

# Minimum Information Management and Price-Abundance Relationships in a Fishery

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This version: August 23, 2021

*Keywords:* Minimum Management Information; Commercial Fishery Management; Time-Series Analysis; Forecasting; VEC; MIDAS.

*JEL Classification:* Q22; C22.

*Acknowledgments:* We sincerely thank two anonymous reviewers for helpful comments on earlier drafts of the manuscript and Maria Crawford for skillful editing.

*Disclaimer:* The opinions expressed herein are those of the authors and do not necessarily reflect the views of NOAA.

## Abstract

We explore the information content of dockside prices and fishing costs in the estimation of stock abundance. Our approach is two-pronged: we first examine whether the implied biomass, that is, the biomass that is consistent with a simple microeconomic model calibrated with observed prices and costs, offers an approximation of actual stock assessments: both agree over the first 20 years of observation, but diverge over the last five. In a second approach, we use annual data in Vector Autoregressive (VAR), Bayesian VAR (B-VAR), and Vector Error Correction (VEC) frameworks and add monthly data in a mixed-frequency data analysis including Mixed-Frequency Bayesian VAR (MF-BVAR) and Mixed-Data Sampling (MIDAS) frameworks for log-differenced time series. Parameter uncertainties are addressed through Bayesian regression and forecasting methods. We find a statistically significant correlation between biometric estimates and changes in a price-based indicator that is robust to the inclusion of confounding factors. We conclude that the combination of price data and per-trip landings, when interpreted with care, can serve as a complementary, but comparatively affordable and timely, source of information for stock assessments.

## Résumé

Nous étudions le contenu informationnel des prix du poisson à la criée et des coûts d'exploitation dans le but d'estimer l'abondance des stocks. Notre approche comporte deux volets : dans un premier temps, nous calculons la biomasse implicite, c'est à dire la biomasse qui, compte tenu des prix et des quantités débarquées, est en accord avec un simple modèle d'optimisation des profits. La biomasse implicite et l'estimation biométrique des stocks sont en concordance sur une période de 20 ans, puis divergent sur les cinq dernières années. Dans un deuxième temps, nous utilisons les données annuelles dans le cadre du modèle autorégressif vectoriel (VAR), du VAR bayésien (B-VAR), et du modèle vectoriel à correction d'erreur (VEC). Nous incorporons ensuite les données mensuelles pour une analyse à fréquences mixtes des séries chronologiques en différence logarithmique, y compris le VAR bayésien à fréquences mixtes (MF-BVAR) et le modèle de données échantillonales à fréquences mixtes (MIDAS). Les incertitudes relatives aux paramètres sont adressées par le biais de régressions et prévisions bayésiennes. Nous trouvons une corrélation statistiquement significative entre la mesure d'abondance biométrique et un indice basé sur les prix, corrélation robuste malgré la considération d'une variété de facteurs confondants. Nous concluons qu'une interprétation judicieuse des prix et des quantités débarquées peut produire un complément d'information rapide et peu dispendieux.

## 1 Introduction

Effective and successful stewardship of fisheries relies on accurate stock assessments. The art and science of fish stock assessments rely on complex, dynamic biomass models that are revised, updated, and recalibrated periodically in response to new observations such as biological data on reproduction and mortality rates, food web interactions with other species, and measures of fishers' productivity. Like all scientific measurements, biomass estimates are subject to uncertainty and are therefore reported with confidence intervals. Data collection is also so onerous and time-consuming that full reevaluations and updates are published only every few years.

Unlike empirical studies of long-term price trends for non-renewable resources dating back to Barnett and Morse (1963), Slade (1982), and Moazami and Anderson (1994), to the best of our knowledge, the literature exploring the extent to which price and cost data can usefully signal abundance for a renewable resource such as fish is scant. While market prices are codetermined by a slew of factors and may also be distorted by regulatory constraints, proper control for these factors may yield empirical estimates of a relationship between abundance of species and market-based indicators that could conceivably constitute a useful 'minimum information' tool for policymakers. When assessments are performed with some regularity, such a tool could provide timely information on biomass, especially in the wake of catastrophic environmental events such as oil spills; where biometric stock assessments are not performed, the approach could serve as a warning of changing biomass for fisheries.

Our paper is most closely related to Batstone and Sharp (2003), who use the asset value of perpetual individual quota rights for the red snapper commercial fishery in New Zealand waters as a reflection of market participants' beliefs about expected future abundance. However, their approach is restricted to the context of established individual quota rights.

Using the specific case of the northern red snapper<sup>1</sup> (*Lutjanus campechanus*) fishery in the Gulf of Mexico (GoM) as an example, we take a two-pronged approach: we first look at the implications of a basic microeconomic model that recognizes that fishers are operating under evolving regulatory and technological constraints. A Schaefer production function captures the underlying assumption that biomass abundance affects fishing productivity and thus the per-unit cost of production. Equally important is the assumption of profit maximization: changing relative prices of inputs and output may affect fishing intensity and, with it, average productivity. In this initial approach, we find that the *implied* biomass, that is, the biomass that is consistent with profit-maximization under observed prices and costs, offers a good approximation of stock assessments for the first 20-odd years in our dataset but diverges significantly thereafter. Specifically, our results point to decreasing stocks after 2012, at odds with the rapidly increasing stock assessment estimates for that period, leaving us to speculate on the reasons for the discrepancy.

In our second approach, we run a battery of multivariate time-series analyses to further explore the relationship between stock, prices, and costs,

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<sup>1</sup>The northern red snapper is native to the Gulf of Mexico, the Caribbean, and Atlantic Ocean and is not to be confused with the New Zealand "red snapper" (*Centroberyx affinis*), a taxonomically different fish species.

taking into account other potentially relevant factors, such as the price of grouper (a substitute in consumption as well as a potential joint output) and the price of fuel. In-sample and out-of-sample forecasts confirm the usefulness of the approach. In contrast to our initial findings, this approach suggests that stock assessments have been consistent with the fishery's economic performance.

Our focus on the GoM's red snapper fishery is to some extent arbitrary as the exercise is meant as a mere proof of concept, but it is also justified by the fishery's economic importance in these waters and its experiences with a diverse set of management regimes over the past 30 years. It is also a politically contentious fishery, pitting commercial interests against conservationists, fishers against regulators, and commercial fishers against the recreational fishing industry. Furthermore, there has been some very recent controversy about this fishery's true stock size: the March 2021 release of an independent assessment, the fruit of a 12-million-dollar research project spearheaded by the Harte Research Institute<sup>2</sup> at Texas A&M-Corpus Christi, surprised fishers and regulators alike by reporting a red snapper count three times higher than NOAA's 2018 SEDAR 52 assessment.<sup>3</sup> Even though the newly discovered red snapper populations are located in the low relief areas of the Gulf of Mexico, which are not targeted by fishers and are therefore of limited relevance for the proper regulation of the red snapper fishing industry, fishers have seized on this significantly higher stock assessment to push for an equally significant increase in the total allowable catch

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<sup>2</sup><https://www.harte.org/snappercount>

<sup>3</sup>SouthEast Data, Assessment, and Review (<https://sedarweb.org/sedar-52>).

(TAC), the annual cap imposed by the regulator.

The remainder of the paper is organized as follows. We provide some background information in Section 2, including a brief history of fisheries management in the GoM, a description of stock assessment methodology, and a short discussion of the intricacies of measuring fishing effort. In Section 3, we derive the concept of implied biomass and compare it to actual stock assessment data. We present the data and estimate an index for effort in Section 4 and the time-series analysis in Section 5. Section 6 concludes with a discussion.

## 2 Background

### 2.1 Management of the Red Snapper Fishery in the GoM

There are several types of externalities in open access fisheries. Particularly notable is a production externality stemming from the harvesting process, in which resource stock enters a firm's production function. Each firm's harvest imposes a production diseconomy on other fishers, and vice versa. This reciprocal stock externality results in excessive fishing effort and over-exploitation of the resource. In 1976, the Magnuson-Stevens Act required fishery management councils to consider optimum yield in establishing annual catch limits in order to prevent overfishing. As a consequence, various methods of regulating the commercial and recreational fishing of red snapper were instituted in the early 1990s to rebuild the overfished red snapper population. These include the imposition of a quota known as the total allowable catch (TAC), limiting the prosecution of juvenile red snappers by imposing a

minimum fish size<sup>4</sup>, and imposing trip limits, i.e., a cap on pounds caught on a single trip. Initially, the TAC represented a common fishing quota (CFQ) in that it was enforced by limiting fleet access through seasonal closures. Regulatory adjustments were made in 2007 by introducing the individual transferable quota (ITQ) program with the express objectives of reducing both overcapacity in the commercial fishery and the adverse effects of derby fishing that were brought about by the CFQ regime. Furthermore, the introduction of the ITQ system also saw the abolishment of previous regulatory constraints such as trip limits and seasonal closures.

Under the ITQ management system, fishers were initially awarded dedicated access privileges<sup>5</sup> to a percentage of TAC. These percentages of harvesting rights are known as shares.<sup>6</sup> The TAC for the year is determined by the fisheries council. The amount of fish (in pounds) a participant is allowed to catch is referred to as ITQ allocation and defined as the product of TAC and shares.<sup>7</sup> Quotas have historically been binding; the latest red snapper ITQ report indicates that the percentage of landings relative to TAC since inception of the ITQ program ranged from 95.8 to 99.9, with 98.2% as the average (NMFS, 2020).

An ITQ system eliminates the externality associated with the race-to-fish

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<sup>4</sup>A minimum size limit of 15 inches total length was imposed in 1995, then lowered to 13 inches in 2007.

<sup>5</sup>Anderson (2006) argues that ITQ management regulation provides dedicated access to fish, not a right to fish themselves.

<sup>6</sup>In the case of red snapper in the GoM, these initial catch privileges were awarded to fishers on the basis of historical landings.

<sup>7</sup>All allocations expire at the end of the year, and banking of unused allocation is disallowed. While there is a 6.0203 percent limit on the accumulation and transfer of ITQ shares a single shareholder is allowed to hold, ITQ allocations are not subjected to such a limit. Accounts without shares may still participate in the program by obtaining allocations from ITQ shareholder accounts in the allocation market.



incentives of common quotas and allows fishers to engage in cost-decreasing, rather than cost-increasing, competition (Boyce, 1992). Although there are several variations of ITQ systems, Arnason (1990) argues that the quota market in an ITQ institutional arrangement is typically a “minimum information management system” that allows resource managers to achieve efficiency by relying on decentralized market mechanisms.<sup>8</sup>

Later, Arnason (2007a) develops a bargaining game model to show that while ITQ quota holders’ behavior as a group may not be socially optimal because of information and incentive problems, they nevertheless allow for more effective management. Elsewhere, Arnason (2007b) describes other limitations of ITQs; for example, they are often set at an aggregate level over a finite time period of typically one year. Heterogeneity in the sub-stocks and fluctuations in the biomass over time make ITQs inefficient. Moreover, ITQs may not lead to an optimal investment in fishing capital if there are distortions in the system such as sharecropping, in which labor is paid from the gross output. The ITQ program has also had mixed success in reducing overcapacity but was successful in mitigating derby fishing behavior and preventing TAC overages (NMFS, 2013; Agar et al., 2014).

## 2.2 Stock Assessment Methods

Abundance in fisheries was initially gauged by mere standardized catch rates (e.g., Schaefer, 1954). In the case of red snapper, the stock assessment process gained in sophistication in 1999, when catch-at-age data allowed for

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<sup>8</sup>In a nod to Arnason, as well as to Batstone & Sharp (2003), we use the expression ‘minimum information management’ in the context of biomass estimation, even though our approach is not limited to ITQ-managed fisheries.

cohort analysis of the fish population. With the availability of a wider range of fishery data, integrated stock assessment analysis methods have become increasingly more complex. Many of the more recent stock assessments in the U.S., including the 2018 SEDAR 52 red snapper stock assessment, use an integrated method known as stock synthesis, which relies on a statistical age-structured fish population modeling framework (Methot & Wetzel, 2013). The stock synthesis method utilizes variables such as catch per unit of effort (CPUE); abundance surveys; discards; length, age, and weight composition; and tag-recapture data.

Hilborn and Peterman (1996) have expressed concerns about uncertainties in the projections of fish stock assessments, which could stem from a wide range of sources including measurement of the state of fish abundance, model structure, parameter estimates, regulations, and environmental conditions. While the modeling of stocks has improved over time, some sources of uncertainty remain. Perhaps the biggest uncertainty for the GoM red snapper stock assessment, and most assessment models in general, is the relationship between spawning stock biomass and resulting recruitment (i.e., the stock-recruitment relationship). Typically, stock assessments assume a fixed value for stock-recruitment relationships. However, the dynamic of this relationship can change over time, invalidating the estimated size of the stock (NMFS, 2013). SEDAR 52 (2018, p.58) acknowledges that while the constant recruitment assumption may be acceptable for short-term projections, it may no longer be appropriate for long-term projections. Due to their reliance on strong assumptions, SEDAR 52 projections must be interpreted carefully and should not be used for equilibrium calculations. In

other words, regular updates of catch limits are necessary to account for changes in recruitment dynamics.

At least in the case of GoM red snapper, marine biologists have also expressed concern about the informativeness of CPUE as a metric for biomass, viewing it as an unhelpful complement to the large number of fishery-independent indices available for that species, especially as complex regulations have made CPUE standardization increasingly difficult. Indeed, a sensitivity analysis has shown that removing this variable from the SEDAR 52 base model only had a limited impact on the model's performance (NMFS, 2020) and, as a result, NOAA marine biologists believe that CPUE indices should no longer be used in future red snapper stock assessments.

### **2.3 Measurement of Effort and Empirical Evidence on ITQs**

Empirical studies of the effects of ITQs are faced with complexities in the measurement of effort in fisheries, which has been defined differently in various estimations of the capacity and production functions in fisheries. Clearly, variations and inaccuracies in the measurement of effort have diminished the reliability of CPUE as stock assessment indicators.

Effort can be viewed as an aggregate (or composite) input made of different factors of production. Beverton and Holt (1957) introduce the concept of relative fishing power (RFP) and discuss the need to standardize effort. Later, Griffin et al. (1976) argue that effort must be standardized to reflect heterogeneity in fishing power across water bodies or time. They develop an effort index relative to a standard vessel, (i.e., an RFP index), using vessel characteristics such as horsepower and length. Since these seminal works

were published, standardization of effort has been the subject of many discussions and applied in several empirical studies of fishery industries, including a study by Griffin et al. (1997) in which they apply the concept of RFP to the GoM shrimp fleet by modifying fishing effort (days at sea) based on changes in fishing power over time. They consider variables such as vessel characteristics (horsepower, vessel length, gear type, etc.) as well as the skill of the captain and the crew to arrive at a standardized measure of effort.

In their study of overcapacity in multi-species fisheries in France, Le Pape and Vigneau (2001) also deal with the issue of measurement of effort to create a sustainable balance in resources. They distinguish between nominal and effective fishing effort, where nominal effort is typically measured by fishing time or days at sea, while effective effort considers other factors such as technological progress and strategies such as use of multiple gears. The authors argue that technological advances such as increases in the horsepower of the vessel fleet enhance effective effort and contribute to overcapacity. Their principal component analysis on vessel characteristics and crew size identifies fishing intensity (amount of gear used simultaneously) as the primary cause of variations in nominal fishing effort for fixed gear vessels, while time is the cause of variations in nominal fishing effort for mobile gear vessels. They also discover that vessel characteristics affect monthly fishing time for mobile gear vessels.

Several studies have focused on evaluating the effectiveness of ITQ resource management systems in fisheries, including their impact on the fisher's choice of effort level. The introduction of the ITQ system in other parts of the U.S. has led to a reduction in excess capacity by reducing the total num-

ber of vessels and increasing the number of trips per vessel (Adelaja et al., 1998; Lian et al., 2010). Initial evidence shows that since the institution of the ITQ program, the number of both vessels and trips has fallen, as has the volatility of the number of trips (Agar et al., 2014). A more recent analysis of the effect of the ITQ on the GoM red snapper fishery suggests that TAC decreases and a sustained biomass recovery occurred during the years prior to the regime switch, offering a complementary explanation for the observed fleet size reduction. Indeed, had the TAC been high relative to biomass recovery, the regime switch could conceivably have led to new entries (Dakhliya and Marvasti, 2019).

### 3 Implied Biomass

#### 3.1 A Basic Model

We base our analysis on the canonical Schaefer (1954) production function in which *per-trip* output depends on both biomass  $B_t$  and effort  $e_t$ :

$$y_t = q_t B_t e_t^\alpha, \quad (1)$$

where  $\alpha$  is the output elasticity of effort. We assume decreasing returns to effort, so that  $0 < \alpha < 1$ . Parameter  $q_t$  is known as the “catchability” coefficient. Catchability can increase rapidly over time with the introduction of technological innovations such as radar and sonar or, alternatively, may decrease if, say, environmental factors cause fish to migrate farther away from shore, thereby blurring the effect of changing biomass. Here, we make

the simplifying assumption that catchability progressively improves at rate  $r$  as fleets become more efficient, so that  $q_t = (1 + r)q_{t-1}$ .

Effort is defined as an aggregate level of variable inputs, since we are focusing on month-to-month variation, whereas the effect of long-term changes in fixed inputs (e.g., vessel size) would be captured by the catchability coefficient. Note that under this specification, CPUE, i.e.,  $y_t/e_t$ , is proportional to biomass only for the special case of constant returns to effort ( $\alpha = 1$ ) and invariant catchability.<sup>9</sup>

Each firm maximizes annual (operating) profit  $\Pi$  in two separable steps: It first maximizes *trip-level* profit  $\pi_t$  with respect to per-trip effort

$$\max_{e_t} \pi_t = (1 - \ell)p_t y_t - w_t e_t, \quad (2)$$

where  $\ell$  stands for the share of revenue paid to labor under the generally practiced lay system,  $p_t$  is the market price of output, and  $w_t$  is the unit price of effort.

In the second step, the firm maximizes *annual* profit  $\Pi$  by deciding on the number of trips per year  $T$ ,

$$\max_T \Pi = T\pi_t^* - E(T), \quad (3)$$

where  $E$  stands for (largely unobserved) effort such as maintenance, wear and tear, as well as risk-taking, associated with the higher probability of fatal and non-fatal injuries when taking more trips in a year and finding it

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<sup>9</sup>Maunder et al. (2006) discuss how CPUE data can be a misleading measure of biomass when, among other things, changing catchability is not properly factored in.

more difficult to avoid dangerous weather conditions.

This conceptual separation of profit-maximization into two distinct steps clarifies our focus on trip-level decisions and trip-level cost data. Indeed, the first-order condition for a profit maximum with respect to  $T$  ( $E'(T) = \pi_t$ ) yields no additional information on biomass under the simplifying (but standard) assumption that biomass remains constant in the short run within each one-year period.<sup>10</sup>

### 3.2 The Open-Access, Unregulated Case

While our data do not cover the pre-1990 period of unregulated access, the open-access case nevertheless offers a simple framework to derive a basic relationship between price and biomass. From the first-order condition with respect to effort  $e_t$ , we obtain

$$y_t = (q_t B_t)^{\frac{1}{1-\alpha}} \left( \frac{\alpha(1-\ell)p_t}{w_t} \right)^{\frac{\alpha}{1-\alpha}} \quad (4)$$

so that implied biomass is given by

$$B_t = \frac{1}{q_t} \left( \frac{w_t}{\alpha(1-\ell)p_t} \right)^{\alpha} y_t^{1-\alpha}, \quad (5)$$

simply stating that the relationship between biomass and trip-level output is (1) nonlinear and (2) affected by the (net) price of output and the per-unit cost of effort. Thus, while prices are assumed to be exogenous to individual fishers, they are nevertheless key modifiers of the relationship between biomass and output.

<sup>10</sup>E.g., see Zhang & Smith (2006).

Note that since  $w_t/(\alpha(1 - \ell)p_t) = y_t/e_t$ , we can equivalently write

$$B_t = \frac{1}{q_t} \left( \frac{y_t}{e_t} \right)^\alpha y_t^{1-\alpha}, \quad (6)$$

so that the implied biomass can also be inferred from a nonlinear function of CPUE and output.

### 3.3 The CFQ with Trip-Limit Case

For the red snapper fishery, the CFQ period was marked by two concurrent regulatory restrictions: the TAC and per-trip catch limits set at 2,000 lb. for Class 1 and at 200 lb. for Class 2 permit holders.<sup>11</sup> As shown in Figure 1a, the 2007 increase in trip-level output by vessels targeting red snapper, when the CFQ management regime was replaced by ITQs and per-trip catch limits were abolished, suggests that the trip limits had generally been a binding constraint.

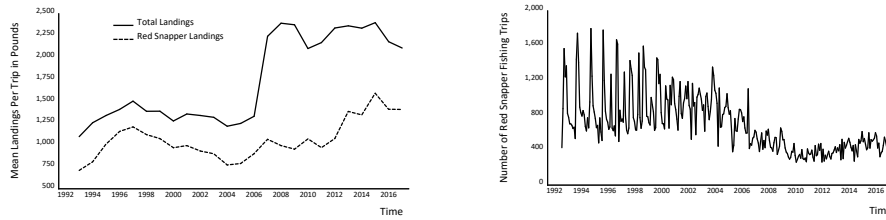


Figure 1: (a, left) Per-trip landings by vessels targeting red snapper (annual). (b, right) Number of trips (monthly)

Trip-level output was then arguably not affected by ex-vessel red snapper prices, as long as revenue exceeded variable costs. In other words, because

<sup>11</sup>These trip size restrictions were introduced in 1992, although the corresponding Class 1 and 2 licenses were only introduced in 1998.



of binding regulatory constraints, catch prices may have had little bearing on the optimal allocation of resources in response to biomass scarcity.

A fisher's annual catch, then, would be determined by the number of fishing trips. Because of the common-pool nature of CFQs, fishers had an incentive to take these trips in rapid succession to maximize their share of TAC. (See Figure 1b.) This race for fish would lead to costs such as an increased risk of accidents as well as wear and tear on equipment that were not systematically captured by logbook entries. However, as shown in the Appendix, the intensity of derby fishing has no implication for implied biomass that could be easily exploited with our limited data, so we must fall back onto far simpler considerations: Since per-trip output is determined by trip limits, not by the price of catch, we can restrict our attention to the average variable costs defined at the trip level. Specifically, letting  $\bar{y}_t$  denote the per-trip catch limit, if estimates of trip-level *average* variable cost  $c_t$  are available, then

$$c_t \bar{y}_t = w_t e_t = w_t \left( \frac{\bar{y}_t}{q_t B_t} \right)^{1/\alpha}, \quad (7)$$

so that implied biomass is given by

$$B_t = \frac{1}{q_t} \left( \frac{w_t}{c_t} \right)^\alpha \bar{y}_t^{1-\alpha}. \quad (8)$$

Since  $w_t/c_t = y_t/e_t$ , we can equivalently write

$$B_t = \frac{1}{q_t} \left( \frac{y_t}{e_t} \right)^\alpha \bar{y}_t^{1-\alpha}, \quad (9)$$

i.e., the implied biomass can again be inferred from a nonlinear function of CPUE and output.

### 3.4 The ITQ Case

The ITQ case is more straightforward, in particular because the cap on per-trip catch was abolished when the ITQ regime was introduced in 2007. Under the ITQ, management chooses an annual total allowable catch (or quota), TAC, and the per-pound allocation is traded in a free market. Denoting  $k_t$  the price of a one-pound allocation, the price net of allocation and labor's share of revenue is  $(1 - \ell)(p_t - k_t)$ . The first-order condition for a profit maximum then yields

$$y_t = (q_t B_t)^{\frac{1}{1-\alpha}} \left( \frac{\alpha(1-\ell)(p_t - k_t)}{w} \right)^{\frac{\alpha}{1-\alpha}}, \quad (10)$$

so that implied biomass is given by

$$B_t = \frac{1}{q_t} \left( \frac{w_t}{\alpha(1-\ell)(p_t - k_t)} \right)^\alpha y_t^{1-\alpha}, \quad (11)$$

which, save for the cost of allocation, is similar to the open-access case.

### 3.5 Calculation of Implied Biomass

Our monthly price, cost, and landings data, which we present in more detail in Section 4.1, allow us to calculate each period's implied biomass as derived in equation (8) for the 1993-2006 CFQ and equation (11) for the 2007-2017 ITQ regime. Our estimate for the output elasticity of effort is  $\alpha = 0.86$  (st.

err. = 0.04), but we conduct a sensitivity analysis and calculate implied biomass for a wide range of values for  $\alpha$ . Intuitively, the greater  $\alpha$ , the greater the role of prices in gauging biomass. Furthermore, we assume an annual rate ( $r$ ) of technological progress equal to a low 1% per year, a small figure aimed at attributing most gains in output to biomass growth.<sup>12</sup> We also calibrate the initial catchability parameter ( $q_{1993}$ ) such that our implied biomass matches the 1993 SEDAR 52 stock assessment.

As shown in Figure 2, in all cases the 12-month moving average of our computed implied biomass tracks SEDAR 52's annual stock assessment estimates rather closely until 2011, but then diverges from it sharply by pointing to an actual decline from 2012 on.

We are left to conjecture on the reasons for this divergence of the 2012-2017 estimates based on a simple microeconomic model from SEDAR 52's biometrically assessed stock. Rather than question the SEDAR 52 data, which is outside our area of expertise, we restrict our attention to the economic model. For instance, our model assumes a uniform and constant fleet, ignoring questions of entry and exit into the fishery. However, accounting for structural changes in which the least efficient vessels can exit the fleet would only further displace the role of biomass in any observed productivity gains. Furthermore, given that fishing trips are characterized by significant upfront fuel costs of traveling from port to fishing grounds and back, our

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<sup>12</sup>The extant literature reports a rather wide range of growth rate estimates, though: Tidd et al. (2016) find an average 3.8% increase in the Western Pacific purse-seine fleet's productivity (Malmquist index) over the 1993–2010 period. Ritzau et al. (2014) estimate that catchability increases by 3.2% per year due to technological developments. Kim et al. (2012) estimate an average 6% *drop* in the total factor productivity of 12 Korean offshore fisheries over the 1997-2009 period, the change ranging from a 16.6% drop of the trawl fishery and a 4.8% increase of the long line fishery.

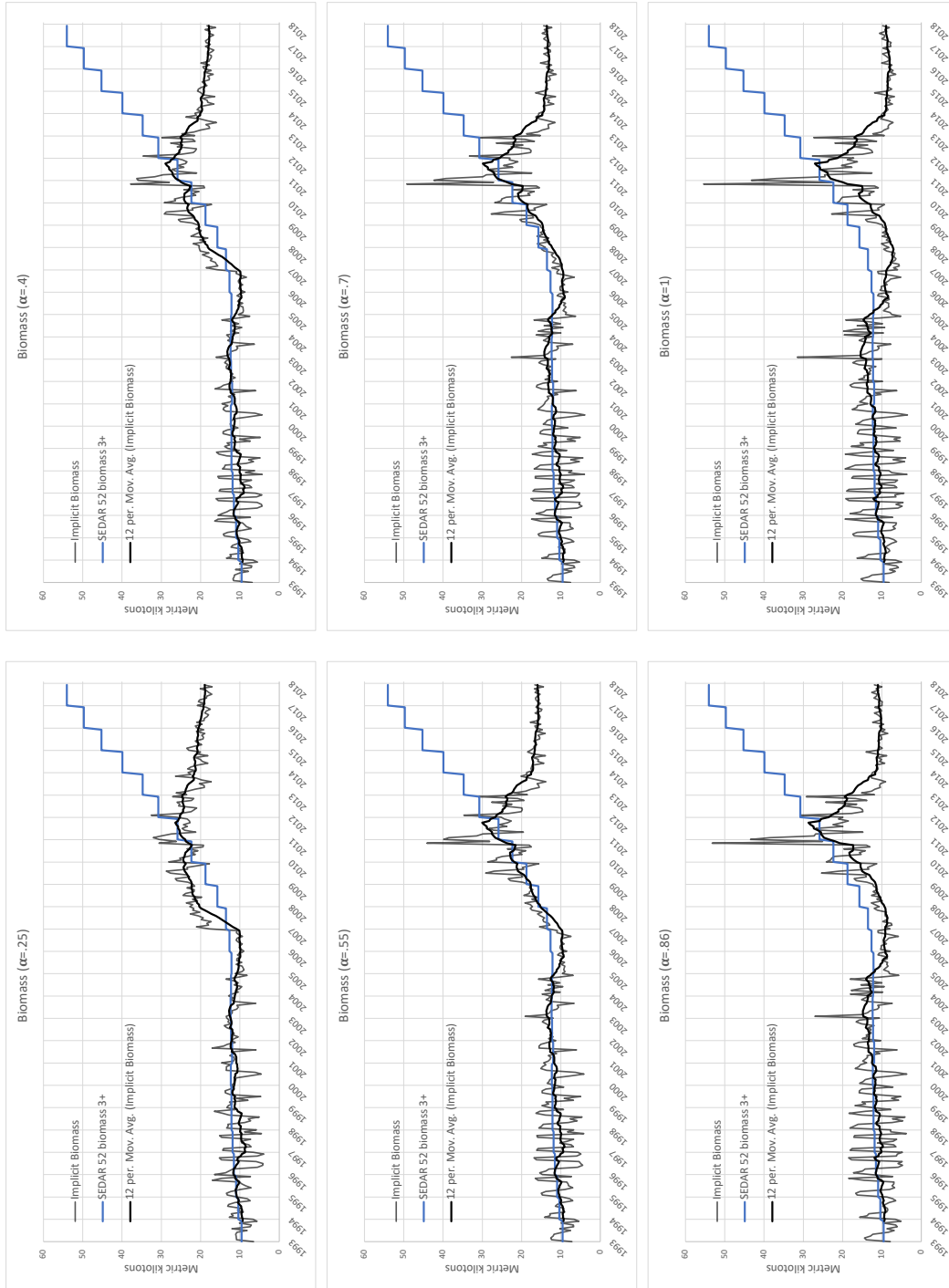


Figure 2: Implied biomass vs. stock assessment for range of returns-to-scale parameter

model may be challenged for its assumption of a globally concave trip-level production function, although an economies of scale argument would help explain the large gains in productivity brought about by the abolishment of trip limits in 2007, but not the drop some five years later. Our results may also be due to incomplete or inaccurate cost data, although data quality arguably improved over time as data collection protocols were refined. Finally, catchability,<sup>13</sup> rather than biomass *per se*, may have progressively decreased after 2012, possibly as a delayed consequence of the Deepwater Horizon oil spill in 2010, as suggested by Ainsworth et al. (2018), who estimate that the *biomass* of large reef fish may have decreased by 25% to 50% in the areas most affected by the spill.

#### 4 Data and Measurement of Effort

Given that CPUE has been a standard, though contentious, metric for abundance, we start by estimating a more general trip-level Cobb-Douglas production function for red snapper that, in line with usual CPUE calculations, takes into account both fixed (vessel characteristics) and variable (fuel and labor) inputs. This allows us to compare the resulting CPUE with the implied biomass calculations of the previous section.

We then proceed with a deeper empirical analysis of the relationships over time between prices, costs, and SEDAR estimates of species abundance and run a battery of time-series analyses that take into account additional variables such as the price of grouper, which is a joint output (as well as a

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<sup>13</sup>See Wilberg et al. (2009) for a survey of the use of a time-varying catchability parameter.

substitute for red snapper in terms of consumption), and dummy variables for policy changes.

The relationship between biomass and price is complicated by TAC changes as well as lags between policy changes and biological outcomes. In open-access fisheries, the relationship between biomass and price tends to be more predictable: increasing biomass improves productivity and increases landings, which in turn places a downward pressure on price. To the extent that high landings deplete biomass in the long run, landings would again fall and prices rise. In regulated fisheries like red snapper in the GoM, however, the stock dynamics are directly affected by changes in TAC, a policy variable. When biomass is declining, the fishery council typically lowers the TAC to ensure sustainability, and prices rise as a result. As biomass recovers under the restrictive TAC, we may observe a *positive* contemporaneous correlation between biomass and price. Conversely, once the stock has sufficiently recovered, the council may increase the TAC to accommodate fishers's demands for a larger harvest. This condition produces a positive relationship between biomass and TAC, but a negative relationship between biomass and price. In short, the contemporaneous relationship between stock abundance and prices may depend on TAC changes both past and present. The potentially ambiguous relationship between price and biomass is illustrated in Figure 3b, which shows the log-difference of the two series.

#### 4.1 Data

We compile a large array of data on the GoM red snapper fishery. Based on the availability of the various data components, the analysis covers the

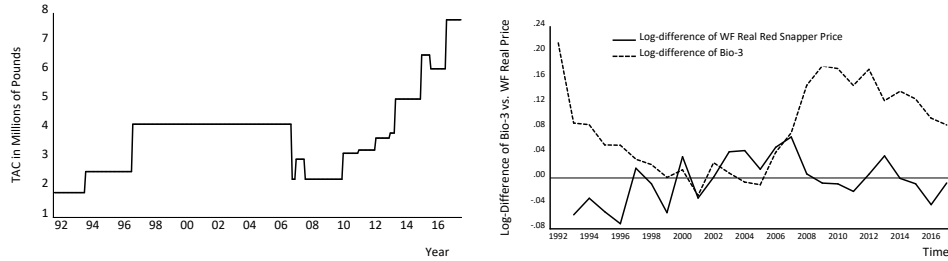


Figure 3: (a, left) Commercial TAC. (b, right) Log difference of TAC vs. Bio-3.

25-year period from January 1993 to December 2017. Landings and ex-vessel prices for whole fish are obtained from the NMFS, Southeast Coastal Fisheries Logbook Program, which is available for different bodies of water in the GoM. Prices are converted into real terms using the consumer price index, with 1984 as the base year.

The red snapper management unit in the GoM, controlled by the GoM Fishery Management Council, extends from the United States-Mexico border in the west through the northern Gulf waters and west of the Dry Tortugas and the Florida Keys. The annual stock assessment data are obtained from the Southeast Data Assessment Review 52 (SEDAR 52, 2018) process. We use the estimates for two measures of stock abundance: total biomass (Bio-0 or  $B_0$ ), measuring the weight of fish of all ages, and the biomass of fish that are at least three years of age (hereafter, Bio-3 or  $B_3$ ). The three-year age limit is consistent with the minimum fish size constraint often in effect. Population estimates are provided separately for the East and the West Gulf, separated roughly by the Mississippi River, as SEDAR red snapper assessments have identified differences in population trends for the two regions. The log of West Gulf total stock abundance is shown in Figure 4a

shows, while stock growth is shown in Figure 4b.

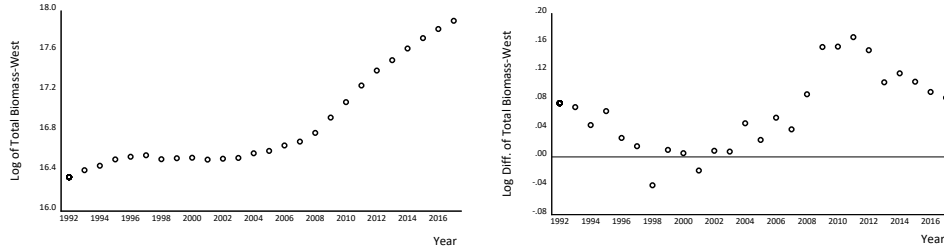


Figure 4: (a, left) Log of Bio-0. (b, right) Growth rate of Bio-0.

We match the West Gulf stock assessment data with the Florida Gulf Coast ex-vessel price data,  $p_t$ , which is the only complete historical price series.<sup>14</sup> Figure 5a shows the log of  $p_t$  and Figure 5b its growth rate.

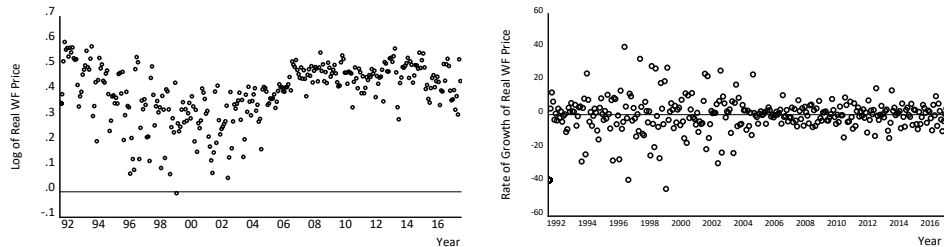


Figure 5: (a, left) Log of real  $p_t$ , 1984=100. (b, right) Growth rate of  $p_t$ .

In line with the theoretical model presented in Section 3, we employ a (log-transformed) time series of an input price index, as well as a “price-cost” (PC) variable that corresponds to the denominators in equations (8) and (11), namely the average variable cost of production (not including labor) for the CFQ case and the net price after paying for labor and allocation cost

<sup>14</sup>Price data are missing for all other GoM states, especially for Mississippi and Alabama: the percentages of missing price observations for Alabama, Louisiana, Mississippi, and Texas are 25, 15, 25, and 9, respectively. Note that GoM commercial red snapper fishing activities primarily take place in the Western part of the Gulf, off the coast of Florida.



for the ITQ case:

$$PC_t = \begin{cases} c_t & \text{for 1993-2006} \\ \alpha(1 - \ell)(p_t - k_t) & \text{for 2007-2017.} \end{cases} \quad (12)$$

The input price index (CI) is defined as the convex combination of the #2 diesel fuel price index (for one third), since diesel accounted for roughly one third of non-labor variable costs in 1993 (as well as on average), and the consumer price index (for two thirds) to account for price variations in other non-labor variable inputs such as ice, bait, and groceries. PC and CI are shown in Figures 6a and 6b.

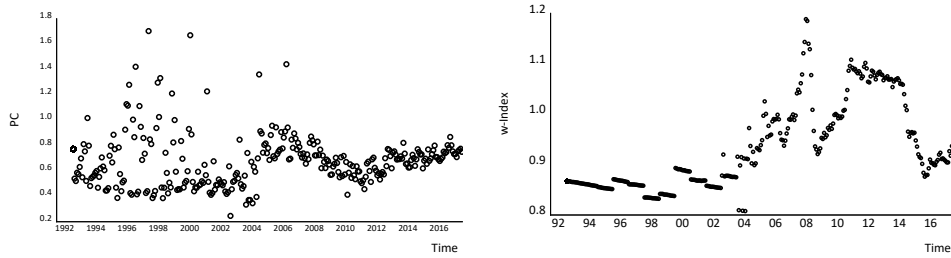


Figure 6: (a, left) Price-Cost variable. (b, right) Input price index.

## 4.2 Effort and CPUE

In order to measure fishing effort, compute CPUE, and examine its relation to red snapper abundance, we use data on crew size, vessel holding capacity, vessel length, horsepower, days at sea, and landings. The vessel characteristics dataset comes from NMFS’s vessel registration Permit Information Management System (PIMS), and the landing data are from the Southeast Coastal Fisheries Logbook Program. Following Griffin et al. (1976), we

consider a Cobb-Douglas type production function,

$$\begin{aligned} \ln LA_t = & \alpha_0 + \alpha_1 \ln HP_t + \alpha_2 \ln VL_t \\ & + \alpha_3 \ln HC_t + \alpha_4 \ln CS_t + \alpha_5 \ln DS_t + \varepsilon_t, \end{aligned} \quad (13)$$

where LA, HP, VL, HC, CS, and DS stand for landings, horsepower, vessel length, holding capacity, crew size, and days at sea, respectively. For homogeneity of fishing technologies, we focus on vessels using vertical-line and longline gears, which account for close to 98 percent of red snapper landings. Based on the unit root test results, we estimate equation (13) in a log-differenced manner. Production function estimates are made using annual and monthly data, allowing us to use the effort index in both the subsequent annual and mixed-frequency VAR estimations. The least-squares estimates for both the annual and the monthly data are reported in Table 1.

On the basis of the Akaike Information Criterion (AIC), Model 2 offers a superior fit for annual data, while Model 1 offers a better fit for data with monthly frequency. However, the value of the Durbin-Watson (DW) statistic in Model 1 suggests serial correlation, which, based on the correlogram of the residuals, is resolved in Model 2. We therefore select Model 2 for both data frequencies. The estimated production function coefficients are then used to construct both annual and monthly effort indices. Moreover, although the coefficients of a few variables in equation (13) are negative due to multicollinearity, unlike Del Valle et al. (2003)<sup>15</sup>, we choose not to com-

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<sup>15</sup>To demonstrate the inadequacy of the TAC, Del Valle et al. (2003) estimate a primal

Table 1: LS Estimates of Production Function

Variables	Annual		Monthly	
	Model 1	Model 2	Model 1	Model 2
HP <sub>t</sub>	-0.3120 (0.5052)	0.3310 <sup>a</sup> (0.5534)	-1.4254 <sup>a</sup> (0.2816)	-1.3595 <sup>a</sup> (0.1923)
VL <sub>t</sub>	3.5102 <sup>b</sup> (1.4057)	3.5679 <sup>b</sup> (1.4843)	5.7975 <sup>a</sup> (0.7697)	7.3844 <sup>a</sup> (0.4511)
HC <sub>t</sub>	0.0100 (0.0125)	-0.0008 (0.0093)	-0.0227 (0.0220)	-0.0130 (0.0115)
CS <sub>t</sub>	0.5280 (0.4698)	1.2167 <sup>b</sup> (0.5831)	0.5662 (0.5195)	0.6902 <sup>c</sup> (0.3699)
DS <sub>t</sub>	0.3608 <sup>c</sup> (0.1924)	0.5430 <sup>c</sup> (0.2997)	-0.7217 <sup>a</sup> (0.1265)	-0.7857 <sup>a</sup> (0.0826)
AR(1)	-	-0.6228 <sup>c</sup> (0.3317)	-	-0.5102 <sup>a</sup> (0.0276)
Constant	0.0382 (0.0233)	0.0186 (0.0194)	0.0073 (0.0369)	0.0069 (0.0232)
Adj. R <sup>2</sup>	0.38	0.5	0.38	0.52
F- Stat. (prob.)	3.87(0.01)	4.31(0.01)	37.74(0.00)	47.85(0.00)
AIC	-1.79	-1.93	1.96	1.7
DW	2.66	2.22	2.89	2.17

*a, b, c* denote statistical significance at the 1, 5, 10% levels, respectively. Standard errors are in parentheses.

bine input variables as they are merely used to develop the effort index.<sup>16</sup>

Table 2 reports the descriptive statistics for the variables used in equation (13) as well as the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root test results. All variables have unit roots and become stationary when the first difference is taken. From the orders of magnitude of the variables and the estimated coefficients, it is apparent that vessel length

production function for the anchovy fishery in Europe, which includes fishing effort as an index of boat days, vessel characteristics (gross registered tonnage and horsepower), and fishers’s skill as inputs. However, due to the nature of the data, the authors could not employ a varying measure of stocks.

<sup>16</sup>There is strong evidence of multicollinearity among the elements of the production function. The simple correlation coefficient between vessel length and crew is 0.99; 0.97 between holding capacity and horsepower. Also, the variance inflation factors (VIF) for vessel length, holding capacity, horsepower, and crew are 0.97, 0.97, 0.97, and 0.96, respectively. However, since the objective is to generate an effort index and no inferences are made regarding the individual coefficients, we chose to maintain all standard production function variables in the model.

is the most influential variable in the effort index.

The vector product of the estimated coefficients and the log-differenced values of the model variables used in equation 13 defines an index for the *growth* of fishing effort, shown in Figure 7a. The 6-month moving average of the conversion into a level variable is shown in Figure 7b. The graphs

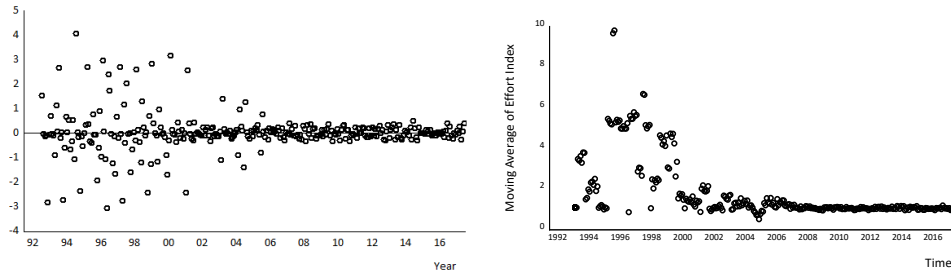


Figure 7: (a, left) Monthly growth of effort. (b, right) Effort index (6-month mov. avg.).

document that the ITQ regime greatly reduced fluctuations in fishing effort but did not reduce the overall level of fishing effort.<sup>17</sup> The Bai-Perron test is applied to examine up to five structural breaks in the variance of the series.<sup>18</sup>

<sup>17</sup>A similar observation can be made for the price time series shown in Figure 5, the 2007 switch to the ITQ system introducing a new regime of low price volatility.

<sup>18</sup>Table 2 shows that the annual and monthly effort indices are both stationary and appear to have a constant zero mean (0.007). Also, Table 3 suggests that the annual effort index is nearly normally distributed where skewness is -0.40, kurtosis is 3.14, and J.B. is 0.62 (prob. 0.73). However, the annual effort index deviates from a normal distribution: skewness is 0.62, kurtosis is 9.86, and J.B. is 606.60 (prob. 0.00). Finally, a Wald test Chi-square statistic for the constant (0.08, prob. = 0.78) and for trend (0.07, prob. = 0.79) reject the presence of a trend or a constant in the annual data. The Wald test also rejects the presence of a constant (0.01, prob. = 0.92) or a time trend (0.00, prob. = 0.98) in the monthly data. Assuming a constant mean, the following Bai-Perron multiple structural change test with a constant is applied for the existence, number, and timing of breaks in the transformed values of the effort index into variance:

$$y_t = x_t'q + z_t'\delta_j + \mu_t, \text{ where } t = T_{j-1} + 1, \dots, T_j \text{ for } j = 1, \dots, m + 1.$$

Here  $y_t$  is the dependent variable,  $x_t(p \dots 1)$  and  $z_t(q \dots 1)$  are vectors of covariates,  $q$  and  $\delta_j(j - 1, \dots, m + 1)$  are coefficient vectors, and  $\mu_t$  is the error term. More detailed information can be found in Bai and Perron (2003).

Table 2: Unit Root Tests and Descriptive Statistics (in Log)

Variables	Mean	Med.	Max.	Min.	St.D.	Skew.	Kurt.	N	Unit Rt Test: Level		Unit Rt Test: First Diff.	
									ADF	PP	ADF	PP
LA: Landings	6.47	6.84	7.61	2.93	1.03	-1.82	5.16	300	2.45 (11)	-7.41 <sup>a</sup>	-15.35 <sup>a</sup> (10)	-49.26 <sup>a</sup>
HP: Horsepower	5.84	5.84	6.17	5.12	0.15	-0.48	4.75	300	0.99 (11)	-0.68	-10.76 <sup>a</sup> (10)	-78.56 <sup>a</sup>
VL: Vessel Length	3.68	3.67	3.87	3.45	0.07	0.03	3.61	300	-0.17 (14)	0.01	-6.46 <sup>a</sup> (13)	-63.93 <sup>a</sup>
HC: Holding Cap.	7.37	8.49	11.29	0.15	2.26	-1.65	4.54	300	0.62 (5)	1.68 <sup>c</sup>	-12.43 <sup>a</sup> (4)	-87.11 <sup>a</sup>
CS: Crew Size	1.06	1.06	1.29	0.49	0.1	-1.57	8.52	300	0.22 (10)	-0.04	-12.96 <sup>a</sup> (9)	-36.41 <sup>a</sup>
DS: Days at Sea	1.29	1.49	2.08	0.57	0.31	0.34	2.29	300	0.44 (11)	-1.55	-13.64 <sup>a</sup> (10)	-74.95 <sup>a</sup>
EI: Effort Index	0.01	-0.03	4.04	-3.09	0.81	0.62	9.86	300	-15.39 <sup>a</sup> (10)	-49.55 <sup>a</sup>		
WP: $p_t$	0.4	0.42	0.6	-0.01	0.11	-0.93	3.66	300	-2.80 (11)	-10.16 <sup>a</sup>	-13.19 <sup>a</sup> (10)	-98.55 <sup>a</sup>
PC: Price-Cost	0.65	0.66	0.10	1.98	0.33	0.70	3.59	300	9.58 <sup>a</sup> (0)	3.61 <sup>b</sup>		
CI: Cost Index	0.85	0.88	0.61	-0.99	0.09	0.66	2.23	300	-2.26 (4)	2.58	-8.77 <sup>a</sup>	-23.50 <sup>a</sup>
PG: Pr. Grouper	0.46	0.45	0.69	0.19	0.1	0.22	2.49	300	-1.57 (12)	7.77 <sup>a</sup>	8.53 <sup>a</sup> (11)	-76.66 <sup>a</sup>
B0: Bio-0	16.87	16.59	17.90	16.34	0.50	0.95	2.37	26	-2.06 (0)	-0.41	-0.81 (0)	-0.82
B3: Bio-3	16.65	16.33	17.81	15.99	0.56	0.91	2.36	26	-2.81 (1)	-0.50	-0.79 (0)	-0.80
EI: Effort Index	0.02	0.01	0.20	-0.20	-0.09	-0.40	3.14	26	-4.10 <sup>a</sup> (0)	-4.08 <sup>a</sup>		
WP: $p_t$	-0.41	-0.79	6.5	-7.26	3.65	-0.03	2.25	26	-3.52 <sup>a</sup> (0)	-3.47 <sup>a</sup>		
PC: Price-Cost	0.56	0.44	0.22	1.12	0.28	0.64	1.97	26	0.10 (0)	-1.64	-4.06 <sup>a</sup> (0)	4.00 <sup>a</sup>
CI: Cost Index	0.84	0.88	0.66	0.95	0.09	0.62	2.00	26	-1.71 (0)	-1.71	-5.07 <sup>a</sup> (0)	-5.16 <sup>a</sup>
PG: Pr. Grouper	0.43	0.41	0.62	0.31	0.08	0.87	2.85	26	-1.69 (0)	-1.69	-6.76 <sup>a</sup> (0)	-12.45 <sup>a</sup>

<sup>a</sup> (<sup>b</sup>) significant at the 1% (5%) level. Unit root tests are specified with a constant and trend for all variables except the biomass variables. Numbers of lag length are in parenthesis. All variables except the effort index are in log difference (growth rate). The biomass series becomes stationary after second differencing.

The resulting sup F statistic for the monthly effort index is 0.56 and WD max F is 1.75, thus rejecting any statistically significant structural break. For the annual effort index, the Bai-Perron test sup F statistic is 11.03 and WD max F is 46.68, pointing to the presence of multiple structural breaks. We could not identify a unique structural break in either of the two measures of effort data, suggesting that changes in effort have occurred gradually rather than as a sudden shift with the 2007 introduction of the ITQ program.

Because days at sea is an important component of the effort index, we present it separately in Figure 8a, corroborating the observation that fluctuations in effort greatly decreased after the inception of the ITQ system.

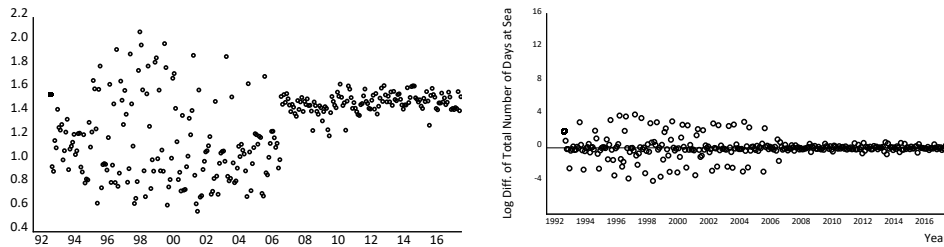


Figure 8: (a, left) Trip duration in days. (b, right) Log difference of trip duration.

CPUE, calculated as the ratio of landings to the estimated effort index, is generally increasing, in particular so after 2012, putting into stark relief the divergent inferences between our previous, price-informed approach and one merely based on the ratio of physical quantities.

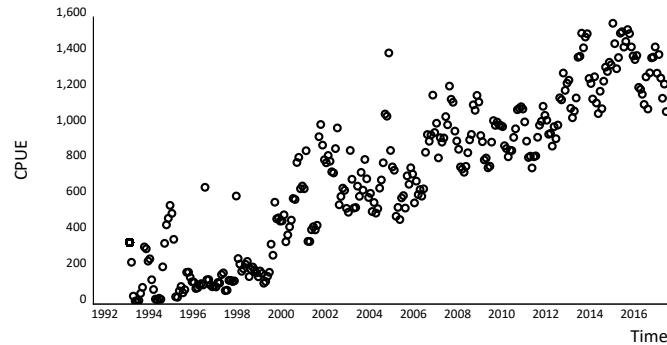


Figure 9: 6-month moving average of CPUE.

## 5 Time-Series Analyses

### 5.1 Methodologies

The mixed-frequency nature of the data—stock assessment data are annual while all other data are monthly—presents an empirical challenge. Having established that all time series are stationary after first-differencing, we first employ the traditional method of aggregating the high-frequency data to obtain a balanced dataset with a common frequency. We start with a standard VAR model and then, to account for parameter uncertainty, employ Bayesian VAR regression. Neither provides useful results, which we attribute to the loss of information from the conversion of high-frequency variables to the lowest frequency.

As a solution, we turn to mixed-frequency approaches, namely MF-BVAR with Wishart prior and MIDAS. In addition, we deal with the mixed-frequency nature of the data by using the annual data in the cointegration technique, which is concerned with long-run equilibrium (Granger, 1988). Here, the dynamics of the Vector Error Correction (VEC) model traces the

movement of the variables in any period to the previous periods' deviation from the long-run equilibrium of the cointegrated series.

For completeness, we briefly review the time-series models used in this study.

### **Standard VAR**

Standard VAR models require all variables in the VAR to have the same frequency. The standard (unrestricted) VAR in reduced form is specified as:

$$y_t = \varphi_0 + \pi_1 y_{t-1} + \cdots + \pi_p y_{t-p} + \varphi_1 x_t + \mu_t, \quad (14)$$

where  $y_t$  is a vector of endogenous variables,  $x_t$  is a vector of exogenous variables, and  $\mu_t$  is a white-noise disturbance. Here, since only lagged values of the endogenous variables appear on the right-hand side of the VAR equations and innovations are assumed to be uncorrelated with lagged innovations and the exogenous regressors, standard orthogonality conditions hold and the least-squares method yields consistent estimates.

### **Bayesian VAR**

The B-VAR approach deals with over-parametrization of VAR, especially when data are limited, by applying priors as a logical and consistent method of imposing parameter restrictions in order to shrink the unrestricted model into a more parsimonious one. For this purpose, the B-VAR approach uses a set of prior beliefs that are formed using evidence contained in the data.



The B-VAR model for the  $M$ -vector of endogenous variables, i.e.,  $y_t = (y_{1t}, y_{2t}, \dots, y_{Mt})'$ , and  $p$  number of lags can be written as:

$$y_t = \delta_0 + \sum_{j=1}^p A_j y_{t-j} + \gamma_p F_t + \varepsilon_t, \quad (15)$$

where  $\delta_0$  is a vector of intercept coefficients,  $A_j$  is a matrix of lag coefficients,  $\gamma_t$  is a vector of exogenous variables, and  $\varepsilon_t$  is an  $M$ -vector of errors where  $\varepsilon_t \sim \tilde{N}(0, \Sigma)$  (Koop and Korobilis, 2010). A few priors are tested in B-VAR estimates. Based on the RMSE of the forecast, we select the normal Wishart prior, which assumes normality of the covariance matrix but relaxes the assumption of the posterior being known.

### Mixed-Frequency Bayesian VAR

Here, the interest is in the dynamic relationship between variable  $y_t$ , which has an annual frequency, and variables  $m_t$ , which have a monthly frequency. The VAR contains  $k_L$  variables  $y_L^i$  observed at low frequency and  $k_H$  variables  $y_H^i$  observed at high frequency. Let  $y_{L,t_L}^i$  represent the  $i$ th low-frequency variable observed during low-frequency period  $t_L$ , and  $y_{H,t_H}^i$  represent the  $i$ th high-frequency variable observed in the  $t$ th high-frequency period during low-frequency period  $t_L$ . A mixed-frequency VAR model, as developed by Ghysels (2016), can thus be written by stacking the  $k_L$  and  $k_H$  variables into matrices  $y_L$  and  $y_H^i$  respectively as:

$$\begin{bmatrix} Y_{H,t_L,1} \\ \vdots \\ Y_{H,t_L,1} \\ Y_{L,t_L} \end{bmatrix} = \sum_{j=1}^p \begin{bmatrix} \Pi_j^{1,1} & \dots & \Pi_j^{1,m} & \Pi_j^{1,m+1} \\ \vdots & \ddots & \vdots & \vdots \\ \Pi_j^{m,1} & \dots & \Pi_j^{m,m} & \Pi_j^{m,m+1} \\ \Pi_j^{m+1,1} & \dots & \Pi_j^{m+1,m} & \Pi_j^{m+1,m+1} \end{bmatrix} \begin{bmatrix} Y_{H,t_L-j,1} \\ \vdots \\ Y_{H,t_L-j,1} \\ Y_{L,t_L-j} \end{bmatrix} + \begin{bmatrix} E_{H,t_L,1} \\ \vdots \\ E_{H,t_L,1} \\ E_{L,t_L} \end{bmatrix} \quad (16)$$

where  $\Pi_j^{a,b}$  is  $k_H \times k_H$ ,  $\Pi_j^{m+1,b}$  is  $k_L \times k_H$ , and  $\Pi_j^{a,m+1}$  is  $k_H \times k_L$ , for all  $j, a, b = 1, \dots, m$ , and  $\Pi_j^{m+1,m+1}$  is  $k_H \times k_L$ . The Ghysels model uses a prior similar to that of Litterman/Minnesota for external distributional information for the parameters, which leads to simple posterior inference with a normal distribution. While the Litterman/Minnesota prior does not include a full Bayesian treatment of  $\Sigma$  as an unknown parameter (Koop and Korobilis, 2010), the Ghysels prior has a subtle difference in allowing for cross-frequency variances.

MF-BVAR is sensitive to the choice of hyperparameters (Schorfheide and Song, 2015). We select the default of 5 for  $\lambda_1$ , which measures the overall tightness of the prior. The ideal number of observations in the frequency conversion is 12, which is consistent with the dynamic of the annual/monthly system.

## MIDAS

We apply a MIDAS regression for time-series analysis of data at different frequencies where conditional expectations are specified as a distributed lag of regressions recorded at some higher sampling frequency. To capture the dynamics of the series, a conventional approach of an Almon polynomial distributed lag (PDL) regression includes a lagged dependent and current

and lagged independent variables (Ghysels, et al., 2009; Andreou, et al., 2013; Ghysels, 2016).<sup>19</sup> Here, we are interested in the dynamic relationship between variable  $y_t$ , which has an annual frequency, and variables  $m_t$ , which have a monthly frequency. Adapting the multivariate linear MIDAS regression model by Ghysels, Santa-Clara, and Valkanov (2004),

$$y_t = q_0 + \sum_{i=1}^P \phi_i y_{t-P} + \sum_{i=1}^n q_i m^{K_i}(\theta_i, L) x_{t,i}^{K_i} + \nu_t, \quad (17)$$

where  $\phi_i$  is a matrix of lag coefficients and  $x_t$  is a vector of  $n$  right-hand time-series variables sampled with  $K_i$  periodicity. In other words,  $x_{t,i}^{K_i}$  is sampled  $1/K_i$  times for each  $y_t$  period. In our case of annual and monthly data, equation (17) is a projection of yearly  $y_t$  onto monthly data  $x_{t,i}^{K_i}$  using up to 12 monthly lags. The overall impact of each of the lagged  $x_{t,i}^{K_i}$  variables on  $y_t$  is captured by parameters  $q_i$ . The lag coefficient in  $(\theta_i, L)$  of the corresponding lag operator  $L$  is parameterized as a function of a small dimensional vector of parameters  $\theta$ , where  $\theta$  is the weight. The MIDAS Almon PDL method uses a weighted regression that takes a number of the higher-frequency variables and fits them into a lower-order polynomial. The PDL weighting function is also used to place restrictions on lag coefficients in an autoregressive model where for each high-frequency lag up to  $k$ , the regression coefficients are modeled as a  $P$ -dimensional lag polynomial in the MIDAS parameters  $\theta$ . The maximum number of lags is set at 12 and the polynomial ( $P$ ) degree is 2, except in the presence of singularity, when polynomial degree 1 is used. In contrast to MF-VAR, MIDAS offers a more

<sup>19</sup>The number of observations is insufficient to run an unconstrained distributed lags model (U-MIDAS).

parsimonious model with fewer parameters to be estimated.

### Vector Error Correction

In this approach, the Johansen (1995) cointegration test is first conducted to ensure the existence of cointegrating equations. The VEC model, which is a restricted variation of the VAR model, is then used with an error correction term for each cointegrating equation. For example, if the series follows a standard ADF test specification where:

$$\Delta y_t = \alpha + \delta t + \rho y_{t-1} + \lambda \Delta y_{t-1} + e_t, \quad (18)$$

that has a mean and a time trend but the cointegrating equations have only intercepts, the VEC becomes:

$$\Delta y_{1,t} = \delta_1 + \gamma_1(y_{2,t-1} - \mu - \rho y_{1,t-1}) + e_{1,t}, \quad (19)$$

and

$$\Delta y_{2,t} = \delta_2 + \gamma_2(y_{1,t-1} - \mu - \rho y_{2,t-1}) + e_{2,t}, \quad (20)$$

where  $\mu$  is the mean and  $e_t$  is the error term. The VEC model attempts to correct for  $e_t$  through a series of short-run adjustments such that the behavior of the variables converges to their cointegrating relationship.

## 5.2 Regression Results and Forecasting Evaluations

We begin with a naïve system that focuses on the Bio-0 stock measure and the price-cost variable (PC) defined in equation (12), the primary focus of the empirical analysis. In subsequent models, we progressively add control variables. In Model 2, we follow the results from the theoretical model's equations (8) and (11) by adding landings and the input price index. We add the ITQ dummy variable in Model 3 and the price of grouper (PG) in Model 4.<sup>20</sup> Because of singularity errors due to linear correlations and limited degrees of freedom, other control variables such as the TAC reduction dummy and trip length TL were not added to the system. The process is then repeated for the Bio-3 stock.

Analysis of the data based on each estimation method is followed by in-sample and 2-step-ahead ( $h = 1, 2$ , i.e., a two-year forecast horizon) out-of-sample forecasts based on the best fit. The forecasting evaluation that follows can be thought of as a model validation procedure. We use a static forecast where the actual value of the dependent variable is used for each subsequent forecast, which reduces the margin of errors.

While longer time-series data might have improved the estimates, we find the first three models (VAR, B-VAR, and MF-VAR) to be poor fits for the data and insufficiently reliable for forecasting: the coefficients of most variables, except the lagged dependent variable, are statistically insignificant, while the adjusted  $R^2$  in some cases is negative. The results from these

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<sup>20</sup>We excluded imports from the VAR analysis because we expect the effect of imports to be reflected in domestic prices. Empirical findings on the relationship between the prices of imported and domestic fish also confirm market integration and the law one price in fisheries (Asche, et al., 2004 and 2012).

models have been relegated to Tables A1, A2, and A3 in the appendix.

## MIDAS

The least-squares estimates of the MIDAS PDL models are reported in Tables 3 and 4. The Almon PDL lag lengths are selected based on their statistical significance.<sup>21</sup> The residual autocorrelations are also examined to make sure that they are white noise. PDL1 produces highly significant results for the Bio-0 system in all model specifications. The PDL2 coefficient is also statistically highly significant in the first three model specifications. The sign of the coefficients for PC confirm the negative correlation between stock biomass and the price-cost variable. We examine the root of the characteristic polynomial for the stability condition of the VAR systems. The necessary and sufficient condition for stability is that all characteristic roots lie inside the unit circle. The characteristic polynomial is of full rank, and all variables are stationary. We find no root lies outside the unit circle for any model specifications, so the stability condition is met.

The three most common measures of predictive accuracy based on loss functions, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Theil inequality coefficient, are reported in Tables 3 and 4. While MAE is dependent on the scale of the dependent variable, it is less sensitive to large deviations than is RMSE. The Theil inequality coefficient measures the RMSE in relative terms. Therefore, the Theil inequality coefficient is scale invariant and lies between zero and one, where one is a

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<sup>21</sup>While there is a potential problem with multicollinearity when standard distributed lag models are used, Almon PDL used in a MIDAS regression prevents this problem.

Table 3: MIDAS Almon PDL: Bio-0

	Annual		Monthly	
	Model 1	Model 2	Model 3	Model 4
<b>Full-Sample MIDAS:</b>				
PC (PDL1)	-0.1142 <sup>a</sup> (0.0350)	-0.1036 <sup>a</sup> (0.0292)	-0.1232 <sup>a</sup> (0.0406)	-0.0815 <sup>a</sup> (0.0221)
PC (PDL2)	0.0163 <sup>a</sup> (0.0039)	0.0194 <sup>a</sup> (0.0050)	0.0352 <sup>a</sup> (0.0185)	0.0011 (0.0034)
CI (PDL1)		-0.1975 <sup>b</sup> (0.0895)	0.9397 <sup>a</sup> (0.3227)	0.7059 <sup>b</sup> (0.2584)
CI (PDL2)		0.0758 <sup>a</sup> (0.0191)	-0.3991 <sup>a</sup> (0.1278)	-0.3880 <sup>a</sup> (0.1238)
LA (PDL1)		0.0005 (0.0128)	-0.0418 <sup>a</sup> (0.0114)	0.0177 <sup>b</sup> (0.0073)
LA (PDL2)		0.0057 (0.0042)	-0.0043 <sup>a</sup> (0.0012)	-0.0050 <sup>a</sup> (0.0010)
ITQ (PDL1)			-1.2206 (2.7079)	2.1551 (2.3033)
ITQ (PDL2)			0.4439 (0.5286)	-0.2229 (0.6394)
PG (PDL1)				-52.0509 <sup>a</sup> (9.7273)
PG (PDL2)				15.1549 <sup>a</sup> (3.0349)
Adj. $R^2$	0.84	0.90	0.90	0.96
Log Likelihood	-52.41	-43.47	-42.03	-29.85
AIC	4.70	4.29	4.34	3.49
<b>In-Sample Forecast:</b>				
RMSE	2.1487	1.4805	1.3943	0.8394
MAE	1.6979	1.1922	1.0190	0.7308
Theil Inequality Coeff.	0.8500	0.7041	0.6858	0.3039
<b>Out-of-Sample Forecast:</b>				
RMSE	0.8900	0.3565	3.1198	0.8394
MAE	0.8393	0.3564	3.0724	0.7308
Theil Inequality Coeff.	1.4099	0.4318	4.4885	0.3039
Stability Test	Yes	Yes	Yes	Yes

Note: Automatic lag selection, max lags=12.  $a$ ,  $b$ , and  $c$  denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

Table 4: MIDAS Almon PDL: Bio-3

	Annual		Monthly	
	Model 1	Model 2	Model 3	Model 4
<b>Full-Sample MIDAS:</b>				
PC (PDL1)	-0.0954 <sup>b</sup> (0.0389)	-0.0765 <sup>b</sup> (0.0299)	-0.0826 <sup>a</sup> (0.0279)	-0.1054 <sup>a</sup> (0.0228)
PC (PDL2)	0.0139 <sup>a</sup> (0.0042)	0.0051 (0.0052)	0.0081 (0.0048)	0.0141 <sup>a</sup> (0.0029)
CI (PDL1)		-0.2356 <sup>b</sup> (0.0926)	-0.1588 <sup>c</sup> (0.0827)	-0.0874 (0.0670)
CI (PDL2)		0.0930 <sup>a</sup> (0.0180)	0.0802 <sup>a</sup> (0.0166)	0.0437 <sup>b</sup> (0.0160)
LA (PDL1)		0.0154 (0.0112)	0.0130 (0.0087)	0.0026 (0.0091)
LA (PDL2)		-0.0015 (0.0024)	-0.0032 <sup>b</sup> (0.0013)	-0.0029 <sup>b</sup> (0.0015)
ITQ (PDL1)			5.2814 <sup>b</sup> (2.3345)	7.3066 <sup>a</sup> (1.8296)
ITQ (PDL2)			-0.7409 <sup>b</sup> (0.3450)	-1.0296 <sup>a</sup> (0.2710)
PG (PDL1)				5.0516 (11.5206)
PG (PDL2)				-13.0960 <sup>b</sup> (6.7336)
Adj. $R^2$	0.84	0.93	0.95	0.97
Log Likelihood	-55.05	-42.54	-37.56	-30.42
AIC	4.92	4.21	3.96	3.54
<b>In-Sample Forecast:</b>				
RMSE	2.3982	1.4238	1.1570	0.8593
MAE	1.9791	1.4105	0.9770	0.7301
Theil Inequality Coeff.	0.5732	0.3377	0.2165	0.4876
<b>Out-of-Sample Forecast:</b>				
RMSE	0.9918	1.4276	2.7952	2.7940
MAE	0.7711	1.1363	2.5223	2.7935
Theil Inequality Coeff.	0.1372	0.3255	3.4668	2.6504
Stability Test	Yes	Yes	Yes	Yes

Note: Automatic lag selection, max lags=12.  $a$ ,  $b$ , and  $c$  denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.



perfect fit. Based on the value of AIC, Model 4 offers the best fit estimate of the MIDAS regression for Bio-0. A comparison of the MAE and Theil inequality coefficient values across the four model specifications also suggests that Model 4 provides the best in-sample and out-of-sample forecasts.

Since the effect of the biomass stock regressor on price happens over time rather than once, PDL coefficients are essentially lag weights and together comprise the lag distribution of the effects. In other words, PDL coefficients capture the dynamics of marginal effects and provide insight on the magnitude and timing of the effect of changes in biomass. The immediate effect of an increase in Bio-0 in Model 3, for example, is a drop in PC. The cumulative effect is the sum of the coefficients and represents the long-run effect. Therefore, based on the reported results for the PDL coefficients in Table 3, Bio-0 and PC are negatively correlated in the long run. In fact, the results from all model specifications suggest a similar effect.<sup>22</sup>

Turning to the more selective Bio-3 measure of abundance, PDL2 again generates the best fit. Based on the value of AIC, Model 4 offers the best fit. Based on the value of MAE, Model 4 also offers the best fit for in-sample forecasts of Bio-3 stock, while Model 1 outperforms others for out-of-sample forecasts. Model 4 estimates are used for in-sample forecasts of (growth of) Bio-0 and Bio-3 and are shown in Figures 10a and 10b, respectively. The forecasts fairly closely follow the actual biomass changes. We also used

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<sup>22</sup>The initially negative correlation between biomass and price may reflect a drop in TAC to rebuild the stock; then, as the stock recovers, TAC rises and the price drops. In fact, in alternative model specifications (not included in Tables 3 and 4) where ITQ is replaced with TAC-R, a TAC-reduction dummy, due to singularity, the coefficient of TAC-R points to an initial inverse relationship between TAC and biomass. As time passes, the relationship becomes positive, reflecting increases in TAC as stocks recover.

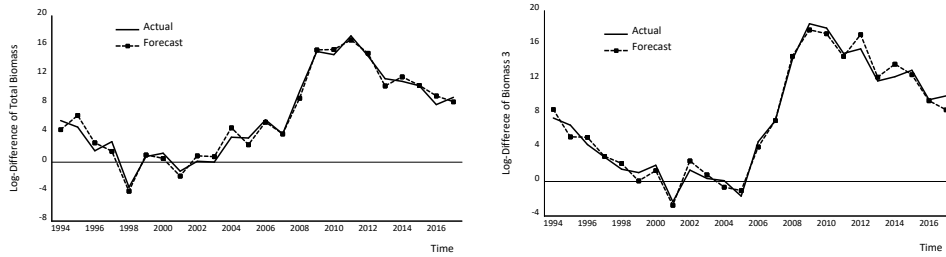


Figure 10: In-sample forecasts of Bio-0 growth (a, left) and Bio-3 growth (b, right)

Model 4 estimates for 2-step-ahead out-of-sample forecasts of (growth of) Bio-0 and Bio-3, which are presented in Figures 11a and 11b, respectively. While the forecast for 2016 Bio-0 is fairly accurate, the model predicts a

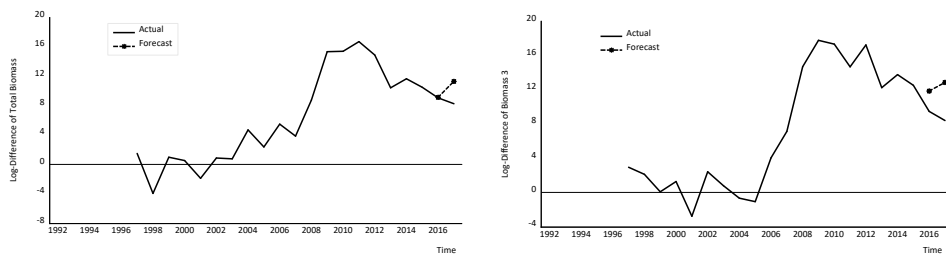


Figure 11: Out-of-sample forecasts of Bio-0 growth (a, left) and Bio-3 growth (b, right)

much higher total biomass in 2017 than the SEDAR 52 estimate. Figure 11b shows a similar pattern for the out-of-sample forecast of Bio-3 for 2016 and 2017. Reduction in predictive accuracy as the time horizon increases is common in forecasting.

While the focus in forecasting is generally on a model’s predictive ability rather than on the control variables’ estimated coefficients, we nevertheless briefly discuss the estimated signs. We expect a positive sign for the input cost index, which controls for changes in input prices, causing a shift in the

cost function (stock-PC relationship). While the Bio-0 Model 2 estimate in Table 3 has the wrong sign, the sign is as expected in Models 3 and 4, which take into account the price of grouper. However, in the Bio-3 models shown in Table 4, none the models yield positive estimates for the input price index.

Since increases in stock biomass are expected to increase landings per trip, the coefficient for landings is expected to be positive, which is the case for all specifications except the Bio-0 Model 3. The sign for the price of grouper is negative, and the sum of the PDL1 and PDL2 coefficients for this variable is rather high, suggesting that increases in the price of grouper deter fishing for red snapper. Most of the ITQ effect is likely to have been captured by the shift in the PC variable, when the right to fish red snapper begins to have a market value. While the coefficient for the ITQ dummy variable is statistically insignificant in Models 3 and 4 of the Bio-0 estimates, its coefficient is positive and highly significant in the same model specification for Bio-3.

In summary, because the VAR, B-VAR, and MF-BVAR regression models produce statistically insignificant results, we focused on the MIDAS estimates. A review of the empirical literature on mixed-frequency data by Forni and Marcellino (2013) concludes that while the consensus is that exploiting data at different frequencies improves estimation fit, the superiority of one method over others is unclear. In the mixed-frequency MIDAS regressions used here, the low-frequency biomass variables are explained by high-frequency indicators using parsimonious distributed lags. The results provide support for our comparative statics proposing a negative correlation

between the growth in stocks and change in the price-cost variable. Our out-of-sample forecasts from the MIDAS method presented in Figures 11a and 11b show that our best fit models have produced a fairly accurate forecast for period one (2016), but a much higher forecast for period two (2017).

## VEC

The VEC approach, which uses only annual data, requires the existence of at least one cointegrating vector. The unit root result in Table 2 does not confirm that all series are integrated of the same order, but when there are more than two variables in the model, cointegration of all individual series involved is not required. The VEC model is applicable as long as at least two series, or their linear combination with the third, are cointegrated (Engle & Granger, 1987). An  $I(0)$  series, however, cannot enter the cointegrating equation. Prior to the application of the VEC model, the Johansen cointegrating test is used to analyze stationarity of the variables further and ensure that there is at least one cointegrating equation in each model.

We focus on the system that is both consistent with the microeconomic model and offers the best fit estimate under MIDAS regressions. Table 5 lists the eigenvalues from the largest (most stationary) to the smallest (closest to unit root), as well as the likelihood ratios and their critical values for both Bio-0 and Bio-3. The number of non-zero eigenvalues determines the number of cointegrating vectors and, based on the likelihood ratio test, both models exhibit the existence of at least one cointegrating vector at the 5% level. Clearly, cointegration does not prove causality. However, as Friedman and Kuttner (1992) argue, cointegration establishes co-movements between

Table 5: Johansen Cointegration Test

Variables	Eigenvalue	Trace Statistic	5% Critical Value	Probability	Hypothesized No. of CE(s)
B0	0.8860	106.02	47.86	0.00	None
LA	0.8060	60.40	29.80	0.00	At most 1
PC	0.4935	25.97	15.50	0.00	At most 2
CI	0.4267	11.68	3.84	0.00	At most 3
Trace test indicates 4 cointegrating eq. at the 0.05 level					
B3	0.9453	119.76	47.86	0.00	None
LA	0.8314	58.73	29.80	0.00	At most 1
PC	0.5302	21.34	15.50	0.01	At most 2
CI	0.2297	5.48	3.84	0.02	At most 3
Trace test indicates 4 cointegrating eq. at the 0.05 level					

variables.

We apply the VEC model using the Maximum Likelihood method including biomass, landings, the price-cost variable, the input price index, and the ITQ dummy variable. The normalized cointegrating equation estimates with respect to stock biomass are reported in Table 6. Although all coefficients are reported, the coefficients for the PC variable are the primary concern. The results are consistent with the MIDAS regression models where the rising PC variable signals falling stock biomass. In terms of the control variables, the input price index in the Bio-0 estimate of the VEC model has an unexpected negative sign, while it is statistically insignificant in the estimate of the Bio-3 function. The coefficient for landings is positive and statistically significant in both variations of the biomass estimates in Table 6, reflecting the fact that during most of the study period stocks have been recovering allowing landing per trip to rise.

Model estimates from Table 6 are used for in-sample forecasts of (growth of) Bio-0 and Bio-3 and are shown in Figures 12a and 12b., respectively.

Similar to the MIDAS in-sample forecasts, the forecasts closely trace the

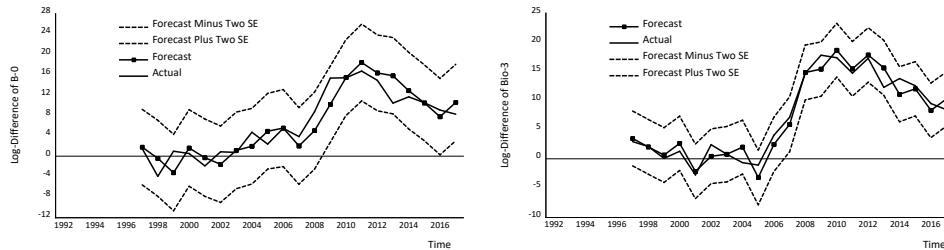


Figure 12: In-sample forecasts of Bio-0 growth (a, left) and Bio-3 growth (b, right)

actual biomass changes. Out-of-sample forecasts for Bio-0 and Bio-3 are presented in Figures 13a and 13b. Forecasts are also calculated with two-

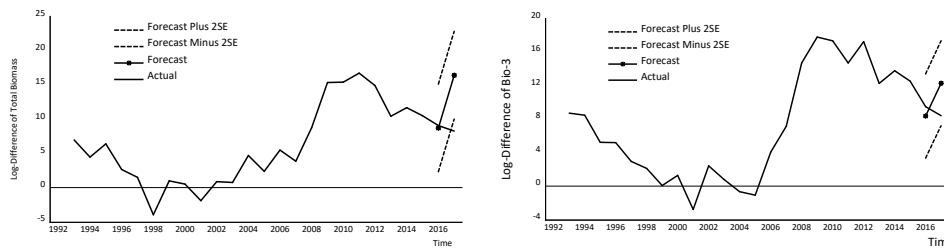


Figure 13: Out-of-sample forecasts of Bio-0 growth (a, left) and Bio-3 growth (b, right)

standard-error confidence intervals. Therefore, with 95% confidence, the forecast values for Bio-3 measure of stock biomass do not deviate from the estimated (actual) values from SEDAR 52. However, the estimated (actual) Bio-0 is outside of the 95% confidence interval. Furthermore, both estimates would fail if the standard error were tightened to one.<sup>23</sup>

Comparing the in-sample and out-of-sample forecast accuracy measures

<sup>23</sup>To compare the performance of our estimates with a naïve model, we also produced an out-of-sample forecast from a simple exponential trend model for the Bio-0 and Bio-3 measures of stocks. The forecast from the naïve models are less accurate and have wider confidence intervals than either the MIDAS or the VEC estimates.

Table 6: Normalized Cointegrating Equation from VEC Models

Variables	Model 1 (Bio-0)	Model 2 (Bio3)
PC	-0.3599 <sup>a</sup> (0.0633)	-0.4483 <sup>a</sup> (0.0580)
CI	-0.8131 <sup>a</sup> (0.1264)	-0.2243 (0.1542)
LA	0.0726 <sup>a</sup> (0.0057)	0.0384 <sup>a</sup> (0.0060)
Exogenous Variables:		
ITQ	Yes	Yes
Log Likelihood	-295.55	-295.55
AIC	32.72	32.72
<b>In-Sample Forecast:</b>		
RMSE	2.5850	3.8525
MAE	2.0471	3.2539
Theil Inequality Coeff.	0.1436	0.2041
<b>Out-of-Sample Forecast:</b>		
RMSE	5.7672	2.8464
MAE	4.2513	2.4912
Theil Inequality Coeff.	0.2645	0.1464

Note: *a* denotes statistical significance at the 1% level. Standard errors are in parentheses.

from the VEC models in Table 6 suggests that the MIDAS estimations, which combine the data frequencies, produced more accurate forecasts.

We next turn to the question of whether this empirical analysis can be used to signal the need for an updated stock assessment. Unlike the MIDAS estimates, the forecasts from the VEC models generate standard errors, which can be used to compare the SEDAR 52 stock assessment estimates with the estimates in this study, which focuses on market signals. The out-of-sample forecasts for Bio-0 and Bio-3 in the first period, shown in Figure 13, are fairly accurate and fall within the 95% confidence intervals. In other words, there is only a 5% chance for a deviation from the actual stock assessment estimates in SEDAR 52: the market signals used in this study confirm that the stock assessment is consistent with the economic

performance in the fishery. However, the out-of-sample forecast in the second period for BIO-0 falls outside of the 95% confidence level, which is not surprising.

### 5.3 Summary

In our time-series analysis, we considered four variations of VAR analysis and a VEC estimation. The standard VAR, B-VAR, and MF-BVAR models produced poor fits. In the latter case, the poor fit was likely due to the combination of over-parameterization inherent in the method and the small sample size in this study. We therefore focused on the estimates from the MIDAS approach, which is essentially a PDL regression and does not suffer from the over-parametrization in the MF-BVAR approach, and those from the VEC approach, which is a restricted variation of the VAR model with fewer parameters to estimate. Controlling for changes in input prices, landings, the price of grouper, and a dummy for the introduction of the ITQ program, the results from our best-fit model estimate (Model 4) PDL coefficients suggest that the immediate effect of an increase in biomass (both Bio-0 and Bio-3) is a drop in the PC variable, while a modest increase occurs in the subsequent period. The long-term (cumulative) effect, which is captured by the sum of the two PDL coefficients, supports the presence of an inverse relation between PC and stock size.

The results from the VEC model, too, indicate that increases in the PC variable are negatively correlated with a falling stock size. While the MIDAS forecasts are more accurate, the VEC procedure has the advantage of producing confidence intervals around the forecasts, allowing us to conclude



that the VEC forecasts give no reason to question current stock assessments.

## 6 Conclusion

To ensure the sustainability of renewable resources, governments need reliable measures of stock. Studies of non-renewable resources have provided evidence that market indicators like prices can signal changes in resource stocks (Slade, 1980; Moazzami and Anderson, 1994). Establishing a link between market indicators and common-good *renewable* resources such as fish is a more complex endeavor because the stock size is itself dependent on the rate of utilization dictated by policy.

We use a simple microeconomic model to capture the economic and ecological linkages in fisheries under various management systems and identify the relevant variables that influence a commercial fisher's decision to fish. These variables include the size of the catch, the ex-vessel price for red snapper, the cost of obtaining the right to fish under an ITQ management system, and an input price index. The implied biomass calculations, that is, stock sizes that are consistent with both profit-maximizing behavior and the data, suggest that, contrary to SEDAR assessments, the population of red snapper has been decreasing since 2012. While market indicators such as prices and harvesting costs are no substitutes for biometric assessments, they may at least serve as relatively affordable early warning systems to trigger more careful stock assessments. The findings in the first part of this paper are to be interpreted in that vein.

The empirical analysis of time-series data in the second part of the paper

establishes a relation between the assessed biological stocks and the relevant market variables identified in the theoretical model. In line with studies of nonrenewable resources, we find a negative correlation between changes in ex-vessel prices and two measures of abundance estimates, both with the (mostly) monthly data used in the MIDAS approach and with the aggregated annual data used in the VEC approach. In-sample and out-of-sample forecasts from the successful models indicate that estimated Bio-0 and Bio-3 stock assessment measures from SEDAR 52 are within the 95% confidence intervals of the estimated biomass from our models for the first period, while we do not have the same level of confidence for a longer horizon. Overall, the time-series analysis in the second part of the paper does not raise the same red flags as our initial results.

We faced the challenge of a mismatch in data frequency, which is not uncommon in time-series analysis, although it exacerbated the issue of a relatively short time series. In contrast to studies on the long-term prices of largely unregulated nonrenewable resources, which had access to a century of data (e.g., Slade 1980), our observations only stretch over 25 years with two distinct regulatory periods.<sup>24</sup> We met the challenge and obtained statistically reliable results by using parsimonious models and econometric techniques such as MIDAS and VEC that estimate fewer parameters.

We thus demonstrate that both single-frequency and mixed-frequency data can be used in forecasting biological stock, as long as the period for the time-series data is sufficiently long. However, our approach cannot be

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<sup>24</sup>Data collection efforts only began years after the marine fishery conservation and management legislation known as the Magnuson-Stevens Act of 1976 and its subsequent reauthorizations.

replicated for other fisheries or regions, unless the model specifications are adapted to the specific environmental conditions and resource management regimes.

Our study shows that it is possible to infer unobserved stock changes from observed price changes, which is in the spirit of a minimum information management system as proposed by Arnason (1990). Price information can serve as a signal mechanism to alert for changes in stocks and thus the need for assessment and could potentially also be used for species that are neither managed nor assessed, in particular to the extent that the stock-price relationship may be less complex for unmanaged species.

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## A Appendix

### A.1 Race to Fish under CFQ

Because the fisheries council had to impose seasonal closures, the annual quota restrictions must have been binding. Assuming that individual firms were unable to cooperatively agree to limit their annual harvests to their fair share of the quota, the modeling of profit-maximizing behavior should explicitly take into account competition for access (race to fish), in which a vessel  $i$ 's share  $\sigma_i$  of the TAC is determined by relative racing effort  $E_i$ , e.g.,

$$\sigma_i = \frac{E_i}{\sum_{j=1}^N E_j}. \quad (21)$$

Letting  $\bar{y}$  stand for the trip limit and  $Q$  for a year's TAC, a fisher's annual catch will be  $T\bar{y} = \sigma_i Q$ . Therefore the fisher's optimization problem becomes

$$\max_{E_i} \Pi_i = \frac{E_i}{\sum_j E_j} \frac{Q}{\bar{y}} \pi_t - E_i \quad (22)$$

and at the symmetric Nash equilibrium  $E_i = E$ , a firm's racing effort will be

$$E = \frac{N-1}{N^2} \frac{Q}{\bar{y}} \pi_t. \quad (23)$$

Since  $T = \frac{Q}{N\bar{y}}$ , the expression for profit is

$$\begin{aligned}\Pi &= \frac{Q}{N\bar{y}}\pi_t - \frac{N-1}{N^2}\frac{Q}{\bar{y}}\pi_t \\ &= \frac{Q}{N^2\bar{y}}\left((1-\ell)(p_t - k_t)\frac{Q}{NT} - w_t\left(\frac{Q}{NTqB}\right)^{1/\alpha}\right),\end{aligned}\quad (24)$$

which implicitly defines biomass. Unfortunately, without reliable data on annual profits and, in particular, the hidden costs of derby fishing, these results do not allow for biomass inference.

## A.2 Tables

Table A1: Standard VAR - Annual Data

	Total Biomass			
	Annual		Monthly	
	Model 1	Model 2	Model 3	Model 4
<b>Full-Sample VAR:</b>				
PC ( $L^1$ )	-0.0031 (0.0864)	0.0125 (0.0741)	-0.0133 (0.0940)	0.0119 (0.0908)
PC ( $L^2$ )	-0.0267 (0.0733)	-0.0042 (0.0985)	-0.0328 (0.0695)	-0.0355 (0.0804)
Adj. $R^2$	0.69	0.62	0.77	0.79
F-Stat.	12.59	5.36	8.08	7.66
Log Likelihood	-55.38	-54.48	-47.18	-43.93
AIC	5.49	-5.77	5.29	5.18
System Variables	B3, PC	+ LA, CI	+ ITQ	+ PG
<b>In-Sample Forecast:</b>				
RMSE	3.1534	4.9840	3.4585	3.0258
MAE	2.7313	4.0913	2.8972	2.6713
Theil Inequality Coeff.	0.6356	0.5589	0.3272	0.2786
<b>Out-of-Sample Forecast:</b>				
RMSE	2.6144	7.9591	6.0694	4.7810
MAE	2.2343	6.0863	5.036	4.7537
Theil Inequality Coeff.	0.6051	0.8787	0.9359	0.8948
<b>3-Plus Biomass</b>				
<b>Full-Sample VAR:</b>				
PC ( $L^1$ )	-0.0654 (0.0689)	-0.0759 (0.0653)	-0.0837 (0.0525)	-0.0739 (0.0557)
PC ( $L^2$ )	0.0367 (0.0706)	0.0790 (0.0720)	0.0388 (0.0562)	0.0271 (0.0630)
Adj. $R^2$	0.76	0.79	0.88	0.87
F-Stat	17.76	11.11	16.70	12.92
Log Likelihood	-54.76	50.20	42.23	40.92
AIC	5.43	5.38	4.84	4.90
System Variables	B3, PC	+ LA, CI	+ ITQ	+ PG
<b>In-Sample Forecast:</b>				
RMSE	10.5337	4.5585	3.9253	3.4624
MAE	8.5489	3.8455	3.3529	3.0011
Theil Inequality Coeff.	0.6936	0.4789	0.3852	0.3276
<b>Out-of-Sample Forecast:</b>				
RMSE	11.7413	8.5035	8.6442	5.6901
MAE	11.4044	7.0780	7.1965	4.1894
Theil Inequality Coeff.	0.9669	0.8541	0.8572	0.8505

Note: Automatic lag selection, max lags = 12.  $a$ ,  $b$ , and  $c$  denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

Table A2: B-VAR with Normal-Wishart Prior

	Total Biomass			
	Annual		Monthly	
	Model 1	Model 2	Model 3	Model 4
<b>Full-Sample B-VAR:</b>				
PC ( $L^1$ )	-0.0031 (0.0712)	0.0125 (0.0741)	-0.0170 (0.0654)	0.0112 (0.0582)
PC ( $L^2$ )	-0.0267 (0.0733)	-0.0042 (0.0985)	-0.0305 (0.0504)	-0.0373 (0.0530)
Adj. $R^2$	0.69	0.62	0.77	0.79
F-Stat.	12.59	5.36	8.05	7.62
Marg. Log Likelihood	-212.33	-616.50	-623.78	-763.15
System Variables	B3, PC	+ LA, CI	+ ITQ	+ PG
<b>In-Sample Forecast:</b>				
RMSE	2.8786	2.7500	1.9768	1.7149
MAE	2.2421	2.1254	1.5490	1.2588
Theil Inequality Coeff.	0.1731	0.1646	0.1170	0.1011
<b>Out-of-Sample Forecast:</b>				
RMSE	0.9815	0.9966	4.8504	3.3883
MAE	0.9311	0.9249	3.8089	3.3797
Theil Inequality Coeff.	0.0537	0.0546	0.1821	0.1635
<b>3-Plus Biomass</b>				
<b>Full-Sample B-VAR:</b>				
PC ( $L^1$ )	-0.0654 (0.0580)	-0.0759 (0.0491)	-0.0856 <sup>b</sup> (0.0389)	-0.0786 (0.0373)
PC ( $L^2$ )	0.0367 (0.0595)	0.0790 (0.0541)	0.0421 (0.0419)	0.0232 (0.0426)
Adj. $R^2$	0.76	0.79	0.88	0.87
F-Stat	17.76	11.11	16.43	12.54
Marg. Log Likelihood	-213.18	-616.28	-632.28	-781.50
System Variables	B3, PC	+ LA, CI	+ ITQ	+ PG
<b>In-Sample Forecast:</b>				
RMSE	1.7861	2.2613	1.5858	1.5174
MAE	1.5048	1.6718	1.2567	1.2266
Theil Inequality Coeff.	0.0916	0.1086	0.0758	0.0724
<b>Out-of-Sample Forecast:</b>				
RMSE	2.7943	2.6248	3.4538	4.4673
MAE	2.3005	2.3977	3.4589	4.3787
Theil Inequality Coeff.	0.1350	0.1673	0.1669	0.1999

Note: Number of draws = 2000; overall tightness ( $\lambda$ ) = 5.  $a$ ,  $b$ , and  $c$  denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

Table A3: MF-VAR

	Total Biomass			
	Annual		Monthly	
	Model 1	Model 2	Model 3	Model 4
<b>Full-Sample MF-VAR:</b>				
Adj. $R^2$	0.79	0.85	-0.126	-0.24
F-Stat.	6.02	3.63	-0.0536	971.20
SSE	2.70	116.09	882.24	-0.08
System Variables	B3, PC	+ LA, CI	+ ITQ	+ PG
Nbr. Freq. Conversions	12	12	6	6
<b>In-Sample Forecast:</b>				
RMSE	2.6708	1.1059	11.5340	4.9962
MAE	2.1385	0.6435	8.4077	3.1403
Theil Inequality Coeff.	1.1620	0.0643	0.5093	0.2731
<b>Out-of-Sample Forecast:</b>				
RMSE	3.8295	11.7436	11.7913	26.2926
MAE	3.7954	8.8306	422.4173	23.5273
Theil Inequality Coeff.	0.2829	0.6984	0.9990	0.8017
<b>3-Plus Biomass</b>				
<b>Full-Sample MF-VAR:</b>				
Adj. $R^2$	0.88	0.70	0.48	0.25
F-Stat	11.56	1.41	522.01	757.82
SSE	125.18	299.48	0.41	0.1079
System Variables	B3, PC	+ LA, CI	+ ITQ	+ PG
Nbr. Freq. Conversions	12	12	6	6
<b>In-Sample Forecast:</b>				
RMSE	2.2809	1.4235	2.998	5.1306
MAE	1.7418	1.0494	1.9455	3.4499
Theil Inequality Coeff.	0.1098	0.0673	0.1395	0.2354
<b>Out-of-Sample Forecast:</b>				
RMSE	3.4305	82.8299	10.5257	57.6549
MAE	3.2585	78.9378	8.2836	57.5024
Theil Inequality Coeff.	0.1621	0.9307	0.6165	0.8422

Note: Number of draws = 2000; overall tightness ( $\lambda$ ) = 5. While the initial estimates of the model are Bayesian, the forecast uses the classical point method because the Bayesian forecast could not be made.  $a$ ,  $b$ , and  $c$  denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.