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A Trip to Reach the Target?

-The Labor Supply of Swedish Baltic Cod Fishermen

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Abstract

Fishing offers a unique opportunity to investigate the relationship between income and labor supply. The variation of working hours, depending on the length of a fishing trip, and variation in income, depending on the catch, is high compared to other occupations. This variation is an advantage for researchers but also poses a challenge to fishermen. One way to handle the issue of highly variable income might be to set specific revenue targets, i.e. to stop fishing when a certain revenue level has been reached. This means that if revenues are higher than expected at some stage of a fishing trip fishermen are more likely to return to port as they would reach their target income earlier. In this paper, the revenue target hypothesis is investigated using the case of Swedish Baltic Sea cod trawlers. Trip-specific revenue targets as well as weekly revenue targets are used. The results do not support the idea of revenue targets since the evidence show that cod fishermen, on average, choose to continue fishing if revenues are higher than expected. This suggests that fishermen are, on average, risk seeking.

Introduction

Revenues from fishing are uncertain and vary on different trips, and even at different times on the same trip. Also, working hours for fishermen are irregular since a fishing trip can take many hours and often last for several days. Furthermore, the decision-making process can be characterized as relatively short-term since many decisions on board a vessel have to be made continuously through the trip, i.e. choice of fishing place, time of setting of trawls and decisions on how many hauls to make. This makes the fishing trip an ideal setting for investigating the idea of revenue targeting, i.e. investigating whether fishermen are aiming for specific short-term revenues rather than maximizing expected utility over a longer time period. The issue of revenue targeting in fisheries has been investigated previously, with the evidence being mainly in support of revenue target behavior (Giné, Martínez-Bravo, and Vidal-Fernández 2010; Eggert and Kahui 2012; Nguyen and Leung 2013; Ran, Keithly, and Yue 2014), but there is also recent evidence disputing the idea of revenue targeting in fisheries and suggesting that fishermen substitute labor for leisure intertemporally (Stafford 2015).

Traditional labor market theory proposes that the amount of labor supplied in the long run is determined by substitution and income effects. Higher incomes will make workers substitute labor for leisure but they will also make workers richer and increase their demand for leisure, which in turn decreases the amount of time spent working. The effect of increasing incomes is thus indecisive in the traditional model. The traditional model can be contrasted with the revenue target hypothesis. The idea is that workers adapt their level of labor supply depending on whether they have reached a predetermined target level for their incomes in a specified, often very short time period.

The idea of target revenues derives from prospect theory, which was introduced as an alternative to traditional expected utility theory by Kahneman and Tversky (1979). Prospect theory proposes that it is changes in income that matter rather than final wealth during a lifetime. Changes in welfare around a reference point are measured using a value function that is concave for gains and convex for losses, and is often steeper for losses than for gains. This implies that individuals are risk-averse for gains, risk-seeking for losses and that losing a sum of money is often worse than gaining the same amount (Kahneman and Tversky 1979). The point at which losses are replaced by gains is the reference point, and in the context of revenue targeting this is a point that serves as a desirable short-term target for the individual (Camerer et al. 1997). The exact determination of the reference point is difficult but a reasonable definition is that targets are somehow related to expectations held by individuals. Kőszegi and Rabin (2006) build on the ideas of Kahneman and Tversky and develop a theory that implies that targets are defined by probabilistic beliefs held by a person in the recent past. This allows targets to vary considerably between individuals and over time.

The purpose of this article is to investigate revenue targeting behavior in the fishery sector. Labor supply of fishermen is related to changes in short-term unexpected revenues using the example of fishermen working on Swedish Baltic Sea cod trawlers. More specifically, the effect of unexpected changes in revenues on the probability of stopping at the time of different hauls is investigated using the estimation method suggested by Farber (2005, 2008). To my knowledge, this approach has not been tested outside the realm of taxi drivers before. By using controls at a detailed level I attempt to avoid the problem that expected revenues (that are used to form potential target levels) cannot be separated from unexpected ones. This also enables me to interpret the results in line with the model of reference-dependent preferences suggested by Kőszegi and Rabin (2006) where a reference point is determined endogenously by the economic environment.

Most studies investigating revenue targeting look at small businesses, often comprising one self-employed individual (e.g. a taxi driver, a stadium vendor or a bicycle messenger). The question of whether reference-dependent behavior is also prevalent when work is organized in a more collective manner is thus interesting. I also consider potential constraints that could affect the decision to return to port. Since fisheries might be constrained by government regulations (such as quotas) and the physical capacity of the vessels I will also discuss how these constraints might influence the labor supply of fishermen. An advantage of using the example of fisheries is also that prices are determined on a larger market and cannot be affected by individual fishermen – hence the number of fishermen out at sea on a certain day or week does not affect revenues.

Since it is not clear how long the decision-making horizon might be for individuals exhibiting revenue target behavior I suggest two different time horizons over which I test the revenue target hypothesis. First, I assume that it is the fishing trip that matters for the fishermen since it seems natural that leaving port and arriving back at port should constitute the time limits over which decision making is made. But fishing in the case study is also conducted with a weekly pattern where many vessels make several trips in a week but stop fishing as the weekend approaches. For this reason I also test the revenue hypothesis for weekly targets. Finally, since the effect on revenues should be strongest at the point when the target has been reached, I estimate expected targets and use these in the stopping model.

Understanding of fishermen's behavior can allow us to make better predictions of how fishermen react to changes in environmental conditions and policies. If profits in fisheries are not maximized in the long run the results from traditional economic fishery models might be unreliable. Recently, new regulations in many countries have given increased flexibility to fishermen through the introduction of individual quotas and transferable quotas. Fishermen have increased opportunities to decide on when and where to fish and how much time to spend on individual fishing trips. For example, when the system of yearly individual quotas was introduced for Swedish cod trawlers in 2011 there were concerns that supplies might become irregular for processors (Blomquist, Hammarlund, and Waldo

2015). If fishermen choose to spend more time fishing for cod when revenues are high the concern might be warranted. But if fishermen are target earners on a trip basis, landings are more likely to remain regular over the year.

Previous applications

There are a large number of studies investigating wage elasticities (a survey is found in Blundell and Macurdy (1999)). In general, the wage elasticities that are found are small, implying that labor supply is not very responsive to wage changes (Blundell and Macurdy 1999). In empirical studies with short-term wage changes the long-term income effect from the traditional model is normally ignored since fluctuations in wages can be viewed as transitory. The substitution effect can in this case be viewed as temporal; it is beneficial to substitute labor for leisure when wages are high since lower wages are expected in the future. Thus, in the traditional model where there are no target revenues the expectation is that temporary increases in wages increase the supply of labor.

An empirical study that has received much attention is Camerer et al. (1997) studying reference targets of New York taxi drivers. The authors found that daily working hours for taxi drivers were negatively correlated with average hourly earnings, i.e. on average, taxi drivers worked shorter hours when wages were high. Together with the result that wages were correlated within days (so that drivers could expect more or less the same hourly wage during the day) and uncorrelated across days (to make sure wages were transitory across days) this was interpreted as evidence of a daily income target and as support for the ideas of prospect theory.

Some weaknesses of the Camerer et al. (1997) study have been pointed out by Farber (2005). One concern is that the correlation within days may not be applicable to other settings, which makes it difficult to use average income per hour as a dependent variable. Farber (2005) does not find any correlation within days in his study of New York taxi drivers in the period June 1999 through May 2001. Rather than using the wage equation, Farber (2005) suggests using an optimal stopping model where the probability of stopping on a day is estimated as a function of accumulated hours, accumulated revenues and other factors. Using accumulated variables makes it unlikely that a shift for the taxi driver would end because of a time-specific slowdown of traffic during the day. It also avoids the need for strong within-day wage correlation and reduces the risk of getting downward-biased estimates caused by measurement problems when using hours worked on both sides of the equation. Farber (2005) finds that the probability of stopping daily work after a particular trip is strongly related to the number of hours worked so far and not significantly related to cumulative income earned so far and concludes that these findings are not supportive of the target income hypothesis.

Transitory wage changes were further investigated by Fehr and Goette (2007) in an experiment involving bicycle messengers. As an experiment, the commission rate for bicycle messengers was temporarily increased by 25 percent for a four-week period. The results show that bicycle messengers work more hours with the higher wages in line with the traditional theory of intertemporal labor supply. But although the main effect is an increase of total hours supplied, Fehr and Goette also show that bicycle messengers decrease their effort per shift worked, where effort can be affected by riding at higher speed, listening to the radio more carefully or finding shortcuts along the way. Two alternative explanations for the reduction in effort were suggested and a second experiment was carried out. First, it is possible that messengers that work longer hours experience increasing disutility of effort during the day; hence they have an incentive to decrease effort even if wages are higher. Second, there is a possibility that messengers have a reference income level and if they exceed this level their marginal utility of income will decrease and hence they will decrease effort. The second experiment tests whether bicycle messengers are loss-averse when using a lottery (Do they prefer to prevent a loss in one lottery rather than to gain the same amount in another lottery?) and whether there is correlation between being loss-averse and decreasing effort. The authors find such a relationship and interpret this as evidence of the income target hypothesis, or that the hypothesis is valid for at least some individuals.

In 2008, Farber developed the stopping model further and assumed that revenue targets can vary across days for different taxi drivers (Farber 2008). The results show that drivers are more likely to continue driving before the reference income level has been reached. But still Farber does not think that he had found any substantial evidence of the target income hypothesis since most taxi drivers would stop before they reached their income target level and because the reference income level for a given driver varies unpredictably from day to day. In addition, a large unexplained within-driver variation in income is not believed to be in line with drivers having income targets. Using Farber's model, Doran (2014) analyzes the labor supply of taxi drivers in response to short-term and long-term wage increases. He finds that taxi drivers decrease hours in response to short-term wage increases but not to long-term wage increases. Thus, contrary to the conclusions of Farber (2005); Farber (2008) he believes that he has found support for the reference-dependent behavior of taxi drivers.

The issue of how to determine reference points was not considered to any substantial extent in the early studies on reference dependence, but has been increasingly discussed in the last decade. Kőszegi and Rabin (2006) suggest that reference points are determined endogenously by the economic environment. For this reason the authors suggest a model where a reference point is formed by rational expectations held in the recent past. In an application they show that in a labor supply decision a worker is less likely to continue work if income earned so far is unexpectedly high, but more likely to show up as well as continue to work if expected income is high. Similar results are found in the empirical studies of Abeler et al. (2011) and Chang and Gross (2014). Kőszegi and Rabin (2006) also believe that the variation of targets found in Farber's work can be explained by their model of expectations.

Crawford and Meng (2011) follow the approach in Kőszegi and Rabin (2006) and develop the empirical analysis made by Farber (2005, 2008) further. More specifically, targets for hours and income that are determined by proxied rational expectations are included in the Farber model. In a first analysis the authors split the sample into good and bad days by using the earnings from the first hour of driving. A good day is when the first hour's earnings are larger than expected and a bad day is when this relationship is the reverse. The expected hours and revenues are proxied by the sample averages up to but not including the day in question. Crawford and Meng also use a dummy for above and below the proxied target for both hours and income in a second analysis.

The results show that on a day when earnings are higher than expected, the probability of stopping increases with the number of hours spent driving. There is no effect of increasing cumulative revenues. The authors suggest that the reason for this pattern is that the revenue target is reached before the hours target and the former will, for this reason, not affect the stopping probability. For a day when earnings are worse than expected, the effect is the opposite: There is no effect of an increase in cumulative hours but there is an effect of cumulative revenues, i.e. the revenue target is affecting the stopping probability but the hours target is not. Using the dummy for the above targets the authors find that there are larger positive effects above the targets than below on the stopping probability. This is in line with the reference-dependent model with rational expectations according to the authors.

Farber would not settle with this. In a recent analysis (Farber 2014), collecting data from all taxi drivers in New York during 2009-2013, he again claims that he cannot find any support for the idea of revenue targeting among taxi drivers. He finds that drivers respond positively to both expected and unexpected increases in wages and that the positive response grows with the experience of the drivers (Farber 2014).

An example of a study on labor supply in fisheries is Gautam, Strand, and Kirkley (1996) who investigate leisure and labor trade-offs in the mid-Atlantic sea scallop fishery. The results suggest that there is a short-run backward-bending supply of fishing labor, i.e. when profits per day are low or average captains will increase their time offshore, but as profits per day reach sufficiently high levels, captains will increase their time onshore and hence reduce their time at sea. Furthermore, the authors find that anticipation of future profits influences the current labor supply in line with the intertemporal model. Fishermen decrease their labor supply if they expect profits to be higher later on in the season. Although the revenue target hypothesis was never mentioned in Gautam, Strand, and Kirkley (1996) the results could be interpreted as support of the hypothesis with expected targets (Kőszegi and Rabin 2006) since high unexpected daily revenues seem to reduce work hours.

Since fishermen experience transitory changes in revenues and often have considerable flexibility regarding work hours there have been a number of studies using the approach of Camerer et al. (1997) to estimate labor supply in fisheries. Nguyen and Leung (2013) investigate revenue targeting in the Hawaii-based long-line fishery and estimate the effect of daily average revenue on the number of fishing days on a trip. The key finding is that daily fishing revenue has a negative and significant impact on the number of fishing days and these results are interpreted as support for the idea that Hawaiian fishermen have revenue targets. A similar study is that of Eggert and Kahui (2012) who discuss reference-dependent behavior of paua[1] divers in New Zealand and estimate the relationship between the number of hours that divers choose to work each day and the average daily wage. A negative relationship is again found here.

In contrast to the above studies, Stafford (2015) does not find that fishermen work less when earnings are high in her study on the daily labor supply of Florida lobster fishermen. She looks at the wage elasticity as well as the participation elasticity, i.e. the effect of wage on the probability of taking part in the fishery on a certain day, and takes econometric problems such as endogeneity of wages, self-selection into participation and measurement error in hours into consideration. Rather than finding a negative wage elasticity like Camerer et al. (1997) she finds that the wage elasticity of hours worked is significantly positive, although small. Furthermore, she also finds that the participation elasticity is large and positive. Thus, higher wages are primarily associated with a higher likelihood of participating in the fishery on a certain day rather than working longer hours on that day. The results are also compared to results received when using the method in Camerer et al.

[1] Paua is Maori for three types of edible sea snail.

(1997) and show that the wage elasticity becomes negative. Stafford concludes that the behavior of the lobster fishermen is consistent with a neoclassical model of labor supply and that the estimation strategy may explain the negative wage elasticities found in previous studies.

Giné, Martínez-Bravo, and Vidal-Fernández (2010) investigate how boat owners' labor participation in a South Indian fishery is related to expected earnings and recent earnings. Expected earnings are calculated as the predicted values from a regression of log earnings per day on a number of explanatory variables. Recent earnings are the sum of earnings during the last seven days and if these earnings have a negative effect on labor supply it is assumed that it is more likely that the reference income has been achieved. The findings of a positive effect on participation of expected earnings together with a negative effect of recent earnings are thus interpreted as evidence of revenue targeting.

In summary, the evidence of target revenues is still mixed; different models and settings give different results. In addition, it is clear that it is difficult to make assumptions of what the expected target might be. In the following chapter, the data that are used in this study are presented together with some preliminary statistics suggesting that the Swedish Baltic cod fishery is an interesting case for investigating the revenue target hypothesis with rational expectations.

The case of the Swedish Baltic cod fishery

The Baltic cod fishery is historically one of the most important fisheries in Sweden; in 2013, around 10 percent of the value of all landings of fish and seafood in Sweden consisted of cod. The fishing areas mainly include the Western and Eastern Baltic and the majority of the cod from these areas is landed on the south coast (Swedish Agency of Marine and Water Management 2013c). The fishery is regulated by EU legislation and national legislation and includes the setting of quotas, fishing bans, limitations on the number of days out of port, a requirement for a special permit for cod fishing, and technical regulations for the equipment (Swedish Board of Fisheries 2004; European Commission 2005, 2007). The fish stock has varied substantially over the years and affected the landed amounts. In 2013, the cod landings were considerably smaller than in previous years; the value of landings from the south coast of Sweden had decreased from ca 140 million SEK (Swedish krona) in 2011 to 61 million SEK in 2013.

Using the case of Swedish Baltic cod trawlers for investigating the revenue target hypothesis has a number of advantages. Since markets for cod are international, with some local variations, prices can be regarded as exogenous, i.e. they will not be affected by the behavior of individual fishermen (Hammarlund 2015). The problem encountered in taxi studies, where the number of taxi drivers out on the street affects the wage, is thus not an important problem in the current setting. Also, the quantities caught on different hauls by the same vessel on the same trip are highly variable, since it is difficult for fishermen to control the size of the catch, which in turn depends on uncontrollable biological conditions (e.g. the density of shoals and the size and quality of the fish). This variability can be exploited to investigate the effect on the labor supply of fishermen of revenue changes that are largely unexpected.

Work hours of Swedish fishermen are normally not regulated since fishermen are self-employed. The operating profits are shared between vessel owners and crew according to a share system. A fisherman could have owner shares as well as crew shares and normally crew shares are equal for fishermen that have participated on trips in the period before the revenues are counted. The shares are split among the vessel owners and fishermen on a regular basis and at least once a month. The operating profit is calculated as the value of fish sold minus variable costs of ice, boxes, diesel, provisions, vessel fees etc. Decision making regarding the fishing activities of the crew is conducted in consultation with the members of the team, although in cases of dispute the view of the captain should prevail according to the statutes of the standard crew cooperation agreement (SFR 2011). In practice, the captain is the main decision maker.[2]

Although fishermen (or the captains)[3] are free to set their work hours in a way that is considerably more flexible than that of an ordinary worker, it can be argued that fisheries are regulated by government agencies in numerous ways and that these regulations to some extent limit the trip revenues and flexibility of work hours. Below I will argue that I have a case where revenues and work hours are largely unaffected by regulating restrictions in the short run, i.e. fishermen behavior is endogenous.

In 2011, yearly catch quotas were introduced in the Swedish Baltic Sea cod fishery. Previously, quarterly catch quotas had been used and a year earlier quotas had been given to fishermen on a biweekly basis. Short-term quotas are more likely to affect the length of the fishing trip and constitute a capacity constraint and for this reason the time period investigated is restricted to the time period after the yearly quotas were introduced. The yearly quota is given to each vessel based on the gross tonnage of the vessel (Swedish Board of Fisheries 2004) and it is possible for a vessel to reach its quota level before the year ends. However, every year since 2011, further quotas have been issued as fishermen are not filling their quotas. Already in May 2011, the year when the annual quotas were introduced, the quotas were increased in the Eastern Baltic and in September that year the quota restriction was abandoned completely in the Western Baltic whereas quotas were further increased in the Eastern Baltic (Swedish Agency of Marine and Water Management 2011b; Swedish Board of Fisheries 2011a, b). Later that year, in October 2011, quotas were abandoned completely in the Baltic Sea (Swedish Agency of Marine and Water Management 2011a). Although the quotas increased, the fishermen did not manage to catch more than 76% of the original quota (Table 1).

Table 1: Quotas, catches and values of landed cod in 2011, 2012 and 2013

	Quota (tons)	Actual catches in live weight (tons)	Catch as a share of the quota	Value of landings (Million SEK)
2011	16,645	12,644	0.76	140
2012	19,103	12,460	0.65	115
2013	17,445	7,002	0.40	61

Note: The Swedish quota is as defined in the EU regulations of the previous year and is calculated as the sum of the quotas for the Western and Eastern Baltic.

Sources: (European Commission 2010, 2011, 2012; Swedish Agency of Marine and Water Management 2012d, 2013c, 2014).

Similarly, in 2012, quotas were increased during the year. On three occasions, in September, October and November, quotas were increased for fishing in the Eastern Baltic (Swedish Agency of Marine

[2] Personal information from Staffan Larsson 2014-06-09.

[3] There will be no distinction between the captain and other members of the crew in the following. The term “fishermen” will refer to the group of fishermen that makes decisions on the vessel or the captain of the vessel.

and Water Management 2012a, b, c). The share of cod landed of the total quota decreased to 65% that year (Table 1). The new quotas issued in 2013 were left untouched until July 18th when the quota for the Western Baltic was increased (Swedish Agency of Marine and Water Management 2013b). However, in the autumn of that year, fishing in the Western Baltic was left without quota restrictions (Swedish Agency of Marine and Water Management 2013a). Increasing the quotas did not, however, result in the Swedish cod fishery becoming closer to filling the original quota: In 2013, only 40% of the original quota was filled (Table 1). The fact that the availability of fish deteriorated during the period studied (ICES 2014) thus made it increasingly difficult for vessels to reach their quota limits. The evidence suggests that quota limits did not constitute an important constraint to the Swedish cod fishery in the Baltic Sea between April 1st 2011 and December 31st 2013.

Other regulations that could potentially affect the work hours of cod fishermen are regulations concerning closed areas and limitations on the number of days absent from port. There are two closure periods in the Baltic Sea: From April 1st until April 30th the Western Baltic Sea (the April closure) is closed and from July 1st until August 31st fishing is prohibited in the Eastern Baltic Sea (the summer closure). In addition, the Gdansk deep, the Bornholm deep and the Gotland deep are closed from May 1st to 31st October (European Commission 2007). For example, a fishing trip could potentially finish because the summer closure period has started. The regulations of closed areas could perhaps limit the length of a fishing trip and be correlated with revenues. Although this is not a major issue any estimation method will have to take these limitations into consideration.

Finally, the number of days at sea is regulated in the EU regulations. Vessels with a cod fishing permit are limited to 163 days' absence from port in the Western Baltic Sea and 160 days' absence from port in the Eastern Baltic Sea (European Commission 2010, 2011, 2012). In total, a maximum of 163 days' absence from port in both areas together is allowed. In 2012, it became possible to trade days between vessels under certain conditions (HVFMS 2012:39). The decision to continue a trip or not could potentially be affected by the days-at-sea limitations, but it is unlikely that these limitations would affect decisions on trips in the investigated setting. Checking the data reveals that vessels seldom reach the limit of 163 days. In fact, the average number of days at sea was 81 per year in 2011–2013. On only four occasions, in 2013, did the number of days exceed 150 for any vessel and on one of these occasions the number of days exceeded 163, which was possible since fishing days could be traded between vessels. In conclusion, the number of days at sea allowed cannot be considered as an important factor in deciding the length of a fishing trip in my example.

Data and preliminary statistics

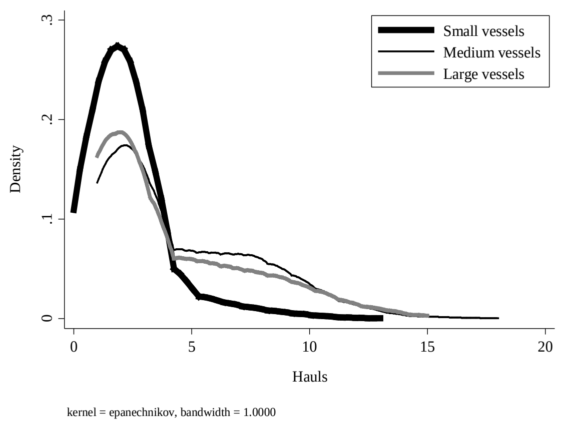
The data used in this study is logbook data from Swedish Baltic cod trawlers limited to vessels that caught at least 85 percent[4] cod per year from April 1st 2011 until December 31st 2013, i.e. the main activity of these vessels is cod fishing and the period of interest is after the yearly quota system was introduced. For each vessel I have data on the date and time when the vessel left port, the date when the fishing activity took place, the time of setting of each trawl, the number of hours' fishing before each haul and the date and time when the vessel arrived back in port. This allows me to calculate the time spent out at sea, the time from leaving port until setting the first trawl, the time from setting of the first trawl until hauling of the first trawl, the time from hauling of the first trawl

[4] The figure of 85% is of course arbitrary; however, a sensitivity check where the main model of the paper was run with vessels that caught at least 90 percent cod per year did not reveal any important differences in results.

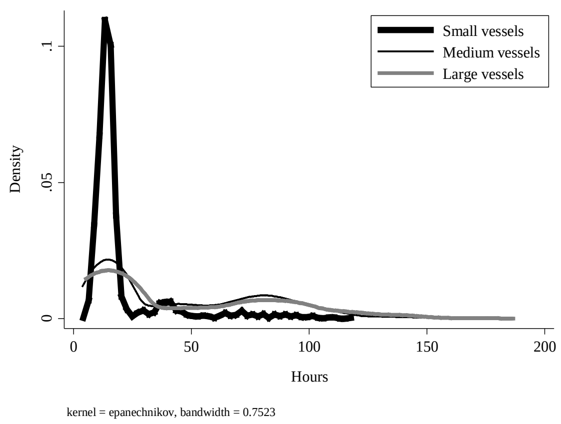
until setting of the second trawl, and so on. In addition, I have data on the quantity of cod caught on each haul and average prices of cod given to trawlers in the area[5] at the time the vessel left port that have been used to calculate revenues from each haul. If the price on the leaving date is missing, the price on the nearest previous available date is used. Prices are for gutted cod whereas the quantities reported in the logbooks are for whole cod, thus a conversion factor of 1.15 has been used (Swedish Agency of Marine and Water Management 2013c) to calculate revenues. To take weather changes into account the average temperature in an area to the northeast of the island of Bornholm is used.[6] Four different daily temperatures at 00:00, 06:00, 12:00 and 18:00 are used.

The data consists of 16,111 observations of hauls on 4432 trips made by 43 vessels between April 1st 2011 and December 30th 2013. There are 12 small vessels (12–18 m), 22 medium vessels (18–24 m) and 9 large vessels (24–40 m) in the data set. A fishing trip typically starts on a Monday (35% of the trips) and ends on a Tuesday, Wednesday or Thursday (64% of the trips). Looking at how the number of observations is spread over the years it is evident that cod fishing is more intense during the spring months, and that there is a slowdown during the Easter holiday and a peak in May before a slowdown during the summer. The slowdown starts around mid June and continues until the end of August. This is related to the summer closure of the Eastern Baltic fishery that starts on July 1st and ends on August 31st. In September, fishing activity increases again and fishermen are very active until the beginning of December, when there is a sharp decline in activity, especially around the week of the Christmas holidays. The seasonal patterns are rather similar across years, although there is a significant slowdown in fishing activity in the autumn of 2013. This is related a sharp decline in fishable biomass, i.e. the availability of cod that was above the minimum landing size (38 cm) decreased in the latter part of 2013 (ICES 2014).

Below are kernel densities of the number of hauls, revenues, quantity caught and hours spent out at sea presented on a trip level (Figure 1).

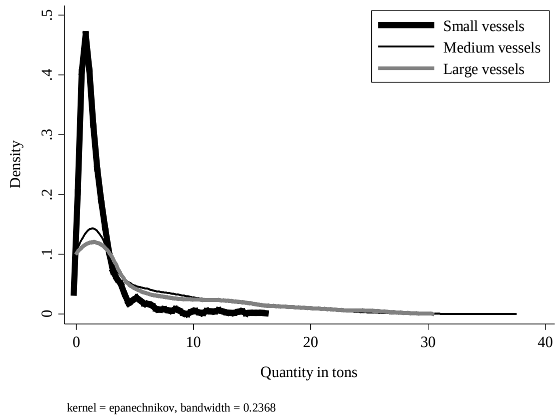


A. Number of hauls per trip.

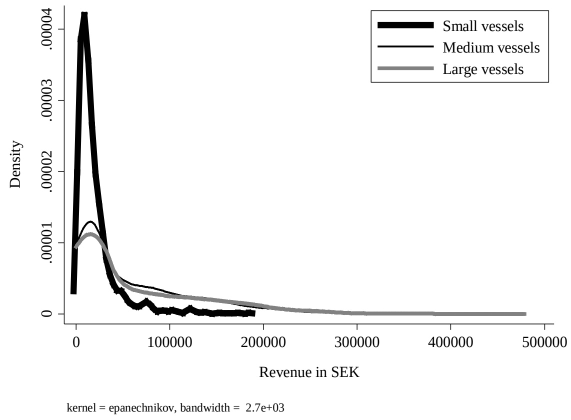


B. Hours spent out at sea per trip.

[5] The relevant area consists of 24 ports in southern Sweden where cod can be legally landed.
[6] The temperature is measured at longitude 16.25 and latitude 56.25, which is situated between the Bornholm and Öland Islands in the Baltic Sea.



C. Quantity in tons per trip.



D. Revenues per trip, revenues above 500,000 SEK are excluded (six trips).

Figure 1: Distributions of the number of hauls, hours spent out at sea, quantity caught and revenue received per trip.

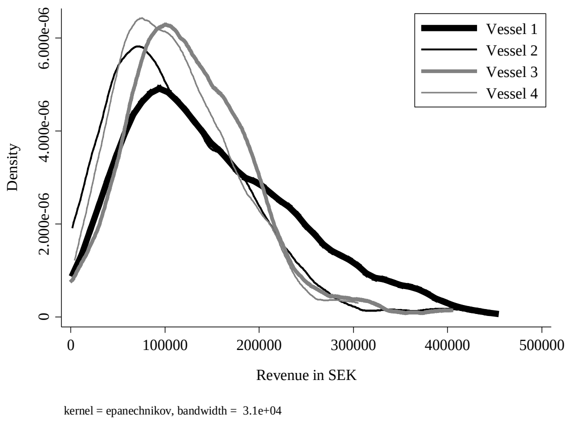
Figure 1A shows the kernel density estimate of the number of hauls per trip. Although the number of hauls varies considerably between trips it is relatively common for a trip to contain two hauls. In fact, 38 percent of the trips end after the second haul. This is related to the fact that small vessels make a larger number of trips that are relatively short. Small vessels on average haul 3.31 times whereas the corresponding figures for medium and large vessels are 6.64 and 6.59. Looking at individual vessels, the number of hauls made on a trip varies considerably. Although small vessels make fewer hauls than large vessels there is a lot of variation in the data: There are cases when small vessels make more than 10 hauls on a trip.

On average, a fishing trip lasts for 38 hours but there are differences between vessel sizes as shown in Figure 1B. Small vessels stay out at sea for 20 hours on average whereas medium and large vessels both stay out for 47 hours on average. Over time there is a tendency for smaller vessels to spend less time out at sea on each trip and for medium vessels to spend more time out at sea. Large vessels do not show any such pattern.

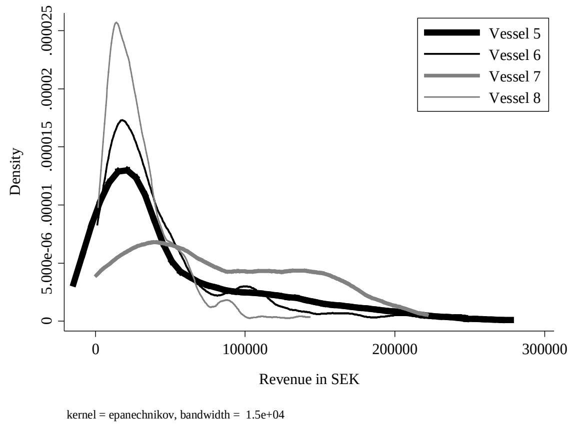
Looking at the quantity of cod caught and the revenue on each trip a similar pattern is revealed (Figure 1C and Figure 1D). This is not surprising since prices do not change much compared to quantities caught. Small vessels catch 1.90 tons of cod on average on a trip, medium vessels 5.66 and large vessels 5.68 tons. On average, small vessels earn 20,600 SEK on a fishing trip, medium vessels 61,200 SEK and large vessels 61,600 SEK.[7] As indicated in Figure 1C, catches can vary considerably between trips and at times they can be very large (the right-hand tail of the distribution is very long). This is not surprising, given that fishing is an unpredictable business. If there is a common revenue target present in any of the vessel groups, peaks can be expected in the kernel densities. This seems to be clearest in the case of small vessels but there are also quantity and revenue bumps for medium and large vessels.

[7] 1000 Swedish krona was equal to 123 USD as of 2014-01-16.

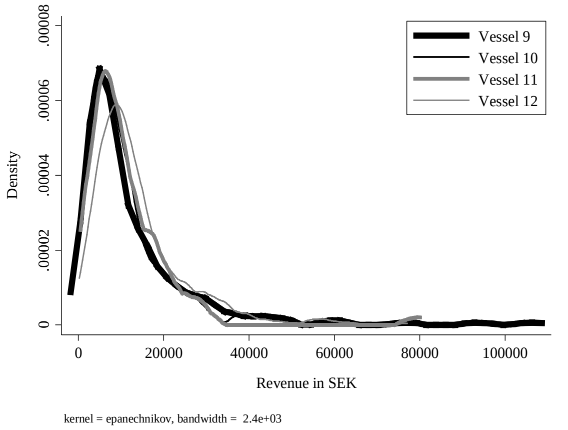
Rather than a common revenue target for all vessels in a size class it is more likely that different revenue targets exist for individual vessels, since the skills and expectations of the vessel crew might differ between vessels and vessels might have different types of equipment. Looking at revenue densities for individual vessels could reveal whether there are peaks in these distributions. As an example, vessels that made more than 100 trips during the time period are selected to check for revenue peaks. Excluding one vessel with extremely large revenues, the revenue distributions of 16 vessels making 100 trips or more are shown in Figure 2.



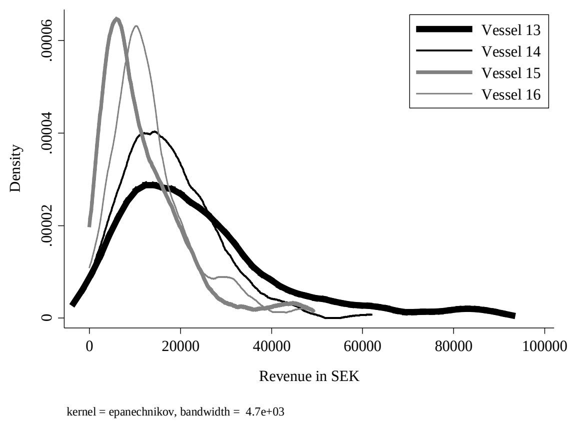
A. Trip revenues of four medium vessels.



B. Trip revenues of two medium vessels (5,6) and two small vessels (7,8).



C. Trip revenues of two medium vessels (9,12), one small (11) and one large (10) vessel.



D. Trip revenues of four small vessels.

Figure 2: Distributions of revenue received per trip for 16 different vessels.

Vessels 1–6, 9 and 12 are medium vessels, vessel 10 is large and the remaining vessels are small vessels. All vessels have clear peaks at the beginning of their distributions and right-hand tails that are rather long, with the exception of vessel 7, which has a flatter distribution of trip revenues. The pattern is similar to the overall pattern but it is also evident that different vessels have different peaks (note that the length of the x-axis varies between figures). Vessels 1–4 are all medium vessels with revenue peaks around 100,000 SEK per trip, vessels 5–8 have revenue peaks around 20,000 SEK and the remaining vessels in Figures 2C and 2D have peaks around 10,000 SEK.[8]

In conclusion, the summary statistics reveal that smaller vessels make a smaller number of hauls, stay out at sea for a shorter time, catch less per trip and earn less revenue per trip. Medium and large vessels show very similar patterns. It is not evident from the summary statistics whether there are revenue targets for the cod fishers in the sample, although "peak" revenues seem to exist. Peak revenues also seem to differ between vessels and revenue distributions have long right-hand tails, i.e. most vessels seem to experience some trips with unusually high revenues.

Estimation strategy

As a starting point, this study assumes that fishermen consider one trip at a time and make decisions on trip length based on trip-specific conditions. The idea is that fishermen might simplify decisions by "bracketing" the decision-making horizon between the time they leave port and the time they arrive back in port. This can be motivated by the fact that fishing is uncertain, implying that decisions are made with a short-run perspective. The choice of location, the time spent trawling in each location and the decision on whether to set another trawl are all decisions that are made with a short-run perspective. The fishing trip has also been used as the relevant decision-making horizon in previous studies where days at sea have been used to measure trip length (Giné, Martínez-Bravo, and Vidal-Fernández 2010; Nguyen and Leung 2013; Ran, Keithly, and Yue 2014). But, since many vessels make day trips and because there is a weekly pattern of fishing, it is also possible that the "bracket" is wider than the trip. For this reason decision making with a weekly horizon will also be considered in this study.

A common approach to test the income target hypothesis is to use the wage elasticity function where the average wage is regressed on the number of hours worked. This approach has been used in several previous studies with temporary wage increases (Camerer et al. 1997; Eggert and Kahui 2012; Nguyen and Leung 2013; Farber 2014; Stafford 2015). One precondition for the average wage to work as a measure of the wage is that this wage does not change much during the time horizon that is investigated. In the context of fishermen it would be necessary that revenues from different hauls on a trip are similar or in particular, that the revenues from hauls in the beginning of a trip are similar to hauls made later on. If trips end because smaller revenues are expected later on, this is in line with the intertemporal model of labor supply rather than the model of reference dependence. The degree of revenue dependence during the trip is thus interesting for the choice of model.

Checking the data on cod trawlers reveals that the standard deviation of revenues from different hauls is large. The average revenue from a haul is 13,500 SEK for the entire sample and the standard deviation is 16,100 SEK. Checking the variation within trips using a fixed-effects regression reveals that there is also a lot of variation left when controlling for trip effects: within-trip variation is still 12,900 SEK. Since revenues can be expected to vary because of the time of the day, the geographical position and the hour of the day, these variables were also added to the regression, reducing within-trip variation only slightly to 12,800 SEK. Hence, high within-trip variation suggest that fishermen

[8] Staffan Larsson, representative of the Swedish Producer Organization of cod fishermen, mentions that a good trip might make the fishing trip shorter and that the largest vessels that are out for several days aim for a catch of 10 to 15 tons. He also confirms that it is not unlikely to catch 10 tons in one haul, but it is unusual (personal information from Staffan Larsson 2014-06-09).

cannot expect constant revenues from different hauls on a trip even if they adjust their expectations because of knowledge of the area or time-specific conditions.

The correlation between adjacent hauls might also matter for the fishermen. If the previous haul was successful it might be expected that the next haul will be so as well. The correlation between the current and the next haul within trips is estimated using a regression with the current haul as a dependent variable. The results show that the relationship is insignificant (Table 2, Model 1). In a second specification day-of-the-week effects, hour-of-the-day effects and dummies for geographical position are added, the motivation being, as above, that fishermen could expect revenues to depend on these variables. However, the dependence of the current haul on the previous haul is even smaller given these aspects. This suggests that it is unlikely that fishermen expect good hauls to be followed by equally good hauls and vice versa.[9]

Table 2: Revenues from hauls regressed on lagged revenues from hauls within trips

	(1)	(2)
Coefficient of lagged revenue	324.79	196.01
Standard error	212.27	214.04
t-value	1.53	0.92
p-value	0.126	0.360
R2	0	0.017

Note: Regression (1) is $y_{ht} = \alpha + \beta y_{h-1,t} + \mu_t + \varepsilon_{ht}$, where y_{ht} and $y_{t,h-1}$ are current and previous revenues from hauls, t indexes the trip and h indexes the particular haul and μ_t are trip fixed effects. Regression (2) is the same model with day-of-the-week effects, hour-of-the-day effects and dummies for geographical position added. The number of observations is 11,660.

Although it might be the case that fishermen consider the entire revenue from a haul when deciding whether to continue fishing it is also possible that the time spent trawling matters and that what matters for fishermen is the revenue earned per hour. Since fishermen spend time on board their vessel for several days and have irregular working hours on board it is difficult to distinguish between time spent working actively on the one hand and time traveling, time for breaks and sleeping hours on the other. One way is to consider all hours spent on board as work hours since being on a fishing trip prevents the fisher from taking part in family activities or other land-based recreational activities. Another possibility is that only time spent trawling is considered as working hours and that other time spent on board is spare time.

Calculating revenues per hour for each haul using the entire time spent on board shows that revenues per hour is 1944 SEK/hour for the entire sample with a standard deviation of 7547 SEK/hour. Also, within-trip variation is very large, 8074 SEK/hour, suggesting that there is more variation within trips than between trips. However, it is possible that sleeping hours gives low revenues per hour when using the entire time spent on board. Using only time spent trawling when calculating revenue per hour gives a higher revenue per hour: 3194 SEK/hour with a standard deviation of 4889 SEK/hour. Checking within-trip variation reveals that this variation is 4229 SEK/hour without additional controls and 4198 SEK/hour with additional controls. Thus, it seems as

[9] It is possible that revenues from hauls earlier on during a trip (lag>1) have an effect on the revenues from the current haul. However, the number of observations would decrease significantly using more than one lag, and this kind of specification is therefore avoided.

though the conclusion when using only revenues from hauls is confirmed by using revenues per hour, whether hours from the entire trip is used or only hours spent fishing, i.e. revenues during a fishing trip vary to a large extent.

Regressing the lag of revenues per hour on revenue per hour using the two different time measures shows that there is little dependence between revenue per hour from different hauls (Table 3). Using all time spent on board does not reveal any dependency between hourly revenues (Models 1 and 2), and using only time spent fishing shows some positive dependency between hourly revenues. However, this latter dependency becomes insignificant when more controls are added to the regression.

Table 3: Revenues per hour from hauls regressed on lagged revenues per hour from hauls within trips

	(1)	(2)	(3)	(4)
Coefficient of revenue per <u>hour spent on board</u>	-241.764	-81.841		
Standard error	126.781	137.181		
t-value	-1.91	-0.6		
p-value	0.057	0.551		
Coefficient of lagged revenue per <u>hour spent fishing</u>			145.488*	131.947
Standard error			70.749	71.304
t-value			2.06	1.85
p-value			0.04	0.064
R2 of regression	0	0.01	0.001	0.021

Note: Regression (1) and (3) is $y_{ht} = \alpha + \beta y_{h-1,t} + \mu_t + \varepsilon_{ht,}$ where y_{ht} and $y_{t,h-1}$ are current and previous revenues per hour using two different measures of hours as described in the text, t indexes the trip and h indexes the particular haul and μ_t are trip fixed effects. Regression (2) and (4) are the same models with day-of-the-week effects, hour-of-the-day effects and dummies for geographical position added. The number of observations is 11,660.

The fact that revenues have high variation might affect the expectations of fishermen. A reasonable adjustment would be that very high revenues are considered as rather unusual and that revenues closer to the average are more common. Using logged values of the revenue variables[10] gives significant results for the revenue variable when the revenue from the entire haul is used (a 1 percent increase in revenue in the previous haul increases the current haul by 1.83 %). However, using revenue earned per hour (using all hours or only trawling hours) produces insignificant results. The correlation is thus only evident when using revenues of hauls.

The conclusion from this exercise is that there is not much support for dependence between adjacent revenues on a trip, although there is some dependence between revenues from hauls when using logged variables. In general, a fisherman cannot expect good revenues to be followed by equally good revenues or that bad revenues will persist during the day. Thus, using the average revenue from a trip would not make sense in this case. I will use a version of the stopping model with cumulative revenues suggested by Farber (2005, 2008). In this model, fishermen are assumed to make decisions based on all revenues collected previously on the trip.

[10] The results are not presented here but are available upon request.

From a decision-making point of view, the most important time points during a fishing trip are the times of the hauls since I assume that the fisherman must decide whether to continue fishing or return to port at these points in time. For a decision point to be relevant it is necessary that the vessels are able to set at least a second trawl; if a vessel has no such capacity it would return to port after hauling for the first time and there would be no relevant decision point. Calculating the maximum number of hauls of each vessel reveals that each vessel made two or more hauls on at least one of their trips. Thus, there should exist at least one decision point for every vessel in the sample.

Assuming that the time of the haul is a decision point for the fisherman the stopping point is modeled as a function of the log of the number of hours worked so far (*cumh*) and the log of the revenue collected so far (*cumr*).[11] The number of hours worked are calculated as the total number of hours spent on board until the time of the haul assuming that all hours spent on board are work hours. The basic linear probability model will look as follows:

$$P(Stop = 1|\boldsymbol{x_i}) = \beta_0 + \beta_1 cumh_i + \beta_2 cumr_i + \varepsilon_i. \tag{1}$$

At each decision point the fisherman will decide whether to continue to fish, i.e. to place another trawl in to the water, or whether to return to port.[12] The revenue target model predicts that the likelihood of quitting is related to the income earned so far during the trip. Conditional on the number of hours worked so far, the income reached so far should be positively related to the probability of going home, i.e. if two trips have lasted the same amount of hours it is more likely that a vessel with higher revenues returns to port.

Since it is unlikely that there is one common revenue target for every vessel or even for the same vessel on different trips it makes sense to assume that potential targets are based on expectations formed in the recent past as suggested by the rational expectations model developed by Kőszegi and Rabin (2006). Thus, assuming that the trip is the relevant decision horizon, expected revenues are assumed to be formed by beliefs that the captain and crew hold when starting the trip and will differ depending on the season, fishermen characteristics and other trip-specific conditions. High expected revenues are assumed to result in longer working hours in line with the intertemporal model and in order to look for potential revenue targets of unexpected revenue changes it is important to control for factors that are important in determining expected revenues.

Assuming, to start with, that the trip is the relevant decision-making horizon motivates the use of trip fixed effects, assuming that factors that are unchanged during a trip correlate with the time spent at sea and the revenues collected. Using trip-specific effects controls for factors such as seasonal differences, vessel characteristics (such as size, gear and engine power), crew and captain characteristics and skills, effects of what happened on previous trips and fixed costs of the trip. Also, the effect of prices is kept constant, since the price used is the price given at the beginning of each trip. It can also be argued that trip-specific effects control for weather conditions since the decision to make the trip might be based on weather prognoses available when starting the trip.

[11] Using logged variables is motivated by the skewed distribution and facilitates the interpretation of the coefficients.
[12] It is possible to decide to haul at any time since the weight of the trawl gives some indication of the quantity of the catch, so the decision whether to stop could in practice occur just before the haul.

Additional factors that affect the trip length and revenues "within" a trip are also used in the model. These are the geographical position of the fishing place (***geopos***), the day of the week (***dow***) and the time of the day (***tod***). The geographical position is added since it might change during the trip and because biological conditions could differ between different positions. The positions are areas used by the International Council for the Exploration of the Seas (ICES) that divide the Baltic Sea into rectangles with a longitude of 1 degree and a latitude of 0.5 degrees (ICES 2011). Day-of-the-week effects are motivated by noticing that fishermen have different preferences for working on different days of the week. For example, fishermen are more likely to finish earlier or not fish at all on weekends. Using day-of-the-week effects also controls for seasonal closures and limited periods that prevailed during the time of the trip. Time of the day also accounts for time preferences since fishermen are more likely to return to port in the evening than in the morning. The geographical position controls for area-specific effects. Thus the extended fixed-effects model is:

$$P(Stop = 1|\boldsymbol{x_{it}}) = \beta_0 + \beta_1 cumh_{it} + \beta_2 cumr_{it} + \boldsymbol{geopos\delta_{it}} + \boldsymbol{dow\gamma_{it}}$$
$$+\boldsymbol{tod\theta_{it}} + \boldsymbol{\gamma_i} + \varepsilon_{it}, \qquad (2)$$

where the variables for haul *t* on trip *i* are defined as described above.

One potential problem when estimating the effect of increasing revenues on stopping probability is that vessels might have reached a physical capacity limit, i.e. there is no more room for fish on board, and thus vessels have to return to port. If high revenues are correlated with reaching such a capacity limit it might be that high revenues are associated with a high probability of returning without there being a revenue target for the trips. Previous studies have handled the capacity problem by adding dummy variables for vessel length or the existence of an ice breaker on board (Nguyen and Leung 2013) or by noting that maximum capacity is hardly ever reached (Eggert and Kahui 2012). It is, however, difficult to measure the influence of capacity constraints using dummy variables since such variables will only control for differences in capacities between vessels. Given that vessels have different physical capacities, they might still reach their vessel-specific capacities and return to port for this reason.

Returning to Figures 1c and 1d and Figure 2 it is evident that the distributions of catches and revenues on a trip level are highly skewed to the right, i.e. catches can sometimes be considerably larger than the average catch. This suggests that reaching or even getting close to a capacity limit is not very common. Using the maximum catch of a vessel during the time period as the capacity limit and counting the number of trips that reached 75% or more of this maximum reveals that only 6% of the trips (264 trips) were close to or at the maximum catch. The maximum catch of the vessel might, however, be a strict definition of the maximum catch since many vessels in the sample make only a few trips during the time period. Using the maximum catch of vessels in the same size category as the capacity limit (i.e. small, medium or large) shows that a vessel reaches 75% of the maximum on 47 trips, which corresponds to 1% of the trips in the sample. Although it is unusual that a vessel gets close to a capacity limit, a version of the model where trips that reached 75% of their vessel-specific revenue maximum is omitted in the main specifications of this study.[13]

[13] Including a variable that measures capacity (cumulative or as a dummy variable) in the original model is difficult since there is high correlation between reaching a potential capacity level and accumulating revenues.

Three additional variables that might affect the stopping probability are also added to the model. These are temperature changes during the trip, by-catches per haul and the average revenues from previous hauls made by all fishermen in the same fishing area including the vessel of interest. Temperature changes during the trip might affect how pleasant it is to fish at different stages of the trip, higher temperatures are expected to make it less likely for fishermen to return. The effects of by-catches, i.e. catches of species other than cod, are not obvious but I assume that an increase in by-catch will decrease profits because of increased handling and distribution costs. An increase in by-catch is thus expected to increase the disutility of fishermen and increase the probability to return to port. Finally, the average revenues from the previous 20 hauls (alternatively 10 previous hauls) is a proxy variable for information exchange from other fishermen in the area. If fishermen receive information about increased earnings opportunities they expect to receive higher revenues and the prediction is that they will stay out fishing longer.

By controlling for factors that can be observed by the fishermen (e.g. trip-specific effects, day of the week, time of the day and previous catches) an increase in revenue can be interpreted as a proxy for an increase in revenue that is unexpected, or not possible to control or observe for the fisherman.[14] Since revenues are highly volatile it is difficult for fishermen to control exactly what is caught in a trawl; often, the density of shoals and the quality and size of the fish vary and are not observed until the fish are on board. Also, sudden weather changes (winds) can change the amount of fish that is caught. Thus, it is the effect of unexpected revenue changes on the likelihood of returning to port in line with the theory of Kőszegi and Rabin (2006) that I attempt to measure.

In summary, the predictions of my model are:

1. The likelihood of returning to port is positively related to the number of hours worked so far on a fishing trip.
2. If the revenue target hypothesis is relevant the effect of revenue earned so far should be positively related to the likelihood of returning to port at least at some stage of the trip.
3. If the intertemporal hypothesis is relevant the effect of revenue earned so far should be insignificant.

The coefficient on hours worked will necessarily be positive since I am looking at within-trip variation. The longer a trip has lasted the more likely it is that the vessel will return to port since the length of a trip will decrease with fatigue and the ability to keep fish fresh. This variable is mainly used as a control variable for making comparisons between vessels that have been out at sea for the same amount of time. If the revenue target hypothesis is the correct hypothesis a trip with higher revenue than expected should be more likely to end when two trips have lasted for the same length of time. If the intertemporal model is the correct hypothesis the coefficient on the revenue variable will be insignificant, the effect of previous revenues negative and the effect of by-catch positive.

In this paper, the linear probability model will be used rather than a nonlinear model such as the probit or logit model. A number of problems with the linear probability model are often mentioned in the literature. Standard errors are heteroskedastic, parameters close to zero or one are difficult to interpret and sometimes the interpretation of parameters is not representative of the relationship

[14] In reality, it might be that the fishermen can observe factors that the researcher cannot; for this reason the variable is a proxy.

between the independent and dependent variables (Wooldridge 2006). To deal with binary choices it might make sense to use different kinds of distribution functions. However, any nonlinear function is problematic when fixed effects are present since the number of observations within panels is often small. Adding fixed-effects parameters results in inconsistent estimation of these parameters and because of the nonlinearity these parameters will also affect other parameters of the regression, resulting in inconsistency for all the parameters of the model (the incidental parameters problem) (Cameron and Trivedi 2010). In this paper, the linear probability model has been chosen, given that the numbers of hauls are small, and that there are many panels with only a few observations. However, it is not necessary to assume that the effect of revenues is linearly related to the stopping probability, even when using a model that is linear in parameters. Increasing revenues might have different effects as the trip proceeds; in particular, if there is a target revenue level, we might expect a higher probability of returning when such a target has been reached. Interacting revenue earned with hours worked, haul number and day of the week is therefore used in different specifications to investigate whether the effect of higher revenues is nonlinear.

Results

Trip-targets

Table 4 shows the results from the stopping probability model when targets are assumed to be trip-specific. Hours worked have a negative coefficient and revenue earned so far has a positive coefficient in the first model (a cross section model). This model does not take the heterogeneity of different vessels and time periods into consideration and is only presented for reference. Model 2, where trip fixed effects are added, controls for everything that is unchanged during a trip. The coefficient on hours worked shows that the longer a trip has lasted, the greater the probability that the vessel returns to port. Interpreting this coefficient indicates that the probability of returning to port increases by 0.44 on average for a 1% increase in trip length. Model 2 does not suggest that the level of revenue earned has any effect on stopping probability given that a vessel has been out for a certain length of time. However, when revenue earned is interacted with hours worked there is an additional negative effect on stopping probability, indicating that the longer the trip has lasted the more important high revenues are for the likelihood of continuing.

Table 4: Hazard of stopping after a haul: estimates from a linear probability model

	(1)	(2)	(3)	(4)
Hours worked	-0.044*	0.435***	0.429***	0.439***
Revenue earned	0.041**	-0.036	-0.076***	-0.094***
Revenue*Hours	0.029	-0.066*	-0.028	-0.047**
Temperature	-0.007***	-0.036***	-0.002	-0.003
Previous catches	-0.111***	-0.060***	0.006	-0.004
By-catch	0.054***	0.067***	0.049***	0.048***
Constant	3.088***	9.556***	-1.082	-0.472
Trip fixed effects	No	Yes	Yes	Yes
Geographical position effects	No	No	Yes	Yes
Day-of-the-week effects	No	No	Yes	Yes
Hour-of-the-day effects	No	No	Yes	Yes
N	15916	15916	15916	14949
R2	0.088	0.353	0.474	0.489

Note: Standard errors are clustered on vessels in all models. Hours worked, Revenue earned and By-catch are in logs. Revenue and Hours are centered around their means for the calculation of the interaction. Significant levels are * for $p<0.05$, ** for $p<0.01$, and *** for $p<0.001$.

Model 3 refines Model 2 by adding more variables. Since fishermen are more likely to return to port in the evening or on specific days in the week, variables indicating the hour of the day and the day of the week are added to the model. Since a certain geographical position could also be related to the decision of a fisherman, dummy variables for different areas in the Baltic Sea are added. The added variables seem to strengthen the idea that high unexpected revenues increase the willingness to continue fishing since the main effect of revenues is also significant and negative now. Finally, when trips where the proxy for a capacity limit is reached or is about to be reached are removed from the sample (Model 4), the estimates suggest that the physical capacity limit is not very important on average; the coefficients on revenue earned are similar in Model 3 and Model 4. But Model 4 indicates that there is a combined effect of revenues and hours since the interaction variable now becomes significant. Using the 95% confidence interval from Model 4 shows that a revenue increase of 1% is associated with a decrease in the probability of returning to port by 6–13 percentage points on average. The interaction effect suggests that the likelihood of continuing is more affected by higher revenues if the fishing trip has lasted for a longer time. In summary, these results do not lend support to the revenue target hypothesis since higher revenues than expected do not result in shorter working hours for fishermen. Rather, fishermen tend to continue fishing when revenues are higher than expected suggesting that they increase their risk taking as revenues increase.

The temperature and information variables (average revenues from previous hauls) are only significant in Models 1 and 2. This suggests that the dummy variables for geographic position, day of the week and hour of the day control for temperature and information exchange. Interestingly, the information variable in Model 2 is negative, which indicates that when previous catches (catches from the vessel of interest as well as catches from other vessels are included) are good the probability that a fishing trip will continue increases. This is in line with the intertemporal model with expected revenues; expecting revenues to be high in the future will make it more likely to continue fishing.[15] The temperature variable in Model 2 also has the expected sign, since warmer weather increases the trip length somewhat. The coefficient of the by-catch variable is positive and significant in all models, suggesting that an increase in catches other than cod increases the probability that fishermen will stop fishing. One interpretation could be that, for these fishermen, catching species other than cod increases the sorting and handling costs and is a disutility for the fishermen and thus also decreases the probability of continuing the trip.

To further account for nonlinear effects of cumulative revenues and to search for revenue targeting behavior at different stages of the trip, the effect of revenue increases at the time of different hauls is estimated. The motivation for choosing haul-times is that the times of the hauls are decision points for the fishermen and thus constitute interesting points for the decision whether to continue fishing or return to port. The hauls are labeled haul 1, haul 2, haul 3 etc. and are also added as main effects to the regression. Table 6 shows the results of the coefficient of the revenue variable interacted with different haul numbers, for large, medium and small vessels using the model of Equation (2) and the sample where trips that are reaching a potential capacity constraint have been removed (compare Model 4 Table 4). Coefficients of the interaction variables after haul 10 are not shown as these are relying on a few number of observations. Two versions of the model are calculated – one where the effect of hours is kept log-linear and one where the effect is allowed to vary for different haul numbers. It could be argued that the effect of hours worked has different effects on the probability of returning to port at different stages of the trip. Working an extra hour at haul 1 might for example have a different effect than working an extra hour at haul 5.

[15] Two alternative measures of revenues from previous hauls were used, one with the average revenue per hour spent trawling from 20 previous hauls and one with the average revenue per hour from 10 previous hauls. Both variables have negative and significant coefficients in Model 1 and Model 2 and insignificant coefficients in Models 3 and 4.

Table 6: Hazard of stopping after each haul: with linear and non-linear effects of hours worked on a haul.

	(1)	(2)
Revenue earned at each haul		
1	-0.029	-0.030*
2	-0.136***	-0.076***
3	-0.099***	-0.033
4	-0.086**	-0.056*
5	-0.071*	-0.042
6	-0.021	0.009
7	0.001	0.02
8	0.011	0.032
9	0.073	0.116**
10	0.062	0.094
Hauls after 10 are not presented (these hauls constitute ca 2 % of the observations).		
Hours worked	0.573***	
Hours worked at each haul		
1		0.641***
2		0.194***
3		0.152*
4		0.405***
5		0.323***
6		0.402***
7		0.851***
8		0.859***
9		0.233
10		0.482*
Hauls after 10 are not presented (these hauls constitute ca 2 % of the observations).		
Temperature	-0.002	-0.004
Previous catches	-0.012	-0.019
By-catch	0.047***	0.046***
Constant	-1.163	-14.852
Haul effects	Yes	Yes
Trip-fixed-effects	Yes	Yes
Geographical-position-effects	Yes	Yes
Day-of-the-week-effects	Yes	Yes
Hour-of-the-day-effects	Yes	Yes
N	14 973	14 973
R2	0.51	0.542

Note: All models are based on Equation 2, results from other coefficients are not presented for reasons of space. Standard errors are clustered on vessels. Significant levels are * for $p<0.05$, ** for $p<0.01$, and *** for $p<0.001$.

In general, the results suggest that higher revenues conditional on the number of hours spent out at sea is negative, at least at some stages of the trip. For the model with log-linear hours there seem to be a negative effect of increasing revenues at haul 2, 3, 4 and 5. However, when controlling for different effects of hours worked at different hauls, there is an effect of increasing revenues only at haul 1, 2 and 4. The effect of hours worked do appear to be non-linear since the effect is f.ex. larger for haul 1 than for haul 2 or haul 3. Increasing the number of hours worked by 1 % at haul 1 seem to affect the probability of returning more than increasing the number of hours worked by 1 % at haul 2 or 3. After haul 3 the effect of more hours worked seem to increase again. For the second model there is a positive effect of increasing revenues at haul 9. However, only a small number of trips (183) end after haul 9 making it difficult to draw any general conclusions. The main conclusion from the non-linear revenues analysis is that larger revenues have a negative effect on the probability of fishermen to return to port, i.e. earning more makes fishermen want to work longer. However, the effect is not as clear when the effect of hours worked is assumed to be non-linear as well. Again, these results do not support the idea of revenue targeting but rather suggest that fishermen are risk-seeking at some stages of the trip.[16]

Weekly targets

Using the trip as the relevant decision-making horizon is intuitive but it might be that some vessels use a longer decision-making horizon, especially vessels that go on day trips several times a week. On average, a vessel makes 1.74 trips a week, but smaller vessels make more trips (2.39) than medium and large vessels (1.55 and 1.54). Thirty-one percent of the hauls in the data set are made by vessels that make at least one day trip on a particular week. Assuming that the week is the relevant decision horizon the hypothesis that fishermen have weekly income targets is tested. Using the week necessitates the use of a breaking point where weeks are defined in a way that is logical from the fishermen's perspective. Turning to the data, it is evident that there are relatively few trips starting at the weekend (11% of the trips) and that most trips start on a Monday (35% of the trips). Information from fishermen additionally suggests that many trips start on a Sunday (personal information Staffan Larsson 2014-06-09). For this reason, the break point of the week is assumed to be the night between Saturday and Sunday and the hypothesis that is tested is that a vessel has a weekly income target that is reached at some time before 00.00 hours on Sunday.

Working hours of the week for each vessel are calculated as all hours on board the vessel on a specific week. This includes sleeping hours if the fishermen stayed on the vessel overnight, which might exaggerate the measure of hours worked for long trips. On the other hand, sleeping on board could perhaps be considered as an inconvenience that should be compensated for. Using the log of hours, however, decreases the effect of long working hours.

The fixed effects used in the analysis of weekly targets are vessel-week specific, i.e. all factors that are unchanged for a certain vessel during a certain week are kept constant. The interpretation is therefore similar to the interpretation of the trip-specific model, although the number of fixed

[16] The literature on revenue targeting is often concerned with the heterogeneity of subjects, for example the degree of loss aversion might differ between subjects making some subjects target earners and others substituting intertemporally (Fehr and Goette 2007; Nguyen and Leung 2013; Farber 2014). Since there is no individual data or information about experience of fishermen a test was carried out for vessels of different size. But since the results did not provide any substantial differences between vessels I omit them from this presentation.

effects reduces to 2495 as compared to 4355 in the trip-specific models. Dummy variables for the day of the week, the hour of the day and geographical position are added as before and with the same motivation. Also, as before, to account for physical capacity constraints, trips that are about to reach maximum physical capacity are excluded from the analysis.

To account for nonlinearities in revenue targeting, revenue is interacted with hours but, in a different specification, also with different days of the week. The idea is that it is more likely for the fishermen to reach a target later on in the week. The results are presented in Table 7.

Table 7: Assuming weekly targets and nonlinear revenue effects

	(1)	(2)	(3)
Hours worked	0.103***	0.068*	
Revenue earned	-0.032*		
Revenue*Hours	0.023*		
Temperature	0.002	0.002	0.002
Previous catches	-0.023*	-0.024*	-0.02
By-catch	0.029***	0.029***	0.028***
Revenue earned on …			
Monday		-0.070***	-0.048***
Tuesday		-0.055***	-0.053***
Wednesday		-0.038**	-0.057***
Thursday		0.008	-0.024
Friday		0.042	-0.002
Saturday		-0.02	-0.051
Sunday		0.016	-0.006
Hours worked on ….			
Monday			-0.038
Tuesday			0.045
Wednesday			0.111**
Thursday			0.144***
Friday			0.168***
Saturday			0.134*
Sunday			0.117
Constant	-1.576**	-1.436**	-1.283*
Vessel-week effects	Yes	Yes	Yes
Geographical position effects	Yes	Yes	Yes
Hour-of-the-day effects	Yes	Yes	Yes
N	14964	14964	14964
R2	0.344	0.347	0.35

Note: Standard errors are clustered on vessels. Significant levels are * for $p<0.05$, ** for $p<0.01$, and *** for $p<0.001$. Revenue and Hours are centered around their means for the calculation of the interaction in Model 1 and Model 2.

Model 1 shows that the main effect of revenue earned so far in the week is negative and the interaction of revenue and hours is positive. However, both effects are small and the interaction effect is not large enough to support the idea of a revenue target at any stage of the trip. There is a negative effect of previous catches and a positive effect of bycatch. The interpretations are the same as in the trip-model.

Interacting revenues earned with the day of the week to account for nonlinearities in revenue effects gives the results of Model 2. High revenues at the beginning of the week make it less likely that the fishing week will end whereas the effect of high revenues later on in the week is insignificant. Fishermen on most vessels (those making day trips as well as those making longer trips) end their week-of-fishing on a Wednesday or a Thursday (56 % of the vessels). Only 25 % of the vessels are left when Thursday ends and Friday begins.

Finally, in model 3, the effect of the number of hours out at sea is assumed to be non-linear and vary on different days of the week. It is evident that the probability of returning increases by the end of the week up until Friday. The results on the revenue variable is similar to model 2, high revenues early on in the week makes it more likely that the fishermen will fish later on in the week. Interestingly the negative effect of revenues increases between Monday and Wednesday in the final model.

The general conclusion is similar to the conclusion of the trip-specific model: if fishermen have experienced good revenues early on in the week they will continue fishing. Although revenues are largely unexpected fishermen display a risk seeking behavior as they prefer to continue fishing when revenues are higher. There is no evidence of fishermen reaching a revenue target at any stage of the trip.

Expected targets

Above it has been argued that the revenue target that we are looking for is an expected target. Knowing what this expected target might be is difficult but if we are far away from the target we might not expect the same behavior as when we are close to this target. In fact, one of the main ideas of prospect theory is that the behavior of individuals is substantially different below and above the reference point (Kahneman and Tversky 1979). One possibility is to estimate expected targets for each trip or week and test if the stopping probability is affected when reaching or getting close to these targets. Although it is not obvious how to estimate expected targets I will make an attempt and use predicted values from a regression of revenues on a number of variables. This approach has been used previously (Giné, Martínez-Bravo, and Vidal-Fernández 2010; Farber 2014). The regression used is:

$$r_{iv} = \beta_0 + \beta_1 h_{iv} + \beta_2 pr_{iv} + \beta_3 temp_{iv} + \boldsymbol{yr\vartheta_{iv}} + \boldsymbol{week\tau_{iv}} + \boldsymbol{geopos\delta_{iv}} + \boldsymbol{dow\gamma_{iv}}$$

$$+\boldsymbol{tod\theta_{iv}} + \boldsymbol{\gamma_v} + \varepsilon_{iv}$$

Where r_{iv} is the log of revenue for vessel *v* on trip *i*, h_{iv} is the amount of hours spent on trip *i* (as a proxy for the planned amount of hours), pr_{iv} is the previous revenue earned on a trip, $temp_{iv}$ is the average temperature on the trip (as can be expected by checking the weather prognoses), $\boldsymbol{yr\vartheta_{iv}}$, $\boldsymbol{week\tau_{iv,}}$, $\boldsymbol{dow\gamma_{iv}}$ and $\boldsymbol{tod\theta_{iv}}$ and are the year, the week, the day-of-the-week and the time of time-of-the-day when the trip started. $\boldsymbol{geopos\delta_{iv}}$ is the first geographical position that the vessel is heading for on a trip. Finally, vessel-specific-effects, $\boldsymbol{\gamma_v}$, are added to the model. Running the regression with ordinary least squares gives an R2-value of 0.68. Predicted values from this regression are used as observations of expected targets.

The next step is to get a variable that can be used in the stopping regression. A dummy variable is created that is indicating when the cumulative revenue from a haul exceeds the expected target (the narrow target). As an alternative, the dummy variable is indicating when revenues are getting close to reaching the target by indicating revenues for the haul that is preceding or following the exceeding revenue (the wider target).

The results of adding a target dummy to the stopping model are shown in Table 8. The stopping model with trip-fixed-effects, additional dummy variables and where trips that are getting close to a capacity limit are removed from the sample, is used. The new variable, the dummy variable indicating if the expected target has been exceeded, is insignificant for the narrow version of the target and negative for the wider version of the target. Reaching the expected revenue has, if anything, a negative effect on stopping probability and hence there is no evidence of income target behavior using this model.

Table 8: Adding a dummy variable for the expected target – the trip-specific model.

	(1)	(2)
Hours worked	0.420***	0.407***
Revenue earned	-0.081***	-0.059***
Target (narrow)	-0.03	
Target (wide)		-0.160***
Temperature	-0.002	0
Previous catches	-0.012	-0.011
By-catch	0.047***	0.045***
Trip-fixed-effects	Yes	Yes
Geographical-position-effects	Yes	Yes
Day-of-the-week-effects	Yes	Yes
Hour-of-the-day-effects	Yes	Yes
N	14958	14958
r2	0.483	0.502

Note: All models are based on Equation 2, results from other coefficients are not presented for reasons of space. Standard errors are clustered on vessels. Significant levels are * for $p<0.05$, ** for $p<0.01$, and *** for $p<0.001$.

Similarly expected targets for the weekly model can be calculated. A similar regression is used although the dummy variables for the week are exchanged for monthly dummy variables. The R2 of the OLS regression is 0.64. Predicted values are used as measures of expected targets and compared to the cumulative revenues of each vessel for each week. A dummy variable indicating when the target is exceeded is then calculated and used in the stopping model. And as for the trip-specific model, a wider version of the target is used, where the dummy variable is equal to one for hauls where the expected target is reached on the next haul, the current haul or the previous haul. The results are presented in Table 9.

Table 9: Adding a dummy variable for the expected target – the weekly model.

	(1)	(2)
Hours worked	0.086**	0.088**
Revenue earned	-0.043***	-0.031**
Target (narrow)	0.003	
Target (wide)		-0.087***
Temperature	-0.002	0
Previous catches	-0.012	-0.011
By-catch	0.047***	0.045***
Vessel-week-effects	Yes	Yes
Geographical-position-effects	Yes	Yes
Day-of-the-week-effects	Yes	Yes
Hour-of-the-day-effects	Yes	Yes
N	14958	14958

r2	0.483	0.502

Note: All models are based on Equation 2, results from other coefficients are not presented for reasons of space. Standard errors are clustered on vessels. Significant levels are * for p<0.05, ** for p<0.01, and *** for p<0.001.

Again, the results do not indicate that fishermen stop fishing when the expected target is reached. On the contrary, the probability of returning to port is smaller if the target has been reached, at least when the wider version of the target is used. In summary, these attempts to get closer to the true target fail to find any support to the idea that fishermen are revenue targeters.

Discussion

Although uncertainty is an issue for taxi drivers it is more so for fishermen. If fishermen are reaching for expected revenue targets any unexpected revenues that exceed these targets would imply that fishermen stop working. If revenue targeting behavior is an important aspect of economic life it would perhaps be more so for fishermen than for taxi drivers.

Since many factors that fishermen are aware of are controlled for (i.e. trip-specific conditions, day of the week, geographical position etc.) it is assumed that fishermen expect certain revenues based on those factors. The idea that the willingness to continue is displaying a risk-seeking behavior assumes that future revenues cannot be controlled or expected. Assuming that expected revenues can be controlled for might, however, be a strong assumption. Fishermen on board a vessel might clearly have information, correct or incorrect, that cannot be measured in any way using available logbook data. The negative coefficient on the probability of returning to port for early hauls and early on in the week could thus be due to unknown factors correlating with revenues.

It might be possible that fishermen have other targets in addition to revenue targets. In that case, if the revenue target is only one of the targets to be reached and if it is not the last reached target, there will not be any correlation between ending a fishing trip and reaching the revenue target. Crawford and Meng (2011) assume that taxi drivers have revenue targets as well as hours targets and that both have to be reached before the taxi driver ends his shift. Controlling for time-specific effects (such as day of the week and time of the day) picks up some time-related differences in preferences but the issue could be further investigated. On the other hand, if it is the relationship between working hours and revenues that is of interest it is implicitly assumed that hours are a function of revenues and not an independent goal as such.

So far, most of the evidence of revenue targeting has been limited to workers that are independent in their decision-making process, i.e. taxi drivers who decide themselves when and where to work. If revenue targeting is an important aspect of economic life and if it is important to consider targets when forming policies it is necessary to prove that they exist outside the realm of certain independent self-employed workers. A fisherman working on a trawler, although self-employed, is more dependent on cooperation and the decisions of the captain. The evidence provided here does not suggest that revenue targeting is an important aspect for this kind of worker. On the other hand, it is more difficult to determine whose preferences are actually measured, and although there is no collective revenue target for the entire crew of the vessel, I have no information on the behavior of individual fishermen.

Conclusions

This paper investigates the revenue target hypothesis for fishermen. More specifically, relationship between short-term unexpected revenues and the time spent out at sea, i.e. the working hours of fishermen, is tested for Swedish cod fishermen in the Baltic Sea. So far, the empirical literature has not found substantial evidence supporting the revenue hypothesis, neither for fishermen nor for other workers.

The main results indicate that a fishing trip is more likely to continue if revenues are unexpectedly high. This implies that fishermen are on average risk seeking. The revenue target hypothesis is however not very relevant for explaining the behavior of Swedish Baltic Sea fishermen since higher revenues are not associated with an increased probability of returning to port at any stage of the trip. Constraints (i.e. physical capacity of the vessel, quota limitations or other regulations) do not seem to influence the results. Assuming that revenue targets are weekly rather than trip-specific give similar results.

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