Tacit Collusion and Voluntary Disclosure:
Theory and Evidence from the U.S. Automotive Industry

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Abstract

This study examines how industry peers share information when they are engaged in tacit collusion. We develop a model of firms' information sharing and production decisions and use it to establish that firms engaged in tacit collusion are more likely to share information when current market demand is low and when the firms' decision horizon is long. Using 31 years of monthly production forecast data shared among the Big Three U.S. automobile manufacturers, we find empirical evidence that is generally consistent with the predictions of the model. The frequency, horizon and accuracy of the shared production forecasts decrease when the expected demand increases, suggesting less information sharing when firms have greater incentives to compete aggressively to capture greater current demand rather than to tacitly agree to restrict production. The production forecast frequency and horizon also decrease when the firms focus more on short-term profit, consistent with less information sharing when firms place less weight on the future benefit from tacit collusion.

1. Introduction

Prior theory in accounting has analyzed how product market competition among industry peers affects their incentive to voluntarily disclose in a one-shot interaction (Verrecchia 1983, Darrough 1993). Empirical studies have used these one-period models as a basis for developing and testing associated hypotheses with mixed results (Bamber and Cheon 1998, Li 2010). However, firms in most industries typically interact repeatedly. Research in industrial organization (Green and Porter 1984, Rotemberg and Saloner 1986, Bresnahan 1987) has established how repeated interactions can discipline firms to restrict production and reduce the intensity of competition, leading to tacit collusion in production among the firms. In a repeated interaction context, a firm that deviates from the tacit

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collusive agreement by increasing production in the current period can earn high current profit, but at the cost of intensive future competition. When the threat of intense future competition outweighs the benefit of increased current profit, firms will honor the tacit agreement to restrict production in the current period. While firms engaged in tacit collusion concerning operational decisions are likely to share information among themselves in a distinctive manner, few studies have investigated this issue. We analyze the role of tacit collusion with information sharing by first modeling how firms engaged in tacit collusion share information among themselves, and then empirically testing the model's predictions using production forecasts by the three major automakers.

Our model examines a duopoly in which the firms engage in repeated quantity competition. In each period, both firms observe a public signal about current industry demand conditions and each firm also observes an additional private signal about the industry demand. The common public signal might represent a macroeconomic forecast that is likely to affect demand for industry products. The private signal reflects each firm's unique information about the strength of consumer demand. We assume that firms publicly commit to whether to share their private signal after observing the public signal but prior to making their production decisions for the period. Each firm then chooses their production quantity to maximize their expected profits based on all available information.

Information sharing has two effects on product market competition in a one-period interaction with quantity competition. First, it gives both firms the ability to adapt their production quantity more precisely to current demand, thereby coordinating the industry toward more profitable production plans. Second, information sharing creates a potential proprietary cost by allowing each firm to better forecast the quantity chosen by its competitor, which increases the potential payoff to a given firm from expanding production to capture greater market share. Similar to the analysis in Gal-Or (1985) and Darrough (1993), we show that because the latter proprietary cost effect dominates, each firm is better off not sharing their demand information in a one-period interaction.

A multi-period tacit agreement preserves the first effect while providing a means of disciplining the second, proprietary cost effect. The first effect represents the potential benefit of increased profit via coordinated restrictions on production, and continues to hold in all future periods as long as the tacit agreement is sustained. In contrast, the second proprietary cost effect in the form of increased competition to gain market share in the current period can now be disciplined by the threat of future retaliation in such a form as price wars. Under a tacit collusion agreement, the threat of future intense competition (price wars) discourages firms from deviating from the tacit agreement by expanding production, and thus reduces the proprietary cost of information sharing. Hence, information sharing is more attractive in a multi-period tacit collusion setting.

Factors that strengthen the tacit agreement will reduce the current competition intensity and the associated proprietary costs of information sharing, leading to more information sharing. Following Rotemberg and Saloner (1986), when expected current demand is low, firms reap relatively less additional profit via deviating from the tacit agreement by expanding their current production, making the disciplining threat of competition in future periods relatively more effective. Hence, our first cross-sectional prediction is that in periods of low expected current market demand (i.e., a low public signal about industry demand), the tacit agreement is more effective and firms are more likely to share their private information with each other. Our second prediction concerns the decision horizon of firms. To the extent that firms weigh current period profit more and future profit less, the disciplining threat of competition in future periods will be less effective, leading to more current competition and less information sharing.

We empirically test these predictions using data on shared information in the form of U.S. automobile industry production forecasts from 1965 to 1995. For most of this sample period, GM, Ford and Chrysler accounted for more than 70% of total U.S. automobile industry revenue. Throughout the 31 years of the sample period, the industry enjoyed significant protection from competition as a result of various barriers to entry, such as scale economies, technology and trade protection. Further, these three geographically concentrated firms interacted repeatedly. The limited number of competitors, significant entry barriers and repeated interaction among the competitors all facilitate tacit collusion (Bresnahan 1987).[1]

Over our sample period, each of the three major firms chose each month whether to disclose information in the form of monthly production forecasts to Wards, an automobile industry trade publication. For all months in which all three firms supplied production forecasts, Wards then published the forecasts in its weekly newsletters. In this way each firm strategically chose whether to share its production forecast with rivals via Wards weekly newsletters. Compared with earnings forecasts, these production forecasts are likely to be more informative about the strength of market demand, enabling the industry to coordinate total output more precisely. We next describe our empirical analysis of tacit collusion and information sharing over this sample period.

Given that the automakers have discretion on the frequency, horizon and accuracy of their production forecasts for each production month, we measure the extent of information sharing along these three dimensions. We define forecast frequency as the total number of forecasts issued for a given production month, forecast horizon as the number of days from the issue of the first forecast for that production month to the end of the production month, and forecast error as the absolute difference between the actual production and the forecast issued at the beginning of each production month, deflated by each firm's average actual production during the sample period, following Doyle and Snyder (1999). We measure the strength of economic demand using the unemployment

[1] See Bresnahan (1987) for further evidence of collusion in the automotive industry. Consistent with our model, Bresnahan finds that periods of greater industry profitability weaken the tacit agreement.

rate and define the firms' decision horizon in two ways. The first is based on the extent of financial distress the firms face, as measured by the lowest ZSCORE among the three firms. This measure reflects that firms under greater financial stress are likely to place greater emphasis on short-term profits. The second decision horizon measure is an indicator variable that equals one when at least one of the three firms has a CEO who is about to leave the company, again promoting a short-term focus in firm decisions.

Consistent with our first conjecture that more information sharing will take place when the expected demand is low, we find that the automakers issue production forecasts more frequently, issue their first forecast for a given month earlier, and issue more accurate forecasts when the unemployment rate is higher. In terms of economic magnitude, when the unemployment rate increases from the first quartile to the third quartile; i.e., by 2%, the three firms issue two more forecasts for a production month, their first forecast is issued 28 days earlier, and their forecast error declines 1.9% compared to the average forecast error of 4.6%. We also find that automakers issue production forecasts less frequently and issue their first forecast for a given month later during short-horizon periods, supporting our second conjecture that there is less information sharing when at least one firm faces strong pressure to focus heavily on short-term performance. We do not find significant evidence that automakers decrease their forecast accuracy during short-horizon periods.

We conduct four additional analyses to corroborate our findings. First, to provide direct evidence on information sharing, we confirm that the firms incorporate more information from their peers' production forecasts into their own forecasts when the unemployment rate is high. Second, when we exclude the years 1990-1995 during which the three firms' combined market share fell below 70% from our sample, the empirical results continue to hold. Third, the absolute forecast error increases with both forecast bias and noise. Doyle and Snyder (1999) show that the production forecasts are on average optimistically biased. To control for the bias, we also measure production forecast accuracy based on the R-squared statistic or the standard deviation of the residual from a regression of actual production on production forecasts. We find that the unemployment rate is significantly and positively associated with the R-squared value and negatively associated with the standard deviation of residuals, consistent with our first prediction. Finally, our results are also robust to using an alternative financial distress indicator, which equals one if at least one of the three firms receives a non-investment grade credit rating.

The study contributes to the voluntary disclosure literature by focusing on information sharing among firms engaged in tacit collusion in a particular industry. The industrial organization literature has shown that firms in different industries interact in various ways, ranging from Cournot to Bertrand competition and from fierce competition to tacit collusion. Darrough (1993) establishes that these different interactions can lead to different information sharing patterns among industry peers. Because prior studies have not modeled information sharing among industry peers in multi-period tacit collusion, we first develop a model to derive predictions concerning the form of such information sharing in tacit collusion. We then empirically test the model's predictions on disclosure characteristics using the automobile industry data described above. We find that information sharing can arise in industries as highly concentrated as the U.S. auto industry. We also demonstrate that when economic conditions worsen, as evidenced by higher unemployment rate, firms issue production forecasts more frequently and issue more accurate forecasts, consistent with more information sharing when the proprietary cost of the information sharing is reduced.

Our paper extends the voluntary disclosure literature by providing combined analytical and empirical evidence on the information sharing of firms engaged in tacit agreements. Although we use the automobile industry to test our predictions, the intuition would appear to generalize to other industries in which there is evidence of tacit collusion, including certain manufacturing sectors, the airline industry, the telecommunication industry, and the electricity (utilities) industry (see Ciliberto and Williams, 2014; U.S. v. Apple 2013; US v. AU Optronics 2012; Bajari and Yeo, 2009; Knittel and Stango 2003; Bolle, 1992; Slade, 1987; U.S. v. Container Corp. 1969). Our findings also have potential regulatory implications. The cases of *American Column Co.* v. *United States* (1921) and *Maple Flooring Mfrs. Ass'n* v. *United States* (1925) document early antitrust actions against information sharing in trade associations. To our knowledge, our paper is the first to show how information sharing under tacit agreement can potentially facilitate coordination of total industry production to the detriment of consumers.

2. Literature Review

The early accounting and economics disclosure literature examines the determinants of voluntary disclosure in the context of financial reporting when the informed seller of a firm can make a truthful disclosure to maximize market perceptions about the firm's financial condition. The unraveling theory (Grossman 1981, Milgrom 1981) establishes conditions that result in full-disclosure because firms with more favorable information in any withholding region would always be better off disclosing their information. Empirical evidence, however, is generally at odds with this prediction. For example, executives contend that disclosed information is likely to be used by competitors in ways that impose proprietary costs on the disclosing firm. A large follow-up literature thus argues that proprietary costs create the tension that limits voluntary disclosures (Verrecchia 1983, Dye 1986).

Darrough (1993) demonstrates that in competitive environments the coordination benefits of disclosure may or may not exceed the proprietary costs. In particular, she shows that in a single period Cournot duopoly competition, the proprietary costs will exceed the coordination benefits and firms will prefer not to share information. The only study of which we are aware to analyze voluntary disclosure in a tacit collusion setting is Bertomeu and Liang (2015). They address the decision of a single firm concerning whether or not to disclose a private signal, permits different firms to use asymmetric disclosure strategies. Our approach has more in common with Darrough (1993) in that firms make symmetric choices with respect to the precision of the information system. Subsequent literature identifies features of the competitive environment that can affect the magnitude of proprietary costs, such as the regulatory regime in place or the effect of proprietary costs on entry or exit of competitors (Feltham, Gigler and Hughes 1992, Chen and Jorgensen 2012, Suijs and Wielhouwer 2012).

Theoretical models demonstrate how firms' disclosure strategies vary with the nature of the interaction among industry peers. In contrast, rather than analyzing the characteristics of the interaction in different industries, empirical studies on competition and disclosure focus primarily on how disclosure characteristics vary with some general measures of competition, such as industry concentration levels, market to book ratios and industry profitability. The associated findings are mixed. For example, Bamber and Cheon (1998) predict that when proprietary costs are high, firms prefer to issue less accurate earnings forecasts and release the forecasts through a venue to which information users have limited access. They argue that firms with more growth opportunities and in more concentrated industries bear higher proprietary costs. The empirical findings in Bamber and Cheon are generally consistent with their predictions. In contrast, Li (2010) assumes that firms in more concentrated industries face lower competition from their industry peers and bear lower proprietary costs. She finds that firms in more concentrated industries are more likely to issue forecasts for future earnings and capital expenditure than firms in less concentrated industries. Ali, Klasa and Yeung (2014) argue that both public and private firms need to be included when calculating an industry concentration ratio. After including private firms in the ratio calculations, they find that firms in more concentrated industries are less likely to issue earnings forecasts and their forecast horizon is shorter.

Several studies analyze a particular industry characterized by economic conditions or the presence of observable information that support testing a theory of voluntary disclosure. For example, Doyle and Snyder (1999) use the production forecasts issued by the big three automakers and document that the automakers incorporate the production forecasts issued by their peers in their subsequent production forecasts. Bhojraj, Blacconiere and D'Souza (2004) examine the impact of increased competition after the deregulation of the electric utility industry on the information content in firms' annual financial reports. They focus primarily on the trade-off between competition and external financial reporting needs. None of prior studies, however, have considered how firms engaged in tacit collusion voluntarily disclose information.

A concurrent study by Rogers, Schrand and Zechman (2014) investigates whether and how multiple firms engage in tacit collusion by withholding industry-wide bad news in response to stock price pressure. Despite the common focus on tacit collusion, our paper differs from Rogers et al. in several ways. First, the tacit collusion in Rogers et al. is with respect to what information to disclose to investors, whereas in our study tacit collusion is with respect to how much each firm will produce. Second, Rogers et al. demonstrate that firms in certain industries jointly withhold industry-wide bad news through tacit collusion due to capital market pressures, while we show that firms engaged in tacit collusion with respect to production volume are more likely to share information with their industry peers when economic conditions are poor. Finally, we set up an analytical model and then empirically examine the information sharing in one industry that features the characteristics of tacit collusion. In contrast, Rogers et al. empirically identify industries in which firms are likely to jointly withhold industry-wide bad news and examine the characteristics of the industries.

3. Model

This section develops the main research hypotheses within a simple model that illustrates the main tensions and intuition. We assume two firms $i = 1, 2$ engage in repeated interactions and possess information that can be shared before operating decisions are made. The game takes place over an infinite horizon, with time indexed by $t = 0, \ldots, +\infty$. Investors value future cash flows with discount rate $1/(1 + r) = \beta \in (0, 1)$.

The game begins at $t = 0$ and in each period a state of the economy s_t is realized, representing the industry's expected market demand. The state s_t is publicly observable and varies over time. In each period, the state of the world is drawn from an i.i.d. process with support over $[\underline{s}, +\infty)$.[2] In each period, firms compete by choosing production and achieve the following profit, expressed as quantity sold $q_{t,i}$ times the selling price $P_{t,i}$:

$$\Pi_{t,i} = q_{t,i} \underbrace{(s_t + \sum_{i=1}^{2} u_{t,i} - q_{t,i} - \alpha q_{t,-i})}_{P_{t,i}} \tag{1}$$

where the selling price $P_{t,i}$ is a function of the state of the economy s_t, private signals about demand received by each firm $u_{t,i}, u_{t,-i}$, the quantity produced by both firms $q_{t,i}, q_{t,-i}$ and the extent α to which the competitor's product are substitutes.

Because we focus on incentives to share information related to market demand, we consider common-value demand information. Since all information would be shared even without any tacit agreement if α is small or negative (Raith 1996), as for example in the

[2] In this type of model, Bagwell and Staiger (1997) discusses how the i.i.d. assumption can be extended to a mean-reverting process.

case of price competition, we assume that $\alpha > 2(\sqrt{2}-1)$ so that not all information is necessarily shared. For similar reasons, we rule out perfect substitutes in which not sharing information is always preferred. Each demand shock signal $u_{t,i}$ is observed by firm i and we assume that $u_{t,i}$ is i.i.d. and normally distributed with mean zero and variance σ^2, with p.d.f. $g(.)$ and c.d.f. $G(.)$.

In each period t, at $t.1$, firms commit whether or not to share information by revealing their observed $u_{t,i}$ to the trade association, which circulates information only if both firms have provided their information. At $t.2$, firms either observe the report made by the trade association $(u_{t,1}, u_{t,2})$ or the association makes no report. Firms then choose a quantity $q_{t,i}$ for the period. If the information is not shared, firms then choose $q_{t,i}$ based on their own private information $u_{t,i}$. At $t.3$, firms realize their current profit $\Pi_{t,i}$ and observe the quantity sold by the competitor.[3] Period $t+1$ then begins and the firms can condition how they now compete in $t+1$ as a function of their actions and observations of past periods.

Similar to Darrough (1993), one limitation of information sharing with commitment is that it does not allow for ex-post changes in the sharing decision; i.e., a firm can commit to the information system but cannot deviate to share (or not to share) after it observes its private information.[4] In the context of the data available, this allows us to focus on precision, given that firms do not seem to selectively withhold high or low production plans. We do not model the decision to exit the trade association after observing large unexpected *private* signals, as for example in Wagenhofer (1990) or Bertomeu and Liang (2015).

The strategic interaction in each period features an information sharing decision followed by an operation decision. We refer to this interaction over one period of the game as a stage game and first define strategies for a stage game.

Definition 3.1 *A stage-game strategy Γ is defined as:*

(a) An information sharing decision $H(s) \in \{d, nd\}$ which maps any state of the world to a decision whether to share information ($H = d$) or not share information ($H = nd$) and,

(b) a quantity choice decision $Q_{nd}(s, u_i) \in \mathbb{R}^+$ if information is not shared and $Q_d(s, \sum_{j=1}^{2} u_j)$ if information is shared.

If firm 1 adopts strategy Γ_1 and its competitor adopts strategy Γ_2, we define $V(\Gamma_1, \Gamma_2; s)$ as the payoff of firm 1 in the current period. Denote $V(\Gamma; s) \equiv V(\Gamma, \Gamma; s)$ and $V(\Gamma) \equiv \mathbb{E}(V(\Gamma, \Gamma; s))$.

[3] The assumption is relatively mild given that, if firms can share information prior to production, they will also be able to share their information after production.

[4] There is an extensive literature in this area, see for example Clarke (1983), Gal-Or (1985) or Raith (1996).

We are interested here in symmetric equilibria (i.e., equilibria with the same payoffs in all periods for both firms), that are ex-ante preferred by all firms in the industry. The equilibrium takes the form of trigger strategies (i) firms adopt the stage game strategy Γ^* in every period unless (ii) an action inconsistent with Γ^* is observed, in which case, all firms ignore reputations and instead play the Nash equilibrium of the single-period game. We denote the latter strategy as the punishment path, and hereafter refer to an equilibrium of this sort in the repeated game as a tacit agreement.[5]

Definition 3.2 *The preferred tacit agreement consists of a stage game strategy* Γ^* *that is the solution of the following program:*

$$\begin{array}{ll} \max_{\Gamma} & V(\Gamma) \\ \textit{s.t., for any } s, & V(\Gamma; s) + \beta\frac{V(\Gamma)}{1-\beta} \geq \max_{\Gamma'} V(\Gamma', \Gamma; s) + \beta\frac{V(\Gamma^n)}{1-\beta} \end{array}$$

where Γ^n *is the Nash equilibrium of the stage game, i.e.,*

$$\Gamma^n \in argmax V(\Gamma, \Gamma^n) \tag{2}$$

In a single-period game, all firms play the stage-game strategy Γ^n, ignoring the possible repercussions of an aggressive competitive stance on future periods. In a tacit agreement, on the other hand, firms fully consider the potential loss of reputation in future periods. In particular, the threat of future penalties can potentially provide a disciplining mechanism that coordinates firms to implement lower production quantities than what they could implement if the interaction were one-shot.

Whether firms in an industry can implement such a tacit agreement is an empirical question, but there are strong reasons to suspect that such an agreement could potentially emerge in an industry structured as the US automobile industry has been over our sample period. Although the US antitrust law explicitly prohibits organizing an industry as a cartel, the enforcement of antitrust requires proof of anticompetitive practices. The US automobile industry also features many industry forums, meetings and trade associations that facilitate informal communication.

Most examples of tacit agreements studied in the industrial organization literature are not renegotiation-proof (Green and Porter 1984, Rotemberg and Saloner 1986, Bagwell and Staiger 1997, Athey and Bagwell 2001). For example, in this model, a firm that deviates from the tacit agreement by producing too much in one period would trigger the punishment path but could solicit the competitor to renegotiate toward the initial tacit agreement and, given that the deviation occurred in the past, improve industry payoffs moving forward. Of course, such logic would defeat any possible tacit agreement because

[5]We use the Nash equilibrium of the stage game as the punishment path for simplicity, but the results are unchanged if we use any other punishment path.

the disciplining mechanism would be expected to be renegotiated away. This limitation of our study and the associated literature can be understood as partly behavioral - because some parties are unwilling to candidly renegotiate with a trade partner who previously cheated. It also reflects the specific context of industries under regulator monitoring where an open negotiation to avoid a price war would be suspect to antitrust authorities.[6]

To analyze information sharing, we begin with the stage game Nash equilibrium of (Darrough 1993) as a benchmark. Later on, we shall find information sharing that is inconsistent with the benchmark but consistent with a tacit agreement.

Proposition 3.1 *In the Nash equilibrium of the stage game Γ^n, firms do not share information for any s_t and choose an equilibrium quantity:*[7] $Q_{nd}(s,u) = s/(2+\alpha) + u/2$. *Firms achieve a per-period profit:* $V(\Gamma^n; s) = \frac{\sigma^2}{4} + \frac{s^2}{(2+\alpha)^2}$.

This classic no-sharing result stems from the fact that in this setting a firm's expected profit is convex in the equilibrium quantity, so that the firm prefers greater variability in the equilibrium outputs. Sharing information in this setting tends to reduce the variance in outcomes because each firm's response to shared information serves to dampen the effect of that information. For example, when one firm shares a positive signal , the other firm also responds by increasing output, which dampens the effect of the first firm's response.

We next examine the optimal strategy in a tacit agreement by first analyzing the quantitie that are necessary to sustain tacit collusion, depending on whether or not information is shared. Next, we compare profits with versus without information sharing to determine whether information should be shared for each level of market demand, s.

First, assuming that the tacit agreement prescribes disclosing, $H(s) = d$, and the shared information signals reveals u_1+u_2. Within a tacit agreement, firms now implement a production quantity lower than the quantity in the single-period game using the threat of future punishment via price wars as a disciplining mechanism. Letting $Q_d(s, u_1+u_2)$ be the quantity prescribed in the tacit agreement, the incentive-compatibility condition required to ensure that each firm will honor the collusive arrangement becomes:

$$Q_d(s, u_1+u_2)(s + u_1 + u_2 - (1+\alpha)Q_d(s, u_1+u_2)) + \beta\frac{V(\Gamma^*)}{1-\beta}$$

[6] Indeed, renegotiations are more commonly analyzed in contexts where renegotiations are legal and organized, as for the case of debt contracting (Magee and Sridhar 1996). Mailath and Samuelson (2006) give a few examples of games with asymmetric punishments that are renegotiation-proof. While internally consistent, such strategies are overly complex compared to the simple trigger strategies that we consider. We do not know whether asymmetric punishment strategies could be made renegotiation-proof in our context.

[7] To save space, we omit the off-equilibrium path.

$$\geq \underbrace{\max_q q(s+u_1+u_2-q-\alpha Q_d(s,u_1+u_2))}_{V^{dev}} + \beta\frac{V(\Gamma^n)}{1-\beta} \tag{3}$$

The left-hand side of this inequality is the profit if the firm sets its quantity following the prescription of the tacit agreement, thereby obtaining the tacit collusion profit $V(\Gamma^*)$ in future periods. The right-hand side of the inequality is the surplus obtained by a firm deviating from the tacit agreement in the current period, after which the agreement is broken and firms achieve their single-period profit $V(\Gamma^n)$ in all future periods.

In the right-hand side of equation (3), the current profit that that one firm can achieve when it deviates for one period while the other firm honors the agreement can be calculated explicitly as:

$$V^{dev} = \frac{1}{4}(s+u_1+u_2-\alpha Q_d(s,u_1+u_2))^2$$

Substituting this expression into equation (3) and rearranging, we can express as the smallest (i.e., the most restrictive) production quantity that can be made incentive compatible:

$$Q_d(s,u_1+u_2) \geq \frac{1}{2+\alpha}(s+u_1+u_2-2\underbrace{\sqrt{\frac{\beta(\mathbb{E}(V(\Gamma)-V(\Gamma^n)))}{1-\beta}}}_{K}) \tag{4}$$

The first term in (4), that is, $(s+u_1+u_2)/(2+\alpha)$, is the quantity chosen in the single-shot game, conditional on sharing information. The second term, that is, $-2K/(2+\alpha)$, captures the penalty effect that arises in future periods as a result of deviating in the current period. This disciplining effect lowers feasible quantities and potentially makes the industry profit maximizing monopoly profit feasible.

Next, Proposition 2.2 derives the choice of quantities in the tacit agreement after firms share information.

Proposition 3.2 *Consider a tacit agreement in which firms share information after observing public demand signal s,*

(i) If $s+u_1+u_2 < 4\frac{1+\alpha}{\alpha}K$, firms implement their monopoly quantities:

$$Q_d(s,u_1+u_2) = \frac{1}{2(1+\alpha)}(s+u_1+u_2)$$

(ii) Otherwise, firms implement the following higher quantity that exceeds the monopoly quantity

$$Q_d(s,u_1+u_2) = \frac{1}{2+\alpha}(s+u_1+u_2-2K)$$

Figure 1 illustrates the tacit agreement with total demand on the horizontal axis and production quantity on the vertical axis. First, the solid line from the origin represents the

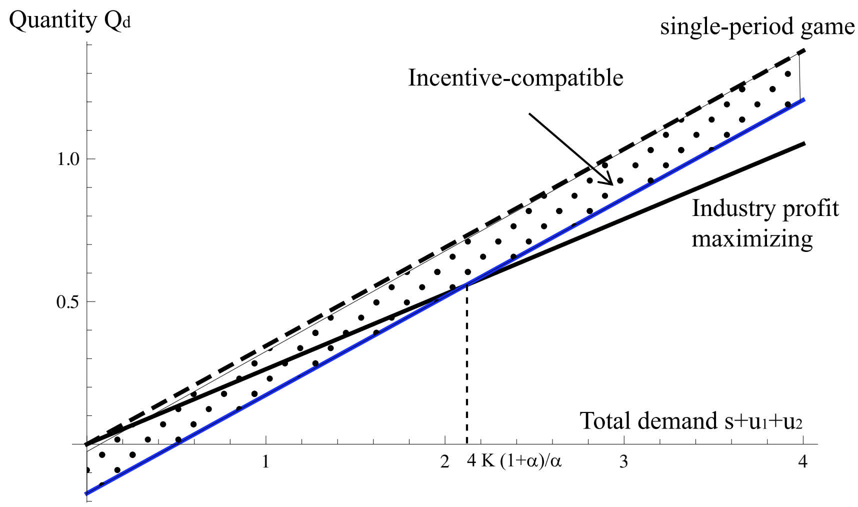


Figure 1: Production quantity with information sharing

monopoly quantities that maximize total industry profits, reflecting complete freedom to restrict production to increase prices and maximize profits. Second, the upper dashed line represents the greater quantities that are produced in a single-period Nash equilibrium in which intense competition constrains the firms' ability to increase profits by coordinating to restrict production. Third, the dotted region represents quantities that become feasible in the repeated game in which the threats of future punishment facilitate restricting production in the current period.

Finally, when $s + u_1 + u_2$ is low, the industry profit maximizing quantity can be implemented. In contrast, when demand exceeds this intersection point, firms cannot achieve the industry profit maximizing quantity because this quantity falls below the smallest feasible restriction in the dotted region. Put differently, greater industry demand makes a current deviation too tempting relative to the value of preserving tacit collusion in future periods. However, tacit collusion remains feasible by increasing the agreed production quantities to those on the lower boundary of the dotted region. These quantities are greater, and hence less profitable than the monopoly quantity, but they are smaller and more profitable than the single period Nash equilibrium solution on the upper dashed line. In this region, the tacit agreement prescribes a higher quantity but at the cost of achieving lower industry profits, consistent with the classic result of Rotemberg and Saloner (1986). In summary, the equilibrium tacit collusion with information sharing quantity has two regions. When total demand is below the intersection point, the quantity is the monopoly profit maximizing quantity. Above the intersection point the quantity is defined by the lower boundary of the feasible incentive-compatible region.

Next, assume that the tacit agreement prescribes not sharing information among competing firms. As for the case of information sharing, the future disciplining threat of price wars if a collusive agreement is broken will allow the firms to restrict production to lower quantities than those that would prevail in a single-period game. Specifically, the optimal tacit no-disclosure agreement solves the following problem:

$$Q_{nd}(s,u) \in \max_{Q(u),q^m} \int Q(u)(s+u-Q(u)-\alpha q^m)g(u)du$$

s.t.

$$q^m = \int Q(u)g(u)du$$

$$\text{for any } u, \quad Q(u)(s+u-Q(u)-\alpha q^m)+\beta\frac{V(\Gamma)}{1-\beta} \geq \max_q q(s+u-q-\alpha q^m)+\beta\frac{V(\Gamma^n)}{1-\beta}$$

This program is similar to the case of information sharing with a few notable differences. First, the tacit agreement now prescribes quantities $Q_{nd}(s,u)$ that depend only a firm's own private information, rather than on both firms' private signals. Given that the products are imperfect substitutes, this more limited information tends to prevent firms from fully responding to all demand shocks and reduces total industry profits. Second, the incentive-compatibility condition must now reflect the expected quantity produced by the competitor. The firm cannot tailor the quantity deviation to all available information, making a deviation less profitable.

Proposition 3.3 *Consider a tacit agreement in which information is not shared for a realization of s, then:*

(i) If $s \leq 4K(1+\alpha)/\alpha$, firms implement their monopoly quantities:

$$Q_{nd}(s,u) = \frac{1}{2(1+\alpha)}s + \frac{u}{2}$$

(ii) Otherwise, firms implement a quantity higher than their monopoly quantity, as given by:

$$Q_{nd}(s,u) = \frac{s}{2+\alpha} + \frac{u}{2} - \frac{2}{2+\alpha}K$$

Without information sharing, both firms choose production quantities based on the public signal s and their private signal. To be incentive-compatible, a tacit agreement must involve an expected production quantity that is not too low relative to the disciplining power of the threat of future price wars. This implies that when the expected market demand is sufficiently low, the expected quantity that maximizes total industry profit with no private information disclosure can be implemented. On the other hand, when market demand is greater, the tacit agreement cannot restrict production as much and the firms will produce more in response to their incomplete information about market demand. A graphical representation of these findings is very similar to the former case of information sharing in Figure 1, except that the horizontal axis must now be understood as the expected market demand s and the vertical axis must be relabeled as the expected quantity $\mathbb{E}(Q_{nd}(s,u))$.

We next compare the information sharing and no information sharing strategies, as a function of the market demand. As noted earlier, the first-best monopoly industry profit can only be attained if firms share information and adapt their quantities to all available information. When expected demand is low, the threat of future competition is sufficient to almost always enforce monopoly quantities and thus the monopoly surplus becomes nearly feasible (Proposition 3.3). This implies that sharing information must be preferred when the expected demand based on the public signal s is low enough. Conversely, when the expected demand is sufficiently high, current potential profits from deviating from the tacit agreement are large enough relative to the K, the loss in future profits, that the firm would prefer to deviate and produce the single period Nash quantity. In this setting not sharing information is preferred and firms realize a profit in the current period that is the similar to the payoff in the single-shot game. These are formalized in the next Proposition.

Proposition 3.4 *In an optimal tacit agreement, there exists a threshold τ such that firms share information when $s < \tau$ and firms do not share information when $s > \tau$.*

The tacit agreement features two regimes. When market demand is low, so that industry profit maximizing quantities can be implemented using reputations via such mechanism as the threat of future price wars, the tacit agreement features information disclosure which permits a a more efficient industry-wide use of information. When market demand is higher, the tacit agreement first softens competition by not disclosing or sharing private information about the level of industry demand. This allows for lower quantities to be implemented (following the same intuition as the single-period game) and higher industry profits. This intuition is further illustrated in Figure 2 where $\mathbb{E}(\Pi^{share}|s)$ is plotted against $\mathbb{E}(\Pi^{noshare}|s)$.

4. Empirical Evidence

4.1. Empirical Hypotheses

Proposition 2.4 predicts countercyclical information sharing behavior in which information sharing is more extensive when the market demand in the current period is low, and vice versa. Specifically, when the market demand in the current period is relatively low, firms have limited potential to generate additional profit by deviating from a tacit agreement by expanding their production. Therefore, the threat of future intense competition becomes effective in disciplining firms not to overproduce and firms tacitly collude to produce the monopoly quantity. Under this scenario, sharing information generates no proprietary

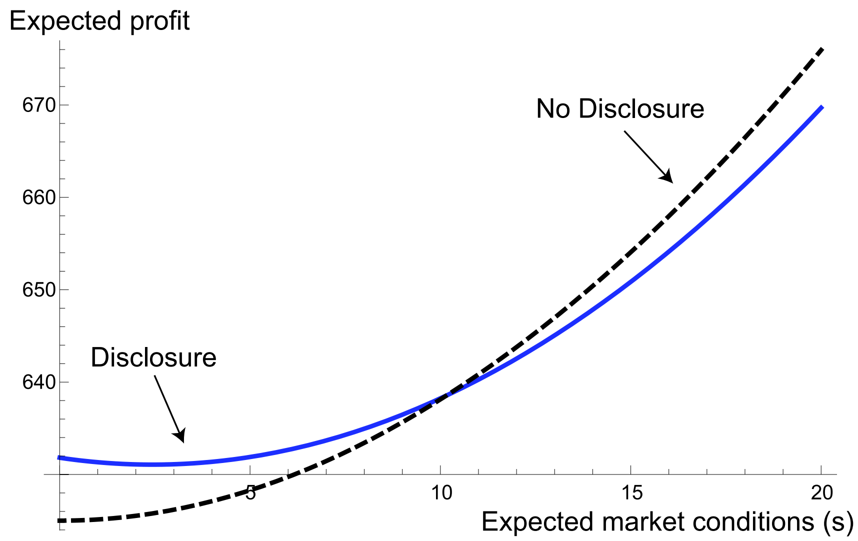


Figure 2: Sharing versus not sharing with the tacit agreement ($\sigma = 50$, $K = 1$, $\alpha = .9$)

costs, but yields benefits by helping the industry to tailor the total output to the precise market demand. Hence, compared with not sharing information, sharing is preferred because it yields higher profit.

When the market demand in the current period is high, firms could generate significant additional current period profit by deviating from the tacit agreement by expanding their production. Therefore, in such situations the threat of future intense competition is not sufficient to discipline the firms to jointly behave as a monopoly. Instead, firms will produce more than the monopoly quantity and will engage in some degree of competition with each other. If information were shared, it would be used by the firms to compete against each other, reducing each firm's profit and generating proprietary cost. If the proprietary cost is greater than the benefit of information sharing, sharing information would yield lower profit than not sharing. Hence, firms would prefer not sharing information when the current demand is sufficiently high. Thus, our first hypothesis, stated in the alternative form, is:

Hypothesis 4.1 *When the expected current market demand is greater, information sharing among industry peers is less extensive.*

As discussed above, the extent of information sharing largely depends on how effectively the threat of future intense competition can discipline firms not to overproduce by competing aggressively. We expect firms to weigh current period profit more and future profit less under certain circumstances, such as when firms face significant current financial distress or experience CEO turnover. In these situations, executives have strong incentives to increase current profitability by expanding production even though the expansion could lead to intense future competition and low profit. Hence, when firms are more short-term focused, the competition in the current period is intense and the proprietary costs of information sharing are high, leading to less information sharing. Our second hypothesis, stated in the alternative form, is:

Hypothesis 4.2 *When companies are more short-term focused, information sharing among industry peers is less extensive.*

4.2. Sample Selection, Variable Definitions and Descriptive Statistics

4.2.1 Sample Selection and Variable Definitions

The U.S. automobile manufacturing industry is a good setting in which to examine our tacit collusion hypotheses. With GM, Ford, and Chrysler accounting for 60-90% of new vehicles sold in the U.S. during the period 1965 to 1995, this concentrated industry structure gave the three firms the potential opportunity to use shared production forecasts to coordinate their actual production volume decisions.[8] At the beginning of almost every production month, GM, Ford and Chrysler each issue a production forecast for the current month, which we refer to as the "production month." In addition, each firm may also issue additional forecasts for that same production month either before or during the production month. For example, for the production month of March 1970, GM issued its first forecast of 412,700 cars on January 12 of that year. Next, at the beginning of March 1970, GM forecasted production of 365,000 cars for the month of March 1970. Finally, GM issued an updated forecast for March 1970 of 363,000 cars on March 9 of that year.

Wards Automotive Report releases the forecasts to its subscribers only after receiving a forecast from each of the three firms.[9] Our three sample firms subscribe to this report, making it a natural venue for information sharing about current production plans. Our sample includes monthly production forecasts for each of the three firms during the years 1965-95, as reported by Wards Automotive Report. The final sample includes 366 monthly observations, reflecting forecasts for all but six months over the 31-year sample period.[10]

[8]Tacit collusion is more likely to emerge and be sustained when there are few firms in an industry, high entry barriers and frequent interaction among industry peers, market shares among firms are roughly equal, sales and prices are transparent, market demand is relatively stable with less innovation (Ivaldi, Jullien, Rey, Seabright and Tirole 2003).

The automobile industry in our sample period demonstrates many characteristics that are consistent with these factors with two exceptions. First, Chrysler is much smaller than Ford and GM. If Chrysler can deviate from the tacit collusion to capture sufficient market shares from GM and Ford, Chrysler will have incentive to deviate. However, this argument assumes that Chrysler operates without a significant production capacity constraint. Second, in some months the market demand for cars did fluctuate significantly, which created a strong incentive for firms to deviate when the demand was extremely high. Consistent with this, Bresnahan (1987) documents that the automakers experienced a price war in 1955 when the market demand for cars was very high.

[9]We thank Maura Doyle and Christopher Snyder for sharing these data.

[10]Our results do not change qualitatively if we include the six observations in our forecast frequency tests.

We use three measures to reflect the extent of information sharing - forecast frequency, horizon and accuracy.[11] We define forecast frequency (FREQ) as the total number of forecasts issued for a given production month, where each forecast includes a production estimate from each of the three firms. This measure assumes that firms share information to a greater extent if they issue forecasts for a given month more frequently. Forecast horizon (HORIZON) is based on the first forecast issued for a month, and is calculated as the number of days from the first forecast for that production month to the end of the production month. This measure assumes that the earlier the firms start to issue production forecasts for a month, the more useful the information is to their industry peers because they have more time to adjust their production plan accordingly. We define forecast error (ERROR) based on the forecast issued at the beginning of each production month over the sample period.[12]

Following Doyle and Snyder (1999), we define forecast error as the absolute difference between the actual production and the forecast, deflated by each firm's average actual production during the sample period.[13] When firms have stronger incentives to share information, they may invest more resources in information collection, resulting in more accurate production forecasts. For the above example of GM in the production month of 1970 March, FREQ equals three, reflecting the three forecasts noted above, HORIZON equals 78, the number of days between January 12, 1970 and March 31, 1970. The unscaled forecasting ERROR equals 17,600, the absolute difference between the actual March production of 347,400 and the forecast of 365,000 made at the beginning of March. Because Wards Automotive Report includes production forecasts either for all three automobile manufacturers or for none of the three, our measures of FREQ and HORIZON in any given month are identical for the three manufacturers.

To test the H1 prediction that information sharing is less extensive when the expected current market demand is high, we use the monthly unemployment rate (UNEMP) from the Bureau of Labor Statistics to proxy for the expected current demand in the automobile industry. The unemployment rate should be a relatively good proxy for demand because prior research documents that it explains approximately 89% of the variance in new vehicle sales (Langer and Miller 2008, Sivak and Schoettle 2009). Because the unemployment rate is negatively related to consumers' expected disposable income, when the unemployment

[11] This paper focuses on how industry peers use the production forecasts. Other stakeholders, such as investors and employees, can also observe the information and could potentially use this information. Regarding investors, we find that there are significant abnormal absolute stock returns around production forecast issuance dates. Regarding employees, in a sensitivity analysis, we create dummy variables when there are major contract renegotiations and strikes, including corresponding dummies in our regressions, and the results do not change qualitatively.

[12] In our model, firms either issue a production forecast or not. Empirically, the three sample firms appear to share information to varying degrees with firms seldom sharing no information at all. Hence, rather than being dichotomous, our information sharing measures are continuous, reflecting different degrees of information sharing.

[13] Our results do not change qualitatively if we use the average sales revenue as a scalar.

rate is higher, more consumers face reduced disposable income, leading them to postpone their purchase of new vehicles. To test the H2 prediction that less information will be shared when the automobile companies are primarily short-term focused, we use CEO turnover (CEO_TURNOVER) and z-score (ZSCORE) as proxies for increased pressure to focus on short-term results. Specifically, we set CEO_TURNOVER equal to one in any month in which at least one of the CEOs from the three firms will voluntarily leave the firm within the next twelve months, and zero otherwise.[14] We expect a CEO who is about to leave the company to focus primarily on the firm's short-term results and to be less concerned with information sharing and long-term consequences. ZSCORE captures the financial distress of the three automakers, which we measure as the minimum z-score (Altman 1968) of the three firms, where lower scores reflect greater financial distress. A firm in financial distress is very likely to focus primarily on short-term financial results rather than longer term consequences of information sharing.

We also obtain data for several control variables, including capacity utilization (CAP), industry inventory level (INVT), industry production volatility (VOL), inflation, as measured by the change in the Consumer Price Index (ΔCPI), and input prices, as measured by the change in producer price indices for iron and steel (ΔIRON), industrial electric power (ΔELECTRIC), and petroleum (ΔPETROL). We use the seasonally adjusted U.S. city average Consumer Price Index from the Bureau of Labor Statistics. The iron, steel, electric power, and refined petroleum price indices measure major automobile industry input prices (Langer and Miller 2008, Cameron and Schnusenberg 2009) and are also from the Bureau of Labor Statistics (series id: WPU101, WPU0543, WPU057). We obtain capacity utilization (CAP) data from the Federal Reserve (industrial production and capacity utilization G.17; Motor vehicles and parts NAICS=3361-3). We use Compustat annual data to calculate industry inventory level (INVT) as the sum of the three firms' inventories divided by the sum of their total assets. Finally, we measure industry uncertainty using industry production volatility (VOL), measured as the average standard deviation of production levels among these three firms in a calendar year.

4.2.2 Descriptive Statistics

Figure 3 shows that the average number of forecasts per firm for a given production month increased from approximately two (use the left-hand vertical axis) over the earlier 1965-74 period to approximately five over the 1975-95 period. Over the same periods the average forecast horizon, measured from the first forecast for a given production month, increased from the 1965-74 period to the 1975-90 period and then declined again after 1990. Forecast frequency and forecast horizon both generally increase over time during our

[14] We exclude involuntary CEO turnover from our measure because the CEO involved may not anticipate the turnover decision. Most CEO turnover events are due to retirements. Our results do not change qualitatively if we include the involuntary CEO turnover.

sample period, but the data also reflect significant annual fluctuations in the number of forecasts and in the forecast horizon. We examine whether the expected industry demand and firms' decision horizons explain these variations in forecast frequency and forecast horizons.

Table 1 shows that the industry average forecast error across the three sample firms has a mean at 4.62% with a standard deviation of 6.60%.[15] The average unemployment rate over the sample period is 6.25% with a standard deviation of 1.58%. The 1965-95 sample period spans four business cycles with peak unemployment rates in 1971 (6%), 1975 (9%), 1982 (10%), and 1992 (8%). The mean CEO_TURNOVER of 0.33 indicates that during approximately one-third of the sample months at least one of the sample firms has a CEO who is close to departure, and hence faces a short horizon. The average value of the industry minimum z-score (ZSCORE) is 1.33 with a standard deviation of 0.48.

For our sample variables, Table 2 reports Pearson correlations above the diagonal and Spearman correlations below the diagonal. UNEMP is positively correlated with FREQ and HORIZON (Pearson: 0.59 and 0.60, two-tailed $p < 0.001$; Spearman: 0.58 and 0.56, two-tailed $p < 0.001$), and negatively correlated with ERROR (Pearson: -0.20, $p < 0.001$; Spearman: -0.25, $p < 0.001$). These results are consistent with our expectation that when the expected industry demand is low (high UNEMP), the degree of information sharing is high, as reflected by high FREQ, high HORIZON, and low ERROR. CEO_TURNOVER is negatively related to FREQ (Pearson: -0.11, $p = 0.03$; Spearman: -0.07, $p=0.17$), but is not significantly correlated with either HORIZON or ERROR. The significant correlation between CEO_TURNOVER and FREQ suggests that firms issue fewer forecasts when their CEO is about to leave the firm. The correlations of ZSCORE with FREQ, HORIZON and ERROR are generally weak.

The Pearson correlation between UNEMP and CAP is -0.61 ($p < 0.001$), consistent with greater capacity utilization when UNEMP is low, reflecting high expected demand. Inflation (ΔCPI) is positively correlated with the changes in the prices of industrial components, such as ΔIRON, ΔELECTRIC, and ΔPETROL (Pearson: 0.23-43, $p < 0.001$; Spearman: 0.26-0.37 ($p < 0.001$). Finally, we note that the correlations among ZSCORE, INVT, and VOL are high (Pearson: 0.53 - 0.89, $p < 0.001$; Spearman: 0.52 - 0.78, $p < 0.001$).

4.3. Empirical Model and Results

Hypothesis 1 predicts that forecast frequency, forecast horizon, and forecast accuracy decrease with the current market demand. Hypothesis 2 predicts that less extensive information sharing, indicated by lower forecast frequency, shorter forecast horizons, and higher absolute forecast errors, will occur when the sample firms are more short-term

[15]Compared with the actual production, 63% of production forecasts are optimistically biased while 37% are pessimistically biased.

focused. We test these predictions using the following OLS regression:

$$
\begin{aligned}
FREQ_t/HORIZON_t/ERROR_t = b_0 + b_1 UNEMP_t + b_2 CEO\_TURNOVER_t/ZSCORE_t + \\
b_3 CAP_t + b_4 INVT_t + b_5 VOL_t + b_6 \Delta CPI_t + b_7 IRON_t + b_8 \Delta ELECTRIC_t + \\
b_9 \Delta PETROL_t. \quad (5)
\end{aligned}
$$

We expect UNEMP to be positive in the FREQ and HORIZON regressions and negative in the ERROR regression because higher unemployment rate indicates low current market demand. We expect CEO_TURNOVER (ZSCORE) to be negative (positive) in the regressions of FREQ and HORIZON and positive (negative) in the regression of ERROR because high CEO turnover and low ZSCORE represent greater short-term focus. Because automobile production is likely to be seasonal, we include monthly fixed effects and cluster standard errors by month in the time-series regressions. We also include a time trend in the regressions to capture long-term structural changes in the auto industry.

We include capacity utilization (CAP) because higher CAP leaves less room for firms to adjust their production volume and may thus influence the extent of information sharing. When the industry inventory level (INVT) is high, sample firms may constrain production to avoid oversupply. Therefore, INVT may restrict firms' ability to coordinate production, leading to less effective tacit agreements. Similarly, industry uncertainty, captured as production volatility (VOL), affects firms' ability to forecast. We include it to control for its influence on firms' incentive not to disclose. Inflation (ΔCPI) reflects the purchasing power of both consumers and producers and is likely to influence both the supply and demand for cars. ΔIRON, ΔELECTRIC, and ΔPETROL are key input price components for automobile manufacturers, so we include them as control variables.

Table 3 presents the regression results for forecast frequency. Model (1) includes only UNEMP and CEO_TURNOVER, while Models (2) and (3) gradually add control variables. In all three columns, the coefficient on UNEMP is significantly positive with a two-tailed p-value less than 0.01, consistent with the H1 prediction that automobile manufacturers will issue production forecasts more frequently, thereby sharing more information, when demand is weaker, as proxied by the higher unemployment rate. When the unemployment rate increases from the first quartile to the third quartile, an increase of two percentage points, the three firms issue two additional forecasts, which is an economically significant 45.1% increase over the sample average of 4.4 forecasts for a given month.

Consistent with H2, we find that the coefficient on CEO_TURNOVER is significantly negative in Models (1) to (3), suggesting that automobile manufacturers issue production forecasts less frequently when the CEO in at least one of the sample firms will leave within a year. Among the control variables, we find that the automakers issue forecasts more frequently when capacity utilization is low, reflecting more benefit to information sharing because there is more room to adjust production. In terms of economic significance, the firms issue one fewer forecast each month when at least one of their CEOs is about to leave the company. Models (4) to (6) use ZSCORE to measure the decision horizon of automakers. We exclude INVT from Models (4) to (6) because the high correlation of 0.89 between ZSCORE and INVT may cause a multicollinearity issue.

The results are similar to the first three columns. Specifically, the coefficient on UNEMP continues to be positive and statistically significant except in Column (6), where it is positive but not significant. The estimated coefficients on ZSCORE are positive and significant in Models (4) - (6). Overall, the results are consistent with both H1 and H2. As ZSCORE moves from the first quartile to the third quartile, the sample firms each issue three additional forecasts, representing a 61.4% increase relative to the mean forecast frequency in the sample of 4.43 forecasts per month. This result indicates that firms share more information by issuing more forecasts when they are financially healthy than when they are in financial distress.

Table 4 presents the regression results for our model of forecast horizon. In all six columns, the coefficient on UNEMP is significantly positive with p-values less than 0.01, consistent with automobile manufacturers issuing the first production forecast earlier when the demand for new vehicles is weaker. As the unemployment rate moves from the first quartile to the third quartile, the forecast horizon increases by 28 days, a 29.7% increase above the sample average horizon of 94.37 days. The coefficient on CEO_TURNOVER is significantly negative and the coefficient on ZSCORE is significantly positive, suggesting that firms issue their first forecast later when they face shorter decision horizons.

Table 5 presents the regression results for our forecast error model. In Models (1) to (3), the coefficient on UNEMP is significantly negative with a p-value less than 0.01, indicating that when the industry experiences weaker demand, the absolute forecast error decreases, consistent with more extensive information sharing. An increase in the unemployment rate from the first to the third quartile would decrease the forecast error by 1.9 percentage points, representing an economically significant 41.1% decrease relative to the sample average forecast error of 4.6%. The coefficient on CEO_TURNOVER is positive and weakly significant in Model (1) but becomes insignificant when we include the control variables.

In Models (4) - (6) of Table 5 the coefficient on UNEMP is insignificant when the regression includes ZSCORE , which is also insignificant. The negative coefficient on CAP is marginally significant, suggesting lower absolute forecast errors when capacity utilization (CAP) is greater. In summary, we find evidence generally consistent with automobile manufacturers communicating with each other more intensely, reflected in more frequent production forecasts and longer forecast horizons, when the expected demand in the industry is lower and when the firms face longer decision horizons. Finally, we note that one would normally expect that when aggregate demand is weaker, demand uncertainty should increase, leading to greater forecast errors. On the contrary, we document lower forecast errors when unemployment rates are high, which is consistent with the H1 prediction that weaker demand leads to more production coordination among the three automobile manufacturers.

4.4. Additional Analyses

4.4.1 Alternative Measure of Forecast Accuracy

The absolute forecast error increases with both forecast noise and systematic forecast bias. As an alternative way to capture the forecast noise, we also measure production forecast accuracy using the R-squared value and the standard deviation of residuals in a regression of actual production on production forecasts. The standard deviation of residuals captures the amount of variation in actual productions that is not explained by production forecasts.

We use the standard deviation of residuals because Gu (2007) shows that the R-squared statistic is not comparable due to scaling effects. Specifically, we sort all production months into terciles based on the unemployment rate. Months in the top tercile define the high unemployment state and months in the bottom tercile define the low unemployment state. We then scale actual production and production forecasts by the average actual production or production forecast in the high or low unemployment states, respectively. Finally, we estimate separate time-series regressions of the scaled actual production on the scaled production forecasts for the high and the low unemployment subsamples.

The R-squared value and the standard deviation of residuals from the regressions are the alternative measures of forecast accuracy. If firms coordinate more intensely when industry demand is low, the results should be higher R-squared and lower standard deviation of residuals in high unemployment states. Consistent with this expectation, results in Table 6 show that the adjusted R-squared is 0.93 in the high unemployment state versus 0.84 in the low unemployment state.

We bootstrap one hundred iterations to generate a distribution of R-squared values for each state and then calculate the t-statistics for the difference in R-squared. The resulting difference in R-squared values is statistically significant ($p < 0.001$). The standard deviation of residuals is 0.07 in a high unemployment state and 0.12 in a low state, and this difference is also statistically significant ($p < 0.001$). We find the same results in the firm-level analysis.[16]

[16] When scaling actual productions and production forecasts by production or forecasts from the same month in the prior year, we also find that production forecasts explain actual productions better in a high unemployment state than in a low unemployment state. In addition, we also use the standardized variable, which is the variable minus the mean then divided by the standard deviation, and find consistent results. When we run a corresponding time-series regression for each individual firm, the results again indicate that production forecasts have a greater explanatory power in a high unemployment state. Taken together, these results provide robust evidence that information sharing is more pervasive when

4.4.2 Extent to Which Forecasts Reflect Peers' Forecasts

The preceding results show that the three sample automakers issue forecasts earlier and more frequently and these forecasts are also more accurate when the unemployment rate is high. To provide further evidence on the relation between the unemployment rate and information sharing, we investigate whether automakers incorporate more information from peers' production forecasts into their own forecasts and actual production when the unemployment rate is low. Specifically, we estimate the following OLS regression:

$$FORECAST_{t,i} = b_0 + b_1 FORECAST_{t,i-1} + b_2 PEER\_FORECAST_{t,i-1} +$$
$$b_3 FORECAST_{t,i-1} * UNEMP_{t-1} + b_4 PEER\_FORECAST_{t,i-1} * UNEMP_{t-1} +$$
$$b_5 UNEMP_{t-1} + b_6 HORIZON_t, \tag{6}$$

where $FORECAST_{t,i-1}$ is the level of the i-1 production forecast for month t.

$PEER\_FORECAST_{t,i-1}$ takes the average of the i-1 production forecasts for month t issued by the two peer firms. HORIZON is the number of days from the first forecast date to the end of a production month. We expect b_4, the coefficient on the interaction between PEER_FORECAST and UNEMP, to be positive because we expect high unemployment to be associated with more information sharing. Based on Doyle and Snyder (1999), we expect the coefficients on FORECAST and PEER_FORECAST to be positive.

In Table 7, Columns (1) and (2) report results for how peer forecasts are related to a firm's forecasts. The results in Column (1) include the regression results of the second and later forecasts issued for a month on the immediately preceding forecasts, while the results in Column (2) include the regression results of the second forecasts issued for a month on the first forecasts. Column (3) shows the results of actual production quantity on the forecasts issued at the beginning of the month. Consistent with our prediction, b_4 is significantly positive in all three columns, indicating that automakers incorporate the production forecasts issued by their peers in the subsequent forecasts and actual production to a greater extent when the unemployment rate is greater. Similar to Doyle and Snyder (1999), the coefficient on FORECAST is positive and statistically significant in columns (1) and (2). However, the coefficient on PEER_FORECAST is significantly negative, suggesting that the positive coefficient documented in Doyle and Snyder (1999) could be driven by the high unemployment rate period.

4.4.3 Alternative Measure of Financial Distress

As an alternative measure of financial distress, we create a dummy variable (NOINVEST) that equals one in any period in which one or more of the firms receives a non-investment grade credit rating, and zero otherwise. After replacing ZSCORE with this

the expected industry demand is low.

non-investment-grade dummy variable in Models (4)-(6) of Tables (3)-(5), we find that firms issue one fewer forecast ($p < 0.001$), and their first forecasts are released 13 days later ($p < 0.001$) during these non-investment-grade years.The coefficient on NOINVEST is insignificant in the regression of the forecast error. These results suggest that firms issue forecasts less frequently and later when one firm is in financial distress, consistent with H2.

4.4.4 Subsample Period 1965-1989

Data from Wards Automotive Report show that the three sample firms' market share declined in the 1990s, reflecting increased competition from international car manufacturers. Because this increased competition is likely to reduce the effectiveness of the tacit collusion among the three automakers, we exclude 1990-1995 from our sample period as a robustness check. We find that UNEMP continues to be positively related to forecast frequency ($p < 0.05$), is positively correlated with forecast horizon ($p < 0.001$), and has a negative but insignificant relation with forecast error ($p=0.14$).

The negative relations between CEO_TURNOVER and forecast frequency and between CEO_TURNOVER and forecast horizon persist ($p < 0.001$), but again there is no significant correlation between CEO_TURNOVER and forecast error. Surprisingly, ZSCORE is only weakly correlated with forecast horizon, and is not significantly correlated with forecast frequency and forecast error. When replacing ZSCORE with a non-investment-grade dummy variable, forecast error is 3.3% lower ($p=0.03$), compared to the average forecast error of 4.6%.

5. Conclusion

This paper examines how firms' voluntary production forecasting behavior is affected by the market demand in an implicitly collusive industry. Our model shows that, in a concentrated industry, tacit collusion involves more information sharing during periods of low market demand. We predict a negative correlation between disclosure and the effectiveness of reputation mechanism that is affected by the market demand condition and the patience of firms. The U.S. automobile industry is a good setting to test this hypothesis, because it is geographically concentrated (during the sample period), features few large firms, is somewhat too strategic to trigger aggressive antitrust actions, and, lastly, features recurrent voluntary disclosures of production forecasts via the trade association journal Ward's automotive report.

Empirical results using unemployment as the measure for market demand condition are consistent with this prediction. As the market demand increases, companies disclose their production forecasts less frequently, in a less timely manner and less accurately. We also test whether disclosure is affected by the company's discount factor. Following the literature we use a set of financial ratios to measure the financial distress. Higher level of financial distress would lead to more discount of future profits. We also document that firms with exiting management tend to disclose less.

Our study thus provides a clean setting where evidence of a special form of proprietary costs can be found. The results suggest that proprietary costs emerge under collusion when demand is high, but not otherwise; thus, more broadly, our analysis suggests to search for proprietary costs as a function of market demand.

Bibliography

Ali, Ashiq, Sandy Klasa, and Eric Yeung (2014) 'Industry concentration and corporate disclosure policy.' *Journal of Accounting and Economics* 58(2), 240–264

Altman, Edward I (1968) 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy.' *The journal of finance* 23(4), 589–609

Athey, Susan, and Kyle Bagwell (2001) 'Optimal collusion with private information.' *RAND Journal of Economics* 32, 428–465

Bagwell, Kyle, and Robert Staiger (1997) 'Collusion over the business cycle.' *RAND Journal of Economics* 28, 82–106

Bajari, Patrick, and Jungwon Yeo (2009) 'Auction design and tacit collusion in fcc spectrum auctions.' *Information Economics and Policy* 21(2), 90–100

Bamber, Linda S., and Youngsoon S. Cheon (1998) 'Discretionary management earnings forecast disclosures: Antecedents and outcomes associated with forecast venue and forecast specificity choices.' *Journal of Accounting Research* 36(2), 167–190

Bertomeu, Jeremy, and Pierre Jinghong Liang (2015) 'Voluntary disclosure and industry fluctuations.' *Working Paper.* Management Science, forth.

Bhojraj, Sanjeev, Walter G. Blacconiere, and Julia D. D'Souza (2004) 'Voluntary disclosure in a multi-audience setting: An empirical investigation.' *The Accounting Review* 79(4), 921–947

Bolle, Friedel (1992) 'Supply function equilibria and the danger of tacit collusion: the case of spot markets for electricity.' *Energy economics* 14(2), 94–102

Bresnahan, Timothy F. (1987) 'Competition and collusion inthe american automobile industry.' *Journal of Industrial Economics* 4(June), 457–82

Cameron, Ken, and Oliver Schnusenberg (2009) 'Oil prices, suvs, and iraq: An investigation of automobile manufacturer oil price sensitivity.' *Energy Economics* 31(3), 375–381

Chen, Hui, and Bjorn N. Jorgensen (2012) 'Firm exit through bankruptcy - the effect of accounting bias on product market competition.' KAT Accounting Conference 2012

Ciliberto, Federico, and Jonathan W Williams (2014) 'Does multimarket contact facilitate tacit collusion? inference on conduct parameters in the airline industry.' *The RAND Journal of Economics* 45(4), 764–791

Clarke, Richard N. (1983) 'Collusion and the incentives for information sharing.' *Bell Journal of Economics* 14(2), 383–394

Darrough, M. (1993) 'Disclosure policy and competition: Cournot vs. bertrand.' *The Accounting Review*

Doyle, M.P., and C.M. Snyder (1999) 'Information sharing and competition in the motor vehicle industry.' *Journal of Political Economy* 107, 1326–1364

Dye, Ronald A. (1986) 'Proprietary and nonproprietary disclosures.' *Journal of Business* 59(2), 331–366

Feltham, Gerald, F. Gigler, and J. Hughes (1992) 'The effects of line-of-business reproting on competition in oligopoly settings.' *Contemporary Accounting Research*

Gal-Or (1985) 'Information sharing in oligopoly.' *Econometrica* 53(2), 329–343

Green, Edward J., and Robert H. Porter (1984) 'Noncooperative collusion under imperfect price information.' *Econometrica* 52, 87–100

Grossman, Sanford J. (1981) 'The informational role of warranties and private discloure about product quality.' *Journal of Law and Economics* 24(3), 461–483

Gu, Zhaoyang (2007) 'Across-sample incomparability of r2s and additional evidence on value relevance changes over time.' *Journal of Business Finance & Accounting* 34(7-8), 1073–1098

Ivaldi, Marc, Bruno Jullien, Patrick Rey, Paul Seabright, and Jean Tirole (2003) 'The economics of tacit collusion.' *IDEI Working Paper*

Knittel, Christopher R, and Victor Stango (2003) 'Price ceilings as focal points for tacit collusion: evidence from credit cards.' *American Economic Review* pp. 1703–1729

Langer, Ashley, and Nathan H Miller (2008) 'Automobile prices, gasoline prices, and consumer demand for fuel economy.' *Economic Analysis Group Discussion Paper EAG* pp. 08–11

Li, Xi (2010) 'The impacts of product market competition on the quantitiy and quality of voluntary disclosures.' *Review of Accounting Studies* 15(3), 663–711

Magee, Robert P., and Sri Sridhar (1996) 'Financial contracts, opportunism, and disclosure management.' *Review of Accounting Studies* 1(3), 225–258

Mailath, George J., and Larry Samuelson (2006) *Repeated Games and Reputation: Long-Run Relationship* (Oxford University Press)

Milgrom, Paul R. (1981) 'Good news and bad news: representation theorems and applications.' *The Bell Journal of Economics* 12(2), 380–391

Raith, Michael (1996) 'A general model of information sharing in oligopoly.' *Journal of Economic Theory* 71(1), 260–288

Rogers, Jonathan L, Catherine M Schrand, and Sarah LC Zechman (2014) 'Do managers tacitly collude to withhold industry-wide bad news?' *Chicago Booth Research Paper*

Rotemberg, Julio J., and Garth Saloner (1986) 'A supergame-theoretic model of price wars during booms.' *American Economic Review* 76(3), 390–407

Sivak, Michael, and Brandon Schoettle (2009) 'Economic indicators as predictors of the number and fuel economy of purchased new vehicles'

Slade, Margaret E (1987) 'Interfirm rivalry in a repeated game: an empirical test of tacit collusion.' *The Journal of Industrial Economics* pp. 499–516

Suijs, Jeroen, and Jacco L. Wielhouwer (2012) 'Disclosure regulation in duopoly markets: Proprietary costs and social welfare'

Verrecchia, Robert E. (1983) 'Discretionary disclosure.' *Journal of Accounting and Economics* 5, 179–194

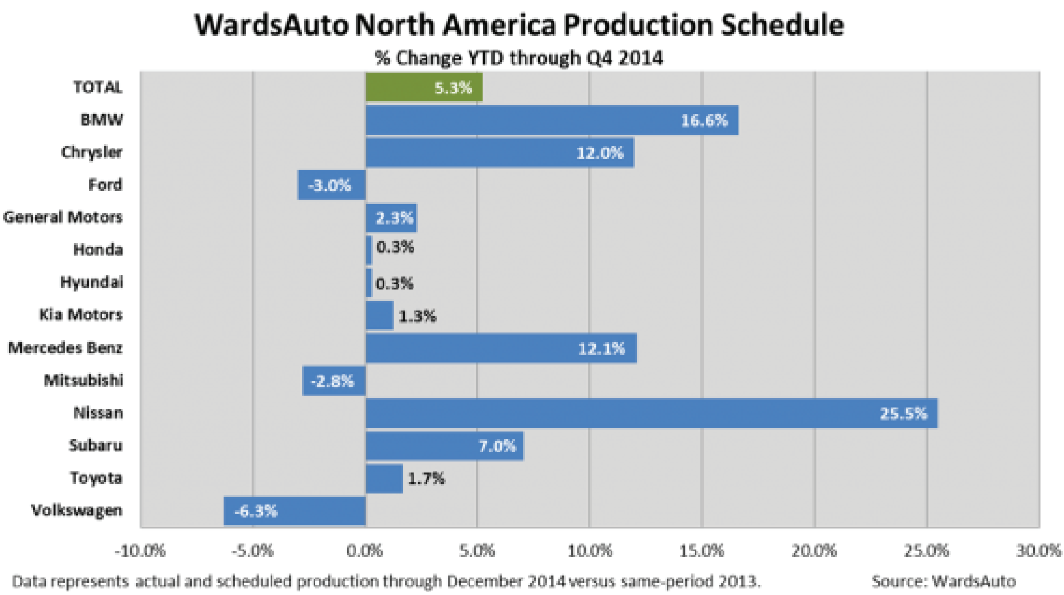
Wagenhofer, Alfred (1990) 'Voluntary disclosure with a strategic opponent.' *Journal of Accounting and Economics* 12, 341–363

A. Appendix

A.1. Example of Wards Auto Monthly Production Forecasts Report

2014 NA Output Set for Third-Best Finish Sep 4, 2014Al Binder | WardsAuto

Helped by record truck output, North American output will reach a third-best level of 17.3 million units in 2014.



North America Production Schedule Q4, September 2014

Just five years after falling to its lowest level in the past 29 years, North American car and truck production is likely to breech the 17.0 million-unit mark for only the third time in history.

Having run at a rapid pace for most of the year, car and truck assembly plants now are scheduled to build 4,443,000 units in the fourth quarter, a 5.6% increase over like 2013's 4,172,000 completions.

The strong fourth-quarter slate is enough to push vehicle output to 17.3 million-plus units, a 5.3% gain on 2013's 4,112,000 completions, to third position behind the record 17,659,700 units built in 2000 and the 17,616,121 vehicles turned out in 1999.

The industry's strong finish would come just five years after output sank to just 8,761,823 units in 2009, at the height of the economic meltdown.

Although 2014 car production, at a scheduled 7,057,800 units, is 78.2% higher than the 3,961,589 built in 2009, truck output is set to reach an all-time record of 10,313,100 units this year, more than double the 4,800,234 built five years earlier and 4.4% more than the prior benchmark of 9,876,983 turned out in 2004.

A look at just-released October-December output plans shows December has been earmarked for 1,292,100 completions, a 19.4% increase from prior-year's 1,081,800 assemblies. In comparison, October production is expected to net a 2.7% increase, while output in November, barring changes, is expected to trail year-ago by 1.7%.

The Q4 slate follows a robust third-quarter tally, set to reach a planned 4,226,800 units, 6.8% ahead of prior-year's 3,956,800.

Among the major automakers, only Ford is seen building fewer vehicles this year than in like-2013.

Although Ford has yet to reveal its official Q4 plans, output for the Dearborn automaker currently is forecast by WardAuto at 720,500 units, 4.2% less than the 752,100 vehicles it built on October-December a year earlier. That is better than the 4.4% third-quarter decline Ford has programmed, but the company is still likely to end the year with a 3.0% shortfall compared with 2013, thanks to an 11.1% falloff in car output.

GM production has been programmed for a 4.2% Q4 decline that is expected to net a 3.0% downturn for the year, with a 4.9% truck output gain partially offset by a 1.9% decline in car assemblies.

In contrast, Chrysler is expected to end the year with a 12.0% output gain on 2013, due in part to a planned 5.3% fourth-quarter boost, coming on the heels of an estimated 16.6% year-over-year third-quarter gain.

A.2. Omitted Proofs

Proof of Proposition 2.1: Since the result is a special case of Raith (1996), we give here only a short self-contained proof. Suppose information is not shared and denote $q^m = \mathbb{E}(Q_{nd}(s,u)|s)$, then, $Q_{nd}(s,u) \in \text{argmax}\ q(s+u-q-\alpha q^m)$. Differentiating with respect to q, $s+u-2Q_{nd}(s,u)-\alpha q^m = 0$ and, taking expectations, $s-2q^m-\alpha q^m = 0$ which implies that $q^m = s/(2+\alpha)$. Substituting into the first-order condition and solving for $Q_{nd}(s,u)$, we then have that $Q_{nd}(s,u) = s/(2+\alpha)+u/2$. To obtain the expected profit, note that $\mathbb{E}(\Pi|s) = \mathbb{E}(Q_{nd}(s,u)^2|s) = \sigma^2/4 + s^2/(2+\alpha)^2$. If, on the other hand, firms share information, the choice of quantities will solve $Q_d(s,u_1+u_2) \in \text{argmax}\ q(s+u_1+u_2-q-\alpha q')$ which implies that: $s+u_1+u_2-\alpha q'-2q = 0$ so that, in equilibrium, $Q_d(s,u_1+u_2) = (s+u_1+u_2)/(2+\alpha)$. The ex-ante profit from sharing information is therefore given by: $\mathbb{E}(\Pi|s) = \mathbb{E}(Q_d(s,u_1+u_2)^2|s) = s^2/(2+\alpha)^2 + 2\sigma^2/(2+\alpha)^2$ which is less than without sharing.□

Proof of Proposition 2.2: Suppose that the incentive-compatibility condition does not bind. Then, the optimal quantity is given by:

$$Q_d(s,u_1+u_2) = \ \text{argmax}\ q(s+u_1+u_2-q-\alpha q)$$

That is,

$$Q_d(s,u_1+u_2) = Q_d^1(s,u_1+u_2) \equiv \frac{1}{2(1+\alpha)}(s+u_1+u_2)$$

This quantity choice is lower than the quantity that prevails in the single-period game and achieves the maximal total industry profit. Note that this quantity will satisfy the incentive-compatibility condition if and only if:

$$\frac{1}{2(1+\alpha)}(s+u_1+u_2) \geq \frac{1}{2+\alpha}(s+u_1+u_2-2K)$$

That is,

$$s+u_1+u_2 \leq 4\frac{1+\alpha}{\alpha}K$$

As long as this inequality is satisfied, the monopoly achieves its maximal feasible profit, i.e.,

$$\Pi^{share} = \frac{1}{4(1+\alpha)}(s+u_1+u_2)^2$$

If $s + u_1 + u_2 > 4(1+\alpha)/\alpha K$, the incentive-compatibility constraint binds. From Equation (4),

$$Q_d(s, u_1+u_2) = Q_d^2(s, u_1+u_2) \equiv \frac{1}{2+\alpha}(s+u_1+u_2-2K)$$

Then, firms achieve the following profit:

$$\Pi^{share} = \frac{1}{(2+\alpha)^2}(s+u_1+u_2)^2 + \frac{2\alpha K}{(2+\alpha)^2)}(s+u_1+u_2) - \frac{4(1+\alpha)}{(2+\alpha)^2}K^2$$

□

Proof of Proposition 2.3: Denote λ the multiplier associated to the constraint $q^m = \int Q_{nd}(u)g(u)du$. If one incentive-compatibility condition does not bind, the optimal $Q_{nd}(s,u)$ is given by:

$$s + u - 2Q_{nd}(s,u) - \alpha q^m - \lambda = 0$$

$$Q_{nd}(s,u) = \frac{s+u-\alpha q^m - \lambda}{2}$$

As before, we substitute this Equation into the incentive-compatibility condition to check whether it is satisfied:

$$\frac{s+u-\alpha q^m-\lambda}{2}(s+u-\frac{s+u-\alpha q^m-\lambda}{2} - \alpha q^m) + K^2 \geq \frac{1}{4}(s+u-\alpha q^m)^2$$

This Equation simplifies to:

$$K \geq \frac{\lambda}{2} \tag{7}$$

Note that this condition is not a function of u so that either all incentive-compatibility conditions bind or none does.

We thus consider two possibilities. Assume that Equation (7) is satisfied, then:

$$Q_{nd}(s,u) = (s+u-\alpha q^m - \lambda)/2$$

Taking expectations on both sides and solving for q^m,

$$q^m = \frac{1}{2+\alpha}(s-\lambda)$$

Therefore:

$$Q_{nd}(s,u)(s+u-Q_{nd}(s,u)-\alpha q^m) = \frac{1}{4(2+\alpha)^2}(2s+(2+\alpha)u-2\lambda)(2s+(2+\alpha)u+2(1+\alpha)\lambda)$$

Reinjecting this expression into the objective function,

$$\mathbb{E}(\Pi^{noshare}|s) = \int g(u)Q_{nd}(u)(s+u-Q_{nd}(s,u)-\alpha q^m)du$$

$$= \frac{1}{(2+\alpha)^2}(\alpha\lambda s + s^2 - (1+\alpha)\lambda^2) + \frac{\sigma^2}{4}$$

Choosing the constant term λ to maximize the firm's profit in the tacit agreement,

$$\lambda = \frac{\alpha}{2(1+\alpha)}s$$

This implies that:

$$\begin{aligned}
q^m &= \frac{s}{2(1+\alpha)} \\
Q_{nd}(s,u) &= \frac{s}{2(1+\alpha)} + \frac{u}{2} \\
\Pi^{noshare} &= \frac{2s^2 + 4s(u_1+u_2) + (1+\alpha)(u_1^2 + 2(2-\alpha)u_1u_2 + u_2^2))}{8(1+\alpha)} \\
\mathbb{E}(\Pi^{noshare}|s) &= \frac{s^2}{4(1+\alpha)} + \frac{\sigma^2}{4}
\end{aligned}$$

For these strategies to be incentive-compatible, Equation (7) must be satisfied, i.e.,

$$K \geq \frac{\lambda}{2} = \frac{\alpha s}{4(1+\alpha)}$$

Assume next that $K < \frac{\alpha s}{4(1+\alpha)}$. Then the incentive-compatibility condition binds for any u,

$$Q_{nd}(s,u) = \frac{s+u-\alpha q^m}{2} - K$$

Taking expectations on both sides and solving for q^m,

$$q^m = \frac{1}{2+\alpha}(s-2K) \tag{8}$$

$$Q_{nd}(s,u) = \frac{s}{2+\alpha} + \frac{u}{2} - \frac{2}{2+\alpha}K \tag{9}$$

$$\mathbb{E}(\Pi^{noshare}|s) = \frac{1}{(2+\alpha)^2}(-4(1+\alpha)K^2 + 2\alpha K s + s^2) + \frac{\sigma^2}{4} \tag{10}$$

□

Proof of Proposition 2.4: We compare the profit under sharing to the profit under no sharing.

$$\mathbb{E}(\Pi^{share}|s) = \int_{-\infty}^{4K(1+a)/a} \sigma\sqrt{2}\frac{1}{2(1+\alpha)}(s+x)(s+x-\frac{1+\alpha}{2(1+\alpha)}(s+x))g(\frac{x}{\sqrt{2}})dx$$

$$+\int_{4K(1+a)/a}^{+\infty}\frac{1}{2(1+\alpha)}(s+x-2K)(s+x-\frac{1+\alpha}{2(1+\alpha)}(s+x-2K))g(\frac{x}{\sqrt{2}})dx$$

Differentiating this expression with respect to s,

$$\frac{\partial^2\mathbb{E}(\Pi^{share}|s)}{\partial s^2}=\frac{4+4\alpha+\alpha^2G(\frac{4(1+\alpha)K-\alpha s}{\sqrt{2}\alpha})}{2(1+\alpha)(2+\alpha)^2}$$

Define $\Delta=\mathbb{E}(\Pi^{share}|s)-\mathbb{E}(\Pi^{noshare}|s)$ and consider first $s\leq 4K\frac{1+\alpha}{\alpha}$, then:

$$\mathbb{E}(\Pi^{noshare}|s)=\frac{s^2}{4(1+\alpha)}+\frac{\sigma^2}{4}$$

Therefore:

$$\frac{\partial^2\Delta}{\partial s^2}=\frac{4+4\alpha+\alpha^2G(\frac{4(1+\alpha)K-\alpha s}{\sqrt{2}\alpha})}{2(1+\alpha)(2+\alpha)^2}-\frac{1}{2(1+\alpha)}<\frac{4+4\alpha}{2(1+\alpha)(2+\alpha)^2}-\frac{1}{2(1+\alpha)}=0$$

Note also that, for s small,

$$\begin{aligned}
\mathbb{E}(\Pi^{share}|s) &\sim \mathbb{E}(\frac{1}{4(1+\alpha)}(s+u_1+u_2)^2) && (11)\\
&\sim \frac{1}{4(1+\alpha)}(s^2+2\sigma^2) && (12)\\
\Delta &\sim \frac{1}{4(1+\alpha)}(s^2+2\sigma^2)-(\frac{s^2}{4(1+\alpha)}+\frac{\sigma^2}{4}) && (13)\\
&\sim \sigma^2/(2(1+\alpha))-\sigma^2/4>0 && (14)
\end{aligned}$$

Consider next $s>4K\frac{1+\alpha}{\alpha}$, then:

$$\mathbb{E}(\Pi^{noshare}|s)=\frac{1}{(2+\alpha)^2}(-4(1+\alpha)K^2+2\alpha Ks+s^2)+\frac{\sigma^2}{4}$$

$$\frac{\partial^2\Delta}{\partial s^2}=\frac{4+4\alpha+\alpha^2G(\frac{4(1+\alpha)K-\alpha s}{\sqrt{2}\alpha})}{2(1+\alpha)(2+\alpha)^2}-\frac{2}{(2+\alpha)^2}>\frac{4+4\alpha+\alpha^2}{2(1+\alpha)(2+\alpha)^2}-\frac{2}{(2+\alpha)^2}=0$$

It follows that Δ is convex on $(4K(1+\alpha)/\alpha,+\infty)$.

In addition, as s becomes large,

$$
\begin{aligned}
\mathbb{E}(\Pi^{share}|s) &\sim \mathbb{E}(\frac{1}{(2+\alpha)^2}(s+u_1+u_2)^2 + \frac{2\alpha K}{(2+\alpha)^2)}(s+u_1+u_2) - \frac{4(1+\alpha)}{(2+\alpha)^2}K^2|s) \\
&\sim \frac{1}{(2+\alpha)^2}(s^2+2\sigma^2) + \frac{2\alpha K}{(2+\alpha)^2)}s - \frac{4(1+\alpha)}{(2+\alpha)^2}K^2 \\
\Delta &\sim \frac{1}{(2+\alpha)^2}(s^2+2\sigma^2) + \frac{2\alpha K}{(2+\alpha)^2)}s - \frac{4(1+\alpha)}{(2+\alpha)^2}K^2 \\
&\qquad -(\frac{1}{(2+\alpha)^2}(-4(1+\alpha)K^2 + 2\alpha K s + s^2) + \frac{\sigma^2}{4}) \\
&\sim \frac{(-\alpha^2-4\alpha+4)}{4(2+\alpha)^2}\sigma^2 < 0
\end{aligned}
$$

In summary, we know that (a) $\lim_{s\to-\infty}\Delta > 0$, (b) $\lim_{s\to+\infty}\Delta < 0$, (c) Δ is concave then convex. From (a) and (b), Δ has at least one root. From (c), $\partial\Delta/\partial s$ can change sign no more than twice, which implies one of the following cases: 1. Δ is decreasing, 2. Δ is decreasing, then increasing, 3. Δ is increasing, then decreasing, 4. Δ is increasing, then decreasing, then increasing, 5. Δ is decreasing, then increasing, then decreasing. All of these cases jointly with the boundary conditions (a) and (b) imply a unique root.

To conclude the proof, we need to guarantee that the zero can occur for $s > \underline{s}$. Indeed, if the reputational factor is small (i.e., low discount factor), the equilibrium will still be no-disclosure for all s, which would correspond to a threshold $\tau = \underline{s}$. However, one can evaluate Δ at $\underline{s}$ and let K become large (which is equivalent to β becoming close to one). In that case, the function Δ will necessarily be positive at $\underline{s}$.$\square$

A.3. Empirical Analyses

Table 1: Summary Statistics

Our sample includes monthly production forecasts and actual productions of GM, Ford, and Chrysler for the period 1965-95, as reported by *Wards Automotive Report*. Forecast frequency (*FREQ*) is the total number of forecasts issued by the auto makers for a production month. Forecast horizon (*HORIZON*) is the number of days from the first forecast date to the end of a production month. Forecast error (*ERROR*) is the absolute difference between the actual production and the one-month-ahead forecast then deflated by the average actual production of each firm. One-month-ahead forecasts are those issued one month before the end of a production month. Monthly unemployment rates (*UNEMP*) are in percentage and from Bureau of Labor Statistics. *CEO_TURNOVER* equals one if the CEO of GM, Ford, or Chrysler is going to leave voluntarily within one year, and zero otherwise. *ZSCORE* is the minimum z-score of the three firms and firm-level z-score is based on the formula in Altman (1968). Monthly capacity utilization (*CAP*) is also in percentage and from the Federal Reserve. Industry inventory level (*INVT*) is the sum of these three firms' inventories divided by the sum of their total assets. Inventories and total assets are from Compustat. Industry production volatility (*VOL*) is the average standard deviation of production levels among these three firms in a calendar year. Inflation (Δ*CPI*), the change in Consumer Price Index, and changes in iron and steel price (Δ*IRON*), in industrial electric power price (Δ*ELECTRIC*), and in refined petroleum price (Δ*PETROL*) are all in percentage and from Bureau of Labor Statistics.

Variable	N	Mean	25th	Median	75th	Std Dev
Forecast frequency (FREQ)	366	4.43	2.00	4.00	6.00	2.66
Forecast horizon (HORIZON)	366	94.37	61.00	95.00	124.00	43.19
Industry average forecast error (ERROR)	366	4.62	1.58	2.97	4.95	6.60
Unemployment rate (UNEMP)	366	6.25	5.30	6.00	7.30	1.58
CEO_TURNOVER	366	0.33	0.00	0.00	1.00	0.47
Industry minimum Z-score (ZSCORE)	366	1.33	0.65	1.52	1.65	0.48
Industry capacity utilization (CAP)	366	78.61	73.84	79.82	86.76	12.01
Industry inventory level (INVT)	366	0.55	0.19	0.68	0.78	0.27
Industry production volatility (VOL)	366	42.87	32.50	39.80	50.48	14.46
Inflation (ΔCPI)	366	0.43	0.24	0.35	0.56	0.31
Change in iron and steel price (ΔIRON)	366	0.41	-0.10	0.18	0.69	0.98
Change in industrial electric power price (ΔELECTRIC)	366	0.50	0.00	0.32	1.22	1.59
Change in refined petroleum price (ΔPETROL)	366	0.50	-0.79	0.27	1.92	3.91

Table 2: Correlation Matrix (Right: Pearson; Left: Spearman)

Our sample includes monthly production forecasts and actual productions of GM, Ford, and Chrysler for the period 1965-95, as reported by *Wards Automotive Report*. Forecast frequency (*FREQ*) is the total number of forecasts issued by the auto makers for a production month. Forecast horizon (*HORIZON*) is the number of days from the first forecast date to the end of a production month. Forecast error (*ERROR*) is the absolute difference between the actual production and the one-month-ahead forecast then deflated by the average actual production of each firm. One-month-ahead forecasts are those issued one month before the end of a production month. Monthly unemployment rates (*UNEMP*) are in percentage and from Bureau of Labor Statistics. *CEO_TURNOVER* equals one if the CEO of GM, Ford, or Chrysler is going to leave voluntarily within one year, and zero otherwise. *ZSCORE* is the minimum z-score of the three firms and firm-level z-score is based on the formula in Altman (1968). Monthly capacity utilization (*CAP*) is also in percentage and from the Federal Reserve. Industry inventory level (*INVT*) is the sum of these three firms' inventories divided by the sum of their total assets. Inventories and total assets are from Compustat. Industry production volatility (*VOL*) is the average standard deviation of production levels among these three firms in a calendar year. Inflation (Δ*CPI*), the change in Consumer Price Index, and changes in iron and steel price (Δ*IRON*), in industrial electric power price (Δ*ELECTRIC*), and in refined petroleum price (Δ*PETROL*) are all in percentage and from Bureau of Labor Statistics. Two-tailed p-values are in in italics.

	FREQ	**HORIZON**	**ERROR**	**UNEMP**	**CEO_ TURNOVER**	**ZSCORE**	**CAP**	**INVT**	**VOL**	**ΔCPI**	**ΔIRON**	**ΔELECTRIC**	**ΔPETROL**
FREQ		0.86	-0.22	0.59	-0.11	-0.10	-0.46	-0.31	-0.53	0.02	-0.08	0.06	-0.04
p-value		*<.0001*	*<.0001*	*<.0001*	*0.03*	*0.07*	*<.0001*	*<.0001*	*<.0001*	*0.73*	*0.13*	*0.28*	*0.42*
HORIZON	0.88		-0.12	0.60	-0.02	-0.14	-0.38	-0.34	-0.58	0.01	-0.12	0.07	-0.08
p-value	*<.0001*		*0.03*	*<.0001*	*0.75*	*0.01*	*<.0001*	*<.0001*	*<.0001*	*0.82*	*0.03*	*0.16*	*0.15*
ERROR	-0.39	-0.30		-0.20	0.03	0.09	-0.03	0.21	0.28	0.11	0.05	0.01	0.04
p-value	*<.0001*	*<.0001*		*<0.01*	*0.62*	*0.09*	*0.62*	*<.0001*	*<.0001*	*0.03*	*0.32*	*0.88*	*0.46*
UNEMP	0.58	0.56	-0.25		-0.01	0.07	-0.61	-0.13	-0.68	-0.02	-0.10	0.05	-0.09
p-value	*<.0001*	*<.0001*	*<.0001*		*0.90*	*0.16*	*<.0001*	*0.01*	*<.0001*	*0.67*	*0.05*	*0.33*	*0.07*
CEO_TURNOVER	-0.07	-0.03	0.07	0.03		-0.12	-0.16	0.01	-0.06	0.20	0.11	0.17	0.14
p-value	*0.17*	*0.55*	*0.19*	*0.59*		*0.03*	*<0.01*	*0.82*	*0.29*	*<0.01*	*0.04*	*<0.01*	*0.01*
ZSCORE	-0.08	-0.07	0.01	0.13	-0.11		0.15	0.89	0.53	0.32	0.19	0.14	0.07
p-value	*0.14*	*0.16*	*0.87*	*0.01*	*0.03*		*<0.01*	*<.0001*	*<.0001*	*<.0001*	*<0.01*	*0.01*	*0.17*
CAP	-0.41	-0.34	0.03	-0.54	-0.24	0.30		0.11	0.41	-0.11	0.08	-0.11	0.05
p-value	*<.0001*	*<.0001*	*0.52*	*<.0001*	*<.0001*	*<.0001*		*0.03*	*<.0001*	*0.03*	*0.15*	*0.03*	*0.31*
INVT	-0.32	-0.31	0.23	-0.08	-0.01	0.78	0.14		0.70	0.42	0.30	0.21	0.15
p-value	*<.0001*	*<.0001*	*<.0001*	*0.13*	*0.83*	*<.0001*	*0.01*		*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<0.01*
VOL	-0.53	-0.52	0.26	-0.63	-0.02	0.52	0.40	0.72		0.18	0.14	0.04	0.13
p-value	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.72*	*<.0001*	*<.0001*	*<.0001*		*<0.01*	*0.01*	*0.40*	*0.01*
ΔCPI	0.06	0.02	0.10	0.00	0.11	0.36	-0.06	0.43	0.31		0.28	0.23	0.43
p-value	*0.27*	*0.67*	*0.06*	*0.95*	*0.03*	*<.0001*	*0.24*	*<.0001*	*<.0001*		*<.0001*	*<.0001*	*<.0001*
ΔIRON	-0.11	-0.16	0.06	-0.11	0.04	0.22	0.12	0.29	0.21	0.26		0.19	0.20
p-value	*0.03*	*<0.01*	*0.29*	*0.04*	*0.42*	*<.0001*	*0.02*	*<.0001*	*<.0001*	*<.0001*		*<0.01*	*<0.01*
ΔELECTRIC	0.04	0.02	0.02	0.11	0.21	0.18	-0.15	0.25	0.08	0.26	0.18		0.09
p-value	*0.48*	*0.74*	*0.75*	*0.04*	*<.0001*	*<0.01*	*<0.01*	*<.0001*	*0.14*	*<.0001*	*<0.01*		*0.07*
ΔPETROL	-0.03	-0.08	0.02	-0.06	0.13	0.13	0.07	0.17	0.16	0.37	0.17	0.12	
p-value	*0.53*	*0.12*	*0.66*	*0.22*	*0.02*	*0.01*	*0.21*	*<0.01*	*<0.01*	*<.0001*	*<0.01*	*0.02*	

Table 3: Forecast Frequency

Our sample includes monthly production forecasts and actual productions of GM, Ford, and Chrysler for the period 1965-95, as reported by *Wards Automotive Report*. Dependent variable, forecast frequency (*FREQ*), is the total number of forecasts issued by the auto makers for a production month. Monthly unemployment rates (*UNEMP*) are in percentage. *CEO_TURNOVER* equals one if the CEO of GM, Ford, or Chrysler is going to leave voluntarily within one year, and zero otherwise. *ZSCORE* is the minimum z-score of the three firms and firm-level z-score is based on the formula in Altman (1968). Monthly capacity utilization (*CAP*) is also in percentage. Industry inventory level (*INVT*) is the sum of these three firms' inventories divided by the sum of their total assets. Industry production volatility (*VOL*) is the average standard deviation of production levels among these three firms in a calendar year. Inflation (ΔCPI), the change in Consumer Price Index, and changes in iron and steel price ($\Delta IRON$), in industrial electric power price ($\Delta ELECTRIC$), and in refined petroleum price ($\Delta PETROL$) are all in percentage. Coefficients and standard errors (in italics) are reported. * two-tailed p<0.10; ** p<0.05; *** p<0.01.

	Model (1)		**Model (2)**		**Model (3)**		**Model (4)**		**Model (5)**		**Model (6)**	
UNEMP	**0.79**	***	**0.75**	***	**0.93**	***	**0.58**	***	**0.26**	***	**0.19**	
std. error	***0.04***		***0.06***		***0.11***		***0.04***		***0.08***		***0.14***	
CEO_TURNOVER	**-0.71**	***	**-0.84**	***	**-0.95**	***						
std. error	***0.10***		***0.08***		***0.06***							
ZSCORE							**1.46**	***	**2.38**	***	**2.73**	***
std. error							***0.19***		***0.24***		***0.47***	
CAP			-0.04	***	-0.04	***			-0.06	***	-0.07	***
std. error			*0.01*		*0.00*				*0.01*		*0.01*	
INVT			-0.24		-3.05	***						
std. error			*0.24*		*0.97*							
VOL			0.05	***	0.05	***			0.03	**	0.03	***
std. error			*0.01*		*0.01*				*0.01*		*0.01*	
ΔCPI					1.19	**					-0.59	
std. error					*0.55*						*0.56*	
ΔIRON					0.25	***					0.06	
std. error					*0.09*						*0.05*	
ΔELECTRIC					0.03						-0.07	
std. error					*0.06*						*0.08*	
ΔPETROL					-0.01						0.02	
std. error					*0.03*						*0.03*	
Time trend	0.09	***	0.13	***	0.07	***	0.16	***	0.24	***	0.25	***
std. error	*0.02*		*0.02*		*0.02*		*0.02*		*0.02*		*0.02*	
Month fixed effect	Y		Y		Y		Y		Y		Y	
Clustering by month	Y		Y		Y		Y		Y		Y	
N	366		366		366		366		366		366	
Adj. R-squared	0.47		0.50		0.52		0.48		0.53		0.53	

Table 4: Forecast Horizon

Our sample includes monthly production forecasts and actual productions of GM, Ford, and Chrysler for the period 1965-95, as reported by *Wards Automotive Report*. Dependent variable, forecast horizon (*HORIZON*), is the number of days from the first forecast date to the end of a production month. Monthly unemployment rates (*UNEMP*) are in percentage. *CEO_TURNOVER* equals one if the CEO of GM, Ford, or Chrysler is going to leave voluntarily within one year, and zero otherwise. *ZSCORE* is the minimum z-score of the three firms and firm-level z-score is based on the formula in Altman (1968). Monthly capacity utilization (*CAP*) is also in percentage. Industry inventory level (*INVT*) is the sum of these three firms' inventories divided by the sum of their total assets. Industry production volatility (*VOL*) is the average standard deviation of production levels among these three firms in a calendar year. Inflation (Δ*CPI*), the change in Consumer Price Index, and changes in iron and steel price (Δ*IRON*), in industrial electric power price (Δ*ELECTRIC*), and in refined petroleum price (Δ*PETROL*) are all in percentage. Coefficients and standard errors (in italics) are reported. * two-tailed p<0.10; ** p<0.05; *** p<0.01.

	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
UNEMP	**11.89**	***	**13.19**	***	**14.32**	***	**7.23**	***	**6.21**	***	**5.86**	***
std. error	***0.63***		***0.83***		***0.92***		***0.77***		***0.89***		***1.08***	
CEO_TURNOVER	**-2.58**	**	**-3.19**	***	**-3.80**	***						
std. error	***1.16***		***1.13***		***1.18***							
ZSCORE							**32.49**	***	**38.72**	***	**40.61**	***
std. error							***4.66***		***4.48***		***4.63***	
CAP			-0.12		-0.05				-0.53	***	-0.56	***
std. error			*0.12*		*0.13*				*0.11*		*0.14*	
INVT			24.85	**	6.42							
std. error			*10.20*		*11.44*							
VOL			0.92	***	0.97	***			0.69	***	0.73	***
std. error			*0.26*		*0.28*				*0.24*		*0.25*	
ΔCPI					9.77	**					-3.73	
std. error					*4.24*						*4.31*	
ΔIRON					0.78						-0.06	
std. error					*1.16*						*0.94*	
ΔELECTRIC					1.03						0.52	
std. error					*1.11*						*1.30*	
ΔPETROL					-0.47						-0.17	
std. error					*0.38*						*0.31*	
Time trend	1.83	***	3.65	***	3.25	***	3.45	***	4.56	***	4.67	***
std. error	*0.30*		*0.38*		*0.31*		*0.37*		*0.36*		*0.34*	
Month fixed effect	Y		Y		Y		Y		Y		Y	
Clustering by month	Y		Y		Y		Y		Y		Y	
N	366		366		366		366		366		366	
Adj. R-squared	0.59		0.61		0.61		0.63		0.65		0.64	

Table 5: Industry Average Forecast Error

Our sample includes monthly production forecasts and actual productions of GM, Ford, and Chrysler for the period 1965-95, as reported by *Wards Automotive Report*. Dependent variable, forecast error (*ERROR*), is the absolute difference between the actual production and the one-month-ahead forecast then deflated by the average actual production of each firm. One-month-ahead forecasts are those issued one month before the end of a production month. Monthly unemployment rates (*UNEMP*) are in percentage. *CEO_TURNOVER* equals one if the CEO of GM, Ford, or Chrysler is going to leave voluntarily within one year, and zero otherwise. *ZSCORE* is the minimum z-score of the three firms and firm-level z-score is based on the formula in Altman (1968). Monthly capacity utilization (*CAP*) is also in percentage. Industry inventory level (*INVT*) is the sum of these three firms' inventories divided by the sum of their total assets. Industry production volatility (*VOL*) is the average standard deviation of production levels among these three firms in a calendar year. Inflation (Δ*CPI*), the change in Consumer Price Index, and changes in iron and steel price (Δ*IRON*), in industrial electric power price (Δ*ELECTRIC*), and in refined petroleum price (Δ*PETROL*) are all in percentage. Coefficients and standard errors (in italics) are reported. * two-tailed p<0.10; ** p<0.05; *** p<0.01.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
UNEMP	**-0.51 *****	**-0.85 *****	**-0.93 *****	**-0.34**	**-0.56**	**-0.40**
std. error	***0.12***	***0.22***	***0.25***	***0.28***	***0.38***	***0.38***
CEO_TURNOVER	**0.62 ****	**0.03**	**0.04**			
std. error	***0.29***	***0.26***	***0.31***			
ZSCORE				**-1.21**	**0.30**	**-0.40**
std. error				***2.26***	***1.97***	***2.01***
CAP		-0.13 **	-0.13 **		-0.13 ***	-0.11 *
std. error		*0.06*	*0.07*		*0.05*	*0.06*
INVT		5.23	6.56			
std. error		*3.61*	*4.32*			
VOL		0.16	0.16		0.18 *	0.18
std. error		*0.11*	*0.11*		*0.11*	*0.11*
ΔCPI			-1.02			0.52
std. error			*1.95*			*1.60*
ΔIRON			-0.17			0.06
std. error			*0.33*			*0.32*
ΔELECTRIC			0.25			0.34
std. error			*0.21*			*0.21*
ΔPETROL			-0.01			-0.03
std. error			*0.05*			*0.05*
Time trend	-0.13 **	0.21 ***	0.25 **	-0.18	0.10	0.08
std. error	*0.05*	*0.07*	*0.11*	*0.14*	*0.06*	*0.08*
Month fixed effect	Y	Y	Y	Y	Y	Y
Clustering by month	Y	Y	Y	Y	Y	Y
N	366	366	366	366	366	366
Adj. R-squared	0.08	0.14	0.13	0.08	0.13	0.13

Table 6 Robustness Test for Industry Average Forecast Error and Unemployment Rate

All production months for the period 1965-95 are sorted into terciles based on unemployment rates. Months in the top tercile are defined as a high unemployment state and months in the bottom tercile are defined as a low unemployment state. Then we run time-series regressions of actual productions on production forecasts for the high and the low unemployment states separately to estimate the adjusted R-squared and the standard deviation of residuals. Actual productions and production forecasts are scaled by the actual production or the production forecast from the same month in the prior year. We bootstrap on hundred times to compute the t-statistics for the difference. The scalar is the average actual production in each unemployment state. P-values are based on a two-tailed test.

	Adj. R-squared	**Standard deviation of residuals**
High unemployment	*0.93*	*0.07*
Low unemployment	*0.84*	*0.12*
Diff in mean	0.09	-0.05
t-stat for the diff	*9.02*	*-11.81*
p-value for the diff	*<.0001*	*<.0001*

Table 7 Additional Evidence on Information Sharing and Unemployment Rate

This table extends the analysis in Doyle Snyder (1999) by adding the interaction term of lagged forecasted production level and the monthly unemployment rate. The dependent variable is the level of production forecast or actual production. Peer forecast takes the average of two peer firms. Monthly unemployment rates (*UNEMP*) are in percentage and from Bureau of Labor Statistics. *HORIZON* is based on lagged forecast. In model (1), lagged forecast is the first, second,… or the second last forecast. In model (2) lagged forecast is the first forecast. In model (3), lagged forecast is the one-month-ahead forecast, which are those issued one month before the end of a production month. Time trend is a numeric variable that increases by one from year to year. Coefficients and standard errors (in italics) are reported.
* two-tailed p<0.10; ** p<0.05; *** p<0.01.

Model:	(1)		(2)		(3)	
Dependent variable:	**The second or subsequent forecasts**		**The second forecast**		**Actual production**	
Peer lagged forecast × UNEMP	**0.007**	***	**0.012**	**	**0.010**	**
std. error	***0.002***		***0.005***		***0.005***	
Own lagged forecast × UNEMP	0.002		0.003		*0.002*	
std. error	*0.002*		*0.004*		0.003	
Peer lagged forecast	-0.049	*	-0.083	**	*-0.043*	
std. error	*0.028*		*0.039*		0.032	
Own lagged forecast	0.972	***	0.970	***	*0.953*	***
std. error	*0.017*		*0.028*		0.026	
UNEMP	-2.059	***	-3.355	**	*-1.896*	
std. error	*0.718*		*1.561*		1.228	
HORIZON	0.046	***	0.022			
std. error	*0.014*		*0.017*			
Time trend	-0.099		-0.063		*-0.009*	
std. error	*0.165*		*0.161*		0.107	
Month fixed effect	Y		Y		Y	
Clustering by month	Y		Y		Y	
N	3762		927		930	
Adj. R-squared	0.99		0.99		0.97	

Figure 3 Forecast Frequency and Horizon over Business Cycles

Blue bar (left axis) presents quarterly average forecast frequency (*FREQ*) and red dot (right axis) shows forecast horizon (*HORIZON*). The shaded area indicates periods when there is a high unemployment rate, identified as those greater than 7.5%.