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Ghosal, Vivek

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Vivek Ghosal *

Impact of Uncertainty and Sunk Costs on Firm Survival and Industry Dynamics

* Georgia Institute of Technology

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Wissenschaftszentrum Berlin für Sozialforschung gGmbH,
Reichpietschufer 50, 10785 Berlin, Germany, Tel. (030) 2 54 91 – 0
Internet: www.wz-berlin.de

ABSTRACT

Impact of Uncertainty and Sunk Costs on Firm Survival and Industry Dynamics

by Vivek Ghosal*

This paper examines the role played by uncertainty and sunk costs on the time-series fluctuations in industry structure as captured by the number of firms and establishments, and concentration. Using an extensive dataset covering 267 U.S. manufacturing industries over a 30-year period, our estimates show that time periods of greater uncertainty, especially in conjunction with higher sunk costs, results in: (i) decrease in the number of small firms and establishments; (ii) less skewed size distribution of firms and establishments; and (iii) marginal increase in industry output concentration. Large establishments are virtually unaffected. We also control for technological change and our estimates show that technical progress decreases the number of small firms and establishments in an industry. While past studies have emphasized technological change as a key driver of industry dynamics, our results indicate that uncertainty and sunk costs play a crucial role. Our findings could be useful for competition policy, study of firm survival, models of creative destruction, evolution of firm size distribution, and mergers and acquisitions.

Keywords: Industry dynamics, firm survival, firm size distribution, uncertainty, sunk costs, technological change, creative destruction, option value, financing constraints.

JEL Classification: L11, D80, O30, G10, L40.

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ZUSAMMENFASSUNG

Die Bedeutung von Unsicherheit und 'sunk costs' für das Überleben von Unternehmen und die Weiterentwicklung von Industrien

In diesem Diskussionspapier wird die Rolle untersucht, die Unsicherheit und ‚sunk costs' auf die Zeitreihenfluktuationen in der Industriestruktur, wie sie durch die Anzahl der Unternehmen abgebildet wird, und in der Unternehmenskonzentration haben.

Dafür wird ein umfassender Datensatz verwendet, der 267 Firmen des verarbeitenden Gewerbes in den U.S.A. über einen Zeitraum von 30 Jahren enthält. Unsere Schätzungen zeigen, daß sich Zeiten größerer Ungewißheit auf die Industrie auswirken, vor allem wenn die Unsicherheit mit höheren sunk-costs verbunden ist, indem (i) die Zahl kleinerer Unternehmen abnimmt; (ii) die Verteilung der Unternehmen nach ihrer Größe weniger schief-verteilt ist; und (iii) ein Grenzzuwachs an Outputkonzentration der Industrie zu verzeichnen ist. Große Einrichtungen bleiben dagegen nahezu unberührt. Wir habe unsere Untersuchung darüberhinaus auf technologischen Wandel hin kontrolliert und festgestellt, daß die technische Weiterentwicklung die Zahl der kleinen Unternehmen eines Industriezweigs ebenfalls reduziert. Während frühere Studien gerade den technologischen Wandel als den treibenden Faktor für die dynamische Entwicklung von Industrien herausgestellt haben, weisen unsere Ergebnisse allerdings den Faktoren Unsicherheit und ‚sunk-costs' die entscheidende Rolle zu. Diese Ergebnisse können fruchtbar für weitere Studien im Bereich der Wettbewerbspolitik sein, für Studien zum Überleben von Firmen, für Modelle kreativer Zerstörung, der Evolution von Firmengrößenverteilung und nicht zuletzt für Unternehmensaufkäufe und -zusammenschlüsse (M&A).

I. Introduction

Several stylized facts are well established (Caves, 1998; Sutton, 1997a): (i) there is significant turnover of firms in mature industries; (ii) the typical entering (exiting) firm is small compared to incumbents; and (iii) incumbent larger firms are older with higher survival probabilities. Given these findings, it is crucial to identify the forces that drive intertemporal dynamics of industry structure and the evolution of firm size distribution. Starting with Gort and Klepper (1982), much of the literature has focused on technological change as a key factor driving industry life-cycles and turnover in mature industries (Audretsch, 1995; Caves, 1998; Sutton, 1997a). However, other key forces identified in theory have been somewhat neglected in the empirical literature. The primary objective of this paper is to provide an understanding of the role played by *uncertainty* and *sunk costs* on the time-series variations in the number of firms and establishments, and concentration, in relatively mature industries.

The primary channel we examine relates to uncertainty and sunk costs which imply an option value of waiting and alter the entry/exit trigger prices (Dixit, 1989; Dixit and Pindyck, 1994). This suggests that uncertainty and sunk costs are likely to be an important determinant of the intertemporal dynamics of industry structure (Section II(i)). Our study is motivated by the fact that while the theory is well developed, empirical evaluation of these models appears limited.[1] A potentially second channel is financial market frictions (Cooley and Quadrini, 2001; Cabral and Mata, 2003; Greenwald and Stiglitz, 1990; Williamson, 1988). This literature suggests that uncertainty and sunk costs, among other factors, exacerbate financing constraints, which may affect decisions of entrants and incumbents and shape industry dynamics (Section II(ii)). Finally, following the previous literature, we examine other forces, including technology, that may drive industry dynamics (Section III).

Our empirical analysis is conducted using a within-industry time-series framework. We assembled an extensive database covering 267 SIC 4-digit manufacturing industries over 1958-92, with data on the number of firms and establishments (by size groups), output concentration, alternative proxies for sunk capital costs, and use time-series data to measure uncertainty and technical change (Section IV). We use a dynamic panel data model to estimate the impact of uncertainty on the intertemporal dynamics of industry structure (Section V). Our estimates (Section VI) show that periods of greater uncertainty, especially in conjunction with higher sunk costs, result in: (i) reduction in the number of small establishments and firms; (ii) less skewed size distribution of firms, and (iii) marginally higher industry concentration. Large

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[1] Sutton (1997.a; p.52-54) writes that fluctuations in industry profits influence entry and exit, and (p.53) *"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 analyzing the different thresholds associated with entry decisions which involve sunk costs and decisions to exit..."*

establishments are virtually unaffected. Second, technological progress has an adverse impact on the number of small firms and establishments in an industry - a finding similar to Audretsch (1995).

Our findings could be useful in several areas. First, 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; thus, uncertainty could be an added consideration in the forces governing market structure. Second, 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 reallocation of capital; do the assets exit the industry or are they reallocated via M&A? It may be useful to explore whether uncertainty helps explain part of M&A waves. Third, while skewed firm size distribution is well documented, empirical analysis of the determinants of it's evolution is limited. Our results suggest that periods of greater uncertainty, in conjunction with sunk costs, may play a role. Fourth, Davis, et al. (1996) find that job destruction/creation decline with firm size/age; Cooley and Quadrini (2001) and Cabral and Mata (2001) suggest that small firms may have greater destruction (exits) due to financial frictions. Our results provide additional insights: periods of greater uncertainty, in combination with higher sunk costs, appear to significantly influence small firm turnover. Finally, they could provide insights into the evolution of specific industries: e.g., the U.S. electric industry is undergoing deregulation and we are observing numerous mergers involving firms of different sizes. Also, uncertainty about prices and profits are well documented resulting in utilities experiencing financial distress. Our findings could predict a future path that leads to greater concentration and weeding out of smaller firms.

II. Uncertainty and Sunk Costs

II(i). Option Value

Dixit (1989), Dixit and Pindyck (1994) and Caballero and Pindyck (1996) provide a broad framework to study time-series variations in entry, exit and the number of firms.[2] To streamline our discussion, we introduce some notation. As in the above models, let $\Omega(\mathbf{K})$ be sunk costs, which are assumed proportional to the entry capital requirement; **Z** the stochastic element with the conditional standard deviation of Z, $\sigma(\mathbf{Z})$, measuring uncertainty; and $\mathbf{P^H}$ and $\mathbf{P^L}$ the entry and exit trigger prices - over $(0,P^H)$ the potential entrant

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[2] Hopenhayn (1992), Lambson (1991) and Pakes and Ericsson (1998), e.g., study firm dynamics assuming firm-specific uncertainty. The latter also evaluate models of firm dynamics under active v. passive learning. These models can be better subjected to empirical evaluation using micro-datasets, as in Pakes and Ericsson.

holds on to its option to enter, and over (P^L,∞) an incumbent does not exit. Dixit (1989) shows that uncertainty and sunk costs imply an option value of waiting for information and this raises P^H and lowers P^L. During periods of greater uncertainty, entry is delayed as firms require a premium over the conventional Marshallian entry price, and exit is delayed as incumbents know they have to re-incur sunk costs upon re-entry. 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 entry/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. 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 ours) shows that sunk costs and industry-wide uncertainty cause the entry (investment) trigger to exceed the cost of capital.

For our empirical analysis, we would like to know whether during periods of greater $\sigma(Z)$, is P^H affected more than P^L or vice versa? General analytic answers are difficult to obtain. But numerical simulations in Dixit and Pindyck (Ch. 7, 8) show that increase in $\sigma(Z)$ given $\Omega(K)$ - or increase in $\Omega(K)$ given $\sigma(Z)$ - results in P^H increasing by more than the decrease in P^L; **Figure 1 (a, b)** illustrates this. This implies that during periods of greater uncertainty, entry is affected more than exit leading to *negative net entry*; i.e., an industry is likely to show a decrease in the number of firms.

Turning to imperfect competition, first consider a duopoly setting (Dixit and Pindyck, p.309-315). 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 ϵ above the entry trigger, neither firm wants to wait for 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) demonstrate 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, therefore, highlight the dependence of outcomes on model assumptions and difficulties of arriving at clear predictions.

Links to Empirical Analysis

Following the framework provided by theory, our empirical analysis will examine time-series variation in industry structure variables; e.g., the number of firms. Before summarizing the predictions, we note two issues. First, within-industry firm size distribution is typically skewed (Ijiri and Simon, 1977; Sutton, 1997.a). Our data (Section IV(i)) reveals this to be the typical characteristic. Previous studies show that (i) entrants are typically small compared to incumbents and have high failure rates, (ii) typical exiting firm is small and young, and (iii) larger firms are older with higher survival rates.[3] We address the small v. large firm issue in our empirical analysis. Second, our SIC 4-digit manufacturing industry data, which cover a 30-year span, contains information on the total number of firms and establishments (by size class) 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.[4] In Section IV(i) we show that our data contains reasonable within-industry time-series variation in net entry, which is encouraging for our empirical analysis.

For our within-industry time-series analysis, we summarize the implications as follows:

(A) Net entry. We noted that periods of greater σ(Z) are likely to result in *negative net entry*. Would small v. large firms be affected differentially? Large firms are older and have "cumulatively" greater investments in, e.g., advertising and R&D; see Sutton (1991, 1997.b) and Caves (1998). Advertizing and distribution networks contain sunk investments which erode upon exit and would have to be re-established if the firm re-enters in future; similarly exit entails loss of human and physical capital related to product and process innovation. Thus, larger firms are more likely to show greater inaction regarding exit. Since data shows that entrants are rather small, entry of large firms is typically not an important consideration. Overall, we expect greater inaction in large firm net entry (little/no entry and lower exits) during periods of greater uncertainty.

Entry cohorts typically consist of relatively small firms, and exit cohorts of young and small firms. Based on the results discussed earlier, periods of greater σ(Z) will delay entry more than exit, resulting in negative net entry; i.e., we can expect a decrease in the number of smaller firms. Further, based on the predictions from theory, this effect will be exacerbated when sunk costs, Ω(K), are higher.

(B) Size distribution. If there is greater attrition among small firms, then firm size distribution will become

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[3] 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.

[4] Cable and Schwalbach (1991), Dunne, Roberts and Samuelson (1988), Evans and Siegfried (1994) and Geroski (1995). For SIC 4-digit industries over the 1963-82 Censuses (similar to ours), Dunne et al. 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.

less skewed, and this effect will be more pronounced in high sunk cost industries.

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

II(ii). Financing Constraints

Several recent studies have examined the impact of financing constraints on firm survival. 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. Smaller/younger firms borrow more and have higher probability of default; with increasing size/age, the default probability falls dramatically. Due to financial frictions, smaller/younger firms have higher probability of exit. Empirical results in Cabral and Mata (2001) suggest that financing constraints cause lower survival probability and higher exits among small firms.

An earlier literature has examined some of the underlying factors that may contribute to financial market frictions. First, consider *uncertainty*. 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 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 survival is adversely affected by financing constraints. Second, 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 (Williamson, 1988).[5] In Shleifer and Vishny (1992), asset specificity is a determinant of leverage and explains time-series and cross-industry patterns of financing; the ease of debt financing is inversely related to asset specificity. Lensink, Bo and Sterken (2001) provide a lucid discussion of financing constraints in the related context of investment behavior.

In short, periods of greater uncertainty, in conjunction with higher sunk costs, increase the likelihood of bankruptcy and exacerbate financing constraints. Incumbents who are more dependent on borrowing and adversely affected by tighter credit are likely to have lower probability of survival and expedited 'exits'. Firms more likely to be adversely affected are those with little/no collateral, inadequate history and shaky

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[5] On asset recovery by debt holders, 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..."*

past performance. Similarly, 'entry' is likely to be retarded for potential entrants who are more adversely affected by the tighter credit conditions. Thus, periods of greater uncertainty, and in conjunction with higher sunk costs, are likely to accelerate exits and retard entry; i.e., negative net entry.

Links to Empirical Analysis

A large literature suggests that financial market frictions are more likely to affect smaller firms.[6] Using this we postulate that small firms are more likely to be affected by financing constraints during periods of greater uncertainty. In addition, the effect will be greater in industries with higher sunk costs.

(A) <u>Net entry</u>. For smaller firms, periods of greater uncertainty are likely to increase exits and lower entry; the industry will experience loss of smaller firms. This effect will be magnified in high sunk cost industries.

(B) <u>Size distribution</u>. If periods of greater uncertainty cause negative net entry of smaller firms, industry firm size distribution will become less skewed; the effect will be more pronounced under high sunk costs.

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

III. Other Factors

In this section we briefly discuss some of the other factors which have been considered in the literature and are likely to influence industry dynamics.

III(i). Technological Change

Technological change has been linked to industry life-cycle (Gort and Klepper, 1982; Jovanovic and MacDonald, 1994) as well as ongoing turnover in relatively mature industries (Audretsch, 1995; Sutton, 1997a). While we briefly present the arguments for both, given our data we will be primarily concerned with the latter.

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

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[6] E.g., Cabral and Mata (2003), Cooley and Quadrini (2001), Evans and Jovanovic (1989), Fazzari, et al. (1988), and Gertler and Gilchrist (1994). The latter note (p. 314): *"...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."*

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 (1997.a, 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 (i) is negatively associated with startups and survival of new firms and (ii) hastens small firm exit. Thus, even in mature industries, ongoing innovations are likely to play a key role in industry dynamics. Our paper is not about studying industry life cycles, but about examining time-series variations in the number of firms and establishments in relatively mature industries. In this sense our focus on technology is similar to that by Audretsch. In our empirical analysis, we construct a measure of technical change (Section IV(iv)) and examine its impact on the time-series variation of the number firms, and small and large establishments, in an industry.

III(ii). Other Variables

We explicitly or implicitly control for some other variables that may influence industry dynamics. We explicitly control for industry growth -**GROW**- and profit margins -Π. Evidence on the link between GROW and entry 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. The link is likely to be conditioned on entry barriers, macroeconomic conditions and the stage of the industry's life cycle; hence the ambiguity. Regarding profit-margin Π, while the expected sign is positive, it will be conditioned on the above mentioned factors (for GROW). Absent entry barriers, e.g., 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, advertizing 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 constant, which we include in our dynamic panel data model, will capture aspects of this relatively time-invariant component.[7] I am not aware of SIC 4-digit time-series data on advertising or R&D for our 267 industries over 1963-92.[8] To the extent that part of R&D and advertising intensities are in steady state levels and have a time-invariant component, this will be captured by the industry-specific constant.[9] Since our empirical model includes a time-series in broad technological change, this may partly capture 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.

IV. Measurement

Our approach is as follows. First, (all variables are industry-specific): (i) we use time-series data to create measures of uncertainty; (ii) using insights in Kessides (1990) and Sutton (1991), construct measures of sunk costs and create low *versus* high sunk cost groups; and (iii) measure technological change and other control variables. Second, following our discussion in Section II, we examine the impact of uncertainty on the time-series variations in industry structure, as measured by the number of firms, number of small *versus* large establishments, and concentration. We examine the relationship for our full sample as well as industries segmented into low *versus* high sunk cost groups. Our data are at the SIC 4-digit level of disaggregation; see Appendix A for details. An important consideration in this choice was the availability

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[7] In Section IV(ii), following Sutton (1991), we construct a measure of minimum efficient scale (MES) for 1972, '82 and '92 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.

[8] 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.

[9] 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.

of relatively long time-series which is critical for measuring uncertainty and technological change, as well as availability of data on industry structure and sunk costs for a large number of industries over time. The industry-specific annual time-series data are over 1958-94. Data on industry structure and sunk costs are from the 5-yearly Census of Manufactures; these data are not available annually, implying that in our empirical estimation we use data at a 5-yearly frequency. Below we describe the key variables.

IV(i). Industry Structure

Industry-specific time-series data from the 1963-92 Censuses include: (i) total number of firms - **FIRMS**; (ii) total number of establishments - **ESTB**; (iii) ESTB by size classes; and (iv) four-firm concentration ratio -**CONC**. Unlike ESTB, the Census does not provide data on FIRMS by size class. An establishment is an economic entity operating at a location; as is common in the literature, we use the number of employees to measure "size". The Census size classes 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. The ESTB data is used to create small v. large establishment groups. The U.S. Small Business Administration (*State of Small Business: A Report of the President*, 1990), e.g., classifies "small business" as employing "less than 500 workers"; this 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; Ghosal and Loungani (2000) provide discussion of this benchmark. However, 500 employees may sometimes constitute a relatively large/wealthy business. Since there is no well defined metric by which we can define "small", we created additional small business groups. Overall, our groups are: (i) All establishments; (ii) relatively large businesses with ≥500 employees; (iii) small businesses with <500 employees; and (iv) even smaller businesses as classified by (a) <250, (b) <100 and (c) <50 employees. We did not push the size categories to greater extremes at either end as this 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. In the table below, we calculated the ratio (ESTB/FIRMS) for each industry (for the Census years 1963-92) and examined the percentile distribution of this ratio across industries.

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 fairly close to 1 and even at the 75th percentile level. These values imply 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 "representative" industry, **Figures 2(a)-2(g)** display data on the establishment size distribution over our seven Census years. Typically, about 25% of the total number of establishments in an industry belong to the smallest size category, and only about 3% belong to the largest size group. Given the statistics of the ratio (ESTB/FIRMS), figures 2(a)-2(g) also roughly displays the size distribution of firms. The data reveals a skewed size distribution for the typical industry as well as fluctuations in this distribution over time. The skewed size distribution has been well documented (Ijiri and Simon, 1977; Sutton 1997.a).

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

IV(ii). 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 (1997.a, 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 systematic components. The standard deviation of residuals, which represent the *unsystematic* component (or forecast errors), measure profit-

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[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.

[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.

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 VI we construct an alternative measure of profit-margins and uncertainty which accounts for 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), 'i' and 't' index industry and time.

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

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 uncertainty measure. As noted earlier, industry structure data are for 1963, ‘67, ‘72, ‘77, ‘82, ‘87 and ‘92. The s.d. of residuals over, e.g., 1967-71 serves as the uncertainty measure for 1972; similarly, s.d. of residuals over 1982-86 measures uncertainty for 1987, and so on. We get seven time-series observations on $\sigma(\Pi)_{i,t}$.[16] **Table**

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[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.

[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) (continued...)

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

When estimating (1), we initially assume k, m, n=1,2; i.e. allow for two lags of each variable. To check for robustness, Section VI presents some additional results using alternative specifications for the profit equation (1). These include:

(i) varying the lag length of the explanatory variables;

(ii) following Ghosal (2000) and replacing the business cycle indicator, unemployment rate, by federal funds rate (FFR) and energy price growth (ENERGY);

(iii) estimating a basic AR(2) forecasting equation;

(iv) estimating the profit equation in growth rates instead of levels;

(v) including industry-specific cost variables; and

(vi) using an alternative measure of profit-margins that accounts for depreciation.

IV(iii). 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

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[16](...continued)
models to measure uncertainty. After imposing the restrictions (Hamilton, 1994, Ch. 21), we estimated second-order ARCH for each 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.

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 proxy sunk costs following Sutton (1991). The theoretical models (Section II) assume that sunk costs are proportional to entry capital requirements. Sutton's measure mimics 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 ($j=1,\ldots,m$.). Let $Ms_j=(S_j/n_j)$; $S_e=(1/m)\Sigma_j(Ms_j)$; 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 $\Omega(K/S)$ as **SUNK(EC)** (sunk costs-entry capital). Sutton (p.98) uses the cross-industry variation in SUNK(EC) to proxy cross-industry variation in sunk costs, and notes several limitations.[19] We calculated SUNK(EC) for the Census years 1972, 1982 and 1992 (same years as for

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[17] RENT and USED could be 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.

[19] E.g., (i) he assumes the K/Q ratio of the median plant is representative of the entire industry, and this is unlikely; (ii) book values are used to compute K/Q, but book values underestimate current replacement cost; (iii) the computation assumes that the age structure of capital does not vary across industries, and this is unrealistic. In addition, we note that SUNK(EC) is based on an estimate of the "median plant size" of incumbents. As noted in Section II(i), the typical entrant is small compared to incumbents, and it takes time for new entrants to attain optimal scale. This implies that the median plant size typically overstates the entry capital requirements. Further, this bias may be greater in industries where optimal scale is relatively large, since the entrant will be farther away from optimal scale; where the median plant size is small, new entrants are more likely to be closer to this size.

USED, RENT and DEPR).

Sunk Cost Sub-Samples

Our approach is to 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, 82 and 92; **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 v. low sunk cost sub-samples. If SUNK(EC)<50th percentile, indicating relatively lower entry capital requirements, then sunk costs are low; high if SUNK(EC)≥50th percentile. Similarly, sunk costs are low if RENT or USED or DEPR ≥50th percentile; high if RENT or USED or DEPR <50th 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 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 ≥50th percentile"; 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".

IV(iv). Other Variables

Regarding technological change, we need a time-series measure for our analysis. The previous literature has used several measures: e.g., specific innovations for selected industries (Gort and Klepper, 1982); commercially introduced innovations (Audretsch, 1995); and R&D and patents (Cohen and Levin, 1989). Unfortunately, time-series data on these variables are not available for our 267 industries over the 1958-92 period (also see footnote 8). Given the data limitations, 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).[20] Burnside (1996) assumes

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[20] Since cyclical utilization of inputs like capital imparts a procyclical bias to the basic Solow residual, Burnside (continued...)

that gross output Q is a differentiable function of unobserved capital "services" (S), labor hours (H), materials (M) and energy (E): $Q_t = Z_t F(S_t, H_t, M_t, E_t)$, 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**:

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

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.[21] 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 the rate of technological change.

The final two variables are industry profit-margins - Π - and growth - **GROW**. Π is measured as described in Section IV(iii). The industry structure variable in period 't' is explained by Π over the preceding period; e.g., the number of firms in 1972 is explained by the mean level of Π over 1967-1971.[22] 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

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[20](...continued)
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 don't 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.

[21] 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 services (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 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.

[22] 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'll 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.

cross-industry and within-industry summary statistics on Π. Our proxy for industry growth is the mean rate of new (net) investment. New investment entails sunk costs; thus if new investment is increasing, it is likely to indicate expanding market opportunities. As is standard (e.g., 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; e.g., 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 VI we report estimates using industry sales growth as a proxy for growth; our results regarding uncertainty are not affected.

V. 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), e.g., 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 get:

$$STR_{i,t} = \lambda STR_{i,t}^{*} - (1-\lambda) STR_{i,t-1} \qquad (3),$$

where i and t denote industry and time, STR^* the equilibrium structure in period t, and λ the partial-adjustment parameter. STR^* is not observed and is modeled as a function of the following industry-specific variables: (i) profit uncertainty, $\sigma(\Pi)_{i,t}$; (ii) technological change, $TECH_{i,t}$; (iii) profit-margin, $\Pi_{i,t}$; and (iv) growth, $GROW_{i,t}$. Apart from (i)-(iv), the panel data model includes the following controls: (v) 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 III(ii)); and (vi) 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:

$$STR_{i,t} = \alpha_i + \xi_1 \sigma(\Pi)_{i,t} + \xi_2 TECH_{i,t} + \xi_3 \Pi_{i,t} + \xi_4 GROW_{i,t} + \xi_5 ASTR_t + \xi_6 STR_{i,t-1} + \epsilon_{i,t} \qquad (4).$$

The variables STR, $\sigma(\Pi)$, Π, GROW and ASTR are measured in *logarithms*; thus, these coefficients are interpreted as elasticities. TECH is not measured in logarithms as it can be negative or positive (see Section IV(iv) for construction of TECH). Next, we clarify the setup of (4). Let $STR_{i,t}$ be $FIRMS_{i,1972}$. Then $\sigma(\Pi)_{i,1972}$ is standard deviation of residuals over 1967-1971; $TECH_{i,1972}$ the mean rate of technical change over 1967-71; $\Pi_{i,1972}$ the mean profit-margin over 1967-71; $GROW_{i,1972}$ the mean rate of net investment over 1967-71; $AFIRMS_{1972}$ the total number of firms in manufacturing in 1972; and $FIRMS_{i,1967}$ (the lagged dependent variable) the total number of firms in the 4-digit industry in 1967. As discussed in Section III(ii), 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 (4) for all industries in our sample as well as the sunk cost sub-samples.

Estimation Method

First, as shown in the literature on estimation of dynamic panel data models, we need to instrument the lagged dependent variable $STR_{i,t-1}$. 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, e.g., 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 panel regressions.

VI. Estimation Results

Estimates From the Full Sample

Table 6 presents results from estimating equation (4). First, we focus on the σ(Π) estimates; the coefficients are interpreted as elasticities since the industry structure variables and σ(Π) are measured in logarithms. First, examining the broader picture, during periods of greater σ(Π) there is a decrease in FIRMS and increase in CONC. Looking at the underlying distribution of establishments, the coefficients are negative and significant for all establishments and the small establishment groups; the coefficient is positive and insignificant for the large establishment group. As establishment size decreases (e.g., Size<500; Size<250; Size<100; Size<50), the σ(Π) elasticity gets larger. Regarding quantitative effects, a one-s.d. increase in σ(Π) results in a drop of 60 FIRMS over the 5-year Census interval, starting from a mean value of 558 FIRMS; and there is a 5 point increase in the four-firm concentration ratio, starting from a mean value of 39%. For 'small' establishment groups, a one-s.d. increase in σ(Π) leads to decrease of 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. While we have data on establishments by size groups, we only have data on the total number of firms. So we can't make a direct inference on whether the number of small or large firms are decreasing. But we can make an indirect inference. First, summary statistics presented in Section IV(i) indicate rough equivalence between an establishment and a firm with the 50th (75th) 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, periods of greater uncertainty lead to a reduction in the number of small firms and establishments, and increases industry concentration. Given the results on small v. large firms and establishments, we can say that the firm (establishment) size distribution becomes less skewed.

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, technical change reduces the number of small firms and establishments, increases industry concentration and makes the firm (establishment) size distribution less skewed. Our results are quite similar to those in Audretsch (1995) where industry-wide innovation has 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 appear to be similar to those observed in some of the previous literature (see Section III(ii)). Finally, apart from CONC, the lagged dependent variables are positive and significant.

Sunk Cost Sub-Samples

The predictions from theory were that presence of higher sunk costs are likely to exacerbate the impact of uncertainty; we examine this. In **Table 7** we only present the $\sigma(\Pi)$ estimates; 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 in the low sunk cost samples; (d) For large establishments (Size ≥ 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 size class get smaller (Size<500; ...; Size<50), the $\sigma(\Pi)$ elasticities get larger in the high sunk cost categories. The exception being the SUNK(EC) groups where greater $\sigma(\Pi)$ 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 (Section IV(ii)). While the results are similar to those in Table 7, the elasticities in Table 8 present a starker effect of uncertainty on the dynamics of small firms and establishments. As before, uncertainty does not have an effect on the number of large establishments in an industry irrespective of the degree of sunk costs. Regarding industry dynamics, the broad picture emerging from Tables 7 and 8 is that periods of greater uncertainty in conjunction with high sunk costs: (i) reduces the number of small firms and establishments; (ii) has no impact on the number of large establishments; (iii) results in a less skewed firm/establishment size distribution; and (iv) 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 $\sigma(\Pi)$ estimates. Panel A reproduces the estimates from Table 6 for easy reference.

(a) 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 in Panel B. Second, we estimated an AR(2) model; these results are in Panel C.

(b) 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 $\sigma[\Pi(\text{alt})]$. 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.

(c) 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); results are in Panel E. 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.

(d) 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 V) 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.

VII. Concluding Remarks

Our results suggest that periods of greater uncertainty about profits, in conjunction with higher sunk costs, have a quantitatively large *negative* impact on the survival rate of smaller firms, retard entry and lead to a less skewed firm size distribution; the impact on industry concentration is *positive*, but quantitatively small. Our findings shed light on some of the factors influencing the intertemporal dynamics of industry structure and the evolution of firm size distribution, and lend support to Sutton's (1997.a, p.53) insight that fluctuations in industry profits may be of primary importance in understanding industry dynamics. How do these findings square up with respect to the *option value* and *financing constraints* channels discussed in Section II? For the option value channel, numerical simulations in Dixit and Pindyck 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; the effect would be exacerbated under higher sunk costs. Further, we argued 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 firms (incumbents and likely entrants) more than larger firms. Our empirical results also appear supportive of this channel. The broad nature of our data make it difficult to assess the relative importance of these two channels. Detailed longitudinal studies, along with data on entry and exit, may help disentangle the effects and provide deeper insights.

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 (adjusted Solow residual) than employed in the previous literature (R&D, innovations, patents), our findings are similar to Audretsch (1995) where industry-wide innovation adversely affects 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.

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: (i) “Not elsewhere classified” since they do not correspond to well defined product markets; (ii) 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 (iii) 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

Notes:

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 value 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 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

Notes:
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 presents 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 column presents summary statistics for these s.d.'s. For example, for the number of firms the representative industry had a s.d. of about 129.
4. E.g., from 2 and 3, 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)

Notes: See Section IV 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

Notes: See Section IV for details on the construction of variables.

1. 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.
2. Row labeled "Std. Deviation": For each industry we computed the "within-industry" standard deviation (s.d.) for the relevant variable. This column presents summary statistics for these s.d.'s. For example, for σ(Π) the representative industry had a s.d. of about 0.0117.
3. E.g., using 2 and 3, the typical industry had a "within-industry" mean value of uncertainty of 0.0236 and s.d. of 0.0117; coefficient of variation being about 50%.

Table 5. Sunk Cost Summary Statistics

	Median	Mean	Std. Dev.
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

Notes: See Section IV(iii) 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.

Equation (4): $STR_{i,t}=\alpha_i+\xi_1\sigma(\Pi)_{i,t}+\xi_2 TECH_{i,t}+\xi_3\Pi_{i,t}+\xi_4 GROW_{i,t}+\xi_5 ASTR_t+\xi_6 STR_{i,t-1}+\epsilon_{i,t}$.

	Industry Structure Variable: STR							
			Number of Establishments 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
#Industries	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)

Notes:

1. Estimation is via the instrumental variables method; instruments are described in Section V. *p-values* (two-tailed test) computed from heteroscedasticity-consistent standard errors are in parentheses; ** and * indicate significance at least at the 5% and 10% levels.
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 V, the variables 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 IV): 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.

Equation (4): $STR_{i,t}=\alpha_i+\xi_1\sigma(\Pi)_{i,t}+\xi_2 TECH_{i,t}+\xi_3\Pi_{i,t}+\xi_4 GROW_{i,t}+\xi_5 ASTR_t+\xi_6 STR_{i,t-1}+\epsilon_{i,t}$.

		Sunk Cost Sub-Samples							
	ALL Industries	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 Obs. #Industries	1869 267	938 134	931 133	938 134	931 133	938 134	931 133	931 133	938 134

Notes: Only the uncertainty coefficients are presented (see Table 6 for details). We estimated equation (4) for each sunk cost sub-sample; see section IV(iii) 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; ** and * indicate significance at least at the 5% and 10% levels.

Table 8: Additional Sunk Cost Sub-Samples. Only the Uncertainty Coefficients are Reported.
Equation (4): $STR_{i,t}=\alpha_i+\xi_1\sigma(\Pi)_{i,t}+\xi_2 TECH_{i,t}+\xi_3\Pi_{i,t}+\xi_4 GROW_{i,t}+\xi_5 ASTR_t+\xi_6 STR_{i,t-1}+\epsilon_{i,t}$.

		Sunk Cost Sub-Samples			
	ALL Industries	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 Obs. #Industries	1869 267	310 62	305 61	250 50	245 49

Notes: 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 50th percentile" constitutes the low sunk cost sample; high if these are less than 50th percentile. In panel B, the combination "USED and RENT and DEPR greater than 50th percentile and SUNK(EC) less than 50th percentile" forms the low sunk cost sample; high otherwise.

Table 9. Additional Results for All Industries. Only the Uncertainty Coefficients are Reported.

Equation (4): $STR_{i,t}=\alpha_i+\xi_1\sigma(\Pi)_{i,t}+\xi_2TECH_{i,t}+\xi_3\Pi_{i,t}+\xi_4GROW_{i,t}+\xi_5ASTR_t+\xi_6STR_{i,t-1}+\epsilon_{i,t}$.

		Number of Establishments 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: $\Pi_{i,t}=\lambda_0+\lambda_1\Pi_{i,t-1}+\lambda_2\Pi_{i,t-2}+\lambda_3SALES_{i,t-1}+\lambda_4SALES_{i,t-2}+\lambda_5FFR_{t-1}+\lambda_6FFR_{t-2}+\lambda_7ENERGY_{t-1}+\lambda_8ENERGY_{t-2}+\epsilon_{i,t}$							
-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: $\Pi_{i,t}=\lambda_0+\lambda_1\Pi_{i,t-1}+\lambda_2\Pi_{i,t-2}+\epsilon_{i,t}$							
-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.

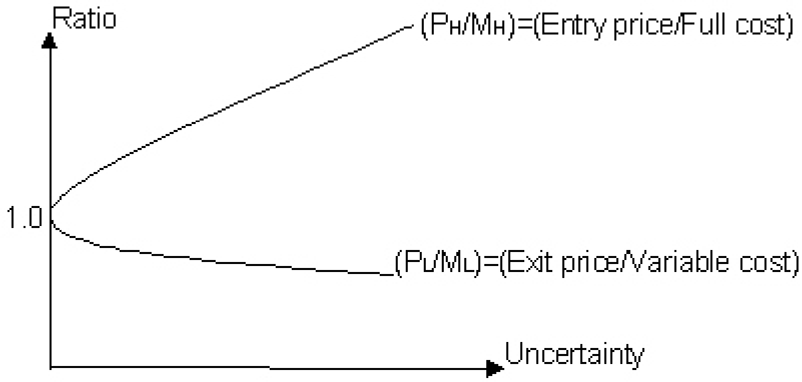

Figure 1(a). Increase in uncertainty and the entry/exit trigger

Notes: P_H and P_L denote the entry and exit triggers.
M_H and M_L denote the conventional Marshallian entry and exit triggers.

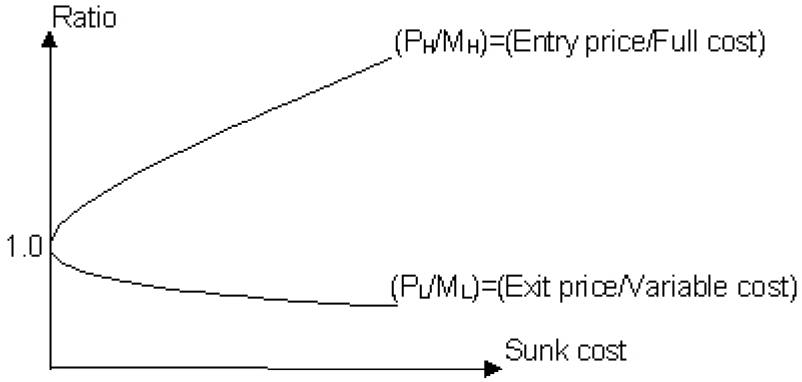

Figure 1(b). Increase in sunk cost and the entry/exit trigger

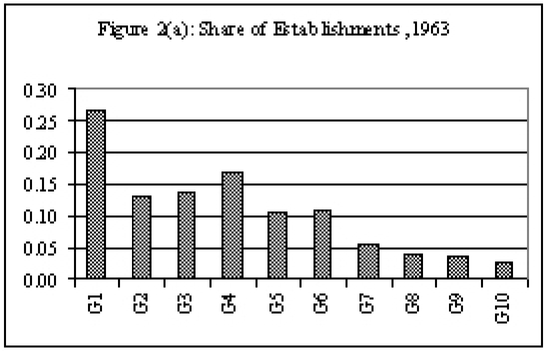
Figure 2(a): Share of Establishments, 1963

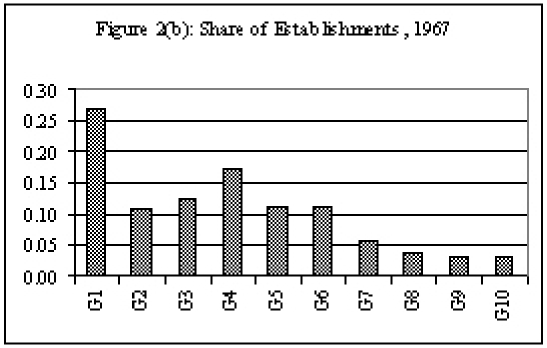
Figure 2(b): Share of Establishments, 1967

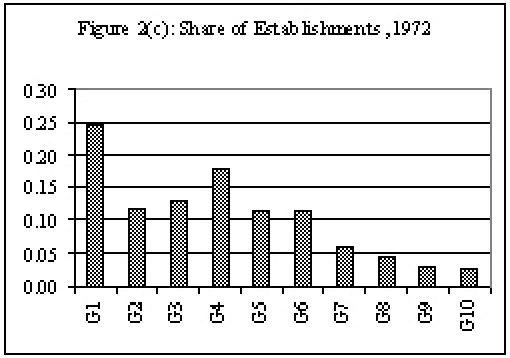
Figure 2(c): Share of Establishments, 1972

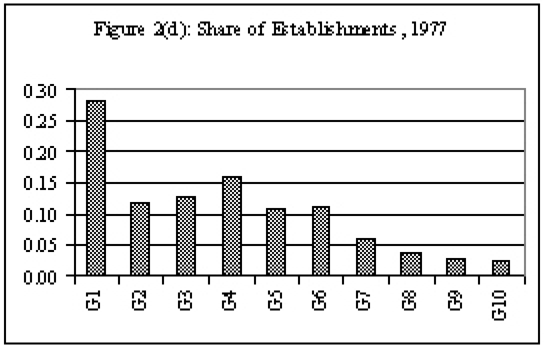
Figure 2(d): Share of Establishments, 1977

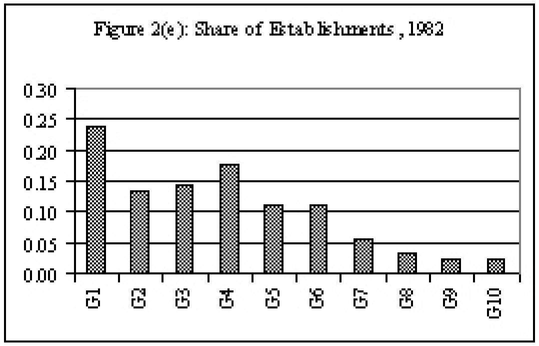
Figure 2(e): Share of Establishments, 1982

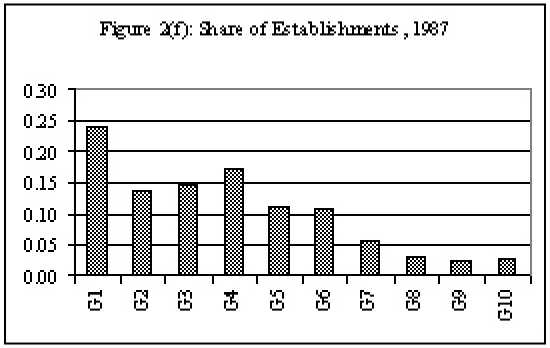
Figure 2(f): Share of Establishments, 1987

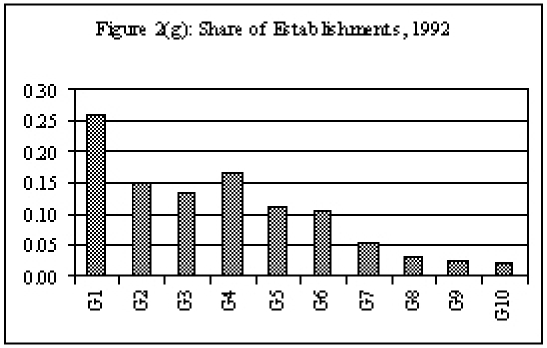
Figure 2(g): Share of Establishments, 1992

Notes for Figures 2(a)-2(g): The figures represent the establishment size distribution for the "representatitive" 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.

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