dropped from all regressions. * indicates 10% significance; ** 5% significance; *** 1% significance.

Hedge Fund Risk Premia: Transparency, Liquidity, Complexity, and Concentration

Sergiy Gorovyy
Columbia University

Olga Kuzmina*
New Economic School

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Abstract

We use a proprietary dataset obtained from a fund of funds to study the risk premia associated with hedge fund transparency, liquidity, complexity, and concentration over the period from April 2006 to March 2009. We are able to directly measure these qualitative characteristics by using the internal grades that the fund of funds attached to all the funds it invested in, and that represent the unique information that cannot be obtained from quantitative data alone. Consistent with factor models of risk premium, we find that during the normal times low-transparency, low-liquidity, low-complexity, and high-concentration funds delivered a return premium, with economic magnitudes of 5% to 10% per year, while during bad states of the economy, these funds experienced significantly lower returns. We also offer a novel explanation for why highly concentrated funds command a risk premium by revealing that it is mostly prevalent among the non-transparent funds where investors are unaware about the exact risks they are facing and hence cannot diversify them away.

Keywords: Hedge funds, Risk premia, Transparency, Liquidity, Complexity, Concentration.

JEL codes: G01, G11, G23, G32.

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1 Introduction

In the modern era of delegated portfolio management hedge funds constitute one of the most interesting and the most complicated investment vehicles. Usually they operate in a way that does not require them to disclose details about their operations. This does not mean that hedge funds do not disclose this information, but that they are not obliged to do so and as a result the level of disclosure is an internal decision by the hedge fund manager. The fund's structure and disclosure level is rarely modified after the fund's initiation since the fund's investors expect it to maintain the same structure and disclosure level during its operation.

The question of whether hedge funds should be required to disclose the information regarding their trades and positions is very important, especially in the light of the recent regulatory changes, including the Dodd-Frank Wall Street Reform Act passed in July 2010, in particular. This act requires managers of hedge funds with more than $150 million in assets under management to register with the Securities and Exchange Commission and become subject to its disclosure rules. Although the consequences of this act are yet to be evaluated, in this paper we attempt to explore the connection between hedge fund reporting levels and their returns. The primary goal of this paper is thus to determine whether there is a significant return premium associated with more secretive, less transparent hedge funds.

The contribution of our paper is three-fold. First of all, by using a novel proprietary dataset obtained from a fund of funds that spans April 2006 to March 2009, we are able to directly measure the transparency level of a fund, a qualitative characteristic that is missing in public hedge fund databases, and to use it to uncover and quantify the non-transparency risk premium which amounts to 5.4% per year. Importantly, the use of the data that come from both good and bad states of the economy allows us to directly test the risk-premium story against the alternative of better managers being selected into managing low-transparency funds. Second, by investigating how excess returns vary with other fund characteristics, such as fund liquidity, complexity of its strategy, and concentration of its investments, we document the presence of several other risk premia in a

cross-section of hedge fund returns. Finally, we explore how transparency, liquidity, complexity, and concentration help explain the fund return volatility and capital inflows.

A few papers in the asset pricing literature have raised the issues of transparency as related to hedge funds, presumably due to the absence of adequate data to explore this question. Anson (2002) outlines different types of transparency and discusses why investors may want higher degree of transparency; Hedges (2007) overviews the key issues of hedge fund investment from a practitioners perspective; Goltz and Schroder (2010) survey hedge fund managers and investors on their reporting practices and find that the quality of hedge fund reporting is considered to be an important investment criterion. Aggarwal and Jorion (2012) study quantitatively effects of hedge funds' decisions on whether to provide or not to provide managed accounts to their investors. They interpret the incidence of accepting managed accounts as an indicator of the willingness of the fund to offer transparency and do not relate the results to risk premium. In contrast, we are able to directly measure the level of transparency of a fund by using proprietary fund of funds scores that are based on formal and informal interactions with hedge funds, such as internal reports, meetings with managers and phone calls. To the best of our knowledge, we are also the first paper to explore and quantify the risk premium associated with low transparency.

To illustrate the risk-premium channel, let us consider a risk-averse investor who faces two alternative hedge funds. If investment with one of them is considered to be more risky from the point of view of investors, this fund will have to deliver superior returns during normal times in order to attract any investment at all, i.e. investors are said to be compensated for bearing the risk. At some point these risks will realize, and this is when the riskier fund underperforms.

To further relate this to transparency, notice that hedge funds that choose to provide less information about their positions and strategy details to investors leave them uncertain about the underlying risks of investing with these hedge funds. In particular, when a transparent fund starts to diverge from its declared strategy, investors can quickly disinvest if they dislike the turnaround, while in the case of a non-transparent fund investors will only learn about the change in the fund strategy later and have to face the consequences. This means that risk-averse investors should

be compensated for bearing the risks associated with non-transparency. In particular, during the normal times low-transparency hedge funds are expected to perform better than high-transparency hedge funds by delivering an additional non-transparency risk premium. During the bad times, on the other hand, the risks associated with non-transparency can realize, meaning that the low-transparency funds will deliver lower returns as compared to high-transparency funds.

The time frame of our dataset that spans from April 2006 to March 2009 allows us to separately study the return premia that realized during the good and bad states of the economy. In particular, this period covers the collapse of large global investment banks – Bear Stearns and Lehman Brothers, in March and September 2008, respectively. The overall fear of investors to get stuck with bad uncontrolled investments could reasonably generate the demand for transparency. Therefore, it is realistic to assume that non-transparency risks indeed realized during the later period of our data. Indeed, our empirical results suggest that during the crisis period from April 2008 to March 2009 more transparent funds outperformed the less transparent funds by about 7.1% per year.

We also document the presence of hedge fund illiquidity risk premium. This is consistent with a large literature on risk premia associated with illiquidity across a variety of asset classes.[1] In general, illiquidity premium is a premium for investment in more illiquid assets. For example, when the investor faces two alternative assets with one being more liquid than the other, she is able to disinvest from a more liquid asset with a lower loss when faced with a liquidity shock. Therefore, risk-averse investors invest in less liquid assets only if they expect to get superior returns from them. The most liquid funds in our dataset are the funds that both invest in higher liquidity assets and have fewer restrictions with regard to investment withdrawal (such as the lockup period). We estimate the illiquidity premium to be about 5.7% to 7.8% per year depending on the empirical specification. Our paper is related to Liang (1999) and Aragon (2007) who show that funds with longer lockup periods outperform other funds.

Given the richness of our dataset, we are also able to explore the risk premia associated with

[1] See Amihud and Mendelson (1986) for the seminal contribution, as well as Pastor and Stambaugh (2003), and Acharya and Pedersen (2005).

more complicated strategies used by hedge funds, as well as with more concentrated investments. We find that during normal times high-complexity hedge funds underperformed low-complexity hedge funds by 3.9% per year in a specification controlling for other qualitative characteristics, while the results for later period are mixed.

We also find some evidence of a concentration risk premium. It is interesting to note that concentration of hedge fund investments should not matter in the light of the standard finance theory theory due to the theoretical ability of investors to diversify away the non-systematic (idiosyncratic) risks. This is in contrast to a recent empirical study by Ang et al (2009) who find that idiosyncratic volatility bears a significant premium. In our paper we are able to offer a novel explanation of why investors may not be able to diversify their risks, by exploring among which funds the concentration premium is mostly pronounced. Intuitively, hedge fund investors should be compensated for the risks associated with concentrated investments of a fund when they do not know what constitutes these investments, i.e. do not know which risks to diversify away. Hence, we expect to see a concentration risk premium only among the non-transparent hedge funds. Indeed, we verify this prediction using the interactions between concentration and transparency variables in our empirical setup.

Our paper is close in spirit to Brown, Goetzmann, Liang, and Schwarz (2008) who use SEC filing data to construct a so called $\omega-$score, which is a combined measure of conflict of interests, concentrated ownership, and leverage, and show that it is a significant predictor of the projected fund life. In a subsequent paper, Brown, Goetzmann, Liang, and Schwarz (2012) use proprietary due diligence data to construct an operational risk variable as a linear combination of variables that correspond to mistakes in statements, internalized pricing, and presence of an auditor in the Big 4 group. We consider operational risk in a broader sense, where the willingness of hedge fund managers to provide details of their strategies, as well as hedge fund liquidity, investment concentration, and the ability of the investors to understand fund's operations are important.

We also study hedge fund return volatility and capital flows and find that the return volatility can be partially explained by the high degrees of hedge fund concentration and liquidity, with

up to 37% of the explained variation in the full-sample specification. During each of the periods considered the difference between volatilities of high-concentration versus low-concentration funds constitutes on average 2% per year, while the volatility of high-liquidity funds is on average about 1% lower than the volatility of low-liquidity funds. Both these magnitudes are economically significant given that the average hedge fund volatility over the sample is equal to 11% per year.

Finally, we also study how hedge fund capital flows are related to their transparency, liquidity, complexity, and concentration and find that among our qualitative variables only the level of liquidity can robustly explain capital flows across different periods in our sample. In particular, we find that low-liquidity funds experienced heavier outflows, especially during the crisis period from April 2008 to March 2009, where the difference between the flows from low-liquidity and high-liquidity funds amounted to 26.6 percentage points.

Our paper is organized as follows: Section 2 describes the data and variables used in our study, Section 3 explains the estimation procedure and the empirical setup, Section 4 discusses the main results on the risk premia associated with transparency, liquidity, complexity, and concentration, as well as additional results and robustness checks, and Section 5 concludes.

2 Data

We use a unique dataset obtained from a fund of funds that contains detailed fund-year information over the 2007–2009 period. This fund of funds is one of the largest in the U.S. The data provide information on hedge fund returns net of fees, their assets under management, and long and short exposures. Most importantly, these data include scores for hedge fund transparency, liquidity, complexity, and concentration as rated by the fund of funds on a scale from 1 to 4. Once a year at the end of March the fund of funds grades all the hedge funds it invests in based on its interactions with them during the previous twelve months. These interactions consist of weekly or monthly reports to the fund of funds, meetings with managers, phone calls, etc. Due to the nature of the scoring process and a significant level of effort put into the construction of the scores we feel

confident that they represent unique information about funds' operation that cannot be captured by the quantitative data alone. Such qualitative measures are not present in public hedge fund databases, such as CISDM, HFR, or TASS. Therefore, we think our data are especially well-suited for studying the return premia associated with different qualitative characteristics of hedge funds.

The definitions of transparency, liquidity, complexity, and concentration as used by the fund of funds are natural and intuitive. In particular, hedge fund transparency represents the willingness of the hedge fund manager to share information about the fund's current activities and investments with its investors. Hedge fund liquidity measures the liquidity of investments with the hedge fund from the point of view of investors. It comprises of both the liquidity of fund's assets and restrictions on investment withdrawal, such as the presence and the length of lockup periods. Hedge fund complexity corresponds to the complexity of hedge fund strategy and its operations. For example, an offshore hedge fund that uses derivative instruments and swap agreements is considered to be complicated, since it is very hard for investors to understand exactly the kinds of risks it faces by investing with such fund. Finally, hedge fund concentration represents the level of concentration of hedge fund investments.

After filtering out various versions of the funds we are left with 355 observations of 167 different hedge funds that are evenly spread across the three years, with 121 observations in 2007, 122 – in 2008, and 112 – in 2009. Since our qualitative grades are given at the end of March, we use 2007, 2008, and 2009 to denote April 2006 to March 2007, April 2007 to March 2008, April 2008 to March 2009 periods, correspondingly. For example, the annualized return of a fund from April 2006 to March 2007 is matched to transparency, liquidity, complexity, and concentration grades that the fund of funds issued at the end of March 2007. This approach ensures that all interactions with the hedge fund that constitute the basis for the grades are conducted in the same period when the fund return is delivered.

Our time frame is purposefully divided into three very distinct periods, since the risk premium story which we attempt to illustrate should reveal different subsets of funds to perform better during good versus bad states of the economy. According to the Financial Crisis Inquiry Report

(2011), the period from April 2006 to March 2007 can be considered a normal growth year. The beginning of the period from April 2007 to March 2008 also corresponds to a good state of the economy, but the end of this period was already associated with a recession in US. The collapse of Bear Stearns in March 2008 declared the beginning of the financial crisis, which makes us treat the period from April 2007 to March 2008 as an intermediary period. Finally, the period from April 2008 to March 2009 was clearly a period corresponding to a bad state of the economy, highlighted by the bankruptcy filing by Lehman Brothers, one of the largest investment banks. [2] Importantly, the exogeneity of the global financial crisis allows us to provide more evidence towards the risk premium explanation, since we are able to observe both the return premia during normal times as well as manifestations of the corresponding risks during the crisis period.

Hedge funds in our dataset represent a broad set of strategies. In particular, there are credit (CR), event-driven (ED), equity (EQ), relative-value (RV), and tactical trading (TT) hedge funds. Credit hedge funds trade mostly corporate bonds and CDS on those bonds; event-driven hedge funds seek to predict market moves based on specific news announcements; equity hedge funds trade equities; relative value hedge funds seek pair trades where one asset is believed to outperform another asset independent of macro events; and tactical trading funds seek to establish favorable tactical positions using various combinations of the above strategies.

Each fund is identified by a single strategy. Moreover, this characteristic is time-invariant for a given hedge fund (at least during the period considered). This is not surprising given that funds are created in order to pursue a particular strategy and investors expect the fund to follow it continuously over time. Panel A of Table 1 tabulates the number of hedge funds by various strategies for each of the periods considered. Approximately half of the hedge funds in the database are equity funds, with relative-value and event-driven as the next popular strategies. This distribution of strategies across funds is comparable to other databases, as reported, for example, by Bali, Brown, and Caglayan (2011) for TASS.

[2] It is also worth mentioning, that according to NBER April 2006 to November 2007 was a growth period while December 2007 to March 2009 was a recession period.

Panel B of Table 1 reports the mean, standard deviation, 25-th, 50-th, and 75-th percentiles, and the number of observations for hedge fund annualized returns, volatility, and assets under management (AUM) separately for each of the periods considered. Hedge funds performed well as a group during the normal period from April 2006 to March 2007 delivering on average a 13.59% per annum return with a 6.53% standard deviation. During the intermediate period they delivered on average a 3.72% return with a higher 10.92% volatility, while during the crisis period they delivered on average a negative –16.56% return with a 15.81% volatility.

The funds in our dataset are somewhat larger, than funds in CISDM, HFR, or TASS databases, since we filter out copies of the same funds, that although legally constitute different hedge funds are in fact just different versions of the same fund (and hence have same returns, as well as transparency, liquidity, complexity, and concentration scores). An example of such situation would be an onshore and an offshore versions of a fund (different for tax treatment) or versions denominated in different currencies that have identical portfolios. Ang, Gorovyy, and van Inwegen (2011) use the same data to explore hedge fund leverage and note that funds in the dataset are not subject to selection bias. Therefore, we are confident that funds in our dataset are representative of the hedge fund industry.

For each of the qualitative characteristics (transparency, liquidity, complexity, and concentration) we define their High, Medium, and Low levels. The fund of funds gives original grades in such a way that a grade of 1 would represent the lowest level of problem with a particular characteristic from the point of view of risk for an investor. In particular, funds with high levels of transparency and liquidity and funds with low levels of complexity and concentration are rated with a 1.

For consistency purposes and the ease of interpretation we define all the variables in such a way that a High value represents a high level of the *variable itself* rather than a high level of *problem* with that variable. Therefore, whenever we speak of high transparency or high complexity, for example, we always mean a high *level* of transparency and a high *level* of complexity, respectively. We define Medium and Low levels in a similar way. There is a very small percentage of funds that

are ever rated with a 4, henceforth we combine the grades of 3 and 4 into one category in order to ensure that we have a reasonable number of observations in each category.

Panel C of Table 1 reports the pairwise rank correlations between transparency, liquidity, complexity, and concentration, computed using Kendall's (1938) τ_B-method to account for the categorical nature of the variables and ties, for each year. As can be seen from these results, the pairwise correlations are quite robust over time. More transparent funds are also more liquid, with the correlation statistically significant at 5% level for 2007 and at 10% level for 2008 and 2009. More transparent and more liquid funds are also less complex on average. Finally, more liquid funds are also less concentrated. These results document the interesting patterns in the cross-sectional distribution of fund characteristics.

3 Empirical strategy

We study the hedge fund return premia associated with transparency, liquidity, complexity, and concentration using the following empirical specification:

$$\begin{aligned} r_{it} = {} & \alpha^{\mathrm{H}}_{\mathrm{Tran}} D^{\mathrm{H}}_{\mathrm{Tran},it} + \alpha^{\mathrm{H}}_{\mathrm{Liq}} D^{\mathrm{H}}_{\mathrm{Liq},it} + \alpha^{\mathrm{H}}_{\mathrm{Com}} D^{\mathrm{H}}_{\mathrm{Com},it} + \alpha^{\mathrm{H}}_{\mathrm{Con}} D^{\mathrm{H}}_{\mathrm{Con},it} \\ & + \alpha^{\mathrm{M}}_{\mathrm{Tran}} D^{\mathrm{M}}_{\mathrm{Tran},it} + \alpha^{\mathrm{M}}_{\mathrm{Liq}} D^{\mathrm{M}}_{\mathrm{Liq},it} + \alpha^{\mathrm{M}}_{\mathrm{Com}} D^{\mathrm{M}}_{\mathrm{Com},it} + \alpha^{\mathrm{M}}_{\mathrm{Con}} D^{\mathrm{M}}_{\mathrm{Con},it} \\ & + \gamma X'_{it} + d_t + \epsilon_{it} \end{aligned} \tag{1}$$

where r_{it} denotes the annual excess return of fund i in year t. α is a set of regression coefficients with respect to the corresponding indicator variables D_{it}, where the subscript refers to the qualitative characteristic of the fund (transparency, liquidity, complexity, or concentration) and the superscript refers to the level of that characteristic (High or Medium). For example, the indicator variable $D^{\mathrm{H}}_{\mathrm{Tran},it}$ is equal to 1 if fund i in year t has a high level of transparency, and 0 otherwise. Similarly, the indicator variable $D^{\mathrm{M}}_{\mathrm{Com},it}$ is equal to 1 if fund i in year t has a medium level of complexity, and 0 otherwise. In some specifications we also allow for a vector of controls X'_{it} that includes the return volatility and the natural logarithm of fund's assets under management, to

account for a potential difference in performance of funds that have different level of volatility or size.

Since risk premia for transparency, liquidity, complexity, and concentration can be different for different years, we estimate the above relationship separately for each year. Furthermore, in our full-sample results that cover all three years of data we include year fixed effects d_t in order to account for macroeconomic effects that are common to all hedge funds. Finally, ϵ_{it} denotes the error term in the above-specified regression model.

The low levels of our qualitative variables of interest are naturally omitted in the regression specification. Funds with low levels of transparency, liquidity, complexity, and concentration serve as the base category. α-coefficients can be interpreted as the corresponding risk premia with respect to these groups of funds.

Although there is a panel component to our data, the qualitative characteristics of interest are highly persistent within a fund. For example, among all the funds that have a transparency level present for two years or more, 89% actually have the same level of transparency in all years. Similarly, 91%, 94%, and 83% of funds have the same level of liquidity, complexity, and concentration, respectively, in all years. The observation that the fund disclosure level and its structure in general are rarely modified after the fund's initiation is not surprising, because fund investors expect the fund to maintain the same configuration over time. Given the high persistency of fund qualitative characteristics, we do not attempt to estimate the within-fund return premia for transparency, liquidity, complexity, and concentration, especially since we believe that the cross-sectional relationship in this case is more insightful.

We also include strategy fixed effects to allow for a differential performance of funds pursuing different strategies in some regression specifications. Such specifications allow to explore how fund returns vary with transparency, liquidity, complexity, and concentration across funds of the same strategy or style. Finally, in all our specifications we report standard errors that are robust to heteroskedasticity, as well as within-fund correlation over time in full-sample results.

4 Results

4.1 Performance of hedge funds: univariate regression results

We start with univariate regressions of hedge fund performance on the indicator variables corresponding to our qualitative characteristics in order to take the first look on the differences between hedge funds that have different levels of transparency, liquidity, complexity, and concentration. Table 2 reports the results of such specifications. We see that, consistent with our predictions from Section 1, high-transparency hedge funds and medium-transparency hedge funds considerably underperformed the low-transparency hedge funds during the normal time period from April 2006 to March 2007 (Panel A). This underperformance is statistically significant at the 1% significance level. Moreover, the economic magnitude of this coefficient is large, suggesting for an average difference in returns between low- and high-transparency hedge funds of 5.7% per year. At the same time, medium-transparency hedge funds underperformed low-transparency hedge funds by 4.3% per year.

During the intermediate April 2007 to March 2008 period the difference in performance becomes less significant both economically and statistically. During the crisis period (April 2008 to March 2009), however, we see a clear reversal in the sign of the difference between high-transparency and low-transparency hedge fund returns. According to the theory, if risks associated with low-transparency funds are realized in this period, we should see the high-transparency funds to be performing better during this period. Indeed, the high-transparency funds outperform the low-transparency funds by the economically significant 7.1% per year. However, due to the high volatility of returns during this period (as documented in Panel B of Table 1, the difference in performance between high-transparency and low-transparency funds is not statistically different from 0, yielding a p-value of 14%.

Turning to our liquidity measure in Panel B, we observe that the difference in performance between high- and low-liquidity hedge funds is even more pronounced than the difference in per-

formance between high- and low-transparency hedge funds. Table 2 reports that during April 2006 to March 2007 period high-liquidity hedge funds underperformed low-liquidity hedge funds by 7.8% per year and medium-liquidity hedge funds underperformed them by 5.5% year with both coefficients being highly economically and statistically significant. In the intermediate April 2007 to March 2008 period we observe that the signs of the coefficients get reversed with high-liquidity hedge funds outperforming low-liquidity hedge funds by 8.2%. Finally, during the crisis period we observe that high-liquidity hedge funds outperformed low liquidity hedge funds by an extraordinary 28.2%, while medium-liquidity hedge funds outperfomed them by 13.3%. These results are again both highly economically and statistically significant. Consistent with the illiquidity-risk premium story, during the good period low-liquidity funds deliver higher return as a compensation for the illiquidity risk premium, while during the bad period the risk manifests in the underperformance of these funds.

Interestingly, we do not find any evidence for the existence of a risk premium associated with the complexity of the strategies employed by funds, at least in the univariate framework. The results in Table 2 Panel C suggest that in all periods considered there is no statistical or economical difference between returns of high-complexity and low-complexity funds, suggesting that the risk premium associated with fund complexity is small if it exists at all.

We observe a similar to hedge fund transparency and liquidity picture with regard to hedge fund concentration reported in Table 2 Panel D. During the normal April 2006 to March 2007 period highly concentrated hedge funds outperform low-concentration funds by 7.4%, while medium-concentration funds outperfom low-concentration hedge funds by 4.4%. During the April 2007 to March 2008 period we observe that the realized risk premium is close to zero and during the crisis period of April 2008 to March 2009 we see a reversal with highly concentrated hedge funds underperforming low-concentration hedge fudns by 12.3%. These results are consistent with the existence of risk premium associated with more concentrated (less diversified) funds.

In the last column of each Panel we also consider regressions that include all three time periods and allow for a different average return in each year by including year fixed effects into this

specification. We observe that the coefficients for transparency and concentration lose their significance. This is not surprising in light of the risk premium story, since our three years both cover the years of expansion and the years of recession. Low and insignificant coefficients for the qualitative variables over time help to rule out the alternative story that would suggest that fund managers with persistently better performance are all selected into managing low-transparency and/or high-concentration funds. The exogenous variation introduced by the downturn of the economy in 2008-2009 enables us to observe the performance of funds in different states of the world, and to provide a direct support for the risk premium story that is represented by funds earning a positive premium during growth periods and negative premium during crisis periods when the embedded risk manifests.

At the same time we observe that the difference in performance between high- and low-liquidity funds is positive and significant, which seems to be driven by the very high difference in performance between high-liquidity and low-liquidity hedge funds during the crisis period. Since the recession years are less frequent than the growth periods, we expect the significance of liquidity coefficient to drop if the time frame of the study were prolonged to include more years of data.

In light of the above results it is interesting to explore whether the documented risk premia still exists if we take a more general approach allowing for all of our measures to influence returns at the same time, as well as investigate whether our results are driven by other potential factors such as fund return volatility, size or the strategy employed. This is the approach we take next.

4.2 Performance of hedge funds: multivariate regression results

Table 3 reports the results of multivariate regressions that use all of our qualitative variables at the same time, as well as controls for hedge fund size, volatility and strategy. These results are very similar to the results we obtained in univariate regressions. For example, during the normal April 2006 to March 2007 period high-transparency funds underperformed low-transparency funds by 5.4% per year, controlling for the level of other qualitative characteristics. At the same time, high-

liquidity funds underperformed low-liquidity funds by 5.7% per year or 6.1% in the specification which includes additional controls for size of the hedge fund, its return volatility and the strategy employed.

It is especially important to control for all of our qualitative characteristics at the same time, since many of them are correlated with each other, as reported in Panel C of Table 1. The results in Table 3, however, suggest that each of the main variables of interest is important irrespective of the values of other variables, and risk premium for low-transparency funds, for instance, is not driven by illiquidity or concentration premia. These results are also robust to the inclusion of the logarithm of assets under management (a proxy for the size of the hedge fund), return volatility, and strategy fixed effects, suggesting that the observed risk premia are not driven by funds being larger or more volatile, or by a potentially different performance of funds employing different strategies[3] .

Similarly to our univariate results, the regression coefficients are mostly insignificant during the intermediate April 2007 to March 2008 period, while during the crisis period we observe a reversal in the signs of the coefficients for high-transparency and high- and medium-liquidity funds, with the latter two being statistically significant at the 1% level both in the specifications with and without additional controls.

As compared to the univariate regression results we find some evidence of a low-complexity risk premium. In particular we observe that high-complexity funds significantly underperformed the low-complexity funds during the normal April 2006 to March 2007 period by about 3.7%-3.9% per year depending on the specification. This suggests that the absence of evidence towards a low-complexity risk premium in the univariate case (Panel C of Table 2) is likely driven by a negative correlation of complexity with transparency and liquidity (as reported by Panel C of Table 1), given

[3] Ideally, we would like to estimate a separate specification for each strategy to explore potential differences in magnitudes of the risk premia across various strategies. However, the number of strategy-year observations is too small to fit so many parameters, so we have to leave this intriguing question for future research. Instead, we estimate a set of specifications where we drop one strategy at a time and find that the results are robust.

that high levels of both command a return premium during normal times. It is therefore important to look at all qualitative variables together in order to implicitly account for interrelations between them. The results in Table 3 can thus be interpreted as the presence of risk premia associated with low transparency, low liquidity, low complexity and high concentration, conditional on the level of all qualitative characteristics as well as additional controls.

4.3 Robustness checks and volatility and flows results

The data sample consists of observations when the fund of funds actually chose to invest with a given fund in a given year, so a potential concern for our results is that the fund of funds selected a different subsample of funds every year and for this reason some high-transparent funds underperformed some low-transparent funds in the normal period from April 2006 to March 2007 while other high-transparent funds outperformed other low-transparent funds in the crisis period from April 2008 to March 2009. To explore further the issue of the selection and as a robustness check, we also provide the results of estimating the same set of specifications in a balanced panel in Table 4, where we require funds to be present during all three periods. This leaves us with 73 observations per year.

We note that the magnitudes of the risk premia associated with transparency and liquidity are almost identical when we condition on the presence of the fund in all three periods. Furthermore, the picture with regard to complexity and concentration risk premia becomes even more clear. In particular, controlling for other qualitative characteristics, high-complexity funds underperformed low-complexity funds by 5.2% per year during the normal April 2006 to March 2007 period. When we additionally control for volatility, size of the fund, and strategy employed, this coefficient stays highly statistically significant with a simillar economic magnitude of 4.6% per year. Interestingly, high-concentration funds overperformed low-concentration funds by 10.5% per year, or 8.5% per year when additional controls are taken into account. Taken together, the evidence in Table 4 suggests that our results are not driven by a different composition of funds from year to year, but

rather by the same funds earning a risk premium during good times and facing a loss when a negative economy shock realizes.

The results in Tables 2, 3 and 4 provide evidence for the presence of various risk premia, in particular the one associated with high levels of concentration of hedge fund investments. The standard finance theory, however, suggests that investors should be able to diversify away all non-systematic (idiosyncratic) risk (see Markowitz, 1952, for the seminal paper). Therefore, such a premium should exist only if investors' diversification capabilities are limited.[4] A recent empirical investigation by Ang et al. (2009), indeed, shows that idiosyncratic stock volatility bears a premium.

To the best of our knowledge the question of why investors do not fully diversify the risks associated with holding a concentrated portfolio has not been explored in the context of hedge funds. In this paper we provide an explanation for why investors demand a premium for investing with concentrated funds that is unrelated to some market frictions or incomplete information. To do that we explore the interaction between the hedge fund transparency and concentration. The rationale behind such an investigation is that concentration should only command a premium when hedge fund investors do not know hedge fund holdings and hence cannot diversify associated risks away. On the other hand, when investors perfectly know what underlying assets the fund is trading, even if the fund is concentrated, they can diversify the corresponding risks and hence should not require a risk premium.

In terms of our empirical framework, this suggests that we should observe the concentration risk premium mainly prevalent among low-transparency funds. To implement this intuition, we regress fund excess returns on their qualitative characteristics (transparency, liquidity, complexity, and concentration) by year, where we additionally introduce all pairwise interactions of the levels of transparency and concentration. Indeed, the results in Table 5 suggest that it is exactly the low-transparency high-concentration funds that command a return premium during normal times.

[4] See, for example, Merton (1987).

In particular, during the April 2006 to March 2007 period among the low-transparency funds, high-concentration funds earned 11.7% more than the low-concentration ones, where this difference is significant at a 1% level. At the same time, among the high-transparency funds the return premium of high-concentration funds over the low-concentration funds constituted a mere $11.7\% - 9.6\% = 2.1\%$ per year, which is statistically indistinguishable from zero. The -9.6% difference between these two return premia thus has an interpretation of a difference-in-differences estimate and is significant at a 1% level. Overall, the results of Table 5 corroborate our intuition that investors are in fact able to diversify the risks associated with investing in funds that hold concentrated asset portfolios as long as they know what these portfolios consist of.

In some of the previous specifications we have used our measure of volatility as a control variable in order to rule out a potential explanation of less transparent, less liquid, less complex, or more concentrated funds having lower idiosyncratic volatility and hence commanding a premium in the spirit of Ang et al (2009). Nevertheless, we would also like to explore how our qualitative variables of interest can help explain the volatility of hedge fund returns. This is what we do next.

Table 6 reports results of multivariate regressions of hedge fund return volatility on transparency, liquidity, complexity, and concentration indicators, for each year as well as for all three years of data controlling for an average level of volatility using year fixed effects in the last column. We observe that some portion of volatility can be attributed to these qualitative variables, with up to 37% of explained variation in the full-sample specification. The signs of the coefficients are in general similar across years. The high-liquidity funds are generally less volatile, with a 0.9% lower annualized volatility as compared to low-liquidity funds. This result is very intuitive since higher levels of liquidity of fund holdings lead to smaller jumps in returns on a month-to-month basis as compared to those of illiquid funds which can experience such jumps due to updates in prices of their assets. This evidence is consistent with the one presented in Huberman and Halka (2001) who document that more liquid stocks have a lower idiosyncratic volatility. As expected, this effect is most pronounced during the crisis period from April 2008 to March 2009, given that the overall propensity to experience sudden changes in asset prices is higher during this period.

We also observe high-concentration hedge funds to be significantly more volatile than the low-concentration funds, with a difference in annualized volatility of about 2% across different specifications. This is also an intuitive result since high-concentration funds diversify less and so similar shocks to prices of individual asset lead to larger changes in returns of these funds as compared to the low-concentration funds. This magnitude is economically significant given that the average hedge fund volatility over the sample is equal to 11% per year. Interestingly, we do not find any difference in volatility of hedge fund returns between high-transparency and low-transparency funds.

Finally, we also study how hedge fund capital flows are related to their transparency, liquidity, complexity, and concentration by considering multivariate regressions of hedge fund flows on these variables. Results of the regressions are reported in Table 7. We find that hedge fund flows are in general very volatile and that among our qualitative variables only the level of liquidity can robustly explain capital flows across different periods in our sample. In particular, we find that high-liquidity funds experienced bigger inflows than low-liquidity funds, especially during the crisis period from April 2008 to March 2009. Given that the actual values of these flows were negative, we interpret this result as low-liquidity funds experiencing heavier outflows than high-liquidity funds, with the difference of about 26.6 percentage points.

5 Conclusion

In this paper we use proprietary data obtained from a fund of funds to study the risk premia associated with hedge fund transparency, liquidity, complexity, and concentration. We are able to contribute to the literature by directly measuring the transparency level of a fund, a qualitative characteristic that is missing in public hedge fund databases, and to use it to quantify the non-transparency risk premium which amounts to about 5.4% per year during growth periods. Importantly, the use of the data that come from both good and bad states of the economy allows us to directly test the risk-premium story against the alternative of better managers being selected into

managing low-transparency funds.

We also investigate how excess returns vary with other fund characteristics, such as fund liquidity, complexity of its strategies, and concentration of its investments. We find a significant risk premia associated with low-liquidity, low-complexity, and high-concentration funds, where the latter is mostly pronounced among non-transparent funds. This result can be interpreted as a novel explanation for why investors cannot diversify away the non-systematic risks.

Finally, we explore how transparency, liquidity, complexity, and concentration help explain the fund return volatility and capital inflows. In particular, the returns of funds with higher levels of liquidity and lower levels of concentration are less volatile. This result is not surprising since high concentration of illiquid investments can lead to significant jumps in the prices of hedge fund portfolios. With regard to hedge fund capital flows we find that during the crisis period low-liquidity funds experienced significantly heavier outflows than high-liquidity funds.

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Table 1: Summary Statistics of Data

Panel A: Number of funds by strategy

Strategy	2007	2008	2009
CR	11	13	10
ED	18	19	20
EQ	65	65	51
RV	20	20	25
TT	7	5	6
Total	121	122	112

Panel B: Hedge fund characteristics

Variable	Year	Mean	Std	q_{25}	q_{50}	q_{75}	N
Return	2007	13.59%	8.62%	9.03%	13.32%	18.02%	121
	2008	3.72%	14.52%	-5.00%	2.61%	10.58%	122
	2009	-16.56%	19.64%	-28.30%	-16.21%	-5.32%	112
Volatility	2007	6.53%	4.34%	3.68%	5.89%	7.80%	121
	2008	10.92%	6.70%	6.44%	9.04%	13.09%	122
	2009	15.81%	10.06%	9.30%	12.67%	20.38%	112
AUM	2007	905m	1.67b	128m	364m	1.05b	121
	2008	1.04b	1.86b	145m	399m	1.28b	122
	2009	810m	1.47b	121m	249m	1.03b	112

Panel C: Pairwise rank correlations of qualitative variables by year

Year		Transparency	Liquidity	Complexity	Concentration
2007	Transparency	1.000			
	Liquidity	0.187^{**}	1.000		
	Complexity	-0.144^{*}	-0.155^{*}	1.000	
	Concentration	-0.025	-0.175^{**}	0.090	1.000
2008	Transparency	1.000			
	Liquidity	0.159^{*}	1.000		
	Complexity	-0.335^{***}	-0.159^{*}	1.000	
	Concentration	0.071	-0.140^{*}	-0.135	1.000
2009	Transparency	1.000			
	Liquidity	0.147^{*}	1.000		
	Complexity	-0.269^{***}	-0.241^{***}	1.000	
	Concentration	0.073	-0.193^{**}	-0.269^{***}	1.000

This table reports various descriptive statistics of our data. Panel A reports the number of funds in our sample by strategy by year. CR denotes credit hedge funds, ED – event-driven hedge funds, EQ – equity hedge funds, RV – relative-value hedge funds, and TT – tactical-trading hedge funds. 2007 stands for April 2006 to March 2007, 2008 – for April 2007 to March 2008, and 2009 – for April 2008 to March 2009. Panel B reports the summary statistics of hedge fund returns, volatility, and assets under management (AUM) for each of the time periods. Mean denotes the annualized sample average, Std denotes the annualized sample standard deviation, q_{25}, q_{50}, and q_{75} denote the 25-th, 50th, and the 75th quantiles, respectively. Finally, N denotes the number of observations. Panel C reports the pairwise rank correlations between transparency, liquidity, complexity, and concentration, computed using Kendall's (1938) τ_B-method to account for the categorical type of the variables and ties. *, **, and *** indicate significance at the 10%, 5%, and 1% levels correspondingly.

Table 2: Hedge fund performance: Univariate regression results

Panel A: Transparency

Variable	Level	APR06-MAR07	APR07-MAR08	APR08-MAR09	APR06-MAR09
Transparency	High	-0.057^{***}	-0.039	0.071	-0.015
		(0.020)	(0.046)	(0.048)	(0.024)
	Medium	-0.043^{**}	-0.029	-0.008	-0.024
		(0.018)	(0.035)	(0.043)	(0.022)
Observations		121	122	112	355
Adjusted R^2		0.042	0.007	0.018	0.352

Panel B: Liquidity

Variable	Level	APR06-MAR07	APR07-MAR08	APR08-MAR09	APR06-MAR09
Liquidity	High	-0.078^{***}	0.082^{*}	0.282^{***}	0.105^{***}
		(0.017)	(0.042)	(0.034)	(0.022)
	Medium	-0.055^{***}	0.045	0.133^{***}	0.048^{**}
		(0.018)	(0.032)	(0.035)	(0.019)
Observations		121	122	112	355
Adjusted R^2		0.103	0.036	0.251	0.385

Panel C: Complexity

Variable	Level	APR06-MAR07	APR07-MAR08	APR08-MAR09	APR06-MAR09
Complexity	High	-0.010	0.020	0.031	0.014
		(0.016)	(0.045)	(0.050)	(0.026)
	Medium	0.023	0.023	-0.027	0.004
		(0.017)	(0.027)	(0.043)	(0.020)
Observations		121	122	112	355
Adjusted R^2		0.015	0.006	0.011	0.351

Table 2 Continued

Panel D: Concentration

Variable	Level	APR06-MAR07	APR07-MAR08	APR08-MAR09	APR06-MAR09
Concentration	High	0.074^{*}	0.008	-0.122^{**}	-0.020
		(0.041)	(0.037)	(0.053)	(0.029)
	Medium	0.044^{***}	-0.008	-0.035	0.005
		(0.013)	(0.026)	(0.038)	(0.016)
Observations		121	122	112	355
Adjusted R^2		0.105	0.002	0.059	0.352

This table reports the results of linear univariate regressions of annual hedge fund excess returns on indicator variables representing different fund characteristics, as described in Sections 2 and 3, separately for each time period considered (April 2006 to March 2007, April 2007 to March 2008, and April 2008 to March 2009), as well as for all three years, where the year fixed effects are included. Panel A, B, C, and D report the results for transparency, liquidity, complexity, and concentration, respectively. The base category are the funds with low levels of transparency, liquidity, complexity, and concentration, so that the obtained slope coefficients can be interpreted as the corresponding return premia earned by high- and medium-level funds with respect to the low-level groups of funds. Standard errors, robust to heteroskedasticity, as well as to within-fund correlation in full-sample results, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels correspondingly.

Table 3: Hedge fund performance: Multivariate regression results

Variable	Level	APR06-MAR07		APR07-MAR08		APR08-MAR09		APR06-MAR09	
Transparency	High	-0.054^{***}	-0.054^{**}	-0.045	-0.022	0.052	0.035	-0.030	-0.009
		(0.019)	(0.022)	(0.048)	(0.046)	(0.040)	(0.039)	(0.024)	(0.024)
	Medium	-0.042^{**}	-0.043^{**}	-0.025	-0.019	-0.027	0.006	-0.030	-0.012
		(0.018)	(0.021)	(0.039)	(0.035)	(0.034)	(0.026)	(0.022)	(0.019)
Liquidity	High	-0.057^{***}	-0.061^{**}	0.102^{**}	0.063	0.279^{***}	0.176^{***}	0.116^{***}	0.047^{**}
		(0.016)	(0.028)	(0.047)	(0.041)	(0.038)	(0.043)	(0.024)	(0.023)
	Medium	-0.051^{***}	-0.052^{**}	0.056	0.032	0.156^{***}	0.132^{***}	0.059^{***}	0.025
		(0.018)	(0.022)	(0.036)	(0.031)	(0.038)	(0.033)	(0.021)	(0.019)
Complexity	High	-0.037^{***}	-0.039^{**}	0.021	-0.075	0.064	-0.012	0.016	-0.053
		(0.013)	(0.020)	(0.049)	(0.063)	(0.043)	(0.052)	(0.024)	(0.033)
	Medium	0.001	-0.004	0.040	0.037	0.024	-0.021	0.016	-0.004
		(0.016)	(0.020)	(0.031)	(0.044)	(0.045)	(0.026)	(0.023)	(0.023)
Concentration	High	0.057	0.088^{**}	0.027	0.018	-0.044	0.050^{*}	0.004	0.062^{***}
		(0.040)	(0.043)	(0.037)	(0.035)	(0.051)	(0.029)	(0.028)	(0.023)
	Medium	0.039^{***}	0.048^{***}	0.004	0.021	-0.002	-0.003	0.015	0.036^{**}
		(0.013)	(0.017)	(0.026)	(0.029)	(0.036)	(0.030)	(0.016)	(0.016)
Ln(AUM)			-0.003		0.016^{*}		0.003		0.008
			(0.004)		(0.010)		(0.008)		(0.005)
Volatility			-1.390		-0.637		-4.705^{***}		-3.581^{***}
			(0.985)		(0.891)		(0.378)		(0.370)
Strategy fixed effects			Y		Y		Y		Y
Observations		121	121	122	122	112	112	355	355
Adjusted R^2		0.222	0.249	0.063	0.290	0.300	0.722	0.394	0.566

This table reports the results of linear multivariate regressions of annual hedge fund excess returns on indicator variables representing different fund characteristics, as described in Sections 2 and 3, separately for each time period considered (April 2006 to March 2007, April 2007 to March 2008, and April 2008 to March 2009), as well as for all three years, where the year fixed effects are included. The base category are the funds with low levels of transparency, liquidity, complexity, and concentration, so that the obtained slope coefficients can be interpreted as the corresponding return premia earned by high- and medium-level funds with respect to the low-level groups of funds. Every other column also includes the controls for the size of the hedge fund (proxied by the logarithm of its assets under management), annualized volatility, and strategy fixed effects. Standard errors, robust to heteroskedasticity, as well as to within-fund correlation in full-sample results, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels correspondingly.

Table 4: Hedge fund performance: Balanced panel multivariate regression results

Variable	Level	APR06-MAR07		APR07-MAR08		APR08-MAR09		APR06-MAR09	
Transparency	High	-0.058^{**}	-0.052^{**}	-0.096^{*}	0.008	0.065	0.038	-0.035	-0.015
		(0.024)	(0.025)	(0.050)	(0.044)	(0.042)	(0.035)	(0.029)	(0.026)
	Medium	-0.045^{**}	-0.043^{**}	-0.080^{*}	-0.038	-0.043	-0.007	-0.047^{*}	-0.020
		(0.018)	(0.018)	(0.042)	(0.036)	(0.038)	(0.025)	(0.027)	(0.022)
Liquidity	High	-0.059^{***}	-0.061^{**}	0.137^{**}	0.114^{**}	0.278^{***}	0.147^{***}	0.115^{***}	0.062^{**}
		(0.018)	(0.027)	(0.067)	(0.049)	(0.048)	(0.045)	(0.036)	(0.030)
	Medium	-0.043^{**}	-0.041^{**}	0.043	0.023	0.164^{***}	0.112^{***}	0.055^{*}	0.023
		(0.017)	(0.020)	(0.049)	(0.040)	(0.037)	(0.026)	(0.030)	(0.025)
Complexity	High	-0.052^{***}	-0.046^{***}	0.044	-0.004	0.042	-0.063	0.008	-0.057
		(0.016)	(0.016)	(0.071)	(0.072)	(0.044)	(0.047)	(0.036)	(0.044)
	Medium	-0.025	-0.024^{*}	0.029	0.059	0.075	0.007	0.018	0.008
		(0.015)	(0.014)	(0.050)	(0.049)	(0.050)	(0.027)	(0.029)	(0.028)
Concentration	High	0.105^{***}	0.085^{***}	-0.006	-0.024	-0.089	0.010	-0.006	0.056^{**}
		(0.025)	(0.030)	(0.049)	(0.057)	(0.059)	(0.029)	(0.038)	(0.025)
	Medium	0.036^{***}	0.031^{**}	0.031	0.049	-0.019	-0.005	0.019	0.047^{**}
		(0.013)	(0.014)	(0.034)	(0.038)	(0.041)	(0.027)	(0.021)	(0.021)
Ln(AUM)			-0.005		0.032^{**}		0.010		0.018^{***}
			(0.004)		(0.014)		(0.006)		(0.005)
Volatility			0.467^{*}		0.116		-1.371^{***}		-1.104^{***}
			(0.238)		(0.511)		(0.100)		(0.115)
Strategy fixed effects			Y		Y		Y		Y
Observations		73	73	73	73	73	73	219	219
Adjusted R^2		0.480	0.520	0.168	0.410	0.340	0.831	0.511	0.683

This table reports the results of linear multivariate regressions of annual hedge fund excess returns on indicator variables representing different fund characteristics, as described in Sections 2 and 3, separately for each time period considered (April 2006 to March 2007, April 2007 to March 2008, and April 2008 to March 2009), as well as for all three years, where the year fixed effects are included, on a balanced panel of funds. The base category are the funds with low levels of transparency, liquidity, complexity, and concentration, so that the obtained slope coefficients can be interpreted as the corresponding return premia earned by high- and medium-level funds with respect to the low-level groups of funds. Every other column also includes the controls for the size of the hedge fund (proxied by the logarithm of its assets under management), annualized volatility, and strategy fixed effects. Standard errors, robust to heteroskedasticity, as well as to within-fund correlation in full-sample results, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels correspondingly.

Table 5: Hedge fund performance: Transparency and concentration interaction results

Variable	Level	APR06-MAR07	APR07-MAR08	APR08-MAR09	APR06-MAR09
Transparency	High	-0.043^{*}	0.093	0.078	0.021
		(0.023)	(0.074)	(0.061)	(0.035)
	Medium	-0.040^{*}	0.094	-0.007	0.008
		(0.023)	(0.074)	(0.059)	(0.035)
Liquidity	High	-0.059^{***}	0.131^{***}	0.284^{***}	0.124^{***}
		(0.018)	(0.050)	(0.041)	(0.025)
	Medium	-0.051^{***}	0.083^{**}	0.161^{***}	0.067^{***}
		(0.019)	(0.042)	(0.039)	(0.023)
Complexity	High	-0.034^{**}	0.065	0.069	0.030
		(0.016)	(0.055)	(0.048)	(0.026)
	Medium	0.002	0.060^{*}	0.030	0.024
		(0.022)	(0.034)	(0.048)	(0.024)
Concentration	High	0.117^{***}	0.277^{***}	-0.035	0.085^{*}
		(0.024)	(0.081)	(0.031)	(0.050)
	Medium	0.025	0.145^{*}	0.013	0.065^{*}
		(0.033)	(0.082)	(0.061)	(0.038)
Interactions	High&High	-0.096^{***}	-0.268^{***}	0.024	-0.078
		(0.033)	(0.125)	(0.072)	(0.061)
	High&Med	0.005	-0.217^{**}	-0.083	-0.096^{*}
		(0.048)	(0.108)	(0.090)	(0.050)
	Med&High	-0.062	-0.273^{***}	-0.016	-0.091
		(0.074)	(0.096)	(0.094)	(0.065)
	Med&Med	0.018	-0.156^{*}	-0.036	-0.051
		(0.036)	(0.093)	(0.072)	(0.043)
Observations		121	122	112	355
Adjusted R^2		0.237	0.119	0.305	0.400

This table reports the results of linear multivariate regressions of annual hedge fund excess returns on indicator variables representing different fund characteristics, as described in Sections 2 and 3, separately for each time period considered (April 2006 to March 2007, April 2007 to March 2008, and April 2008 to March 2009), as well as for all three years, where the year fixed effects are included. Additionally the regressions include the interactions between transparency and concentration variables. The first level in the interaction terms notation represents the level of transparency, while the last one corresponds to the level of concentration. For example, High&Med is a dummy variable that is equal to 1 if a fund has a high level of transparency and a medium level of concentration. The base category are the funds with low levels of transparency, liquidity, complexity, and concentration, so that the obtained slope coefficients can be interpreted as the corresponding return premia earned by high- and medium-level funds with respect to the low-level groups of funds. Standard errors, robust to heteroskedasticity, as well as to within-fund correlation in full-sample results, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels correspondingly.

Table 6: Hedge fund return volatility: Multivariate regression results

Variable	Level	APR06-MAR07	APR07-MAR08	APR08-MAR09	APR06-MAR09
Transparency	High	0.0041	0.0035	−0.0046	0.0026
		(0.0036)	(0.0062)	(0.0063)	(0.0036)
	Medium	0.0026	−0.0002	0.0064	0.0035
		(0.0026)	(0.0042)	(0.0044)	(0.0024)
Liquidity	High	0.0029	−0.0131**	−0.0165***	−0.0090***
		(0.0041)	(0.0061)	(0.0049)	(0.0036)
	Medium	0.0010	−0.0112**	−0.0027	−0.0043
		(0.0030)	(0.0051)	(0.0060)	(0.0033)
Complexity	High	−0.0037	−0.0046	0.0008	−0.0024
		(0.0035)	(0.0046)	(0.0050)	(0.0028)
	Medium	−0.0093***	−0.0116***	−0.0042	−0.0076**
		(0.0027)	(0.0035)	(0.0072)	(0.0032)
Concentration	High	0.0225***	0.0177***	0.0223**	0.0205***
		(0.0046)	(0.0045)	(0.0095)	(0.0042)
	Medium	0.0049***	−0.0002	−0.0020	0.0012
		(0.0020)	(0.0033)	(0.0047)	(0.0021)
Observations		121	122	112	355
Adjusted R^2		0.342	0.298	0.213	0.373

This table reports the results of linear multivariate regressions of annual hedge fund return volatilities on indicator variables representing different fund characteristics, as described in Sections 2 and 3, separately for each time period considered (April 2006 to March 2007, April 2007 to March 2008, and April 2008 to March 2009), as well as for all three years, where the year fixed effects are included. The base category are the funds with low levels of transparency, liquidity, complexity, and concentration, so that the obtained slope coefficients can be interpreted as the corresponding volatility difference between high- and medium-level funds as compared to the low-level groups of funds. Standard errors, robust to heteroskedasticity, as well as to within-fund correlation in full-sample results, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels correspondingly.

Table 7: Hedge fund inflows: Multivariate regression results

Variable	Level	APR06-MAR07	APR07-MAR08	APR08-MAR09	APR06-MAR09
Transparency	High	0.222	0.453	−0.031	0.205
		(0.237)	(0.420)	(0.077)	(0.173)
	Medium	0.096	0.100	−0.070	0.046
		(0.157)	(0.230)	(0.058)	(0.095)
Liquidity	High	0.157	0.240	0.266***	0.224
		(0.370)	(0.392)	(0.092)	(0.197)
	Medium	−0.265*	−0.067	0.155**	−0.056
		(0.152)	(0.211)	(0.062)	(0.093)
Complexity	High	0.283*	0.297	0.120	0.235*
		(0.168)	(0.361)	(0.077)	(0.140)
	Medium	−0.061	0.265	0.156**	0.139
		(0.174)	(0.175)	(0.069)	(0.085)
Concentration	High	0.233	−0.026	0.091	0.087
		(0.201)	(0.194)	(0.068)	(0.098)
	Medium	0.280*	0.062	0.045	0.141
		(0.163)	(0.197)	(0.063)	(0.094)
Observations		109	107	95	311
Adjusted R^2		0.133	0.055	0.123	0.189

This table reports the results of linear multivariate regressions of annual hedge fund inflows (measured as a percentage of past assets under management) on indicator variables representing different fund characteristics, as described in Sections 2 and 3, separately for each time period considered (April 2006 to March 2007, April 2007 to March 2008, and April 2008 to March 2009), as well as for all three years, where the year fixed effects are included. The base category are the funds with low levels of transparency, liquidity, complexity, and concentration, so that the obtained slope coefficients can be interpreted as the corresponding volatility difference between high- and medium-level funds as compared to the low-level groups of funds. Standard errors, robust to heteroskedasticity, as well as to within-fund correlation in full-sample results, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels correspondingly.