THE EFFECT OF SALES INCENTIVES
ON BUSINESS SEASONALITY

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ABSTRACT

This paper shows that, in addition to varying with the calendar business cycle, manufacturing firms' sales are significantly higher at the end of the fiscal year, and lower at the beginning, than they are in the middle. The causes of these fiscal-year effects are investigated, emphasizing the role of salespeople and their motivation to meet quotas and earn a bonus. In many industries firms have substantially lower average prices toward the end of fiscal years, but price changes cannot explain all the effect of fiscal years on revenue seasonality. It is shown that the industry variation in the fiscal year revenue and price effects are correlated with type of product, distribution method, and the industry average salesperson turnover rate. The results are consistent with a sales quota model of fiscal seasonality, where all salespeople can vary their effort throughout the fiscal year but only some salespeople can influence the timing of their customers' purchases.

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1. Introduction

The fiscal year is an important unit of operation for most American companies because budgeting and financial reporting conform to fiscal calendars. The fiscal year is also the unit of time over which many bonus and compensation schemes are measured. Executive bonus plans are commonly based on fiscal year results and many sales compensation plans include a discrete bonus for meeting a sales quota during the fiscal year. These pay schemes provide incentives for managers and salespeople to manipulate prices and timing of business to maximize their own incomes, rather than their firms' profits.

The effects of such agency issues are measured below by exploiting variation in fiscal year ends. Although most firms choose the calendar year as their fiscal year, over a third end their fiscal year between January and November. Because of this variation, I can separately identify the calendar and fiscal year seasonality of revenue and prices. I find that fiscal year timing influences the seasonality of business in most manufacturing industries.

Explanations for the existence of fiscal-year effects center on decisions made by managers or salespeople. I focus on the role of salespeople. Seeking to reach their annual revenue or profit quota, and therefore earn a bonus, salespeople may influence business seasonality by either adjusting their effort levels and/or manipulating the timing of sales. Furthermore, when salespeople have control over pricing, their efforts to make quota may also affect the firm’s profitability.

I develop an explicit model of salesperson behavior under a quota, taking into account the salesperson’s ability to vary effort throughout the fiscal year. In addition, I model the ability of some salespeople (such as those who work closely with customers over a long buying cycle) to influence the

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2Asch (1990) documented such behavior among Navy recruiters and Dorsey (1994) provides an entertaining anecdotal account of how quotas affect salespeople’s behavior. In a non-sales context, Chevalier and Ellison (1995) analyze how incentives change the optimal risk strategies of mutual fund managers as the end of the year approaches.
timing of customer purchases. The optimal actions of salespeople in this model imply that revenue will be greater at the end of a fiscal year for all firms with quota-based sales plans, and that this fiscal year seasonality will be amplified in firms where salespeople can affect the date of customer purchases.

To motivate this analysis of salesperson behavior and fiscal-year effects, consider the two graphs in figure 1. Each graph displays 1985-1992 revenue for a pair of competing firms. The horizontal axis represents the calendar quarter and the vertical axis is the relevant quarter’s sales as a percentage of the last four quarters’ sales. The paired companies have different fiscal year ends, and the circled and squared observations signify fourth fiscal quarters. Because the pair of companies in each graph are direct competitors, one would expect the same calendar seasonality in the markets for their respective products. This seems to be true for the two consumer goods vendors in the lower graph. But the two computer manufacturers in the top graph show a marked increase in sales in their respective fourth fiscal quarters. At these companies, each sale requires considerable time and the salespeople make close customer contact. Therefore, the computer salespeople have more influence on the timing of sales than their consumer goods counterparts. This may account for the difference in the importance of fiscal years.

I expand on the inter-industry variation in fiscal-year effects that figure 1 suggests by analyzing the impact of sales quotas on fiscal year seasonality. I relate industry fiscal-year effects to the type of product sold, the type of customers and the channels used to reach them, and characteristics of salespeople. The results are consistent with theoretical predictions of the behavior of salespeople who face a quota and, therefore, identify salespeople as a previously unrecognized instrument in macro-economic cycles and seasonal volatility in the stock market. The paper also suggests that sales incentives undermine attempts to smooth production, while potentially locking successful salespeople into their jobs through the end of the fiscal year.

Section 2 measures the effect of fiscal year ends on revenue seasonality and establishes that this effect is not the result of firms manipulating fiscal year ends to coincide with the peak season in their
industry. Section 3 discusses the possible causes of fiscal-year effects, shows that sales compensation plans provide incentives which can lead to fiscal-year effects, and presents a model of salesperson behavior under a quota. Section 4 measures changes in manufacturers' prices throughout the fiscal year and shows that price changes alone cannot explain fiscal-year effects. Section 5 explores the inter-industry relationship between fiscal-year effects and product and salesperson characteristics. Section 6 concludes with directions for future research.

2. Fiscal-Year Effects on Revenue Seasonality

By the end of August, [the Xerox sales manager’s] team had reached only [half its quota.] If he was to get to Palm Springs, his people needed to sell as much equipment in the last four months of the year as they’d sold in the first eight months.

_The Force_, David Dorsey

A. Empirical Strategy

In this section, I exploit variation in fiscal year ends to separately identify calendar and fiscal-year effects on revenue seasonality. "Fiscal revenue effects" are the change in sales that a company can expect at different points in its fiscal year, holding the calendar seasonality of its business constant.

Consider the firms within a single industry. Let \( S_{it} \) represent the sales of firm \( i \) in calendar period \( t \), which is firm \( i \)'s fiscal quarter \( q \).\(^2\) I assume that sales are a function of a firm-specific size term, \( A_i \), an _industry-wide_ calendar seasonality effect, \( C_q \), an _industry-wide_ fiscal quarter effect, \( F_q \), cumulative firm-specific growth, \( G_{it} \), and a noise term, \( \Psi_{it} \). This implies

\[
S_{it} = A_i C_q F_q G_{it} \Psi_{it}. \tag{I}
\]

Taking the natural log of both sides yields

\(^2\)For example, if firm A's fiscal year ends in December, and firm B's ends in June, then for the quarter from October to December, firm A has \( q = 4 \) and firm B has \( q = 2 \).
\[ s_{tg} = a_t + c_t + f_q + g_{tg} + \psi_{tg} \]  

(2)

Define \( g \) to be the cumulative growth of the firm and \( \eta \) to be the growth rate in any given period, so

\[ g_{tg} = g_{tp-1,r-1} + \eta_{tg}. \]  

(3)

\( s_{tg} \) can be expressed

\[ s_{tg} = a_t + c_t + f_q + g_{tg-1,r-1} + \eta_{tg} + \psi_{tg}, \]  

(4)

but, for estimation purposes, it is more useful to look at

\[ z_{tg} = s_{tg} - s_{tg-1,r-1} = \Delta c_t + \Delta f_q + \Delta \eta_{tg} + \Delta \psi_{tg}. \]  

(5)

\( \eta \) is assumed to be orthogonal to the fiscal and calendar effects, so it can be considered part of the noise term in the estimation.\(^4\) The coefficient of interest is \( f_q \), the "fiscal revenue effect" in quarter \( q \). I assume that the fiscal effects are the same in fiscal quarters 2 and 3 and use these as the base quarters. Therefore, \( f_1 \) and \( f_4 \) are approximately the percentage by which revenues in fiscal quarters 1 and 4, respectively, differ from fiscal quarters 2 and 3.

B. Data

The company data are from the Standard and Poor's Compustat 1994 Quarterly Industrial file and cover firms' 1985 to 1993 fiscal years. The data are quarterly observations of firm revenue, cost of goods sold (see section 3), fiscal year end, and 4-digit SIC code. A total of 31,936 quarterly observations are available, covering 981 manufacturers. 3-digit Census classifications and 2-digit SIC codes were

\(^4\)I also estimated the model assuming that the growth rate followed a random walk. Differencing the \( z \) terms allows a random error term to absorb the growth rate. I ran the regressions below using change in the \( z \) term as the dependent variable, but the results were basically unchanged from those presented in tables 2 and 7.
determined from the 4-digit SIC code.\textsuperscript{3} Mean and median quarterly sales are $730.9 million and $106.5 million, respectively. Appendix table 1 shows the number of companies and observations by 3-digit code.

As shown in table 1, the likelihood of having a fiscal year end in a particular month varies by industry.\textsuperscript{4} The paper industry, for example, does not have the fiscal year end variation that is critical to the identification of fiscal revenue effects. A 2-, 3-, or 4-digit industry classification had to meet the following requirements to be included in the empirical analysis:

1) Not more than 80\% of firms in the industry have a December fiscal year end. This excluded 19 industries and 258 companies from the 3-digit analysis.

2) Data are available for at least five companies. This excluded 13 industries and 32 companies from the 3-digit analysis.

Sixteen 2-digit industries, thirty-seven 3-digit industries, and fifty-one 4-digit industries meet these criteria and are included in the analysis below.\textsuperscript{5}

C. Results

Table 2 shows the results of estimating equation (5) without fiscal quarter controls (column 1), with first and fourth fiscal quarter indicator variables (column 2), and with first and fourth fiscal quarter indicators interacted with a set of 3-digit industry indicators (column 3). All three regressions include controls for calendar month indicators interacted with 3-digit industry indicators, thereby allowing for

\textsuperscript{3}I deviate from 2-digit SIC codes in separating Consumer and Industrial Chemicals. This follows Peck (1982) and is based on the premise that selling industrial chemicals differs from selling soap and pharmaceuticals.

\textsuperscript{4}See Huberman and Kandel (1989) for a detailed analysis of fiscal year ends by firm size and industry.

\textsuperscript{5}Industries also had to include at least three different fiscal year ends and had to have at least one company with a fiscal year end between March and September. However, these restrictions did not exclude any 2 or 3-digit industries. Two 4-digit industries were excluded by the three fiscal year ends rule and no 4-digit industries were excluded by the March to September restriction.
different calendar seasonality by industry.\textsuperscript{8}

The average firm has 4.8% lower sales in the first fiscal quarter, and 2.7% higher sales in the fourth fiscal quarter, than it does in the second or third quarter (see column 2). Both coefficients are highly statistically significant, indicating that firms' fiscal timing has an effect on seasonality.

The industry-level fiscal effects, which are measured in column 3 of table 2 and detailed in table 2a, vary considerably across industries. The "first quarter dip" and "fourth quarter spike" are insignificant in some industries such as pharmaceuticals (industry 181) and grain (industry 110), while the dip and spike are -6.4% and 5.3%, respectively, in computers (industry 322). The F-statistic testing whether the additional regressors in column 3 are jointly significant is 7.99, so the null hypothesis that the fiscal effects are the same in all industries can be rejected at the 1% level. Sections 4 and 5 will examine this inter-industry variation in detail by testing whether price changes cause fiscal revenue effects and by looking for industry level characteristics that explain fiscal revenue effects.

D. Endogeneity of Fiscal Year Ends

The choice of fiscal year ends is not random or exogenous. If fiscal year ends are chosen to coincide with a firm's busy season or to be before a slow period, then the results in section 2-C may be due to seasonality in a firm's business causing the choice of fiscal year end.

The question of causality can be approached in several ways. First, I investigate how the fiscal revenue effects change when controlling for finer and finer levels of industry classification. If fiscal years

\textsuperscript{8}The growth rate is autocorrelated due to cyclical business and the average shocks differ across firms, so estimation of (5) leads to highly autocorrelated and heteroskedastic error terms which cannot be approximated by an AR(1) or other simple format. Therefore, although the OLS estimates of the fiscal and calendar coefficients in equation (5) are consistent and unbiased, the standard errors must be adjusted. Newey and West (1987) developed a method of estimating a variance-covariance matrix that does not require i.i.d. error terms. I use their methodology and weighting algorithm, where necessary, allowing for five lags to contribute to the variance-covariance matrix.

Also note that the calendar effects could vary by year due to changes in seasonality and/or the business cycle. I ran the regressions in table 2 adding controls for calendar quarter by year, but I could not reject that the calendar effects are equal in all years.
are chosen to end in a busy season and start in a slow season, then estimates of the fiscal quarter effects would be smaller when controlling for calendar seasonality by specific industry classifications than when controlling for calendar seasonality at a more aggregated industry level. That is, as the firms in an industry classification become more similar, the calendar effects would also become more similar and the fiscal effects would become less significant. However, table 3 shows that this is not the case because the fiscal effects do not change significantly as the level of industry aggregation changes.

The second test of causality is to see how business seasonality changes when a firm is acquired and, as a result, undergoes a change in its fiscal year end. Two such acquisitions took place in 1986. In the first, Unisys was formed by the merger of Sperry and Burroughs, two computer companies of roughly equal size. Unisys adopted a calendar fiscal year, as did Burroughs before the merger. Before the merger, Sperry’s fiscal year had ended in March. In the second example, General Foods, whose fiscal year had ended in March, was acquired by Philip Morris, which used a calendar fiscal year both before and after the acquisition.

Columns 1 and 2 of table 4 show the calendar seasonality of Sperry and Burroughs before the merger. Column 3 treats Sperry and Burroughs as a hypothetical combined company before the merger, while column 4 is the combined post-merger company. Finally, column 5 measures calendar seasonality of the combined company and how seasonality changed as a result of the merger. Table 5 shows similar regressions for Philip Morris’s acquisition of General Foods. If fiscal years cause revenue seasonality, then the changes in fiscal years after the acquisitions should have the following three effects on Unisys’s and Philip Morris’s seasonality:

1) The coefficient on the first calendar quarter indicator variable will decrease after the merger. This is because the first calendar quarter will no longer be the fourth fiscal quarter for part of the company, but will instead be the entire post-merger company’s first fiscal quarter.

2) The coefficient on the fourth calendar quarter indicator variable will increase because the fourth
quarter represents the entire post-merger company's fourth fiscal quarter.

3) The coefficient on the second calendar quarter indicator variable will increase because it is no longer the first fiscal quarter for part of the company.

Column 5 of table 4 shows that all of these effects occur in the Unisys case, although the change in the second quarter is insignificant. Simply by changing its fiscal year, the seasonality of the Sperry portion of Unisys changed. At Philip Morris, as shown in column 5 of table 5, two of the three expected changes in fiscal seasonality took place at the time of the merger. The coefficients on the fourth and second calendar quarter indicator variables increased, but the first calendar quarter coefficient also increased. This suggests that other changes in seasonality affected at least the first calendar quarter or that fiscal effects are not as important in General Foods' business as they are in Sperry's.  

3. Salespeople and Fiscal-Year Effects

While the calendar seasonality of a firm is likely to be driven largely by customer demand, the fiscal year end of a company is irrelevant to its customers. Therefore, the fiscal-year effects in section 2 are the result of decisions made within producing firms, or at least are driven by customer expectations of how the producing firms will react to their fiscal seasonality.

Upper management is one group that may affect fiscal year seasonality. Top executives can vary prices and use other means to control the timing of revenue, and managers have incentives to manipulate the timing of sales. For example, Healy (1985) found that managers try to manipulate earnings to maximize their bonuses. However, he did not suggest or look for any systematic seasonality in the manipulation of earnings and revenues. While managers may, in fact, be partially responsible for fiscal effects, the rest of this paper explores the role of another set of agents -- salespeople.

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9Another test of the causality of fiscal effects is to look at changes in seasonality at firms that change their fiscal year. I performed this analysis for two firms that changed their fiscal year end in the 1980's: Photo Control and Black and Decker. Though consistent with table 2, the small sample made the results statistically insignificant.
A. Sales Compensation Schemes and Salesperson Incomes

If salespeople were paid like most other workers -- that is, a fixed wage -- or if they were paid a fixed percentage commission for all sales, they would have no incentive to bunch sales. However, few sales incentive schemes consist entirely of a salary and/or a linear commission. Most salespeople have a quota for the fiscal year and "making quota" often involves a sizable bonus or reward.\textsuperscript{10} Figure 2 shows four examples of actual sales plans. Though these plans vary in slope and magnitude, they all involve a discrete bonus for meeting quota\textsuperscript{11} and the commission rate varies over possible sales outcomes. As will be seen below, the discrete bonus for meeting quota can lead to incentives for salespeople to bunch sales at the end of the fiscal year.\textsuperscript{12}

Before modeling salesperson behavior, I will establish that salespeople's earnings are more variable than that of other professionals, and that salespeople are more likely to receive large bonuses. I gathered data from the 1984-1988 Survey of Income and Program Participation (SIPP). The SIPP has data on income for each month and therefore provides a means to measure how incomes vary within a year. I constructed a dataset of salespeople, sales managers, executive/managers, and professionals, with the latter two groups used as a control group of white-collar workers. Appendix table 2 contains summary statistics for each of the four groups. An observation is an uninterrupted year of employment

\textsuperscript{10}See Joseph and Kalwani (1995) for a detailed discussion of the prevalence of quota-based sales plans.

\textsuperscript{11}The bonus is not necessarily cash. See Dorsey (1994) for an account of the importance of non-cash benefits of reaching quota and see Cohen (1995) for examples of non-cash bonuses for meeting quota.

\textsuperscript{12}This paper will not investigate the reasons why a firm would choose to use a quota/bonus system. Instead, I take the quota as a given. Park (1995) provides a principal-agent justification for sales quotas. An alternative explanation put forth by many salespeople and sales managers is that quotas are necessary because people work best when they have goals and/or competition. Camerer, et al (1995) documents the use of goals by self-employed workers, so sales quotas may reflect a system that salespeople prefer. The results in this paper support the claim that internal competition provides effective motivation because otherwise firms would smooth sales by staggering the sales years of their salespeople. However, I do not know of any firms which do this.

Note that many firms have quota systems which cause non-linearities in compensation, without including a discrete bonus. The following analysis is relevant to most of these contracts, but I stick to the quota/bonus scheme for computational consistency and simplicity.
in the same job. Since respondents are interviewed over two years, one person can account for up to two observations. The dataset consists of 1,668 salesperson and sales manager observations, covering 1,163 people.\textsuperscript{13} Including the control group, there are a total of 4,743 observations.

Columns 1 and 2 of table 6 show the results of a wage regression. Column 2 limits the analysis to manufacturing, to be comparable with section 2. For every dollar a salesperson earns, an executive makes about $1.20 and a sales manager makes about $1.10. Professionals earn roughly the same amount as salespeople.

Columns 3 and 4 of table 6 establish the high variation in salesperson incomes within a year. As expected, salespeople have the most variable monthly incomes. The variable component of sales manager compensation is based on the sales of the people they manage. By the Central Limit Theorem, they should have less variable income than salespeople. As the table shows, this is the case and, in fact, the variability of the incomes of sales manager and executives are not significantly different.

Columns 5 and 6 of table 6 address the issue of receiving sizable bonuses. Using the same explanatory variables, columns 5 and 6 show the results of a logit where the dependent variable is 1 if the observation includes a month in which income is more than 25% higher than the average monthly income in the year. As expected, salespeople are the most likely to have such an extreme month, sales managers are the next most likely, followed by executives.

The SIPP observations are consistent with salespeople being relatively likely to receive bonuses and deriving a relatively large portion of their income from incentive pay. In conjunction with the pay schemes in figure 2 and the survey evidence in Joseph and Kalwani (1995), this suggests that salespeople

\textsuperscript{13}To insure that this sample was fairly representative, I also studied salespeople in the 5% sample of the 1990 census. Summary statistics are included in Appendix Table 2. The SIPP sample includes a higher percentage of male salespeople than the Census, possibly because of the requirement that the salesperson be in the same job for at least a year. The SIPP and Census data are comparable in demographics characteristics, as well as the return to these variables in an income regression. The Census sample is generally better paid than the SIPP sample, possibly because the surveys were at different times.

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have incentives to maximize their incomes by manipulating their output.

In the next two sub-sections, I explore salespeople’s reaction to non-linear incentives. I lay out a model that is consistent with fiscal revenue effects, and provides an explanation for why fiscal revenue effects might vary across industries. The model has other empirical implications, some of which are explored in the sections that follow, with still others left for future research.

B. Agent Behavior under Quotas: "Effort Gaming"

You put up a good front of earnest and strenuous work early in the year.
You shot for a not unreasonable budget in January, February, and March. Yet you didn’t take it seriously. Few machines got sold.
_The Force_, David Dorsey

This section develops a model of optimal sales effort timing under a sales quota. It relaxes the oversimplification of many principal-agent models that the effort decision is made once and cannot be changed during the measurement period. In practice, salespeople choose effort continually, in an attempt to maximize utility. Such variation in effort is referred to as "effort gaming" throughout this section. The model of effort gaming has two important implications: because salespeople discount future expected utility, they tend to work harder later in a fiscal year than earlier, and effort gaming provides an incentive for the firm to have "reasonable" quotas.

Lal and Srinivasan (1993) solve for the optimal compensation plan when the salesperson can adjust effort continuously. Their findings rely on a normal distribution for sales and exponential salesperson utility. This section also allows the salesperson to adjust effort but does not restrict the functional forms of utility or the sales distribution. However, I take a narrower view by looking only at the salesperson’s strategy, while assuming that a bonus for meeting a quota is part of the sales compensation package.
Assume that a risk neutral firm employs a risk neutral salesperson, who is paid a bonus (b) if sales during the year reach a quota ($Q'$). The year is split into two fiscal periods. The agent chooses a level of effort for the first fiscal period ($e_1$), observes sales for the first fiscal period ($x_1$), chooses effort for the second fiscal period ($e_2$), and observes $x_2$. If $x_1 + x_2 \geq Q'$, the agent is paid b.\(^{15}\)

Assume $x_1$ is distributed $g(x \mid e)$, with cumulative density $G(x \mid e)$, where $g$ is differentiable in $x$ and $e$, for $x \in [0, \bar{x}]$. Assume $g(x \mid e)$ increases to a single peak and then declines and assume $G_\delta(x \mid e)$ is strictly negative at any $x$ which has positive density. Also assume that the salesperson discounts expected utility by a discount factor of $\delta < 1$ per fiscal period and that, each fiscal period, the salesperson’s disutility of effort is $ve^2$.

The agent chooses effort in each fiscal period to maximize expected utility for the fiscal year, where expected utility is discounted expected bonus payments minus discounted expected disutility of effort:

$$E[utility] = \delta b \cdot Pr(make \ quota) - \nu(e_1^2 + \delta E(e_2(x_2^2))) \quad (6)$$

e_2$ is a function of $x_1$ because the salesperson chooses second-period effort after seeing his position relative to quota. Appendix A shows the calculations for determining the agent’s optimal $e_2$ for any $x_1$ and then solves backwards for the optimal agent effort in the first fiscal period. That is, given $e_2(x_1)$, it is possible to determine $E(e_2)$ for any $e_1$ and, therefore, to determine the first order condition for the agent’s choice of first period effort. Appendix A shows that this first order condition is

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\(^{14}\)The assumption of risk neutral agents, in addition to simplifying the analysis, can be justified by the relatively high sales variance of salespeople (see Table 6), which should lead to less risk averse people opting to become salespeople.

\(^{15}\)The analysis in this and the following sections holds under other non-linear sales compensation schemes. For example, if the contract in Raju and Srinivasan (forthcoming) is employed, effort gaming is even more likely to lead to sales bunched at the end of the year and the results in section 3-C, though more complicated, are basically unchanged. Also, the bonus may not be cash, so the salesperson is indifferent between the bonus and a lump-sum cash payment of b.
\[ e_1 = \delta E(e_1) - \left( \frac{\delta v}{2} \right) \frac{dE(e_1^2)}{de_1}. \] (7)

Since \( \delta \) is less than one, multiplying \( E(e_1) \) by \( \delta \) tends to make \( E(e_2) > e_1 \), but the effect of the other term is not as obvious. Discounting future utility induces salespeople to work harder and sell more as the year progresses. If the right-most term of (7) is not too large, the effect of discounting dominates.

In fact, for quotas above a certain level, effort and sales will be lower, on average, in the first period than in the second period.\(^6\) Similarly, effort and sales are higher in the first period if the quota is low enough, so there exists some quota such that effort and sales are the same, on average, in the two periods. Figure 3 shows how the expected dissymmetry changes with the quota. The figure also illustrates the two empirical predictions of effort gaming: (1) extreme quota levels lead to extreme effort gaming by the salesperson; and (2) for any quota that is challenging enough, sales will be higher on average in the second fiscal period.

C. Agent Behavior under Quotas: "Timing Gaming"

[The Xerox sales manager] was prepared to go out on any call with any of his reps, pushing to close orders that might lag into the next month, the next quarter, the next year.

_The Force_, David Dorsey

Consider a salesperson who sells cereal to supermarkets. The supermarket has a certain space allotted to cereal and orders the amount needed to keep its shelf stocked between sales visits. Now consider a salesperson who sells complex and expensive computer systems to corporations. This sale requires customer education and trust developed over time. The salesperson may get to know the customer well and be in a position to share or hide information about price and technology changes. In

\(^6\)This is proven in appendix A.
this way, unlike the cereal salesperson, the computer salesperson can influence the date of purchase and installation of his product. This allows the computer salesman more flexibility in maximizing his chances of attaining quota in current and future years.

I refer to this form of sales manipulation as "timing gaming." Note that this timing influence can take on two forms. The salesperson can "pull in" potential business from the next fiscal year to make quota this year, or the salesperson, knowing he already has achieved quota or giving up on it for the current year, can "push out" potential business to the next fiscal year. Without knowing the turnover rate of salespeople, the effect the salesperson can have on customer timing, and the form of the sales distribution, it is not possible to determine for sure whether the pull-in or push-out effect dominates. However, the model of timing gaming below implies that the pull-in effect is likely to dominate.

Before turning to the model, it is worth considering the effect of salesperson turnover on sales timing. If the salesperson expects to leave his territory at the end of the fiscal year, or expects to be transferred, he will pull in as many sales as possible from the following year because he will receive no benefit from sales made in that territory the following year. Given significant salesperson turnover rates, there is a strong bias towards sales being pulled in from the following year. Therefore, sales will be higher at the end of the fiscal year than at the beginning. The following modified model abstracts from turnover effects. It investigates the likely form of asymmetry for salespeople who expect to keep their territory for more than the current year.

As in section 3-B, consider a fiscal year with two fiscal periods and let the sales quota be based

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17For example, the SIPP sample of salespeople discussed above have an average annual turnover rate of 20.2%. This is an underestimate of relevant salesperson turnover because it does not include salespeople who leave their sales territory but stay at the same company.

18Any loss of efficiency caused by turnover related pulling-in is not a result of the quota/bonus plan, since any plan with variable compensation can lead to maximum pulling-in by those leaving a sales territory. However, turnover will not affect the seasonality of the firm's revenues under a commission plan since the pulling-in will not be related to the fiscal year.
on sales over the whole fiscal year. The salesperson optimizes expected utility over the current fiscal year (year y) and the next one (year z), where the quota and the bonus are constant over the two years. Thus, he is concerned with four fiscal periods, with respective sales $x_1, ..., x_4$. To be specific: the salesperson receives a bonus, $b$, at the end of year $y$ (i.e., the end of the second fiscal period), if $x_1 + x_2 \geq Q'$, where $Q' < 2\bar{x}$ and $\bar{x} < \infty$. He receives $b$ at the end of year $z$ (fourth period), if $x_3 + x_4 \geq Q'$.

To focus on timing gaming, assume a pre-determined salesperson effort level that is constant across all four periods. After observing $x_i$, the salesperson decides how much of the potential business that would naturally fall into period 3 he will try to pull into period 2. In order to pull in business, however, the salesperson has to offer a price break that is greater than the firm’s discount factor, $\delta$. Alternatively, the salesperson may push out period 2 business into period 3, thereby lowering the expected value of such sales by $\delta$.

Define $\lambda$ to be a summary statistic of the salesperson’s optimal pull-in/push-out decision, given $x_i$, where $\lambda = 1$ is the "natural" level or the level for salespeople who cannot influence the timing of sales. $\lambda > 1$ indicates that the salesperson is pulling in business from the following period, while $\lambda < 1$ means he is pushing out potential business. The distribution of sales in period $i$ ($i = 1, ..., 4$) is now represented by $g(x_i | \lambda)$. In periods 1 and 4, there is no incentive to game the system and $\lambda$ is always equal to 1.

The decision about where to set $\lambda$ comes down to a comparison of three values.\(^{29}\) First, define $B_i$ (or year $y$ cost/benefit) to be the salesperson’s expected marginal increase (decrease) in year $y$ bonus payments due to increasing (decreasing) $\lambda$ from 1, given $x_i$. That is, $B_i$ is the expected marginal compensation from the first bit of pulling in. Second, define $B_{i-}$ to be the discounted expected marginal

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\(^{19}\)Many salespeople do not have direct authority over pricing. However, even salespeople who need management approval for discounts can affect pricing by taking advantage of the lack of information that management has about their customers and convince management that a deal can only be closed if a price break is offered.

\(^{29}\)Appendix B contains calculations of the cost/benefit functions that follow and proves the claims in this section.
increase in year z bonus payments due to pushing out (note that this is not dependent on \( x_i \)). Finally, define \( B_\text{m} \) to be the expected marginal decrease in year z bonus payments due to pulling in and note that the price discount to pull in business implies \( B_\text{m} > B_\text{i} \).

The salesperson will follow these decision rules:

a) Pull in potential sales from year z (i.e., increase \( \lambda \) above 1) if \( B_\text{m} > B_\text{i} \).

b) Push out potential sales to year z (i.e., set \( \lambda < 1 \)) if \( B_\text{m} < B_\text{i} \).

c) Do not manipulate timing (set \( \lambda = 1 \)) if \( B_\text{m} > B_\text{i} > B_\text{m} \).

A possible case where \( Q' \) is neither extremely high nor low is illustrated in figure 4a. The horizontal axis in the figure is realized first fiscal period sales and the vertical axis measures the cost/benefit functions. The graph shows the pull-in region, the push-out regions, and the regions where the salesperson will not manipulate sales timing.

If the penalty for pulling in is not "too big", then there will be a range of \( x_i \) for which the salesperson will choose a pull-in strategy. As figure 4a shows, for quotas that are not extreme, the pull-in region includes the densest first-period sales outcomes.\(^{21}\) Therefore, if the pull-in penalty is not too large, the pull-in effect may dominate the push-out effect.

On the other hand, if the quota is either very high or very low (see figures 4b and 4c), the push-out effect will clearly dominate because the salesperson will often give up on making quota this year, or already have reached his quota, after the first fiscal period. Therefore, because gaming is greater at extreme quotas, there will be an interior quota such that the probability of gaming is minimized, and an interior quota at which the absolute value of the difference in the probabilities of pulling in and pushing out is minimized. This reinforces the section 3-B result that setting "reasonable" quotas minimizes salesperson gaming.

Another way to minimize gaming is to add a linear commission to compensation. Commissions

\(^{21}\)This is proved in appendix B.
are a disincentive to pulling-in and pushing-out because they increase the returns to leaving sales in their "natural" period. Referring to figure 4a, introducing a commission raises the top horizontal line more than it raises the curve, which is, in turn, raised by more than the lower horizontal line.22

D. Implications of Salesperson Gaming

Key implications of effort gaming and timing gaming that can be tested empirically include:

1) *Any company with challenging enough sales quotas can expect a fourth quarter spike and a first quarter dip in its revenues.* This does not require further testing since section 2 made it clear that the average company does experience this fiscal pattern in its revenue. Of course, there is no proof yet that fiscal revenue effects are caused by salespeople.

2) *The magnitude of fiscal revenue spikes and dips will vary with salespeople's ability to influence the timing of transactions.* This will be tested in section 5 by using measures of salespeople's ability to use timing gaming to explain the fiscal revenue effects measured in section 2.

3) *Fiscal revenue effects cannot be completely explained by price changes.* Part of how salespeople implement timing gaming may be to change prices. However, if price can explain all fiscal revenue effects, then upper management may be solely responsible and there is no reason to believe that the salesperson's effort or other sales activities are an instrumental part of fiscal revenue effects. This will be addressed in section 4 by measuring how prices change throughout the fiscal year.

4) *If firms want to minimize salesperson gaming, they should choose "reasonable" quotas.* This is just an economic justification for the rule of thumb found throughout the sales management literature that salespeople are best motivated by quotas which are not overly simple or difficult to achieve.23

---

22See appendix B for proof of the effect of "reasonable quotas" and commissions.

23For example, according to Cohen (1995), a key to sales incentives is, "Realistic yet challenging goals should be set."
5) *Higher commissions and lower bonuses for meeting quota lead to smoother sales.* That is, steady, steeper slopes in figure 2 lead to less salesperson incentive to game the system. To test this empirically, data from individual companies about their incentive structures are needed and, therefore, it is left for future research.

4. Fiscal-Year Effects on Price

The cunning [customers] stall you until December, when they suspect you’ll be more willing to lower the price by giving away your commission.

*The Force*, David Dorsey

A. Empirical Strategy and Data

The aim of this section is to determine if the fiscal effects in section 2 are due to price changes. If the answer is yes, then it is impossible to determine whether salespeople or executives are driving the price and revenue effects and there is no evidence of effort variation. Therefore, if prices can completely explain fiscal revenue effects, there is no reason to believe that salespeople play an instrumental role in fiscal seasonality.

Price data is not available, but relative changes in price can be inferred using Compustat cost data. The following assumptions and calculations will isolate the effect of price, given the data limitations. Assume that dollar sales of company \( i \) in fiscal quarter \( q \) and calendar period \( t \), \( S_{iqt} \), are the product of average price, \( P_{iqt} \), and unit volume, \( V_{iqt} \). Price is assumed to be determined by underlying supply and demand factors, while volume sold is a function of the firm’s price and economic conditions. Assume average price is the product of a firm-specific effect, \( A_{t}^{i} \), a calendar effect, \( C_{t}^{i} \), and a fiscal quarter effect, \( F_{q}^{i} \). Therefore, (1) can be re-written

\[
S_{iqt} = P_{iqt} V_{iqt} = (A_{t}^{i} C_{t}^{i} F_{q}^{i}) V_{iqt}.
\]  

(8)
I further assume that the unit cost of production, \( M_{uq} \), is determined by an individual firm’s cost structure, \( A^u \), the seasonal effect of product procurement costs, \( C^s \), and a random cost shock, \( \Theta^u \). The fiscal year is assumed to be orthogonal to costs, except as discussed below. Costs can be expressed

\[
M_{uq} = A^u C^s \Theta^u.
\]  

(9)

Since the goal is to measure the effect of fiscal seasonality on price, the coefficient of interest is \( F^s \). This coefficient can be disentangled from \( S_{uq} \), by looking at the gross margin, where gross margin is profit after production costs as a percentage of revenues. Mathematically,

\[
Gross\ Margin = \frac{\frac{P_{uq}}{V_{uq}} - \frac{M_{uq}}{V_{uq}}}{\frac{P_{uq}}{V_{uq}}} = 1 - \frac{M_{uq}}{P_{uq}} = 1 - \frac{A^u C^s \Theta^u}{A^u C^s F^s}. 
\]

(10)

Some manipulation of (10) is required to get to a form that can be estimated. Specifically, by subtracting one from (10), taking the negative, and then taking the natural log, the fiscal price effect can be isolated. Define \( h \) as

\[
h_{uq} = \ln \left( \frac{M_{uq}}{P_{uq}} \right) = \left[ a^u + c^s + \Theta^u \right] - \left[ a^p + c^p + f^p \right].
\]

(11)

Differencing leads to the simple linear equation

\[
z^{\nu}_{uq} = h_{uq} - h_{uq, t-1} = \Delta c^{\nu} - \Delta f^s + \Delta \Theta_{uq}
\]

(12)

where \( c^{\nu} \) combines the calendar effects on price and cost. Equation (12) can be used to estimate the coefficient of interest, \( f^s \). Since I assume that \( f^s = f^p \) and use the second and third quarters as the basis of comparison, estimates of \( f^s \) and \( f^s \) reflect the amount that average price differs in the first and fourth quarter, respectively, from the second (or third) quarter. \( h_{uq} \) is constructed as the natural log of one.
minus gross margin. "Costs" is the cost of goods sold (COGS) and includes the cost of materials, direct labor, and an allocation for manufacturing overhead. In the following regressions, I assume that unit COGS is uncorrelated with unit volume.\textsuperscript{25}

B. Results

Tables 7 and 7a report the results of estimating (12).\textsuperscript{26} The coefficients in column 2 of table 7 are the fiscal price effects, $f_q$, measured for all industries together, where the fiscal price effect is the percentage by which a typical firm's price in fiscal quarter $q$ differs from fiscal quarter 2 or 3. Column 2 of table 7 indicates that the average firm's fourth fiscal quarter price is 1.7% lower, and its first quarter price 0.7% higher, than its second or third quarter price. Both of these coefficients are statistically significant at any reasonable level. Together with the results in section 2-C, this indicates that, on the margin and on average, customers are flexible enough about the timing of purchases to make short-term demand elastic. This is because in the quarters where prices are higher (lower), revenues are lower (higher).

Column 3 of table 7 adds fiscal quarter indicator variables by 3-digit industry. As reported in table 7a, the fiscal effects on price differ by industry. The F-statistic for the addition of industry specific fiscal effects (that is, for moving from column 2 to column 3 of table 7) is 2.45, which indicates that

\textsuperscript{25}Compustat reports cost of goods sold by quarter.

\textsuperscript{26}For materials and direct labor, this assumption seems reasonable since these unit costs should not change much as a result of relatively small changes in volume. The overhead allocation, however, may be correlated with unit volume at firms which update their overhead rates more often than annually. That is, if a firm applies a constant overhead rate over the course of a fiscal year, then unit costs should be unchanged between quarters even if there are volume changes. But if a firm sets its overhead rate quarterly by dividing manufacturing costs by quarterly unit volume, then quarters with relatively low volume will appear to have low gross margins. This potential bias will be considered when interpreting the empirical results below.

\textsuperscript{27}As in section 2, homoskedastic and serially independent errors can be rejected, so the Newey-West standard error methodology is used.
equality of the fiscal effects across industries can be rejected at the 1% level.\textsuperscript{27}

The results in tables 7 and 7a indicate that fiscal revenue effects are partially due to price changes. However, the first quarter fiscal revenue effect is of a larger magnitude than the fourth quarter fiscal revenue effect, while the opposite is true of fiscal price effects. This is not consistent with price changes being the sole driver of fiscal revenue effects and suggests that someone within firms is using more than just price to drive revenue seasonality.

C. Relationship to Fiscal Revenue Effects

To provide more insight into how fiscal revenue effects and fiscal price effects are related, I now look at the correlation between fiscal revenue effects and fiscal price effects. I calculated the difference between the fiscal fourth quarter revenue effect and the fiscal first quarter revenue effect (that is, $f_4 - f_1$), and the difference between the fiscal price effects ($f'_4 - f'_1$). These differences (which I will call the "fiscal revenue difference" and the "fiscal price difference") are such that they are both positive in most industries. I then calculated the correlation coefficient between these two differences.\textsuperscript{28} The correlation between the fiscal price difference and the fiscal revenue difference is -0.218, which is not significantly different from 0 (p-value = .195). Figure 5, which graphs the two fiscal effects, also indicates that there is essentially no relationship between fiscal revenue and fiscal price effects.

This inability of price to explain the inter-industry variation in sales may be partially due to

\textsuperscript{27}As discussed above, fiscal price effects could be biased due to overhead cost allocation. However, Section 2 showed that firms tend to have higher sales volume in the fourth quarter, and lower volume in the first quarter. Therefore firms which revise their overhead rates quarterly will tend to have higher (lower) costs in the first (fourth) quarter, resulting in lower (higher) gross margins. This could lead to an underestimation (overestimation) of the first (fourth) fiscal quarter price effect, so the actual fiscal price effects may be larger in magnitude than those in tables 7 and 7a, but should maintain the same sign.

\textsuperscript{28}The correlations were calculated unweighted and weighted by the reciprocal of the standard errors from the estimation of the fiscal revenue and price effects. Neither the use nor the choice of weights alter the results much, so I report only unweighted correlations.
differences in price elasticities of demand across industries. However, along with the results in section 4-B, it indicates that something other than price is driving fiscal year revenue seasonality and that the results in this and the previous section are consistent with the sales quota models of effort and timing gaming.

5. Do Salespeople Have a Role in Fiscal-Year Effects?

A. Methodology and Data

The models of salesperson gaming in section 3 are, at a very simple level, consistent with the fiscal year revenue effects documented in section 2. In most industries, firms do more business at the end of the year than at the beginning of the year, but this tendency varies by industry. In an attempt to link salespeople more directly with fiscal seasonality, this section looks for factors that influence the inter-industry variation in fiscal revenue effects.

I will also try to explain the inter-industry variation in fiscal price spikes and dips. However, this is not a test of the sales quota models, because the models can make no specific predictions about the relationship between fiscal price effects and salespeople's ability to influence the timing of transactions. The chief determinants of how much salespeople manipulate prices to meet their quotas are the leeway management gives them in determining price and the price elasticity of demand for their product. The price elasticity is not necessarily related to the salesperson's ability to influence purchase timing, so measures of timing influence may or may not be correlated with fiscal price effects.

My strategy for explaining fiscal revenue and price effects is to run second-stage regressions where the fiscal effects measured in sections 2 and 4 are the dependent variable. Explanatory variables, their sources, and a brief discussion of how they relate to salespeople follow.29

29A challenge in this analysis is that some of the factors that may affect the salesperson's ability to employ timing gaming are not measurable. For example, products which are purchased less often and cost more, such as capital equipment, may allow the salesperson more room to manipulate the sale timing. However, it is not easy to
1) An indicator variable for durable goods industries. This variable is determined by Census Department classifications. Durable goods are purchased infrequently and are a relatively large investment, providing the salesperson with discretion to influence the timing of sales. So I expect more dramatic fiscal revenue effects at durable goods manufacturers.

2) The percentage of industry shipments sold through direct channels and by customer type. This comes from the 1987 Census of Manufacturers. Indirect sales are defined as those to retail and wholesale customers, while direct sales are to manufacturers, the government, or other non-manufacturers. Salespeople who interact directly with consumers have more opportunity to influence purchase timing, so I expect industries with more direct sales to have larger fiscal revenue effects.

3) The industry average annual salesforce turnover rates. This variable is calculated with the same SIPP data used in section 3-A. The sample size of 3,197 salespeople in manufacturing industries is bigger than in section 3-A because I no longer require a minimum employment period. This still results in several 3-digit industries having small sample sizes in the calculation of turnover and makes calculating 4-digit industry turnover infeasible. I anticipate that higher salesperson turnover leads to bigger fiscal revenue effects. This is because, as discussed in section 3-C, those salespeople who are leaving a sales district have incentive to pull in as much business as possible.

4) Industry averages of salesforce age, gender, income, and education. These data, which were used in section 3-A, are from the 1990 Census. This sample is considerably larger than the SIPP sample and it is larger and more recent than a salesforce survey done by the Conference Board (see Peck, 1982). I expect that companies that give their salespeople more discretion over timing and price employ salespeople who are better trained (i.e., have more education) and pay them relatively well (i.e., they will have higher incomes). This would lead to bigger fiscal effects in industries with more educated and better

find an industry's average purchase frequency, so the durable goods indicator must be used instead. The lack of data points and the inability to quantify all relevant variables lead to second stage regressions where the right hand side does not include all appropriate explanatory variables, which may cause omitted variable bias.
paid salespeople. The model of timing gaming does not lead to an expected effect of age and gender.

B. Empirical Strategy

In this section’s regressions the dependent variable is the set of regression coefficients estimated in sections 2-C or 4-B. In the case of 3-digit classifications, these coefficients are in tables 2a and 7a. The equation to be estimated is

\[ f_{ij} = \beta x_{ij} + e_{ij} \]  

(13)

where \( f_{ij} \) is the fiscal revenue or price effect for industry \( j \) in quarter \( q \), \( x_{ij} \) is a vector of characteristics for industry \( j \) interacted with quarter \( q \), and \( e_{ij} \) accounts for measurement error and randomness.

As Hanushek (1974) showed, (13) cannot be estimated efficiently using ordinary least squares. His solution is to use Feasible Generalized Least Squares (FGLS), weighting by \( \Omega^{-1} \), where

\[ \Omega = \Omega_f + \Sigma_{m} \]  

(14)

\( \Omega_f \) is the variance-covariance matrix from estimating the \( f \)'s using (5) or (12) and the \( n, m \) element of \( \Sigma_m \) is \( E[e_{im}e_{jm}] \). I approximate this by weighting the estimation of (13) by the inverse of the variance-covariance matrix from sections 2 and 4, where the \( f \)'s were estimated. Therefore,

\[ \beta = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}F \]  

(15)

where \( X \) is the matrix of \( x \)'s in (13), \( F \) is the vector of \( f \)'s in (13), and \( \Omega \) is the portion of the variance-covariance matrix from estimating (5) or (12) that corresponds to the \( f \)'s.\(^8\)

\(^8\)If the actual \( f \)'s were available and (13) could be estimated by OLS, then \( \Sigma_m \) would be a constant times the identity matrix. By dropping this constant from the diagonal of \( \Omega \) during estimation, I am giving greater weight to the industries which had relatively little error in the section 2 estimates of fiscal revenue effects.
C. Results -- Determinants of Fiscal Revenue Effects

The second-stage regressions can be run on the 2-, 3-, or 4-digit coefficients from fiscal revenue regressions, depending on the reliability of the regressors at each level. Finer industry definitions are preferred where possible, because they lead to more data points and to companies within an industry being more similar. However, the SIPP and the Census do not categorize industries at the 4-digit level and the SIPP has small sample sizes at the 3-digit level, so some industry and salesperson characteristics are hard to measure at the 3- and 4-digit level. The results for the 4-, 3-, and 2-digit regressions are in tables 8a, 8b, and 8c, respectively.

In the case of the durable goods indicator and the distribution channels, 4-digit is the appropriate level of detail because the data are accurately measured to this level. As shown in table 8a, the “fourth quarter spike” is significantly affected by the indicator for durable goods and the industry’s distribution channels. As expected, companies selling durable goods have larger fourth quarter spikes than those selling non-durable goods and those selling direct to customers have larger fourth quarter spikes than those selling through indirect channels. Column 3 of table 8a, which uses a more specific definition of distribution channels, indicates that products sold directly to non-government non-manufacturers are particularly likely to be sold in the fourth fiscal quarter. This may be because these products are not being sold to resellers and they are not being used as raw materials, so the purchasers are particularly flexible about the timing of sales.

Other causes of fiscal revenue effects may be present, but, possibly because the regressions in tables 8b-8c have limited observations, the results are not statistically significant. The effect of salesperson turnover, which cannot be measured at the 4-digit level, is shown in columns 1 and 2 of table 8b. The table indicates that higher turnover may lead to larger fourth quarter spikes (p-value = 0.18). As mentioned above, the turnover rates are measured with some error, which could indicate that the result in table 8b is understated. This connection between turnover and fiscal spikes and dips, if it can be made
more strongly, is also consistent with the sales quota model of salesperson behavior. However, a better measure of turnover, preferably at the 4-digit SIC level, is required to make this result meaningful.

The salesperson demographic characteristics are also weakly consistent with the sales quota model. Column 3 of tables 8b and 8c indicates that fiscal revenue effects are more pronounced in industries where salespeople are better paid, but this result is not statistically significant (p-values are 0.11 and 0.17 for the 2- and 3-digit regressions, respectively). The percentage of saleswomen in an industry and average salesperson age were found to have no explanatory power.

D. Results -- Determinants of Fiscal Price Effects

As table 8a shows, the durable goods indicator and whether the product is sold directly to the customer are not significant in explaining fiscal price effects. However, some of the salesforce characteristics influence fiscal price effects. Higher salesperson turnover is associated with larger fourth quarter price declines. This may be because customers who expect rapid salesperson turnover press for discounts at the end of the salesperson's fiscal year. Though not statistically significant in a 3-digit regression (see columns 4 and 5 of table 8b), turnover significantly effects price in a 2-digit regression (see columns 4 and 5 of table 8c). This difference could be a result of attenuation bias because the small 3-digit sample sizes probably lead to substantial measurement error in turnover rates.

The average salesperson education also has a significant effect on fourth fiscal quarter price, in a 3-digit second stage regression.\(^3\) Industries with better educated salespeople drop their prices more in the fourth quarter. This could be due to companies that will give their salespeople more pricing responsibility requiring better educated salespeople. Alternatively, it could be a result of better educated salespeople having bigger bonuses at stake and therefore having more incentive to make their quotas.

\(^3\)Note that the 3-digit education and earnings variables, which are based on the 1990 Census, are not as subject as turnover, which is based on the SIPP, to measurement error because they are derived from a much bigger sample.
However, this explanation is not consistent with column 3, which indicates that education has no effect, or possibly a small negating effect, on fiscal revenue effects.

6. Concluding Comments

This paper used variation in company fiscal years to show that revenue seasonality in many manufacturing industries is affected by fiscal timing. This is partially a pricing issue because prices tend to drop in peak fiscal quarters and increase in slow quarters. However, price changes cannot explain all the fiscal revenue seasonality.

Based on analysis of the inter-industry variation in these fiscal-year effects, the patterns in the fiscal spikes are consistent with a model of salespeople operating under a quota. The clearest link is that business tends to be stronger (weaker) at the end (beginning) of a fiscal year than in the middle of a fiscal year. The large fiscal effects in durable goods industries, and industries where products are sold through direct channels, provide further evidence that sales incentives are behind fiscal effects.

The results, however, do not establish a causal link between salespeople and fiscal effects, nor do they preclude upper management as an explanation for fiscal seasonality. One way to make a stronger connection between salespeople and fiscal effects would be to use sales data from within companies. This would allow analysis of how salespeople's success varies with their position relative to quota and throughout the fiscal year.32 Another potential direct test of the effect of sales incentives on business seasonality is suggested by the recent experience of PeopleSoft Inc., a software company with a calendar fiscal year. According to a Goldman Sachs research report (Sherlund, 1995), "PeopleSoft changed its salesforce yearend from December to March... there is a strong incentive to close business in the March quarter. We expect a bit slower bookings in the June quarter as a result." One can imagine PeopleSoft

32Asch (1990) documented the quota/fiscal effects link by showing that military recruiters with an annual quota are more productive towards the end of the year. However, the recruiters' lack of financial incentive limits the applicability to sales representatives.

27
being one observation in a "natural experiment" of the effect of sales incentives on business seasonality. However, this is the only case I have identified where a firm's fiscal and sales year ends differ.

The importance of fiscal effects can be researched in many areas of economics. Because fiscal year ends are bunched, fiscal year ends may be behind some of the macroeconomic seasonality discussed by Barsky and Miron (1989). A very crude calculation, based on the $R^2$ in the table 2 regressions, suggests that fiscal year timing can explain about a quarter of the seasonal variation in business revenues. Also, fiscal effects are probably an important factor in the additional variance in stock prices upon the announcement of fourth quarter earnings (see Beaver, 1968).

But perhaps the most interesting path for future research is to consider fiscal effects' implications for the generally accepted fact that smooth production benefits firms, especially manufacturers. If this is the case, why do manufacturers employ compensation plans that add unnatural seasonality and how big must the benefits of a quota/bonus compensation system be to justify the revenue spikes they create?
References


Figure 1
Fiscal Year Seasonality

On-Line-Transaction-Processing

Fiscal Year Ends: Tandem - September, Stratus - December

Consumer Goods

Fiscal Year Ends: Colgate-Palmolive - December, Proctor and Gamble - June

Year markers on horizontal axes denote fourth calendar quarter. Circled and square observations indicate fourth fiscal quarter.
Figure 2

Sample Sales Compensation Plans

Electronics

Food Manufacturer

Magazine Advertising Pages

Large Software Systems
Figure 3

"Effort Gaming" in a Two-Fiscal Period Model

First Period Effort ($e_1$)

Expected Second Period Effort $E(e_2)$

Effort

Quota

Maximum Sales for Both Periods
Figure 4

"Timing Gaming" in a Two-Year, Two-Fiscal Period Model

Panel A -- "Reasonable" Quota

Panel B -- Very High Quota

Panel C -- Very Low Quota
Figure 5

Fiscal Revenue and Price Effects

Each observation represents a 3-digit industry
<table>
<thead>
<tr>
<th>Fiscal Year Ends for Selected 3-Digit Industries</th>
<th>Paper (1921)</th>
<th>Drugs (1921)</th>
<th>Electric Machinery (1921)</th>
<th>Scientific Instruments (1921)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All</strong></td>
<td>13</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>January</td>
<td>21</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>February</td>
<td>44</td>
<td>0</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>March</td>
<td>14</td>
<td>0</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>April</td>
<td>21</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>May</td>
<td>86</td>
<td>0</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>June</td>
<td>26</td>
<td>0</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>July</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>August</td>
<td>71</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>September</td>
<td>30</td>
<td>0</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>October</td>
<td>19</td>
<td>0</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>November</td>
<td>624</td>
<td>33</td>
<td>33</td>
<td>36</td>
</tr>
<tr>
<td>December</td>
<td>28</td>
<td>31</td>
<td>48</td>
<td>39</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>981</td>
<td>33</td>
<td>48</td>
<td>39</td>
</tr>
</tbody>
</table>

Numbers in parentheses are 3-digit Census industry classifications.
Table 2
Fiscal Quarter Revenue Effects

Dependent Variable: ln(sales,) - ln(sales_{t-1})

3-digit Industry Classifications

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiscal Quarter = 1</td>
<td>---</td>
<td>-.0481 **</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0030)</td>
<td></td>
</tr>
<tr>
<td>Fiscal Quarter = 4</td>
<td>---</td>
<td>0.0267 **</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0030)</td>
<td></td>
</tr>
<tr>
<td>Fiscal Quarter Effects by Industry</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Calendar Month Effects by Industry</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

N (company quarters) | 19,732 | 19,732 | 19,732 |
R²                   | .141   | .167   | .191   |

** indicates significant at 1% level using Newey-West Standard Errors

¹These individual coefficients and standard errors are reported in table 2a.
<table>
<thead>
<tr>
<th>3-digit Industry</th>
<th>1st Quarter Effect</th>
<th>(NW S.E.)¹</th>
<th>4th Quarter Effect</th>
<th>(NW S.E.)¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat (100)</td>
<td>-0.062</td>
<td>(0.0123)</td>
<td>0.0293</td>
<td>(0.0135)</td>
</tr>
<tr>
<td>Canned Food (102)</td>
<td>-1.274**</td>
<td>(0.2555)</td>
<td>-0.0437</td>
<td>(0.0253)</td>
</tr>
<tr>
<td>Grain (110)</td>
<td>-0.0035</td>
<td>(0.0179)</td>
<td>-0.0093</td>
<td>(0.0174)</td>
</tr>
<tr>
<td>Beverages (120)</td>
<td>-0.0517*</td>
<td>(0.0261)</td>
<td>0.0151</td>
<td>(0.0287)</td>
</tr>
<tr>
<td>Other Food (122)</td>
<td>-0.1066*</td>
<td>(0.0350)</td>
<td>-0.0556</td>
<td>(0.0350)</td>
</tr>
<tr>
<td>Knitting (132)</td>
<td>-1.049**</td>
<td>(0.0293)</td>
<td>0.0341</td>
<td>(0.0307)</td>
</tr>
<tr>
<td>Yarn, Thread (142)</td>
<td>-0.0546**</td>
<td>(0.0184)</td>
<td>0.0541**</td>
<td>(0.0209)</td>
</tr>
<tr>
<td>Apparel (151)</td>
<td>-0.0212</td>
<td>(0.0161)</td>
<td>-0.0183</td>
<td>(0.0188)</td>
</tr>
<tr>
<td>Printing (172)</td>
<td>-0.0820**</td>
<td>(0.0129)</td>
<td>-0.0151</td>
<td>(0.0119)</td>
</tr>
<tr>
<td>Drugs (181)</td>
<td>-0.0160</td>
<td>(0.0141)</td>
<td>-0.0016</td>
<td>(0.0125)</td>
</tr>
<tr>
<td>Soap (182)</td>
<td>-0.0166</td>
<td>(0.0264)</td>
<td>0.0017</td>
<td>(0.0198)</td>
</tr>
<tr>
<td>Paint (190)</td>
<td>0.0343</td>
<td>(0.0341)</td>
<td>0.1345**</td>
<td>(0.0390)</td>
</tr>
<tr>
<td>Agric Chem (191)</td>
<td>-0.0200</td>
<td>(0.0574)</td>
<td>0.0446</td>
<td>(0.0623)</td>
</tr>
<tr>
<td>Footwear (221)</td>
<td>-0.2817**</td>
<td>(0.0422)</td>
<td>0.1413**</td>
<td>(0.0447)</td>
</tr>
<tr>
<td>Wood Homes (232)</td>
<td>-0.0702</td>
<td>(0.0380)</td>
<td>0.0313</td>
<td>(0.0341)</td>
</tr>
<tr>
<td>Furniture (242)</td>
<td>-1.017*</td>
<td>(0.0187)</td>
<td>0.0411*</td>
<td>(0.0186)</td>
</tr>
<tr>
<td>Cement, etc. (251)</td>
<td>-1.736*</td>
<td>(0.0787)</td>
<td>-1.173*</td>
<td>(0.0494)</td>
</tr>
<tr>
<td>Steelworks (270)</td>
<td>-0.0022</td>
<td>(0.0116)</td>
<td>0.0020</td>
<td>(0.0113)</td>
</tr>
<tr>
<td>Fab Metal (282)</td>
<td>-0.0080</td>
<td>(0.0240)</td>
<td>0.0711**</td>
<td>(0.0201)</td>
</tr>
<tr>
<td>Screw Mach (290)</td>
<td>0.0210</td>
<td>(0.0537)</td>
<td>0.0011</td>
<td>(0.0608)</td>
</tr>
<tr>
<td>Metal Forgings (291)</td>
<td>-0.0001</td>
<td>(0.0177)</td>
<td>0.0023</td>
<td>(0.0169)</td>
</tr>
<tr>
<td>Misc Fab Met (300)</td>
<td>-0.0307*</td>
<td>(0.0141)</td>
<td>-0.0125</td>
<td>(0.0139)</td>
</tr>
<tr>
<td>Engines (310)</td>
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<td>(0.0303)</td>
<td>0.0055</td>
<td>(0.0249)</td>
</tr>
<tr>
<td>Farm Mach (311)</td>
<td>-2.667**</td>
<td>(0.0496)</td>
<td>0.0773</td>
<td>(0.0471)</td>
</tr>
<tr>
<td>Constr Mach (312)</td>
<td>-0.0623*</td>
<td>(0.0252)</td>
<td>0.0585*</td>
<td>(0.0248)</td>
</tr>
<tr>
<td>Office Mach (321)</td>
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<td>(0.0150)</td>
<td>0.0431**</td>
<td>(0.0155)</td>
</tr>
<tr>
<td>Computers (322)</td>
<td>-0.0640**</td>
<td>(0.0173)</td>
<td>0.0528**</td>
<td>(0.0176)</td>
</tr>
<tr>
<td>Machinery (331)</td>
<td>-0.0567**</td>
<td>(0.0093)</td>
<td>0.0285*</td>
<td>(0.0112)</td>
</tr>
<tr>
<td>Radio, TV (341)</td>
<td>-0.0314*</td>
<td>(0.0124)</td>
<td>0.0162</td>
<td>(0.0145)</td>
</tr>
<tr>
<td>Elec Mach (342)</td>
<td>-0.0233**</td>
<td>(0.0067)</td>
<td>0.0093</td>
<td>(0.0079)</td>
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<td>Motor Veh (351)</td>
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<td>(0.0150)</td>
<td>0.0256</td>
<td>(0.0184)</td>
</tr>
<tr>
<td>Aircraft (352)</td>
<td>-0.0524*</td>
<td>(0.0208)</td>
<td>0.0002</td>
<td>(0.0218)</td>
</tr>
<tr>
<td>Missiles (362)</td>
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<td>(0.0290)</td>
<td>0.0907**</td>
<td>(0.0269)</td>
</tr>
<tr>
<td>Science Instr (371)</td>
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<td>(0.0092)</td>
<td>0.0483**</td>
<td>(0.0099)</td>
</tr>
<tr>
<td>Optical Supp (372)</td>
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<td>(0.0128)</td>
<td>0.0620**</td>
<td>(0.0126)</td>
</tr>
<tr>
<td>Photo Equ (380)</td>
<td>-0.0757*</td>
<td>(0.0294)</td>
<td>0.0423</td>
<td>(0.0288)</td>
</tr>
<tr>
<td>Misc Mfg (391)</td>
<td>-1.081**</td>
<td>(0.0276)</td>
<td>0.0168</td>
<td>(0.0320)</td>
</tr>
</tbody>
</table>

¹Newey-West Standard Errors
* indicates significant at 5% level
** indicates significant at 1% level
### Table 3

**Fiscal Quarter Revenue Effects by Industry Classification**

Dependent Variable: \( \ln(\text{sales}_t) - \ln(\text{sales}_{t-1}) \)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiscal Quarter = 1</td>
<td>-0.0443**</td>
<td>-0.0477**</td>
<td>-0.0481**</td>
<td>-0.0517**</td>
</tr>
<tr>
<td></td>
<td>(.0028)</td>
<td>(.0029)</td>
<td>(.0030)</td>
<td>(.0041)</td>
</tr>
<tr>
<td>Fiscal Quarter = 4</td>
<td>.0245**</td>
<td>.0262**</td>
<td>.0267**</td>
<td>.0264**</td>
</tr>
<tr>
<td></td>
<td>(.0028)</td>
<td>(.0030)</td>
<td>(.0030)</td>
<td>(.0039)</td>
</tr>
<tr>
<td>Calendar Month Effects</td>
<td>yes</td>
<td>by 2-digit industry</td>
<td>by 3-digit industry</td>
<td>by 4-digit industry</td>
</tr>
</tbody>
</table>

N (company quarters) | 23,708 | 23,708 | 19,732 | 12,840 |

\( R^2 \) | .0441 | .1044 | .1665 | .2418 |

** indicates significant at 1% level using Newey-West Standard Errors
### Table 4

**Unisys Fiscal Year Seasonality**

In 1986, Sperry (March fiscal year end) and Burroughs (December fiscal year end) merged to form Unisys (December fiscal year end).

Dependent Variable: $\ln(\text{sales}_t) - \ln(\text{sales}_{t-1})$

<table>
<thead>
<tr>
<th></th>
<th>1880-1993</th>
<th>(Pre-Merger)</th>
<th>(Post-Merger)</th>
<th>All Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calendar Quarter = 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sperry</td>
<td>0.2440**</td>
<td>-.0032</td>
<td>0.1429**</td>
<td>-.0224</td>
</tr>
<tr>
<td>(0.0247)</td>
<td>(0.0250)</td>
<td>(0.0131)</td>
<td>(0.0155)</td>
<td>(0.0188)</td>
</tr>
<tr>
<td>Burroughs</td>
<td>0.0189</td>
<td>0.0668**</td>
<td>0.0419**</td>
<td>0.0454*</td>
</tr>
<tr>
<td>(0.0217)</td>
<td>(0.0222)</td>
<td>(0.0115)</td>
<td>(0.0184)</td>
<td>(0.0164)</td>
</tr>
<tr>
<td>Hypothetical Combined Company</td>
<td>0.0734**</td>
<td>0.1701**</td>
<td>0.1161**</td>
<td>0.2036**</td>
</tr>
<tr>
<td>(0.0217)</td>
<td>(0.0222)</td>
<td>(0.0115)</td>
<td>(0.0184)</td>
<td>(0.0164)</td>
</tr>
<tr>
<td>Unisys</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Calendar Quarter = 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(CQ = 1) * (PostM = 1)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>(CQ = 2) * (PostM = 1)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>(CQ = 4) * (PostM = 1)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

N (quarters)   25         26         25         26         51

R²           .876       .834       .881       .904       .893

* indicates significant at 5% level
** indicates significant at 1% level
"PostM" = Post-Merger

NOTE: This table is not comparable to the previous tables since the calendar and fiscal effects are measured together.
### Table 5

**Philip Morris Fiscal Year Seasonality**

In 1986, General Foods (March fiscal year end) was purchased by Philip Morris (December fiscal year end). The merged company has a December fiscal year end.

Dependent Variable: ln(sales$_t$) - ln(sales$_{t-1}$)  
1982-1993

<table>
<thead>
<tr>
<th></th>
<th>Pre-Merger</th>
<th>Hypothetical Combined Company</th>
<th>Post-Merger</th>
<th>Combined Company</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>General Foods</td>
<td>Philip Morris</td>
<td>Combined Company</td>
<td>Philip Morris</td>
</tr>
<tr>
<td>Calendar Quarter = 1</td>
<td>0.0403 (.0241)</td>
<td>-0.0692** (.0069)</td>
<td>-0.0410** (.0069)</td>
<td>-0.0104 (.0112)</td>
</tr>
<tr>
<td>Calendar Quarter = 2</td>
<td>0.0588** (.0203)</td>
<td>-0.0041 (.0076)</td>
<td>0.0108 (.0076)</td>
<td>0.0402** (.0097)</td>
</tr>
<tr>
<td>Calendar Quarter = 4</td>
<td>-0.0046 (.0214)</td>
<td>-0.0710** (.0081)</td>
<td>-0.0563** (.0081)</td>
<td>-0.0069 (.0097)</td>
</tr>
<tr>
<td>(CQ = 1) * (PostM = 1)</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>(CQ = 2) * (PostM = 1)</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>(CQ = 4) * (PostM = 1)</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>

| N (quarters) | 26 | 23 | 23 | 28 | 51 |
| R$^2$ | .320 | .855 | .796 | .882 | .678 |

* indicates significant at 5% level  
** indicates significant at 1% level  
"PostM" = Post-Merger

**NOTE:** This table is not comparable to the tables above because the calendar and fiscal effects are measured together.
### Table 6
Manager and Salesperson Incomes

Measured over a continuous year on the same job -- 1984-1988 SIPP

<table>
<thead>
<tr>
<th></th>
<th>(1) All Industries</th>
<th>(2) Manufacturing</th>
<th>(3) All Industries</th>
<th>(4) Manufacturing</th>
<th>(5) All Industries</th>
<th>(6) Manufacturing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income Regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.0763*** (0.0028)</td>
<td>0.0739*** (0.0040)</td>
<td>-0.0004 (0.0009)</td>
<td>-0.0025 (0.0013)</td>
<td>-0.0159 (0.0152)</td>
<td>-0.0243 (0.0245)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.2943*** (0.0156)</td>
<td>-0.2834*** (0.0212)</td>
<td>-0.0051 (0.0049)</td>
<td>-0.0136 (0.0070)</td>
<td>-0.0874 (0.0848)</td>
<td>-0.1738 (0.1284)</td>
</tr>
<tr>
<td>Age</td>
<td>0.0110*** (0.0006)</td>
<td>0.0126** (0.0008)</td>
<td>-0.0006** (0.0002)</td>
<td>-0.0008** (0.0003)</td>
<td>-0.0143*** (0.0033)</td>
<td>-0.0172** (0.0050)</td>
</tr>
<tr>
<td>Married</td>
<td>0.1074** (0.0142)</td>
<td>0.1048** (0.0197)</td>
<td>0.0024 (0.0045)</td>
<td>0.0051 (0.0065)</td>
<td>0.0041 (0.0768)</td>
<td>-0.0661 (0.1178)</td>
</tr>
<tr>
<td>Executive/Manager</td>
<td>0.2037** (0.0172)</td>
<td>0.1663** (0.0221)</td>
<td>-0.0288** (0.0054)</td>
<td>-0.0335** (0.0073)</td>
<td>-0.3884*** (0.0924)</td>
<td>-0.3783** (0.1293)</td>
</tr>
<tr>
<td>Professional</td>
<td>0.0070 (0.0208)</td>
<td>-0.0459 (0.0268)</td>
<td>-0.0423** (0.0065)</td>
<td>-0.0511** (0.0088)</td>
<td>-0.5438*** (0.1136)</td>
<td>-0.6256** (0.1623)</td>
</tr>
<tr>
<td>Sales Mgr</td>
<td>0.0949** (0.0212)</td>
<td>0.1149 (0.0858)</td>
<td>-0.0225** (0.0067)</td>
<td>0.0578* (0.0282)</td>
<td>-0.2472*** (0.1122)</td>
<td>0.2704 (0.4913)</td>
</tr>
<tr>
<td>N</td>
<td>4,743</td>
<td>2,301</td>
<td>4,743</td>
<td>2,301</td>
<td>4,743</td>
<td>2,301</td>
</tr>
</tbody>
</table>

R²                | .429               | .493               | .059               | .081              | ---                | ---               |

1Columns 1 and 2: OLS where dependent variable is ln(average monthly income).
2Columns 3 and 4: OLS where dependent variable is standard deviation of monthly income.
3Columns 5 and 6: Logit where dependent variable = 1 if year contains a month where pay > 25% higher than an average month in the year.

Each Estimate includes controls for state and 3-digit industry.
Omitted Occupation Category is Salesperson.

* indicates significant at 5% level
** indicates significant at 1% level
Table 7
Fiscal Quarter Price Effects

Dependent Variable:
\[-(\ln(1 - \text{gross margin}_q) - \ln(1 - \text{gross margin}_{q-1}))\]

3-digit Industry Classifications

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiscal Quarter = 1</td>
<td>---</td>
<td>0.0072**</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0018)</td>
<td></td>
</tr>
<tr>
<td>Fiscal Quarter = 4</td>
<td>---</td>
<td>-.0166**</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.0019)</td>
<td></td>
</tr>
<tr>
<td>Fiscal Quarter Effects by Industry</td>
<td>no</td>
<td>no</td>
<td>yes*</td>
</tr>
<tr>
<td>Calendar Month Effects by Industry</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

|               | 18,792 | 18,792 | 18,792 |
| N (company quarters) |       |        |        |
| R²              | .0303  | .0385  | .0476  |

NOTE: Coefficients are the effect on price. A positive coefficient implies a higher price. Also, there are fewer observations than in table 2 because some quarterly cost of goods sold observations are unavailable.

** indicates significant at 1% level using Newey-West Standard Errors

*These individual coefficients and standard errors are reported in table 7a.
Table 7a  
Fiscal Quarter Gross Margin Effects by Industry

(Coefficients from Regression Detailed in Column 3 of Table 7)  
3-digit Classifications

<table>
<thead>
<tr>
<th>3-digit Industry</th>
<th>1st Quarter Effect</th>
<th>(NW S.E.)¹</th>
<th>4th Quarter Effect</th>
<th>(NW S.E.)¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat (100)</td>
<td>.0108</td>
<td>(.0087)</td>
<td>-.0078</td>
<td>(.0062)</td>
</tr>
<tr>
<td>Canned Food (102)</td>
<td>.0279*</td>
<td>(.0135)</td>
<td>-.0032</td>
<td>(.0138)</td>
</tr>
<tr>
<td>Grain (110)</td>
<td>.0112</td>
<td>(.0112)</td>
<td>-.0052</td>
<td>(.0144)</td>
</tr>
<tr>
<td>Beverages (120)</td>
<td>.0739**</td>
<td>(.0284)</td>
<td>.0347</td>
<td>(.0185)</td>
</tr>
<tr>
<td>Other Food (122)</td>
<td>-.0184</td>
<td>(.0112)</td>
<td>-.0038</td>
<td>(.0108)</td>
</tr>
<tr>
<td>Knitting (132)</td>
<td>.0006</td>
<td>(.0069)</td>
<td>.0024</td>
<td>(.0063)</td>
</tr>
<tr>
<td>Yarn, Thread (142)</td>
<td>.0059</td>
<td>(.0102)</td>
<td>.0065</td>
<td>(.0152)</td>
</tr>
<tr>
<td>Apparel (151)</td>
<td>.0133</td>
<td>(.0104)</td>
<td>-.0160*</td>
<td>(.0067)</td>
</tr>
<tr>
<td>Printing (172)</td>
<td>-.0036</td>
<td>(.0058)</td>
<td>-.0185</td>
<td>(.0101)</td>
</tr>
<tr>
<td>Drugs (181)</td>
<td>.0011</td>
<td>(.0148)</td>
<td>-.0184</td>
<td>(.0120)</td>
</tr>
<tr>
<td>Soap (182)</td>
<td>.0003</td>
<td>(.0135)</td>
<td>-.0672**</td>
<td>(.0189)</td>
</tr>
<tr>
<td>Paint (190)</td>
<td>.0173</td>
<td>(.0098)</td>
<td>-.0124</td>
<td>(.0105)</td>
</tr>
<tr>
<td>Agric Footwear (191)</td>
<td>.0595**</td>
<td>(.0216)</td>
<td>-.0722**</td>
<td>(.0217)</td>
</tr>
<tr>
<td>Footwear (221)</td>
<td>.0055</td>
<td>(.0110)</td>
<td>.0354**</td>
<td>(.0104)</td>
</tr>
<tr>
<td>Wood Homes (232)</td>
<td>-.0033</td>
<td>(.0059)</td>
<td>-.0089</td>
<td>(.0140)</td>
</tr>
<tr>
<td>Furniture (242)</td>
<td>-.0004</td>
<td>(.0098)</td>
<td>-.0059</td>
<td>(.0127)</td>
</tr>
<tr>
<td>Cement, etc. (251)</td>
<td>-.0543*</td>
<td>(.0237)</td>
<td>-.0358*</td>
<td>(.0168)</td>
</tr>
<tr>
<td>Steelworks (270)</td>
<td>.0044</td>
<td>(.0052)</td>
<td>.0021</td>
<td>(.0053)</td>
</tr>
<tr>
<td>Fab Metal (282)</td>
<td>.0067</td>
<td>(.0099)</td>
<td>-.0086</td>
<td>(.0061)</td>
</tr>
<tr>
<td>Screw Mach (280)</td>
<td>.0341</td>
<td>(.0257)</td>
<td>.0437</td>
<td>(.0254)</td>
</tr>
<tr>
<td>Metal Forgings (291)</td>
<td>.0000</td>
<td>(.0081)</td>
<td>-.0084</td>
<td>(.0168)</td>
</tr>
<tr>
<td>Misc Fab Met (300)</td>
<td>-.0011</td>
<td>(.0128)</td>
<td>-.0223</td>
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²The omitted category is manufacturing.
* indicates significant at 5% level
Table 8b
Determinants of Fiscal Revenue and Price Effects
3-digit Industry Classifications

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<td>6</td>
<td>188</td>
</tr>
<tr>
<td>Toys (390)</td>
<td>13</td>
<td>424</td>
</tr>
<tr>
<td>Misc Mfg (391)</td>
<td>14</td>
<td>492</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>981</strong></td>
<td><strong>31,935</strong></td>
</tr>
</tbody>
</table>
### Appendix Table 2

**Summary Statistics for Managers and Salespeople**

<table>
<thead>
<tr>
<th></th>
<th>1984-1988 SIPP¹</th>
<th></th>
<th>1990 Census</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Salespeople</td>
<td>Sales Managers</td>
<td>Managers</td>
<td>Professionals</td>
</tr>
<tr>
<td>Age</td>
<td>38.3</td>
<td>38.9</td>
<td>42.3</td>
<td>38.2</td>
</tr>
<tr>
<td></td>
<td>(11.2)</td>
<td>(10.3)</td>
<td>(10.4)</td>
<td>(10.9)</td>
</tr>
<tr>
<td>Years of Education</td>
<td>14.4</td>
<td>13.8</td>
<td>14.9</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td>(2.1)</td>
<td>(2.2)</td>
<td>(2.3)</td>
<td>(2.1)</td>
</tr>
<tr>
<td>% Female</td>
<td>16.9%</td>
<td>9.6%</td>
<td>18.0%</td>
<td>42.1%</td>
</tr>
<tr>
<td>% Married</td>
<td>70.4%</td>
<td>74.4%</td>
<td>78.1%</td>
<td>62.0%</td>
</tr>
<tr>
<td>% Minority</td>
<td>4.8%</td>
<td>2.9%</td>
<td>3.5%</td>
<td>8.1%</td>
</tr>
<tr>
<td>Salary</td>
<td>$34,482</td>
<td>$35,714</td>
<td>$47,521</td>
<td>$34,186</td>
</tr>
<tr>
<td>(1990 dollars)</td>
<td>(17,824)</td>
<td>(19,591)</td>
<td>(23,821)</td>
<td>(17,448)</td>
</tr>
<tr>
<td>Monthly</td>
<td>0.172</td>
<td>0.154</td>
<td>0.141</td>
<td>0.127</td>
</tr>
<tr>
<td>Standard Deviation²</td>
<td>(0.137)</td>
<td>(0.124)</td>
<td>(0.123)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Spike³</td>
<td>43.5%</td>
<td>39.7%</td>
<td>33.6%</td>
<td>30.4%</td>
</tr>
<tr>
<td>% Annual Turnover</td>
<td>20.2%</td>
<td>13.5%</td>
<td>15.0%</td>
<td>12.7%</td>
</tr>
<tr>
<td>Observations</td>
<td>1,083</td>
<td>585</td>
<td>2,257</td>
<td>818</td>
</tr>
</tbody>
</table>

¹Except for the turnover measure, each observation is a job-year where the person stayed in the same job. One person can account for up to two observations.

²Within-year standard deviation of the log of monthly earnings.

³% of observations with at least one month where earnings are more than 25% greater than average monthly earnings for the year.

Standard Deviations are in Parentheses
Appendix A: Mathematical Appendix to Section 3-B -- “Effort Gaming”

Assume that a risk neutral firm employs a risk neutral salesperson, who is paid a bonus \( b \) if sales during the year reach a quota \( Q' \). The year is split into two fiscal periods. The agent chooses a level of effort for the first fiscal period \( (e_1) \), observes sales for the first fiscal period \( (x_1) \), chooses effort for the second fiscal period \( (e_2) \), and observes \( x_2 \). If \( x_1 + x_2 \geq Q' \), the agent is paid \( b \).

Make the following assumptions: \( x_i \) is distributed \( g(x_i | e) \), with cumulative density \( G(x_i | e) \), where \( g \) is differentiable in \( x \) and \( e \), for \( x \in \mathbb{R} \) where \( \bar{x} < \infty \); \( g(x_i | e) \) increases to a single peak and then declines; \( G_e(x_i | e) \) is strictly negative at any \( x \) which has positive density; the salesperson discounts expected utility by a factor of \( \delta < 1 \) per fiscal period; and the salesperson’s disutility of effort is \( v e^2 \) each fiscal period. The salesperson chooses effort each fiscal period to maximize expected utility for the fiscal year, where expected utility is discounted expected bonus payments minus discounted expected disutility of effort:

\[
E[utility | e_1, e_2, (x_i)] = \delta b (1 - \int_0^{Q'} G(Q' - x_i | e_i) g(x_i | e_i) dx_i) = \nu (e^2 + \delta \int_0^{Q'} e_i^2 g(x_i | e_i) dx_i). \tag{A1}
\]

\( e_i \) is a function of \( x_i \) because the salesperson chooses second-period effort after seeing his position relative to quota.

The agent’s second-period problem,

\[
\max_{e_2} -\nu e_2^2 + b (1 - G(Q' - x_i | e_i)) \tag{A2}
\]

leads to the first order condition

\[
e_2 = \frac{-b G(Q' - x_i | e_i)}{2 \nu}. \tag{A3}
\]

Working backwards, the salesperson’s first-period problem is

\[
\max_{e_1} -\nu e_1^2 - \delta E[\nu e_2^2] + \delta E[bonus] \tag{A4}
\]

which, based on (A3), can be restated
\[ \max_{t_i} -v e_i^2 - \frac{b^2 \delta}{4v} \int_0^{\sigma^*} G_i(Q^*-x_i | e_i) g(x_i | e_i) dx_i + \delta b \int_0^{\sigma^*} G(Q^*-x_i | e_i) g(x_i | e_i) dx_i. \] (A5)

This leads to the first order condition

\[ e_i = \delta E(e_i) - \frac{\delta b}{8v^2} \int_0^{\sigma^*} G_i(Q^*-x_i | e_i) g(x_i | e_i) dx_i \] (A6)

or

\[ e_i = \delta E(e_i) - \left( \frac{\delta v}{2} \right) \frac{dE(e_i)}{de_i}. \] (A7)

For quotas above a certain level, effort and sales will be lower, on average, in the first period than in the second period. This can be proved as follows. Define \( e^* = e_i + E(e_i) \) at the optimal solution for the salesperson. Assume that \( e_i = \delta E(e_i) \) (so that \( e^* = (1+\delta)e_i \) at the optimal solution). The derivative of the salesperson's optimization of \( e_i \), from (A5) and (A6), is

\[ 2\delta \delta e_i - \frac{\delta b^2}{4v} \int_0^{\sigma^*} G(Q^*-x_i | e_i) g(x_i | e_i) dx_i. \] (A8)

For quotas near enough to \( 2\sigma \), the integral term will only include values of \( x_i \) for which \( g(x_i | e_i) > 0 \).

Thus, the entire derivative will be negative and the salesperson would choose to lower first period effort. Since first period effort is already lower, on average, than second period effort, it must be true that optimal first period effort is less than expected second period effort.

Similarly, effort and sales are higher in the first period if the quota is low enough, so, by the Intermediate Value Theorem, there exists some quota such that effort and sales are the same, on average, in the two periods. This is illustrated in figure 3.
Appendix B: Mathematical Appendix to Section 3-C -- "Timing Gaming"

Consider a fiscal year with two fiscal periods and let the sales quota be based on sales over the whole fiscal year. The salesperson optimizes expected utility over the current fiscal year (year y) and the next one (year z), where the quota and the bonus are constant over the two years. Thus, he is concerned with four fiscal periods, with respective sales $x_1$, ..., $x_4$. To be specific: the salesperson receives a bonus, $b$, at the end of year y (i.e., the end of the second fiscal period), if $x_1 + x_2 \geq Q'$, where $Q' < 2\bar{x}$ and $\bar{x} < \infty$. He receives $b$ at the end of year z (fourth period), if $x_3 + x_4 \geq Q'$.

Assume a pre-determined salesperson effort level that is constant across all four periods. After observing $x_1$, the salesperson decides how much of the potential business that would naturally fall into period 3 he will try to pull into period 2. In order to pull in business, however, the salesperson has to offer a price break that is greater than the firm’s (and the salesperson’s) discount factor, $\delta$. Alternatively, the salesperson may push out period 2 business into period 3, thereby lowering the expected value of such sales by $\delta$.

Define $\lambda$ to be a summary statistic of the salesperson’s optimal pull-in/push-out decision, given $x_1$, where $\lambda = 1$ is the “natural” level or the level for salespeople who cannot influence the timing of sales. Assume that sales are now determined by $x_i = r(\lambda) + \eta_i$ and $x_i = s(\lambda) + \eta_i$, where $r$ is monotonically increasing in $\lambda$ and $s$ is monotonically decreasing in $\lambda$. The distribution of sales in period i ($i = 1, 2, 4$) is now represented by $g(x_i | \lambda)$, with first and fourth period sales always distributed $g(x_i | 1)$ and $g(x_i | 1)$, respectively. Because $\lambda$ has opposite effects on the second and third periods, let $f(x_i | \lambda)$ be the sales distribution for the third period.

Let $E[x_i | \lambda = 1] = x'$. The salesperson, after observing $x_1$, chooses a pull-in/push-out strategy which determines $\lambda \in [\lambda_{\min}, \lambda_{\max}]$ at the end of the first period. Maximum and minimum $\lambda$ depend on how customers make their purchasing decisions, but it must be the case that $1 \geq \lambda_{\min} \geq 0$ and $1 \leq \lambda_{\max} \leq 1 + \delta$. Assume $E[x_i | \lambda] = \lambda x'$. That is, the salesperson can attempt to take some of the potential business from the third period and move it into the second, or vice versa. If the salesperson sets $\lambda <
1, sales are made later at a discounted present value. When \( \lambda > 1 \), he is pulling in though it is not in the firm’s best interests, so \( \mathbb{E}[x_t | \lambda > 1] < \delta(2-\lambda)x^\ast \). Assume \( \mathbb{E}[x_t | \lambda] = (2-\lambda)x^\ast \) if \( \lambda \leq 1 \), but \( \mathbb{E}[x_t | \lambda] = (2-\alpha\lambda)x^\ast \) if \( \lambda > 1 \), where \( \alpha > 1/\delta \).

These effects on the expected value of sales imply

\[
-F\lambda(x|1-e) = G\lambda(x|1-e) \quad \text{and} \quad (B1)
\]

\[
|F\lambda(x|1+e)| > |G\lambda(x|1+e)| \quad (B2)
\]

for small, positive \( e \). \( f(x|x) \) holds with strict equality for \( e = 0 \), so there is a discontinuity in \( f\lambda(x|x) \) at \( \lambda = 1 \).

To insure a solution, assume that the objective function of the agent (when choosing \( \lambda \)) has a single interior maximum when the first period outcome is high enough to make it possible to reach quota without gaming, but \( \lambda = \lambda_{\text{max}} \) (i.e., there is a corner solution) when \( Q^- - x_t \geq \bar{x} \). Then it will be clear when the salesperson will pull in and when he will push out. I use the likelihood of pulling in versus pushing out as an indicator of unnatural seasonality.

The decision about where to set \( \lambda \) comes down to a comparison of three values. First, without loss of generality, normalize the bonus such that \( b = 1 \) and define \( B_y \) to be the salesperson’s expected marginal increase (decrease) in year \( y \) bonus payments due to increasing (decreasing) \( \lambda \) from 1, given \( x_t \).

\[
B_y = \int_0^{Q^- - x_t} G\lambda(x_t | \lambda = 1)dx_t = -G\lambda(Q^- - x_t | \lambda = 1) \quad (B3)
\]

Second, define \( B_{z} \) to be the discounted expected marginal increase in year \( z \) bonus payments due to decreasing \( \lambda \) from 1 (note that this is not dependent on \( x_t \)).

\[
B_{z} = \delta \int_0^{Q^- - x_t} G(Q^- - x_t | 1)f\lambda(x_t | \lambda = 1-e)dx_t \quad (B4)
\]

Integrating by parts yields
\[ B_{x} = \frac{3}{9} F_{1}(x_{r}|\lambda = 1) g(Q^* - x_{r}|\lambda = 1 - \varepsilon) \, dx_{r} \quad (B5) \]

For any \( Q^* < 2 \bar{x} \), \( B_{x} > 0 \).

Finally, define \( B_{x} \) to be the expected marginal decrease in year \( z \) bonus payments due to increasing \( \lambda \) from 1. From (B1) and (B2), \( B_{x} > B_{z} > 0 \). The salesperson's decision rules are detailed in section 3-C.

If \( \alpha \) is not "too big", then there will be a range of \( x_{r} \) for which the salesperson will choose a pull-in strategy. This range will include \( x_{r} = Q^* - x^{\alpha} \) where \( x^{\alpha} \) is the modal outcome of \( x \), given \( \lambda = 1 \), as long as \( 0 < Q^* - x^{\alpha} < \bar{x} \). To see why, note that \( B_{x} \) is maximized at \( x_{r} = Q^* - x^{\alpha} \) if \( Q^* - x^{\alpha} \) is positive and can be reached in the first period. For the \( x_{r} \) at which \( B_{x} \) is maximized, it must be the case that \( B_{x} > B_{z} \) because \( B_{x} \) is the maximum of \( G_{z} \), while \( B_{x} \) is less than the expected value of \( G_{z} \). Now define \( h(\alpha) \) such that \( B_{x} = h(\alpha)B_{z} \), where \( h(\alpha) > 1 \) and \( h' < 0 \). If \( \alpha \) is small enough, then the maximum \( B_{y} \) will be greater than \( B_{x} \) and the salesperson will pull in business from year \( z \).

If the quota is either very high or very low, the push-out effect will dominate because the salesperson will often give up on making quota this year, or already have reached his quota, after the first fiscal period. Therefore, because the amount of gaming is large at extreme quotas, there will be an interior quota (that is, \( 0 < Q^* < 2 \bar{x} \)) such that the probability of gaming is minimized, and an interior quota at which the absolute value of the difference in the probabilities of pulling in and pushing out is minimized.

To prove this, note that as \( Q^* \) approaches \( 2 \bar{x} \) or 0, the probability that the salesperson will push out goes to 1. However, as the quota is moved away from these extremes, the likelihood that there will be no gaming (that is, that \( x_{r} \) will satisfy \( B_{x} < B_{y} < B_{z} \)) must increase because \( B_{x} \) and \( B_{z} \) are moving apart and the \( x_{r}'s \) that satisfy no gaming are becoming higher density outcomes. Thus, both the probability that there will be no gaming and the absolute value of the difference in the probability of
pushing out and the probability of pulling in decrease as $Q'$ moves away from the extreme values and so there must be an interior $Q'$ at which each of these measures of sales dissymmetry are minimized.

Another way to minimize gaming is to add a linear commission to compensation. Commissions are a disincentive to pulling-in and pushing-out because they increase the value of leaving sales in their "natural" period. Mathematically, if a linear commission of $c$ is added to the compensation scheme, then $B_1$ is increased by $cx^*$, while $B_{-1}$ is increased by $\delta cx^*$ and $B_0$ is increased by $a \delta cx^*$. This makes (a) and (b), in the decision rules in section 3-C, less likely.