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Publication Date
2012

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Essays on the Determinants of Aggregate Economic Performance

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Economics

by

Joel Michael David

2012

ABSTRACT OF THE DISSERTATION

Essays on the Determinants of Aggregate Economic Performance

by

Joel Michael David

Doctor of Philosophy in Economics

University of California, Los Angeles, 2012

Professor Hugo Hopenhayn, Chair

This dissertation contains two essays exploring the avenues through which economies can experience gains in aggregate productivity, a primary determinant of economic growth and welfare. The first essay investigates the role of mergers and acquisitions in redistributing resources across firms and the resulting impact on aggregate economic performance. The second essay investigates the relationship between market structure, innovation, and achieved firm performance, assessing in particular the role of competitive pressure in stimulating innovation activities and gains in economic performance.

The dissertation of Joel Michael David is approved.

Andrew Atkeson

Pierre-Olivier Weill

Andrea Eisfeldt

Mark Wright

Hugo Hopenhayn, Committee Chair

University of California, Los Angeles

2012

To Nicki, who has been there for me throughout,

Isabelle and Sasha, who always brighten my day,

and my brother and parents, for their constant support.

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Acknowledgments

I thank my advisor Hugo Hopenhayn for his invaluable guidance and support, as well as Andy Atkeson, Pierre-Olivier Weill, and Andrea Eisfeldt for many insightful comments and suggestions. I have also benefited from conversations with Ariel Burstein, Pablo Fajgelbaum, and Connan Snider.

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CHAPTER 1

The Aggregate Implications of Mergers and Acquisitions

Mergers and acquisitions can play a transformative role in the evolution of firms and industries and have become an important feature of the US economy, representing about 5% of GDP and 80% of total capital reallocation among large US firms. In this paper, I develop a search-theoretic model of mergers and acquisitions in a dynamic general equilibrium setting and assess the implications for aggregate economic performance. I use a transaction-level dataset to document a number of empirical patterns in US merger activity: (1) acquiring firms are generally larger and more profitable than their targets; (2) there is a large degree of positive assortative matching between transacting firms; and (3) acquirers tend to be the largest and most profitable firms, but targets are not the smallest or least profitable. I build a parsimonious model that is able to address these facts and nests several existing theories of merger activity as special cases. I explore the merger patterns predicted by these theories and show that each meets difficulties in fitting the full set of empirical facts. I calibrate the model to match moments from the transaction-level data, as well as other salient features of the US economy. The calibrated model is capable of replicating the stylized facts quite closely and sheds new light as to how surplus is generated from merger and how the gains are split. I find that merger activity generates potentially large long-run gains in aggregate performance, measuring about 30% in aggregate productivity and output, and about 11% in welfare.

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1.1 Introduction

In 1987, Microsoft purchased Forethought Inc. for $14 million, its first significant acquisition. The software developed by Forethought is now Microsoft PowerPoint. Yahoo!'s first large acquisition was of Four11 Corporation in 1997 for $92 million. Four11's RocketMail product forms the basis of Yahoo! Mail, which boasted 281 million subscribers by 2010. In 2004, Google acquired Where 2 Technologies, a Sydney-based startup company where two Danish brothers were developing a mapping software. This application is now Google Maps, the number 1 mapping site in the world.[1]

Mergers and acquisitions (M&A) play an important and even transformative role in the evolution of many firms and industries. For example, Microsoft has made 138 acquisitions since 1987, Google has made 93 since 2000, and Yahoo! has made 70 since 1997. [2] Indeed, as illustrated by the examples above, many of the products that we most closely associate with individual brands were in fact developed by others. Moreover, it is not necessarily the largest transactions that have the most significant impact on later performance. Rather, the constant transfer of new or lesser developed ideas and products may be an important factor in shaping the ex-post evolution of the transacting firms and the industries in which they operate.

M&A plays an equally prominent role in the aggregate economy and has become an important feature of the US business environment. From 1980 to 2009, M&A has averaged a massive 5% of GDP annually, a figure that has been trend-

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[1]For PowerPoint, see *The New York Times*, 1987, "Company News: Microsoft Buys Software Unit," July 31. Ironically, PowerPoint was first developed for the Apple Macintosh computer. For Yahoo! Mail, see *Cnet News*, 1997, "Yahoo Buys Four11 for Free Email," October 8 and *The Wall Street Journal*, 2010, "Yahoo Revamps Mail Service," September 11. For Google Maps, see *Cnet News*, 2005, "Google Mapper: Take Browsers to the Limit," July 28, *The Sydney Morning Herald*, 2009, "Look Out Outlook, Google's Wave is Coming," May 29, and https://sites.google.com/a/pressatgoogle.com/zamaps/fun-facts-about-maps.

[2]Data from Alacra, Inc., downloaded from http://www.alacrastore.com/.

ing upward with a peak of almost 16% in 1998.[3] Because the capital-output ratio in the private business sector is approximately 1, the rate of capital reallocation occurring through M&A is similar, averaging about 4.5% annually and reaching a high of nearly 15% in 1998.[4] Finally, M&A composes the lion's share of total capital reallocation taking place among large US firms. From 1971 to 2007, M&A has averaged about 65% of total capital reallocation annually among these firms, with its share growing to over 80% in 2007.[5] By these measures, M&A represents an important, and indeed dominant, vehicle for capital reallocation in the US economy.

Would Google and Microsoft have achieved their current status if they had not acquired the products that they have, such as Google Maps and PowerPoint? In reverse, would these products have achieved their prominence had they not been transferred to Google and Microsoft via M&A? Indeed, would their developers have even entered the market if they had not had the prospect of being acquired and incorporated into the product portfolio of their larger competitors? Finally, how does this reallocation of ideas and resources across firms influence aggregate performance and shape the economic landscape in which firms operate? Despite the ubiquity of M&A both for individual firms and for the economy as a whole, the economic role and significance of M&A activity is still not well understood.

In this paper, I assess the implications of M&A for aggregate economic performance. To do so, I build a theory of the M&A market, the incentives driving individual M&A decisions, and the mechanisms through which firm outcomes from

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[3]Data are from SDC Platinum and the Bureau of Economic Analysis and are described in more detail below. To the extent that SDC does not include all M&A activity, its share of GDP is likely to be understated.

[4]The reallocation rate is calculated as the value of M&A divided by the total value of the US capital stock. The capital stock is measured as the stock of private, nonresidential fixed assets. Data are from the same sources as above and the same disclaimer about possible understatement applies. M&A has averaged about 42% of de novo business investment over this same period.

[5]Following [ER06], total reallocation is defined as the sum of expenditures on acquisitions and sales of property, plant and equipment. Data are for Compustat firms and are downloaded from Andrea Eisfeldt's website at http://www.kellogg.northwestern.edu/faculty/eisfeldt/.

M&A aggregate to affect macroeconomic performance. M&A serves as a vehicle for resource reallocation, transferring products and ideas among firms. Through this process, M&A influences economic aggregates by reshaping the distribution of resources across firms and changing the dynamic incentives for entry and exit. Some firms grow through acquisition, others capitalize on their ideas by selling them and exiting the industry, and the prospect of participating in the M&A market affects the entry decisions of entrepreneurs with new product ideas.

The model I develop is one of a dynamic industry in the spirit of [Hop92] and [Mel03]. Heterogeneous firms are monopolistically competitive on the output market and make standard pricing, entry, and exit decisions. Additionally, firms have the opportunity to participate in a merger market, in which the products being exchanged are the firms themselves. Mergers provide firms an avenue to potentially enhance their characteristics by incorporating those of another firm. Upon merger, the characteristics of the continuing firm evolve as an aggregate over those of the two pre-merger entities, the path determined by a "merger technology" to which firms have access. This setup lends itself to a natural tradeoff. Firms would like to grow through acquisition or realize the immediate gains from sale, but not every firm is a profitable partner in the sense of generating positive surplus through merger.

The corporate finance literature has highlighted the importance of search, screening, and bargaining in the M&A market.[6] In this light, I propose a search-theoretic model of the merger market in the spirit of [SS00] and [SS01a]. Firms must make costly investments in searching for candidate partners to purchase or to sell themselves to. Upon meeting, the parties bargain over any surplus that may be generated and decide whether to consummate or reject the transaction. Whether the transaction creates positive surplus depends quite intuitively on whether the value of the post-merger entity exceeds the sum of the two pre-merger firms.

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[6]See, for example, [DeP09] and [RR08b], discussed in more detail below.

In a departure from standard search environments, the model allows for repeat acquisitions, a phenomenon that is common in the data. The presence of firm heterogeneity in conjunction with search and matching frictions gives rise to a rich set of potential matching patterns, a feature I exploit to explore the implications of existing theories of merger activity and to discipline the merger technology in the numerical analysis.

I obtain data on individual M&A transactions in the US over the period 1977-2009 and establish a number of stylized facts regarding M&A activity among US firms. Several striking empirical patterns emerge. Consistent with previous evidence, acquiring firms are generally larger and more profitable than their targets.[7] However, while acquirers are generally larger and more profitable than the median firm, targets are not the smallest nor the least profitable. Indeed, the median target is almost identical to the median firm. Next, I show that there is a large positive correlation between the size and profitability of acquirers and their targets. Large and profitable firms tend to transact with other large and profitable firms and small firms with other small firms. The joint distribution of acquirer and target characteristics reveals a large degree of positive assortative matching in mergers.[8]

To properly measure the aggregate effects of M&A, we must first understand the incentives driving individual M&A decisions and so the technology generating gains upon transaction. Although the model does not in general yield analytic solutions, I am able to characterize the predicted matching patterns under several prevalent theories of merger activity that are nested by the merger technology. These include a theory of no gains from bundling, where mergers are motivated solely by scale efficiencies through fixed cost savings, the q-theory of mergers for the transfer of resources from low to high productivity firms as outlined by [JR02],

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[7]See, for example, [AMS01].

[8][RR08b] point out a similar sorting pattern when examining the market-to-book ratios of paired acquirers and targets.

and lastly a theory of synergistic mergers through asset complementarities as in [RR08b]. I show that each of these theories meets difficulties in fitting the full set of observed matching patterns and explore the economic intuition underlying these results.

In this light, I proceed by calibrating the model to match several of the empirical facts from the transaction-level data. I use the observed merger patterns to infer the parameters governing the merger technology, as well as the bargaining process and the costs of search. Intuitively, observing the characteristics of transacting firms reveals information as to how surplus is generated (or not) from various possible combinations of independent entities, enabling me to discipline the shape of the merger technology, in particular, the parameters determining the role of synergies and productivity enhancement. I use data on the rate of merger and the merger premium to pin down the costs of search and the split of surplus, respectively, exploiting an intuitive relationship between the merger premium and the bargaining powers of the transacting parties revealed by the model. I calibrate the remaining parameters of the model to match a number of salient features of the US economy, and in particular, the firm size distribution. The calibrated model is able to match the targeted moments quite closely and performs well in replicating many of the non-targeted empirical merger patterns. The parameter estimates themselves are of independent interest, as they shed new light as to how surplus is generated upon merger and how the gains are split between the parties.

Finally, I use the calibrated model to quantitatively assess the impact of M&A activity on aggregate economic performance. To do so, I compare the aggregate outcomes from the calibrated economy to one with no M&A. The latter is essentially a closed economy version of [Mel03], a world that has been thoroughly explored in the literature, making it a natural benchmark to understand and quantify the influence of M&A on economic outcomes. At the aggregate level, there is a tradeoff between the beneficial effects of M&A through more efficient

industrial performance and the increased resource costs imposed by M&A activity. M&A imposes direct costs on the economy by absorbing resources in search on the merger market, as well as indirect costs by changing the number of operating firms and the amount of new firm creation that the economy must sustain. After accounting for these margins, the model suggests that M&A has a great potential for improving long-run economic performance. In particular, I find that in stationary equilibrium, M&A activity generates gains of about 30% in both aggregate productivity and output, a similar decline in the aggregate price level, and a welfare increase of about 11%.

This paper relates to several branches of literature. There are, of course, vast bodies of work in industrial organization and corporate finance on the causes and consequences of M&A. Where these have tended to focus on the antitrust implications and financial market aspects of M&A, respectively, I take a different perspective in analyzing the empirical patterns of M&A and assessing its aggregate effects in a dynamic general equilibrium framework.[9] As I cannot hope to do justice to the numerous contributions made in industrial organization and finance, I will focus on a few strands of literature that are particularly relevant.

First, there is a small body of existing work addressing M&A activity from a macroeconomic perspective. [JR02] propose the q-theory of mergers, one of pure reallocation in which mergers serve as a vehicle for resources to flow from low to high productivity firms. Because productivity is embodied in the firm, perhaps

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[9]For recent reviews of these lines of work, see, for example, [Whi07] and [AMS01]. In Table 1.1, I show that the median transaction value among US firms from 1977-2009 was $31 million in real 2005 dollars, falling well below the current threshold of about $63 million that requires the transaction to be reported to the FTC and DOJ under the Hart-Scott-Rodino Act. The majority of transactions are not the headline-grabbers involving two large corporations coming together, but rather, most are small enough to never come to the attention of the US regulatory agencies. Further, only a small number of transactions reviewed by the competition authorities warrant a review. For example, between 2001 and 2010, an annual average of only 3% of reported transactions necessitated a second request, with only a subset of these resulting in a legal challenge (see the Hart-Scott-Rodino Annual Reports available at http://www.ftc.gov/bc/anncompreports.shtm). Together, these facts motivate my focus on the redistributional effects of M&A from an aggregate perspective.

due to superior management or projects, the transferred resource inherits the productivity of its purchaser, giving room for surplus to be generated when firms of differing productivities transact. [JR08] show how merger waves can arise as a response to the availability of a new general purpose technology, such as electricity or IT. In the spirit of the q-theory, mergers serve as a way for resources to be transferred to those firms most capable of deploying the new technology. [ER06] rely on the q-theory in measuring the gains to reallocation and investigating the cyclical properties of reallocative activity. In the finance literature, [RR08b] document positive sorting on the market-to-book ratios of acquirers and targets and develop a synergistic model of mergers driven by asset complementarities to match this fact. Among several notable differences between my paper and these, I allow for endogenous productivity evolution through M&A at the firm level and consider the impact of M&A activity on economic aggregates through reallocation, entry, and exit in a general equilibrium framework. In contrast, these papers have taken firm-level productivity as exogenous and invariant to M&A activity, and have not considered its aggregate effects. Additionally, I allow for a more general merger technology which I discipline quantitatively by matching the empirical merger patterns. Both the q-theory and the theory of purely synergistic mergers are nested in my model and I address their implications in detail in the text of the paper.

Second, there is a recent and growing literature on the potential for aggregate performance gains through the reallocation of resources to more efficient firms. Recent examples include [HK09] and [RR08a]. In considering the potentially beneficial effects of reallocation across heterogeneous firms, these papers share a common agenda with mine. This line of work has typically focused on the potential gains from reallocation stemming from the removal of a set of more abstract distortions preventing full allocative efficiency.[10] In contrast, I model

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[10]Somewhat relatedly, [ER08] focus on a specific distortion and show how agency frictions can hinder resource reallocation across managers of differing quality, resulting in lower levels

a particular vehicle for reallocation and the associated costs, the market that is formed for such activities, and incorporate the empirical facts on observed reallocation activity to discipline the gains accruing to the transacting firms. By doing so, I show another mechanism through which reallocation can spur performance improvements and the potentially detrimental impact of a different sort of policy, that is, one preventing M&A activity.

Lastly, the search-theoretic setup of the merger market connects this paper to a recent literature on the properties and matching predictions of search environments with ex-ante heterogeneous agents. Particularly relevant papers include [SS00] and [SS01a], as well as an earlier predecessor, [LM96]. I extend the standard environment by allowing for repeat matching without need of dissolving one's previous match, and for heterogeneity in the value of rejecting a candidate partner, captured by the value of the firm as a standalone entity. Moreover, I endogenize the values of the agents in the model both in accepting and rejecting matches through their prospects on the output market. An additional contribution comes through the calibration and computation of the model's equilibrium, as I am unaware of any other work that has done so in this type of environment. Finally, this paper shows, I believe, that the M&A market represents an interesting and important application of this general framework.

The remainder of the paper is organized as follows. In the next section, I present the empirical facts regarding observed merger activity. I include a discussion of the roles of search and repeat acquisitions, features of the market that will prove important in the theoretical framework. In Section 3, I outline the model and characterize the matching predictions of existing theories of merger activity, with particular focus on how they line up with the stylized facts. I describe the calibration and numerical results in Section 4, highlighting the parameter esti-

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of aggregate productivity. [Lag06] shows a similar result stemming from frictions in the labor market.

mates, as they are of some independent interest, as well as the performance of the model in matching some salient non-targeted features of the M&A market. In Section 5, I quantitatively explore the aggregate impact of M&A activity. Section 6 concludes.

1.2 The Patterns and Processes of Mergers and Acquisitions

In this section, I present a number of stylized facts regarding the patterns of M&A activity observed in the universe of US firms. Additionally, I describe the process underlying a typical M&A transaction as outlined in the corporate finance literature and highlight the central roles of search, matching, and bargaining in the dealmaking process. Finally, I make note of the importance of repeat acquisitions, a phenomenon that stands in distinction to the markets typically analyzed in the search literature.

1.2.1 Empirical Patterns in Mergers and Acquisitions

I begin by documenting a number of stylized facts regarding the empirical patterns in observed M&A activity. I obtain transaction-level data on US mergers and acquisitions from the Thomson Reuters SDC Platinum database. SDC Platinum includes all transactions involving at least 5% of the ownership of a company where the transaction was valued at $1 million or more (after 1992, all deals are covered) or where the value of the transaction was undisclosed. Public and private transactions are covered. I extract transactions announced between 1977 and 2009. I include domestic transactions with a deal value exceeding $1 million. I limit the sample to completed transactions and those not classified as hostile takeovers. I exclude transactions in which the acquirer owns less than 50% of the target post-merger, or owned over 50% prior to merger. Finally, I remove firms

with non-relevant ownership status (e.g., government-owned) and obvious data entry errors. The final sample consists of 57,858 transactions.

Deal characteristics contained in SDC include the transaction value (purchase price) and the merger premium, which is defined as the percentage by which the purchase price exceeds the current market value of the target, when available. Additionally, SDC contains a number of pre-transaction statistics on the parties involved in each deal. In particular, I obtain sales, employment, property, plant, and equipment (PP&E), earnings before interest, taxes, depreciation, and amortization (EBITDA), and market value for both the acquirer and target firm. PP&E and EBITDA are used as proxies for the size of the firm's capital stock and profitability. Firm-level performance variables in SDC are generally calculated for the 12 month period preceding the deal announcement. I deflate all nominal variables to constant 2005 dollars using the CPI. The firm-level operating data in SDC is only available for a subset of transactions, in large part because many of the firms in the database are privately owned and are not required to report operating statistics to any regulatory agency. I describe the SDC data in more detail in the Appendix.

I obtain the same set of statistics for the universe of Compustat firms over the period ranging from 1977, which corresponds to the first announcement year in the SDC data, through 2009. This yields 210,275 firm-year observations. I match the SDC database to Compustat in order to associate the transacting firms with Compustat operating data. The match between SDC and Compustat is not straightforward, as the two datasets use different firm-level identifiers. I describe the matching process in detail in the Appendix. Of the approximately 58,000 transactions, 31,343 acquirers and 7,437 targets are successfully matched to Compustat. Not surprisingly, the set of successful matches corresponds quite closely to the set of firms classified as public in SDC. In contrasting the characteristics of transacting firms to the overall population of firms, it is important to ensure that

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the data is comparable. To this end, I use the Compustat operating statistics in any calculations that involve industry aggregates, e.g., industry means or medians. I use the SDC statistics in any calculations that do not, mainly because SDC provides more coverage of private companies, in particular targets. For example, sales are available for about 6,800 targets using Compustat and for 18,500 targets using SDC. I describe the Compustat data in more detail in the Appendix.

1.2.1.1 Summary Statistics

In Table 1.1, I report summary statistics of transaction values and merger premia. The merger premium is defined as the percent by which the purchase price exceeds the current market value of the target firm. The premium shown is calculated using the market value of the target firm 4 weeks prior to the merger announcement. This is to avoid the known runup in share prices once rumors of the merger begin to circulate. The mean transaction value is quite modest at $267 million as is the median at only $31 million. The difference reflects a great deal of right-skewness in the distribution of transaction values, that is, the majority of mergers are quite small with some very large outliers. The largest transaction by value is the merger between AOL and Time Warner in the year 2000, a deal valued at about $187 billion in 2005 dollars.

After omitting about 500 transactions with negative premia (less than 8% of transactions where premia are available), there are about 6,000 transactions with reported premia. The mean premium is about 53% and the median 39%. The level of the merger premium is substantial, implying that the majority of transactions are characterized by a purchase price substantially above the current market value of the target firm.

Table 1.1: Transaction Values and Premia

	Trans. Val. ($M)	Premium (%)
Mean	267.4	52.6
Median	31.0	39.0
SD	1,911.5	65.8
Max	186,824.1	1,937.0
Min	0.9	0.0
N	57,858	5,976

1.2.1.2 Buyers and Sellers

In what seems a natural starting point to examine the patterns in M&A activity, I begin by comparing the characteristics of acquirers and targets in individual matches. To do so, I calculate the mean and median log difference between acquirers and targets on several dimensions, including sales, employment, capital stock, profitability, and market value. I show the results in Table 1.2. The first set of columns show statistics using the data as reported. The second set of columns show the same statistics after scaling by the industry medians for the acquirer and target, respectively. I make this adjustment to ensure that the results are not skewed by cross-industry differences between the transacting firms. Industries are defined at the 4-digit SIC level as reported in Compustat. Turning to the first set of columns, we see that acquirers are generally larger and more profitable than targets, on the scale of 2 log points (a factor of about 7.4) consistently across all dimensions. Moreover, this is the case in about 90% of transactions. These patterns are qualitatively robust to scaling each firm by the median firm in its industry. In the large majority of transactions, acquirers are significantly larger and more profitable than the target they are purchasing. This fact is in line with the motivation behind the q-theory as outlined by [JR02], i.e., the characteristics of acquirers and their targets suggest that the former exhibit higher productivity than the latter, perhaps due to better projects or superior management.

Table 1.2: Log Differences in Matched Acquirers and Targets

	Reported			Scaled by Industry Medians		
	Mean	Median	%>0	Mean	Median	%>0
Sales	2.0	1.9	89.0	1.6	1.4	81.7
Employment	2.0	1.8	87.1	1.4	1.3	79.3
PP&E	2.1	1.9	88.2	1.6	1.5	79.9
EBITDA	2.1	1.9	90.0	1.7	1.6	83.2
Market Value	2.3	2.1	95.3	1.9	1.7	86.4

Next, I ask how merger participants compare to the overall population of firms. Table 1.3 reports log differences between acquirers and targets and the median firm in their respective industries. Acquirers tend to be significantly larger than the median in their industry along every dimension. The mean and median differences are both substantial, hovering around 0.8 and 0.7 log points (a factor of about 2), respectively. Despite the large average differences, however, a considerable number of acquirers, generally slightly over one-third, actually fall below the industry median. Thus, it is not the case that acquirers are always the largest and most profitable firms. Turning to targets, interestingly (and perhaps surprisingly), the average target actually tends to be larger or approximately the same as the industry median. On 3 out of 5 dimensions, targets on average exceed the median firm in their industry. On the remaining two dimensions, the average target is only slightly smaller than the median firm. The differences are relatively small on all dimensions, especially as compared with the magnitudes by which acquirers differ from the median and by which acquirers exceed targets. Similarly, the median target generally lines up quite closely with the median firm, such that targets are just about equally represented on both sides of the median. Thus, we see that targets are actually not the smallest and least profitable firms, but rather, tend to be quite similar to the median firm in their industry.

In Figure 1.1, I show how the distributions of acquirers and targets compare to the distribution of all firms in their respective industries. Specifically, I calculate

Table 1.3: Log Deviations from Industry Median

	Acquirer			Target		
	Mean	Median	%>0	Mean	Median	%>0
Sales	0.75	0.58	64.6	0.14	0.00	49.4
Employment	0.67	0.50	63.1	0.10	0.00	48.8
PP&E	0.79	0.61	63.8	0.11	0.00	49.7
EBITDA	0.74	0.57	64.1	-0.07	-0.01	45.7
Market Value	1.01	0.86	69.0	-0.01	0.00	47.1

the deciles of the firm size distribution (measured in sales) across all firms in each industry-year.[11] I then count the proportion of acquirers and targets that fall into each decile. If transacting firms were distributed similarly to all firms, there would be about 10% of transacting firms in each decile, which is represented by the dashed line. Deciles above this line are overrepresented in that more than 10% of transacting firms are drawn from them, and deciles below the line are underrepresented. Examining first Panel A, acquirers, we see that the majority of acquirers come from the top deciles of their industries. The proportion of acquirers is monotonically increasing as we move up the deciles. The bottom 5 deciles are all underrepresented and the top 5 all overrepresented. The disparity is fairly large, from less than 6% in the bottom two deciles to almost 16% in the top. Turning to targets in Panel B, the results are quite different. Targets disproportionately come from the middle of the distribution, deciles 3 to 8. Conditional on being in this group, they are spread fairly evenly, hovering between 10% and 12%. Targets are underrepresented at both extremes, in deciles 1-2 and 9-10. Even here, however, there is some activity. Figure 1.1 confirms that while acquirers tend to be large, targets do not tend to be small.

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[11]I focus on sales as the size metric as this gives the most available observations. The patterns shown are qualitatively similar no matter the size metric chosen.
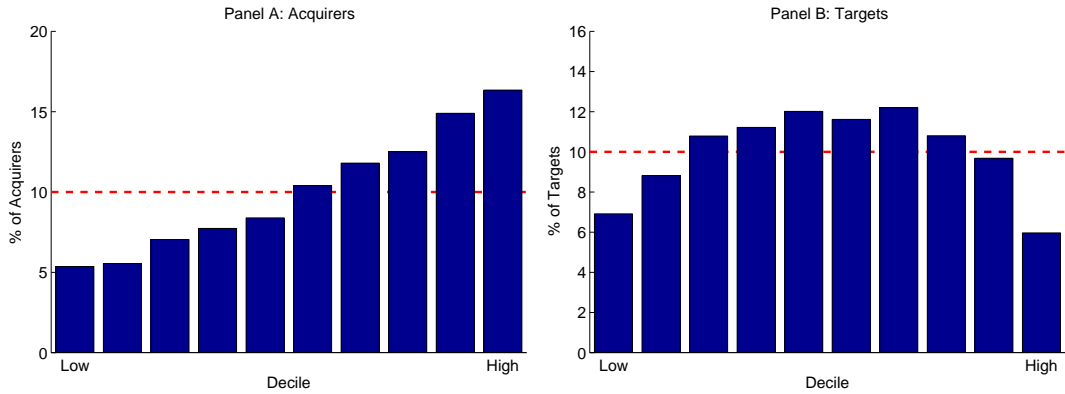
Figure 1.1: Decile Shares of Transacting Firms

1.2.1.3   Assortative Matching

Table 1.2 revealed that acquirers tend to be considerably larger and more prof-
itable than their targets. In this section, I show that a closer look at the data
reveals an additional pattern, that is, the characteristics of acquirers and targets
are highly correlated and display a good deal of positive assortative matching. In
Table 1.4, I report the log correlations of the characteristics of acquirers and tar-
gets in individual matches. The first set of columns reports the correlations from
the data as reported and the second after rescaling by the industry medians. The
results are striking. There is a large positive correlation between acquirers and
targets along all dimensions of the data, on the order of about 0.6. Although the
magnitudes fall slightly, this pattern is robust to rescaling by industry medians.

In Figure 1.2, I show as an example the scatter plot of acquirer vs target
sales.[12] Each point in the figure represents one transaction. In Panel A, I show
sales as reported. In Panel B, I show sales after rescaling by the industry median.
There are about 12,000 transactions in the first panel and 4,500 in the second. To
get a sense of the strength of the relationship, I include the linear regression line
as well as the 45 degree line. The figure clearly illustrates the significant positive

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[12]Again, a similar figure is obtained when using any other size metric. My focus on sales is
motivated by the number of observations available.

correlation between the two groups.

Table 1.4: Log Correlations of Acquirer and Target Characteristics

	Reported	Scaled
Sales	0.62	0.42
Employment	0.58	0.38
PP&E	0.69	0.39
EBITDA	0.63	0.43
Market Value	0.64	0.48
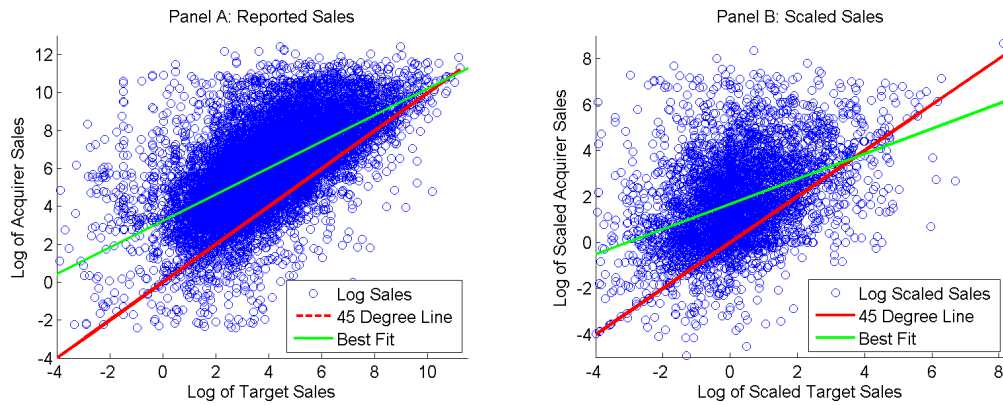
Figure 1.2: Acquirer vs Target Sales

To further assess how matches are formed, Table 1.5 displays the joint distribution of acquirer and target sales. Specifically, I calculate the deciles over the distributions of sales for both acquirers and targets. I then sum the number of transactions in each joint decile of the two distributions. For example, the top left cell displays 535, which is the number of transactions in which both the acquirer and target are in the top deciles of their respective distributions. Finally, I bracket the cells containing the maximum number of transactions for each acquirer and target decile. Each bracketed cell then represents the maximum in a column or row, where the former is the largest target decile from which a given decile of acquirers draw their targets, and the latter the largest acquirer decile to which a given decile of targets sell. Perfectly assortative matching would imply that all bracketed cells lie on the diagonal of the matrix. The table clearly shows

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the large degree of positive sorting that occurs. For acquirers, the largest target decile is the same as their own in 6 out of 10 cases, and similarly, 7 out of 10 cases for targets. The remaining top deciles are all adjacent to the diagonal. Moreover, the numbers are generally decreasing as we move away from the diagonal in any direction. Thus, conditional on participating in the merger market, the largest acquirers tend to partner with the largest targets, and the smallest with the smallest. This fact is in line with [RR08b], who discover a similar pattern when examining acquirer and target market-to book-ratios, and posit a resulting theory of synergistic mergers driven by asset complementarities.

Table 1.5: Joint Distribution of Acquirers and Targets

Target Decile	Acquirer Decile ⟶									
↓	High	9	8	7	6	5	4	3	2	Low
High	535	317	121	42	22	16	7	4	3	7
9	268	293	218	149	102	22	14	5	10	6
8	222	241	211	163	133	101	47	29	13	4
7	141	197	196	201	183	117	98	40	36	17
6	110	158	148	208	198	155	130	107	45	27
5	65	105	127	170	165	187	164	127	87	47
4	59	67	125	126	156	165	195	178	165	87
3	60	44	77	97	122	164	184	191	216	164
2	23	35	37	93	91	108	139	233	300	251
Low	35	23	39	49	42	91	108	144	254	433

1.2.2   The Role of Search

As mentioned above, the corporate finance literature has increasingly recognized the potential importance of search in the M&A market. Recent examples include [RR08b] and [Mar08]. To get a sense of the mechanics of the M&A market, Figure 1.3 outlines the process behind a typical acquisition as described in [DeP09]. In brief, after deciding that an acquisition or merger is desirable and outlining the acquisition plan, i.e., the objectives for the transaction, firms begin the search for potential partners. Search is based on a number of criteria, and typically involves

a lengthy and potentially costly process, entailing the use of databases, directories, and perhaps the hiring of expensive intermediaries such as investment banks and law firms. The list of candidate partners is narrowed through a screening process, and finally, contact is made and a potentially lengthy negotiation begins. If an agreement is reached, the deal is consummated. Otherwise, negotiations are broken off and the firms continue to search.

Business Plan

Acquisition Plan

Search

Screen

First Contact

Negotiation and Purchase Decision

Figure 1.3: The Empirical Search Process

[BM07] describe a similar selling process. Firms typically make a strategic decision to search for a potential buyer. They proceed to contact bidders, either through an intermediary investment bank or directly. In the sample studied by [BM07], about half of firms contacted one bidder, while the other half contacted on average almost 21.

The role of search and matching thus emerges quite clearly. The idea that firms decide if a merger is desirable, embark on a time-consuming and perhaps costly search process, select or discard potential partners based on a number of criteria, and finally negotiate a mutually-agreed upon price leads quite naturally to a search and matching framework. Indeed, the M&A market would seem a prime example of one that is not well described by the Walrasian benchmark of a centralized

market. There are other features of the M&A market that motivate a search and matching setup. Intermediaries, mainly in the form of investment banks, play an important role in connecting buyers and sellers. As we have seen, acquirers generally pay a significant premium over the target's current value, suggesting that the bilateral match has generated surplus to be shared.

1.2.2.1 Repeat Acquisitions

An important feature of the M&A market is that acquiring firms are free to reenter the market following a completed transaction. This is in distinction to usual search markets, such as the labor market or the marriage market, in which it is difficult for an agent to form a new match without dissolving the old. Table 1.6 show the distribution of transactions by the number of times the acquirer has made an acquisition during the sample period. In only one-third of transactions is the acquirer a one-time purchaser. Indeed, there are only 28,945 unique acquirers across the 57,858 transactions. In about a quarter of transactions, the acquirer has made either 2 or 3 purchases, another quarter between 4 and 10, and the remainder more than 10. Thus, the acquisition-filled histories of Microsoft, Google, and Yahoo documented in the introduction are not anomalies, but rather, serial acquisition is quite common.

1.2.3 The Facts

Before moving on to the model, I summarize the key empirical findings:

1. The majority of mergers are small, with a few very large transactions.

2. The average merger premium is substantial.

3. Acquirers are typically larger and more profitable than their targets.

4. Acquirers tend to be the largest and most profitable firms; targets are not the smallest or least profitable.

Table 1.6: Transactions by Number of Acquirer Purchases

Acquirer Purchases	Transactions	Percent
1	18,870	32.6
2-3	13,301	23.0
4-5	7,345	12.7
6-7	4,695	8.1
8-10	4,311	7.5
11-15	4,251	7.3
16-20	2,100	3.6
21-30	1,914	3.3
31-40	751	1.3
More than 40	320	0.6
Total	57,858	100.0

5. There is significant positive correlation between the characteristics of acquirers and targets; observed transactions exhibit a large degree of positive assortative matching.

6. Firms must make a potentially costly and time-consuming search for potential partners; not all candidates are a good match and firms choose with which partners to proceed.

7. The majority of acquirers make multiple purchases on the merger market.

1.3   The Model

In this section I present a model of merger activity in a dynamic general equilibrium setting. The active agents in the model are a set of heterogeneous firms operating in a monopolistically competitive differentiated goods industry. Firms offer a product portfolio composed of a bundle of individual varieties. In addition to hiring labor, producing output, and reaping profits, firms act in a merger market, in which they can buy other firms and expand, or sell themselves and exit the industry. Mergers give firms the opportunity to incorporate new varieties and enhance their product portfolio. Following a merger, the productivity of the

acquiring firm evolves as an aggregate over those of the two pre-merger firms. The acquirer then continues on in production, and importantly, retains the option of participating again in the merger market.

In line with the empirical merger process described above, the merger market is characterized by search and matching frictions. Firms must make a costly investment in search which gives a Poisson arrival of meeting a prospective partner. Upon meeting, firms bargain over the purchase price and choose to consummate some transactions and reject others. There is endogenous entry into the industry subject to a setup cost. The prospects of participating in the merger market along with the general equilibrium effects of merger activity on industry aggregates influence firm entry and exit decisions. Thus, merger activity affects aggregate industry performance by redistributing resources across operating firms and changing the dynamic incentives for entry and exit. I will focus on a stationary equilibrium in which individual firms are constantly entering, exiting and merging, but the economy replicates itself in such a way as to keep aggregate variables constant.

1.3.1 Preferences and Final Production

Time is continuous and indexed by τ.[13] The economy is populated by a constant measure L of identical consumers. Consumers inelastically supply labor and have preferences of the form

$$\int_0^\infty e^{-\kappa\tau} \log\left(C_\tau\right) d\tau \tag{1.1}$$

where C_τ denotes time τ consumption of a final good, described below, and $\kappa > 0$ is the rate of time discount. In a stationary equilibrium, this gives rise to a constant real interest rate given by $r = \kappa$.

The final good is produced by competitive firms from a continuum of differentiated intermediate goods, indexed by ω. Final good producers operate with a

---

[13]The focus on a stationary equilibrium will obviate the need to track time and henceforth I suppress time subscripts.

constant returns to scale CES production technology of the form:

$$Y = \left[\int_{\omega \in \Omega} q\left(\omega\right)^{\rho} d\omega \right]^{\frac{1}{\rho}} \tag{1.2}$$

where Ω denotes the set of intermediate products and $0 < \rho < 1$ such that the products are substitutes with associated elasticity of substitution $\sigma = \frac{1}{1-\rho} > 1$. Standard arguments give the aggregate price index

$$P = \left[\int_{\omega \in \Omega} p\left(\omega\right)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \tag{1.3}$$

and demand and expenditure functions for each product

$$q\left(\omega\right) = Y \left[\frac{p\left(\omega\right)}{P} \right]^{-\sigma}, r\left(\omega\right) = R \left[\frac{p\left(\omega\right)}{P} \right]^{1-\sigma} \tag{1.4}$$

where $R = PY$ denotes aggregate expenditure on the final good.

1.3.2 Intermediate Production

A continuum of monopolistically competitive firms operate with heterogeneous productivities $\tilde{z}$ to produce the set of intermediate products Ω. Firms may offer multiple products as they add varieties through acquisition. For convenience, I assume that a firm is characterized by a single productivity level that is applicable to all of its products. Then, we can think of each firm as offering a single product portfolio composed of a bundle of individual varieties.[14] In a process to be described below, the firm's productivity $\tilde{z}$ may evolve as the firm grows through acquisition. Thus, despite the absence of productivity shocks subsequent to entry, the firm's productivity level is in part endogenous and determined by its outcomes on the merger market, as is the size of its product portfolio.

---

[14]The idea that the firm has a single productivity level for all products nests the case in which each product retains an individual productivity level in a straightforward manner.

Labor is the only factor of production and the wage w is normalized to 1 and serves as numeraire. For each product j produced by a k-product firm with productivity $\tilde{z}$, the production technology exhibits constant returns to scale in labor and takes the form $q_j(\tilde{z}) = \tilde{z}^{\frac{1}{\sigma-1}} l_j$. I follow [AB10] in rescaling $\tilde{z}$ by the exponent $\frac{1}{\sigma-1}$, which implies that firm revenues, labor demand, and variable profits are proportional to $\tilde{z}$. This will prove convenient in generating a particularly simple interaction between the number of products in a firm's product portfolio k and its productivity $\tilde{z}$, greatly easing the computation of the model.

The total output of a k-product firm with productivity $\tilde{z}$ is then

$$q(k, \tilde{z}) = \sum_{j=1}^{k} \tilde{z}^{\frac{1}{\sigma-1}} l_j = k\tilde{z}^{\frac{1}{\sigma-1}} l_j \tag{1.5}$$

where I have used the fact that product-level production labor l_j is determined by the firm's common productivity level $\tilde{z}$ and so will be identical across all of its products. We can see that $\tilde{z}^{\frac{1}{\sigma-1}}$ represents the per-product productivity of the firm and total output will scale with the size of the firm's product portfolio, measured by the number of products it offers.

Standard arguments give the common output price set by the firm for each of its products as

$$p(\tilde{z}) = \frac{1}{\rho \tilde{z}^{\frac{1}{\sigma-1}}} \tag{1.6}$$

In order to produce and remain in the industry, firms must pay a fixed cost of operation of c_f units of the final good. It is straightforward to show that labor demand, revenues, and variable profits from sales net of fixed costs for a k-product

firm are then equal to

$$l(k, \tilde{z}) = \rho^\sigma R P^{\sigma-1} k\tilde{z}$$

$$r(k, \tilde{z}) = R(\rho P)^{\sigma-1} k\tilde{z}$$

$$\pi(k, \tilde{z}) = \frac{R}{\sigma}(\rho P)^{\sigma-1} k\tilde{z} - Pc_f$$

An important implication of the production technology is that the number of products a firm offers and its physical productivity enter everywhere multiplicatively into its product market outcomes. Defining an index $z = k\tilde{z}$, we have

$$l(z) = \rho^\sigma R P^{\sigma-1} z \qquad (1.7)$$

$$r(z) = R(\rho P)^{\sigma-1} z$$

$$\pi(z) = \frac{R}{\sigma}(\rho P)^{\sigma-1} z - Pc_f$$

such that z represents a sufficient statistic for firm profits and size. As we will see below, all decisions of the firm can be determined by its z and the relevant economic aggregates, so that the firm's individual state has been reduced to one dimension. Additionally, I will show that the aggregates themselves can be determined by the distribution of z, and hence do not require tracking the joint distribution of k and $\tilde{z}$. I will call z "effective productivity," since it is this combination of k and $\tilde{z}$ that effectively determine the firm's size and profitability. Intuitively, firm outcomes are determined by both the size of its product suite and its level of productive efficiency. The ratio of any two firms' labor demand, revenues and variable profits (gross of fixed costs) is equal to $\frac{z_1}{z_2}$. Henceforth, we can treat our multi-product firms as offering only a single product, which we know to be composed of a bundle of individual varieties, with effective productivity z.[15]

---

[15]In the Appendix, I develop a version of the model using a single homogenous good and decreasing returns to scale in production a la Lucas span of control. This version of the model gives identical implications, while eliminating the need to track the size of the firm's product portfolio.

1.3.3 The Merger Market

In addition to hiring labor, producing, and reaping profits on the output market, firms can participate in a merger market, in which the firms themselves represent products to be bought and sold. Firms enter the merger market in order to trade the blueprints or knowledge to produce a product or suite of products (an alternative interpretation would be the team of assembled labor with the particular expertise to manufacture these products). After a merger takes place, the acquirer incorporates the products formerly held by the target into its portfolio, pays a one-time acquisition price to the selling firm, and continues on in production. Target firms sell their suite of products, receive the merger payment from the purchasing firm, and exit the market. Importantly, acquirers retain the option to participate in the merger market after a transaction occurs, that is, once a transaction is concluded, the continuing firm is free to pursue more opportunities on the merger market.

1.3.3.1 Merger Technology

Upon merger, the characteristics of the acquiring firm evolve as a function of the characteristics of the two pre-merger firms. In particular, the effective productivity of the post-merger entity z_m is determined as an aggregate over those of the pre-merger acquirer and target, z_a and z_t, according to the following CES merger technology:

$$z_m = s\left(z_a, z_t\right) = A\left[\alpha z_a^\gamma + \left(1 - \alpha\right) z_t^\gamma\right]^{\frac{\nu}{\gamma}} \tag{1.8}$$

It is intuitive that the effective productivity of the new entity depends on those of the two pre-merger firms. This captures the idea that the size and efficiency of the pre-merger firms jointly determine the outcome from merger. In practicality, the acquiring firm is bundling formerly separate streams of revenues and profits, which we have seen depend on the individual firms' effective productivities. The

parameters of the merger technology can be interpreted analogously to their role in a CES production function. γ determines the substitutability between z_a and z_t, ν governs the returns to scale of the technology, α is a weighting factor, and A allows for some degree of autonomous change from merger, independent of z_a and z_t.

Recall that the firm's effective productivity z is composed of the size of its product base k and its physical productivity $\tilde{z}$. Because mergers do not result in the creation (or destruction) of products, we have that $k_m = k_a + k_t$, i.e., the merged firm's portfolio is the sum over those of the two pre-merger firms. Then the evolution of $\tilde{z}$ is such that (1.8) holds. This technology is convenient in providing a good deal of flexibility in modeling the transformation from two pre-merger firms to a single post-merger entity. Below, I consider in detail a number of particular technologies that are nested inside the CES specification and I defer further discussion until then.

1.3.3.2   Search Technology

In line with with the empirical transaction process outlined above, the merger market is characterized by search and matching frictions. The search market here is not two-sided in the standard sense of having two disjoint types seeking to match, as is the case in the labor market with firms and workers or the marriage market with men and women. Rather, firms are searching for one another and may end up on either side of a transaction. To capture this idea, firms are able to search simultaneously on both sides of the market, although their search intensities and rate of transaction are endogenous and depend on their expected surplus from each type of match.

Firms choose search intensities $\lambda(z)$ of meeting a potential target and $\mu(z)$ of meeting a potential acquirer. To obtain these intensities, the firm must expend

$C_\lambda (\lambda)$ units of the final good in seeking potential targets and $C_\mu (\mu)$ in seeking potential purchasers. $C_x (x)$ is convex and satisfies the standard properties $C_x(0) = 0, C'_x(x) > 0, C''_x(x) > 0, \lim_{x \to \infty} C_x (x) = \infty$ for $x = \lambda, \mu$. Denote by $dG(z)$ the endogenous distribution of firm types in the market, which will be described below. The individual search decisions of the firms in the market generate aggregate search intensities $\int \lambda (z) \, dG (z)$ and $\int \mu (z) \, dG (z)$. In a bit of a technicality, it is possible that there is rationing in equilibrium if the aggregate search intensities do not equate, leaving some searchers on the long side of the market unrewarded by a meeting.[16] The aggregate meeting rate takes the form

$$\min \left\{ \int \lambda (z) \, dG (z) , \int \mu (z) \, dG (z) \right\} \tag{1.9}$$

With possible rationing, to obtain the effective meeting rates, search intensities must be be scaled by a proportion factor representing the probability of a meeting per unit of search. These factors take the form

$$
\begin{aligned}
j_a &= \min \left\{ \frac{\int \mu (z) \, dG (z)}{\int \lambda (z) \, dG (z)}, 1 \right\} \\
j_t &= \min \left\{ \frac{\int \lambda (z) \, dG (z)}{\int \mu (z) \, dG (z)}, 1 \right\}
\end{aligned}
\tag{1.10}
$$

for acquirers and targets, respectively.

A type z_a acquirer finds a type z_t target according to a Poisson arrival rate

$$\frac{\lambda (z_a) \, j_a \mu (z_t) \, dG (z_t)}{\int \mu (z) \, dG (z)} = \lambda (z_a) \, j_a \Gamma (z_t) \, dG (z_t) \tag{1.11}$$

Similarly, this target finds this acquirer at rate

$$\frac{\mu (z_t) \, j_t \lambda (z_a) \, dG (z_a)}{\int \lambda (z) \, dG (z)} = \mu (z_t) \, j_t \Lambda (z_a) \, dG (z_a) \tag{1.12}$$

---

[16]We will see in the numerical analysis that this form of rationing does not seem to play an important role in US M&A activity.

where $\Gamma(z_t)$ and $\Lambda(z_a)$ denote the conditional probability (upon some meeting) of meeting a particular target and acquirer, respectively.

Once firms meet a candidate partner, they will assess the characteristics of that partner and choose to either consummate the transaction or reject that particular match and continue operating in their current state. Thus, the firm has two decisions to make in the merger market: first, with what intensity to search for potential partners on each side of the market, and second, whether to complete a deal once a potential match has been formed.

1.3.3.3 Bargaining

Upon meeting, the net surplus generated by proceeding with a merger is

$$\Sigma(z_a, z_t) = V(z_m) - V(z_a) - V(z_t) \tag{1.13}$$

where $V(z_m)$ denotes the value of the post-merger entity, $V(z_a)$ the value of the pre-merger acquirer and similarly $V(z_t)$ for the pre-merger target. Intuitively, the surplus is simply the value of the merged entity less the sum of the values of the two parties as standalone firms. The firms will consummate a merger when $\Sigma(z_a, z_t) \geq 0$, i.e., whenever the value of the post-merger firm is at least as large as the sum of the values of the pre-merger firms. Once a match is formed, the surplus must be divided between the two parties. Bargaining occurs according to the generalized Nash bargaining protocol and results in a commonly agreed upon purchase price $P(z_a, z_t)$. Denoting with β the bargaining power of the acquirer, the purchase price satisfies

$$\begin{aligned} P(z_a, z_t) &= V(z_t) + (1-\beta)(\Sigma(z_a, z_t)) \\ &= V(z_t) + (1-\beta)(V(z_m) - V(z_a) - V(z_t)) \end{aligned} \tag{1.14}$$

where $1 - \beta$ denotes the target bargaining weight. Intuitively, the purchase price reflects both the outside option of the target, which is to continue as a standalone entity, as well as the target's share of the net surplus generated by the merger. The merger premium is easily shown to satisfy

$$\frac{P\left(z_a, z_t\right) - V\left(z_t\right)}{V\left(z_t\right)} = \frac{\left(1 - \beta\right)\left(V\left(z_m\right) - V\left(z_a\right) - V\left(z_t\right)\right)}{V\left(z_t\right)} \qquad (1.15)$$

The premium in each merger depends on the bargaining shares of the two parties as well as the net gains generated. Recall from Table 1.1 that the observed premia are substantial.

I illustrate the timing of the merger market in Figure 1.4.
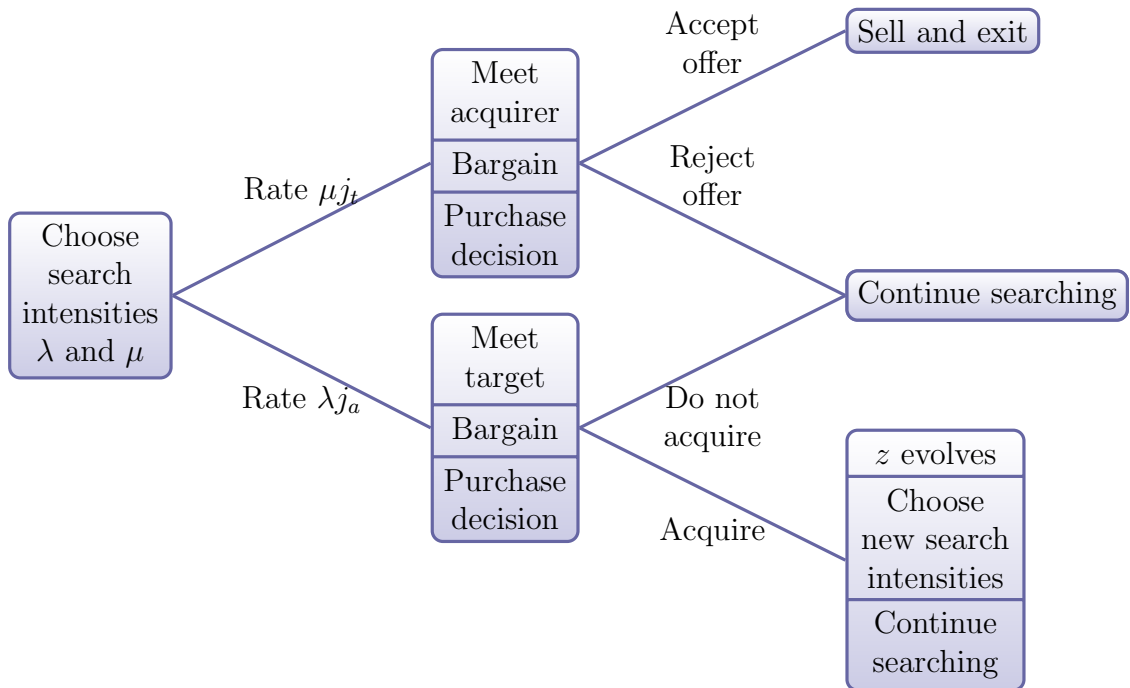
Figure 1.4: The Timing of Actions on the Merger Market

1.3.4 Entry and Exit

The industry is characterized by free entry. There is a large pool of ex-ante identical potential entrants. To enter, firms must expend c_e units of the final good to obtain a draw from an exogenous distribution $F(z), z \in (z_{\min}, \infty)$ with associated density function $dF(z)$.[17]

Once an entrant realizes its initial z, it may enter the market and begin operations, or exit immediately. The fixed cost of operation c_f implies that some firms may draw a low enough z such that the value from entering is negative. The entry decision will be determined by a threshold value $\hat{z}$ defined implicitly by $V(\hat{z}) = 0$, such that firms drawing $z < \hat{z}$ will choose not to enter. Intuitively, firms will enter as long as there is positive value from doing so. Upon entry, the firm's value depends on its profit flows as well as its prospects in the merger market. Thus, the existence of the merger market will influence the entry threshold both by affecting the industry aggregates that in part determine firm profits and by giving firms an additional value stream stemming from expected gains in the merger market.

The free entry condition requires

$$\int V(z) \, dF(z) \leq Pc_e \tag{1.16}$$

i.e., that the expected value of entry is less than or equal to the cost, with equality if there is positive entry in equilibrium.

Following entry, firms are subject to an exogenous common exit shock that arrives at rate δ. However, there are actually several reasons exit may occur, and exit rates may vary systematically across the range of firms in the economy. First, for firms that draw a $z \leq \hat{z}$, exit is immediate. For firms that choose to enter,

---

[17]For simplicity, I assume draws from the entry distribution include both an initial productivity level and an initial number of products, so that firms draw a z directly. Alternatively, we can think of firms as drawing only a random productivity level and beginning with only a single product so that firms are drawing a $\tilde{z}$. Of course, this just means that $z = \tilde{z}$ for the new entrant, and other than complicating notation, has no other implications.

exit can occur either through the realization of the exogenous shock δ, or by being acquired. The rate of exit for an incumbent firm of type z is then given by

$$\delta + \mu(z) j_t \int \Phi\left(\Sigma\left(z_a, z\right)\right) \Lambda\left(z_a\right) dG\left(z_a\right) \tag{1.17}$$

where the latter term is the rate at which this firm type is acquired, composed of the product of the meeting rate and the conditional probability that a transaction is consummated. This last is the integral over the set of firm types that result in positive surplus, weighted by the endogenous distribution of firms types scaled by their search intensity as acquirers. The weights represent the endogenous presence of each firm type on the acquiring side of the market. $\Phi\left(\cdot\right)$ denotes the indicator function equal to 1 if its argument is greater than or equal to zero, else equal to zero. Consistent with well-known empirical facts, new entrants will have a higher rate of exit than incumbents. Within the set of incumbent firms, exit rates will vary systematically to the extent that the rate of being acquired does.

1.3.5   Value Functions and Decision Rules

Having defined the environment and the firm's decision problem, we can write the continuous time value function of an incumbent firm in stationary equilibrium as

$$
\begin{aligned}
(r+\delta) V\left(z\right) \;=\; & \pi\left(z\right) - PC_\lambda\left(\lambda\left(z\right)\right) - PC_\mu\left(\mu\left(z\right)\right) \\
& + \; \lambda\left(z\right) j_a \int \max\left\{V\left(z_m\left(z, z_t\right)\right) - V\left(z\right) - P\left(z, z_t\right), 0\right\} \Gamma\left(z_t\right) dG\left(z_t\right) \\
& + \; \mu\left(z\right) j_t \int \max\left\{P\left(z_a, z\right) - V\left(z\right), 0\right\} \Lambda\left(z_a\right) dG\left(z_a\right)
\end{aligned}
$$

The first line represents the net profit flows of the firm, composed of profits from the output market, which are net of fixed costs, less the cost of search on the merger market. The second line represents the value from being a potential acquirer on the merger market. The firm meets a candidate target at rate λj_a.

The target is drawn randomly from the set of operating firms with probabilities depending on the endogenous distribution of firm types $dG(z)$ and the search intensities of the firms on the target side of the market. The firm then decides whether to consummate the transaction, giving capital gains equal to the value of the new post-merger entity less the value of the existing firm that is lost and the purchase price paid to the target, or reject the match and continue on as a standalone entity, giving capital gains of zero. Similarly, the last line denotes the value from being a potential target and is interpreted analogously. Here, the capital gain from a completed transaction is the price received less the value of continuing as-is.

After imposing the Nash bargaining solution (1.14), which implies that the surplus generated from merger is distributed to the transacting firms according to their respective bargaining weights, we can rewrite the value function as

$$
\begin{aligned}
(r+\delta)V(z) &= \pi(z) - PC_\lambda(\lambda(z)) - PC_\mu(\mu(z)) \\
&+ \lambda(z)j_a\beta \int \max\{\Sigma(z,z_t),0\}\,\Gamma(z_t)\,dG(z_t) \\
&+ \mu(z)j_t(1-\beta) \int \max\{\Sigma(z_a,z),0\}\,\Lambda(z_a)\,dG(z_a)
\end{aligned}
$$

where the firm's expected gains in the merger market are now functions of the bargaining shares and the expected net surplus created from a match.

For ease of exposition, I define

$$
\begin{aligned}
E[M_a(z)] &= \beta \int \max\{\Sigma(z,z_t),0\}\,\Gamma(z_t)\,dG(z_t) \qquad (1.18) \\
E[M_t(z)] &= (1-\beta) \int \max\{\Sigma(z_a,z),0\}\,\Lambda(z_a)\,dG(z_a)
\end{aligned}
$$

as the expected capital gains from meeting a candidate partner as an acquirer and target, respectively, conditional on a potential match having been formed. The

value function is then simply

$$(r + \delta) V(z) = \pi(z) - PC_\lambda(\lambda(z)) - PC_\mu(\mu(z)) + \lambda j_a E[M_a(z)] + \mu(z) j_t E[M_t(z)]$$

(1.19)

The firm makes two types of decisions in the merger market. The first is to choose a pair of search intensities with which to seek potential targets and potential purchasers. Optimal search is governed by a pair of first order conditions:

$$PC'_\lambda(\lambda(z)) = j_a E[M_a(z)]$$ (1.20)

$$PC'_\mu(\mu(z)) = j_t E[M_t(z)]$$

Intuitively, firms choose search intensities that equate the marginal costs of search to the expected marginal gains. This latter is composed of the additional probability of meeting a potential partner multiplied by the expected gain conditional on having formed a potential match.

Once the firm meets a candidate partner, it has the choice of whether to consummate the merger or proceed as a standalone entity. As shown above, there is a common acceptance set for acquirers and targets in which any transaction generating positive surplus is consummated, i.e., while $\Sigma(z_a, z_t) \geq 0$. The firm's decision rule is characterized by two acceptance regions, the first representing the set of targets it is willing to purchase and the second the set of acquirers it is willing to sell itself to. Formally, I define these regions by

$$\Upsilon_t(z) = \{z_t : \Sigma(z, z_t) \geq 0\}$$ (1.21)

$$\Upsilon_a(z) = \{z_a : \Sigma(z_a, z) \geq 0\}$$

Finally, the entry decision is characterized by a threshold $\hat{z}$ where firms drawing $z < \hat{z}$ will choose to exit the industry immediately and firms with $z \geq \hat{z}$ will choose

to enter. The threshold is implicitly defined where the value of operation is exactly zero, i.e., $V(\hat{z}) = 0$. From the firm's value function (1.19), we see

$$V(\hat{z}) = 0 \tag{1.22}$$

$$\Rightarrow \pi(\hat{z}) = -\{\lambda(\hat{z})\, j_a E\left[M_a(\hat{z})\right] + \mu(\hat{z})\, j_t E\left[M_t(\hat{z})\right] - PC_\lambda(\lambda(\hat{z})) - PC_\mu(\mu(\hat{z}))\}$$

Intuitively, the cutoff productivity is set where the firm's profit flows from the output market (net of fixed costs) equals the negative of its expected gains from participating in the merger market. Expected gains in the merger market must be nonnegative, else the firm would optimally choose not to participate in this market at all. Thus, (1.22) reveals that a firm with the cutoff productivity $\hat{z}$ will actually incur negative profits as long as there is any positive value from its prospects in the merger market. Without the possibility of merger, the right hand side of (1.22) would be zero, i.e., the cutoff productivity would be where flow profits are exactly zero. Here, the threshold is lower. Less productive firms are willing to enter the market and incur losses simply to retain the option value of participating in the merger market. Seen another way, once a firm has paid the sunk cost of entry, the prospects of merging make it more reluctant to exit.

Note, however, that this does not necessarily imply that the threshold is lower than in an economy without mergers. The entry decision also depends upon the level of flow profits, which are a function of the industry aggregates. By redistributing resources across firms, the merger market influences industry performance and thus the aggregates that enter the profit function. If the merger process generates aggregates that induce lower levels of flow profits, then the merger market may actually raise the entry threshold, resulting in increased selection at the entry margin. Thus, the effect of mergers on the entry decision is ambiguous, and depends upon the rate at which individual profits fall due to the greater efficiency of the industry versus the rate at which the potential gains from

merger add to the marginal firm's value (in other words, whether the left hand side of (1.22) falls faster or slower than the absolute value of the right hand side increases).

1.3.6 Stationary Equilibrium

In a stationary equilibrium, the economy replicates itself such that the aggregate variables remain constant. This implies that the inflows and outflows of firms in the market must balance for all firm types. The stationary conditions for each individual type z take the form

$$
\begin{aligned}
& M \int \lambda\left(z_a\right) j_a\left[\int_{s^{-1}\left(z, z_a\right)} \Phi\left(\Sigma\left(z_a, z_t\right)\right) \Gamma\left(z_t\right) dG\left(z_t\right)\right] dG\left(z_a\right) + M_e dF\left(z\right) \\
& = \lambda\left(z\right) j_a M dG\left(z\right) \int \Phi\left(\Sigma\left(z, z_t\right)\right) \Gamma\left(z_t\right) dG\left(z_t\right) \\
& + \mu\left(z\right) j_t M dG\left(z\right) \int \Phi\left(\Sigma\left(z_a, z\right)\right) \Lambda\left(z_a\right) dG\left(z_a\right) + \delta M dG\left(z\right) \ \forall z \geq \hat{z}
\end{aligned}
\tag{1.23}
$$

where $s^{-1}\left(z, z_a\right) = \left\{z_t : s\left(z_a, z_t\right) = z\right\}$ denotes the inverse of the merger technology defined in (1.8). For each type, firms flow in as the continuing entity generated from a merger that moves the post-merger firm into that type z and through new entry. Firms flow out through participation in a merger, either as an acquirer or target, and through the realization of the exogenous exit shock. Integrating both sides, we find the aggregate stationary condition

$$
[1 - F(\hat{z})] M_e = \left\{ \delta + \int \mu\left(z\right) j_t \left[\int \Phi\left(\Sigma\left(z_a, z\right)\right) \Lambda\left(z_a\right) dG\left(z_a\right)\right] dG\left(z\right) \right\} M
\tag{1.24}
$$

which requires that the total flow of firms into the market must equal the total flow of firms out, where the latter is the integral over the exit rates defined in (1.17).

There are two feasibility constraints in the economy. First, labor market clear-

ing requires

$$M \int l(z) \, dG(z) = L \tag{1.25}$$

i.e., that demand and supply for labor equate. For the final good, feasibility requires

$$Y = C + Y_s + Y_f + Y_e \tag{1.26}$$

where

$$Y_s = M \left[\int C_\lambda(\lambda(z)) \, dG(z) + \int C_\mu(\mu(z)) \, dG(z) \right] \tag{1.27}$$

denotes the total resources devoted to search activities on the merger market, $Y_f = M c_f$ resources devoted to the fixed costs of production, and $Y_e = M_e c_e$ resources devoted to the creation of new firms. That is, final production is allocated to final consumption and to payment of the various resource costs in the economy.

We are now in a position to define an equilibrium in this economy.

Definition (Equilibrium). A *stationary search equilibrium* consists of

1. aggregate variables $\{Y, P, C, M, M_e, dG(z)\}$

2. intermediate good prices and quantities, entry threshold, and values
   $\{p(z), q(z), \hat{z}, V(z)\}$

3. firm search intensities and acceptance sets on the merger market
   $\{\lambda(z), \mu(z), \Upsilon_t(z), \Upsilon_a(z)\}$

such that

1. consumers maximize utility

2. intermediate and final goods firms maximize expected discounted profits

3. the labor market and final good market feasibility constraints are satisfied

4. the evolution of firm types is consistent with the stationary conditions.

1.3.7 Aggregation

Despite the complexity of the environment, the model aggregates in a simple manner. Defining an index of productivity across firms

$$\bar{Z} = \int_{\hat{z}}^{\infty} z \, dG(z) \tag{1.28}$$

it is straightforward to show that aggregate prices, output, and productivity satisfy

$$
\begin{aligned}
P &= \frac{1}{\rho} \left(M\bar{Z} \right)^{\frac{1}{1-\sigma}} \\
Y &= \left(M\bar{Z} \right)^{\frac{1}{\sigma-1}} L \\
TFP &= \left(M\bar{Z} \right)^{\frac{1}{\sigma-1}}
\end{aligned}
\tag{1.29}
$$

Thus, the impact of M&A on aggregate performance can be summarized through its influence on M and $\bar{Z}$. Notice that the sufficiency of z in characterizing individual outcomes holds in the aggregate as well. Aggregate prices, output and productivity respond equally to an increase in the mass of firms M and in the productivity index $\bar{Z}$. Indeed, once these variables are determined, the economy performs as one with a representative firm with productivity equal to TFP as defined in (1.29). The existence of the merger market endogenizes the components of TFP and determines aggregate performance by affecting both the mass of firms, and the productivity index through the distribution of resources across operating firms $dG(z)$ and the threshold productivity level $\hat{z}$.

Turning to the consumer side, recall from (1.26) that final consumption is equal to final output less the resources devoted to the fixed costs of production, search on the merger market, and the creation of new firms. Given aggregate output Y and an allocation of resources across these uses, we can then evaluate final consumption and welfare. To the extent that the amount of resources absorbed by non-consumption activities changes due to M&A activity, consumer outcomes

may move differently than industrial outcomes such as output and productivity. I quantitatively explore the impact of M&A on aggregate outcomes in a calibrated economy below.

1.3.8   Implications of Merger Theories

The model does not in general yield analytic solutions. It is possible, however, to characterize the predicted matching patterns under some particular specifications of the merger technology. In this section, I use the theoretical framework to evaluate the implications of several existing theories of merger activity. In particular, I analyze the merger market outcomes predicted by these theories and assess their consistency with the stylized facts. We will see that each meets some significant difficulties in matching the full set of empirical merger patterns described above.

What are the incentives to merge in the model? Depending on the specification of the merger technology, there may be three. First, there is a fixed cost saving. Following a merger, the continuing firm has bundled the products of the pre-merger firms, but need only pay the fixed cost of production once. Second, there may be q-related incentives, i.e., the productivity of the acquired resources may increase following acquisition, generating surplus and an incentive for firms of differing productivities to transact. Finally, to the extent that the evolution of the acquiring firm's productivity depends positively on both the pre-merger entities, there may be complementarities, or synergies, in the sense that two like firms coming together generates something more than the sum of the individual parts. I will address each of these theories in turn and show that none alone can explain the merger patterns observed in the data.

I begin with a theory of scale efficiencies through fixed cost savings. Under this theory, there are no particular gains from the bundling of products and but for the fixed cost, two standalone firms generate the same profit flows as the combined

entity. Because the profit functions are linear in z , this theory of no gains from bundling implies a technology of the form $z_m = z_a + z_t$, a case that is nested in (1.8) by setting $\gamma = 1, \nu = 1, \alpha = \frac{1}{2}, A = 2$, corresponding to the typical case of perfect substitutes. Intuitively, the combination of firms used to produce a particular z_m is irrelevant. Substituting for $z = k\tilde{z}$, it is straightforward to show that this technology implies an evolution for the firm's physical productivity of $\tilde{z}_m = \frac{k_a}{k_a+k_t}\tilde{z}_a + \frac{k_t}{k_a+k_t}\tilde{z}_t$, i.e., the merged firm takes on a productivity level that is simply a weighted average of the two pre-merger firms, where the weights are equal to each firm's share of the total number of products transacted. This technology seems a natural starting point to consider the implications of various technologies for merger patterns. Under this theory of the merger technology, the following proposition, which I prove in the Appendix, holds:

Proposition 1. *If the merger technology exhibits no gains from bundling, i.e., $z_m = z_a + z_t$, (i) all meetings will result in merger, (ii) the correlation between the characteristics of targets and acquirers will be zero, (iii) the mean and median difference between targets and acquirers will be zero, and (iv) the median target and the median acquirer will be the same as the median firm.*

The intuition here is clear. Absent gains from bundling, no additional surplus is generated from any particular combination of products, and the gains from merger are constant across all possible meetings. Firms choose identical search intensities and will merge with any partner upon meeting. The proposition is then immediate. Recall that the observed merger patterns exhibit high correlation between targets and acquirers, that acquirers are generally significantly larger than their targets, and that the mean and median acquirer is considerably larger than the median firm. Clearly, this technology predicts merger patterns (or lack thereof) that are quite far from these empirical relationships.[18]

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[18]Note that in an economy with no fixed cost, this technology would imply no merger activity. Merger surplus would be zero, and no firm would make an expenditure on search. For additional

Let us now turn to the predictions of the q-theory. As discussed above, the q-theory posits that surplus is generated through merger by moving resources from less productive to more productive firms and thus that the largest joint gains are realized when the productivity differential between the two parties to a transaction is largest, i.e., $\frac{\partial (\Sigma(z_a, z_t))}{\partial (z_a - z_t)} > 0$.[19] With this assumption on the technology, we can derive the following proposition:

Proposition 2. *If the merger technology embodies the q-theory, i.e., surplus is increasing in $z_a - z_t$, then (i) low z targets and high z acquirers will be in a greater share of matching sets and (ii) will search most intensively for partners. (iii) Low z firms will be overrepresented in the set of targets and high z firms in the set of acquirers. Then (iv) the median target must be below the median firm and the median acquirer must be above the median firm, and (v) the highest rate of transaction occurs between low z targets and high z acquirers.*

Again, the economic intuition here is straightforward. By assumption of the q-theory, for a given acquirer z_a, more surplus is generated by purchasing a lower target z_t, implying that all potential acquirers would like to purchase the least efficient target. Because expected surplus is higher for the lowest z targets, it is precisely these that search for acquirers most intensively and are acquired most rapidly. Analogously, all targets would like to be purchased by the highest z acquirers since the most surplus is generated, and it is this latter set of firms that search most aggressively for targets and make purchases most speedily. Because

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intuition, notice that if we posited exogenous search, that is, λ and μ were free to the firm and exogenous, the model with this technology is analytically solvable and gives a capital gain from merger of $\frac{Pc_f}{r+\delta+\lambda}$, that is, the gain is simply the discounted present value of the fixed cost.

[19]A natural example to keep in mind that is nested in (1.8) is $z_m = 2z_a$, which is easily derived for $\gamma = 1, \nu = 1, \alpha = 1, A = 2$. This implies that $\tilde{z}_m = 2\frac{k_a}{k_a + k_t}\tilde{z}_a$, such that (1) the productivity of the merged firm $\tilde{z}_m$ is independent of that of the pre-merger target, and (2) when an acquirer purchases a firm with the same number of products, its physical productivity is unchanged but its z doubles due to the doubling in the size of its product portfolio. If one were to interpret the q-theory as one of management discipline rather than product bundling, the results are unchanged. In the Appendix, I develop a version of the model with a homogenous product and decreasing returns in production, where mergers allow for the changing of management. As is standard, the two models give the same implications.

the rate of being acquired is decreasing in z, low z firms must compose the majority of targets, driving the median target below the median firm. Similarly, because the rate of acquisition is increasing in z, high z firms must compose the majority of acquirers. Finally, because the highest and lowest z firms search the most intensively and form an acceptable match (indeed, this is the match that generates the greatest gains), they will transact with one another at the highest rate. Thus, we see that the q-theory predicts that targets should come predominantly from the smaller, less productive firms as they generate the most merger surplus and indeed, that even the highest productivity firm prefers the lowest. These predictions stand in contrast to the patterns outlined above, which revealed that target firms do not tend to come from the bottom of the firm size distribution, that the median target is the same as the median firm, and that like firms tend to match, in particular, that large predominantly buys large and only infrequently buys small.

Finally, I address a theory of purely synergistic mergers as described, for example, in [RR08b]. The crux of this theory is that surplus is generated from the bundling of complementarity assets, that is, through assembling assets of similar quality. This is easily nested in the merger technology (1.8) by any set of parameters for which the technology displays both symmetry and supermodularity.[20] In this case, the technology exhibits synergies from bundling in that the marginal product of each z is increasing in the z of the partner. I label this a theory of "pure" synergies, as complementarities imply a tendency for firms to match with like firms, and symmetry implies that from a technological point of view, the identity of the acquirer and target are irrelevant. Under these assumptions, the following proposition emerges:

Proposition 3. *If the merger technology exhibits pure synergies, i.e., is symmetric and supermodular, then (i) $\Sigma(z_1, z_2) = \Sigma(z_2, z_1)$, (ii) matching sets will be*

---

[20]A natural example is $z_m = A(z_a z_t)^\nu$, which is obtained by setting $\gamma = 0$ and $\alpha = \frac{1}{2}$, where in some abuse of notation, I have renormalized $\nu = \frac{1}{2}\nu$.

symmetric around the 45° line, and (iii) the mean and median difference between acquirers and targets will be zero.

Because the technology is symmetric, the same gains are generated from a match with z_1 as the acquirer and z_2 as the target as from the counterpoint match with the roles reversed. Firms' search intensities on each side of the market will be a constant multiple of the other, leading each firm to have an equal matching rate on the two sides of the market. In conjunction with the symmetric acceptance regions, this implies that every match the firm makes as the acquirer will be reflected in equal weight by the opposite match with the roles reversed. Intuitively, from a technological standpoint it is irrelevant who is the acquirer and who is the target and this indifference holds true for firms' search and acceptance decisions. It follows that in the aggregate, the mean and median differences between acquirers and targets will be zero. Again, this prediction runs counter to the data, where we see that the mean and median differences between acquirers and targets are quite large, and that the acquirer is larger than the target in about 90% of transactions.

In sum, existing theories of merger activity meet significant difficulties in matching the array of empirical merger patterns described above. With no advantages to bundling, firms merge solely for fixed cost savings. Because merger surplus is constant, all firms are willing to transact with all others, and as a result, the model predicts almost none of the matching patterns observed in the data. Under a q-theory of mergers, all firms would like to purchase the least efficient, causing these firms to compose the majority of targets. Because the most efficient firms are the most sought-after acquirers, the highest rate of transaction occurs between the highest and lowest productivity firms. These predictions are inconsistent with the empirical finding that targets are actually not the smallest, but tend to come from the middle of the firm size distribution, and that like firms tend to transact with one another, with large only infrequently buying small. Finally, a theory of purely synergistic mergers implies that the identities of the acquirer

and target are irrelevant, leading to symmetry on the two sides of the market, and in the aggregate, no differences between acquirers and targets. Again, this is inconsistent with the empirical finding that acquirers are in general larger and more profitable than their targets. I now move on the numerical analysis, where I exploit the empirical matching patterns to infer the shape of the merger technology and so how surplus is generated from merger, how the gains are split, and use these results to quantitatively assess the implications of merger activity for aggregate economic outcomes.

1.4 Calibration and Numerical Results

In this section I describe the parameterization and calibration of the model and discuss the numerical results. For ease of exposition, I describe the calibration in two blocks, turning first to those parameters that are relatively standard in models of heterogeneous firms, and next to those that are new in the environment described here, where the latter are generally specific to the merger market. Table 1.7 lists the first set of calibrated parameter values. A time period is assumed to be one year. I normalize the mass of consumers L to be 1 and the sunk cost of entry c_e to the same. The real interest rate r is set to 5%. The elasticity of substitution σ is set to 3, which is a standard value used in the reallocation literature.[21] As noted above, the exit rate generated from the model is a combination of firm shutdown through realization of the exit shock and exit through acquisition. Below, I will target the aggregate rate of acquisition, and thus I can pick δ directly to match the empirical exit rate in the US. I follow [RR08a] and set δ so that the overall exit rate is 10%, a figure that roughly coincides with the average rate of establishment exit in the US over the period 1980-2009 as reported by the Census Bureau.[22] This results in a value for δ of 0.063.

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[21]See, for example, [HK09].

[22]Data obtained from http://www.census.gov/econ/susb/.

As a useful benchmark, I calibrate the entry distribution $dF(z)$ such that the endogenous distribution $dG(z)$ takes on a Pareto with shape parameter ξ and where the minimum observed value will be $\hat{z}$. This is consistent with a large number of studies pointing out that the empirical firm size distribution closely approximates a Pareto. I then choose c_f such that $\hat{z}$ is normalized to one. Following [AB10], I set the Pareto shape parameter $\xi = 1.2$, which approximates the relationship between the log of employment and the log of the fraction of total employment within firms with this level of employment or larger for the set of larger firms in the US.

Table 1.7: Calibrated Parameter Values (Standard Parameters)

Parameter	Description	Target	Value
L	Population	Normalization	1
c_e	Cost of entry	Normalization	1
r	Real interest rate	Real interest rate of 5%	0.05
δ	Exogenous exit rate	Overall exit rate of 10%	0.063
σ	Elasticity of substitution	[HK09]	3
c_f	Fixed cost of production	Normalization of $\hat{z}$ to 1	0.061
$dF(z)$	Entry distribution	Pareto $dG(z)$ with shape ξ	1.2

We now come to the new parameters of the model, which are those governing the merger market. I parameterize the search cost functions as

$$C_\lambda(\lambda) = \frac{B}{\eta}\lambda^\eta, C_\mu(\mu) = \frac{C}{\eta}\mu^\eta, \eta > 1, B > 0, C > 0 \qquad (1.30)$$

This gives three parameters to calibrate, those scaling the search costs B and C and that governing the convexity in search η, which I assume for simplicity is the same on the two sides of the market. I begin by noting that the aggregate search intensities on each side of the market are related through their ratio. For example, if $\int \lambda(z)\, dG(z) > \int \mu(z)\, dG(z)$, that is, acquirers search more intensively than targets, then, $j_a = \frac{\int \mu(z)dG(z)}{\int \lambda(z)dG(z)} < 1$ and $j_t = 1$. In reverse, if $\int \lambda(z)\, dG(z) < \int \mu(z)\, dG(z)$, then $j_a = 1$ and $j_t < 1$. The choice of cost parameters will generate

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aggregate search intensities on both sides of the market and give values for j_a and j_t. Inverting this relationship, if we know the aggregate search intensity on one side of the market and the ratios j_a and j_t, we can infer the cost parameters. This is the strategy I take.

First, I choose B such that the aggregate merger rate in the model matches that observed in the data. From the combined SDC and Compustat data, I find that about 3.7% percent of Compustat firms are acquired annually over the sample period, and I set B to target this figure. This estimate is in line with evidence from [MP01] who report that an annual average of 3.89% of large manufacturing plants in the US changed ownership in the Longitudinal Research Database over the period 1974-1992. That the merger rate in the economy is related to the costs of search is of course quite intuitive.

Recall that j_a and j_t reflect the relative aggregate search intensities on the two sides of the market. To the extent that firms are searching more intensively for acquisitions or for buyers, these ratios will deviate from one. For evidence on these statistics, I examine the number of bidders per target. If the number of bidders interested in each target is significantly above one, this would serve as evidence of inequality on the two sides of the market. The SDC data, however, do not show this. Across the almost 58,000 transactions, the average number of reported bidders per target is 1.01 with only about 1% of transactions exhibiting multiple bidders. Similarly, [AMS01] report an average of only 1.1 bidders per target over the period 1973-1998. Noting that much bidding may be non-public, [BM07] examine the sale process in detail for a sample of 400 acquisitions between 1989 and 1999. After accounting for private bids, they find a total of 1.29 bidders per target. In half of the acquisitions they investigate, the target firm only contacted a single potential buyer. In the other half, the target firm contacted an average of 21 buyers, but only received bids from an average of 1.57. Given the absence of compelling evidence that rationing plays an important role in the merger market,

I choose C such that aggregate search intensities are equalized, i.e., $j_a = j_t = 1$.[23]

To set the curvature parameter η, notice that by construction, the model must match the rate of merger observed in the data. η governs exactly how this will occur by influencing the distribution of search intensities across firms. A high value of η implies a fast-increasing cost of search and will push the economy towards spreading out search intensities across the range of firms. A low value of η implies the opposite, allowing for search intensities to be more concentrated within those firms with the most the most to gain from merger. In this light, we can interpret η as regulating the dispersion in search, and I set η to match the dispersion in the size of targets, measured by the coefficient of variation in target sales $\frac{std(r_t)}{mean(r_t)}$. This figure is about 3.96, reflecting the considerable heterogeneity in the size of targets.

Before turning to the merger technology, I address the Nash bargaining weight β. There is a large empirical finance literature investigating how gains from merger are shared among acquirers and targets.[24] Typically, these studies examine abnormal returns in a window surrounding the merger announcement date and assess the reaction of each firm's share value. The results have been mixed, with many studies finding that the majority of gains accrue to target shareholders, and a more recent set of studies finding a more equitable split.[25] Rather than relying on this literature, notice that the structural framework provides a link between the bargaining shares and merger premia. Intuitively, the merger premium reflects both the net gains from merger and the target's share. Once the gains from merger are known, equation (1.15) relates the merger premium directly to the target's bargaining power $1 - \beta$. Hence, I set the bargaining parameter β to match

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[23]Given the equilibrating forces in the model, it is not surprising that these ratios are close to 1. Firms would be hesitant to make additional expenditures on search knowing that there is a low incremental probability of a meeting, a reasoning that would tend to result in this outcome. For a simple example, see the note following the proof of Proposition 1 in the Appendix.

[24]See, for example, [AMS01] and the citations therein.

[25][AMS01] find the former, and report various other studies that do the same. [Ahe10] is a recent example finding an almost equal split.

the mean merger premium of about 53%.

It now remains to calibrate the merger technology governing how a merged firm is formed as the composite of the two pre-merger entities. Not surprisingly, there is a vast literature examining the gains from merger. Again, there has been a strong focus on assessing abnormal returns and the majority of studies have found positive value creation from mergers, although some have found the opposite.[26] In addition to the studies of financial market reactions, a small set of papers has attempted to measure the gains from merger directly by examining the productivities of the pre- and post-merger entities. For example, [MP01] find that the productivity of transferred assets generally improves following an ownership change. [Sch02] finds similarly, but additionally that the productivity of the acquirer generally falls, resulting in a small negative effect for the acquirer. Rather than following these approaches and using financial market reactions or attempting to measure productivity effects directly, I take a different tact and calibrate the merger technology in order to match the empirical patterns of merger activity in the US. Intuitively, I am taking a revealed preference approach, relying on the idea that the patterns we observe in the data should allow us to infer how merger gains are generated.

The relationship between the shape of the surplus generating function (here, the merger technology) and the resulting matching patterns has been explored in a recent strand of search-theoretic literature. A well-known finding is that to exhibit the positive sorting of the type observed in US merger activity, the technology must exhibit a certain degree of supermodularity, although the exact conditions vary with the environment.[27] Most relatedly, [SS00] show that with a similar CES technology in a random search environment, a necessary condition is that $\gamma \leq 0$, i.e., the elasticity of substitution be not greater than one, which corresponds to

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[26]See [AMS01] and the references therein.

[27]See [EK10] for a recent discussion.

the Cobb-Douglas case. In light of this result, I specify the merger technology such that this assumption holds, and in particular, I use the Cobb-Douglas case of $\gamma = 0$, which seems a natural starting point. We will see below that the Cobb-Douglas performs very well in replicating the empirical merger patterns. Thus, I specify

$$z_m = s\left(z_a, z_t\right) = A\left(z_a^{\alpha} z_t^{1-\alpha}\right)^{\nu} = A z_a^{\gamma} z_t^{\nu}, A > 0, \gamma < 1, \nu < 1 \qquad (1.31)$$

where in some abuse of notation, I relabel $\alpha\nu$ as γ and $(1-\alpha)\nu$ as ν, and $\gamma + \nu$ represents the returns to scale of the technology.

The exponents γ and ν jointly determine the effective productivity of the post-merger entity as a function of the two pre-merger firms. Intuitively, I assume that $\gamma < 1$ and $\nu < 1$, i.e., that each firm loses some portion of its initial productivity upon merger. The lower are γ and ν, the more that firms lose of their initial productivity upon merger and the less are the net gains. Knowing that its own individual quality will deteriorate more significantly upon merger induces each firm to be more selective in choosing partners, in the sense of causing matching sets to narrow. Larger values of γ and ν have the opposite effect. As matching sets change, transaction rates for each firm type change as well. The change in the rate of transaction differs across firm types, however, in large part driven by the interaction with the firm size distribution. For example, consider an equivalent widening of matching sets for a high z firm and a low z firm. The impact on the rate of transaction will be small for the high z firm, as there are few marginal firms at the borders of the matching set. For the low z firm, however, many additional firms become acceptable matches, causing a disproportionate increase in transaction rates among these types.[28]

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[28]To gain some additional intuition here, abstract from the fixed cost savings and search market impacts of merger, and imagine a simple tradeoff between the new z_m and the two old z's. Consider an acquirer z_a in a potential match with a target z_t where $z_t = fz_a$, i.e., the target is some percentage f of the size of the acquirer. To merge, it must be that $A z_a^{\gamma} z_t^{\nu} \geq z_a + z_t$ and

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By regulating the size of the matching sets and the surplus generated upon merger, γ and ν in large part determine the rates of search and matching among the set of firms in the market and thus the rate of transaction for each firm type. In this light, I choose γ and ν to jointly match the median deviation of acquirers' and targets' size (measured in the log of sales) from the median in their industries. Referring to Table 1.3, we see these figures are 0.58 and 0, respectively. Finally, to pin down A, notice that any autonomous growth from merger should have the largest effect on the merger decisions of small firms. The surplus from merger for large firms will be mostly driven by the curvature parameters, since the impact of these parameters is increasing in the size of the merger participants. On the other hand, even incremental changes in A should have significant effects on the actions of smaller firms. Thus, I choose A to match the percentage of targets that fall in the bottom decile of the firm size distribution, which Figure 1.1 shows to be 6.9%.

1.4.1 Computation

Before moving on to the parameter estimates and numerical results, I outline the computational algorithm used to perform the calibration. I use a method of moments estimator with a minimum distance criterion to find the parameter values. There are seven parameters to pin down in this way, which I collect in the vector $\Theta = \{\gamma, \nu, A, \beta, \eta, B, C\}$. In brief, for a given candidate vector Θ, I compute the equilibrium and simulate the merger market outcomes. I then construct the

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rearranging gives $z_a^{\gamma+\nu-1} \geq \frac{1+f}{f^\nu}\frac{1}{A}$. For simplicity, assume $\nu = \frac{1}{2}$ (which is close to its calibrated value). Then for $f < 1$, the RHS is strictly decreasing in f, meaning there is a lower bound on the size of an acceptable target. Because the LHS is increasing in γ and the RHS is independent of γ, higher values of γ will induce a lower threshold level of f. Similarly, for $f > 1$, the RHS is strictly increasing in f, meaning there is an analogous upper bound on acceptable targets and higher values of γ will induce a higher upper threshold level of f. Together, we see that higher γ will generate a wider range of acceptable targets for a given acquirer. Similar intuition holds for changes in ν. This simple example shows how changes in γ and ν play a large role in determining matching sets and thus the transaction rates across firm types.

target moments described above from the simulated data $\Psi^s(\Theta)$ and compare them to the moments from the actual data Ψ^d. I iterate on the initial guess of Θ until the distance between the simulated and actual moments is minimized. Formally, the calibrated parameter vector Θ^* is chosen to solve

$$\Theta^* = \arg\min \left(\Psi^s(\Theta) - \Psi^d \right) I \left(\Psi^s(\Theta) - \Psi^d \right)' \tag{1.32}$$

where I is the identity matrix.

I outline the computational algorithm in Table 1.8. Although I believe that calibrating and computing the equilibrium in this type of economy is an important contribution of the paper, I leave the details to the Appendix. Here, I describe the general idea of my strategy and point out several notable features of the routine. In particular, the calibration is done using what I will call an "indirect" method, by which I directly construct several of the equilibrium objects in the economy and infer the parameters that lead to these outcomes. The reasoning here is that the outcomes in the calibrated economy are directly observable in the data, whereas the primitives are not, and so I can invert the mapping between primitives and outcomes to infer the former from the latter. This approach proves convenient in easing computation, particularly in light of the endogenous nature of the firm size distribution $dG(z)$ and the use of a minimization routine that necessitates solving the full equilibrium for each candidate value of the parameter vector.

The calibration follows a nested fixed point algorithm in which I guess a candidate parameter vector, solve the equilibrium under this guess, simulate data and match the simulated moments to their targets. I then iterate over the parameter vector until the objective function in (1.32) is minimized. Three particular features highlight the indirect nature of the algorithm: first, it proves convenient to iterate over a candidate aggregate search intensity $\mu^c = \int \mu(z) \, dG(z)$ and impose the target values of j_a and j_t, rather than loop directly over the cost parame-

Table 1.8: Computational Algorithm

1. Construct $z, dG(z)$ and set direct parameters.
2. Guess candidate vector $\Theta^c = \{\gamma, \nu, A, \beta, \eta, \mu^c, j_a, j_t\}$.
    3. Construct merger matrix $s(\mathbf{z}, \mathbf{z}')$.
    4. Guess candidate $D = RP^{\sigma-1}$. Compute $P, \pi(z)$.
        5. Guess candidate $V(z)$. Evaluate merger matrix.
            6. Guess candidate $\mu(z)$ such that $\int \mu(z) \, dG(z) = \mu^c$.
            7. Solve for $B, \lambda(z), C$, and new $\mu(z)$.
            Iterate on $\mu(z)$ until convergence
        8. Solve for c_f s.t. $V(\hat{z}) = 0$ and construct new $V(z)$.
        Iterate on $V(z)$ until convergence.
    9. Construct $dF(z)$ and check free entry condition.
    Update D until free entry satisfied.
10. Simulate data and construct target moments.
11. Compute objective function in (1.32) and iterate on Θ^c until minimized.

ters B and C. Given values for these endogenous objects, it is straightforward to rearrange the first order conditions governing optimal search in (1.20) to infer the corresponding values for B and C. Second, rather than iterate on the entry distribution $dF(z)$, I directly impose the target distribution $dG(z)$. Notice that this entails directly constructing both the density at each z as well as the entry threshold $\hat{z}$. I then use the stationary conditions in (1.23) and the entry threshold condition (1.22) to infer the exogenous entry distribution $dF(z)$ and the level of the fixed cost c_f that in equilibrium give rise to the target $dG(z)$ and $\hat{z}$. Given these features, the calibration has the recursive structure outlined in Table 1.8 and the interested reader is referred to the Appendix for details.

1.4.2   Parameter Estimates

Table 1.9 lists the calibrated parameter values, as well as the empirical and simulated moments. We see that the model is capable of simultaneously replicating all seven of the target moments. Indeed, all moments are accurate to the third decimal place. In light of their importance in determining how surplus from merger is generated and split, and the longstanding literature on these topics, a brief

discussion of the calibrated merger technology and bargaining shares is in order.

Table 1.9: Calibrated Parameter Values (Merger Market)

Parameter	Estimate	Target Moment	Model	Data
γ	0.9112	Median deviation of $\log(r_a)$	0.577	0.580
ν	0.5314	Median deviation of $\log(r_t)$	0.004	0.000
A	1.0495	% of targets in lowest decile	0.071	0.069
β	0.4289	Mean merger premium	0.526	0.526
η	13.3723	Coefficient of variation of r_t	3.959	3.958
B	3.4072e+011	Acquisition rate	0.037	0.037
C	3.2282e+012	Bidders per target	1.000	1.000

First, in line with the theory, the curvature parameters γ and ν are both less than one, implying that each of the pre-transaction firms loses some of its value upon merger. However, the technology exhibits increasing returns to scale such that the proper combination of firms generates a new entity with higher value than the sum of the old, and merger gains are positive. That $\gamma > \nu$ embodies some degree of q-theory, that is, the productivity of the post-merger entity is determined to a greater extent by the productivity of the acquirer than of the target. The natural interpretation is that there is some room for the acquired assets to experience productivity gains from being incorporated into the product portfolio of the acquirer. However, if z_t is too far below z_a, the prospect of productivity enhancement is trumped by the losses the acquiring firm will experience due to γ. The small value of A implies that firms experience only a minor degree of autonomous growth from merger. While this has small influence on the decisions of large firms, it gives impetus for the amount of merger activity among small firms observed in the data, in addition to the prospect of fixed cost savings. Thus, the merger technology exhibits incentives for both positive sorting due to synergies, through the complementarity of the technology, and for productivity improvements through the asymmetry in γ and ν.

Next, the value of β implies that the gains from merger are split with reason-

able equality, with about 57% of gains going to targets and 43% to acquirers. As discussed above, the corporate finance literature has long pointed out that financial market returns imply that the lion's share of gains go to targets, where a more recent set of studies find a more equitable split. My results are in line with this latter finding. Recall that my estimate relies on interpreting the merger premium as reflecting a combination of target bargaining power and the size of the merger surplus. Given the surplus patterns predicted by the model, bargaining shares must be relatively balanced to imply premia on the order of magnitude observed in the data.

I believe these parameter estimates to hold some independent interest, as they shed new light on exactly how surplus from merger is generated and split. I depart from existing studies by relying on the empirical ex-ante matching patterns to infer how merger gains are generated from various combinations of firms, and how they are shared among the transacting parties. Forming a deeper understanding of the microstructure that would generate a merger technology of the form estimated here, and investigating the process that would imply this split of surplus and why it may not be reflected in financial market performance, are clearly interesting avenues to pursue.

1.4.3 Non-Targeted Moments

Table 1.9 shows that the model is capable of matching the set of targeted moments quite closely. Here, I document how the model performs on some other moments of interest. First, notice that I do not target any moment directly regulating the degree of assortative matching between acquirers and targets. Although the Cobb-Douglas assumption implies some amount of positive sorting, the degree to which firms are willing to match below or above their own type is also to a great extent influenced by the calibrated parameters of the merger technology. In Table 1.10, I compare the log correlations of acquirer and target sales, employment, and

market value from the model and the data. We see that the model predicts an amount of sorting very close to what is observed in the data. Additionally, I show the fraction of transactions in which the size of the acquirer exceeds that of the target from the model compared to the data, where the former is measured by z and the latter is an average over the size metrics in Table 1.2. The model performs quite well in predicting the share of transactions in which the acquirer is larger and more profitable than the target.

Table 1.10: Predicted Matching Moments

Moment	Model	Data
Corr $(\log r_a, \log r_t)$	0.58	0.62
Corr $(\log l_a, \log l_t)$	0.58	0.58
Corr $(\log V_a, \log V_t)$	0.71	0.64
Share of transactions with $z_a > z_t$	0.86	0.90

Next, I assess the ability of the model to replicate the characteristics of the set of transacting firms. In particular, Figure 1.1 revealed that the share of acquirers in each decile of the firm size distribution is monotonically increasing, with acquirers overrepresented in the top deciles and underrepresented at the bottom. In contrast, targets are generally drawn from the middle deciles, and underrepresented at both extremes. In Figure 1.5, I compare the distributions of acquirers and targets across the deciles of the firm size distribution from the model and the data. The top row replicates Figure 1.1 in showing the distributions from the data and the bottom row shows the distributions as computed from the model simulation. The model replicates quite closely the empirical distributions. For acquirers, the model generates the monotonic pattern observed in the data, with acquirers overrepresented in the top 5 deciles and underrepresented in the bottom 5. The model somewhat underpredicts the share of acquirers at the bottom and overpredicts the share of acquirers at the top. This is likely due to an overestimation of merger surplus among the largest firms through the convexity of the

merger technology. Turning to targets, we see that the model matches almost exactly the data. Recall that I target the share of targets in the lowest decile (the bar on the far left) to pin down A, but not the remainder of the distribution. The model predicts that targets are underrepresented at the extreme deciles (2 on either side), and tend to be drawn from the middle of the firm size distribution, exactly the pattern across deciles observed in the data.
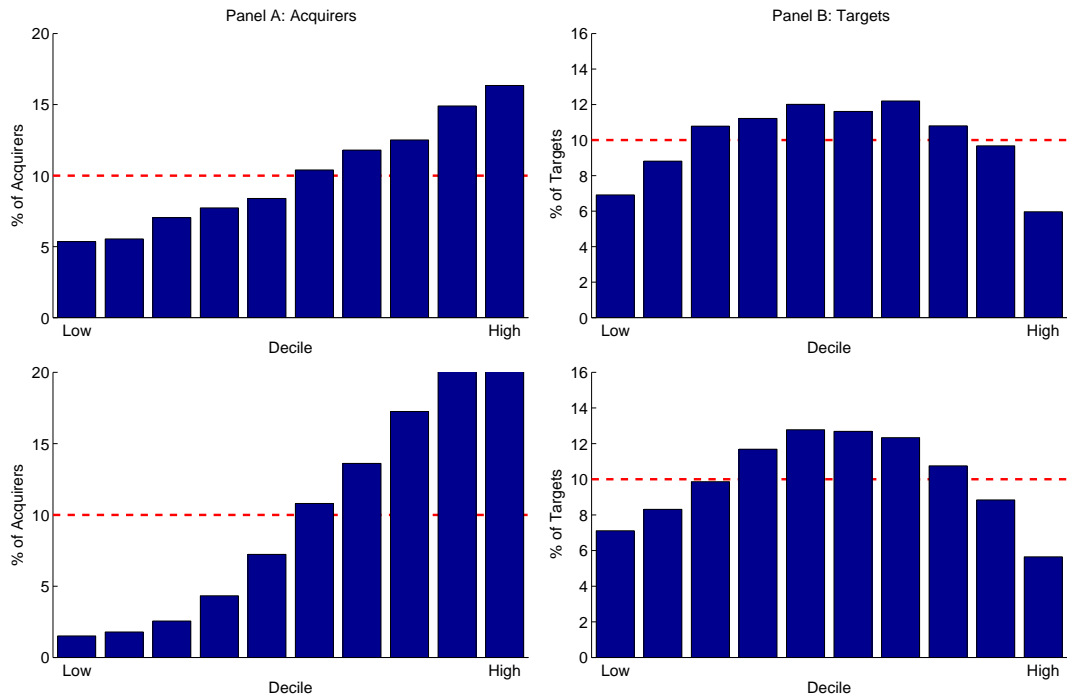
Figure 1.5: Decile Shares of Transacting Firms: Data (top) vs Model (bottom)

1.4.4 Policy Functions

I now turn to firm actions on the merger market. In Figure 1.6, I show the firm policy functions, that is, optimal search intensities and acceptance regions. Panel A shows that search intensities are increasing in z on both sides of the market, an intuitive result given the convexity of the merger technology. The expected surplus from a consummated merger is increasing in firm size for both targets and acquirers. Despite the fact that large firms search most intensively,

the shape of the firm size distribution limits the number of transactions between the largest firms that take place. It is difficult for two large firms to meet simply due to the Pareto distribution, which implies that there are not many large firms in the economy. The figure also reveals that smaller firms tend to search more intensively for potential buyers and large firms for potential targets. Intuitively, for lower z firms, the expected surplus from being acquired is higher than from acquiring another firm. Together, we see how the search intensities of individual firms aggregate to form the pattern of transacting firms seen, for example, in Figure 1.5.

Panel B displays the acceptance regions for completing a transaction. [SS00] show that under certain assumptions on the merger technology, and in particular on the degree of supermodularity, it can be proved that matching sets are convex, closed, and nonempty, implying that they can be characterized by lower and upper bound functions. That is, there exists a minimum and maximum target with which a given acquirer is willing to transact, and that acquirer is also willing to transact with any target falling in between. A symmetric result is true for targets. I make use of this finding here and simply display the bound functions. Any meeting between an acquirer and target falling inside the two bounds is then an acceptable match. Reading across the x-axis, a candidate target z_t is willing to sell itself to any acquirer along the vertical distance between the two bounds functions. Similarly, reading up the y-axis, a candidate acquirer z_a is willing to purchase any target along the horizontal distance between the two bounds.

Referring to the empirical scatterplot of matches in Figure 1.2, we gain some intuition for how the model predicts the observed merger patterns. The data show that firms of a given size tend to have a range of firms with which they are willing to match. The model with search and matching frictions is able to replicate this pattern. Indeed, that search frictions will generate a range of acceptable matches for each type is a central feature of [SS00]. The data also reveal that the range

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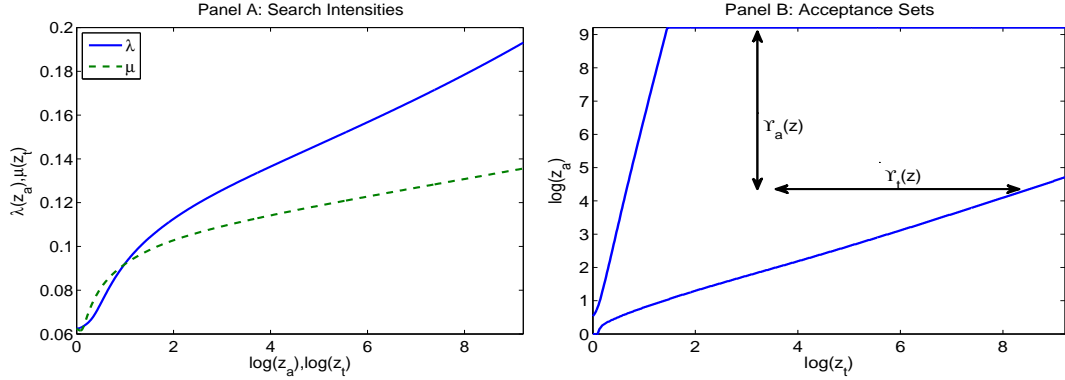
Figure 1.6: Merger Market Policy Functions

of acceptable matches is increasing in firm size, i.e., the acceptable size range for one's partner is increasing in one's own size. This pattern is replicated by the model, which generates bound functions that are increasing in z, that is, higher z firms are willing to match with higher z firms on the other side of the market. This result is in line with [SS00], who prove that it will hold with the proper degree of supermodularity on the surplus technology. Figure 1.6 reveals how firm decisions in the calibrated economy aggregate to replicate the empirical matching sets, which then interact with the firm size distribution to generate search intensities and matching rates consistent with those observed in the data.

1.5 The Aggregate Impact of Mergers and Acquisitions

To evaluate the aggregate impact of mergers and acquisitions, I solve for the stationary equilibrium in an economy with no M&A, calculate the economic aggregates, and compare them to those generated in the economy with M&A. We can interpret the no M&A economy as one where government policies are extremely restrictive in preventing all merger transactions, or where the costs of search are prohibitively high. In the absence of M&A, the economy is essentially the closed-economy version of [Mel03]. As a world investigated thoroughly in the literature, this would seem a natural benchmark to use in exploring the influence of M&A.

After calculating the outcomes in the no-M&A economy, I assess the contribution of M&A to aggregate economic performance. The gains I calculate are from comparisons of two stationary equilibria and so focus only on the long-run effects of M&A.

I present the results in Table 1.11. The table shows the value of each statistic in the stationary equilibrium of the economy with M&A as a percentage of its value in that of the no-M&A economy. Immediately, we see that M&A activity has a significant beneficial impact on aggregate economic performance. Aggregate productivity and output are both 31% higher and the aggregate price level 33% lower with M&A than without. Recall that (1.29) implies that changes in these metrics should be proportional to one another. There is a large increase in the productivity index $\bar{Z}$, inducing much of the change in these outcomes. Additionally, and perhaps surprisingly, the mass of firms is actually somewhat higher with M&A than without. Despite the fact that firms are exiting at faster rate by being acquired, in general equilibrium, the existence of the merger market actually entices additional firms to enter, more than offsetting the reduction caused by acquisition. Intuitively, the value stemming from potential participation in the merger market induces entry by entrepreneurs that may otherwise not have done so. Note that the increase in the mass of firms does not imply that concentration is reduced by M&A. In fact, the model follows standard intuition and predicts the opposite, that M&A will increase industry concentration. While more firms are entering and producing, a greater share of resources is being transferred to the largest firms, and they are reaping an even greater share of industry sales.[29]

Using (1.29), it is straightforward to decompose the gains from M&A into those stemming from a greater number of firms, and those from a higher productivity index $\bar{Z}$. Doing so reveals that about 18% of the gains are due to the former, and

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[29]For example, using the Gini coefficient to measure concentration shows an increase from 0.58 to 0.67 when moving to the economy with M&A, signaling a greater degree of inequality.

Table 1.11: The Aggregate Impact of M&A

Statistic	% of value with no M&A
Aggregate Productivity	131.0
Output	131.0
Aggregate Price	76.3
Mass of firms	110.4
Consumption	113.4
Welfare	110.7

82% to the latter. The reallocative effects of M&A thus account for the lion's share of the aggregate performance gains. To highlight this result, I display in Panel A of Figure 1.7 the initial entry distribution and the endogenous distributions over operating firms in the economies with M&A and without (I truncate the values of z in order to focus on the differences in the distributions). Clearly, the endogenous distributions in both worlds dominate the entry distribution, and that in the economy with M&A dominates that in the economy without. This is a result both of reallocation on the intensive margin, i.e., among firms that choose to operate in both economies, and the extensive margin, i.e., of redistributing mass from firms that fall below the entry threshold in the economy with M&A to those that fall above. In Panel B, I display the pure redistributional effects of M&A, abstracting from the extensive margin. Specifically, I show the type distribution in the economy with M&A and that in the economy without, conditional on falling above the entry threshold with M&A. The distribution with M&A dominates that without M&A over the majority of the long right tail, implying a greater mass for high productivity firms. The crossing of the distributions illustrates how this results from the flow of resources from lower to higher productivity firms. The figure clearly shows how redistribution occurs along both the extensive and intensive margins, and jointly, the aggregate reallocative effects of M&A in transferring resources to the most productive firms.

In line with the positive effects of M&A on industrial performance, consumers
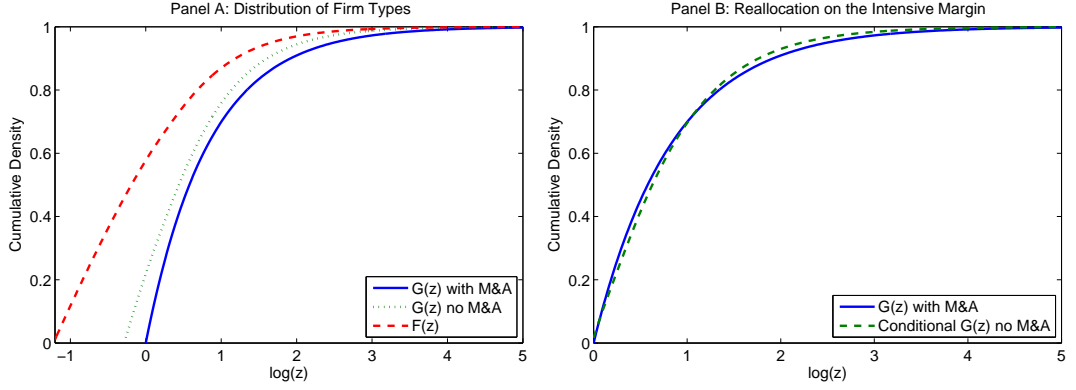
Figure 1.7: The Redistributive Effects of M&A

benefit to a great extent as well. Consumption is 13% larger with M&A and welfare almost 11% higher. Although still considerable, the gains in consumption are quite a bit smaller than those in productivity and output. The reason is that M&A changes the allocation of final output across its various uses. In particular, more of final output must be devoted to the fixed costs of production, the costs of searching on the merger market, and the costs of firm creation. In the economy with no M&A, 22% of output goes towards these uses, a figure that jumps to 33% with M&A. Interestingly, the main culprit is not expenditures on search in the merger market, which represent only about 1% of final output. Rather, there is a large rise in the amount of resources going towards the creation of new firms.

The increase in new firm creation is attributable to several effects. Recall that the total resource costs of new entry are $M_e c_e$ and using (1.24), the mass of entrants is given by

$$M_e = \frac{\left\{ \delta + \int \mu\left(z\right) j_t \left[\int \Phi\left(\Sigma\left(z_a, z\right)\right) \Lambda\left(z_a\right) dG\left(z_a\right) \right] dG\left(z\right) \right\} M}{1 - F\left(\hat{z}\right)} \qquad (1.33)$$

i.e., must equal the aggregate rate of exit multiplied by the mass of incumbent firms divided by the probability of successful entry upon drawing a z. In order to sustain the stationary equilibrium, the increase in the aggregate exit rate caused by the acquisition of targets necessitates a corresponding increase in the mass

of entrants. Second, we have already seen that the merger market induces a higher mass of incumbent firms due to the additional value stream stemming from the potential for merger, also requiring a greater number of entrants. Lastly, increased selection on the extensive margin due to M&A causes a reduction in the probability of successful entry, implying that more potential entrants must make a productivity draw in order to garner the required number of successful entrants. All of these effects work to increase the mass of potential entrants, each of which must pay the sunk cost of entry. Thus, a larger share of resources is devoted to paying the resource costs of new firm creation for both successful and unsuccessful entrants in the economy with M&A than in that without, and this accounts for the majority of the difference in the movements of output and consumption. However, we see that the reallocation of resources away from final consumption is more than offset by the rise in output, leading to net gains in consumption and welfare.

The results suggest that M&A has a great potential for improving long-run economic performance. To check the sensitivity of these findings, I analyze the elasticities of aggregate productivity and consumption with respect to the merger market parameters in Table 1.9, which are those new to the environment outlined above. The elasticities are generally quite small, and hence I do not report the results here.[30] As a last remark, the benchmark economy considered here is extreme in the sense of a complete absence of M&A. Investigating the influence of empirically relevant intermediate policies would prove fruitful for subsequent work, particularly those related to firm size. The effects of policy in this environment are complex and can be either beneficial or detrimental, depending crucially on the particular nature of the policy under consideration and its impact on the decisions of firms across the type spectrum. Additionally, the stylized nature of

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[30]A caveat here is that a small positive shock to γ has a fairly significant effect on aggregate productivity (on the order of plus 4%), although this is largely washed out when moving to consumption, and an equal-sized negative shock induces a response only half that size. The convergence properties of the model become problematic as γ nears 1, likely because the model is approaching an explosive solution, rendering this type of shock unreliable.

the model abstracts from endogenous firm growth through channels alternative to M&A and a corresponding choice of de novo investment. Whether the inclusion of this feature would increase or mitigate the gains to M&A found here is unclear, depending on which firms choose which avenue for growth and the associated costs to society.

1.6 Conclusion

This paper develops a search-theoretic model of mergers and acquisitions in a dynamic general equilibrium setting and assess the implications for aggregate economic performance. I use a transaction-level dataset to document a number of empirical patterns in US merger activity and build a parsimonious framework that is able to address these facts and nests several existing theories of merger activity as special cases. I explore the merger patterns predicted by these theories and show that each meets difficulties in fitting the full set of empirical facts. I calibrate the model to match moments from the transaction-level data, as well as other salient features of the US economy. The calibrated model is capable of replicating the stylized facts quite closely and sheds new light as to how surplus is generated from merger and how the gains are split. I find that merger activity generates potentially large long-run gains in aggregate performance, measuring about 30% in aggregate productivity and output, and about 11% in welfare.

In assessing the implications of mergers and acquisitions in a fully articulated dynamic general equilibrium framework, this paper takes a somewhat different approach from the existing literature, a departure that I believe is rewarded by the new insights the model provides into the causes and consequences of M&A activity. An important area for further exploration is in providing explicit microfoundations for the merger technology. Although I successfully discipline the shape of the merger technology in the sense of closely matching the empirical patterns of M&A,

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I do not model the underlying mechanism through which firms aggregate products and/or managers that generates a technology of this form. A better understanding of this process would make clear exactly how the roles of complementarities and productivity enhancements combine to determine the observed merger technology and so the patterns of matching observed in the data.

While the model highlights the long run benefits associated with M&A activity, the literature has long been interested in its higher frequency behavior in the form of merger waves and cyclical properties. Examples of the former include [JR08] and [Har05] and of the latter, [ER06]. Search environments of the form here have rich dynamic implications, as shown for example, by [LM96] and [SS01b]. Taking the model out of stationary equilibrium and analyzing its short-run dynamic behavior holds some promise in generating new insights into merger waves and the cyclical behavior of merger activity.

Finally, the model abstracts from strategic interactions in merger activity. [Gow99] develops and simulates a dynamic empirical model of mergers with this feature, revealing the assumptions and limitations necessary to maintain tractability in such a framework. Extensions of the model in this direction would clearly be of great interest. The absence of strategic motives does not, however, preclude a role for policy in the current model. As pointed out in [SS01a], search and matching behavior is generally inefficient in this environment due to standard search externalities. The nature of these externalities in the present context, where repeat matching is feasible and agents' values are heterogeneous and determined in general equilibrium is not obvious, and nor is the set of policies that may replicate the social optimum. Interestingly, [SS01b] show that optimal policy in this type of environment may be nonstationary, with the implication for the model here being that merger waves may reflect, at least in part, the optimal matching path.

Appendix to Chapter 1

A   Data

In this Appendix, I describe in more detail the data used in the paper, beginning with SDC. As described in the text, I select from SDC all domestic transactions announced between 1977 and 2009 with a nominal deal value of at least $1 million. I include only completed transactions, those not classified as hostile (only about 300 transactions are classified as hostile takeovers), those in which the acquirer newly gains majority control of the target, and those with relevant ownership status. After this process, and eliminating several observations with obvious data entry errors, there are 57,858 transactions. For each transaction, I obtain the following data (when available): transaction value (total value of consideration paid by the acquirer, excluding fees and expenses), premium (premium of offer price to target closing stock price 4 weeks prior to the original announcement date), and standard performance variables including net sales, employment, PP&E, EBITDA, and market value.

As mentioned in the text, data availability differs across the SDC variables. In Table A.1, I show the number of transactions with available data for acquirers, targets, and both, for each dimension of analysis.

Table A.1: SDC Data Availability

	Acquirer	Target	Both
Sales	31,736	18,541	12,251
Employment	28,050	6,138	3,957
PP&E	28,792	10,095	6,672
EBITDA	26,424	8,208	5,080
Market Value	25,38	6,969	4,112
Premium	*	*	6,474

Moving to Compustat, I obtain data on the universe of firms contained in the

CRSP/Compustat merged database (CCM) from 1977 to 2009. This yields a total of 210,275 observations. The SDC to Compustat match is not straightforward since the two databases use different company identifiers. The most specific identifier provided by SDC is the 6-digit CUSIP for both parties in each transaction. This is not sufficient for the match, however, because Compustat only records the most recent CUSIP rather than a CUSIP history. Because of this, matching on CUSIP may result in missed pairs and erroneous matches.

To perform the match, I use the CRSP translator to associate 6-digit CUSIPs from SDC with the CRSP company identifier. I then match this identifier with the CCM database, which already associates the CRSP identifier with the set of Compustat firms. I follow this process for both acquirers and targets. I associate transactions with the Compustat data for the fiscal year preceding the year of merger announcement. I obtain data on net sales, employees, PP&E (net of depreciation), EBITDA, and market value, where I calculate the latter as the product of common shares outstanding and the closing price at fiscal year end. Table A.2 shows availability of the Compustat data:

Table A.2: Compustat Data Availability

	All Firms	Acquirers	Targets	Both
Sales	191,992	30,453	6,828	4,465
Employment	179,787	28,597	6,186	3,862
PP&E	187,270	28,368	6,608	4,284
EBITDA	152,671	25,472	5,525	3,478
Market Value	206,309	30,890	6,913	4,548

Macroeconomic data are obtained from standard sources. US GDP and stock of fixed assets are from the Bureau of Economic Analysis (http://www.bea.gov/). The CPI is from the Bureau of Labor Statistics (http://www.bls.gov/).

B Span of Control

There is a well-known isomorphism between economies with differentiated varieties, monopolistic competition, and constant marginal costs, and those with a homogenous good, perfect competition, and diminishing returns (increasing marginal costs) in production, as in the [Luc78] span of control model. This translation holds in the present context as well. Here, I outline this latter version of the model.

There is a single homogenous good produced using labor. The production function exhibits diminishing returns and takes the form $q = z^{1-\theta}l^{\theta}$ where the normalization of z plays a similar role as in the text of the paper. Competitive firms take the market price P as given and choose labor to maximize profits, $Pz^{1-\theta}l^{\theta} - l$ where I have normalized the wage $w = 1$ to be numeraire. Standard arguments give labor demand, revenue, and variable profits from sales as

$$
\begin{aligned}
l &= (\theta p)^{\frac{1}{1-\theta}} z \\
r &= P^{\frac{1}{1-\theta}} \theta^{\frac{\theta}{1-\theta}} z \\
\pi &= (1-\theta) P^{\frac{1}{1-\theta}} \theta^{\frac{\theta}{1-\theta}} z
\end{aligned}
$$

and so as above, firm product market outcomes are proportional to z and depend on industry aggregates that are common across all firms, here the span of control parameter θ and the competitive price of output P.

The merger market works analogously to the manner described above, where mergers allow firms to improve their productivity z. The merger technology combines the z's of an acquirer and target and produces a firm with a new z. Because there is only a single homogenous good, the firm's z represents only its physical productivity, rather than the product of its productivity and number of products as in the differentiated goods model in the paper. The merger technology is then

interpreted as directly combining productivities, with no role for the size of the firm's product suite. The interpretation here is one of management discipline, where mergers allow for productivity improvement through the incorporation of new management. All the dynamic equations of the model are the same.

C   Proofs

Proposition 1. Conjecture that the gains from merger are constant and strictly positive across all firm types, i.e., $\Sigma\left(z_a, z_t\right) = \bar{\Sigma} > 0 \; \forall z_a, z_t$. Then, all meetings will result in a completed transaction and we can write the value function as

$$(r + \delta) V\left(z\right) = \pi\left(z\right) - PC_\lambda\left(\lambda\left(z\right)\right) - PC_\mu\left(\mu\left(z\right)\right) + \lambda\left(z\right) j_a \beta \bar{\Sigma} + \mu\left(z\right) j_t\left(1 - \beta\right) \bar{\Sigma}$$

(C.1)

The first order conditions governing optimal search in (1.20) give

$$
\begin{aligned}
PC'_\lambda\left(\lambda\left(z\right)\right) &= j_a \beta \bar{\Sigma} \\
PC'_\mu\left(\mu\left(z\right)\right) &= j_t\left(1 - \beta\right) \bar{\Sigma}
\end{aligned}
$$

which shows that the choice of λ and μ are constant and independent of z. Denoting these common search intensities as $\bar{\lambda}$ and $\bar{\mu}$, we can rewrite the value function as

$$(r + \delta) V\left(z\right) = \pi\left(z\right) - PC_\lambda\left(\bar{\lambda}\right) - PC_\mu\left(\bar{\mu}\right) + \bar{\lambda} j_a \beta \bar{\Sigma} + \bar{\mu} j_t\left(1 - \beta\right) \bar{\Sigma} \qquad \text{(C.2)}$$

The surplus from a merger between a type z_a acquirer and type z_t target is $\Sigma\left(z_a, z_t\right) = V\left(z_m\right) - V\left(z_a\right) - V\left(z_t\right)$. Using (C.2), it is straightforward to show that surplus equals

$$\frac{\pi\left(z_m\right) - \pi\left(z_a\right) - \pi\left(z_t\right) - \bar{\lambda} j_a \beta \bar{\Sigma} - \bar{\mu} j_t\left(1 - \beta\right) \bar{\Sigma} + PC_\lambda\left(\bar{\lambda}\right) + PC_\mu\left(\bar{\mu}\right)}{r + \delta} \qquad \text{(C.3)}$$

Under the assumption that the merger technology displays no gains from bundling, we have

$$\pi\left(z_m\right) - \pi\left(z_a\right) - \pi\left(z_t\right) = Pc_f \tag{C.4}$$

that is, the only gain in flow profits from merging is a single fixed cost savings. Then,

$$\Sigma\left(z_a, z_t\right) = \frac{Pc_f - \bar{\lambda}j_a\beta\bar{\Sigma} - \bar{\mu}j_t\left(1-\beta\right)\bar{\Sigma} + PC_\lambda\left(\bar{\lambda}\right) + PC_\mu\left(\bar{\mu}\right)}{r+\delta} = \bar{\Sigma} > 0 \tag{C.5}$$

Thus, we have proved our initial conjecture that the gains from merger are constant and independent of z and (i) that every meeting will result in merger.

Because each firm searches with the same intensities, and the effective meeting rates on the two sides of the market must equate, each firm has an equal probability of meeting a particular partner as an acquirer or a target. That is, the rate at which acquirer z_1 meets target z_2 equals the rate at which acquirer z_2 meets target z_1. That meetings are random and all result in a completed transaction, that all firms choose the same search intensities, and that each transaction is reflected by the opposite transaction with the roles reversed in equal weight together imply that (ii) the correlation between the characteristics of targets and acquirers is zero, (iii) the mean and median difference between targets and acquirers are zero, and (iv) the median target and median acquirer are the same as the median firm. □

Before moving on to proposition 2, a few additional notes are in order. In particular, let us gain some intuition by parameterizing the search cost functions as in (1.30), and assuming, for example, that $\int \lambda\left(z\right) dG\left(z\right) > \int \mu\left(z\right) dG\left(z\right)$. In

this case, we can derive

$$\bar{\lambda} = \left[\left(\frac{1-\beta}{C}\right)^{\frac{1}{\eta}}\left(\frac{\beta}{B}\right)^{\frac{\eta-1}{\eta}}\frac{\bar{\Sigma}}{P}\right]^{\frac{1}{\eta-1}}$$

$$\bar{\mu} = \left[\frac{1-\beta}{PC}\bar{\Sigma}\right]^{\frac{1}{\eta-1}}$$

$$j_a = \left[\frac{1-\beta}{\beta}\frac{B}{C}\right]^{\frac{1}{\eta}}$$

that is, the ratio of search on the target and acquirer sides of the market is independent of the merger surplus and depends only on the ratio of bargaining shares and real search costs on each side. Because targets are on the short side of the market, their search intensity only depends on their expected surplus and costs of search. Because acquirers are on the long side of the market, their search intensity is increasing in their expected surplus, decreasing in their costs of search, but is increasing (although at a slower rate) in the expected surplus and decreasing in the costs of search for targets. This is because as these latter increase, targets will search more intensively, which increases the effective meeting rate for acquirers. From here, we can solve for the merger surplus up to a single nonlinear equation in $\bar{\Sigma}$:

$$\frac{\eta-1}{\eta}\left(\frac{1-\beta}{PC}\right)^{\frac{1}{\eta-1}}\bar{\Sigma}^{\frac{\eta}{\eta-1}} + (r+\delta)\bar{\Sigma} - Pc_f = 0 \qquad \text{(C.6)}$$

If we had alternatively assumed that $\int \lambda(z)\,dG(z) < \int \mu(z)\,dG(z)$, we would have obtained analogous expressions. Notice that if $c_f = 0$, there is no solution such that $\bar{\Sigma} > 0$ and there will be no mergers. If the merger technology displays no gains from bundling and there is no fixed cost of production, there are no gains to merging, and no firms will expend any resources to do so.

Proposition 2. Assume that merger surplus $\Sigma(z_a, z_t)$ is increasing in the distance between the acquirer and target $z_a - z_t$. Then for a given z_a, surplus is decreasing in z_t, and so the set of acceptable targets $\Upsilon_t(z_a)$ is characterized by an upper

threshold z_t^* such that $\Sigma(z_a, z_t^*) = 0$. That is, acquirer z_a will be willing to purchase any targets with $z \leq z_t^*$. It is straightforward to establish an analogous result for targets, that is, $\Upsilon_a(z_t)$ is characterized by a lower threshold z_a^* such that target z_t will sell itself to any acquirer with $z \geq z_a^*$. Together these imply (i) low z targets and high z acquirers are in a greater share of matching sets. That surplus is decreasing in z_t and increasing in z_a implies that expected surplus conditional on meeting a candidate purchaser or target, defined in (1.18), are also respectively decreasing and increasing in z. From the first order conditions governing optimal search (1.20), we see that search intensities $\mu(z)$ and $\lambda(z)$ must be decreasing and increasing in z respectively, that is, (ii) low z targets and high z acquirers search most intensively for partners. The fact that low z targets and high z acquirers are in a greater share of matching sets and search most intensively together imply that the rate at which firms are acquired $\mu(z) j_t \int \Phi(\Sigma(z_a, z)) \Lambda(z_a) dG(z_a)$ is decreasing in z and similarly the rate at which they make acquisitions $\lambda(z) j_a \int \Phi(\Sigma(z, z_t)) \Gamma(z_t) dG(z_t)$ is increasing in z. It is then immediate that (iii) low z firms are overrepresented in the set of targets and high z firms in the set of acquirers and that (iv) the median target is below the median firm and the median acquirer above. Finally, the greatest number of meetings take place between the highest z acquirer and the lowest z target, which is an acceptable match, giving that (v) the highest rate of transaction occurs between low z targets and high z acquirers. $\qquad\square$

Proposition 3. The assumed symmetry of the merger technology along with the definition of the joint surplus in (1.13) immediately imply that (i) $\Sigma(z_1, z_2) = \Sigma(z_2, z_1)$ and that (ii) matching sets are symmetric around the $45°$ line. Conjecture that $\lambda(z) = K\mu(z), K > 1$, that is, for each firm, search intensity on the acquiring side of the market is some constant proportion of search intensity on the the target side. Then, $\int \lambda(z) dG(z) = K \int \mu(z) dG(z)$, that is, the aggregate search intensity of acquirers is the same proportion of the aggregate search inten-

sity of targets. This implies $j_a < 1$ and $j_t = 1$. Expected surplus conditional on meeting a prospective buyer is

$$
\begin{aligned}
E\left[M_t\left(z\right)\right] &= (1-\beta)\int \max\left\{\Sigma\left(z_a,z\right),0\right\}\Lambda\left(z_a\right)dG\left(z_a\right) \\
&= (1-\beta)\int \max\left\{\Sigma\left(z_a,z\right),0\right\}\frac{\lambda\left(z_a\right)}{\int\lambda\left(z_a\right)dG\left(z_a\right)}dG\left(z_a\right) \\
&= (1-\beta)\int \max\left\{\Sigma\left(z,z_t\right),0\right\}\frac{K\mu\left(z_t\right)}{K\int\mu\left(z_t\right)dG\left(z_t\right)}dG\left(z_t\right) \\
&= (1-\beta)\int \max\left\{\Sigma\left(z,z_t\right),0\right\}\frac{\mu\left(z_t\right)}{\int\mu\left(z_t\right)dG\left(z_t\right)}dG\left(z_t\right) \\
&= (1-\beta)\int \max\left\{\Sigma\left(z,z_t\right),0\right\}\Gamma\left(z_t\right)dG\left(z_t\right) \\
&= \frac{1-\beta}{\beta}E\left[M_a\left(z\right)\right]
\end{aligned}
$$

That is, the expected surplus conditional on meeting a prospective buyer is a constant multiple of the expected surplus conditional on meeting a prospective target, and simply depends on the ratio of bargaining powers. Note that in the third line, I have used the symmetry assumption on the technology, as well as the initial conjecture that search intensities are in constant proportion. From the first order conditions governing optimal search (1.20), we can see that if expected surplus is in constant proportion, than search intensities will as well, verifying our initial conjecture. Similar reasoning holds for the cases of $K < 1$ and $K = 1$.

From (1.11), the mass of meetings where z_1 is the acquirer and z_2 is the target is equal to

$$
\frac{\lambda\left(z_1\right)j_a\mu\left(z_2\right)dG\left(z_2\right)}{\int\mu\left(z\right)dG\left(z\right)}MdG\left(z_1\right) \tag{C.7}
$$

The mass of meetings of the opposite kind where the roles are reversed is

$$
\frac{\lambda\left(z_2\right)j_a\mu\left(z_1\right)dG\left(z_1\right)}{\int\mu\left(z\right)dG\left(z\right)}MdG\left(z_2\right) \tag{C.8}
$$

Substituting $\lambda(z) = K\mu(z)$ in both expressions, we obtain

$$\frac{K\mu(z_1)\, j_a\mu(z_2)\, dG(z_2)}{\int \mu(z)\, dG(z)} M dG(z_1) \text{ and } \frac{K\mu(z_2)\, j_a\mu(z_1)\, dG(z_1)}{\int \mu(z)\, dG(z)} M dG(z_2) \quad \text{(C.9)}$$

which are equivalent. Thus, each transaction is reflected in equal weight by its counterpoint transaction with the roles reversed. It is then immediate that (iii) the mean and median difference between acquirers and targets is zero. $\qquad\square$

D Computational Algorithm

In this Appendix, I describe in more detail the computational algorithm used for calibration of the model.

I discretize the productivity distribution over z into 500 points from a z of 1, which corresponds to the normalization of $\hat{z}$ described above, up to a z of 10,000. Recalling from (1.7) that the ratio of the size of two firms is equal to the ratio of their z's, I follow [RR08a] in constructing a grid such that the largest operating firm will be 10,000 times the size of the smallest, and additionally in log-spacing the grid to ensure greater accuracy over the lower tail of the distribution, where most firms reside. I then construct the endogenous distribution $dG(z)$ over this grid such that $dG(z)$ takes on a Pareto with shape parameter ξ. Next, I guess a candidate value of $\Theta^c = \{\gamma, \nu, A, \beta, \eta, \mu^c, j_a, j_t\}$. With the candidate values of A, γ, and ν, I can construct a "merger matrix" which represents the z_m resulting from each combination of z_a and z_t, where the two pre-merger firms are drawn from the entire set of z's. That is, the merger matrix contains the effective productivity of the merged entity formed by the merger of all possible combinations of z's.

Computation of the equilibrium begins by guessing the industry aggregate $D = RP^{\sigma-1}$, which through (1.7) determines variable profits from sales. From (1.29), it is straightforward to show that total revenue $R = PY = \frac{1}{\rho}L$, that is, total

revenue is pinned down by the elasticity of substitution in production of the final good and the size of the population. Using this, I can compute the aggregate price P. I perform value function iteration to find $V(z), \lambda(z), \mu(z), \Upsilon_t(z), \Upsilon_a(z)$. For a candidate $V(z)$, I use the merger matrix to compute the value of each potential transaction on the merger market and in particular, to find those generating positive surplus. I then use an iterative procedure to construct optimal search intensities, by which I guess a candidate vector $\mu(z)$, solve for $\lambda(z)$ and recompute $\mu(z)$. Recall that Θ^c contains a candidate $\mu^c = \int \mu(z) \, dG(z)$, from which, in conjunction with the values of j_a and j_t, it is straightforward to compute aggregate search on the opposing side of the market $\int \lambda(z) \, dG(z)$. Given a feasible vector $\mu(z)$, a straightforward manipulation of the first order condition (1.20) along with the parameterization (1.30) gives an expression for B that is independent of the individual values of $\lambda(z)$:

$$B = \left(\frac{1}{\int \lambda(z) \, dG(z)} \right)^{\eta-1} \left(\int \{E[M_a(z)]\}^{\frac{1}{\eta-1}} \, dG(z) \right)^{\eta-1} \qquad (D.1)$$

where $E[M_a(z)]$ is as defined in (1.18) and depends on objects that are known (for this candidate parameter vector). With this value of B, I can construct $\lambda(z)$. An analogous procedure gives C. Finally, I compute a new value of $\mu(z)$ as a function of $\lambda(z)$ and the inferred values of B and C. I iterate on this process until $\mu(z)$ converges.

It is now straightforward to construct new values of $V(z)$ in accordance with (1.19). In doing so, I compute the fixed cost c_f that is consistent with this equilibrium by solving $V(\hat{z}) = 0$. Next, I use the firm search and matching decisions to construct the flows in (1.23) and in conjunction with the distribution $dG(z)$, I infer the entry distribution $dF(z)$. Here, I must make a normalization of the minimum possible draw of z, $z_{\min}$, which I set to 0.3. Finally, I use $V(z)$ and $dF(z)$ to construct the free entry condition (1.16) and iterate on the candidate

value of D until the free entry condition is satisfied.

To simulate the economy, I draw 1 million firms from the stationary distribution $dG(z)$ and compute revenues, labor demand, and values functions. Standard arguments show that each acquirer has a probability of meeting a target in a single period equal to $1 - e^{-\lambda(z)}$. Using these probabilities, I calculate the set of potential acquirers and match them to a set of potential targets who are drawn randomly according to their meeting probabilities $1 - e^{-\mu(z)}$. Elimination of matches that generate negative surplus gives a simulated merger dataset with matched acquirers and targets analogous to the actual data described above. It is then straightforward to calculate the target moments and compute the value of the objective function in (1.32). I iterate on the guess of Θ^c until this function is minimized.

CHAPTER 2

Competition, Innovation, and the Sources of Product Quality and Productivity Growth

This paper assesses the simultaneous impact of competition on innovative investments and achieved firm performance. I outline a structural framework to infer product quality and productivity from firm-level performance data and measure their response to changes in the competitive environment. I quantify the various channels through which competition may affect firm performance, including changing investments in R&D. Using a panel of Spanish manufacturing firms, I find that competitive pressure spurs R&D investments and performance improvements. The majority of performance gains come directly through knowledge and technology diffusion or changing managerial and worker incentives, rather than indirectly through R&D-generated innovations.

2.1 Introduction

Does competitive pressure spur innovation and improve achieved economic performance? Recent work has shown that changes in the competitive environment can induce aggregate performance gains through within-firm improvements or via the reallocation of resources to those firms that can use them most effectively. In a recent survey of the evidence on competition and productivity, [HS10] point out that the former within-firm effect is an important driver of aggregrate growth in reponse to greater competitive intensity, and indeed, often times dominates the latter reallocation effect in quantitative significance. However, it is precisely the sources of within-firm growth, and hence, the impact of competitive intensity on this margin, that are still not well understood.[1]

There are several potential channels through which competitive pressure can induce performance gains within an individual firm. Changing incentives for innovative engagement may lead to increased investments in R&D in the hopes of improving future outcomes. Greater exposure to more efficient firms or higher quality products may lead to spillover effects, where the knowledge accumulated by these firms or the more efficient technologies they employ, diffuse to firms further behind the frontier. Finally, competitive intensity may improve managerial incentives and lead to more efficient work practices, garnering performance gains through the more effective use of existing assets within the firm. The quantitative magnitude of these effects is not just of intellectual curiousity, but, as shown for example by [AB11], may have important implications for the impact of competition and innovation policies on aggregate outcomes and welfare. Thus, whether competition induces performance improvements, and if so, the relative importance of each of these channels, remain important unresolved questions.[2]

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[1]For a recent survey on the sources of productivity growth, see [Syv10], who lists "which productivity drivers matter most?" as one of the outstanding "big questions" in the literature.

[2]Indeed, distinguishing the import of these channels in stimulating improved performance has long been on the research agenda, although little progress has been made. See, for example,

There is, of course, a vast body of work examining the impact of competitive forces on both innovative investments and achieved firm performance. In particular, two largely distinct strands of research have emerged. The first is a longstanding effort to understand the effect of competitive pressure on firm-level engagement in innovation activities. In addition to important methodological problems, a conceptual shortcoming in this line of work has been its limitation to analyzing only reported measures of innovative engagement, such as R&D expenditures or patents, and a resulting inability to address the impact of changing competitive intensity on actual performance. Second, there is a growing literature directly examining the impact of competition on achieved performance. However, this literature has been largely silent on the channels through which competitive pressure may induce performance improvements. Additionally, by focusing only on productivity growth or process innovation, this line of work has abstracted from the potential effect of competitive pressure on product quality improvements or product innovation, although this may be an important margin on which firms repond when facing intensified competition.

In this paper, I take a structural approach to empirically assess the impact of competition on innovative investments and achieved firm performance. In a departure from the existing literature, I outline a dynamic structural model of strategic competition and innovation. The economic framework explicitly incorporates the potential simultaneous effects of competitive pressure on innovative investments and achieved performance, where the latter is captured both by process efficiency and product quality. In the model, firms are characterized by two performance measures, their technological efficiency, or productivity level, and the quality of their product offering. Each firm faces a competitive state, composed of the productivity and product quality of its competitors. Firm-level productivity and product quality evolve over time as stochastic processes that can be

[Kor04].

influenced both by investments in innovation through expenditures on research and development (R&D) and by the state of competition. That the competitive state may directly influence the path of a given firm's performance captures the potential of increased competition to spur the diffusion of new knowledge and technologies, or improve managerial incentives and implemented work practices. This is what I deem the "direct effect" by which competitive pressure can induce changes in achieved performance. Additionally, the competitive state can influence firm performance through changing incentives for investments in R&D, in what I analogously call the "indirect effect."

Importantly, the competitive state is subject to an exogenous and serially correlated shock that changes the degree of competitiveness in the firm's operating market and so its future prospects. To match the empirical work, these "competitive shocks" are given the explicit interpretation of tariff reductions in the firm's output market, although they can be seen more generally as any exogenous process shifting the state of competition. By decomposing the impact of a competitive shock induced by a tariff reduction into its effect on the direct and indirect channels, the model allows for quantitative assessment of their relative importance in spurring performance gains in response to competitive pressure.

The theoretical framework lends two major advantages to my analysis. First, I use the model structure to distinguish and compute firm-level productivity and product quality based on actual firm performance. In this way, I measure the gains from innovative activity and its response to competitive pressure by the realized productive efficiency and quality offering of the firm. In contrast, previous studies of competition and innovation rely solely on reported measures of innovative output, such as patent counts, to gauge firm-level success in innovative activities and so the gains from increased competition. These measures may be poor proxies of a firm's true output of productive new knowledge. As an example, the choice of whether to patent or not might be directly related to the competitiveness

of the market in which the firm operates, causing patenting activity to respond to changes in the competitive environment for reasons unrelated to greater production of new knowledge. Moreover, existing work has largely focused on the response of process efficiency to changes in competitive intensity and abstracted from product quality improvements. Indeed, to the best of my knowledge, this paper is the first to simultaneously assess the impact of competitive pressure on both process and product innovation. Second, the structural model allows me to distinguish the impact of competitive pressure along the direct and indirect margins and quantify their relative importance in influencing the path of productivity and product quality. In the absence of a structural framework, the existing literature has been largely silent as to the existence or importance of the various potential channels for performance improvements, despite their importance in determining the impact of competition and innovation policies on aggregate outcomes and welfare.

Estimation of the model's parameters is complicated by the fact that productivity and product quality levels are not directly observable and, as functions of the firm's R&D investments and the competitive state, are endogenous objects. I outline a multistage estimation algorithm to overcome these hurdles. In the first stage, I estimate a flexible demand system, derived from a standard differentiated product Logit model, enabling me to infer product quality and demand elasticities. In the second stage, I extend the methodology of the recent literature on structural estimation of the production function to my setting in order to infer the production technology parameters and recover firm-level productivity. Finally, with values of firm-level productivity and product quality in hand, I estimate the firm's R&D policy function in a final stage. Despite the complexity of the estimation, there is a certain simple symmetry by which I use information from the demand side of the market to infer product quality, its evolution and determinants, and information from the production side to infer the same about productivity.

After estimating the R&D choice function, I can quantify the effect of competitive pressure on firm-level productivity and product quality and compare the relative importance of the indirect channel working through changing investments in R&D and the direct channel working through knowledge and technological diffusion or through improved managerial incentives and work practices.

I use data from a detailed panel of Spanish manufacturing firms during the 1990s and 2000s. In addition to containing standard performance variables, such as sales, capital, labor, intermediate inputs, etc., the data are particularly rich in two areas that are key to my analysis. First, the data contain measures of firm-level innovative activities. These include expenditures and employment devoted to R&D, capturing innovative investments, as well as indicators of the introduction of process and product innovations, capturing, at least to some degree, innovative outcomes. I use the variety of reported measures of innovative engagement both to estimate the structural model and to provide some motivating reduced-form evidence of the effects of competitive pressure.

Second, the data contain firm-level price deflators for both output and inputs, which is the key factor that enables me to empirically distinguish between product and process innovation. With these deflators, I am able to use the demand side of the model to infer product quality. I can also estimate the physical production function implied by the model and construct measures of pure physical productivity untainted by the presence of unobserved price variation. As is well known, absent an assumption of perfect competition, a lack of firm-level price deflators causes standard empirical methods to confound changes in physical productivity with changes in unobserved firm-specific prices. This is particularly problematic in my setting since changes in the competitive state have a significant impact on demand side factors, both directly through pressure on prices, and indirectly through price changes resulting from product innovation. Without firm-level deflators, measured productivity changes would actually reflect the net outcome of

these disparate effects.

Spain's membership in the EU yields exogenous variation in the intensity of competition through changes in import tariffs. Throughout the sample period, the EU was lowering tariffs facing non-EU nations. As an EU member, Spain operates under a unique institutional structure in which it does not negotiate its own tariffs, but rather it adheres to the EU common external tariff schedule. These tariffs are negotiated and approved on behalf of all EU nations by various committees operating at the EU level and it is unlikely that they are significantly influenced by any particular firm in the Spanish manufacturing sector. Absent this particular institutional setting, endogeneity of common measures of the state of competition, including tariffs due to political economy concerns, would prevent clear interpretation of empirical results.

I find that increases in competitive pressure spur greater investments in R&D and improvements in both product quality and productive efficiency. My baseline results show that a 1 percentage point reduction in the import tariff rate generates a 3.1% increase in R&D investment for the average R&D-performing firm, and raises the hazard rate of engaging in R&D by 0.4% for the average non-performer. The direct effect implies that this 1 percentage point reduction in the tariff spurs productivity growth of 0.6% for the average R&D performer and 0.25% for the average non-performer, and product quality improvements of 0.25% and 0.3%, respectively. Because the elasticities of product quality and productivity with respect to R&D are both about 0.006, these values imply a much larger role for the direct effect of knowledge or technological spillovers or changing managerial incentives and worker practices, than for the indirect effect of R&D-generated innovation in stimulating performance improvements in reponse to greater competitive intensity. I show that these findings are robust to controlling for other potential effects of a trade liberalization and that the importance of the direct channel is likely not limited to my particular setting.

This paper relates to several strands of existing literature investigating the relationships between competition, innovation, and performance, and it would be impossible to do justice to all contributions.[3] The effect of competition on productivity has been a particular focus in the trade literature and my use of tariffs as a competitive shifter explicitly links my paper to this body of work. Beginning with [Pav02] for Chilean firms and in a more recent example, [BJS06] for US firms, the trade literature has uncovered some evidence of within-firm productivity growth in response to increased exposure to foreign competition. This literature has tended to focus on increases in aggregate productivity due to the reallocation effects of competition and has not shed much light on the mechanism for within-firm gains. Moreover, there has been a general abstraction from product innovation, which I find to be an important margin in the response to competitive pressure. A particularly relevant recent contribution to this line of work is [De 10]. [De 10] similarly recognizes the confounding influence of price variation when measuring productivity in the presence of imperfect competition and uses a related structural framework to distinguish the demand and production sides of the market in order to assess the productivity response of Belgian textile firms to reductions in trade barriers. In the absence of firm-level price deflators, he imposes a somewhat rigid demand system to control for unobserved prices.[4] In contrast, because I observe firm-level price deflators, I am able to go one step further and use a relatively more flexible demand system to actually infer product quality and include product innovation in my analysis. Additionally, without access to R&D data, [De 10] follows the preceding literature and does not address the channels through which

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[3]For example, the body of work on competition and innovation is widely regarded as the second largest in empirical IO, exceeded only by that examining the relationship between competition and profitability (see, e.g., [CL89] and [Gil06].

[4]In particular, he uses the assumption of monopolistic competition in conjunction with a CES demand system to impute firm-level prices and control for their influence in the estimation. This framework has the features that firms set a constant markup over marginal cost and products are differentiated only on the horizontal dimension. These characteristics are somewhat unattractive in my setting, where I am interested particularly in the impact of changes in competitive intensity on both process and product innovation.

increased competition may affect within-firm productivity.

There are a number of recent industry case-studies documenting the beneficial impact of competitive pressure on productivity. These are summarized in [HS10] and include, for example, [HS01] for the US shipping industry and [Sch05] for the Great Lakes Iron Ore industry. These studies have shown first, that within-firm productivity growth tends to be the predominant driver of aggregate industry gains in response to increases in competition, and second, have provided some evidence on the implementation of new management and worker practices that led to these performance improvements. For example, upon the advent of railroads, longshoremen in the US shipping industry altered the rules governing the unloading of ships in such a way as to reduce time spent in port and increase labor productivity, particularly on cross-country routes that were threatened by railroad competition. Upon the introduction of competition from Brazil, the US iron ore industry changed its work practices to reduce the idle time of machines and the number of non-production repair staff, again spurring productivity gains. While informative, these studies are limited by their application to a single industry and the more anecdotal nature of their analysis. In contrast, I assess the impact of competition across a range of industries within the manufacturing sector and quantify its effects across several potential margins.

There is a recent body of work, surveyed in [Syv10], addressing more generally the sources of productivity growth. Recent additions include [DJ09] and [Xu08] who investigate the impact of R&D investments on achieved productivity levels, and [BSV10], who document the importance of technological spillovers from R&D investments on productivity growth. In finding an important role for the direct channel of performance improvements in reponse to competitive pressure, my results are broadly consistent with the evidence of [HS10] and [BSV10], who find that changing management and worker practices and spillovers of knowledge and technology, respectively, are sources of significant gains.

While the literature previously mentioned has investigated the impact of competitive pressure on achieved performance, there is a vast body of work focusing on the specific reponse of firm-level innovative activities to changes in the state of competition. These studies, which are comprehensively surveyed and critiqued by [CL89] and [Gil06], have typically been limited by a lack of adequate data in measuring both "competition" and "innovation" as well as by methodological problems that have proven difficult to overcome.[5] More recent additions include [ABB05], who present evidence of an inverted-U shaped relationship between competition and innovation in a panel of UK industries. They measure innovation by citation-weighted patent counts and competition by the Lerner index, instrumented by policy reforms. [Tes08] finds that tariff reductions induce increases in R&D expenditures in process innovation but not in product innovation for a panel of Mexican firms. [BDV11] show that increased competition from China spurred R&D investments and technology upgrading in a panel of European firms. In contrast to these studies, this paper uses a structural model to infer the effect of competitive pressure on actual performance, rather than relying only on reported measures of innovation activities, and explicitly models the choice of innovative investment as the solution to a dynamic problem, driven by firm-specific characteristics and the state of competition.

The paper is organized as follows. In the next section, I describe the firm-level microdata and the trade data. I document the competitive effects of tariff

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[5][CL89] summarize their findings concisely by stating

> Our review finds the empirical literature on Schumpeter's hypotheses pervaded by methodological difficulties. Equations have been loosely specified; the data have often been inadequate to analyze the questions at hand; and, until recently, the econometric techniques employed were rather primitive. To the extent that preoccupation with the effects of firm size and concentration on innovation encourages omission of important and potentially correlated explanatory variables, estimates of these very effects have tended to be biased. Despite some recent advances in model specification, data collection, and statistical techniques, the results of this literature must be interpreted with caution.

17 years later, [Gil06] reaches a similar conclusion.

reductions on the domestic market and motivate the structural approach with preliminary evidence from simple reduced-form equations. In Section 3, I introduce the structural model. Section 4 outlines the econometric strategy. I present my results in section 5, and Section 6 concludes.

2.2 Data and evidence

I use firm-level data from the Encuesta Sobre Estrategias Empresariales (Survey on Business Strategies; ESEE), an annual survey of the Spanish manufacturing sector sponsored by the Spanish Ministry of Industry. The survey is an unbalanced panel of firms with 10 or more employees, covering the period 1990-2007. After eliminating observations with missing data, there are a total of 4,260 unique firms, with an annual average of about 1,800. Firms are classified into twenty three-digit industries corresponding to the NACE-93 classification. Initially, all firms with over 200 employees were asked to participate in the survey, and the response rate reached about 70 percent. Firms with between 10 and 200 employees were randomly sampled in a proportional manner by industry and size stratification, with about 5 percent of firms included in the survey. In subsequent years, the representativeness of the survey has been maintained by adding new firms with the same sampling criteria as in the initial year.

The dataset is unusually rich in information about firm-level innovative and production activities. The primary measure of innovative investments reported in the ESEE is total firm-level expenditures on R&D. Additionally, the ESEE reports total employment devoted to R&D activities, with the caveat that this variable is only available every four years beginning in 1990 and ending in 2006.

The ESEE reports several direct measures of innovative outcomes, including indicators of whether the firm introduced a process or a product innovation. Process innovations are defined as "important modifications in the production pro-

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cess," including the introduction of new machinery or the use of new methods for organizing work. Product innovations are defined as "completely new products, or with such modifications that they are different from those produced earlier," entailing novelties such as incorporating new materials, new parts, new design or presentation, or the ability to perform new functions.

I construct the stock of net physical capital using the perpetual inventory method with industry-specific rates of depreciation and deflate the series using the investment price index.[6] Labor input is measured as average employment during the year. Intermediate inputs are defined as purchases of intermediate consumption including raw materials, services, and energy, and are deflated by a firm-specific materials price index.[7] Output is defined as sales less variation in inventories and is deflated using a firm-specific output price index.[8]

Due to its richness, the ESEE has been used in several recent papers. For example, [DJ09] use the R&D data to assess the impact of R&D investments on productivity. [Orn06] exploits the availability of firm-level price deflators to investigate the mismeasurement introduced in production function estimation by the failure to control for unobserved price variation in imperfectly competitive industries.

Tariff data come from the UNCTAD TRAINS database, a standard source in the trade literature.[9] I use EU-wide most favored nation ("MFN") tariffs aggregated to the two-digit level under the ISIC-Rev. 3 classification and weighted by the value of total EU imports. Each firm in the ESEE is placed into one of twenty industries, based upon the aggregation of NACE-93 three-digit industries. At the two-digit level, the ESEE industries are equivalent to those of the ISIC-Rev.

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[6]I obtain the investment price index from the Instituto Nacional de Estadística and industry-specific deflators from [MS97].

[7]This is a Paasche-type index aggregating changes in the prices of raw materials, services, and energy.

[8]Again, this is a Paasche-type index that aggregates the firm's change in price in its five largest geographic markets.

[9]The data are available at http://r0.unctad.org/trains_new/index.shtm.

3 classification system. This correspondence allows me to place each firm in the ESEE into a two-digit ISIC-Rev. 3 industry and so associate it with an import tariff rate from the TRAINS database. Due to some differences in definitions between the ESEE and ISIC-Rev. 3 classifications, I aggregate several of the ESEE industries in order to properly merge the two sets of data. After the matching process is complete, I am left with 17 industries over the years 1990-2007.

I use import penetration rates to investigate the impact of tariff reductions on domestic market conditions. I collect data on imports, exports, and domestic production in each manufacturing industry from the OECD STAN STructural ANalysis database.[10] I define domestic demand for the output of each industry as

$$D_{jt} = Y_{jt} + IM_{jt} - EX_{jt} \tag{2.1}$$

where D_{jt} denotes domestic demand for industry j in time t. Y_{jt} denotes domestic production, IM_{jt} imports, and EX_{jt} exports, all denominated in current values. Import penetration rates are then constructed as

$$IMP_{jt} = \frac{IM_{jt}}{D_{jt}} \tag{2.2}$$

The industries reported in the STAN database are defined at the two-digit level under the ISIC-Rev. 3 system, making it straightforward to match them with the merged ESEE and tariff data.

2.2.1 Descriptive statistics

Table 2.1 contains some descriptive statistics of the ESEE firm-level data. It shows the basic characteristics of the set of firms under study from both the sample in its entirety, and conditional on reporting positive R&D expenditures. Only about

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[10]The data are available at
http://www.oecd.org/document/62/0,3343,en_2649_34445_40696318_1_1_1_1,00.html.

Table 2.1: ESEE Summary Statistics

	Unconditional Mean	Conditional Mean
Sales (000s of Euros)	43,442.75	96,718.47
Total Employment	219.76	455.5
Capital Stock (Replacement Value)	12,706.28	27,506.25
R&D Expenditures (000s of Euros)	632.61	1,836.88
R&D Intensity (Percent)	0.72	2.08
R&D Employment	6.02	17.45
Prob. of Engaging in R&D	0.34	1
Prob. of Process Innnovation	0.32	0.53
Prob. of Product Innovation	0.24	0.48
N	29,135	10,034

Table reports summary statistics from ESEE firm-level data. Only observations including all the measures reported are included, with the exception of R&D employment, which is only available every four years.

one third of the firm-year observations report any formal R&D activity. There is a marked distinction in the characteristics of firms that perform R&D and those that do not. Firms that engage in R&D are much larger than the overall average in terms of sales, employment, and installed capital stock. Not surprisingly, they report higher rates of successful process and product innovations. R&D intensity, calculated as R&D expenditures divided by sales, is low at 0.7% for the firms as a whole and 2% after conditioning on firms reporting positive R&D.[11]

The 1990s and 2000s was a period of incremental reductions in tariffs facing foreign firms seeking to export to the EU. To get a sense of how competitive pressure from abroad was evolving during this timeframe, Table 2.2 reports summary statistics describing the import tariff rates for the initial period in my sample 1990, the end period 2007, as well as an intermediate period, 2000. Tariffs are generally declining over the sample period, with the mean falling by over 4 percentage points, or about 50%, although the annual changes are non-monotonic.

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[11]For example, [DJ09] cite a recent EU report showing R&D intensities for manufacturing firms of 2.1% in France, 2.6% in Germany, and 2.2% in the UK. The same report shows that the R&D intensity of Spanish manufacturing firms is 0.69%, very close to the average of 0.7% in the ESEE data, and well below Spain's European neighbors.

Table 2.2: Evolution of Import Competition

	Import Tariff Rate			Import Penetration Rate		
	1990	2000	2007	1990	2000	2007
Mean	8.53	4.76	4.24	20.02	30.84	33.13
Std. Dev.	4.9	3.36	3.37	14.31	18.6	20.65
Min	2.49	0.59	0	4.82	5.84	4.86
Max	18.59	10.77	10.43	63.07	70.44	80.31

Although there is variation in the tariff movements across industries, the change in tariffs over the sample period is generally substantial.

2.2.2 The effect of tariff reductions on domestic conditions

To illustrate the impact of tariff changes on actual competitive conditions in the domestic economy, Table 2.2 also reports the analogous set of statistics for the import penetration rate. The reductions in import tariffs are accompanied by large increases in import penetration rates. The mean import penetration rate rises about 50% over the sample period, matching the percentage decline in the mean tariff rate. Importantly, not only the changes over the period, but also the levels of import penetration are generally substantial, reinforcing that competition from abroad should be expected to be an important determinant of domestic market conditions. By 2007, imports accounted for about one-third of domestic consumption on average, with their share ranging from 5% to over 80% across industries.

Figure 2.1 plots the annual mean import penetration and tariff rates across firms over the entire sample period. Again, tariffs are generally falling over the period while import penetration is rising. The largest declines in tariffs took place during the 1990s, with smaller changes occurring during the 2000s. The import penetration rate exhibits a similar pattern.

It is important to note that Spain was a member of the EU thoughout the
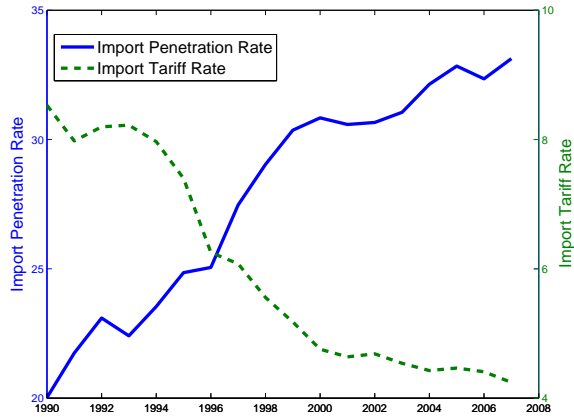
Figure 2.1: Import Competition 1990-2007

sample period, meaning that while variation in tariffs comes only as a result of EU-level negotiations with third party nations, import penetration is driven both by increased exposure to third-party nations, as well as growth in intra-EU trade. The latter is not subject to any tariffs. In this light, reductions in import tariffs are not the only driver of the observed increases in import penetration.

To confirm that changes in third-party tariffs were indeed a significant factor in determining the level of import competition, I statistically analyze the relationship between import penetration and tariffs in the industries under study. The results are displayed in Table 2.3. Not surprisingly, the two variables exhibit a close relationship. A simple regression of the former on the latter at the industry level yields a coefficient of -0.82, implying that a 1 percentage point reduction in the tariff rate is associated with a 0.82 percentage point increase in the import penetration rate, and is significant at the 95 percent level. Adding industry fixed-effects to this regression in order to isolate within-industry variation and abstract from cross-sectional heterogeneity across industries yields a coefficient of -2.8 and is again highly significant. These coefficients suggest that reductions in the import tariff have a strong positive effect on import penetration. The R^2 of the pooled model is low at 0.018 as is standard with cross-sectional data, while the within R^2 of the fixed-effect model is much higher at 0.37, implying that within-industry

Table 2.3: Import Penetration and Tariffs

Coefficient	-0.8218**	-2.7722***
Standard Error	-0.3203	-0.2137
Industry Fixed-Effects	N	Y
R^2	0.018	0.3688

Coefficients are from regressions of the import penetration rate on the import tariff rate across industries. Significance: * 90%, ** 95%, *** 99%.

tariff variations explain a substantial portion of the changes in import penetration These results confirm that tariffs are an important determinant of import competition, and so should be expected to have a significant influence on the competitive state of the domestic industry.[12]

2.2.3 The effect of tariff reductions on domestic firms

Before outlining and estimating the structural model, I investigate the impact of changes in tariffs on some firm-level outcomes of interest in a reduced-form manner. First, I assess the influence of tariff changes on firm product-market performance. In particular, I regress the log of output price and quantity on the tariff rate. I include firm and time effects to control for unobserved firm-specific factors and time-varying aggregate shocks. Next, I estimate regressions of reported measures of innovative investments and outcomes on tariff rates. I use R&D expenditures and employment to measure innovative investments, and the reported indicators of successful process and product innovations to measure innovative output. The exercise here is in the spirit of the existing reduced-form literature on competition and innovation, updated to include more detailed measures of firm-level engagement in innovation. Previous studies of this kind have documented a substantial degree of persistent dispersion in firm-level innovation activities, likely driven by differences in innovative incentives and hazards of success. I include firm and time fixed-effects to control for these factors across firms

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[12]Similar results are obtained when I limit the analysis to imports from non-EU nations.

as well as the influence of time-varying aggregate shocks. The results are reported in Table 2.4.

In Rows [1] and [2], I report the impact of tariff changes on the product-market performance of domestic firms. The positive and significant coefficient in row [1] implies that increases in import competition induced by lower tariffs puts downward pressure on domestic prices, as one would expect. Similarly, the positive coefficient in row [2] indicates that more intense competition causes losses in sales, although the effect is not significant at standard levels. A primary response to import competition seems to be a lowering of prices, confirming that changes in competition from abroad influence the product-market performance of domestic firms.

Row [3] displays the results from a Tobit regression of the log of R&D expenditures on the tariff rate. As I discuss in more detail below, a Tobit model is appropriate due to the left-censoring of the R&D variable at zero. For example, Table 2.1 shows that about two-thirds of firms in the sample do not engage in R&D activities. To control for permanent unobserved heterogeneity across firms, I use the random effects Tobit estimator. The assumption here is that tariff levels are uncorrelated with the specific unobserved characteristic of any individual firm.[13] The value reported in row [3] is the marginal effect of a 1 percentage point change in the tariff rate on the observed (censored) levels of R&D expenditures, evaluated at the mean tariff rate. The effect is negative and significant at standard confidence levels, suggesting that a reduction in the tariff rate has a positive effect on R&D. The value is interpreted as a semi-elasticity and implies that a 1 percentage point reduction in the tariff is associated with a 4% increase in observed R&D expenditures.[14] Row [4] considers an analogous specification

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[13]I discuss the exogeneity of tariffs in detail below.

[14]The magnitude of this result is smaller, although in the same vicinity, as previous estimates. For example, in a similar regression, [Tes08] finds that a 1 percentage point reduction in the tariff is associated with an 8% increase in R&D expenditures in a panel of Mexican firms.

Table 2.4: Firm Performance, R&D, Innovation, and Tariffs

Dependent Variable	Coefficient	Standard Error	N
Log Price	0.0017***	-0.0006	30,743
Log Output	0.0034	-0.0025	30,533
Log R&D Expenditure	-0.0400***	-0.0113	30,515
Log R&D Employment	-0.0136***	-0.0026	8,852
Process Innovation Indicator	-0.0083***	-0.0026	30,730
Product Innovation Indicator	-0.0012	-0.0023	30,729

Independent variable is import tariff rate. R&D regressions report average marginal effects from random effects Tobit. All other specifications are linear. All specifications include firm and time effects. Significance: * 90%, ** 95%, *** 99%.

with R&D employment as the dependent variable. The coefficient is again negative and significant, and implies that at the mean tariff rate, a 1 percentage point decrease in the tariff is associated with a 1.4% increase in the observed number of employees devoted to R&D activities.

Row [5] reports the results from a regression of the process innovation indicator on the tariff. The coefficient is negative and significant, showing that reductions in the tariff correspond to an increase in the rate of process innovation. The magnitude implies that a 1 percentage point decrease in the tariff generates a 0.8 percentage point increase in the hazard of introducing a new process innovation. Row [6] shows the analogous regression for product innovations. Again, the coefficient is negative, suggesting a positive effect of tariff reductions, although not significant at standard confidence levels.[15]

The reduced-form results reported in Table 2.4 suggests that tariff reductions spur intensified product market competition, increased investments in R&D, and a greater rate of successful process innovation, but do not have a meaningful impact on the rate of product innovation. In the remainder of the paper, I analyze the

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[15] Again, this is a similar to [Tes08] who finds no effect of tariff reductions on R&D in product innovation.

relationships between competition, innovation, and achieved performance through the lens of a structural model.

2.3   A model of competition and innovation

In this section I outline a dynamic model of strategic competition and innovation. The framework explicitly incorporates the simultaneous effects of competitive pressure on innovative investments and achieved performance, where the latter is captured both by process efficiency and product quality. The active agents in the model are heterogenous firms that differ over productivity, product quality and scale. Firms compete in the product market and choose optimal levels of investments in R&D and physical capital as a function of their own characteristics as well as those of their competitors to maximize discounted expected profits. R&D investments influence the stochastic processes governing the evolution of firm-level productivity and product quality. The aggregrate state, capturing the intensity of competition, is determined by the characteristics of the firms competing in the market and evolves in response to an aggregate shock coming through changes in tariffs as well as the idiosyncratic shocks to which firms are subject and their resulting actions. In turn, the aggregate state affects individual firm outcomes by changing the incentives for investments in R&D through expectations of future prospects and by directly influencing the path of firm product quality and productivity.

2.3.1   The environment

Time is discrete and indexed by t. Firms produce differentiated products and operate to maximize the PDV of expected profits. The state of a firm is summarized by a triple (ω, φ, K), $\omega \in \Omega$, $\varphi \in \Phi$, $K \in \mathbb{K}$ where ω is an index of the firm's efficiency, φ the quality of its product offering, and K its level of installed physical

capital.[16] The differing states of each firm form the heterogeneity in the model and will be an important driver for the large degree of persistent dispersion in firm-level R&D investment that is seen in the data. The aggregate, or competitive, state of each industry $s \in \mathbb{S}$ is then a vector listing the number of firms in the industry at each possible state of (ω, φ, K), with individual elements labeled $s(\omega, \varphi, K)$.

In each period, firms compete and earn profits on a spot product market. After maximizing over its static choices variables, the current period expected profits of firm i in industry j, $\pi(\omega_{ij}, \varphi_{ij}, K_{ij}, s_{-ij})$, depend on its individual state $(\omega_{ij}, \varphi_{ij}, K_{ij})$ as well as the states of its competitors within the industry s_{-ij}.

It makes sense at this point to explicitly define the notion of the competitive environment in the model. Following the original formulation of [EP95], I assume that competition in the product market generates a preorder over s, denoted by $\succeq$, which characterizes the competitive intensity of the market. For all triples (ω, φ, K), current profits are (weakly) decreasing in s in the sense of $\succeq$. An increase in competition is captured by an increase in s. Intuitively, a shift towards higher productivity, higher product quality, or larger scale of a firm's competitors generates an increase in competitive intensity. This formulation of an ordering of competitive states is convenient in its flexibility and generality in incorporating the characteristics of how "increased competition" has generally been interpreted in the literature.

Foreign firms are able to export into the domestic market subject to an import tariff rate τ, which varies over time and across industries. Tariffs are exogenous and evolve according to a first-order Markov process.[17] By reducing the efffective marginal cost of selling in the domestic market, a reduction in tariffs should spur exporters to increase their sales volumes and new foreign firms to enter the

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[16]I suppress subscripts wherever possible in formulating the theoretical model.

[17]I detail below how the institutional framework for the sample of Spanish firms supports the exogeneity assumption.

market. Because exporters tend to be higher productivity and offer products of higher quality, the "competitive shock" induced by a tariff reduction should cause an increase in the competitive intensity of the domestic industry. Writing the competitive state as the sum of the domestic and foreign firms at each state, $s(\omega, \varphi, K) = s^d(\omega, \varphi, K) + s^f(\omega, \varphi, K)$, the immediate impact of a reduction in τ will be to increase the effective $\omega, \varphi,$ or K (or some combination thereof) of foreign firms with no corresponding change for domestic firms. This is the way in which, *ceteris paribus,* for any $\tau < \tau', s(\tau) \succeq s(\tau')$, that is, tariff reductions generate a more intense competitive environment. Intuitively, we can think of reductions in τ as a competition-augmenting shock, reducing domestic firm profitability by increasing the productivity, product quality, or scale of its foreign competitors, holding fixed the characteristics of its domestic competitiors. Due to the serially correlated nature of τ and the fact that changes in τ cause persistent shifts in s, τ now enters the firm's decision problem as an additional state variable, affecting current profits as well expectations of future prospects.

2.3.2   Demand

I motivate the demand system through the discrete choice literature of [Ber94] and descendants. There is a mass of consumers each purchasing one good. Without detailed product characteristics, I model the utility to consumer c from purchasing the product of firm i in industry j at time t simply as

$$U_{cijt} = \gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P_{ijt}^y + \varphi_{ijt} + \eta_{cijt} \qquad (2.3)$$

where P_{ijt}^y denotes the firm's output price, γ_j a persistent industry-specific component of utility, γ_t a time-varying aggregate shock, and γ_{jt} an industry-time specific shock. η_{cijt} captures consumer specific heterogeneity and is distributed i.i.d. type 1 extreme value. Finally, φ_{ijt} is the quality of the firm's product offering at time

t as defined above, which is unobserved to the econometrician but known by all agents in the economy. This specification implies market shares of the standard form:

$$\sigma_{ijt} = \frac{e^{\gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P^y_{ijt} + \varphi_{ijt}}}{1 + \sum_{l=1}^{I} e^{\gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P^y_{ljt} + \varphi_{ljt}}} \qquad (2.4)$$

The Logit demand model is appealing here for its simplicity, while still yielding the desired competitive effects. It is straightforward to derive the firm's residual demand elasticity

$$\varepsilon_d \left(\sigma_{ijt}, P^y_{ijt} \right) = \alpha P^y_{ijt} \left(1 - \sigma_{ijt} \right) \qquad (2.5)$$

The impact of a competitive shock in the product market in the sense of inducing an $s' \succeq s$ is intuitive. As rivals become more efficient and lower their prices, or increase their product quality or capital base, they will tend to produce more and capture a greater share of the market. This serves as a negative shock to the residual demand curve of a particular firm, which is forced to either reduce price or lose market share. Without imposing a particular form of equilibrium play in the product market, it is clear that firm profitability will be lessened and the market has become more cutthroat.

2.3.3   Production

Firms use capital, labor and intermediate inputs, or materials, to produce output according to a Cobb-Douglas production technology

$$Y_{ij} = A e^{\omega_{ij} + \mu_{ij}} K_{ij}^{\beta_k} L_{ij}^{\beta_l} M_{ij}^{\beta_m} \qquad (2.6)$$

where L and M denote labor and intermediate inputs, or materials. ω denotes the firm's productivity as defined above and μ an i.i.d. shock to production that captures measurement error and/or any idiosyncratic shocks that are not known when input decisions are made. It is important to make a distinction

between the roles of ω and μ. The former represents an efficiency level that is correlated over time and so potentially observable or predictable to the firm when making its current period input choices, whereas the latter represents strictly exogenous and unpredictable shocks that are uncorrelated with any input choices and so captures the period-by-period uncertainty in production to which firms are inherently subject.

The firm's static problem is to choose labor L and materials M to maximize current period profits given its individual characteristics $(\omega_{ij}, \varphi_{ij}, K_{ij})$ and the aggregrate industry state s_{-ij}. Optimality entails the standard condition of choosing quantities to equate marginal revenues to marginal costs. This condition will play an important role in the econometric work below and I defer the details to that section of the paper.

2.3.4 State transitions

In addition to the static choices just described, the firm makes dynamic decisions over R&D investments R and physical capital I. Capital accumulates according to a standard and deterministic neoclassical law of motion

$$K'_{ij} = (1 - \delta_j) K_{ij} + I_{ij}$$

where δ_j is the industry-specific rate of depreciation. R&D investments influence the paths of productivity and product quality, which evolve according to stochastic laws of motion

$$
\begin{aligned}
\omega'_{ij} &= f\left(\omega_{ij}, R_{ij}, s_{-ij}, \tau_j\right) + \xi'_{ij} & (2.7) \\
\varphi'_{ij} &= g\left(\varphi_{ij}, R_{ij}, s_{-ij}, \tau_j\right) + \psi'_{ij} & (2.8)
\end{aligned}
$$

The evolution of a firm's productivity and product quality are functions of several factors: ξ and ψ are i.i.d. and mean zero idiosyncratic shocks to these processes that are only realized in the following period, after all current period choices have been made. These are by construction unpredictable from the standpoint of the current period and capture the uncertainty in the path of a single firm's outcomes. The functions $f(\cdot)$ and $g(\cdot)$ represent the predictable portion of the firm's next period productivity and product quality and depend on its current levels of these characteristics, current R&D expenditures R, the competitive state of the industry s_{-ij}, and the industry tariff level τ_j. That the state of a firm's competitors and the tariff level directly affect its performance captures possible knowledge and technological diffusion from other firms in the market, whether domestic or foreign, as well as improvements in managerial incentives or work practices induced by more intense competition. That is, the inclusion of the competitive state directly in the evolution of the firm's efficiency and product quality incorporates the direct channel of competitive effects described above. These effects should be stronger when there are more efficient or higher quality firms present in the market, or when these firms are producing a greater share of industry output, i.e., when s is larger in the sense of our ordering $\succeq$.

2.3.5   Firm strategies

As a dynamic model of firm competition, I focus on Markov strategies. The value function for a domestic firm i in industry j can be written recursively as

$$
\begin{aligned}
V\left(\omega_{ij}, \varphi_{ij}, K_{ij}, s_{-ij}, \tau_j\right) = & \max_{R_{ij}, I_{ij}} \pi\left(\omega_{ij}, \varphi_{ij}, K_{ij}, s_{-ij}, \tau_j\right) - c_R\left(R_{ij}\right) - c_I\left(I_{ij}\right) \\
& + \beta E\left[V\left(\omega'_{ij}, \varphi'_{ij}, K'_{ij}, s'_{-ij}, \tau'_j | \omega_{ij}, \varphi_{ij}, K_{ij}, s_{-ij}, \tau_j\right)\right]
\end{aligned}
$$

where $\pi(\cdot)$ is the conditional profit function, giving profits as a function of the current state conditional on the optimal static choices of the firm. $c_R(\cdot)$ is the

cost function for R&D investment and $c_I(\cdot)$ for physical capital investment. β is the common rate of discount. The solution to this problem yields policy functions

$$R_{ij} = R(\omega_{ij}, \varphi_{ij}, K_{ij}, s_{-ij}, \tau_j) \qquad (2.9)$$

$$I_{ij} = I(\omega_{ij}, \varphi_{ij}, K_{ij}, s_{-ij}, \tau_j) \qquad (2.10)$$

Equation (2.9) shows that the firm's choice of R&D investments R is the solution to a dynamic problem depending on the firm's individual characteristics and the state of competition. The impact of a shock to the competitive state on the incentives to invest in innovation is not clear. On one hand, firm profits are lower and prospects for the future more dim. On the other hand, firms may benefit through greater exposure to more advanced technology or through improved incentives in the practices of their workers and managers. Both of these channels alter innovative incentives in ways that are ambiguous. In the empirical work below, I use the data to infer whether competitive shocks increase or reduce innovative investments and quantify the effects of both the direct and indirect channels on realized outcomes.

Through the lens of the structural model, the potential impact of changes in competitive intensity on innovation and performance becomes clear. To understand how competitive pressure affects innovative investments, I will analyze how R responds to competitive shocks through reductions in τ. To assess the impact of competition on achieved outcomes and the importance of the direct and indirect channels, I will examine how the new levels of R and τ combine to influence the paths of ω and φ. Thus, equations (2.7), (2.8) and (2.9) are the objects that will reveal the effect of competition on innovation and realized performance. In the next section, I describe the econometric approach I take to consistently estimate these functions from the data.

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2.4 Econometric strategy

Estimation of the model is complicated by the fact that ω, φ, and s are not directly observable in the data. In this section, I outline a multistage algorithm to recover these values. I begin by estimating the demand system. From information on the demand side of the market, I infer product quality φ and residual demand elasticities ε_d. Intuitively, identification of product quality comes from variations in market share conditional on price and other controls in the utility function. It is then straightforward to estimate the transition function of product quality. Next, I move on to estimating the production function, which itself involves a two-stage routine in the spirit of [ACF06]. In a first step, I utilize information from the firm's static profit-maximization first order condition and the demand elasticities already obtained to recover the i.i.d. shock to production μ (a modification of the procedure in [LP03]). Intuitively, identification of μ comes from observing deviations from optimal static choices conditional on time t information. In the second step, having purged the problem of the i.i.d. shocks, I use a GMM framework to infer the parameters of the production function and construct values of ω. Identification here comes from the timing structure of the model and essentially controlling for the endogenous shock ω in the production function. During this stage, I estimate the transition function of productivity. Finally, in a last step, I use the recovered estimates of ω and φ to consistently estimate the the R&D policy function. Following the insight of [BBL07], I take the approach of flexibly regressing observed R&D investments on the now fully observed state vector. The estimation algorithm is illustrated in Figure 2.2.
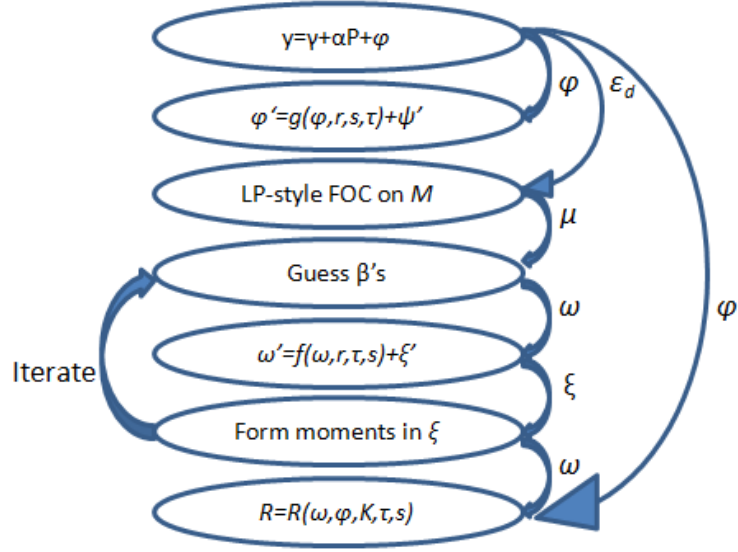
Figure 2.2: Estimation Algorithm

2.4.1 Demand and product quality

Recalling equation (2.4), the market share of firm i in industry j at time t is

$$\sigma_{ijt} = \frac{e^{\gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P^y_{ijt} + \varphi_{ijt}}}{1 + \sum_{l=1}^{I} e^{\gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P^y_{ljt} + \varphi_{ljt}}}$$

Making the standard normalization of the mean utility of the outside good to zero, the share of the outside good can be expressed as

$$\sigma_{0jt} = \frac{1}{1 + \sum_{l=1}^{I} e^{\gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P^y_{ljt} + \varphi_{ljt}}}$$

Combining equations gives a simple linear expression for the log ratio of market shares:

$$\ln\left(\frac{\sigma_{ijt}}{\sigma_{0jt}}\right) = \gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P^y_{ijt} + \varphi_{ijt} \tag{2.11}$$

Estimation of (2.11) requires definition of the outside good, as well as construction of its market share. This is difficult in my setting, where I have relatively aggregate industries and no well-defined outside option. By definition, the share

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of the outside good is the same for all firms within an industry. We can then bring this term to the right-hand side and rewrite the corresponding demand relationship as

$$y_{ijt} = \gamma_0 + \gamma_j + \gamma_t + \gamma_{jt} + \alpha P_{ijt}^y + \varphi_{ijt} \tag{2.12}$$

where the influence of the outside good has been subsumed into the term γ_{jt} and y_{ijt} denotes the natural log of sales. Equation (2.12) represents the demand-side estimating equation.[18]

Because the firm observes the current level of its product quality φ_{ijt}, we would expect prices to respond to the realization of this characteristic, which is unobserved by the econometrician, introducing correlation between prices and the error term. The richness of the ESEE data present a natural instrument for output prices in the form of input prices and this is the approach I follow.

The residuals from (2.12) represent consistent estimates of firm product quality. Recall from equation (2.8) that the evolution of φ depends on its current value, R&D investments, the competitive state, the tariff level, and an unpredictable shock. To estimate this function then requires the construction of the state s_{-ij}. It is infeasible to include the entire state vector in the estimation. Instead, I assume that the relevant measure of competition influencing product quality is sufficiently captured by the sum of the product quality of each competitor in the industry weighted by its capital stock, which is a primary determinant of its size. I construct the relevant state variable accordingly as $s_{-ij}^{\varphi} = \ln\left(\sum_{l \neq i} e^{\varphi_{lj}} K_{lj}\right)$. The economic interpretation here is straightforward. The ability to imitate or learn about product quality from one's rivals, or the pressure they apply to one's own product offering, depends on the degree of exposure to high quality competitors.

To estimate the transtion function (2.8), I specify the function $g(\cdot)$ as an

---

[18]Alternatively, we can make the somewhat unsatisfying assumption that the outside good for each industry is the remainder of the manufacturing sector excluding that industry. Because each firm represents only a very small fraction of the entire manufacturing sector, the results from this procedure are almost identical to those using (2.12).

augmented AR(1) process with a full set of linear interactions. This allows for a great deal of heterogeneity in the path of product quality and in particular, in the impact of R&D investments and changes in the tariff. There are then 15 right-hand side variables, excluding the constant term. As seen in Table 1, a sizable number of firms choose the corner solution of zero R&D. In this light, I follow [DJ09] and allow for a different transition function for firms that do no R&D investment and those with positive R&D. The estimating equation takes the form

$$\varphi_{ijt+1} = \Phi\left(R_{ijt} > 0\right) g_r\left(\varphi_{ijt}, r_{ijt}, s^{\varphi}_{-ijt}, \tau_{jt}\right) \tag{2.13}$$
$$+\Phi\left(R_{ijt} = 0\right) g_{nr}\left(\varphi_{ijt}, s^{\varphi}_{-ijt}, \tau_{jt}\right) + \psi_{ijt+1}$$

where $\Phi\left(\cdot\right)$ is an indicator function equal to 1 if its argument is true or else is equal to zero. $g_r\left(\cdot\right)$ and $g_{nr}\left(\cdot\right)$ denote the predictable component of future product quality conditional on current conditions and choices for R&D performers and non-performers, respectively. The impact of increased competitive pressure through tariff reductions on the path of product quality is made clear in (2.13). The indirect channel through changing investments in innovation are captured by the effect of the marginal change in r on φ and the direct channel by the effect of τ.

2.4.2 Production and productivity

The estimation algorithm I develop to infer ω is an extension of that outlined by [ACF06] to consistently estimate the production function in the presence of an unobserved and serially-correlated productivity term.[19] In particular, this methodology is meant to overcome the simulteneity bias in traditional OLS estimation due to the correlation of productivity and input choices. In my setting, the presence of differentiated products and the endogeneity of productivity through R&D investments add additional layers of complication. Here, I outline a two-step method

---

[19][ACF06] builds on [OP96] and [LP03].
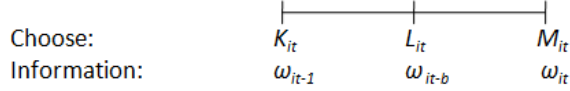
Figure 2.3: Within-Period Timing of Inputs

that enables estimation of the production parameters and so the computation of ω. In brief, I use the results from the demand side of the market to control for the endogeneity of price and incorporate endogenous R&D investments in a similar manner as [DJ09].

2.4.2.1 Stage 1

I rewrite the production function (2.6) in natural logs, which I denote with lower-case letters as

$$y_{ijt} = \beta_0 + \beta_k k_{ijt} + \beta_l l_{ijt} + \beta_m m_{ijt} + \omega_{ijt} + \mu_{ijt} \tag{2.14}$$

where $\beta_0 = \ln A$. [ACF06] show there are collinearity problems in the standard [OP96] and [LP03] procedures that may prevent identification of the labor coefficient in the production function. In this light, I follow their suggested alternative approach and adopt the identifying assumption that materials is the only fully flexible input in the sense of responding to the realization of ω_{ijt}. In particular, I assume that labor L_{ijt} is chosen at period $t - b, 0 < b < 1$, i.e., within period t, but prior to the time that materials are chosen. ω continues to evolve in the interim interval between the labor choice and the materials choice. This timing structure implies that the choice of materials M_{ijt} is a function of the firm's current productivity ω_{ijt} as well as its levels of physical capital and labor.[20] Figure 2.3 illustrates the timing of input choices within a single period.

---

[20]This timing assumption seems especially applicable in the case of the Spanish data used in the empirical analysis below, due to the recognized labor market rigidities prevalent in Western Europe.

With these assumptions, the firm's expected short-run conditional cost function at time t is given by

$$E\left[C\left(\cdot\right)\right] = E\left[P_{ijt}^m \left(\frac{Y_{ijt}}{Ae^{\omega_{ijt}}e^{\mu_{ijt}}K_{ijt}^{\beta_k}L_{ijt}^{\beta_l}}\right)^{\frac{1}{\beta_m}}\right]$$

where P_{ijt}^m denotes the materials price it faces at time t. The expectation is with respect to μ_{ijt}, which is only realized after all input choices have been made. Expected marginal costs can be found as

$$E\left[MC\left(\cdot\right)\right] = E\left[P_{ijt}^m M_{ijt}^{1-\beta_m}\frac{1}{\beta_m}\frac{1}{Ae^{\omega_{ijt}}e^{\mu_{ijt}}K_{ijt}^{\beta_k}L_{ijt}^{\beta_l}}\right] \tag{2.15}$$

To maximize profits, the firm's optimality condition requires that its choice of materials, which fully determines expected output, sets expected marginal cost to expected marginal revenue. This latter takes the standard inverse elasticity form

$$MR\left(\cdot\right) = P_{ijt}^y \left(1 + \frac{1}{\varepsilon_d\left(\sigma_{ijt}, P_{ijt}^y\right)}\right) \tag{2.16}$$

Equating (2.15) and (2.16) and rearranging yields an analytic formula for the firm's productivity level. Taking natural logs gives

$$\begin{aligned}\omega_{ijt} =\ & -\ln\beta_m + \left(1 - \beta_m\right)m_{ijt} - \beta_0 - \mu - \beta_k k_{ijt} - \beta_l l_{ijt} \tag{2.17}\\ & -\left(p_{ijt}^y - p_{ijt}^m\right) - \ln\left(1 + \frac{1}{\varepsilon_d\left(\sigma_{ijt}, P_{ijt}^y\right)}\right)\end{aligned}$$

where $\mu = \ln E\left[e^{\mu_{ijt}}\right]$. Substituting this expression into the production function (2.14) and rearranging yields

$$\left(y_{ijt} + p_{ijt}^y\right) - \left(m_{ijt} + p_{ijt}^m\right) + \ln\left(1 + \frac{1}{\varepsilon_d\left(\sigma_{ijt}, P_{ijt}^y\right)}\right) = -\ln\beta_m - \mu + \mu_{ijt} \tag{2.18}$$

which is a valid estimating equation where the left hand side consists of the log of the inverse of the materials cost share of revenues and a function of the residual demand elasticity and the right hand side simply a constant. Intuitively, the optimality condition sets the marginal revenue product of materials, which depends on the residual demand elasticity, equal to its marginal factor cost. Identification of μ_{ijt} comes through observing deviations from this rule.[21]

Equation (2.18) represents the first stage estimating equation. Although no production parameters are identified here, the residuals represent a consistent estimate of the firm's untransmitted shock to production $\widehat{\mu}_{ijt}$, which I will use in the next stage.

2.4.2.2   Stage 2

In this stage, I use GMM techniques to estimate the production function parameters and recover values for firm-level productivity ω and its transition function. Again following [ACF06], I estimate the parameters of the value-added production function rather than of gross-output. As pointed out by [BS05], it is hard, if not impossible, to identify the coefficient on a static and perfectly variable input in the context of Cobb-Douglas production. In this light, I consider the value-added production function

$$va_{ijt} = \beta_0 + \beta_k k_{ijt} + \beta_l l_{ijt} + \omega_{ijt} + \mu_{ijt}$$

where value-added VA_{ijt} is defined as physical output less physical materials input.[22]

---

[21]Intuition for this equation is easily seen from the perfectly competitive case in which $\varepsilon_d \to \infty$. In this case, the condition collapses to $\beta_M = \frac{P^m_{ijt} M_{ijt}}{P^y_{ijt} Y_{ijt}} + \mu_{ijt}$, i.e., the firm chooses materials such that the materials expenditure share is constant and equal to its elasticity in production. Deviations are then due to the unobserved shock μ_{ijt}.

[22]Thus, the role of materials is purely to distinguish shocks still unrealized at the time input decisions are made. Again, the intuition is that materials are the most flexible input with respect to ω and therefore should be most informative in separating out ω from μ.

Given a candidate vector of the production function parameters $\{\beta_0, \beta_k, \beta_l\}$ and the first stage estimates of the i.i.d. production shock $\widehat{\mu}_{ijt}$, I can construct values for ω_{ijt} as

$$\omega_{ijt} \left(\beta_0, \beta_k, \beta_l \right) = va_{ijt} - \beta_0 - \beta_k k_{ijt} - \beta_l l_{ijt} - \widehat{\mu}_{ijt} \qquad (2.19)$$

where I have made explicit the dependence of ω_{ijt} on the candidate parameter vector $\{\beta_0, \beta_k, \beta_l\}$. Using these values, I can estimate the productivity transition function (2.7). Similar to the transition of product quality, I allow for a great deal of heterogeneity in outcomes and specify the law of motion of ω as an augmented AR(1) with a full set of linear interactions, making for 15 right-hand side variables. I again allow for different functions for R&D performers and non-performers. To construct the aggregate state s_{-ij}, I assume that the potential diffusion of efficient technologies, or the improved incentives from competitive pressure, are sufficiently captured by the capital-weighted sum of rival firm efficiencies and construct the relevant state variable accordingly as $s^{\omega}_{-ij} = \ln \left(\sum_{l \neq i} e^{\omega_{lj}} K_{lj} \right)$. Intuitively, competitive market conditions and the extent to which firms can learn of new techniques from their rivals depend on the interaction of the efficiency of competitors with their scale. This yields an estimating equation of the form

$$
\begin{aligned}
\omega_{ijt+1} \left(\beta_0, \beta_k, \beta_l \right) = \; & \Phi \left(R_{ijt} > 0 \right) f_r \left(\omega_{ijt} \left(\beta_0, \beta_k, \beta_l \right), r_{ijt}, s^{\omega}_{-ijt}, \tau_{jt} \right) \qquad (2.20) \\
& + \Phi \left(R_{ijt} = 0 \right) f_{nr} \left(\omega_{ijt} \left(\beta_0, \beta_k, \beta_l \right), s^{\omega}_{-ijt}, \tau_{jt} \right) + \xi_{ijt+1}
\end{aligned}
$$

where $\Phi \left(\cdot \right)$ again denotes an indicator function equal to 1 if its argument is true or else is equal to zero. $f_r \left(\cdot \right)$ and $f_{nr} \left(\cdot \right)$ denote the predictable component of future productivity conditional on current conditions and choices for R&D performers and non-performers, respectively. The effect of the competitive shock through tariff reductions is similar to that on product quality. The indirect effect will come through the marginal impact of a change in r, and the direct effect through

the change in τ.

The residuals from (2.20) represent an estimate of the idiosyncratic and unpredictable shock in the productivity process ξ. Using these estimates, I can set up the following standard moment conditions which identify the production function parameters:

$$
E \begin{bmatrix} \xi_{ijt}\left(\beta_0, \beta_k, \beta_l\right) \cdot k_{ijt} \\ \xi_{ijt}\left(\beta_0, \beta_k, \beta_l\right) \cdot l_{ijt-1} \\ \omega_{ijt} \end{bmatrix} = 0 \tag{2.21}
$$

The production function is estimated by iterating on the initial guess of the production technology parameter vector until I minimize the sample analogue to these moment conditions.

$$
\frac{1}{J}\frac{1}{I}\frac{1}{T}\sum_j\sum_i\sum_t \begin{bmatrix} \xi_{ijt}\left(\beta_0, \beta_k, \beta_l\right) \cdot k_{ijt} \\ \xi_{ijt}\left(\beta_0, \beta_k, \beta_l\right) \cdot l_{ijt-1} \\ \omega_{ijt} \end{bmatrix} \tag{2.22}
$$

2.4.3 R&D investment

I now turn to estimation of the R&D policy function (2.9). Here, I follow [BBL07] by flexibly regressing observed R&D choices on the state. The implicit assumption is that the data are generated by equilibrium play and so with the caveat that we observe a wide range of states, we can use the data to make inferences about the equilibrium policy functions. As seen in Table 2.1, about two-thirds of firms choose the corner solution of zero R&D. Thus, the distribution of R&D expenditure has positive mass at zero and is continuous over the range of positive values. The presence of this form of left-censoring renders OLS estimates inconsistent and a Tobit model, which explicitly accounts for the left-censoring of the data at zero, is appropriate.

In addition to adjusting for the censored nature of the data, the Tobit model

provides a particularly useful feature in distinguishing the impact of the state variables on the R&D decisions of various subsegments of the population of firms. There are three marginal effects of interest. The first, $\frac{\partial E[r|\cdot]}{\partial \tau}$ represents the impact of the competitive shock on the conditional mean of r, the observed level of R&D spending. This is the effect not on the latent variable in the Tobit model, but on the observed censored values as reported in the data. Second, $\frac{\partial E[r|r>0,\cdot]}{\partial \tau}$ is the impact of the shock on R&D expenditures for those firms reporting a positive level of expenditure. Finally, $\frac{\partial \Pr(r>0|\cdot)}{\partial \tau}$ is the impact on the probability of being uncensored, i.e., of engaging in R&D at all. The first effect captures the overall impact of competitive intensity on engagement in R&D in the population. This can be decomposed into the latter two effects. The first of these captures the intensive margin, i.e., how do current R&D performers react to changes in the competitive environment? The second captures the extensive margin, i.e., how do changes in competitive pressure impact the probability of undertaking R&D at all?

The Tobit model takes the form

$$
\begin{aligned}
r_{ijt}^* &= h\left(\omega_{ijt}, \varphi_{ijt}, K_{ijt}, s_{-ijt}, \tau_{jt}\right) + \iota_{ijt}, \quad \iota_{ijt} \sim N\left(0, \sigma_\iota^2\right) \\
r_{ijt} &= \max\left(0, r_{ijt}^*\right)
\end{aligned}
$$

where r_{ijt} is observed R&D expenditure and r_{ijt}^* is the latent level. I specify $h\left(\cdot\right)$ as a linear function of the state variables and include interactions of τ with each of the other states. To measure s_{-ijt}, I include both s_{-ijt}^φ and s_{-ijt}^ω, for a total of 6 state variables and 11 right-hand side variables, excluding the constant. The impact of τ on r captures the response of innovative investments to shocks to the competitive environment. The combination of the effect of τ on r and in turn, r on φ and ω, together reveal the magnitude of the indirect channel of how competitive pressure affects achieved outcomes through changing engagement in

innovative activities.

2.4.4 Tariff determination

Before moving to my results, the exogeneity of the import tariff is worth a brief comment. A particular feature of my use of Spanish data is that concerns of tariff endogeneity due to political economy issues are largely absent. As a member of the EU, Spanish external tariffs (i.e., those applicable to non-EU nations) are no longer determined by Spain itself. Rather, Spain must adhere to the EU common external tariff schedule. EU trade policies are negotiated by the European Commission on behalf of all member states, in conjunction with the "133 committee." The latter is a committee of 133 delegates from the EU member nations and the European Commission, whose agenda is the discussion and coordination of trade issues affecting the EU. It is through this body that the European Commission receives the endorsement of the member states for policy initiatives. The European Commission reports regularly to the Council of the European Union as well as to the European Parliament. The results of trade negotiations must then be approved by the Council, generally by qualifed majority voting, in order to become effective.[23] As one of the now 27 members of the EU, it is unlikely that any particular Spanish firm has a significant influence on EU-wide common external tariffs. A similar argument for the exogeneity of trade barriers in a particular European nation after integration into the EU is used by [De 10].

2.5 Results

In this section, I present the results from the structural estimation. I begin with the demand and production estimates. I then report the results from the R&D

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[23]See, e.g., "The European Union Trade Policy: Our Work at External Trade," Brussels, December 2008, available at http://ec.europa.eu/trade/gentools/downloads_en.htm

Table 2.5: Demand Estimates		
	OLS	IV
Price Coefficient	-0.8831	-2.4066
	-0.1597	-0.3501
Mean (ε_d)	-0.9918	-2.7030

Both specifications include dummies for industry, time and their interaction. Standard errors are shown in parentheses and are robust to heteroskedasticity and autocorrelation at the firm level. Both coefficients are significant at the 99% level.

policy function. I assess the general reasonableness of my econometric procedure and results by examining the demand and production parameter estimates and the characteristics of the resulting φ's and ω's. Next, I show that my findings are robust to controlling for other potential effects of a trade liberalization. Finally, I summarize the effect of competitive pressure on firm performance as measured by product quality and productivity and the relative importance of the direct and indirect channels.

2.5.1 Demand and product quality

Table 2.5 presents results from the demand estimation (2.12). I report OLS and IV estimates of the price coefficient where the latter uses input prices as an instrument for output prices. In line with the theory outlined above, OLS results in a significant positive bias on the price coefficient. This bias translates into the elasticity estimates. The table show that with OLS, the mean elasticity is slightly less than one in absolute value, implying the unreasonable result that the average firm sets a negative markup. In contrast, the IV estimates are quite reasonable. The implied average elasticity is about -2.7.[24]

I use the demand estimates from Table 2.5 to infer the quality of the product

---

[24]In the IV specification, about 40 observations (less than 0.1%) have implied elasticities less than 1 in absolute value. Because these values are fed into the production function estimation, I set the elasticities of these firms equal to the average in their respective industries.

Table 2.6: <u>Implications of Product Quality Measures</u>

Correlation of φ with	
Nominal Output	0.88
Physical Output	0.86
Output Price	0.15
Capital	0.80

offering of each firm. In Table 2.6, I assess the reasonableness of these values by examining their correlation with some of the observed firm-level characteristics. As we would expect and is predicted by theory, product quality is highly correlated with output, both in nominal and real terms, output price, and the size of the capital stock.

In Table 2.7, I present the results of the product quality transition equation (2.13). Recall that a separate conditional mean function was specified for R&D performers and non-performers. I report the estimates of both functions. For the sake of brevity and ease of interpretation, I report the average marginal effect of each determinant of future product quality φ'_{ij} and relegate the full set of coefficients to Table 2.14 at the end of the paper. Because current product quality φ_{ij}, R&D r_{ij} and the aggregate state s^{φ}_{-ij} are expressed in logs, their marginal effects represent elasticities. The marginal effect of a change in the tariff τ_j is a semi-elasticity and is interpreted as the percent change in product quality associated with a unit percentage point change in the tariff.

Not surprisingly, product quality is highly persistent across both groups of firms. R&D has a positive impact on product quality. The elasticity of product quality with respect to R&D is about 0.006. As I discuss below, this estimate in conjunction with the effect of R&D on productivity implies an elasticity of output with respect to R&D that is in line with previous findings. Clearly, however, the low elasticity of product quality with respect to R&D will limit the potential for the average firm to experience large quality gains through the indirect channel of

Table 2.7: The Evolution of Product Quality

	R&D Performers	Non-Performers
φ_{ij}	0.9793	0.9896
r_{ij}	0.0059	
τ_j	-0.0023	-0.0032
s^{φ}_{-ij}	-0.0112	-0.0081

Table reports average marginal effects from the transition function for product quality $g(\cdot)$. All explanatory variables are significant at the 99% level.

increased R&D investments in response to competitive pressure.

The negative effect of τ implies that tariff reductions have a positive impact on product quality, with a unit percentage point decline in the tariff spurring about a 0.2%-0.3% increase in product quality. Already, we can see the relative importance of this channel, which captures the direct effect of more intense competition. The estimates imply that it would take about a 33% increase in R&D for the average firm to generate the same impact on achieved product quality that is induced through the direct channel.

Finally, the negative sign on s^{φ}_{-ij} suggests that product quality worsens in reponse to increases in the quality of domestic competitors. This implies that dominating any beneficial spillovers or changing performance incentives across domestic firms is the deterioration in a firm's quality position, and hence its market share, as rivals improve or grow larger.

2.5.2 Production and productivity

Table 2.8 reports the estimated production function parameters along with the results from a standard OLS specification. The model produces results well within the standard range found in the literature with a capital elasticity about of 0.39 and labor elasticity of about 0.66. There is a small degree of returns to scale in the production technology, a common finding from firm-level data. Comparing the

Table 2.8: Production Function Parameters

	OLS	Model
Capital	0.2954	0.394
	-0.0103	-0.047
Labor	0.7716	0.6554
	-0.0161	-0.0844
RTS	1.067	1.0494

Estimates are all significant at the 99% confidence level. Model standard errors are block-bootstrapped at the firm level with 500 replications.

Table 2.9: Implications of Productivity Measures

Correlation of ω with	Model	[FHS08]
Nominal Output	0.28	0.17
Physical Output	0.32	0.28
Output Price	-0.46	-0.54
Capital	0.05	0.03

OLS results to those from the model, the coefficients move in the way suggested by theory and that have typically been found in the literature. The upward bias on the labor coefficient under OLS is consistent with the notion that labor is sensitive to current productivity shocks that are observed by the firm, but not by the econometrician. This same bias causes the typical decrease in returns to scale when moving from OLS to the structural estimates.

To investigate the implications of the productivity estimates, I assess their correlations with other observable firm-level characteristics. Table 2.9 shows that productive efficiency is highly correlated with both nominal and physical output, and importantly, highly negatively correlated with output price. These relationships are in line with the theory. The correlation with physical capital is quite low, substantiating the fixed nature of capital investment. [FHS08], one of the few studies I am aware of with access to firm-level price deflators, report a similar set of statistics which I include in the table for purposes of comparison. The two sets of estimates are strikingly similar.

In Table 2.10, I present the results of the productivity transition equation (2.20). Again, for brevity and ease of interpretation, I report average marginal effects for each right-hand side variable and leave a listing of all coefficients for Table 2.15 at the end of the paper. We see that firm efficiency is highly persistent both for R&D performers and non-performers. R&D expenditures have a positive impact on productivity.[25] The elasticity of productivity with respect to R&D is almost identical to the product quality elasticity at 0.006.

The effect of τ is again negative, implying that increased competitive pressure has a positive direct impact on realized productivity. The effect is present for both R&D performers and non-performers, although the magnitudes are fairly different. The values imply that a 1 percentage point reduction in the tariff induces a 0.6% increase in productivity among R&D performers and 0.24% among non-performers. There are several reasons why the productivity response of R&D-performing firms may be more susceptible to competitive shocks. First, there is evidence that in addition to its role in stimulating new innovation, R&D investment also enhances the capacity of firms to absorb and integrate new technologies. For example, [GRV04] document this phenomenon across a panel of OECD countries during the 1970s and 1980s. Another possible explanation is that R&D performers are generally operating in more innovative and dynamic industries, where maintaining efficiency is of utmost importance to remain competitive. In this case, marginal changes in the competitive environment may have greater impact through changing managerial incentives and the implementation of productivity-enhancing work practices. Finally, as I explore in more detail below, this difference may be an artifact of a correlation between import and export tariffs, where the latter have a disproportionate effect on large, more productive firms, which are also those engaged in R&D. Table 2.10 reveals the weight of the direct channel in

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[25]The effect of R&D is significant at the 92% level, which is a common finding, and is simply indicative of the large degree of uncertainty in the path of firm efficiency. For example, [Xu08] finds a similar degree of statistical significance in the effect of R&D on productivity.

Table 2.10: The Evolution of Productivity

	R&D Performers	Non-Performers
ω_{ij}	0.9009	0.9040
r_{ij}	0.0059	
τ_j	-0.0058	-0.0024
s^{ω}_{-ij}	0.0227	0.0138

Table reports average marginal effects from the transition function for productivity $f(\cdot)$. All explanatory variables are significant at the 99% level except for r which is significant at 90%.

the response of productivity to competitive pressure. The average R&D performer would have to almost double its level of R&D investment to garner the same productivity gains it obtains through the direct effect of technology transmission or changing manager and worker incentives.

The aggregate state s^{ω}_{-ij} has a positive impact on productivity growth, in contrast to the negative impact of the analogous measure on product quality. This confirms that the positive effect of potential knowledge or technology transfers from domestic competitors or the continued pressure on manager and worker incentives from facing more efficient competitors plays a significant role in stimulating firm-level productivity growth.

2.5.3   R&D investments

Table 2.11 displays results from the firm's R&D policy function. I report the average marginal effect of each state variable on the three subsegments of the firm population described above, that is, on the conditional mean of observed R&D expenditures, R&D expenditures for firms reporting positive R&D, and on the probability of engaging in R&D. Table 2.16 at the end of paper reports the full set of Tobit coefficients. The impact of the explanatory variables on R&D expenditures can be interpreted as elasticities for ω, k, and s, since they are already expressed in log form and as a semi-elasticity for the tariff rate τ. On the

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Table 2.11: The Determinants of R&D Investments

	$E[r|\cdot]$	$E[r|r>0,\cdot]$	$\Pr(r>0|\cdot)$
k_{ij}	0.7408	0.6055	0.0734
ω_{ij}	0.3448	0.2817	0.0342
φ_{ij}	0.6728	0.5450	0.0666
τ_j	-0.0376	-0.0307	-0.0037
s^{ω}_{-ij}	0.6403	0.5234	0.0634
s^{φ}_{-ij}	-0.4457	-0.3643	-0.0441

Table reports average marginal effects from R&D policy function $h(\cdot)$. All explanatory variables are significant at the 99% level.

extensive margin, the impact of the explanatory variables are interpreted as the percentage point change in the probability of undertaking R&D for the average non-performer.

As we would expect, the amount of installed capital k, productive efficiency ω, and product quality φ each have a large and positive impact on R&D investments. The negative sign on τ implies that more intense import competition induced through reductions in the tariff generate higher levels of engagement in R&D. A 1 percentage point decrease in the tariff rate corresponds to a 3.8% increase in average observed R&D expenditures across all firms. This is composed of a 3.1% increase among current R&D performers and a 0.4% increase in the hazard of undertaking R&D. Clearly, changes in competitive pressure have a significant impact on firms' innovative investments, both on the discrete choice of whether to perform R&D and on the level of investment for firms that choose to do so. The positive coefficient on s^{ω} and the negative coefficent on s^{φ} are consistent with the results found in the transition functions for ω and φ. Firms tend to increase their R&D investments in response to efficiency gains by their competitors, seeking to maintain their proximity to the technological frontier, perhaps by successful imitation or absorption of the more efficient technologies of their rivals. In contrast, the dominant effect of product quality gains by competitors is to cut into the firm's market share, likely reducing the incentives to invest in R&D.

2.5.4 Additional effects of trade liberalization

In Section 2, I presented evidence linking tariff reductions to increases in the competitiveness of the domestic market as seen through the rising market share of foreign firms and the lowering of prices by domestic firms. I use this as motivation for the intuitive notion that competitive pressure induced through such trade shocks underlies my empirical results. However, the literature has posited several additional mechanisms through which a trade liberalization may lead to gains in firm-level performance. In this section, I address the robustness of my findings to the inclusion of these channels and corroborate that the "competitive" channel of tariff reductions is the primary driver of my empirical results.

What other effects of a trade liberalization may lead to domestic performance improvements? First, if tariff reductions are bilateral, there may be a learning-by-exporting phenomenon by which domestic firms experience performance gains not through increased exposure to foreign compettitors in the home market as I model above, but rather via entry into the foreign market. [De 07] and [Bie05] document the potential importance of this channel. Moreover, increased access to foreign markets through tariff reductions may change the incentives of domestic firms to engage in performance-enhancing R&D. [AB10] and [ARX11] investigate the link between trade costs, exporting, and engagement in R&D. Another potential channel for performance improvements and changing R&D investments lies in the impact of a trade liberalization on the cost of inputs, and in particular, the cost of R&D investments.

To investigate whether my results are robust to allowing for these alternative vehicles for performance gains, I collect data on the tariff levels facing Spanish firms exporting to the rest of the world. As with import tariffs, the data are from the UNCTAD TRAINS database. I again use the MFN tariffs aggregated to the same industry level, weighted by the value of Spanish exports of each product to

each country. Not surprisingly, there is a relatively high correlation of export and import tariffs across industry-time cells of about 0.68, suggesting a bilateral nature of trade negotiations, although the relationship is far from perfect. I re-estimate the model with the explicit inclusion of export tariffs in order to control for the potential impact on domestic outcomes caused by a greater ease of access to foreign markets. Additionally, to control for the possible effect of trade liberalization on the cost of R&D investment, I include a vector of time effects in the R&D policy function, under the assumption that the cost of innovative investment is common across firms. To limit the complexity of the estimation and focus on the first-order changes resulting from the inclusion of the additional variables, I employ linear specifications to model the transitions of product quality and productivity as well as the R&D policy function $h(\cdot)$ within the Tobit model.

The main results are consolidated in Tables 2.12 and 2.13 and the full set of results are presented in Tables 2.17 and 2.18 at the end of the paper. Table 2.12 displays the transition functions for product quality and productivity after the inclusion of the export tariffs. The import tariff is denoted by τ_j^{im} and the export tariff that Spanish firms face abroad by τ_j^{ex}. The foreign tariff is generally negative and significant, suggesting that access to markets abroad may have an effect on the performance of domestic firms. Despite this, the negative and significant coefficient on the import tariff across both performance measures and both groups of firms imply that the beneficial effect of increased competition through tariff reductions continues to hold. The qualitative impact of reductions in τ_j^{im} are similar to those found above, where the lowering of import tariffs spurs gains in both product quality and productivity, independent of expenditures on R&D. Clearly, the competitive effects of reductions in the import tariff found above are not driven by changes in the tariffs faced abroad.

Quantitatively, most effects are similar to those in the baseline model above. There are, however, several interesting exceptions. First, there is an increase in

the impact of R&D on product quality as well as in the magnitude of the direct effect of import tariff reductions on product quality. Second, there is a fall in the size of the direct effect on productivity only for R&D performers, and where in the absence of the export tariff, this effect was much larger for performers than non-performers, the two effects are now approximately equal. A fall in export tariffs, which eases access to foreign markets and may facilitate learning-by-exporting, would be expected to predominantly impact exporting firms, which are typically larger and more productive, precisely those that tend to engage in R&D. This suggests that the disproportionately large direct effect of import tariff reductions on the productivity of R&D performers found above may be partially due to a corresponding fall in foreign tariffs.

In Table 2.13, I report average marginal effects from the R&D policy function with the addition of the export tariff and time effects to control for possible changes in the cost of R&D investment. Again, the import tariff continues to have a negative and significant effect, implying that competitive pressure through reductions in the import tariff spur greater innovative investments. Here, the effects of changes in the export tariff are of an order of magnitude smaller than those of changes in the import tariff and the export tariff is not significantly different from zero at standard confidence levels. This suggests that access to foreign markets may not be an important determinant of R&D investments for this group of firms. Additionally, that the import tariff continues to have a significant effect on R&D expenditures after the inclusion of time effects indicates that the impact of import tariff reductions is not driven by a lowering of the cost of R&D investment, and hence is likely the result of increases in competitive pressure, corroborating the main results above.

Table 2.12: The Evolution of Product Quality and Productivity

	φ'_{ij}		ω'_{ij}	
	R&D Performers	Non-performers	R&D Performers	Non-Performers
φ_{ij}/ω_{ij}	0.9832***	0.9907***	0.9025***	0.9071***
r_{ij}	0.0095***		0.0051**	
τ_j^{im}	-0.0040***	-0.0045***	-0.0033**	-0.0028**
τ_j^{ex}	0.0052***	0.0035***	-0.0042***	-0.0009
$s^\varphi_{-ij}/s^\omega_{-ij}$	-0.0054**	-0.0017	0.0203***	0.0126***

Table reports coefficients from linear specification of transition functions for productivity and product quality with the inclusion of foreign tariffs. Significance: * 90%, ** 95%, *** 99%.

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Table 2.13: The Determinants of R&D Investments

	$E[r|\cdot]$	$E[r|r>0,\cdot]$	$\Pr(r>0|\cdot)$
k_{ij}	0.7352	0.6006	0.0728
ω_{ij}	0.4171	0.3407	0.0413
φ_{ij}	0.6779	0.5538	0.0672
τ_j^{im}	-0.0711	-0.0581	-0.0070
τ_j^{ex}	-0.0096	-0.0078	-0.0009
s^ω_{-ij}	0.9239	0.7547	0.0915
s^φ_{-ij}	-0.6315	-0.5158	-0.0626

Table reports average marginal effects from linear specification of the R&D policy function $h(\cdot)$ with the inclusion of foreign tariffs and time effects. All explanatory variables are significant at the 99% level with the exception of foreign tariffs, which are not significant at 90%.

2.5.5 Quantifying the effect of competition

What is the immediate effect of an increase in competitive pressure on firm-level performance? The baseline results imply that in response to a 1 percentage point reduction in the tariff, R&D expenditures for the average R&D performer increase by about 3.1%. Using the parameters from the transition functions, this increase in R&D investments should garner one-period growth in both product quality and productivity of only about 0.02%. Clearly, the response to competitive pressure operating through greater engagement in R&D has only a small incremental effect on performance, whether measured by productivity growth or improvements in product quality. From the transition functions, we see that the direct effect is an order of magnitude greater than the indirect. Through the direct channel, the same 1 percentage point reduction in the tariff spurs product quality growth of 0.23% and 0.32% for R&D performers and non-performers, respectively, and productivity growth of 0.6% and 0.24%.

These values are for the average firm only and the econometric specifications allow for a great deal of heterogeneity in outcomes underlying this average. For some firms, the indirect effect will carry more weight and the direct effect less.

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Some firms may come upon important new innovations through R&D investments that have large effects on product quality or productivity. It would seem, however, that such breakthroughs are the exceptions rather than rule. The average marginal effect of R&D is fairly small. In reponse to competitive pressure, the vast majority of incremental performance improvements come via the transfer of new technology or ideas, or the beneficial impact on managerial incentives and worker practices, rather than through major new R&D-generated innovations.

These results are robust to additional possible effects of a trade liberalization. After explicitly controlling for associated changes in foreign tariffs and the cost of R&D investment in order to further isolate the "competitive" channel, a 1 percentage point reduction in the import tariff generates about a 5.8% increase in R&D expenditures among R&D performers. Using the new transition function estimates, this translates into a 0.05% increase in product quality and a 0.03% increase in productivity. In contrast, the direct channel spurs about a 0.4% increase in product quality and a 0.3% increase in productivity, again an order of magnitude greater than the indirect.

The relative importance of the direct channel is likely not limited to the specific sample of firms used here. For example, [HMM09] survey a wide array of studies of the returns to R&D and report that the average study finds an elasticity of output with respect to R&D of about 0.08. In my setting, R&D-generated innovations increase output both through product quality improvements, enhancing the demand for the firm's product offering and through efficiency gains, reducing the firm's marginal costs and spurring increased output. Summing these effects gives an elasticity of output with respect to R&D of above 0.012, well in line with previous estimates, and indeed, slightly above the average. In this light, the importance of the direct channel is likely to be a more general result, rather than simply attributable to any lack of "R&D efficiency" in Spanish manufacturing firms. Moreover, the predominance of the direct channel is in line with the case-

study evidence reviewed in [HS10], who find that productivity improvements in response to competitive pressure come primarily through changing management and worker practices.

2.6   Conclusions

In this paper, I take a structural approach to empirically assess the impact of competition on innovative investments and achieved firm performance. I outline a structural model of strategic competition and innovation, explicitly incorporating the simultaneous effects of competitive pressure on investments in innovation and realized outcomes. I use the structural framework to infer both product quality and productive efficiency from firm-level performance data and measure their response to changes in the competitive environment, that is, to jointly assess the effect of competitive pressure on product and process innovation. Additionally, I use the model structure to distinguish and quantify the relative importance of various channels through which increased competition may spur improvements in firm performance. I estimate the model on a detailed panel of Spanish manufacturing firms during the 1990s and 2000s, when reductions in tariffs facing non-EU nations led to intensified competition for domestic firms.

I find that competitive pressure spurs greater investments in innovation and performance improvements. On average, a 1 percentage point reduction in the tariff induces a 3.8% increase in R&D expenditures and product quality and productivity gains ranging from 0.25% to 0.6%. The majority of these gains come through the direct effect of knowledge and technology diffusion or changing managerial incentives and worker practices, rather than indirectly through R&D-generated innovation. I show that these findings are robust to controlling for other potential effects of a trade liberalization and that the importance of the direct effect is likely not limited to my particular setting. Moreover, the notion that it

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is the direct effect of competition that stimulates performance gains rather than new innovations through R&D investments is consistent with existing case-study evidence of various industries and their response to competitive shocks.

In carefully assessing the effect of competition on innovation and realized performance in an explicit economic environment, my paper sheds renewed light on these relationships, and in particular, the relative importance of the potential channels for within-firm performance gains resulting from increased competitive intensity. My findings call for a better understanding of the transmission mechanism throuch which knowledge and technology are diffused throughout the economy. Moreover, if competitive pressure stimulates growth through changing managerial incentives and work practices, we run into the often-asked question of why these changes were not implemented prior to the period of intensified competition. With a better grasp of the microstructure underlying these channels, we can begin to consider the implications of policies meant to stimulate competition and innovative investments, their welfare effects, and their potential impact on economic growth and development.

Table 2.14: The Evolution of Product Quality

	R&D Performers			Non-Performers		
	Coefficient	S.E.	P-Value	Coefficient	S.E.	P-Value
φ_{ij}	1.6873	(0.4586)	<0.01	0.7254	(0.0701)	<0.01
r_{ij}	0.3616	(0.1023)	<0.01			
τ_j	0.2998	(0.1517)	<0.01	-0.0702	(0.0149)	<0.01
s^φ_{-ij}	0.1307	(0.0486)	<0.01	-0.0228	(0.0051)	<0.01
$\varphi_{ij}\cdot\tau_j$	-0.0453	(0.0653)		0.0244	(0.0089)	
$\varphi_{ij}\cdot r_{ij}$	-0.0721	(0.0375)				
$\tau_j\cdot r_{ij}$	-0.0335	(0.0138)				
$\varphi_{ij}\cdot\tau_j\cdot r_{ij}$	0.0038	(0.0055)				
$s^\varphi_{-ij}\cdot\varphi_{ij}$	-0.0281	(0.0192)		0.0112	(0.0029)	
$s^\varphi_{-ij}\cdot r_{ij}$	-0.0147	(0.0043)				
$s^\varphi_{-ij}\cdot\tau_j$	-0.0125	(0.0062)		0.0028	(0.0006)	
$s^\varphi_{-ij}\cdot\varphi_{ij}\cdot\tau_j$	0.0018	(0.0027)		-0.0010	(0.0004)	
$s^\varphi_{-ij}\cdot\varphi_{ij}\cdot r_{ij}$	0.0029	(0.0016)				
$s^\varphi_{-ij}\cdot\tau_j\cdot r_{ij}$	0.0014	(0.0006)				
$s^\varphi_{-ij}\cdot\varphi_{ij}\cdot\tau_j\cdot r_{ij}$	-0.0002	(0.0002)				
N	8,841			16,317		
R^2	0.9639			0.9552		

Table reports all coefficients from the transition function for product quality $g(\cdot)$. P-values are from joint test of significance for all terms involving each explanatory variable.

Table 2.15: The Evolution of Productivity

	R&D Performers			Non-Performers		
	Coefficient	S.E.	P-Value	Coefficient	S.E.	P-Value
ω_{ij}	0.9098	(0.9498)	<0.01	0.2812	(0.1343)	<0.01
r_{ij}	0.0846	(0.0747)	0.0807			
τ_j	0.0835	(0.1335)	<0.01	0.0470	(0.0157)	<0.01
s^ω_{-ij}	0.0822	(0.0448)	<0.01	0.0305	(0.0060)	<0.01
$\omega_{ij} \cdot \tau_j$	0.0918	(0.1534)		0.0137	(0.0167)	
$\omega_{ij} \cdot r_{ij}$	-0.0523	(0.0731)				
$\tau_j \cdot r_{ij}$	-0.0026	(0.0112)				
$\omega_{ij} \cdot \tau_j \cdot r_{ij}$	-0.0066	(0.0128)				
$s^\omega_{-ij} \cdot \omega_{ij}$	-0.0007	(0.0454)		0.0307	(0.0065)	
$s^\omega_{-ij} \cdot r_{ij}$	-0.0039	(0.0036)				
$s^\omega_{-ij} \cdot \tau_j$	-0.0045	(0.0063)		-0.0024	(0.0008)	
$s^\omega_{-ij} \cdot \omega_{ij} \cdot \tau_j$	-0.0043	(0.0072)		-0.0007	(0.0008)	
$s^\omega_{-ij} \cdot \omega_{ij} \cdot r_{ij}$	0.0026	(0.0035)				
$s^\omega_{-ij} \cdot \tau_j \cdot r_{ij}$	0.0001	(0.0005)				
$s^\omega_{-ij} \cdot \omega_{ij} \cdot \tau_j \cdot r_{ij}$	0.0003	(0.0006)				
N	8,394			15,663		
R^2	0.7628			0.7881		

Table reports all coefficients from the transition function for productivity $f(\cdot)$. P-values are from joint test of significance for all terms involving each explanatory variable.

Table 2.16: The Determinants of R&D Investments

	Coefficient	S.E.
k_{ij}	1.1726***	(0.1283)
ω_{ij}	0.6025***	(0.1805)
φ_{ij}	2.6870***	(0.1549)
τ_j	2.9340***	(0.4763)
s^{ω}_{-ij}	4.5705***	(0.1861)
s^{φ}_{-ij}	-2.3666***	(0.1781)
$\tau_j \cdot k_{ij}$	0.1526***	(0.0187)
$\tau_j \cdot \omega_{ij}$	0.0616**	(0.0255)
$\tau_j \cdot \varphi_{ij}$	-0.1322***	(0.0222)
$\tau_j \cdot s^{\omega}_{-ij}$	-0.4618***	(0.0296)
$\tau_j \cdot s^{\varphi}_{-ij}$	0.1854***	(0.0253)
N	28,213	
Pseudo R^2	0.1050	

Table reports Tobit coefficients from R&D policy function $h(\cdot)$. Significance: * 90%, ** 95%, *** 99%.

Table 2.17: The Evolution of Product Quality and Productivity

	φ'_{ij}		ω'_{ij}	
	R&D Performers	Non-performers	R&D Performers	Non-Performers
φ_{ij}/ω_{ij}	0.9832***	0.9907***	0.9025***	0.9071***
	(0.0025)	(0.0017)	(0.0059)	(0.0039)
r_{ij}	0.0095***		0.0051**	
	0.0020)		(0.0021)	
τ_j^{im}	-0.0040***	-0.0045***	-0.0033**	-0.0028**
	(0.0013)	(0.0009)	(0.0016)	(0.0011)
τ_j^{ex}	0.0052***	0.0035***	-0.0042***	-0.0009
	(0.0011)	(0.0008)	(0.0014)	(0.0010)
$s^\varphi_{-ij}/s^\omega_{-ij}$	-0.0054**	-0.0017	0.0203***	0.0126***
	(0.0025)	(0.0018)	(0.0037)	(0.0026)
N	8,841	16,317	8,394	15,663
R^2	0.9639	0.9551	0.7608	0.7859

Table reports coefficients from linear specification of transition functions for productivity and product quality with the inclusion of foreign tariffs. Standard errors in parentheses. Significance: * 90%, ** 95%, *** 99%.

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Table 2.18: The Determinants of R&D Investments

	Coefficient	S.E.
k_{ij}	2.0679***	(0.0729)
ω_{ij}	1.1732***	(0.1004)
φ_{ij}	1.9066***	(0.0874)
τ_j^{im}	-0.2001***	(0.0348)
τ_j^{ex}	-0.0269	(0.0291)
s_{-ij}^{ω}	2.5984***	(0.1109)
s_{-ij}^{φ}	-1.7761***	(0.0867)
N	28,213	
Pseudo R^2	0.1053	

Table reports Tobit coefficients from linear specification of the R&D policy function $h(\cdot)$ with the inclusion of foreign tariffs and time effects. Significance: * 90%, ** 95%, *** 99%.

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