Small is Beautiful but Size Matters: The Asymmetric Impact of Uncertainty and Sunk Costs on Small and Large Businesses

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Abstract

Against the backdrop of the theories developed in the real options and financing constraints literatures, this paper examines the impact of profit uncertainty and sunk costs on firms' entry and exit decisions. For our empirical analysis, we compile an extensive dataset containing information on 267 U.S. manufacturing industries over a 30-year period containing industry-specific information on the number of firms and establishments, the size distribution of establishments, measures of sunk capital costs and profit uncertainty, among others. Our dynamic panel data estimates show that greater uncertainty about profits, especially in conjunction with higher sunk costs, results in (1) a marked decrease in the number of small firms and establishments; (2) a less skewed size distribution of firms and establishments; and (3) a marginal increase in industry output concentration. In sharp contrast, large establishments seem virtually unaffected. The results point to uncertainty in conjunction with sunk costs fundamentally affecting firms' decision-making and altering the structure of industries by putting smaller businesses at a disadvantage.
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Keywords: Uncertainty; sunk costs; real options; financing constraints; decision-making; small businesses.

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1. Introduction

Businesses operate in environments that have varying degrees of uncertainty about market conditions. Products that firms sell go through periods of high or low demand due to changing consumer preferences, industry-wide shifts in fortunes or macroeconomic business cycles. Some of these changes are forecastable and businesses can make adjustments to their plans related to production, entry into new product markets, employment, expanding existing product lines and other investments. However, a significant component of the fluctuations in market conditions may catch businesses by surprise. This unforecastable component can play havoc with their decision-making process. Consider an entrepreneur who made careful calculations before entering a market, but, upon entry, realized that market conditions had taken a turn for the worse and were less favorable than expected. Given that the entrepreneur had likely made investments in advertising, R&D and human and physical capital to enter and that immediate exit is costly due to the nature of investments made, the viability of this new firm may be at stake including potential bankruptcy. Such shocks can throw in disarray the shorter and longer-run business strategies and cast a long shadow on the viability of businesses.

Since there is almost always going to be some uncertainty about market conditions, the significant issue with businesses is in dealing with the downside which can lead to exit from the market. If exit were costless, this would be of less concern. But a serious problem is caused by investments that businesses might make that cannot be fully recouped if the firm were to exit from the market. At issue here are the non-recoverable or partially-recoverable components of investments made (sunk costs). For example, investments in the purchase of costly physical capital which, if the firm were to try and sell while exiting, may not fetch fair price. Similarly, any costs incurred in establishing marketing networks, R&D, among others, may be largely non-recoverable. These non-or-partially recoverable investments can compel entrepreneurs to become hesitant in their decision-making when confronted with uncertainty.

Uncertainty and sunk costs have been subject to extensive theoretical modeling in economics, strategic management and finance. Two important strands of this literature have emerged to the forefront. The first one provides insights using the real-options channel. Dixit (1989) and Dixit and Pindyck (1994), for example, show that the presence of uncertainty and sunk costs imply an option-value of waiting and alter firms' decisions to enter and exit via changes in the entry and exit trigger prices. A second channel that may influence intertemporal changes in the number of firms relates to financial market frictions. This literature suggests that uncertainty and sunk costs are likely to exacerbate financing constraints, affecting business decisions related to entry and exit (Greenwald and Stiglitz, 1990; Williamson, 1988). In recent years, a growing applied literature has pointed to the importance of the real options in entrepreneurial decision-making. Using survey data on Irish businesses, Driver and Whelan (2003) find that uncertainty affected the timing of investment. Miller and Folta (2002) and O'Brien, Folta and Johnson (2003) examine the likelihood and timing of new entry in markets characterized by uncertainty. O'Brien et al. find that increased uncertainty about industry conditions makes potential entrepreneurs less likely to start new businesses. Rotheli (1998) examines alternative strategies when managers are confronted with uncertainty. Ghosal and Loungani (1996, 2000), Lensink, Bo and Sterken (2002) and Guiso and Parigi (1999) present overviews of the theory and empirical findings related to capital investment outlays by businesses. This study is motivated by the fact that while the option-value and financing-constraints models point to uncertainty and sunk costs being potentially important, empirical evaluation of these models in the context of the intertemporal dynamics of the number of firms and establishments have been relatively limited.[1]

[1] Sutton (1997a; p.52-54) writes that fluctuations in industry profits influence entry and exit, and "*… a new attack on this problem has been emerging recently, following the work of Avinash Dixit and Robert Pindyck (1994) on investment under uncertainty. Here, the focus is on the different thresholds associated with entry decisions which involve sunk costs and decisions to exit…*" Following Gort and Klepper (1982), a large literature focused on technological change as a key factor driving industry dynamics (see Audretsch, 1995; Caves, 1998; Sutton, 1997a).

In this paper we assemble an extensive database to examine the effects of uncertainty and sunk costs on the number of firms in an industry and, in particular, whether small and large firms are affected differentially. For our empirical analysis we compiled an extensive database covering 267 SIC 4-digit manufacturing industries over the period 1958-1992 containing data on the number of firms and establishments, output concentration, alternative proxies for sunk capital costs and measures of uncertainty. Our estimates from a within-industry dynamic panel data model reveal that periods of greater uncertainty about profits, especially in conjunction with higher sunk costs, result in: (1) reduction of the number of small firms and establishments; (2) less skewed size distribution of firms, and (3) marginally higher industry concentration. Large establishments appear to be virtually unaffected. Our findings shed useful light on the decision-making process of businesses and entrepreneurs when they are confronted with uncertainty and sunk entry costs and could be useful in several areas of research and policy-making which we highlight in our concluding remarks in section 7.

The paper is organized as follows. In section 2 we briefly summarize the theoretical results related to the option-value and financing constraints models. Section 3 reviews some of the other forces that may shape industry dynamics such as technological change. In section 4 we present details on the dataset and the measurement of variables. Sections 5 and 6 present the dynamic panel data model and estimation results and section 7 concludes with a discussion and implications of our findings.

2. Role of Uncertainty and Sunk Costs

In this section we briefly review some of the predictions from the theoretical literature and highlight the implications for our empirical analysis.

However, other forces, such as uncertainty, have been somewhat neglected in the empirical literature.

2.1. Real-Options Channel

Dixit (1989) shows that uncertainty and sunk costs imply an option-value of waiting and this raises the entry trigger price and lowers the exit trigger price.[2] For prices below the entry trigger, the potential entrant holds on to its option to enter, and an incumbent firm does not exit at prices above the exit trigger. Another way of looking at this is that to enter during periods of greater uncertainty, firms would require a premium over the conventional Marshallian entry price. And incumbent firms would wait longer to exit (i.e., let prices fall below average variable cost before they exit) as they know that to re-enter the market they would have to re-incur the sunk entry costs. Sunk entry costs constitute a crucial element in determining the impact of uncertainty. For example, if sunk costs were zero, then firms would be far less hesitant to enter as they know that they can costlessly exit if market conditions turn below expectations; there is no potential downside risk to be minimized by holding a call option. The option to delay entry and exit under uncertainty becomes more important when there are sunk entry costs.[3]

The key results related to entry and exit can be summarized as follows:

(1) Greater uncertainty is expected to lower entry and exit and this effect is exacerbated in the presence of higher sunk costs. Numerical results in Dixit (p.632-33) show that even small amounts of uncertainty and sunk costs are sufficient to generate significant changes in entry and exit patterns.

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[2] Dixit and Pindyck (1994) outline the theoretical framework for studying firms' decision-making regarding entry and exit under uncertainty and sunk entry costs. Ghemawat (1991) discusses the trade-offs between commitment and flexibility that are at the heart of firms' decision-making process related to investments, entry or exit under uncertainty and sunk costs. Hopenhayn (1992), Lambson (1991) and Pakes and Ericsson (1998) study firm dynamics with firm-specific uncertainty. These models can be better subjected to empirical tests using micro-datasets as in Pakes and Ericsson.

[3] Caballero and Pindyck (1996) model the intertemporal path of a competitive industry where negative demand shocks decrease price along existing supply curve, but positive shocks may induce new entry or expansion by incumbents, shifting the supply curve to the right and dampening price increase. Since the upside is truncated by entry but the downside is unaffected, it reduces the expected payoff from investment and raises the entry trigger. In their model, if exit is likely it would create a price floor making firms willing to accept a period of losses. Their data on SIC 4-digit manufacturing industries (similar to the one used in this paper) show that sunk costs and industry-wide uncertainty cause the entry (investment) trigger to exceed the cost of capital.

(2) Numerical simulations in Dixit (1989, p.632-33) and Dixit and Pindyck (Ch. 7, p.224-228; and Ch. 8.) show that an increase in uncertainty with a given amount of sunk costs results in the entry trigger price increasing by more than the decrease in the exit trigger. Similar results were obtained when they increased sunk costs with a given amount of uncertainty. These results reveal that entry is affected more than exit leading to *negative net entry*. In other words, periods of greater uncertainty lead to a decrease in entry but exits, while lower, continue at a closer to normal pace resulting in the industry experiencing a decrease in the number of firms, and this effect is exacerbated in the presence of higher sunk costs.

Turning to imperfectly competitive industries, the results get more complicated. First, consider a duopoly setting (Dixit and Pindyck, p.309-315). As before, the entry price exceeds the Marshallian trigger due to uncertainty and sunk costs, preserving the option-value of waiting. But, there are strategic considerations. Under *simultaneous* decision making, when price is above the entry trigger, neither firm may want to wait for the fear of being preempted by its rival and losing leadership. This could lead to faster, simultaneous, entry than in the *leader-follower* sequential entry setting. Thus fear of pre-emption may necessitate a faster response and counteract the option-value of waiting. Second, Appelbaum and Lim (1985), Dixit (1980) and Spencer and Brander (1992) show the optimality of strategic pre-commitment by the incumbent/first-mover. But under uncertainty, optimal pre-commitment is lower due to greater uncertainty about the success of the entry-deterring strategy. Oligopolistic settings highlight the dependence of outcomes on model assumptions and difficulties of arriving at clear predictions.

Implications for our Empirical Analysis

Apart from assessing the overall impact of uncertainty and sunk costs, one of our interests is to evaluate whether these effects may be different for small and large firms. The motivation for looking at firm size is as follows. It is well known that the within-industry firm size distribution is typically skewed (see Ijiri and Simon, 1977; Sutton, 1997a; Dosi et al., 1995); our data presented in section 4 reveals this to be the typical characteristic for our sample of industries. Further, previous studies have shown that (1) entrants are typically small compared to incumbents and have high failure rates, (2) typical exiting firm is small and young, and (3) larger firms are older with higher survival rates.[4] Given this, in our empirical analysis we examine whether the impact of uncertainty varies across small and large firms.

Following the theoretical results discussed above, we summarize the implications for our empirical analysis as follows:

(A) Net entry. Periods of greater uncertainty are likely to result in *negative net entry* and this effect will be exacerbated in the presence of high sunk costs. Would small and large firms be affected differentially? First, large firms are older and have typically made substantial investments in marketing and distribution networks, advertising and R&D (Caves, 1998; Sutton, 1991, 1997a, 1997b). Advertising and distribution networks contain sunk investments which erode upon exit and would have to be re-built if the firm re-enters in future. Similarly, exit entails loss of human and physical capital related to product and process innovation. Larger firms, therefore, are more likely to show greater inaction regarding exit. Since data show that entrants are typically small (see Caves, 1998; Sutton, 1997a), entry of large firms is not an important consideration in general. Overall, we expect greater inaction in large firm net entry (little or no entry and lower exits) during greater uncertainty. Second, the vast majority of the entry and exit action is in the smaller firm category. Since greater uncertainty, and in conjunction with higher sunk costs, are expected to result in negative net entry, the number of small firms in an industry is expected to decrease.

(B) Size distribution. If there is greater attrition among small firms, then firm size distribution will become less skewed, and this effect will be more pronounced in high sunk cost industries.

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[4] See Audretsch (1995), Dunne et al. (1988), Evans (1987) and Sutton (1997.a). In Audretsch (p.73-80), mean size of the *entering* firm is 7 employees, varying from 4 to 15 across 2-digit industries. Audretsch (p.159) finds 19% of *exiting* firms have been in the industry less than 2 years with mean size of 14 employees; for exiting firms of all ages, the mean size is 23. Dunne et al. (p.503) note that about 39% of firms exit from one Census to the next and entry cohort in each year accounts for about 16% of an industry's output. While the number of entrants is large, their size is tiny relative to incumbents. Data indicate similar pattern for exiters.

(C) Concentration. Given the above, industry concentration is expected to increase marginally since the smaller firms typically account for a minor share of industry output.

2.2. Financing Constraints

Greenwald and Stiglitz (1990) model firms as maximizing expected equity minus expected cost of bankruptcy and examine scenarios where firms may be equity or borrowing constrained. A key result of theirs is that greater *uncertainty* about profits exacerbates information asymmetries, tightens financing constraints and lowers capital outlays. Since uncertainty increases the risk of bankruptcy, firms cannot issue equity to absorb the risk. Brito and Mello (1995) extend the Greenwald-Stiglitz framework to show that small firm exit is hastened by financing constraints. Delli Gatti et al. (2003) build on the contributions by Greenwald and Stiglitz and develop a model in which the financial conditions of businesses affect the capital accumulation and the patterns of entry and exit which affect the distribution of firms differentiated by the equity ratio. In their model flow of exiting firms is endogenously determined through bankruptcy while the flow of entrant firms is affected by stochastic factors. Williamson (1988) shows that higher *sunk costs* imply that lenders will be more hesitant to provide financing because asset specificity lowers resale value implying that collateral has less value.[5] And, in Shleifer and Vishny (1992), the ease of debt financing is inversely related to asset specificity (or sunk costs). Lensink, Bo and Sterken (2001) provide a lucid discussion of financing constraints in the context of investment behavior, including the roles played by uncertainty and sunk costs. Overall, this literature shows that periods of greater uncertainty, and in conjunction with higher sunk costs, increases the

[5] Williamson writes: *(p.571) "Of the several dimensions with respect to which transactions differ, the most important is the condition of asset specificity. This has a relation to the notion of sunk cost..." (p.580) "In the event of default, the debt-holders will exercise pre-emptive claims against the assets in question....The various debt holders will then realize differential recovery in the degree to which the assets in question are redeployable...the value of a pre-emptive claim declines as the degree of asset specificity deepens..."*

likelihood of bankruptcy and exacerbates financing constraints. Incumbents who are more dependent on borrowing and adversely affected by tighter credit will have greater likelihood of exit. Firms more likely to be adversely affected are those with little/no collateral, inadequate history and shaky past performance. Similarly, entry is likely to be impeded for potential entrants who are more adversely affected by tighter credit conditions. Thus, periods of greater uncertainty, and in conjunction with higher sunk costs, are expected to accelerate exits and retard entry leading to *negative net entry* – that is, a decline in the number of firms in an industry.

Regarding small versus larger firm effects, Cooley and Quadrini (2001) model industry dynamics with financial market frictions, where firms finance capital outlays by issuing new shares or borrowing from financial intermediaries, but both are costly. In their model smaller/younger firms borrow more and have higher probability of default. With increasing size/age, the default probability falls dramatically. Thus, due to financial frictions, smaller/younger firms have higher probability of exit. Empirical results in Cabral and Mata (2003) show that financing constraints cause higher exits among small firms. In different strands of this literature, the papers by Evans and Jovanovic (1989) and Fazzari, Hubbard and Petersen (1988) offer results that are in similar vein. Gertler and Gilchrist (1994, p. 314) note:

> "*...while size per se may not be a direct determinant, it is strongly correlated with the primitive factors that do matter. The informational frictions that add to the costs of external finance apply mainly to younger firms, firms with a high degree of idiosyncratic risk, and firms that are not collateralized. These are, on average, smaller firms.*"

Links to Empirical Analysis

Given the above considerations, we postulate that small firms are more likely to be adversely by uncertainty and sunk costs via the financing constraints channel.

(A) Net entry. For smaller firms, periods of greater uncertainty are likely to increase exits and lower entry; the industry will experience loss of smaller firms. Since sunk costs will magnify the financing constraints, the negative effect on small firms will be greater in high sunk costs industries.

(B) Size distribution. If greater uncertainty causes negative net entry of smaller firms, industry firm size distribution will become less skewed and the effect will be magnified in industries with high sunk costs.

(C) Concentration. Since smaller firms are more likely to be affected, the impact on industry concentration while positive, may not be quantitatively large.

3. Other Control Variables

Entrepreneurs are more likely to exploit opportunities and enter those markets where profit-margins are expected to be high and demand for the product is expected to be high and increasing. These could arise either due to product-specific market conditions or in combination with broader economy-wide business cycle conditions. In addition, as noted in Gort and Klepper (1982) and Utterback (1994), entry by new businesses is more likely when the product technology life-cycle is in its early stages due to the technology related barriers-to-entry being lower. In this section we briefly discuss some of the other factors which are likely to influence industry dynamics.

3.1. Technological Change

Technological change has been linked to the ongoing turnover of firms in relatively mature industries (Audretsch, 1995; Caves, 1998; Sutton, 1997a) as well as the industry life-cycle (Gort and Klepper, 1982; Utterback, 1994; Jovanovic and MacDonald, 1994). While we briefly present the arguments for both, given our data we are primarily concerned with turnover of firms and not life-cycle issues. Gort and Klepper (1982) examine industry life cycle and visualize two types of innovations: the infrequent major breakthroughs that launch a new product cycle resulting in *positive* net entry into the industry; and the subsequent and more frequent incremental innovations by incumbents which lead to lower costs and weeding out of inefficient firms resulting in *negative* net entry. Regarding on-going incremental innovations, Gort and Klepper (p.634) write:

> *" [this] innovation not only reinforces the barriers to entry but compresses profit margins of the less efficient producers who are unable to imitate the leaders from among the existing firms. Consequently,...the less efficient firms are forced out of the market."*

Their data on 46 industries provides evidence of the link between technological change and net entry, with wide inter-industry variation in patterns of evolution. Jovanovic and MacDonald (1994) provide additional insights. These models assume low probability of successful innovations, a distribution of production efficiency across firms, and improvements in efficiency levels due to incremental innovations, learning-by-doing and imitation. Due to incumbents' increasing efficiency, entry is reduced to a trickle and exits continue resulting in a reduction in the number of firms.

The above models assume convergence to steady state where industry structure becomes relatively static. But Sutton (1997a, p.52) notes this is at odds with observed data which show high turnover of firms even in mature industries. Audretsch (1995), using data similar to ours, finds significant turnover in mature industries and that industry-wide innovation (1) is negatively associated with startups and survival of new firms and (2) hastens small firm exit. Thus, even in mature industries, ongoing innovations are likely to play a key role in industry dynamics. Since the focus of our paper is on examining time-series variations in the number of firms and establishments in relatively mature industries, our focus on technology is similar to that by Audretsch. In our empirical analysis, we construct a measure of technical change and examine its impact on the time-series variation of the number firms, and small and large establishments, in an industry.

3.2. Other Variables

We explicitly or implicitly control for some other variables that may influence fluctuations in the number of firms in an industry. We explicitly control for industry growth (**GROW**) and industry profit margins (**Π**). Evidence on the link between GROW and number of firms appears mixed. Audretsch (1995, p.61-63) finds new startups are not affected by industry growth, but positively affected by macroeconomic growth. Data in Jovanovic and MacDonald (1994) indicate sharp decline in the number of firms when the industry was growing. Some of the empirical papers in Geroski and Schwalbach (1991) and the discussion in Audretsch (Ch.3) indicate a tenuous link between GROW and industry structure. One reason for the lack of a clear result is that the link is likely to be conditioned on entry barriers, macroeconomic conditions and the stage of the industry's life cycle. A potential entrant is expected to assess the nature and intensity of entry barriers it is likely to encounter in the destination industry (Caves, 1998; Porter, 1980; Sutton, 1997). Regarding industry profit-margin Π, while the expected sign is positive, it will be conditioned on the above mentioned factors (for GROW). Absent entry barriers, greater Π signals lucrative markets and attracts entry. But if barriers are high, the effect is not clear. Some of the estimates presented in the papers in Geroski and Schwalbach indicate considerable variation in the coefficient of Π. Geroski (1995) notes that the reaction of entry to elevated profits appears to be slow.

For scale economies, advertising and R&D, we don't have explicit controls due to lack of time-series data, but we note the following. First, our regression will contain a variable for technological change and one could argue this captures aspects of scale economies. Second, our model includes a lagged dependent variable; to the extent that this incorporates information on scale economies from the "recent past", it provides additional control. Third, scale economies are unlikely to have large short-run variations; if so, an industry-specific fixed-effect, which we include in our dynamic panel data model, will capture aspects of this relatively time-invariant component.[6] I am not aware of SIC 4-digit time-series data on advertising or R&D for our 267 industries over 1963-92.[7] To the extent that part of R&D

[6] In Section 4.3, following Sutton (1991), we construct a measure of minimum efficient scale (MES) for 1972, 1982 and 1992 to proxy sunk entry costs. As noted there, the rank correlation between MES in 1972 and 1992 is 0.94. This provides a basis for arguing that industry fixed-effect may capture an important part of MES.

[7] We examined alternative sources. FTC Line of Business data on advertising and R&D are only available for 4 years; some data are 3-digit and some 4-digit. Advertising data from the U.S. Statistics of Income: Corporate Source Book are typically at the 3-digit level and some 2-digit and there are important gaps which prevents us from constructing a consistent time series. Thus, these data were not useful for our long time-series study.

and advertising intensities are in steady state levels and have a time-invariant component, this will be captured by the industry-specific constant.[8] Since our empirical model includes a time-series in broad technological change, this partly captures R&D effects. Finally, since the lagged dependent industry structure variable captures information on advertising and R&D from the recent past, it provides an additional control.

4. Data and Measurement

We compiled an extensive dataset at the SIC 4-digit level of disaggregation which provides us with a relatively long time-series which is critical for measuring uncertainty, as well as data on sunk costs and industry structure for a large number of industries (see Appendix A). The industry-specific annual time-series data are over 1958-94. Data on industry structure (number of firms, size distribution) and sunk costs are from the 5-yearly Census of Manufactures; these data are not available annually. We do not include industry structure and other data after 1992 as the SIC classifications changed substantially in the 1997 Census making a lot of industry before and after not clearly comparable.

4.1. Industry Structure Variables

Industry-specific time-series data from the 1963-92 Censuses include: (1) total number of firms (**FIRMS**); (2) total number of establishments (**ESTB**); (3) ESTB by *size classes*; and (4) four-firm concentration ratio (**CONC**).[9] Unlike ESTB, the Census does not provide data on FIRMS by size class.

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[8] Domowitz et al. (1987) find far greater cross-industry variation in advertising than within-industry and conclude (p.25) "*that by 1958, most of the industries in our sample had reached steady-state rates of advertising*". This indicates that industry-fixed-effects would capture an important part of the impact of advertising.

[9] Regarding using data on the total number of firms and establishments in an industry, several studies have noted a positive correlation between entry and exit rates. However, these correlations are not necessarily contemporaneous and the studies indicate wide cross-industry variation in patterns of net entry. Cable and Schwalbach (1991), Dunne, Roberts and Samuelson (1988), Evans and Siegfried (1994) and Geroski (1995). For SIC 4-digit industries

An establishment is defined as an economic entity operating at a location. As is common in the literature, we use the number of employees to measure size. The size classes provided in the Census are: 1-4; 5-9; 10-19; 20-49; 50-99; 100-249; 250-499; 500-999; 1,000-2,499; and ≥2,500 employees. We use the ESTB data to create small and large establishment size groups. The U.S. Small Business Administration (*State of Small Business: A Report of the President*, 1990), classifies "small business" as employing "less than 500 workers" and this metric has been used in public policy initiatives and lending policies towards small businesses. Using this, <500 employees constitutes our basic small business group, and ≥500 employees the large business group; see Ghosal and Loungani (2000) for a discussion of this benchmark. However, 500 employees may sometimes constitute a relatively large/wealthy business. We therefore used alternative cutoffs to create additional small business groups. Overall, our groups are: (1) All establishments; (2) relatively large businesses with ≥500 employees; (3) small businesses with <500 employees; and (4) even smaller businesses as classified by (i) <250, (ii) <100 and (iii) <50 employees. We did not push the size categories to greater extremes at either end as this considerably reduced the sample sizes which would magnify the uniqueness of the samples and render inference less meaningful.

Table 1 presents the within-year cross-industry statistics to outline the broad characteristics. For the typical industry, there are about 558 FIRMS, 623 ESTB and CONC of 39%, and data reveal a very large share of small establishments. We calculated the ratio (ESTB/FIRMS) for each industry (for the Census years 1963-92) and then examined the percentile distribution of this ratio across industries. The table below present these statistics.

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over the 1963-82 Censuses (similar to ours), Dunne et al. (1988) find raw correlations between entry and exit rates of 0.18 to 0.33; while positive, they are relatively low implying considerable variation in net entry patterns across industries. Also, after sweeping out industry fixed-effects, the correlations turn negative (-0.028 to -0.249) overturning inference from raw data. As we will shortly see, our data contains reasonable within-industry intertemporal variation in net entry, which is encouraging for our empirical analysis.

Percentile Distribution of the Ratio (Establishments/Firm) for ALL Industries					
	10%	25%	50%	75%	90%
Establishments/Firm	1.05	1.08	1.15	1.36	1.65

The number is close to 1 and even at the 75th percentile level implying near equivalence between the number of establishments and firms in an industry and hence their size distributions. This overall picture conceals a well known fact: larger (typically, older) firms tend to be multi-establishment (and multi-product), whereas smaller (typically, newer) firms are likely to be single-establishment. For the typical industry, **Figures 1(a)-1(g)** display the establishment size distribution for the seven Census years. Typically, about 25% of the total establishments in an industry belong to the smallest size category, and only about 3% belong to the largest size group. Thus, given the statistics of the ratio (ESTB/FIRMS), figures 1(a)-1(g) also roughly display the size distribution of firms. The data reveal a skewed size distribution for the typical industry as well as fluctuations in this distribution over time. This skewed size distribution is consistent with previous findings (Ijiri and Simon, 1977; Sutton 1997a; Dosi et al., 1995).

Key to our empirical analysis, **Table 2** presents summary statistics on the within-industry time-series data on industry structure variables. For the typical industry, the mean value of FIRMS is 558 and within-industry standard deviation of 129; the mean ESTB is 623 and within-industry standard deviation of 138. This within-industry intertemporal variation implies considerable new births and deaths of firms and establishments and is encouraging for our study of the impact of uncertainty and sunk costs on industry dynamics.[10]

[10] Since the published Census data used here does not track individual establishments over time, we are unable to directly address the issue of migration of establishments across size classes. Migration can of course take place in both directions: establishments can grow larger over time, or downsize due to changes in economic conditions, technological change, etc. These aspects can be better addressed using longitudinal data which track individual establishments. However, we will present results on the impact of uncertainty on the "total" number of firms and establishments in an industry (net entry effects) and this is not subject to the migration critique.

4.2. Uncertainty

The stochastic element can be couched in terms of several relevant variables.[11] We focus on a bottom line measure: profit-margins. Arguably, profit-margins are important for firms making entry and exit decisions. Commenting on the industry-specific determinants of turnover of firms, Sutton (1997a, p.52-53) notes the primary importance of volatility of industry profits; Dixit and Pindyck, and Caballero and Pindyck discuss uncertainty about profits and cash-flows. We assume that firms use a profit forecasting equation to predict the level of future profits. The forecasting equation filters out the systematic components. The residuals from the forecasting equation represent the *unsystematic* components (or forecast errors). We use the standard deviation of these residuals as a measure of profit-margin uncertainty.[12] We measure industry profits as short-run profits per unit of sales. Labor, energy and intermediate materials are assumed to be the relatively variable inputs that comprise total variable costs. Short-run profits are defined as:[13] **Π**=[(Sales Revenue *minus* Total Variable Costs)/(Sales Revenue)]. The standard deviation of the unsystematic component of Π measures uncertainty.[14] In Section 6 we construct an alternative measure of profit-margins and uncertainty which accounts for

[11] In the simplest settings, the theoretical models consider uncertainty about prices assuming constant input costs and technology. But Caballero and Pindyck (1996) and Dixit and Pindyck (1994), for example, discuss uncertainty about cash-flows, profits, among other variables.

[12] E.g., Aizenman and Marion (1997), Ghosal and Loungani (1996, 2000) and Huizinga (1993) use the (conditional) standard deviation to measure uncertainty. Lensink, Bo and Sterken (2001, Ch.6) provide an extensive discussion of this and other methods that have been used to measure uncertainty.

[13] This is consistent with the definition of short-run profits (Varian, 1992, Ch.2); see Domowitz et al. (1986, 1987) and Machin and Van Reenen (1993) for it's empirical use. Our measure Π does not control for capital costs. Carlton and Perloff (1994, p. 334-343) and Schmalensee (1989) discuss the pitfalls of alternative measures and note that measuring capital costs is difficult due to problems related to valuing capital and depreciation.

[14] Our industry level analysis implies that our procedure for measuring Π and uncertainty reflects industry-wide average, or "typical", outcomes. Given that there is a distribution of firm sizes, idiosyncratic uncertainty is likely to be important and the true amount of uncertainty facing a particular firm may deviate from that for a typical firm. These issues can be better addressed using firm-level data.

depreciation expenditures.

For our benchmark measure of uncertainty, we use an autoregressive distributed-lag model for the profit forecasting equation (1) which includes lagged values of Π, industry-specific sales growth (**SALES**) and aggregate unemployment rate (**UN**). The justification for this specification is contained in Domowitz, Hubbard and Petersen (1986, 1987) and Machin and VanReenen (1993) who study the time-series fluctuations in Π. In (1), subscripts i and t index industry and time.

$$(1)\ \Pi_{i,t} = \beta_0 + \sum_k \theta_k \Pi_{i,t-k} + \sum_m \zeta_m \mathrm{SALES}_{i,t-m} + \sum_n \gamma_n \mathrm{UN}_{t-n} + \varepsilon_{i,t}.$$

The following procedure is used to create a time-series for profit uncertainty: (a) for **each** industry, we first estimate equation (1) using annual data over the entire sample period 1958-1994.[15] The residuals represent the *unsystematic* components; and (b) the standard deviation of residuals - $\boldsymbol{\sigma(\Pi)_{i,t}}$ - are our measure of uncertainty. As noted earlier, industry structure data are for the five-yearly Censuses 1963, 1967, 1972, 1977, 1982, 1987 and 1992. The standard deviation of residuals over, e.g., 1967-71 serves as the uncertainty measure for 1972; similarly, the standard deviation of residuals over 1982-86 measures uncertainty for 1987, and so on. Using this procedure we get seven time-series observations on $\sigma(\Pi)_{i,t}$.[16]

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[15] We present some summary statistics from the regressions -equation (1)- estimated to measure uncertainty. Across the 267 industries, the mean Adjusted-R^2 and the standard deviation of adjusted-R^2 were 0.62 and 0.25, respectively. The first-order serial correlation was typically low, with the cross-industry mean (std. dev across industries) being -0.002 (0.07). Overall, the fit of the industry regressions was reasonable.

[16] We considered an alternative procedure. We used Autoregressive Conditional Heteroscedasticity (ARCH) models to measure uncertainty. After imposing the restrictions (Hamilton, 1994, Ch. 21), we estimated second-order ARCH for <u>each</u> of the 267 industries. For about 45% of the industries the estimation failed to converge; using alternative starting values, convergence criterion and order of the ARCH specification did not alleviate the problems. This is probably not surprising given the limited number of time-series observations (36, annual) per industry. Finally, our estimation of equation (1) over the entire sample period implies assuming stability of the parameters in (1) over the entire period. If we had longer time-series or higher frequency data (quarterly) we could do sub-sample estimation of (1). But due to the relatively short time series, we did not pursue this.

Table 3 (col. 1) presents within-year cross-industry statistics for σ(Π). The s.d. is relatively high compared to the mean value indicating large cross-industry variation in uncertainty. Key to our empirical analysis, **Table 4** (row 1) presents the within-industry time-series statistics. The typical industry shows a ratio of within-industry s.d. (0.0117) to mean (0.0236) of 50%, indicating significant variation in uncertainty within-industries over time.

When estimating (1), we initially assume the lag-lengths k, m, n=1,2. To check for robustness, Section 6 presents some additional results using alternative specifications for the profit equation (1). These include: (1) varying the lag length of the explanatory variables; (2) following Ghosal (2000) and replacing the business cycle indicator, unemployment rate, by federal funds rate and energy price growth; (3) estimating a basic AR(2) forecasting equation; (4) estimating the profit equation in growth rates instead of levels; (5) including industry-specific cost variables; and (6) using an alternative measure of profit-margins that accounts for depreciation.

4.3. Sunk Costs

Sunk costs are notoriously difficult to measure. The literature, however, suggests some proxies. We use the innovative framework laid out in Kessides (1990) and Sutton (1991) to quantify sunk costs. Drawing on the contestable markets literature, Kessides (1990) notes that the extent of sunk capital outlays incurred by a potential entrant will be determined by the durability, specificity and mobility of capital. While these characteristics are unobservable, he constructs proxies. Let RENT denote the fraction of total capital that a firm (entrant) can rent: **RENT**=(rental payments on plant and equipment/capital stock). Let USED denote the fraction of total capital expenditures that were on used capital goods: **USED**=(expenditures on used plant and equipment/total expenditures on new and used plant and equipment). Finally, let DEPR denote the share of depreciation payments: **DEPR**=(depreciation payments/capital stock). High RENT implies that a greater fraction of capital can be rented by firms (entrants), implying lower sunk costs. High USED signals active market for used capital goods which firms (entrants) have access to, implying lower sunk costs.[17] High DEPR indicates that capital decays rapidly, implying lower sunk costs (which arise from the undepreciated portion of capital). We collected data to construct RENT, USED and DEPR for Census years 1972, 1982 and 1992.[18]

Next, we construct a proxy for sunk costs following the procedure described in Sutton (1991). The theoretical models laid out in Dixit (1989) and Dixit and Pindyck (1994) make the assumption that sunk costs are proportional to entry capital requirements. Sutton's measure described below is consistent with this concept. Let Φ (>0) be the setup cost or the minimal level of sunk cost an entrant must incur, and S denote industry sales (market size). In theory, Φ/S is the sunk cost relative to market size. In quantifying sunk costs, Sutton (1991, Ch.4) measures the relative level of setup costs across industries and sunk costs are assumed proportional to the cost of constructing a single plant of minimum efficient scale (MES). Let Ω measure MES, where Ω is output of the median plant relative to industry output. Assume capital-sales ratio of the median firm is the same as the industry as a whole and denote industry capital-sales ratio by K/S. Then $(\Phi/S)=\Omega(K/S)$. If we can proxy Ω, and have data for industry K and S, we can approximate Φ/S. Ω is constructed using distribution of plants within each 4-digit industry according to employment size. Let 'm' be the number of group sizes within the industry, and n_j and S_j denote number of plants and total sales of the j^{th} size group (j=1,...,m.). Let $Ms_j=(S_j/n_j)$; $S_e=(1/m)\Sigma_j(Ms_j)$;

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[17] RENT and USED are useful proxies in the sense that due to the lemons-problem many types of capital goods suffer sharp drop in resale price in a short time period; e.g., automobile resale prices drop the most in the first year or two. If new entrants have access to rental or used capital, their entry capital expenditures will have a lower sunk component. We provide a couple of examples. The availability of used or leased aircraft, a prevalent feature of that industry, makes life easier for start-up airlines. Similarly, in the oilfield drilling services industry, the key capital equipment is a mobile "rig"; a truck fitted with equipment to service the oilfields. The rig technology has basically been unchanged since 1979-80 and there is a large market for used and leased rigs; we observe a rather fluid market where entrants buy or lease the used rigs.

[18] Collecting these for some of the additional (and earlier) years presented particular problems due to changing industry definitions and many missing data points.

and $S_o=\Sigma_j S_j$. Then $\Omega=(S_e/S_o)$. Using Ω and industry K/S, we obtain a proxy for Φ/S. We label Ω(K/S) as **SUNK(EC)** (sunk costs-entry capital) which is Sutton's measure. Sutton (1991, p.98) uses the cross-industry variation in SUNK(EC) to proxy cross-industry variation in sunk costs, and notes several limitations. We calculated SUNK(EC) for the Census years 1972, 1982 and 1992 (same years as for USED, RENT and DEPR).

Sunk Cost Sub-Samples

In section 2 we noted that the impact of uncertainty will vary depending on the magnitude of sunk costs. With this in mind, we create low *versus* high sunk cost sub-samples and estimate the impact of uncertainty across these groups. To create the sub-samples, we use the average values of RENT, USED and DEPR over 1972, 1982 and 1992 and **Table 5** presents the summary statistics. The measures show large cross-industry variation given the standard deviation relative to the mean. We took a closer look at our measures for the end-points, 1972 and 1992. For the minimum efficient scale, MES, proxy Ω the rank correlation is 0.94 and 0.92 for SUNK(EC), indicating fair amount of stability in the MES and SUNK(EC) measures. The mean (s.d.) for MES and SUNK(EC) were similar over the end-points; the mean (s.d.) for USED, RENT and DEPR were relatively similar across time. We employ two strategies to segment samples. First, we use the cross-industry median values of each of the sunk cost proxies to create high versus low sunk cost sub-samples. If SUNK(EC)<50^{th} percentile, indicating relatively lower entry capital requirements, then sunk costs are low; high if SUNK(EC)$\geq$$50^{th}$ percentile. Similarly, sunk costs are low if RENT or USED or DEPR $\geq 50^{th}$ percentile; high if RENT or USED or DEPR <50^{th} percentile. Second, we created sub-samples by combining alternative characteristics, the argument being that they may produce stronger separation between low and high sunk costs. For example, sunk costs would be considered low if the intensity of rental and used capital markets are high and depreciation is high. More specifically, low sunk costs if "USED and RENT and DEPR $\geq$$50^{th}$ percentile" and high if "RENT and

USED and DEPR <50th percentile". Our final grouping is, low sunk costs if "USED and RENT and DEPR ≥50th and SUNK(EC) <50th percentile"; high if "RENT and USED and DEPR <50th percentile and SUNK(EC) ≥50th percentile".

4.4. Other Variables

Regarding technological change, we need a time-series measure for our analysis. The previous literature has used several measures: for example, commercially introduced innovations (Audretsch, 1995); R&D and patents (Cohen and Levin, 1989); specific innovations for selected industries (Gort and Klepper, 1982). Unfortunately, time-series data on these variables are not available for our 267 industries over the 1958-92 period. Given this data limitation, we pursue an alternative strategy and construct an industry-specific time-series for technological change. We construct a factor-utilization-adjusted Solow technology residual following the insights in Burnside (1996) and Basu (1996).[19] Burnside (1996) assumes that gross output Q is a differentiable function of unobserved capital "services" (S), labor hours (H), materials (M) and energy (E): $Q_t=Z_tF(S_t,H_t,M_t,E_t)$, where Z represents exogenous technology shock. Assuming that S is proportional to materials usage (Basu, 1996), or energy consumption (Burnside, 1996), and competitive factor markets, the log-linear approximation to the production function gives us the adjusted technology residual **TECH**:

$$(2)\ \mathrm{TECH} = \left[\Delta q_t - (\delta_{Kt}\Delta m_t + \delta_{Ht}\Delta h_t + \delta_{Mt}\Delta m_t + \delta_{Et}\Delta e_t)\right],$$

[19] Since cyclical utilization of inputs like capital imparts a procyclical bias to the basic Solow residual, Burnside et al. (1995) use electricity consumption to proxy utilization of capital and obtain corrected Solow residual; Burnside (1996) uses total energy consumption; and Basu (1996) materials inputs. The intuition is that materials and energy do not have cyclical utilization component and are good proxies for the utilization of capital; assuming constant capital stock, if capital utilization increases, then materials and energy usage will typically increase.

where lower case letters denote *logarithms*, δ is input share in total revenue and Δs is replaced by Δm (Basu, 1996) or Δe (Burnside, 1996). Since, in our empirical analysis, our inferences were not affected whether we replaced Δs by Δm or Δe, we use Δm as it is a broad measure of input usage. We use TECH as our benchmark measure of technological change.[20] Table 3 (col. 2) presents within-year cross-industry summary statistics on TECH. Table 4 (row 2) presents within-industry summary statistics. These data indicate high cross-industry as well as within-industry time-series variation in technological change.

The final two variables are industry profit-margins (**Π**) and growth (**GROW**). Π is measured as described in Section 4.2; i.e., profits per unit of sales. The industry structure variable in period t is explained by Π over the preceding period; for example, the number of firms in 1972 is explained by the mean level of Π over 1967-1971.[21] The rationale is that firms get to observe data for the preceding period before making their entry decisions. Apart from using the mean level of Π, we also experimented with using the growth rate of Π over the preceding period. Our key inferences did not change. Table 3 (column 3) and Table 4 (row 3) present the cross-industry and within-industry summary statistics on Π. For industry growth, GROW, we considered two alternative measures: new investment and sales growth. We use the former as our main measure and later report results with sales growth; our central inferences

[20] In an alternative specification Leontief technology is assumed where gross output Q is produced with materials (M) and value-added (V): $Q_t=\min(\alpha_V V_t, \alpha_M M_t)$, where α's are constants. V is produced with CRS and using capital <u>services</u> (S) and labor hours (H): $V_t=Z_t F(H_t, S_t)$, where Z is the exogenous technology shock. Since "S" is unobserved, it is assumed to be proportional to electricity consumption or total energy usage (E); $E=\xi S$. Given this and the assumption of perfectly competitive factor markets, the factor utilization adjusted technology residual is: **TECH(alt)**=$[\Delta v_t - (1-\alpha_{Kt})\Delta h_t - \alpha_{Kt}\Delta e_t]$, where the lower-case letters denote *logarithms* of value-added, labor hours and energy. Using this approach to measure the technology residual did not alter our inferences.

[21] In theory, an entrant should rationally expect profit-margins to fall post-entry, implying that we construct *expected* post-entry margins. In section 2.1(a) we noted that the typical entrant is very small compared to incumbents; given their size it is unlikely that they' will have an impact on industry prices and margins. Further, our typical industry contains about 560 firms (see Tables 1 and 2); given this large base of incumbents, it appears unlikely that an increment of one (small) entrant would affect prices and margins. Thus, we do not attempt to construct measures of expected post-entry margins. Our approach implies that entrants assume pre-entry profit-margins will prevail post-entry, and this is meaningful given the entrants' size and the large number of incumbents.

are not affected by which measure we use. New investment entails sunk costs and if new investments are increasing, they are likely to indicate expanding market opportunities. As is standard (Fazzari et al., 1988), we measure net investment by the ratio ($I_{i,t}/K_{i,t-1}$), where $I_{i,t}$ is total industry investment in the current period and $K_{i,t-1}$ is the end of last period capital stock. The industry structure variable in period ‘t’ is explained by the mean rate of net investment over the preceding period; for example, the number of firms in 1972 is explained by the mean rate of net investment over 1967-1971. Table 3 (column 3) and Table 4 (row 3) present the cross-industry and within-industry summary statistics on GROW. As a check of robustness, in Section 6 we report estimates using industry sales growth as a proxy for growth; our results regarding uncertainty and sunk costs are not affected.

5. Panel Data Model

Entry and exit are not likely to occur instantaneously to restore an industry’s equilibrium under changing conditions, and there is uncertainty regarding the time is takes to restore equilibrium. With these considerations, we use a partial adjustment model to structure our within-industry time-series equation. Martin (1993, Ch.7), for example, reviews studies that have used similar models. Denoting industry structure by **STR**, where STR could be FIRMS, ESTB (and by size groups) or CONC, we have:

$$(3)\ \mathrm{STR}_{i,t} - \mathrm{STR}_{i,t-1} = \lambda(\mathrm{STR}^*_{i,t} - \mathrm{STR}_{i,t-1}),$$

where i and t denote industry and time, STR^* the equilibrium structure in time t, and λ the partial-adjustment parameter. The equilibrium structure $\mathrm{STR}^*_{i,t}$ is unobserved and is modeled as a function of the following industry-specific variables: (1) profit uncertainty, $\sigma(\Pi)_{i,t}$; (2) technological change, $\mathrm{TECH}_{i,t}$; (3) profit-margin, $\Pi_{i,t}$; and (4) growth, $\mathrm{GROW}_{i,t}$. Apart from (1)-(4), the panel data model includes the following controls: (5) an industry-specific fixed-effect α_i to control for unobserved factors that influence the long-run level of industry structure, STR. These include unobserved relatively time-invariant elements of scale economies, advertising and R&D (see discussion in Section 3.2); and (6) an aggregate structure variable, **ASTR**, to control for manufacturing-wide effects common to all industries. Audretsch (1995, Ch.3), for example, finds that macroeconomic factors play an important role; ASTR will capture these aggregate effects.

Incorporating these features, the dynamic panel data model is given by:

$$(4)\ \mathrm{STR}_{\mathrm{i,t}} = \alpha_{\mathrm{i}} + \xi_1 \sigma(\Pi)_{\mathrm{i,t}} + \xi_2 \mathrm{TECH}_{\mathrm{i,t}} + \xi_3 \Pi_{\mathrm{i,t}} + \xi_4 \mathrm{GROW}_{\mathrm{i,t}} + \xi_5 \mathrm{ASTR}_{\mathrm{t}} + \xi_6 \mathrm{STR}_{\mathrm{i,t-1}} + \varepsilon_{\mathrm{i,t}}.$$

The variables STR, σ(Π), Π, GROW and ASTR are measured in *logarithms*; these coefficients are therefore interpreted as elasticities. TECH is not measured in logarithms as it can be negative or positive (see Section 4.4 for construction of TECH). Next, we clarify the setup of equation (4). Let $\mathrm{STR}_{i,t}$ be $\mathrm{FIRMS}_{i,1972}$. Then $\sigma(\Pi)_{i,1972}$ is standard deviation of residuals over 1967-1971; $\mathrm{TECH}_{i,1972}$ the mean rate of technical change over 1967-71; $\Pi_{i,1972}$ the mean profit-margin over 1967-71; $\mathrm{GROW}_{i,1972}$ the mean rate of net investment over 1967-71; AFIRMS_{1972} the total number of firms in manufacturing in 1972; and $\mathrm{FIRMS}_{i,1967}$ (the lagged dependent variable) the total number of firms in the 4-digit industry in 1967. As discussed in Section 3.2, the lagged dependent industry structure variable will capture aspects of scale economies, and advertising and R&D intensities using information from the recent past. We estimate equation (4) for all industries in our sample as well as the low and high sunk cost sub-samples.

Estimation Method

First, as is well known in the literature on estimation of dynamic panel data models, we need to instrument the lagged dependent variable $\mathrm{STR}_{i,t-1}$. Second, industry-specific variables like number of establishments and firms, profit-margins, output, input usage, technical change (constructed from data on industry output and inputs) are all likely to be jointly-determined in industry equilibrium and are best treated as endogenous. Several estimators have been proposed to obtain efficient and unbiased estimates in dynamic panel models (see Kiviet, 1995). Our estimation proceeds in two steps. First, we sweep out the industry intercept α_i by taking deviations from *within-industry* means; the data are now purged of systematic differences across industries in the level of the relevant structure variable. Second, the within-industry equation is estimated using the instrumental variable (**IV**) estimator, treating $\sigma(\Pi)_{i,t}$, $TECH_{i,t}$, $\Pi_{i,t}$, $GROW_{i,t}$, and $STR_{i,t-1}$ as endogenous. We include a broad set of instruments as the literature indicates this is needed to alleviate problems related to bias and efficiency. The variables and their instruments are:

(a) $\sigma(\Pi)_{i,t}$ is instrumented by $\sigma(\Pi)_{i,t-1}$ and $\sigma(\Pi)_{i,t-2}$. In addition, since our data are over 5-year time intervals (e.g., $\sigma(\Pi)_{i,1977}$ is constructed using data over 1972-1976), we also include instruments constructed at a higher level of aggregation that are likely to be correlated with $\sigma(\Pi)_{i,t}$ and uncorrelated with the error term. The objective being to provide a stronger set of instruments. We adopt the following procedure: we segment our data into *durable* (**D**) and *non-durable* (**ND**) goods industries. The business cycle literature indicates that these two types of industries show markedly different fluctuations. It is unlikely that any one D or ND 4-digit industry will systematically influence all the D or ND industries; fluctuations in the entire D or ND group will be driven by factors exogenous to a given industry. Thus, instruments at the D/ND level appear reasonable. The instrument for $\sigma(\Pi)_{i,t}$ is the standard deviation of D/ND profit-margins over the relevant period. For example, for $\sigma(\Pi)_{i,1977}$ the instrument is the standard deviation of Π (for D and ND) over 1972-1976: we label this as $\boldsymbol{\sigma(\Pi\text{: D/ND})_t}$.

(b) For $TECH_{i,t}$, $\Pi_{i,t}$ and $GROW_{i,t}$, we include their own two lags. As with uncertainty, we also include instruments constructed at the D/ND level: $\mathbf{TECH(1\text{: }D/ND)_t}$, $\boldsymbol{\Pi(D/ND)_t}$ and $\mathbf{GROW(D/ND)_t}$.

(c) $STR_{i,t-1}$ is instrumented by $STR_{i,t-2}$ and manufacturing-wide $ASTR_t$ and $ASTR_{t-1}$ since ASTR can be treated as exogenous to a given 4-digit industry.

Finally, we conducted Hausman tests (see Table 6) which easily rejected the null that the industry variables are pre-determined. We examined the fit of the panel first-stage regressions of the endogenous variables on the instruments; the $R^{2'}$s were in the 0.15-0.35 range, which are reasonable for micro panel data regressions.

6. Estimation Results

Estimates From the Full Sample

Table 6 presents results from estimating equation (4). We begin by focusing on the σ(Π) estimates noting that these coefficients are to be interpreted as elasticities since the industry structure variables and σ(Π) are measured in logarithms. First, examining the broader picture, the results in the first two columns show that greater σ(Π) leads to a decrease in FIRMS and increase in CONC. The subsequent columns show the results for the total number of establishments and by size groups. The estimated coefficients are negative and significant for all establishments and the small establishment groups, while the coefficient is positive and insignificant for the large establishment group. As establishment size gets smaller (i.e, the columns further to the right), the estimate of σ(Π) gets larger signaling a larger negative impact of uncertainty on small establishments. Regarding quantitative effects, a one-standard-deviation increase in σ(Π) results in a decrease of 60 FIRMS over the 5-year Census interval and a 5 point increase in the four-firm concentration ratio. For the "small" establishment groups, a one-s.d. increase in σ(Π) leads to decrease of about 75-100 establishments starting from sample mean values of 600-500. The quantitative effects for the number of firms and establishments are clearly economically meaningful given the mean values of the variables noted in table 1. While we have data on establishments by size groups, we only have data on the total number of firms. So we cannot make a direct inferences on whether the number of small or large firms are decreasing. But we can make an indirect inference. First, summary statistics presented in Section 4.1 indicated rough equivalence between an establishment and a firm with the 50^{th} (75^{th}) percentile value of the ratio [#establishments/#firms] being 1.1 (1.3). Second, the decline in the number of small establishments is roughly similar to the drop in number of firms. Thus, it appears reasonable to conclude there is a reduction in the number of small firms in an industry. Overall, we conclude that periods of greater uncertainty lead to a marked reduction in the number of small firms and establishments, and a small increase in industry concentration. Given the results on small versus large firms and establishments, we can say that the firm (establishment) size distribution becomes less skewed with increase in uncertainty.

Turning to the other variables, TECH has a negative impact on FIRMS; the coefficient of CONC is positive but statistically insignificant; reduces the number of small establishments; and the impact on large establishments is positive but insignificant. (Note that TECH is not measured in logarithms.) The point estimate of TECH gets larger as establishment size gets smaller. Regarding quantitative effects, a one-s.d. increase in TECH leads to a decrease of 22 FIRMS over the 5-year Census interval, a 1.6 point increase in CONC, and a decrease of about 30-40 smaller establishments. Thus, technological change reduces the number of small firms and establishments, increases industry concentration and makes the firm (establishment) size distribution less skewed. Our results are strikingly similar to those in Audretsch (1995) where industry-wide innovation had an adverse impact on small incumbent firms and new startups. Our estimates also indicate that the quantitative effect of uncertainty on industry dynamics is greater than that of technological change.

The industry structure variables in general co-vary positively with their aggregate (ASTR) counterparts; the exceptions being the number of large establishments. This indicates that the number of smaller firms and establishments are more sensitive to business cycle conditions. This finding is similar in spirit to those in Audretsch (Ch.3) where new firm startups were more sensitive to macroeconomic growth as compared to industry-specific growth. Profit-margins (Π) appear to have no effect on the number of small establishments and firms, or in the full sample, but have a positive effect on the number of large establishments; industry CONC rises. Industry growth, GROW, has a negative and significant effect on the number of large establishments, and a weak negative effect in the full sample. The general ambiguity of the profit and growth results are similar to those observed in some of the previous literature (see Section 3.2).

Sunk Cost Sub-Samples

A key predictions from theory (section 2) was that presence of higher sunk costs are likely to exacerbate the impact of uncertainty. In **Table 7** we only present the $\sigma(\Pi)$ estimates and for ease of comparison, the first column reproduces the full-sample estimates from Table 6. The following observations emerge:

(a) For FIRMS, the $\sigma(\Pi)$ elasticities are negative and significant only in the high sunk cost sub-samples. The only close call is for the low SUNK(EC) group where the elasticity is negative and close to significance at the 10% level. Given the rough equivalence between establishments and firms, and the results in (e) below, uncertainty reduces the number of small firms in high sunk cost industries;

(b) $\sigma(\Pi)$ elasticities are positive for CONC, but statistically significant only in the high sunk cost samples;

(c) For all establishments (Size All), greater $\sigma(\Pi)$ has a statistically significant negative effect only in the high sunk costs sub-samples. While the elasticities vary somewhat across the alternative sunk cost measures, the qualitative inferences are similar. The $\sigma(\Pi)$ elasticities are insignificant for the low sunk cost samples;

(d) For large establishments (Size $\geq$500), $\sigma(\Pi)$ is statistically insignificant and positive. The exception being the DEPR high sunk cost sub-sample where the $\sigma(\Pi)$ coefficient is negative and significant;

(e) Greater $\sigma(\Pi)$ reduces the number of small establishments only in the high sunk cost groups. And, as the establishment size class get smaller, the σ(Π) elasticities get larger in the high sunk cost categories. The exception being the SUNK(EC) groups where greater σ(Π) reduces the number of small establishments even when sunk cost are low, but the elasticities are larger in the high sunk cost group.

Table 8 presents results from sunk cost sub-samples created by combining alternative measures (see section 4.2). While the results are similar to those in Table 7, the elasticities in Table 8 reveal a much starker negative effect of uncertainty on smaller firms and establishments. As before, uncertainty does not have an effect on the number of large establishments irrespective of the degree of sunk costs.

The broad picture that emerges from Tables 7 and 8 is that periods of greater uncertainty in conjunction with high sunk costs: (1) reduces the number of small firms and establishments; (2) has no impact on the number of large establishments; (3) results in a less skewed firm/establishment size distribution; and (4) leads to an increase in industry concentration.

Some Checks of Robustness

To gauge the robustness of our uncertainty results, we carried out numerous checks. **Table 9** reports some of these results. Since the focus of this paper is on the effect of uncertainty and sunk costs, we only report the σ(Π) estimates (panel A reproduces the estimates from Table 6 for easy reference):
(1) We experimented with alternative specifications for the profit forecasting equation (1). First, following Ghosal (2000), we replaced the broad business cycle indicator, unemployment rate, by the federal funds rate (FFR) and energy price growth (ENERGY) and constructed the uncertainty measure using these residuals. These results are presented in Panel B. Second, we estimated an AR(2) model and these results are in Panel C;
(2) We constructed an alternative measure of industry profit-margins by accounting for depreciation expenses. The data on industry-specific depreciation rates were collected for the Census years 1972, 1982 and 1992 (same as those used to create the DEPR sub-samples). We assumed that the mean

depreciation rate (over 72, 82 and 92) was representative for the full sample period and constructed the measure as:

Π(alt)=[(Total Sales Revenue-Total Variable Costs-Depreciation Expenses)/(Total Sales Revenue)].

Using this measure, we reestimated equation (1) to construct σ[Π(alt)]. We did not report these as our main results since we do not have a time-series in depreciation rates which would be required to make a proper comparison with our main measure σ(Π). The results using σ[Π(alt)] are in Panel D;

(3) In the main regression, we used the rate of new investment to proxy industry growth, GROW. We used an alternative measure, the growth of industry sales, and re-estimated equation (4). These results are in Panel E;

(4) We experimented with: (i) estimating equation (4) using GMM instead of the Instrumental Variables method; (ii) varying the lag length of the explanatory variables in equation (1); (iii) estimating the profit forecasting equation in growth rates instead of levels; and (iv) an alternative instrument for σ(Π) by constructing the (durable/non-durable) D/ND profit uncertainty instrument (section 5) by estimating a forecasting equation and using the residuals, instead of simply taking the standard deviation of D/ND profits. We separately estimated equation (1) with annual (1958-94) data on D and ND profit-margins. Uncertainty was measured using the standard deviation of residuals. There were small quantitative differences, but the broad inferences from Tables 6-8 were not affected;

(5) While in Table 9 we only report the equivalent of Table 6 estimates, we also examined the equivalent of Tables 7 and 8 sunk cost sub-sample estimates; we do not present the latter as they would be very space consuming. The above checks did not alter our broad inferences from Tables 6-8.

7. Discussion and Implications

Our results reveal that periods of greater uncertainty about profits lead to a marked *decrease* in the number of smaller businesses and establishments in an industry. Consistent with the review of theory in section 2, our results also show that this negative effect is considerably larger in industries with higher levels of sunk costs. The results clearly point to *negative net entry* of smaller businesses during periods of greater uncertainty and especially when sunk costs are higher. Given that greater uncertainty leads to attrition of smaller firms, it leads to a less skewed firm size distribution. The impact on industry concentration while *positive*, is quantitatively small. Our findings shed useful light on the role played by uncertainty and sunk costs in firms' entry and exit decisions made by entrepreneurs. Our results also lend support to Sutton's (1997a, p.53) insight that fluctuations in industry profits may be of primary importance in understanding industry dynamics.

In his classic work *Small is Beautiful*, Schumacher (1976) extolled the virtues of small businesses. While small business are desirable in many dimensions and can inject much needed entrepreneurial dynamism into markets, it does appear that they are rather fragile and face a very difficult time weathering volatile market conditions. While small may be beautiful, larger firm size clearly matters in surviving volatile markets.

How do our findings square up with respect to the option-value and financing-constraints channels discussed in Section 2? For the option-value channel, numerical simulations in Dixit (1989) and Dixit and Pindyck (1994, Ch.7) indicated that, during periods of greater uncertainty, the entry trigger price was likely to increase by more than the decrease in the exit trigger price implying negative net entry, and that the effect would be exacerbated when sunk costs were higher. Further, we noted that the preponderance of these effects would be felt by the relatively smaller firms. Our empirical findings appear supportive of this channel. Regarding financing-constraints, uncertainty and sunk costs, which increase the probability of bankruptcy and heighten information asymmetries, were expected to affect smaller businesses (incumbents and likely entrants) more than larger firms. Our empirical results also appear supportive of this channel. The broad industry-level nature of our data make it difficult to assess the relative importance of these two channels.

The difficulty of separating the alternative channels via which uncertainty affects business decision-making has been noted by others. Driver and Whelan (2003) note there are several plausible theoretical models that provide insights into the behavior of businesses and entrepreneurs under uncertainty, but we do not have a good idea about which transmission mechanisms are the most important.[22] Driver and Whelan note that this knowledge gap – regarding which factors influence business decisions the most – may cause problems for policymakers. They note that those entrusted with promoting growth and vitality of markets will have difficulty in pin-pointing where specific market failures might lie. And those charged with reducing risk and promoting stability will have difficulty in knowing the economic variables that are most important to stabilize from the perspective of encouraging investment and entry. While our industry-level analysis offered useful insights into the decision-making process by businesses operating under uncertainty and confronted with sunk costs, richer data from surveys of managers and on firms and establishments operating in specific markets may help disentangle the two effects, provide deeper insights and be of relevance to managers and entrepreneurs.

Finally, we found that technological change reduces the number of small firms and establishments, with little effect on larger establishments. Although we use a very different measure of technical change (corrected Solow residual) than employed in the previous literature (R&D, innovations, patents), our findings are quite similar to those reported in Audretsch (1995) who found that industry-wide innovation adversely affected startups and smaller incumbents. Audretsch noted his findings were consistent with the hypothesis of routinized technological regime. Our findings, however, also appear consistent with the notions outlined in Gort and Klepper (1982) where efficiency enhancing incremental technical change weeds out inefficient firms and creates barriers to entry.

[22] Aside from the channels that were considered in this paper, there is the issue of entrepreneurial risk-preferences, which was a common modeling strategy in the older literature but not modeled in the real-options literature. In their empirical analysis using a sample of Irish businesses, they find the effect of risk-aversion was ubiquitous for

Our findings could be useful in several areas. First and foremost, the findings shed useful light on the decision-making process of businesses and entrepreneurs. Since public policy related to regulation and competition, among others, often need to be formulated to improve the vitality and growth of markets, insights into the driving forces that enhance entry and prevent business failures add significant value. Second, they may provide guidance for competition policy since analysis of entry is an integral part of DOJ/FTC merger guidelines. Sunk costs are explicitly discussed as a barrier to entry, but uncertainty is de-emphasized. Our results suggest that uncertainty compounds the sunk cost barriers, retards entry and lowers the survival probability of smaller incumbents. Therefore, uncertainty could be an added consideration in the forces governing market structure and competition policy evaluation. Third, determinants of M&A activity is an important area of research; see Jovanovic and Rousseau (2001) and the references there. If periods of greater uncertainty lowers the probability of survival and increases exits, it may have implications for the reallocation of capital: e.g., do the assets exit the industry or are they reallocated via M&A? More generally, it may be useful to explore whether uncertainty helps explain part of M&A waves. Fourth, while skewed firm size distribution is well documented, empirical analysis of the determinants of its evolution is limited. Our results suggest that periods of greater uncertainty, in conjunction with sunk costs, may play a role. Fifth, Davis, et al. (1996) find that job destruction/creation decline with firm size/age; Cooley and Quadrini (2001) and Cabral and Mata (2003) suggest that small firms may have greater destruction (exits) due to financial frictions. Our results may provide additional insights: periods of greater uncertainty, in combination with higher sunk costs, appear to significantly influence small firm turnover. Finally, our results could provide insights into the evolution of specific industries. For example, the U.S. electric industry is undergoing deregulation and we are observing numerous mergers involving firms of different sizes. Also, uncertainty about prices and

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the surveyed businesses with little evidence of risk-loving or even risk-neutral behavior.

profits are well documented resulting in utilities experiencing financial distress. Our findings would predict a future path for this industry that leads to greater concentration and weeding out of smaller firms.

Data Appendix

Data on industry structure and sunk cost measures were collected from various Census reports. The table below summarizes the sources and years for which data are available. Industry time-series data are at the SIC 4-digit level; see Bartlesman, Eric, and Wayne Gray. "The Manufacturing Industry Productivity Database," National Bureau of Economic Research, 1998. The following industries were excluded from the sample: (1) "Not elsewhere classified" since they do not correspond to well defined product markets; (2) Industries that could not be matched properly over time due to SIC definitional changes; there were important definition changes in 1972 and 1987. For these industries, the industry time-series and other structural characteristics data are not comparable over the sample period; and (3) Industries that had missing data on industry structure and sunk cost variables. The final sample contains 267 SIC 4-digit manufacturing industries that are relatively well defined over the sample period and have data consistency.

Variable(s)	**Source**	**Years Available**
Number of firms	Census of Manufacturing	1963, 67, 72, 77, 82, 87, 92.
Four-firm concentration	Census of Manufacturing	1963, 67, 72, 77, 82, 87, 92.
Number of establishments by size	Census of Manufacturing	1963, 67, 72, 77, 82, 87, 92.
Used capital expenditures	Census of Manufacturing	1972, 82, 92.
Rental payments	Census of Manufacturing	1972, 82, 92.
Depreciation payments	Census of Manufacturing	1972, 82, 92.
Industry time-series: sales, costs, investment, capital stock, etc.	Bartlesman and Gray (1998).	Annual: 1958-1994
Aggregate: energy price, federal funds and unemployment rate.	Economic Report of the President.	Annual: 1958-1994.

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Table 1. Within-Year Across-Industries: Industry Structure Summary Statistics

			Number of Establishments by Size Class					
			All	Large	→ Smaller →			
Year	FIRMS	CONC	Size: All	Size: ≥500	Size: <500	Size: <250	Size: <100	Size: <50
1963	587.9 (1031)	37.9 (21)	639.9 (1080)	10.8 (17)	629.1 (1079)	614.3 (1072)	572.0 (1037)	518.1 (972)
1967	555.4 (922)	38.2 (20)	612.9 (976)	12.5 (18)	600.4 (975)	583.4 (968)	539.0 (933)	480.6 (862)
1972	530.8 (819)	38.5 (20)	597.1 (880)	12.1 (17)	584.9 (879)	567.5 (872)	522.2 (837)	465.9 (773)
1977	574.6 (869)	38.3 (20)	644.5 (917)	12.1 (17)	632.4 (916)	614.5 (909)	568.2 (876)	512.1 (817)
1982	550.5 (793)	38.3 (20)	620.6 (858)	10.5 (15)	610.1 (857)	593.6 (852)	549.5 (825)	494.1 (772)
1987	545.8 (807)	39.8 (21)	614.1 (875)	9.3 (13)	604.8 (874)	589.1 (869)	545.6 (840)	490.8 (785)
1992	559.9 (828)	40.9 (21)	630.7 (907)	8.8 (13)	621.8 (906)	606.7 (901)	564.7 (874)	511.8 (823)
Average	558	39	623	11	612	596	552	496

1. The data cover 267 SIC 4-digit U.S. manufacturing industries over the seven Census of Manufacturing years 1963-1992.
2. The numbers are the cross-industry mean values of the relevant industry structure variable; the corresponding standard deviations are in parentheses. For example, for 1992 the representative industry had about 560 firms and the s.d. of the number of firms across industries was 828.

Table 2. Within-Industry Across-Years: Industry Structure Summary Statistics			
		Mean	Std. Deviation
FIRMS	Mean	557.8	834.7
	Std. Deviation	129.2	234.3
CONC	Mean	38.8	20.0
	Std. Deviation	5.9	3.6
Size: All	Mean	622.8	895.8
	Std. Deviation	138.3	233.9
Size: ≥500	Mean	10.8	15.2
	Std. Deviation	3.5	4.5
Size: <500	Mean	611.9	895.2
	Std. Deviation	137.7	233.3
Size: <250	Mean	595.6	889.2
	Std. Deviation	136.4	232.3
Size: <100	Mean	551.6	858.1
	Std. Deviation	130.3	228.2
Size: <50	Mean	496.2	799.1
	Std. Deviation	121.4	218.7

1. The data cover 267 SIC 4-digit U.S. manufacturing industries over the seven Census years 1963-92.
2. Row labeled "Mean": For each industry we computed the "within-industry" mean value of the relevant industry structure variable; we get 267 observations. This row displays the summary statistics for these means. For example, over the Census years 1963-92, the representative industry had about 558 firms.
3. Row labeled "Std. Deviation": For each industry we computed the "within-industry" standard deviation (s.d.) for the relevant industry structure variable. This row presents summary statistics for these s.ds. For example, for the number of firms the representative industry had a s.d. of about 129.
4. For example, from the above statistics the typical industry had a "within-industry" mean number of firms of 558 and s.d. of 129.

Table 3. Within-Year Across-Industries: Explanatory Variables Summary Statistics				
Period	σ(Π)	TECH	Π	GROW
1958-62	0.0175 (0.0140)	0.0081 (0.0226)	0.2425 (0.0881)	0.0223 (0.0122)
1963-66	0.0203 (0.0120)	0.0088 (0.0190)	0.2576 (0.0876)	0.0263 (0.0097)
1967-71	0.0213 (0.0127)	0.0013 (0.0212)	0.2681 (0.0851)	0.0309 (0.0118)
1972-76	0.0289 (0.0184)	0.0073 (0.0265)	0.2731 (0.0809)	0.0377 (0.0136)
1977-81	0.0239 (0.0143)	0.0033 (0.0257)	0.2757 (0.0838)	0.0549 (0.0214)
1982-86	0.0275 (0.0155)	0.0046 (0.0243)	0.2832 (0.0922)	0.0584 (0.0228)
1987-91	0.0262 (0.0190)	0.0055 (0.0241)	0.3086 (0.1005)	0.0672 (0.0270)

1. See Section 4 for details on the construction of variables. The numbers are the cross-industry mean value of the relevant variable; the corresponding standard deviations are in parentheses. For example, for σ(Π) the representative industry had value of 0.0175 and the s.d. of σ(Π) was 0.014.

Table 4. Within-Industry Across-Years: Explanatory Variables Summary Statistics			
		Mean	Std. Deviation
σ(Π)	Mean	0.0236	0.0094
	Std. Deviation	0.0117	0.0072
TECH	Mean	0.0070	0.0106
	Std. Deviation	0.0205	0.0099
Π	Mean	0.2727	0.0825
	Std. Deviation	0.0358	0.0185
GROW	Mean	0.0425	0.0117
	Std. Deviation	0.0211	0.0091

1. See Section 4 for details on the construction of variables.
2. Row labeled "Mean": For each industry we computed the "within-industry" mean value of the relevant variable; we get 267 observations. This row presents the summary statistics for these means. For example, over 1958-94, the representative industry had a σ(Π) value of 0.0236.
3. Row labeled "Std. Deviation": For each industry we computed the "within-industry" standard deviation (s.d.) for the relevant variable. This row presents summary statistics for these s.ds. For example, for σ(Π) the representative industry had a s.d. of about 0.0117.
4. For example, from the above statistics the typical industry had a "within-industry" mean value of uncertainty of 0.0236 and s.d. of 0.0117; the coefficient of variation being about 50%.

Table 5. Sunk Cost Summary Statistics			
	Median	Mean	Std. Deviation
USED	0.0795	0.0853	0.0454
RENT	0.0180	0.0269	0.0284
DEPR	0.0558	0.0577	0.0149
SUNK(EC)	0.0055	0.0137	0.0602

1. See Section 4.3 for details on the construction of variables. USED, RENT, DEPR and SUNK(EC) are the average values over the Census years 1972, 1982 and 1992.

Table 6. Estimation Results for All Industries.								
	Industry Structure Variable: STR							
			Number of Establishments (ESTB) by Size Class → Smaller Size →					
	FIRMS	CONC	Size: All	Size: ≥500	Size: <500	Size: <250	Size: <100	Size: <50
$\sigma(\Pi)_{i,t}$	-0.159* (0.003)	0.191* (0.005)	-0.172* (0.001)	0.093 (0.258)	-0.178* (0.001)	-0.209* (0.001)	-0.268* (0.001)	-0.308* (0.001)
$TECH_{i,t}$	-1.642* (0.075)	1.758 (0.193)	-1.737* (0.057)	0.492 (0.729)	-1.809* (0.074)	-2.263* (0.046)	-2.943* (0.028)	-3.418* (0.015)
$\Pi_{i,t}$	0.046 (0.725)	0.507* (0.028)	0.089 (0.504)	0.421* (0.029)	0.029 (0.849)	-0.025 (0.879)	0.001 (0.995)	0.042 (0.837)
$GROW_{i,t}$	-0.011 (0.678)	0.058 (0.144)	-0.041* (0.094)	-0.304* (0.001)	-0.017 (0.521)	-0.003 (0.916)	0.012 (0.726)	0.004 (0.924)
$ASTR_t$	0.001* (0.037)	0.074* (0.003)	0.002* (0.001)	0.001 (0.778)	0.002* (0.001)	0.002* (0.001)	0.003* (0.002)	0.004* (0.001)
$STR_{i,t-1}$	0.267* (0.001)	-0.049 (0.562)	0.252* (0.001)	0.261* (0.001)	0.261* (0.001)	0.253* (0.007)	0.233* (0.005)	0.208* (0.016)
Panel Obs.	1335	1335	1335	1335	1335	1335	1335	1335
#Ind's.	267	267	267	267	267	267	267	267
Hausman Test	92.9 (0.001)	67.8 (0.001)	126 (0.001)	57.2 (0.001)	81.3 (0.001)	52.3 (0.001)	31.8 (0.001)	34.6 (0.001)

1. Estimation is via the instrumental variables method; instruments are described in Section 5. *p-values* (two-tailed test) computed from heteroscedasticity-consistent standard errors are in parentheses. An asterisk * indicates significance at least at the 10% level.
2. Hausman test statistics (*p-value*) easily rejected the null that the industry-specific variables were pre-determined. We also examined fit of the first-stage panel regressions of the endogenous variables on the instruments: the R^2's were in the 0.15-0.35 range, which are reasonably good for panel data.
3. As noted in Section 5, STR, σ(Π), Π, GROW and ASTR in equation (4) are measured in *logarithms*; these coefficients can be interpreted as elasticities. TECH is not measured in logarithms; thus the magnitude of these coefficients cannot be directly compared to others.
4. Variable definitions (see section 4): FIRMS-number of firms; CONC-four firm concentration ratio; SIZE(.)-number of establishments in a given size group; σ(Π)-profit margin uncertainty; TECH-technical change; Π-profit margin; GROW-growth; ASTR-corresponding aggregate structure variable.

Table 7: Estimation Results by Sunk Cost Sub-Samples.
Only the Uncertainty Coefficients are Reported.

		Sunk Cost Sub-Samples							
	ALL	USED		RENT		DEPR		SUNK(EC)	
		Low Sunk	High Sunk	Low Sunk	High Sunk	Low Sunk	High Sunk	Low Sunk	High Sunk
FIRMS	-0.159* (0.003)	-0.053 (0.476)	-0.163* (0.065)	0.033 (0.635)	-0.298* (0.001)	0.007 (0.926)	-0.281* (0.001)	-0.099 (0.125)	-0.144* (0.074)
CONC	0.191* (0.005)	0.027 (0.778)	0.215* (0.038)	0.097 (0.257)	0.278* (0.009)	0.142 (0.206)	0.203* (0.017)	0.009 (0.903)	0.214* (0.047)
Size: All	-0.172* (0.001)	-0.042 (0.580)	-0.175* (0.030)	0.052 (0.467)	-0.306* (0.001)	0.008 (0.910)	-0.289* (0.001)	-0.095 (0.134)	-0.172* (0.022)
Size: ≥500	0.093 (0.258)	0.052 (0.647)	0.041 (0.709)	0.077 (0.526)	0.100 (0.383)	0.197 (0.183)	-0.188* (0.061)	0.173 (0.130)	-0.035 (0.771)
Size: <500	-0.178* (0.002)	-0.052 (0.498)	-0.156* (0.092)	0.055 (0.451)	-0.331* (0.001)	0.005 (0.942)	-0.287* (0.001)	-0.099 (0.124)	-0.175* (0.035)
Size: <250	-0.209* (0.001)	-0.067 (0.395)	-0.198* (0.066)	0.047 (0.523)	-0.391* (0.001)	-0.006 (0.936)	-0.327* (0.001)	-0.110* (0.094)	-0.230* (0.018)
Size: <100	-0.268* (0.001)	-0.087 (0.300)	-0.285* (0.025)	0.033 (0.663)	-0.491* (0.001)	-0.017 (0.833)	-0.400* (0.001)	-0.137* (0.053)	-0.291* (0.013)
Size: <50	-0.308* (0.001)	-0.112 (0.213)	-0.312* (0.029)	0.007 (0.927)	-0.553* (0.001)	-0.041 (0.664)	-0.464* (0.001)	-0.147* (0.060)	-0.353* (0.008)
Panel #Ind's.	1869 267	938 134	931 133	938 134	931 133	938 134	931 133	931 133	938 134

1. Only the uncertainty coefficients are presented (see Table 6 for details). We estimated equation (4) for each sunk cost sub-sample; see section 4.3 and Table 5. USED, RENT or DEPR greater than 50th percentile constitutes the low sunk cost samples; high if these are less than 50th percentile. SUNK(EC) less than 50th percentile forms the low sunk costs sample; high if it is greater than 50th percentile. *p-values* (two-tailed test) computed from heteroscedasticity-consistent standard errors are in parentheses. An asterisk * indicates significance at least at the 10% level. 'Panel' and '#Ind's' are the number of observations in the panel data and the number of industries.

Table 8: Additional Sunk Cost Sub-Samples. Only the Uncertainty Coefficients are Reported.					
		Sunk Cost Sub-Samples			
	ALL	A. Combination of USED, RENT and DEPR.		B. Combination of USED, RENT, DEPR and SUNK(EC).	
		Low Sunk	High Sunk	Low Sunk	High Sunk
FIRMS	-0.159* (0.003)	0.075 (0.436)	-0.332* (0.017)	-0.037 (0.690)	-0.334* (0.038)
CONC	0.191* (0.005)	0.018 (0.882)	0.408* (0.055)	0.108 (0.339)	0.485* (0.047)
Size: All	-0.172* (0.001)	0.138 (0.194)	-0.314* (0.007)	-0.003 (0.976)	-0.325* (0.016)
Size: ≥500	0.093 (0.258)	0.075 (0.708)	-0.110 (0.421)	0.090 (0.621)	-0.074 (0.652)
Size: <500	-0.178* (0.002)	0.135 (0.206)	-0.286* (0.062)	-0.005 (0.959)	-0.300* (0.091)
Size: <250	-0.209* (0.001)	0.134 (0.212)	-0.354* (0.073)	-0.012 (0.903)	-0.389* (0.087)
Size: <100	-0.268* (0.001)	0.127 (0.254)	-0.531* (0.017)	-0.027 (0.798)	-0.576* (0.029)
Size: <50	-0.308* (0.001)	0.102 (0.377)	-0.622* (0.012)	-0.047 (0.674)	-0.665* (0.024)
Panel #Ind's.	1869 267	310 62	305 61	250 50	245 49

1. We estimated (4) for each sub-sample (see Tables 6 and 7 for details). Only the uncertainty coefficients are presented. In panel A, the combination "USED and RENT and DEPR greater than 50^{th} percentile" constitutes the low sunk cost sample; high if these are less than 50^{th} percentile. In panel B, the combination "USED and RENT and DEPR greater than 50^{th} percentile <u>and</u> SUNK(EC) less than 50^{th} percentile" forms the low sunk cost sample; high otherwise.

Table 9. Additional Results for All Industries. Only the Uncertainty Coefficients are Reported.							
		Number of Establishments (ESTB) by Size Class → Smaller →					
FIRMS	CONC	Size: All	Size: ≥500	Size: <500	Size: <250	Size: <100	Size: <50
Panel A: Estimates from Table 6.							
-0.159* (0.003)	0.191* (0.005)	-0.172* (0.001)	0.093 (0.258)	-0.178* (0.001)	-0.209* (0.001)	-0.268* (0.001)	-0.308* (0.001)
Panel B: Uncertainty constructed from profit forecasting equation: $\Pi_{i,t}=\lambda_0+\lambda_1\Pi_{i,t-1}+\lambda_2\Pi_{i,t-2}+\lambda_3 SALES_{i,t-1}+\lambda_4 SALES_{i,t-2}+\lambda_5 FFR_{t-1}+\lambda_6 FFR_{t-2}+\lambda_7 ENERGY_{t-1}+\lambda_8 ENERGY_{t-2}+\varepsilon_{i,t}$							
-0.152* (0.006)	0.179* (0.010)	-0.169* (0.002)	0.078 (0.346)	-0.178* (0.002)	-0.206* (0.001)	-0.258* (0.001)	-0.297* (0.001)
Panel C: Uncertainty constructed from an AR(2) profit forecasting equation: $\Pi_{i,t}=\lambda_0+\lambda_1\Pi_{i,t-1}+\lambda_2\Pi_{i,t-2}+\varepsilon_{i,t}$							
-0.164* (0.004)	0.146* (0.043)	-0.175* (0.002)	0.106 (0.188)	-0.176* (0.003)	-0.208* (0.002)	-0.267* (0.001)	-0.316* (0.001)
Panel D: Same as in panel A, but the profit-margin measure accounts for depreciation expenses: Π(alt)=[(Total Sales Revenue-Total Variable Costs-Depreciation Expenses)/(Total Sales Revenue)].							
-0.138* (0.004)	0.158* (0.010)	-0.170* (0.001)	0.071 (0.341)	-0.176* (0.001)	-0.203* (0.001)	-0.263* (0.001)	-0.294* (0.001)
Panel E: Same as in Panel A, but GROW in equation (7) is growth of sales instead of the rate of new investment.							
-0.232* (0.001)	0.236* (0.001)	-0.189* (0.001)	0.058 (0.484)	-0.182* (0.002)	-0.200* (0.001)	-0.254* (0.001)	-0.291* (0.001)

Notes: In Panel B, FFR denotes the federal funds rate and ENERGY the energy price growth.

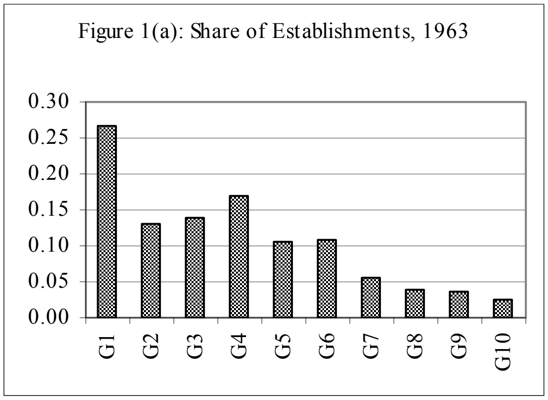

Figure 1(a): Share of Establishments, 1963

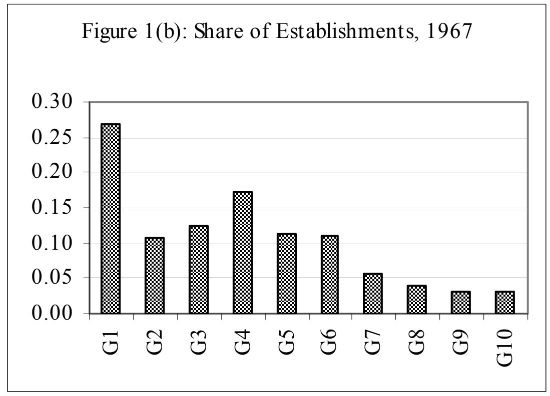

Figure 1(b): Share of Establishments, 1967

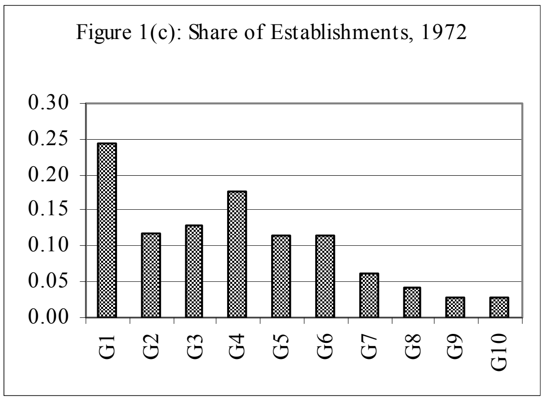

Figure 1(c): Share of Establishments, 1972

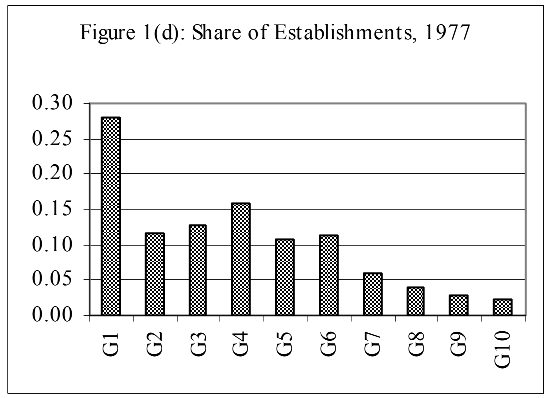

Figure 1(d): Share of Establishments, 1977

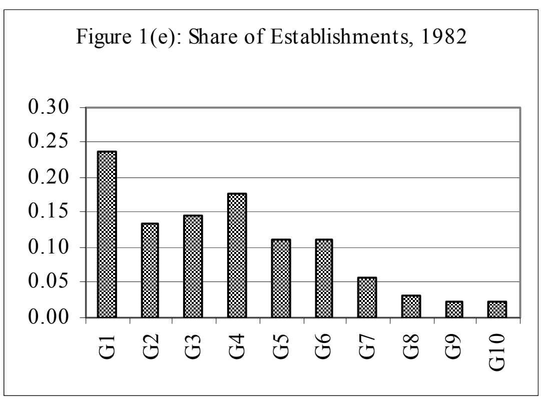

Figure 1(e): Share of Establishments, 1982

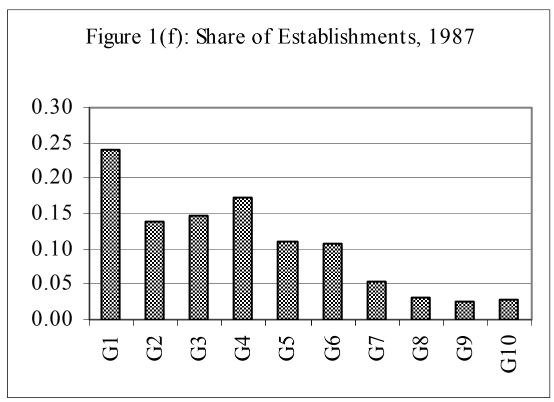

Figure 1(f): Share of Establishments, 1987

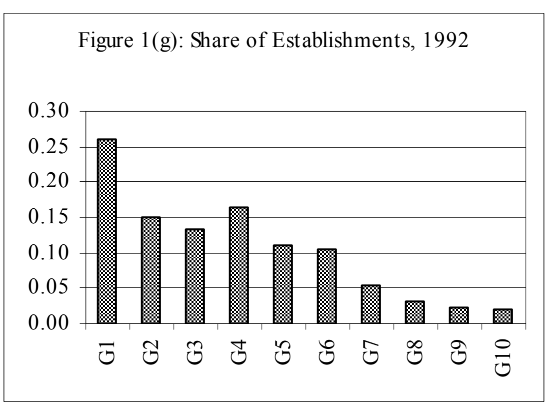

Figure 1(g): Share of Establishments, 1992

The figures represent the establishment size distribution for the typical SIC 4-digit industry (i.e., the average across the 267 industries for a given Census year). The establishment size groups correspond to the following number of employees (in parentheses). G1 (1-4); G2 (5-9); G3 (10-19); G4 (20-49); G5 (50-99); G6 (100-249); G7 (250-499); G8 (500-999); G9 (1,000-2,499); and G10 (2,500 or more). The vertical axis indicates the share of the number of establishments for that group in the industry total.