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FORECASTING MACROECONOMIC EXTREMITIES WITH PREDICTION MARKETS AND QUANTILE REGRESSION

MASTER THESIS

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ABSTRACT

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Macroeconomic indicators play an important role in evaluating the state of economy. Macroeconomic forecasts provide investors, economists and policy-makers with foresight about the expected future economic developments. Forecasts of macroeconomic indicators currently are usually obtained though the surveys of the field experts that give us point forecasts of the macroeconomic indicator of interest. However, economies evolve over time and are subject to intermittent, and sometimes large, unanticipated shocks. Therefore, point forecasts are rarely accurate and do not answer the current needs of increasing emphasis on risk management. Probabilistic forecasts or interval forecasts allowing to estimate the probability density of the macroeconomic indicators are considered as improvement to current forecasting situation. Prediction markets and quantile regression are analyzed in this research as methods providing estimates of probability density of macroeconomic indicators. Expert survey point forecasts, prediction markets forecasted means and quantiles interpolated from probabilities elicited though prediction markets were used as initial data in this research. Added value and accuracy of these methods with different setups are compared, and a combination of prediction markets and quantile regression is considered. It was found that quantile regression on historical data of expert point forecasts can be a good starting point for well calibrated interval forecasting, but prediction markets can add value to the accuracy of these forecasts, and the combination of prediction markets with quantile regression on the probabilities elicited by these prediction markets gives the best results.

Keywords: macroeconomic forecasting, interval forecasts, prediction markets, quantile regression.

SANTRAUKA

Vitkauskas, A. Makroekonominių išskirčių prognozavimas naudojant prognozių rinkas ir kvantilinę regresiją. [Rankraštis]: magistro baigiamasis darbas: ekonomika. Vilnius, ISM Vadybos ir ekonomikos universitetas, 2013.

Makroekonominiai indikatoriai yra svarbūs ekonomikos būklės įvertinimo rodikliai. Makroekonominės prognozės leidžia investuotojams, ekonomistams ir politikams numatyti ateities ekonomikos vystymosi kryptis. Šiuo metu makroekonominių rodiklių prognozės dažniausiai remiasi ekspertų nuomone ir yra pateikiamos nurodant vieną labiausiai tikėtiną reikšmę. Tačiau ekonomikos sparčiai vystosi ir neretai patiria nereguliarius, netikėtus, bet reikšmingus pokyčius. Todėl taškinės tikėtiniausių reikšmių prognozės retai būna tikslios ir nebeatitinka šiuolaikinės rizikos valdymo poreikių. Tikimybinės ar intervalų prognozės, leidžiančios įvertinti makroekonominių rodiklių tikimybinį tankį, laikomos reikšmingu šiuolaikinio makroekonomikos prognozavimo patobulinimu. Šiame darbe nagrinėjami du metodai, leidžiantys prognozuoti makroekonominių rodiklių reikšmių tikimybinį pasiskirstymą: prognozių rinkos ir kvantilinė regresija. Šie metodai buvo taikomi naudojant skirtingus pradinius duomenis: ekspertų prognozes, prognozių rinkų pateikiamas tikėtiniausias reikšmes ir kvantilius, interpoliuotus iš prognozių rinkų pateikiamo tikimybių skirstinio. Buvo vertinama abiejų metodų skirtingų variantų pridėtinė vertė ir tikslumas, bei jų kombinavimo galimybė. Darbo rezultatai leidžia manyti, kad kvantilinė regresija naudojant istorinius ekspertų prognozių duomenis gali duoti tinkamai kalibruotas intervalų prognozes, tačiau naudojant prognozių rinkas galima pagerintų prognozių tikslumą, o kombinuojant kvantilinę regresiją su kvantiliais, interpoliuotais iš prognozių rinkų pateikiamų tikimybių, galima gauti geriausius prognozių rezultatus.

Raktiniai žodžiai: makroekonomikos prognozavimas, intervalinės prognozės, prognozių rinkos, kvantilinė regresija.

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LIST OF ABBREVIATIONS

NFP	Change in Non-Farm Payrolls
RSX	Percentage Change in Retail Sales Excluding Motor Vehicles
ISM	Institute for Supply Management’s Manufacturing Diffusion Index
ICL	Initial Unemployment Claims
NORM	Combined Normalized Data of NFP, RSX, ISM, and ICL
PM	Prediction Markets Forecasted Means
EX	Expert Surveys Forecasted Means
PMQ	Quantiles Interpolated from Prediction Markets
RV	Actual Released Value of the Macroeconomic Indicator

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INTRODUCTION

Macroeconomic indicators play an important role in evaluating the state of economy. Macroeconomic forecasts provide investors, economists and policy-makers with foresight about the expected future economic developments. Forecasts of macroeconomic indicators currently are usually obtained though the surveys of the field experts that provide us with the point estimates of the macroeconomic indicator of interest. However, as Clements and Hendry (2003) state it, "one of the main problems with forecasting in economics is that economies evolve over time and are subject to intermittent, and sometimes large, unanticipated shocks." Therefore, point forecasts are rarely accurate and sometimes can be even misleading. According to Clark (2009):

> *"Policymakers and forecasters are increasingly interested in forecast metrics that require density forecasts of macroeconomic variables. Such metrics include confidence intervals, fan charts, and probabilities of recession or inflation exceeding or falling short of a certain threshold. For example, in 2008 the Federal Reserve expanded its publication of forecast information to include qualitative indications of the uncertainty surrounding the outlook. Other central banks, such as the Bank of Canada, Bank of England, Norges Bank, South African Reserve Bank, and Sveriges Riksbank, routinely publish fan charts that provide entire forecast distributions for inflation and, in some nations, a measure of output or the policy interest rate."*

As the importance of forecasting accuracy is increasing, scholars are looking for better ways to forecast the future performance of economy. Most often encountered errors of forecasters and ways to improve them were analyzed by Stekler (2007) and Clements and Hendry (2008). The need for better forecasting tools has been argued by Kenny and Morgan (2011). One of the first possible improvements in macroeconomic forecasting could be interval forecasts. These are forecasts that are supplemented by prediction intervals that represent the uncertainty of the forecast (Chatfield, 1993). An example of application and practical usage of this technique can be found in Borbély and Meier (2003).

In my thesis, I analyze prediction markets and quantile regression as techniques that can be used to make interval forecasts of macroeconomic indicators. I also compare the added value of prediction markets with the added value of the quantile regression in forecasting the probability distribution of the macroeconomic indicators. Prediction markets, as described in details by Wolfers and Zitzewitz (2004), is a special type of the markets designed specifically for information elicitation and aggregation. In these markets, payoffs of the traded securities depend on the outcomes of the future events. Investors buy the security if they think the event that is tied to it will happen and sell the security if they think the event will not happen. By doing that, investors reveal their believes about the outcome, and aggregation of these believes can be interpreted as a probability of this particular event to happen. This was thoroughly discussed by Gjerstad (2005), Manski (2006), and Wolfers and Zitzewitz (2005). Chen, Pennock et al. (2005) have also shown that prediction markets are doing at least as good if not better than expert opinion polls in terms of providing future forecasts.

Most research of prediction markets at the moment has been done in the areas of elections, sports, and entertainment events. Recently, prediction markets have been increasingly used in many other areas, including macroeconomic forecasting (Luckner, 2008). Inflation and exchange rates forecasting using prediction markets have been researched by Berlemann and Nelson (2005) and Berlemann et al. (2005). Teschner et al. (2011) proposed play money prediction market design specifically tailored to forecast macroeconomic variables and found that "market forecasts performed well in comparison to the Bloomberg survey forecasts". Usefulness of prediction markets for macroeconomic indicators were discussed by Dubil (2007), Gadanecz et al. (2007) and others.

In October 2002, Goldman Sachs and Deutsche Bank started trading the first derivatives directly tied to macroeconomic outcomes. That was the first time when economic derivatives were used by the leading financial institutions in the real business environment. Unfortunately, trades in these derivatives stopped after about 4 years in operations due to low liquidity. However, this was a very useful precedent increasing interest and providing new possibilities for further research in this area. Initial analysis of these markets was carried out by Gürkaynak and Wolfers (2005) who found, in line with the previous research, that "market-based forecasts errors were on average smaller than the survey forecasts" for all analyzed data series.

In my thesis, I would like to argue that the forecasting value of prediction markets has been underestimated by the standard regression approaches that focus on forecasting the conditional mean of the response variable. In addition to providing the forecasts about the conditional mean, prediction markets can be set up to elicit entire probability distribution over the outcomes. Therefore, it can also provide forecasts about the conditional quantiles of the future macroeconomic indicators. As many real world economic data do not follow normal distribution, predicting the extremities of the possible future values of macroeconomic indicators is not usually possible from their expected mean values provided by the expert surveys or other mean forecasting techniques. Limitations of forecasting methods in anticipating extremities or rare events were discussed by Goodwin and Wright (2009). But using the prediction markets approach, we are able to make interval forecasts for the economic indicators in a form of "ISM Manufacturing Diffusion Index will be between 51.58 and 58.00 next month with the 90% certainty", or "there is only 5% chance that ISM Index will be less than 51.58 next month", instead of providing just the usual point forecast of 55.00 given by the expert surveys.

The is a noticeable growth of interest in forecasting quick and extreme changes in the market, as the bigger emphasis on risk management is made in the fields of economy and finance. Therefore, the need for better tools for forecasting the extremities of the macro-economic indicators and other economic and financial data is evident. If interval forecasts would be provided, it would be possible to take into account the width and the certainty of the forecast in anticipation of the rare events or extreme shifts in economy.

Quantile regression is another technique that is not sensitive to the form of distribution of the data which can give us conditional quantiles of the explained variable. Therefore, in this research, I use quantile regression on macroeconomic data predictions provided by expert surveys and prediction markets, and compare the accuracy of these predictions for different quantiles of the actual announced value of macro indicators.

If quantile regressions using the mean forecasts of prediction markets or means of expert surveys as explanatory variables would be found providing with the forecasts of probability distribution of the economic indicators as good as those of probability distribution provided by the full range of prediction markets data, then quantile regression could be seen as a more simple tool to forecast the extremities of the macroeconomic indicators and special prediction markets design to elicit full probability distribution would be regarded as providing no additional value to it. Otherwise, if prediction markets forecasts of probability distribution would be found being more accurate, then the next step would be supplementing these prediction markets forecasts with quantile regressions on forecasted distribution, seeking to test if quantile regression could provide additional value to prediction markets forecasts. If this would be found true, then this combination of prediction markets and quantile regression could be seen as a viable candidate of being a tool for better predictions of macroeconomic extremities, inviting further research in this field.

Data from Goldman Sachs and Deutsche Bank economic derivatives trades, collected and analyzed by Gürkaynak and Wolfers (2005), provides us quite rare possibility to compare both expert opinions and prediction markets participants believes about the changes in macroeconomic indicators. Data of these prediction markets show us not only the expected mean value, as expert surveys does, but also provides with a view on the whole probability distribution of underlying variable, as confirmed by Gürkaynak and Wolfers (2005). Therefore this data is considered as a main source for research proposed here.

Expert surveys data and prediction markets data both give us expected mean values of underlying macroeconomic indicators. Therefore, in the first part of the research, quantile regressions for all quantiles from 5^{th} to 95^{th} in steps of 5 were run taking actually announced macroeconomic data as observed variable and expert surveys data or prediction markets mean expectation as predictor variable respectively. The goodness-of-fit measures, proposed by Koenker and Machado (1999) and explained in details in methodological approach section of this paper, were be calculated for all these regressions to estimate the accuracy of probability distribution forecasts provided by quantile regression, and this was compared with the accuracy of prediction markets forecast of probability distribution respectively for every quantile in question. The method of quantile regression (Koenker, 2005) has minimal assumptions on the form of the error distribution and therefore can be used to construct models for the forecasts of extremities of the variables when errors are non-normal. This suits well our situation with forecasting macroeconomic indicators.

In the second part of the research, quantile regressions for all above mentioned quantiles were run taking actually announced macroeconomic data as observed variable and prediction markets forecasted quantiles as predictor variable. Comparing goodness-of-fit measure of these quantile regressions to the goodness-of-fit measure of prediction markets forecasted quantiles themselves gave us a possibility to test if quantile regression could provide additional value to prediction markets data and enable us to achieve better accuracy in predicting extremities of macroeconomic developments.

Based on comparisons explained above, we are able to rank the forecasting methods that use prediction markets, quantile regression or the combination of these and to provide some recommendations for their practical implementation and application.

1. LITERATURE REVIEW

1.1. Prediction Markets

Prediction markets are the special type of the markets designed specifically for information elicitation and aggregation. In these markets, payoffs of the traded securities depend on the outcomes of the future events. As described in details by Wolfers and Zitzewitz (2004), “the design of how the payoff is linked to the future event can elicit the market’s expectations of a range of different parameters”. These authors distinguish between the three main types of the contracts used in prediction markets: winner-takes-all, index, and spread.

The winner-takes-all type of contract is similar to the binary option when participants of the market bids on whether the particular future event e will happen or not (e.g., there will be more than 320,000 initial unemployment claims registered this week). This type of contract costs \$$x$ and pays \$1 if and only if the underlying event occurs. This way the market price \$$x$ of the contract happens to be between \$0 and \$1 and can be interpreted as the market expected probability of event e to happen, i.e. $P(e) = x$. (E.g., if the price of the contract is \$0.82, we can say that there is an 82% probability that there will be more than 320,000 initial unemployment claims registered this week.) The validity of this interpretation was discussed and proved by many authors, including Gjerstad (2005), Manski (2006) and Wolfers and Zitzewitz (2005).

The index type of contract pays \$1 for every pre-agreed part y of the value of the quantifiable future event e (e.g., contract pays \$1 for every 100,000 of initial unemployment claims registered this week). Then the price of the contract being \$$x$, we can interpret it as an expected value of the quantitatively expressed event e, i.e. $E(e) = xy$. (E.g., if the price of the contract is \$3.24, we can expect that there will be 324,000 initial unemployment claims registered this week.)

And the spread type of the contract pays even money if the value of some quantifiable future event e is more than some value e^* (e.g., contract costs \$1 and pays \$2 if there will be more than 320,000 initial unemployment claims registered next week, and pays 0\$ otherwise). Then the value e^* that the participants of the market bids on in this type of the contract reveals the market expectation of the median outcome, i.e. $P(e > e^*) = ½$.

From above, we can see that, depending on the design of the contracts in prediction markets, market’s expectation of the specific parameter can be revealed: probability, mean or median respectively. But Wolfers and Zitzewitz (2004) point out that “prediction markets can also be used to evaluate uncertainty about these expectations”. If one designs a family of winner-takes-all contracts (e.g., the number of initial unemployment claims registered this week in thousands will be more than: 300, 310, 320 etc.), then the prices of these contracts give us certain points in the entire probability distribution of the market’s expectations. This way, the entire probability distribution can be forecasted and any certain quantile of this distribution can be interpolated from the points forecasted by the family of prediction market contracts.

The winner-takes-all type of contracts and their families is the most popular type used in prediction markets and therefore this research also focuses on the data gathered from prediction markets of this particular type of contracts.

1.2. Prediction Markets in Forecasting Macroeconomic Indicators

Real money prediction markets on macroeconomic data is a rarity. Most real money prediction markets run to the date are based on political or entertainment events. Therefore, markets, that were set up by Goldman Sachs and Deutsche Bank in October 2002 and run for about four years, was quite unique opportunity for researchers to obtain real money prediction markets data on macroeconomic events for their research. Gürkaynak and Wolfers (2005), were the first researches who made the initial analysis of these "economic derivatives":

> *"These new markets allow investors to purchase options whose payoff depends on growth in non-farm payrolls, retail sales, levels of the Institute for Supply Management's manufacturing diffusion index, initial unemployment claims and the Euro-area harmonized CPI. […]*
>
> *In this market "digital" or "binary" options are traded, allowing traders to take a position on whether economic data will fall in specified ranges, thereby providing market-based measures of investors' beliefs about the likelihoods of different outcomes. That is, the option prices can be used to construct a risk-neutral probability density function for each data release."*

As the authors point out, the information about the probability density function of economic indicators was unavailable until the introduction of these markets, and probabilistic or density forecasts still remain quite rare, though interest in interval forecasts as measures of uncertainty is there for a long time (Chistoffersen, 1998).

One of the first findings of Gürkaynak and Wolfers (2005) was that "while surveys do well (despite some behavioral anomalies), markets do somewhat better in forecasting." In their opinion: "If one is only interested in forecasting the mean, using surveys might suffice; however, Economic Derivatives provide a lot more information than just the mean forecast." As was already discussed above, prediction markets (or economic derivatives) can also provide information about the full probability density function of the underlying economic indicators. And the most interesting finding of Gürkaynak and Wolfers (2005), and most important for our research, was that: "The evidence presented […] shows that economic derivatives option prices are accurate and efficient predictors of the densities of underlying events." This particular finding invites us to investigate how accurate and efficient predictors these market prices are, and whether they can be replaced by some other predictors, as good if not better, obtained using different methods and without having any data about the probability distribution on the macroeconomic indicator we are interested in.

1.3. Quantile Regression

One of the methods, that can be used to forecast the probability density of the data, is quantile regression.

As explained by Koenker and Hallock (2001), the τ-th quantile of the data is the number that is bigger or equal than the proportion τ of that data and smaller than proportion $(1-\tau)$ of the data. Thus, half of the data is smaller than the median, and half is bigger than the median. Similarly, quartiles divide data into four parts, quintiles — into five parts, and deciles — into ten parts. The quantiles, also called percentiles, or occasionally fractiles, refer to the general case.

Quantile regression as introduced by Koenker and Bassett (1978) "seeks to extend these ideas to the estimation of *conditional quantile functions* — models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates."

We can define the sample mean as the solution to the problem of minimizing a sum of squared residuals, or the median as the solution to the problem of minimizing a sum of absolute residuals. As Koenker and Hallock (2001) explains this: "The symmetry of the piecewise linear absolute value function implies that the minimization of the sum of absolute residuals must equate the number of positive and negative residuals, thus assuring that there are the same number of observations above and below the median." From the fact that symmetry of the absolute value yields the median, authors conclude that "*asymmetrically* weighted absolute residuals — simply giving differing weights to positive and negative residuals — would yield the quantiles". Therefore, unconditional quantiles can be defined as the solutions to $\min_{\xi\in\Re}\sum\rho_\tau(y_i-\xi)$, where function $\rho_\tau(\cdot)$ is the tilted absolute value function defined as $\rho_\tau(u)=u[\tau-I(u<0)]$ and $I(\cdot)$ being an indicator function that is equal to 1 if its argument is true, and 0 if the argument is false.

Conditional quantiles are further defined in a similar manner as we define the conditional mean. If, given a random sample $Y=\{y_1,y_2,\dots,y_n\}$, we solve for $\min_{\mu\in\Re}\sum_{i=1}^{n}(y_i-\mu)^2$, we obtain the sample mean, an estimate of the unconditional population mean $E(Y)$. Then, if we replace μ with the parametric function $\mu(x_i,\beta)$ and solve for $\min_{\beta\in\Re^p}\sum_{i=1}^{n}(y_i-\mu(x_i,\beta))^2$, we obtain an estimate of the conditional expectation $E(Y|x)$. The same way for quantiles, if we replace the scalar ξ by the parametric function $\xi(x_i,\beta)$, we will be able to estimate any conditional τ-th quantile by solving for:

$$\min_{\beta\in\Re^p}\sum\rho_\tau(y_i-\xi(x_i,\beta)) \qquad (1)$$

where

$$\rho_\tau(u)=u[\tau-I(u<0)] \qquad (2)$$

and

$$I(u < 0) = \begin{cases} 1, \text{if } u < 0 \\ 0, \text{if } u \geq 0 \end{cases} \qquad (3)$$

When $\xi(x, \beta)$ is formulated as a linear function of parameters, the resulting minimization problem can be solved very efficiently by linear programming methods.

1.4. Quantile Regression in Forecasting Macroeconomic Indicators

Correct estimation of probability density is important in financial risk management when using value-at-risk (VaR) approach. Different methods are used for VaR calculations, but quantile regression is playing important role among them. When Chen and Chen (2002) compared performances of VaR calculations with the quantile regression approach to those with the conventional variance-covariance approach, they found that "VaR calculations with the quantile regression approach outperform those with the variance-covariance approach" and "advantages of the quantile regression approach are more obvious in calculating VaR for longer holding periods". Enge and Manganelli (2004) proposed using quantile regression when interpreting VaR as a quantile of future portfolio values conditional on current information as this approach did not require such extreme assumptions as normality or independent identical distribution of returns invoked by other methodologies.

Success of research in financial risk management area using quantile regression method brought attention to this approach into macroeconomic forecasting. Many recent studies in the area of macroeconomic forecasting are focused on using the quantile regression in their research. Gaglianone and Lima (2012) proposed using quantile regression in their econometric model to estimate the conditional density without relying on assumptions about the parametric form of the conditional distribution of the target variable. They applied their model to the US unemployment rate and the survey of professional forecasts and found that specification tests based on Koenker and Xiao (2002) and Gaglianone, Lima, Linton and Smith (2011) indicated that their approach correctly approximated the true conditional density. Laurent and Kozluk (2012), following Cornec (2010), developed a totally model based and judgment free method using quantile regressions to construct a probability distribution of future GDP, as opposed to mean point forecasts. This allowed them to assess uncertainty conditionally on the current state of the economy. Zhao (2012) compares the density forecasting performance of quantile regressions in real-time with that of two conventional density forecast methods using United States of America inflation and output growth data and concludes that "density forecasts using quantile regressions are found to be significantly more accurate than the two conventional density forecasts."

The number of contemporary researches using quantile regression in the area of macroeconomic forecasting shows a growing interest in this approach and their results look promising for the real life applications.

2. RESEARCH PROBLEM DEFINITION

2.1. Is Quantile Regression as Good as Prediction Markets?

As it was discussed in the literature review above, prediction markets can provide us with information about the probability distribution of the underlying macroeconomic indicator. Gürkaynak and Wolfers (2005) show that the prices in prediction markets are unbiased and efficient predictors of the probability distribution of the events. Therefore, probability distribution forecasts interpolated directly from the prices of prediction markets can be used as a benchmark for other methods of interval forecasting.

Quantile regression can also provide us with the forecast of probability density by estimating the conditional quantiles of the macroeconomic indicator. This can be done using expert mean forecasts or prediction markets forecasted means of the economic indicator as regressor and actual released value of the indicator as regressand.

The first proposition to be tested in this research is that probability density forecasts calculated from expert expected values or prediction markets mean forecasts using quantile regression can be as good predictors of probability distribution of economic indicators as prediction markets forecast of probability density using the whole family of winner-takes-all type contracts (see Table 1). If this proposition would be found being true, this would mean that we must not go into full complexity of designing entire family of the contracts in prediction markets, but could instead use just one index type contract forecasting the mean value of the underlying macroeconomic indicator and forecast full probability distribution of the indicator using quantile regression. Same applies to the expert mean forecasts: if quantile regression results with expert opinion as explanatory variable would be found being as good as results of the regression with prediction markets forecasted means as regressor, it would suffice to use expert data with quantile regression.

Table 1. Explanation of the first proposition of the research

Criteria	**Forecasting method**		
	Whole family of winner-takes-all type prediction markets	Quantile regression on index type prediction markets	Quantile regression on expert survey data
Complexity	Complex	Moderate	Simple
Data availability	Has to be specially elicited and collected	Has to be specially elicited and collected	Readily available due to common practice
Forecasting accuracy	Proved to be accurate by previous researches	Expected to be as good as family of winner-takes-all type prediction markets (First Proposition)	Expected to be as good as family of winner-takes-all type prediction markets (First Proposition)

2.2. Can Quantile Regression Add Value to Prediction Markets?

Independently of the results of the first proposition test, it would also be interesting to see if we could improve the forecast of probability density obtained with prediction markets combining it with quantile regression approach.

To test this, we are going to run quantile regression to forecast the full range of quantiles of macroeconomic indicators using quantiles of the same indicator interpolated from prediction market prices as explanatory variable. Another way to express this would be: can probability distribution forecast obtained from prediction market be further improved by applying quantile regression technique on it (see Table 2).

Table 2. Explanation of the second proposition of the research

Criteria	**Forecasting method**	
	Quantiles interpolated from the whole family of winner-takes-all type prediction markets	Conditional quantiles obtained by quantile regression on interpolated quantiles of whole family of prediction markets
Complexity	Complex	Complex
Forecasting accuracy	Proved to be accurate by previous researches	Expected to be more accurate than the family of winner-takes-all type prediction markets (Second Proposition)

To test theses two propositions, we need to have certain measure of goodness-of-fit that would enable us to compare the accuracy of probability distribution forecasts obtained using different methods. The measure that will be used in this research was proposed by Koenker and Machado (1999) and is explained in details in methodological approach part that follows below.

3. METHODOLOGICAL APPROACH

3.1. Description of the Research Data

Real money prediction market data on macroeconomic indicators is a rarity. Goldman Sachs and Deutsche Bank economic derivatives markets run from 2002 to 2005 and described in the literature review part of this work is the most comprehensive source of data on the subject to the best knowledge of the author. This data was collected by Gürkaynak and Wolfers (2005) and courteously provided on their web page together with the results of their research. As my work is focused on further development of the certain result of the work of these authors, the same data will be analyzed in this paper.

The data covers 153 releases of four macroeconomic indicators in total with overall of 2,235 digital call options traded between the year 2002 and 2005. The four macroeconomic indicators that traders could bid on were: the growth in non-farm payrolls (NFP), retail sales excluding autos (RSX), levels of the Institute for Supply Management's manufacturing diffusion index (ISM), and initial unemployment claims (ICL). The market priced options on many different outcomes of each indicator allowing us to obtain forecasts of a full probability distribution of the values of this indicator. Typically around 10-20 different options were traded, each at different strike prices, giving the price of a "digital range" – a contract paying \$1 if the announced economic number lies between two adjacent strike prices. Calling these "digital ranges" bins, we can say that every bounded bin received certain price in the market, representing the probability that the announced indicator will fall into the range of the bin. But it is important to notice that the outer bins were not bounded, i.e. the options paid \$1 if the announced indicator was below certain value for the leftmost bin, or above certain value for the rightmost bin.

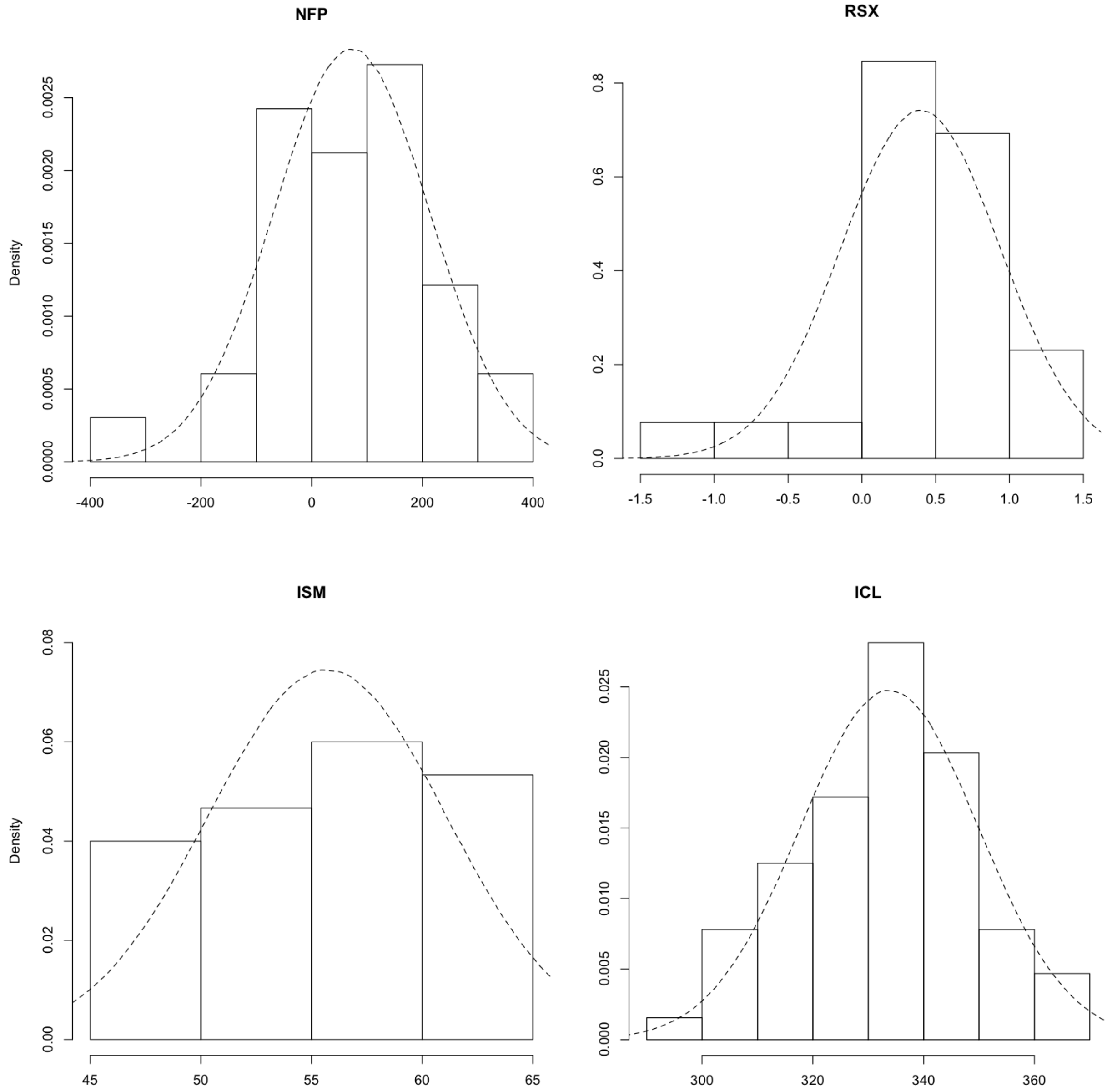
Also the "survey forecast" data released by Money Market Services (MMS) on the Friday before a data release was collected and provided by Gürkaynak and Wolfers (2005). For the MMS forecast, the "consensus" forecast typically averages across around 30 forecasters.

As the data series for the individual indicators are not long, consisting just of 33 non-farm payrolls auctions, 30 business confidence auctions, and 26 retail trade auctions monthly data, and 64 initial claims auctions weekly data, all the data were also normalized and combined into the common data series of 153 points. This way we ended up with total of the five data sets to work on: four sets of individual macroeconomic indicators and one combined normalized data series. Normalization of the data was performed by subtracting the mean of the appropriate announced macroeconomic indicator from every corresponding data value and dividing the difference by the standard deviation of the announced value of the indicator.

$$NORM_i = \frac{X_i - \overline{RV}}{SD(RV)}, \qquad \text{where } X_i \in \{RV, EX, PM, PMQ\}$$

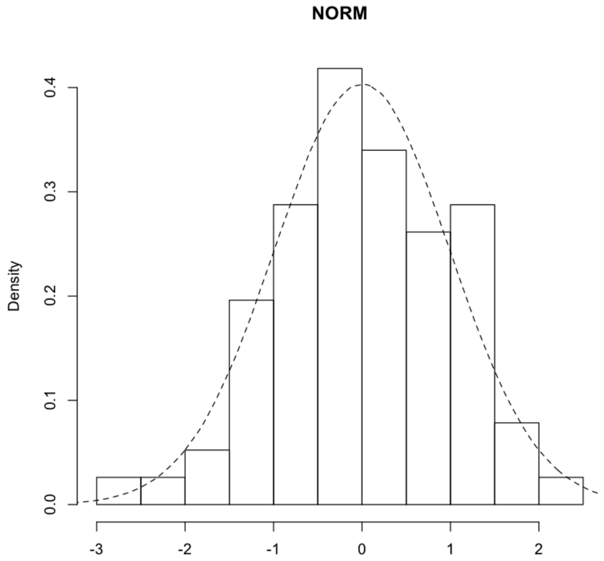
Histograms of the actual released values of all four analyzed macroeconomic indicators are provided below in Figure 1 and histogram of combined normalized data is given in Figure 2. Dashed lines on the histograms represent the probability density functions of the normal distribution with the corresponding mean and variance and are overlaid there for reference.

Figure 1. Histograms of Released Values of NFP, RSX, ISM and ICL



From the histograms provided above, it can be seen that data of these macroeconomic indicators do not follow normal distribution. Hence quantiles of these data, required for interval forecasts, cannot be calculated from the corresponding expected values forecasted by the experts. That well justifies usage of different research methods, like prediction markets and quantile regression, that are indifferent or insensitive to the form of the data distribution.

Figure 2. Histogram of Released Values for Combined Normalized Data Series



More specific details about the data and the market rules used in the auctions for these economic derivatives can be found in the work of Gürkaynak and Wolfers (2005). The data itself and the R programming code used in this research are also available for download online on the website of the author at http://vitkauskas.lt/pmqr.zip.

3.2. Calculation of Prediction Markets Mean Forecast

As 10 to 20 digital ranges (or bins) were traded in every auction forming the whole family of the options traded in this prediction market for every macroeconomic indicator, each particular range had its own price in the market, representing the probability of the announced indicator ending up in the certain range. For the sake of our calculations, we treated this probability distribution as discrete, assuming that all probability mass occurs at the midpoint of the relevant bin. Tail probabilities though had to be treated specially as the tail bins had no left or right bounds. Three different treatments were considered for the tail bins. First, assume that all the probability of the tail bin is concentrated on the known right or left bound point. Second, treat the tail bins as if the probability distribution was normal in the tails. Third, put an artificial bounds on tails in such a way that the range width of the bin was equal to the width of the adjacent bin and assume that probability of the tail bin is concentrated at the mid-point of the artificially bounded bin. The latter approach was found being the most natural and therefore all the calculations used in this report follow this particular method:

$$PM_i = \sum_{j=1}^{k} \frac{UB_j - LB_j}{2} \cdot Pr_j$$

where UB_j and LB_j denote upper and lower bounds of the bins, Pr_j denotes the probability of the corresponding bin as forecasted by prediction markets, and k is the number of the bins (digital ranges) in the particular prediction market arrangement.

3.3. Interpolation of Prediction Markets Forecasted Quantiles

In order to forecast probability distribution of the macroeconomic indicators in this research, we are looking at the range of the quantiles of the variable spanning from the 5th quantile to 95th quantile in the steps of 5. To compare the results given by the quantile regression with the results of the prediction market-generated probability distribution, we need to have all the values of the same quantiles calculated from the prediction market data. As prediction market gives us discrete probability distribution with the points that differ from the quantiles we need, we have to calculate corresponding quantiles for every auction that was carried out in the market. To do that we interpolate the values of the needed quantiles from the discrete probability distribution, assuming that the probability is concentrated at the mid-points of the bins and is uniform within each bin. The same approach of the artificial bounds for the tail bins was used as it was used to calculate the mean forecasts.

$$PMQ_\tau = CP_{\tau_-} + \left(CP_{\tau_+} - CP_{\tau_-}\right) \cdot \frac{\tau - Pr_{\tau_-}}{Pr_{\tau_+} - Pr_{\tau_-}}$$

where CP_{τ_-} , CP_{τ_+} , Pr_{τ_-} , Pr_{τ_+} denote midpoints and probabilities of the bins, surrounding the quantile that we are interpolating, and $\tau \in \{0.05k \mid k = 1, 2, \ldots, 19\}$.

3.4. Goodness-of-Fit Measure for Quantile Regression

For the classical least squares regression we have familiar R^2 goodness-of-fit criterion enabling us to compare similar regression models with different explanatory variables. R^2 is defined as $R^2 = 1 - \hat{S}/\tilde{S}$, where $\hat{S}$ and $\tilde{S}$ is the sum of squared errors of the unrestricted and restricted forms of the model respectively. Conventionally, the restricted model includes only the "intercept" parameter.

Motivated by the same principal, Koenker and Machado (1999) proposes similar goodness-of-fit measure for quantile regression based on the weighted sum of residuals produced by the process defined by equation (1) on page 15 of this report.

If we denote by

$$\hat{V}(\tau) = \min_{\beta \in \Re^p} \sum \rho_\tau(y_i - \xi(x_i, \beta)) \tag{4}$$

the weighted sum of residuals of unrestricted model minimized by the linear programming quantile regression process, and by

$$\tilde{V}(\tau) = \min_{\beta \in \Re} \sum \rho_\tau(y_i - \beta_0) \tag{5}$$

the weighted sum of residuals of corresponding restricted model, we may define the goodness-of-fit criterion as

$$R^1(\tau) = 1 - \hat{V}(\tau)/\tilde{V}(\tau) \tag{6}$$

Using the equation (2) on page 15, the corresponding weighted sum of residuals can also be calculated for the forecasted quantiles interpolated from the prediction markets probabilities as described above. For that we should take $u = RV - PMQ$. This enables us to calculate the R^1 measure for the prediction markets forecasted quantiles and compare this to the R^1 goodness-of-fit measure of the forecasts obtained by quantile regression.

3.5. Sequence of Comparisons

To test the first hypothesis of this research we are going to calculate the R^1 measure for the prediction markets interpolated quantiles and compare it to the R^1 measures of quantile regressions with the explanatory variable being expert mean forecasts and prediction markets mean forecasts respectively. If R^1 measures of the prediction markets interpolated quantiles would be find being consistently better than the R^1 of the quantile regressions for all quantiles from 5th to 95th, then our proposition that quantile regression forecasts can be as good as prediction markets probability distribution forecasts would be regarded as false.

For the first part of the research, the following two sets of quantile regressions were run:

$$\min_{\beta \in \Re^2} \sum \rho_\tau(RV_i - \xi(EX_i, \beta)) \ : \ \xi(EX_i, \beta) = \beta_0 + \beta_1 EX_i, \tag{7}$$

$$\min_{\beta \in \Re^2} \sum \rho_\tau(RV_i - \xi(PM_i, \beta)) \ : \xi(PM_i, \beta) = \beta_0 + \beta_1 PM_i, \tag{8}$$

where $\tau \in \{0.05k \mid k = 1..19\}$, and their R^1 measures for every τ were calculated according to the equation (6), using restricted quantile regression defined as:

$$\min_{\beta \in \Re} \sum \rho_\tau(RV_i - \xi(\beta)) \ : \xi(\beta) = \beta_0. \tag{9}$$

These R^1 measures were compared to R^1 of quantiles interpolated from prediction markets that were calculated using weighted sum of residuals obtained by equation (2), as explained above in section 3.4 of Methodological Approach.

Similarly, if R^1 measures of the quantile regressions on interpolated prediction markets quantiles as explanatory variables would be found consistently better than the R^1 of the interpolated prediction markets quantiles themselves, then our second proposition that prediction markets forecasts can be further improved with quantile regression would not be rejected and would invite further research in this area.

Therefore, for the second part of the research the following set of quantile regressions was run and corresponding R^1 measures were calculated:

$$\min_{\beta \in \Re^2} \sum \rho_\tau(RV_i - \xi(PMQ_i^{(\tau)}, \beta)) \ : \xi\left(PMQ_i^{(\tau)}, \beta\right) = \beta_0 + \beta_1 PMQ_i^{(\tau)}, \tag{10}$$

for all $\tau \in \{0.05k \mid k = 1, 2, \ldots, 19\}$, and corresponding R^1 were compared to R^1 of quantiles interpolated from prediction markets that were already calculated in the first part of the research.

4. EMPIRICAL RESULTS

4.1. Interpolated Quantiles and Coefficients of Quantile Regressions

In the data used for this research, we had series of data for four different macroeconomic indicators: NFP, RSX, ISM and ICL (see explanations in the List of Abbreviations). Actual released values of the indicators and forecasted mean values of experts were directly available in the data sets. Mean values forecasted by prediction markets had to be calculated from the prices of derivatives traded in prediction markets. That was done using the method described in section 3.2 of Methodological Approach part of this report. Resulting values are provided for reference in Table 8 to Table 11 in Appendices. In addition to that, all the individual macroeconomic indicators' data series were normalized and joined together to obtain a combined normalized series as it was explained in section 3.1 of Methodological Approach.

The next step was to interpolate the forecasted quantiles from the probabilities elicited in prediction markets for all analyzed macroeconomic indicators. This was done according to the section 3.3 of Methodological Approach of this report, and the resulting data are provided for reference in Table 12 to Table 15 in Appendices. Same approach was used on combined normalized series to get the longer fifth data series to work with.

After that initial preparation and transformation of the data, all the quantile regressions defined by equations (7), (8), (9), and (10) in section 3.5 of Methodological Approach were run for all quantiles $\tau \in \{0.05k \mid k = 1, 2, \ldots, 19\}$. That way, coefficients of 19 linear equations defining quantiles needed for interval forecasting were obtained for every realization of each macroeconomic indicator (NFP, RSX, ICL, and ISM) using three different explanatory variables: EX, PM, and PMQ. Coefficients of some characteristic quantiles together with their significance levels are provided for reference in Table 3 to Table 6 below.

Table 3. Coefficients of Quantile Regressions for some characteristic quantiles of NFP

Quantiles (τ)	**EX Quantile Regression**		**PM Quantile Regression**		**PMQ Quantile Regression**	
	Intercept	EX	Intercept	PM	Intercept	PMQ(τ)
.05	-328.74 (.0054)***	1.56 (.0067)***	-289.45 (.0024)***	1.34 (.0074)***	-85.11 (.0534)*	1.42 (.0068)***
.25	-84.91 (.0146)**	0.89 (.0013)***	-79.67 (.0312)**	0.85 (.0008)***	-14.67 (.5734)	0.85 (.0082)***
.50	-30.83 (.2215)	0.92 (.0005)***	-27.17 (.3067)	0.90 (.0004)***	-22.91 (.3931)	0.95 (.0002)***
.75	10.19 (.7849)	1.16 (.0008)***	49.04 (.0705)*	0.87 (.0005)***	1.76 (.9514)	0.83 (.0002)***
.95	77.88 (.2638)	1.41 (.0103)**	110.66 (.0001)***	1.35 (.0000)***	-84.80 (.0052)***	1.28 (.0000)***

p-values in parenthesis with asterisks denoting significance at *** 99%, ** 95%, and * 90% levels

Table 4. Coefficients of Quantile Regressions for some characteristic quantiles of RSX

Quantiles (τ)	EX Quantile Regression		PM Quantile Regression		PMQ Quantile Regression	
	Intercept	EX	Intercept	PM	Intercept	PMQ(τ)
.05	-1.35 (.0021)***	2.20 (.0045)***	-0.80 (.0000)***	1.63 (.0000)***	0.32 (.0192)**	1.86 (.0056)***
.25	-0.50 (.1528)	1.53 (.0574)*	-0.54 (.0941)*	1.37 (.0431)**	-0.07 (.6719)	1.35 (.0198)**
.50	-0.19 (.6012)	1.60 (.0752)	-0.05 (.8814)	1.10 (.1121)	-0.06 (.8530)	1.49 (.0477)**
.75	0.35 (.3010)	0.97 (.3109)	0.32 (.1757)	0.97 (.0792)*	0.15 (.6620)	0.85 (.0870)*
.95	-0.11 (.8893)	3.33 (.1023)	0.58 (.0032)***	1.19 (.0142)**	-0.02 (.9534)	1.00 (.0083)***

p-values in parenthesis with asterisks denoting significance at *** 99%, ** 95%, and * 90% levels

Table 5. Coefficients of Quantile Regressions for some characteristic quantiles of ISM

Quantiles (τ)	EX Quantile Regression		PM Quantile Regression		PMQ Quantile Regression	
	Intercept	EX	Intercept	PM	Intercept	PMQ(τ)
.05	-11.23 (.0194)**	1.17 (.0000)***	-4.15 (.0133)**	1.05 (.0000)***	0.47 (.8686)	1.03 (.0000)***
.25	-4.98 (.0869)*	1.07 (.0000)***	-8.12 (.0349)**	1.13 (.0000)***	-6.36 (.0494)**	1.13 (.0000)***
.50	-7.01 (.0569)*	1.12 (.0000)***	-3.44 (.4280)	1.06 (.0000)***	-1.89 (.6883)	1.04 (.0000)***
.75	-2.04 (.6833)	1.05 (.0000)***	0.62 (.9069)	1.00 (.0000)***	-2.73 (.4986)	1.04 (.0000)***
.95	-5.96 (.6127)	1.14 (.0000)***	-6.93 (.4168)	1.17 (.0000)***	-4.93 (.7196)	1.08 (.0002)***

p-values in parenthesis with asterisks denoting significance at *** 99%, ** 95%, and * 90% levels

Table 6. Coefficients of Quantile Regressions for some characteristic quantiles of ICL

Quantiles (τ)	EX Quantile Regression		PM Quantile Regression		PMQ Quantile Regression	
	Intercept	EX	Intercept	PM	Intercept	PMQ(τ)
.05	41.40 (.7407)	0.80 (.0338)**	-10.33 (.9384)	0.95 (.0167)**	162.69 (.1078)	0.48 (.1376)
.25	134.86 (.0304)**	0.57 (.0029)***	147.65 (.0094)***	0.53 (.0020)***	159.82 (.0091)***	0.51 (.0070)***
.50	165.50 (.0516)*	0.50 (.0502)*	149.66 (.0429)**	0.55 (.0143)**	153.77 (.0318)**	0.54 (.0139)**
.75	137.38 (.3115)	0.63 (.1251)	101.08 (.3977)	0.73 (.0429)**	50.15 (.6725)	0.86 (.0148)**
.95	104.62 (.5174)	0.77 (.1145)	144.47 (.0926)*	0.64 (.0139)**	126.90 (.1779)	0.66 (.0160)**

p-values in parenthesis with asterisks denoting significance at *** 99%, ** 95%, and * 90% levels

Coefficients of all quantile regressions demonstrate high statistical significance and are mostly statistically different from zero at 95% level, with many coefficients significantly significant at the level of 99%. This shows that all three regressors used in equations are valid choices for forecasting of quantiles of the regressand. Intercepts in many cases are not statistically different from zero for quantiles close to median, what has to be expected when using forecasted mean value of the regressand as explanatory variable.

Having all the equations for calculation of the fitted values of the quantiles, we can provide with interval forecasts for all analyzed macroeconomic indicators with the level of probability that is required. For example, interval forecasts of 50% probability would be constructed taking the 25th and 75th forecasted quantiles as the boundaries, and 90% probability interval forecasts would be constructed taking the 5th and the 95th forecasted quantiles.

4.2. Calibration of the Interval Forecasts

From the data we have and all the quantile regressions that were run, we are able to construct four different interval forecasts for every realization of the macroeconomic indicator. First, we can construct interval forecasts from quantiles directly interpolated from the probabilities elicited in prediction markets. Second, we can forecast quantiles with quantile regression using expert forecasted means as explanatory variable. Third, we can forecast quantiles with quantile regression using prediction markets forecasted means as explanatory variable. And fourth, we can forecast quantiles using quantile regression on quantiles interpolated directly from prediction markets that were used in the first case. An example of all four interval forecasts with the 50% probability for the first 10 months of the Non-Farm Payrolls (NFP) in our data are provided in Table 7 below. Actual released value of the indicator and expert survey point forecasts are also provided in the table for comparison.

Table 7. Sample 50% probability Interval Forecasts for NFP

Experts Point Forecast	50% probability Interval Forecasts				Released Value
	PMQ	EX Quantile Regression	PM Quantile Regression	PMQ Quantile Regression	
11	[-82; 27]	[-75; 23]	[-95; 34]	[-85; 24]	-43
4	[-70; 22]	[-81; 15]	[-91; 37]	[-74; 20]	-5
29	[0; 101]†	[-59; 44]	[-24; 106]†	[-14; 86]†	-40
21	[-23; 77]†	[-67; 34]†	[-49; 81]†	[-34; 65]†	-101
59	[-18; 112]†	[-33; 78]†	[-28; 102]†	[-31; 94]†	143
13	[-80; 30]†	[-73; 26]†	[-91; 37]†	[-83; 26]†	-308
-26	[-163; -4]	[-108; -20]	[-133; -5]	[-153; -1]	-108
-43	[-216; -60]†	[-123; -40]	[-180; -54]	[-199; -48]	-48
-23	[-130; 19]	[-106; -17]	[-117; 11]	[-125; 17]	-17
1	[-62; 43]	[-84; 11]	[-76; 52]	[-67; 38]	-30

† denotes forecasts where actual released value would be outside the forecasted interval

Different forecasting methods give as different interval forecasts, and there is no one single method to decide which of the forecasted intervals is the best one. But when evaluating interval forecasts, one of the first thing that can be tested is their calibration. We will say that the prediction density is correct and the interval forecasts are well calibrated if the event forecasted to happen with 'x' percent probability will be happening 'x' percent of the time.

To analyze the calibration of our interval forecasts, we will apply the formal procedure as defined by Christoffersen (1998) and used by Gürkaynak and Wolfers (2005). According to these authors, correctly conditionally calibrated interval forecast will provide a hit sequence (a sequence of correct and incorrect predictions) that is independently and identically Bernoulli distributed with the desired coverage probability. Diebold, Gunther, and Tay (1998) show that the i.i.d. Bernoulli property of individual interval forecasts translates into the i.i.d. Uniform(0,1) distribution of the probability integral transform, z_t, defined as

$$z_t = \int_{-\infty}^{y_t} \pi(x)\, dx \sim Uniform(0,1)$$

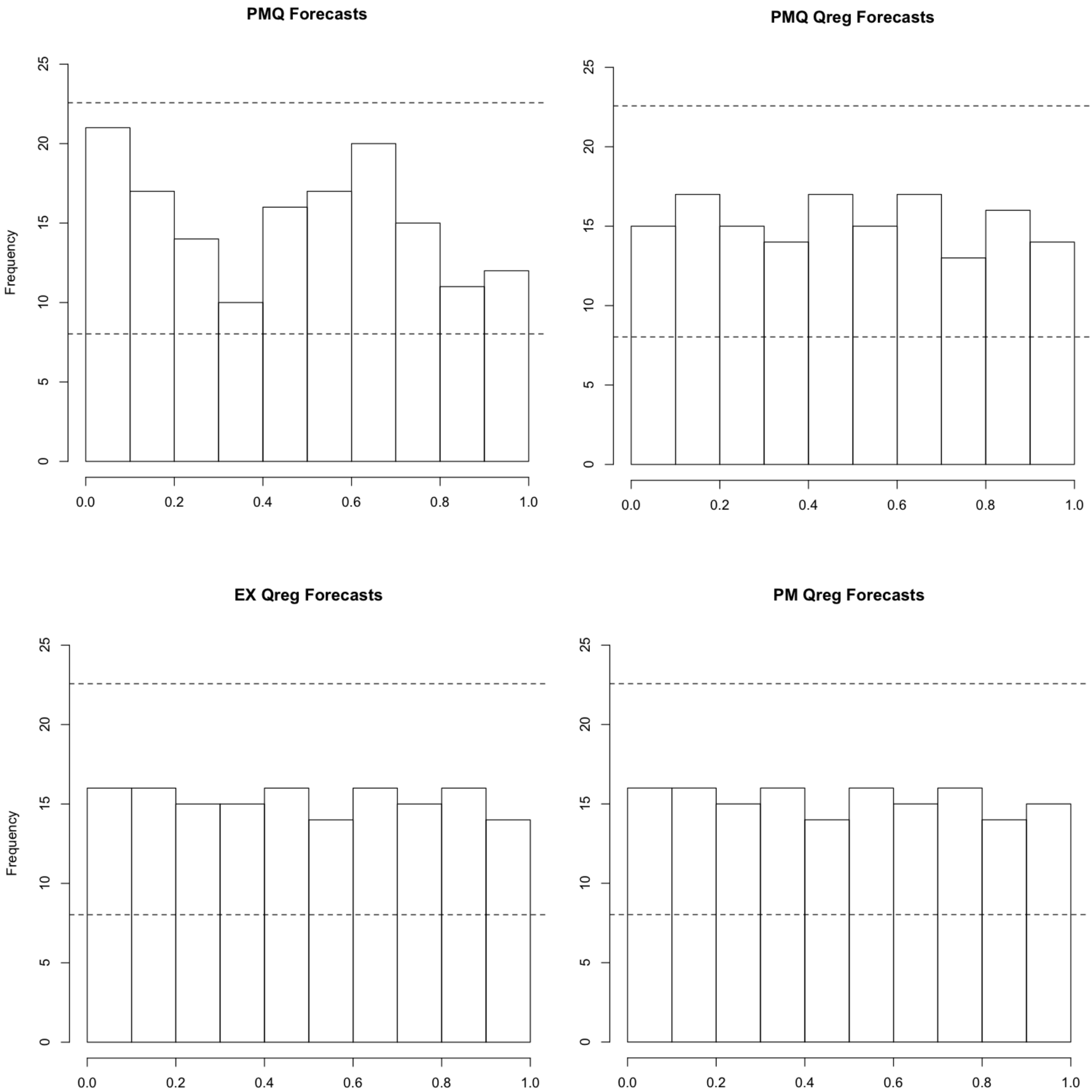
where $\pi(x)$ denotes the price of an option paying \$1 if the realized economic statistic takes on the value x, and y_t is the actual realized value of economic statistic.

In our case, this integral transform z_t can be called "realized quantile". We can then calculate these realized quantiles for all four types of our interval forecasts and test for the uniformity of their distribution. As Gürkaynak and Wolfers (2005) explain it: "A simple way to test for deviations from uniformity derives from inverting the earlier logic: if the distribution is uniform, then the probability that any given realization is in any given bin should follow a Bernoulli distribution with the hit probability equal to the width of the bin, and hence the number of realizations in each bin should follow a binomial distribution."

Using the approach described above to test the calibration of interval forecasts, Figure 3 shows the histograms of realized quantiles for all four interval forecasting methods used in this research. These realized quantiles were calculated for the normalized combined data of all macroeconomic indicators to have longer data series, and the dashed lines on the histograms denote the relevant 95% critical values under the assumption of i.i.d. uniformity.

From the histograms we have to conclude that the distributions of realized quantiles of all interval forecasts are close to uniform as no one frequency in any bin of the histograms falls outside the 95% critical values. Though it has to be noted that the interval between these critical values is quite wide because of the low number of observations we have. If the data series would be longer, the interval between the critical values would contract, and there would be risk of rejecting the hypothesis of uniform distribution for the realized quantiles of the forecasts made by direct interpolation of quantiles from the prices of prediction markets. Therefore, with the visual inspection of the histograms, we could argue that interval forecasts using quantile regression technique are better calibrated that pure prediction markets forecasts. This is particularly well visible for the forecasts that used quantile regression on expected mean values as explanatory variable (the two bottom histograms).

Figure 3. Histograms of Realized Quantiles for the Forecasts Based on PMQ, Quantile Regression on PMQ, Quantile Regression on EX, and Quantile Regression on PM for combined normalized data series of all four macroeconomic indicators



Overall we must conclude that all four methods to calculate quantiles produce interval forecasts that are well calibrated and we can continue with their comparison using other measures, like the goodness-of-fit measure for quantile regression proposed by Koenker and Machado (1999).

4.3. Comparing Prediction Markets and Quantile Regression

To compare the accuracy of the quantiles provided by the quantile regression, we had to calculate the R^1 goodness-of-fit measure for all quantiles interpolated from prediction markets data, and to compare this measure with R^1 of two independent sets of quantile regressions: one run with expert forecasted means as explanatory variable and another with prediction markets forecasted means as explanatory variable. R^1 for quantiles from .05 to .95 in steps of .05 was calculated according to the equation (6) on page 22, and results are given in Table 16 in Appendices.

Comparison of R^1 for prediction markets interpolated quantiles and quantile regression on expert surveys forecasted means for all four analyzed macroeconomic indicators is provided in Figure 4 on page 30 below. As can be seen from this figure, for all individual macroeconomic indicators, prediction markets interpolated quantiles, in general, do not perform better than quantile regression with expert surveys forecasted means as explanatory variable. R^1 of prediction markets quantiles is better (higher) on some quantiles, but worse (lower) on other quantiles, with exception of RSX data, where prediction markets outperform quantile regression on all quantiles except the lowest .05 quantile. For NFP, RSX, and ICL data series R^1 is quite low (lower than .35) what suggests that, in general, both expert surveys and prediction markets provide little new information compared to quantile regression restricted just on the intercept. For ISM data series though, R^1 is high (mostly above .70) and drops below .60 only for quantiles .90 and .95, suggesting that for this particular macroeconomic indicator both expert surveys and prediction markets can provide useful additional information.

Although comparing R^1 for all quantiles on combined normalized data (see Figure 5), we see that prediction markets interpolated quantiles outperform quantile regression on expert forecasted means for all quantiles from .05 to .95. And though R^1 itself is not high (mostly in the range of .25 for prediction markets data), the improvement to R^1 when using prediction markets compared to quantile regression on expert surveys data is significant, especially for the smallest and highest quantiles.

Comparison in Figure 5 is interesting, and it suggests further research with longer data series on prediction markets related to macroeconomic indicators, when available. Overall, with the above analysis of individual NFP, RSX, ISM and ICL indicators, we could not reject our first proposition that quantile regression can be as good as prediction markets in forecasting complete probability distribution of macroeconomic events. But this proposition would be rejected based on analysis on longer combined normalized data from all above indicators joined together. In that case we would say that prediction markets are better for full probability distribution forecasting than more simple quantile regression calculated on expert forecasted means.

Figure 4. R^1 for Prediction Markets Interpolated Quantiles and Expert Means Quantile Regression on data series of NFP, RSX, ISM, and ICL

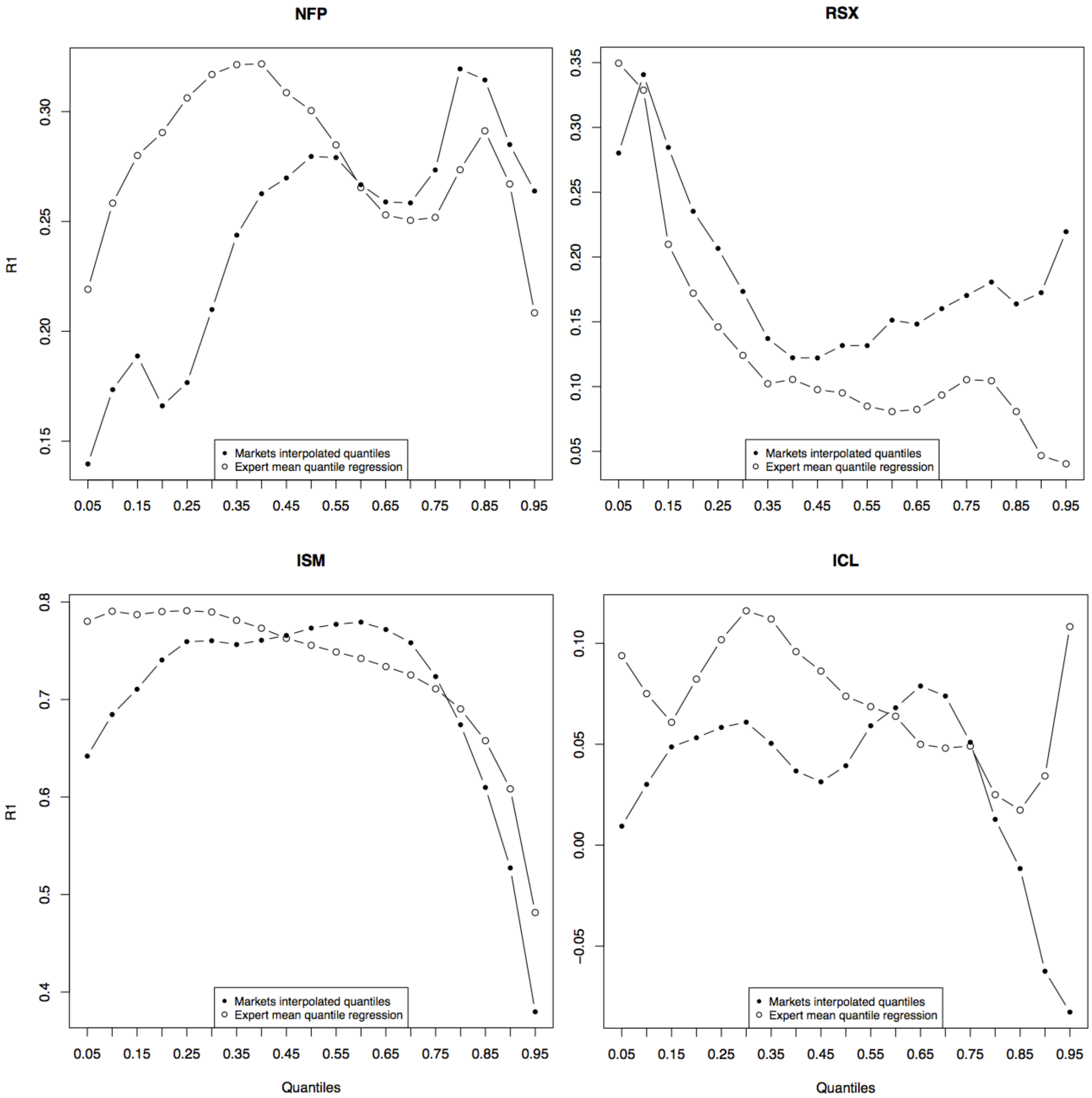
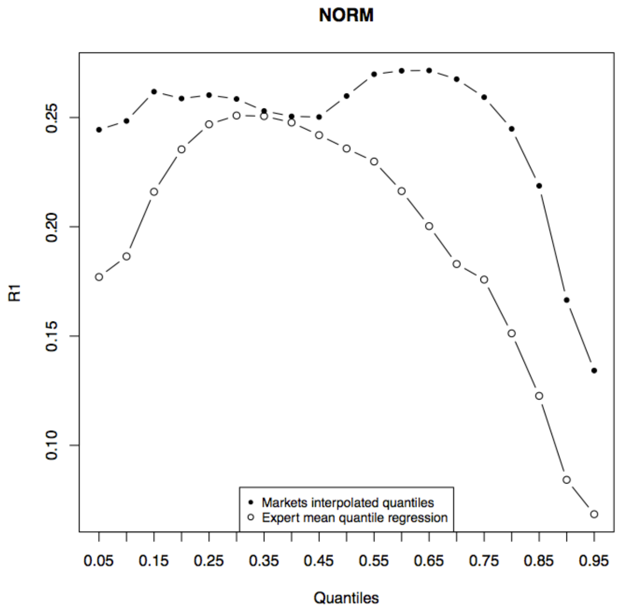


Figure 5. R^1 for Prediction Markets Interpolated Quantiles and Expert Means Quantile Regression on combined normalized data series of all four macroeconomic indicators



The same analysis comparing R^1 of prediction markets interpolated quantiles and quantile regressions with prediction markets forecasted means as explanatory variable is provided below in Figure 6. Looking at the graphs for individual macroeconomic indicators, we see that R^1 of quantile regression based on prediction markets forecasted means is consistently better than R^1 of interpolated quantiles for ICL and ISM indicators, and much better for smaller quantiles and very similar for higher quantiles in NFP and RSX forecasts.

Based on these R^1 comparisons for individual macroeconomic indicators, we could say that quantile regression run with prediction markets forecasted means as explanatory variable can give us results that are equally good or even better for forecasting full probability distribution of macroeconomic indicator, while being a bit less complex method compared to running the whole family of winner-takes-all type prediction markets to obtain the same forecasts.

But this suggestion is not supported by R^1 comparison performed on the combined normalized data. From Figure 7 we see that R^1 is slightly better for most quantiles when interpolating them from probability distribution forecasts given by prediction markets data. R^1 of quantile regression on prediction markets forecasted means is close, but still lower at extreme quantiles.

Figure 6. R[1] for Prediction Markets Interpolated Quantiles and Prediction Markets Means Quantile Regression on data series of NFP, RSX, ISM, and ICL

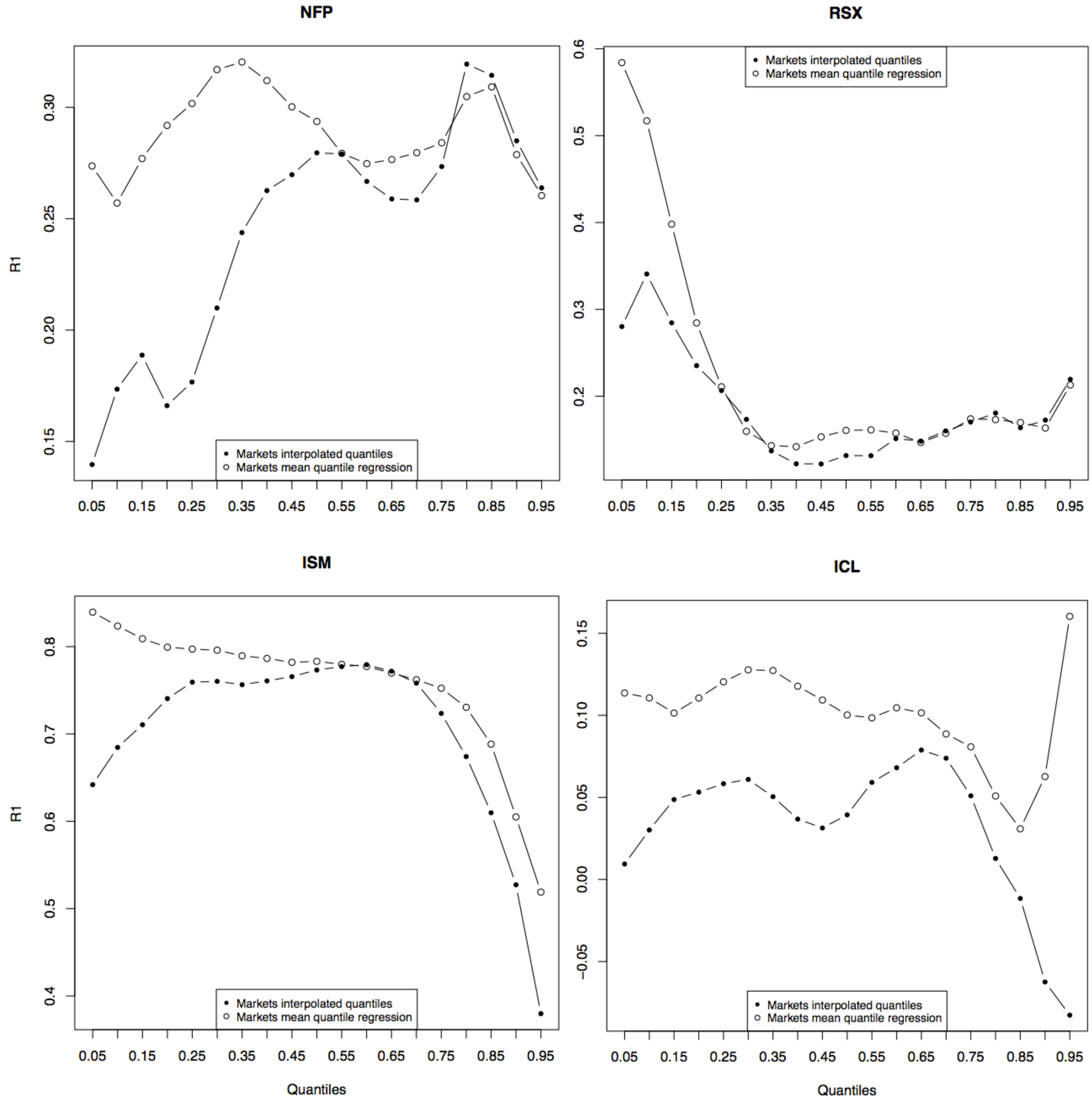
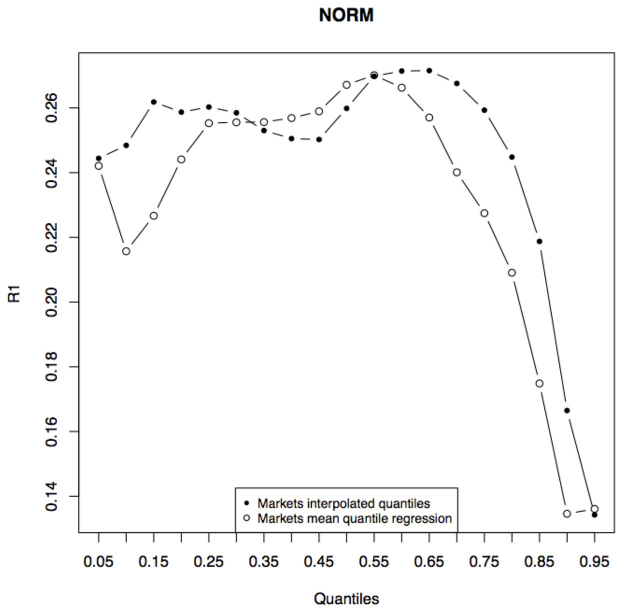


Figure 7. R^1 for Prediction Markets Interpolated Quantiles and Prediction Markets Means Quantile Regression on combined normalized data series of all four macroeconomic indicators



The comparisons done so far suggests that quantile regression can be a viable replacement for full family of winner-takes-all type prediction market contracts, and that quantile regression run on prediction markets forecasted means (that can be obtained with more simple index type prediction market contracts) performs better than quantile regression run on expert forecasted means. This suggestion can be proved by direct comparisons of R^1 of both quantile regressions given in Figure 8 and Figure 9.

In Figure 8, we can see that R^1 of quantile regression run on prediction markets forecasted means is consistently better than R^1 of quantile regression run on expert forecasted means, except for some quantiles in NFP series where it is a fraction smaller. This same tendency is confirmed by the combined normalized data as can be seen in Figure 9. Therefore, from that comparisons, we can say that it is worth running index-type prediction markets to elicit the market forecasted means of economic indicators, as further use of quantile regression based on these market forecasted means gives you better forecasts of full probability distribution of the macroeconomic indicator compared to quantile regression run on expert forecasted means.

Figure 8. R^1 for Prediction Markets Means Quantile Regression and Experts Means Quantile Regression on data series of NFP, RSX, ISM, and ICL

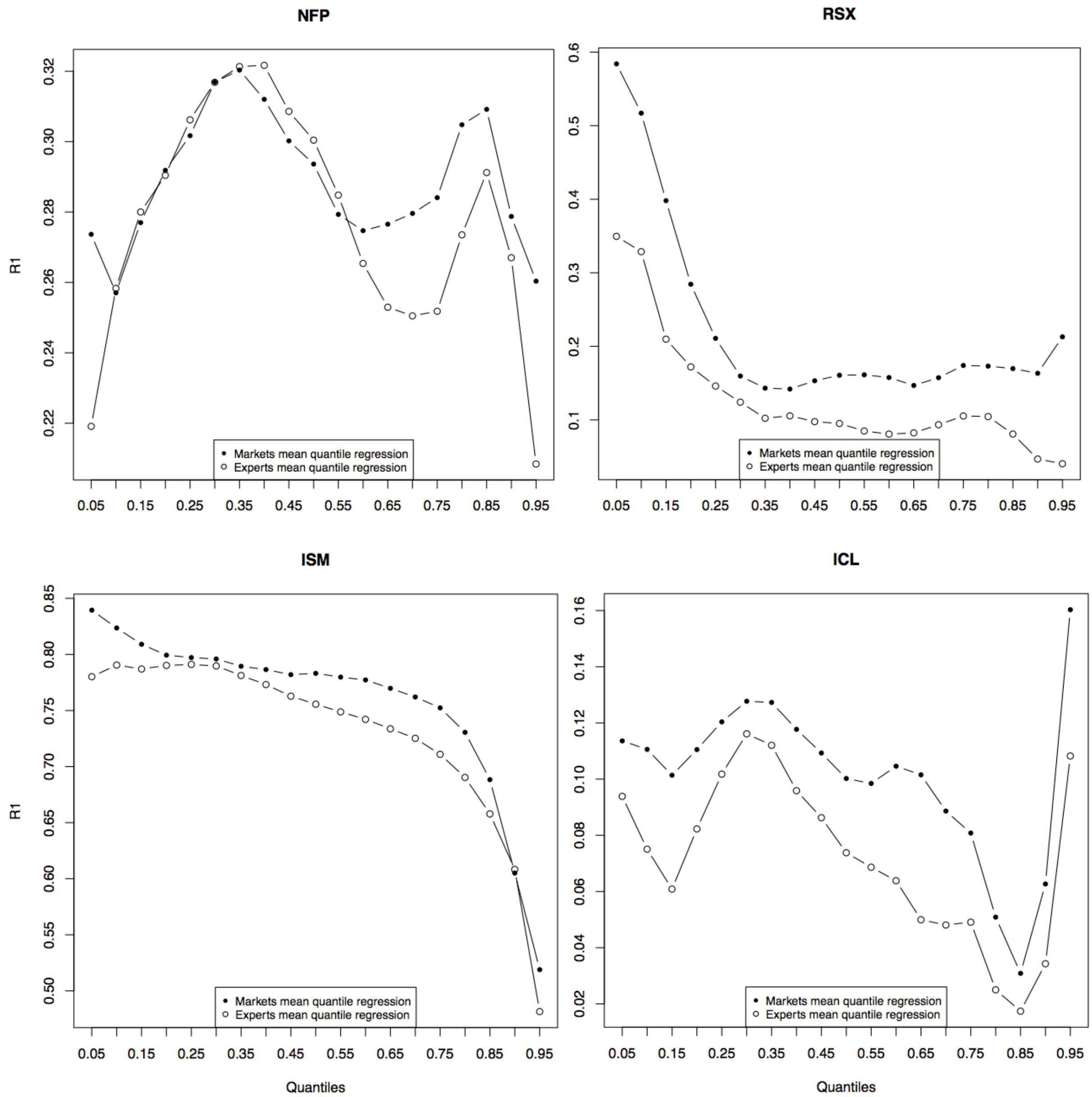
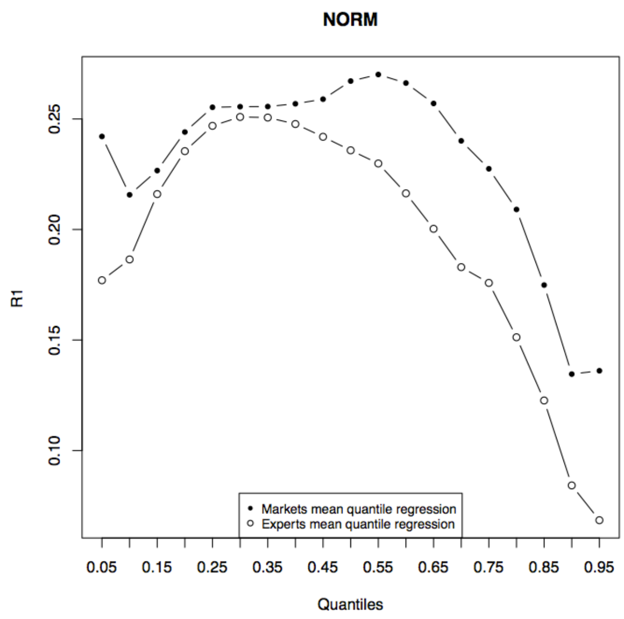


Figure 9. R^1 for Prediction Markets Means Quantile Regression and Experts Means Quantile Regression on combined normalized data series of all four macroeconomic indicators



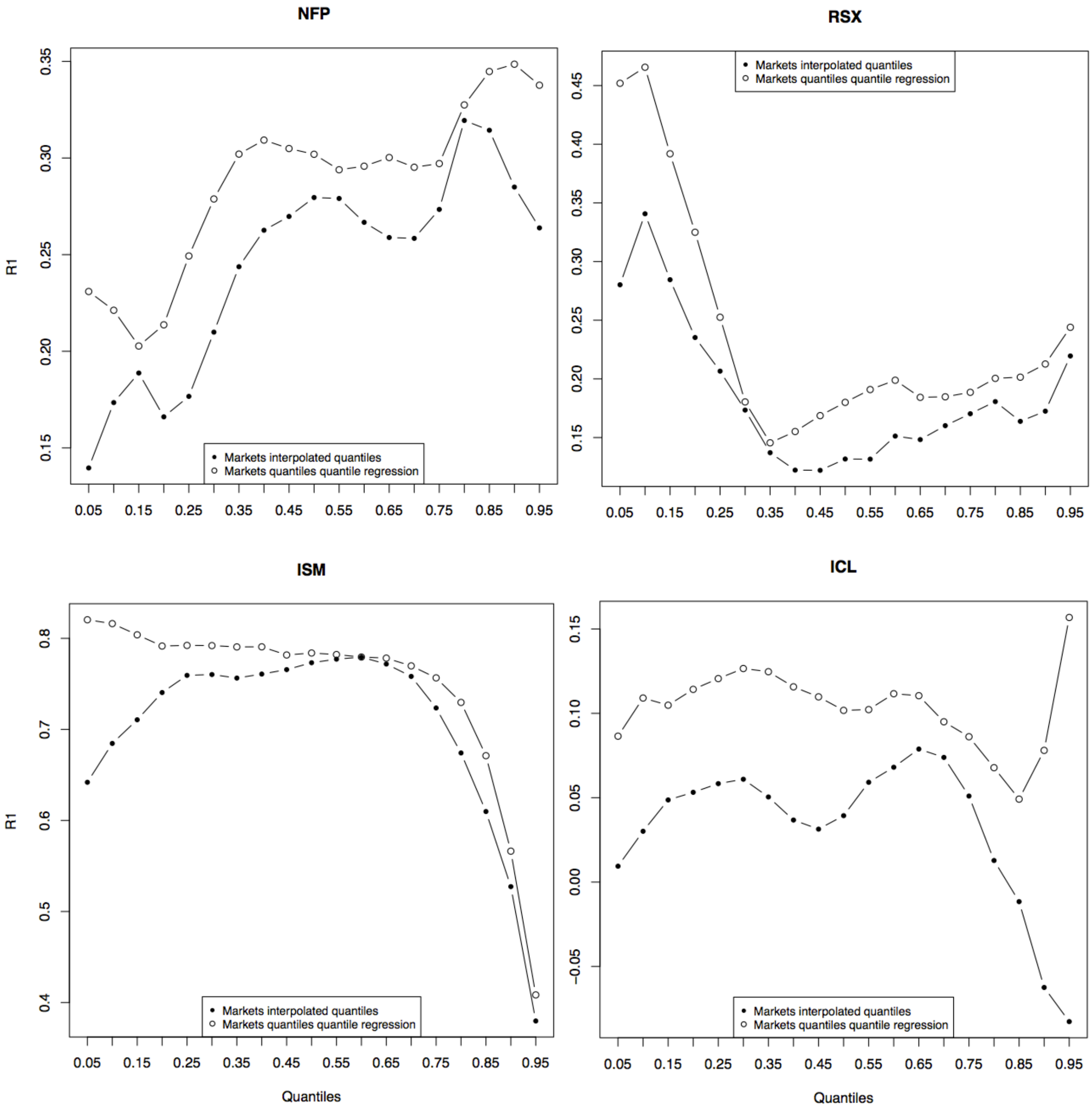
4.4. Combining Prediction Markets with Quantile Regression

Results provided in the first section of empirical research results above do not encourage forecasters of macroeconomic indicators to run full family of winner-takes-all prediction markets to obtain interval forecasts, as it did not prove that these forecasts would always be more accurate compared to somewhat more simple method of running index-type prediction markets to obtain the market forecasted means of macroeconomic indicators and then use quantile regression to get the desired interval forecasts.

But the question still remains if the family of winner-takes-all prediction markets results could be improved by additionally running quantile regression using the quantiles interpolated from the above mentioned prediction markets as explanatory variables.

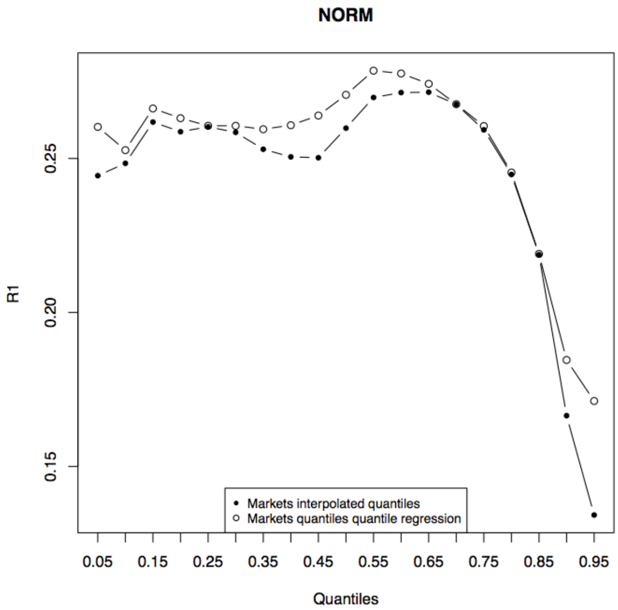
Results of that quantile regression was therefore compared to the results of quantiles interpolated from the family of winner-takes-all type prediction markets, and R^1 of both methods are provided for reference in Table 17 in Appendices. Visual comparisons of this measure of goodness-of-fit for all four series of macroeconomic indicators and for combined normalized data are given below in Figure 10 and Figure 11 correspondingly.

Figure 10. R^1 for Prediction Markets Interpolated Quantiles and Quantile Regression on Prediction Markets Interpolated Quantiles for data series of NFP, RSX, ISM, and ICL



It can be clearly seen in these figures, that running quantile regression on the quantiles interpolated from prediction markets improves the R^1 measure-of-fit consistently for all macroeconomic indicators and also for the combined normalized series. So we can say that quantile regression adds value to full family of winner-takes-all prediction markets and therefore could be recommended as a method of improvement of interval forecasts of macroeconomic indicators.

Figure 11. R^1 for Prediction Markets Interpolated Quantiles and Quantile Regression on Prediction Markets Interpolated Quantiles on combined normalized data series of all four macroeconomic indicators



Now, as in the first part of our empirical research results we did not find quantiles interpolated from the full family of winner-takes-all prediction markets being superior to quantile regression based on the index-type prediction markets forecasted means, it is interesting to compare how well the interpolated quantiles additionally improved by quantile regression score against quantile regression based on prediction markets forecasted means. We do have corresponding R^1 measures already listed in Table 16 and Table 17, and below we can see that measures visually compared in Figure 12 and Figure 13.

From Figure 12 we see that R^1 of both methods are very close to each other for RSX, ISM, and ICL data series, and for NFP series quantile regression on market quantiles scores worse on low quantiles (.05 to .30) and better on high quantiles (.50 to .95). So, for individual series, both methods look equally good, and neither of them could be recommended over the other. Though for combined normalized data series (Figure 13) quantile regression on prediction markets interpolated quantiles scores consistently better than quantile regression on prediction markets forecasted means. This suggests further research in comparison of these two methods with the longer individual macroeconomic indicator data series, when available.

Figure 12. R[1] for Quantile Regression on Prediction Markets Means and Quantile Regression on Prediction Markets Interpolated Quantiles for data series of NFP, RSX, ISM, and ICL

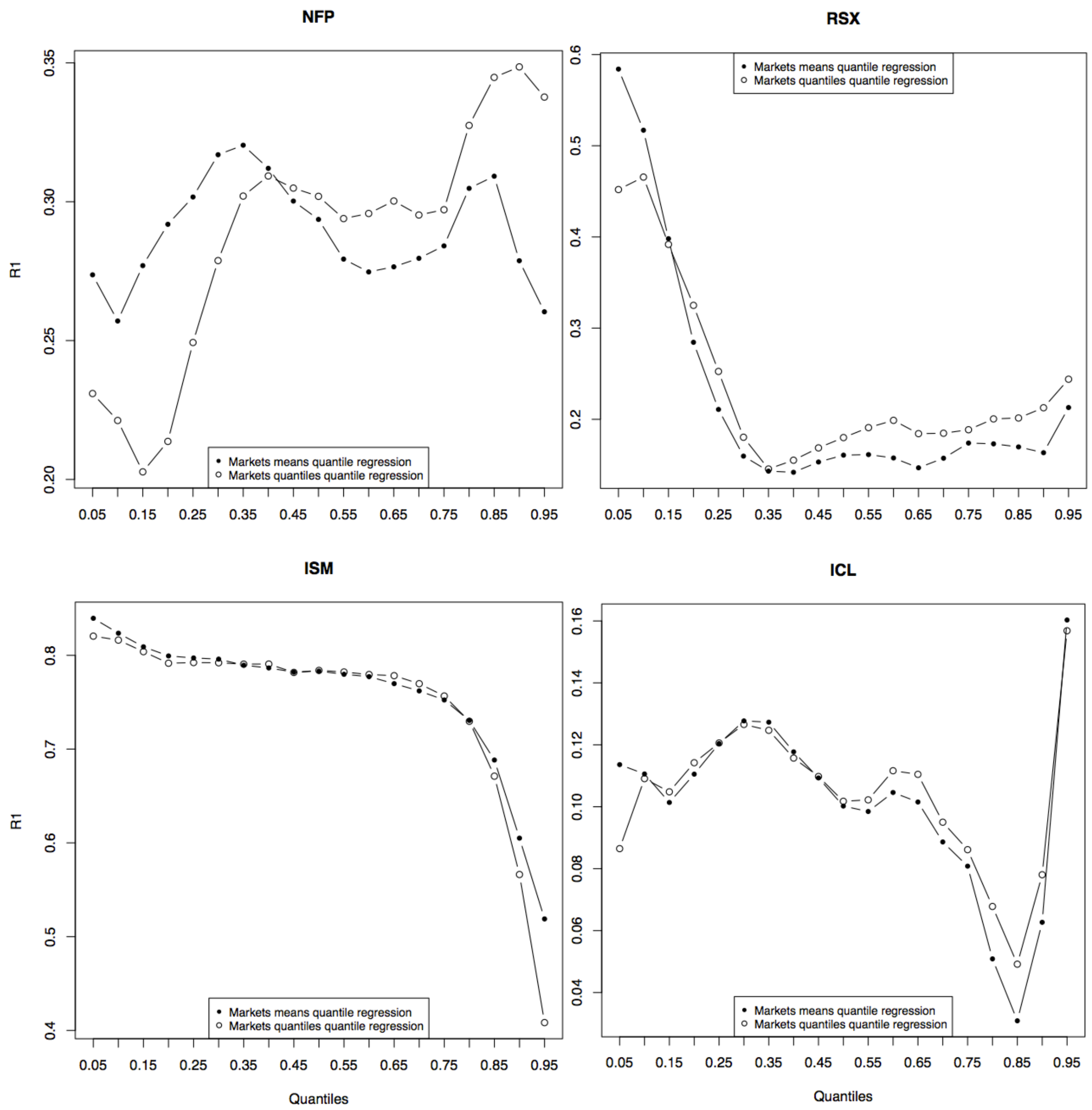
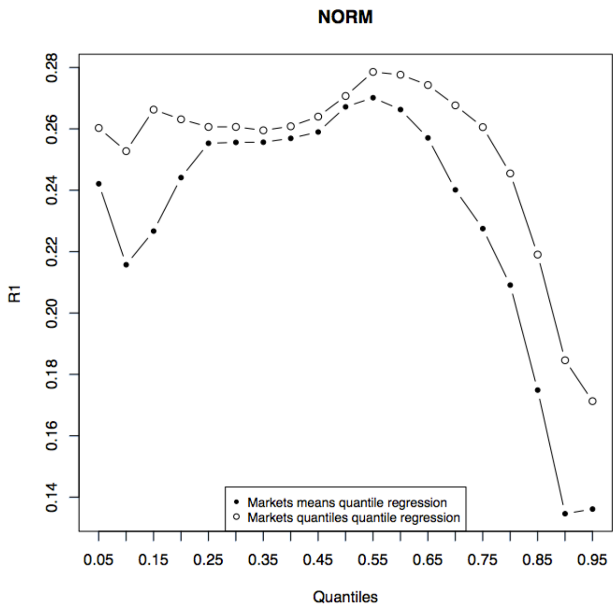


Figure 13. R[1] for Quantile Regression on Prediction Markets Means and Quantile Regression on Prediction Markets Interpolated Quantiles for combined normalized data series of all four macroeconomic indicators



Summarizing the results of the empirical research, we can emphasize the following findings about the possibilities and improvements of interval forecasts of macroeconomic indicators using prediction markets and quantile regression. First, quantile regression is a valuable tool enabling us to obtain better interval forecasts of macroeconomic indicators. Second, for simpler methods, quantile regression on prediction markets forecasted means consistently outperforms the quantile regression run on expert forecasted means, so it is worth running the simple index-type prediction markets on macroeconomic indicators to obtain the market forecasted means. Third, for more complex method of full family of winner-takes-all type prediction markets, quantile regression adds value to the information given by prediction markets themselves and consistently improves the forecasts of quantiles of macroeconomic indicators. So, if decided to go for the complexity of full family of winner-takes-all prediction markets, then it is definitely worth running quantile regression on the results of prediction markets to improve the forecasts.

The answer to the question if it is worth at all going for the complexity of full family of winner-takes-all type prediction markets still stays unclear, as results of this research for individual macroeconomic indicators show that interval forecasts of the same quality can be obtained in a more simple way of using index-type prediction markets to elicit market mean forecasts and then applying quantile regression to forecast the required quantiles. But on the other side, analysis of the longer combined and normalized data series of all available macroeconomic indicators together showed that combination of quantile regression with the full family of winner-takes-all type prediction markets is consistently superior to combination of quantile regression with more simple index-type prediction markets when calculating quantiles needed for interval forecasts.

5. DISCUSSION

With the increasing importance of the macroeconomic forecasting accuracy and bigger emphasis on risk management in order to better predict sudden and dramatic changes in economy, interval forecasts with certain forecasted probability of the leading macroeconomic indicators could be seen as more valuable compared to simple point estimates that are usually given today by the field experts. Forecasts like "ISM Manufacturing Diffusion Index will be between 51.58 and 58.00 next month with the 90% certainty" or "there is a 20% probability that there will be more that 342,200 initial unemployment claims registered next week" give much more information to market participants than just simple point forecasts of 55 or 338,000. Ability to accurately forecast the full probability density of the macroeconomic indicators opens a way to answer the whole new range of questions about the future of the economy.

Prediction markets run as a family of winner-takes-all type of contracts are currently considered as one of the most accurate tools to construct the probability density function of the underlying events. Gürkaynak and Wolfers (2005) show that the prices in prediction markets are unbiased and efficient predictors of the probability distribution of the macroeconomic indicators. Therefore, forecasts obtained by these types of prediction markets can be regarded as a certain benchmark for the forecasts made with alternative techniques.

The results of this research show us that quantile regression can also be helpful in forecasting full probability density of the event. Quantile regression enables us to provide with the probabilistic interval forecasts even without any special means of eliciting additional information about the macroeconomic indicators of interest. Just collecting the historical information about the indicator and the forecasts of the experts on this indicator made the same time before the release of the actual value, enables us to run the set of quantile regressions on this historical data and to use the results to forecast the full probability density of the macroeconomic indicator based on the current forecast of the experts. According to the results of this research, forecasts obtained by quantile regressions run on expert forecasts can be regarded as having good practical value. This research could not prove that probability density forecasts for individual macroeconomic indicators obtained by using prediction markets would be always better than forecasts of probability density based on quantile regression (refer to Figure 4). Therefore quantile regression method should be considered as being equally accurate compared to using the full family of winner-takes-all type prediction markets.

It has to be noted that, contrary to the above, analysis of the combined normalized data series (illustrated in Figure 5) shows that prediction markets are consistently more accurate than quantile regression based on the expert forecasts. But it should also be taken into account that this normalized data series, though being longer, is also artificially constructed by combining four different macroeconomic indicators that could have different intrinsic characteristics and could come from the different types of distribution. Therefore, this combined normalized series should be regarded more as the control series for additional confirmation of the insights, provided by the analysis of the individual indicators, than the main source for conclusions. On the other side, the inverted U shape (∩) of the R^1 graphs of normalized combined data series looks more natural and can be logically explained by the greater difficulty to forecast lowest and highest quantiles compared to quantiles close to median. R^1 graphs for the data series of the individual macroeconomic indicators look more irregular and that can be a result of the short data series available for the research at this time.

Overall it could be said that using just the historical information on macroeconomic indicators and expert forecasts commonly available now in combination with quantile regression enables us to obtain the conditional quantiles and allows to provide useful interval or probabilistic forecasts. But it was also found in this research that these interval forecasts of macroeconomic indicators can be improved by using different types of prediction markets in order to elicit more information about the underlying indicators than expert forecasts can give us.

The first way for improvement could be running simple index type prediction market to forecast expected value of the macroeconomic indicator to substitute that for the expert forecasted mean values. Having that, one can apply quantile regression to obtain certain quantiles required for the forecasts we need to make. This research demonstrated that quantiles calculated by quantile regression using prediction markets forecasted expected values as explanatory variable are consistently more accurate than quantiles calculated by quantile regression based on expert forecasted means (see Figure 8). This was proved to be true for all individual macroeconomic indicators as well as for the combined normalized data series. As there is just one single index type prediction market required to elicit expected value of the macroeconomic indicator of interest, so this is relatively simple and inexpensive to implement, therefore it could be recommended using this type of prediction markets in order to improve interval forecasts that could be obtained through quantile regression.

In addition to that, it could be said that this approach provides improvements to interval forecasts big enough to outperform the forecasts provided by the full family of winner-takes-all type prediction markets that we regard as a benchmark (see Figure 6 and Figure 7). Implementation of a full family of winner-takes-all type prediction markets is much more complicated as it requires to have a whole range of securities traded on the market, instead of just one single security in index type prediction market. But on the other side, the method of using index type prediction market combined with quantile regression requires historical data on prediction market forecasted expected values that would not be available at the start and would take time to collect.

It is important to note that full family of winner-takes-all type prediction markets give you forecasts of full probability density right at the time of the running of these particular prediction markets and do not require any historical information for that. Therefore, this type of prediction markets can still be seen as the best option when decided to go from point forecasts to interval forecasts, as winner-takes-all type prediction markets immediately give you forecasts of the full probability density of the underlying macroeconomic indicator and, at the same time, provide you with the historical data for collection that can be used in the future by additionally implementing quantile regression approach.

This research also demonstrated (Figure 10 and Figure 11) that interval forecasts provided by the family of the winner-takes-all type prediction markets can be further improved by quantile regression when enough historical data is collected. And when this improvement is compared to the index type prediction markets combined with quantile regression, both methods give very similar results for all data series of individual macroeconomic indicators (Figure 12), and only analysis of combined normalized data series gives preference to the winner-takes-all type prediction markets combined with quantile regression. But limitations of conclusions based on this normalized data series was already explained above.

Therefore, in order to improve the macroeconomic forecasting by changing from the point forecasts of expected values to interval or probabilistic forecasts, it could be recommended to start running the winner-takes-all type prediction markets. That would give us immediate possibility of interval forecasts and would also allow us to collect the data series for the future improvements of these forecasts by additionally applying quantile regression to prediction markets data. When long enough data series for the macroeconomic indicator of interest would be collected, the methodology of this research could be applied to compare the accuracy of two possible quantile regressions: one run with the prediction markets forecasted means as regressor and another run with the prediction markets interpolated quantiles as regressor. If the latter would be proved being more accurate (as it is suggested by the analysis of the combined normalized data series of this research), then it would be worth continuing with the winner-takes-all type prediction markets. And if this would not be proved being more accurate, then these winner-takes-all type prediction markets could be replaced by the more simple index type prediction markets.

Related to that, it has to be noted that the length of the data series available for this research was one of its main limitations. The focus of the research was to analyze the different methods seeking to improve macroeconomic forecasting specifically, and the emphasis also was given to prediction markets run with the real money, as real money gives the best incentive for the participants of prediction markets to elicit their true knowledge about the issue. Unfortunately, real money prediction markets on macroeconomic indicators are rarity, so data series available for the research were limited. One of the reasons of the lack of real money prediction markets is the current situation with the legislation related to that activity. At the moment, prediction markets happen to be in between of security trading and betting and therefore regulations of many countries makes it difficult if not impossible to run real money prediction markets as a business endeavor.

Further research in this field of application of prediction markets and quantile regression to forecasting could be carried out using data from other areas, like entertainment industry or politics, if longer data series in that fields would be available. Also, play money prediction markets could be taken into account, as some reports have found that play money prediction markets could be as accurate as real money markets. This would widen the research horizon and would let us better understand the benefits that prediction markets and quantile regression can bring to forecasting.

6. CONCLUSIONS

Altogether we can make the following conclusions about the findings of this research and their practical application to interval forecasting of macroeconomic indicators.

First, we found that quantile regression run with the expert surveys point forecasts of the macroeconomic indicators as the explanatory variable and actual released values of these indicators as explained variable can provide us with the well calibrated interval forecasts. Comparing this quantile regression approach to the forecasts of probability density provided by the family of winner-takes-all prediction markets, we did not find clear evidence that would allow us to favor one method over the other, though analysis of the longer combined and normalized data series showed some hints that prediction markets approach can be more accurate. Overall, quantile regression on expert point forecasts can be recommended as the immediate tool to come up with interval forecasts as all the data needed for this method is already commonly available.

Second, prediction markets set up as a family of winner-takes-all type contracts to cover all the range that macroeconomic indicator can fall in can be used as an alternative way to construct the interval forecasts. Prediction markets are unbiased and efficient estimators of the probability density of the macroeconomic indicators and also provide well calibrated interval forecasts. The benefit of this method is that it does not require any statistical methods and does not need any historical data to come up with the interval forecasts of the future value of the macroeconomic indicator of interest. This makes it possible to have the immediate alternative interval forecasts that could be more accurate compared to forecasts constructed form quantile regression on expert point forecasts, and at the same time it collects historical data of prediction markets prices that can be used later to improve these forecasts as explained below.

Third, quantile regression can be used to improve interval forecasts obtained though prediction markets when enough historical data of these markets are available. In this research, we found that quantile regression run with quantiles interpolated from prediction markets as explanatory variable improves both the accuracy of quantiles and the calibration of the interval forecasts. Therefore combining prediction markets and quantile regression technique has to be regarded as superior method to all other methods analyzed in this research.

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APPENDICES

Table 8. NFP Released Values and Forecasted Means

NFP – The Change in Non-Farm Payrolls Compared to the Previous Month (in thousands)					
No.	Auction Date	Release Date	Released Value	Experts Forecasted Mean	Prediction Markets Forecasted Mean
1	2002-10-03	2002-10-04	-43	10.71	-17.66
2	2002-10-31	2002-11-01	-5	3.96	-13.51
3	2002-12-05	2002-12-06	-40	29.08	65.29
4	2003-01-09	2003-01-10	-101	20.61	36.23
5	2003-02-06	2003-02-07	143	58.74	61.08
6	2003-03-06	2003-03-07	-308	13.28	-13.81
7	2003-04-03	2003-04-04	-108	-25.94	-62.19
8	2003-05-01	2003-05-02	-48	-42.91	-117.88
9	2003-06-05	2003-06-06	-17	-23.43	-43.97
10	2003-07-02	2003-07-03	-30	0.90	3.72
11	2003-07-31	2003-08-01	-44	9.94	17.20
12	2003-09-05	2003-09-05	-93	17.47	8.10
13	2003-10-03	2003-10-03	57	-14.83	-3.60
14	2003-11-07	2003-11-07	126	56.92	88.19
15	2003-12-05	2003-12-05	57	133.77	160.26
16	2004-01-09	2004-01-09	1	144.79	161.16
17	2004-02-06	2004-02-06	112	166.33	171.75
18	2004-03-05	2004-03-05	21	127.53	129.52
19	2004-04-02	2004-04-02	308	110.00	139.37
20	2004-05-07	2004-05-07	288	181.00	187.58
21	2004-06-04	2004-06-04	248	217.00	256.30
22	2004-07-02	2004-07-02	112	236.00	224.76
23	2004-08-06	2004-08-06	32	231.00	239.33
24	2004-09-03	2004-09-03	144	158.00	152.15
25	2004-10-08	2004-10-08	96	138.00	113.58
26	2004-11-05	2004-11-05	337	184.00	168.15
27	2004-12-03	2004-12-03	112	197.00	220.35
28	2005-01-07	2005-01-07	157	185.00	166.05
29	2005-02-04	2005-02-04	146	182.00	193.20
30	2005-03-04	2005-03-04	262	217.00	244.04
31	2005-04-01	2005-04-01	110	219.00	208.85
32	2005-05-06	2005-05-06	274	176.00	188.89
33	2005-06-03	2005-06-03	78	181.00	174.53

Table 9. RSX Released Values and Forecasted Means

RSX – Monthly Percentage Change in Retail Sales Ex-Auto					
No.	Auction Date	Release Date	Released Value	Experts Forecasted Mean	Prediction Markets Forecasted Mean
1	2002-11-13	2002-11-14	0.67	0.25	0.07
2	2002-12-11	2002-12-12	0.50	0.23	0.18
3	2003-01-13	2003-01-14	0.05	0.31	0.28
4	2003-02-12	2003-02-13	1.26	0.41	0.57
5	2003-03-12	2003-03-13	-1.01	-0.07	-0.17
6	2003-04-10	2003-04-11	1.06	0.35	0.46
7	2003-05-13	2003-05-14	-0.94	0.19	-0.08
8	2003-06-11	2003-06-12	0.13	0.20	0.21
9	2003-07-14	2003-07-15	0.71	0.31	0.22
10	2003-08-12	2003-08-13	0.82	0.55	0.66
11	2003-09-12	2003-09-12	0.65	0.75	0.87
12	2003-10-15	2003-10-15	0.26	0.47	0.62
13	2003-11-14	2003-11-14	0.20	0.27	0.14
14	2003-12-11	2003-12-11	0.37	0.37	0.36
15	2004-01-15	2004-01-15	0.12	0.41	0.45
16	2004-02-12	2004-02-12	0.87	0.56	0.64
17	2004-09-14	2004-09-14	0.21	0.20	0.10
18	2004-10-15	2004-10-15	0.64	0.30	0.31
19	2004-11-12	2004-11-12	0.93	0.60	0.63
20	2004-12-13	2004-12-13	0.51	0.30	0.25
21	2005-01-13	2005-01-13	0.29	0.50	0.38
22	2005-02-15	2005-02-15	0.61	0.50	0.51
23	2005-03-15	2005-03-15	0.40	0.80	0.74
24	2005-04-13	2005-04-13	0.15	0.60	0.58
25	2005-05-12	2005-05-12	1.07	0.50	0.73
26	2005-06-14	2005-06-14	-0.19	0.20	0.26

Table 10. ISM Released Values and Forecasted Means

ISM – Institute for Supply Management's Manufacturing Diffusion Index					
No.	Auction Date	Release Date	Released Value	Experts Forecasted Mean	Prediction Markets Forecasted Mean
1	2002-10-31	2002-11-01	48.50	49.03	47.53
2	2002-12-02	2002-12-02	49.20	50.64	50.97
3	2003-01-31	2003-02-03	53.90	53.65	53.30
4	2003-02-28	2003-03-03	50.50	52.17	52.28
5	2003-03-31	2003-04-01	46.20	49.07	48.14
6	2003-04-30	2003-05-01	45.40	47.06	47.05
7	2003-05-30	2003-06-02	49.40	48.68	48.49
8	2003-07-01	2003-07-01	49.80	50.92	51.26
9	2003-07-31	2003-08-01	51.80	51.15	51.80
10	2003-09-02	2003-09-02	54.70	53.62	54.62
11	2003-10-01	2003-10-01	53.70	54.76	53.43
12	2003-11-03	2003-11-03	57.00	55.40	56.20
13	2003-12-01	2003-12-01	62.80	57.64	58.15
14	2004-02-02	2004-02-02	63.60	63.27	64.67
15	2004-03-01	2004-03-01	61.40	61.68	61.14
16	2004-04-01	2004-04-01	62.50	60.20	59.53
17	2004-05-03	2004-05-03	62.40	62.70	62.45
18	2004-06-01	2004-06-01	62.80	61.60	62.18
19	2004-07-01	2004-07-01	61.10	61.80	60.50
20	2004-08-02	2004-08-02	62.00	61.60	61.80
21	2004-09-01	2004-09-01	59.00	59.80	59.49
22	2004-10-01	2004-10-01	58.50	58.70	58.52
23	2004-11-01	2004-11-01	56.80	58.90	58.30
24	2004-12-01	2004-12-01	57.80	56.50	56.98
25	2005-01-03	2005-01-03	58.60	58.30	58.27
26	2005-02-01	2005-02-01	56.40	57.30	56.85
27	2005-03-01	2005-03-01	55.30	56.70	56.93
28	2005-04-01	2005-04-01	55.20	54.80	55.27
29	2005-05-02	2005-05-02	53.30	55.00	54.81
30	2005-06-01	2005-06-01	51.40	51.90	51.71

Table 11. ICL Released Values and Forecasted Means

ICL – Weekly Initial Unemployment Claims (in thousands)					
No.	Auction Date	Release Date	Released Value	Experts Forecasted Mean	Prediction Markets Forecasted Mean
1	2004-02-19	2004-02-19	344	352	355
2	2004-02-26	2004-02-26	350	344	346
3	2004-03-18	2004-03-18	336	344	345
4	2004-03-25	2004-03-25	339	338	339
5	2004-04-08	2004-04-08	328	338	338
6	2004-04-15	2004-04-15	360	332	336
7	2004-04-22	2004-04-22	353	345	342
8	2004-04-29	2004-04-29	338	344	344
9	2004-05-13	2004-05-13	331	323	323
10	2004-05-20	2004-05-20	345	326	327
11	2004-05-27	2004-05-27	344	336	336
12	2004-06-10	2004-06-10	352	333	336
13	2004-06-17	2004-06-17	336	341	338
14	2004-06-24	2004-06-24	349	337	341
15	2004-07-08	2004-07-08	310	341	339
16	2004-07-15	2004-07-15	349	339	348
17	2004-07-22	2004-07-22	339	351	361
18	2004-07-29	2004-07-29	345	340	346
19	2004-08-12	2004-08-12	331	338	340
20	2004-08-19	2004-08-19	331	334	334
21	2004-08-26	2004-08-26	343	329	339
22	2004-09-09	2004-09-09	319	347	345
23	2004-09-16	2004-09-16	333	336	341
24	2004-09-23	2004-09-23	350	338	340
25	2004-09-30	2004-09-30	369	346	347
26	2004-10-07	2004-10-07	335	351	357
27	2004-10-14	2004-10-14	352	338	343
28	2004-10-21	2004-10-21	329	345	349
29	2004-10-28	2004-10-28	350	332	337
30	2004-11-04	2004-11-04	332	340	341
31	2004-11-10	2004-11-10	333	337	339
32	2004-11-18	2004-11-18	334	331	331
33	2004-11-24	2004-11-24	323	332	335
34	2004-12-02	2004-12-02	349	328	330
35	2004-12-09	2004-12-09	357	336	336
36	2004-12-16	2004-12-16	317	343	342
37	2004-12-23	2004-12-23	333	330	335
38	2004-12-30	2004-12-30	326	330	331
39	2005-01-06	2005-01-06	364	329	336
40	2005-01-13	2005-01-13	367	341	347
41	2005-01-19	2005-01-19	319	342	345
42	2005-01-27	2005-01-27	325	330	331
43	2005-02-03	2005-02-03	316	331	332
44	2005-02-10	2005-02-10	303	327	329
45	2005-02-17	2005-02-17	302	319	314
46	2005-02-24	2005-02-24	312	310	310
47	2005-03-03	2005-03-03	310	313	311
48	2005-03-10	2005-03-10	327	310	310

49	2005-03-17	2005-03-17	318	316	315
50	2005-03-24	2005-03-24	324	317	316
51	2005-03-31	2005-03-31	350	319	320
52	2005-04-07	2005-04-07	334	334	330
53	2005-04-14	2005-04-14	330	331	331
54	2005-04-21	2005-04-21	296	328	331
55	2005-04-28	2005-04-28	320	321	318
56	2005-05-05	2005-05-05	333	324	326
57	2005-05-12	2005-05-12	340	324	328
58	2005-05-19	2005-05-19	321	329	331
59	2005-05-26	2005-05-26	323	326	325
60	2005-06-02	2005-06-02	350	327	324
61	2005-06-09	2005-06-09	330	330	330
62	2005-06-16	2005-06-16	333	331	331
63	2005-06-23	2005-06-23	314	331	331
64	2005-06-30	2005-06-30	310	325	325

Table 12. NFP Forecasted Quantiles Interpolated from Prediction Markets

NFP – The Change in Non-Farm Payrolls Compared to the Previous Month (in thousands)																			
No.	Quantiles																		
	.05	.10	.15	.20	.25	.30	.35	.40	.45	.50	.55	.60	.65	.70	.75	.80	.85	.90	.95
1	-187	-155	-128	-105	-82	-59	-48	-38	-28	-16	-4	2	9	16	27	41	50	58	82
2	-164	-138	-102	-80	-70	-59	-43	-35	-29	-23	-14	-5	4	13	22	34	48	62	93
3	-74	-50	-32	-13	0	13	22	31	40	47	54	61	72	85	101	122	144	166	193
4	-132	-63	-46	-33	-23	-13	-4	5	15	25	35	46	59	68	77	85	102	119	132
5	-135	-116	-87	-47	-19	0	17	31	45	58	70	82	92	102	112	126	143	176	221
6	-157	-141	-109	-88	-80	-72	-64	-55	-45	-35	-24	-13	1	15	30	46	63	85	117
7	-219	-214	-184	-173	-163	-134	-124	-114	-101	-88	-70	-53	-38	-21	-4	14	43	71	120
8	-262	-252	-243	-231	-216	-197	-178	-162	-147	-132	-118	-104	-90	-75	-60	-43	-24	1	29
9	-204	-172	-155	-141	-130	-119	-108	-96	-84	-67	-50	-33	-11	3	19	38	55	75	109
10	-123	-104	-91	-76	-62	-48	-36	-26	-16	-7	0	8	18	33	43	53	62	82	119
11	-93	-73	-57	-44	-34	-28	-22	-16	-8	2	12	23	35	44	53	61	70	79	88
12	-108	-85	-69	-55	-42	-34	-27	-21	-15	-8	-1	6	14	25	36	48	61	81	104
13	-153	-130	-114	-96	-80	-65	-52	-39	-27	-14	-1	13	24	36	50	65	79	97	118
14	-53	-22	-4	10	21	30	40	52	63	72	80	90	103	117	133	153	174	191	202
15	14	30	47	65	83	99	114	123	132	142	153	165	180	195	210	227	250	274	304
16	22	43	59	78	93	103	112	122	132	142	154	167	179	191	202	214	248	274	294
17	-5	13	27	43	69	91	108	126	144	159	174	188	206	226	244	259	283	319	345
18	-14	5	22	38	50	63	73	83	94	104	115	129	145	163	179	196	213	252	293
19	-26	6	21	31	44	62	79	94	108	121	134	149	163	179	197	220	251	288	300
20	21	41	52	64	88	107	123	136	160	178	193	206	220	236	263	288	313	321	329
21	74	107	125	143	164	174	184	203	223	239	256	272	288	305	333	350	365	413	425
22	62	95	114	139	149	159	170	183	198	214	222	231	240	258	276	295	313	332	364
23	82	93	112	130	146	162	178	193	207	222	238	253	269	286	303	323	347	368	393
24	-19	-14	14	30	52	75	95	112	127	141	155	169	183	203	229	250	270	291	302
25	-45	-40	-23	-2	13	30	46	61	75	88	104	121	139	159	179	199	224	260	313
26	0	28	48	66	86	101	115	129	143	157	170	182	196	211	227	243	262	299	330
27	34	63	96	118	134	149	163	176	188	202	215	230	247	265	285	311	334	357	382
28	-5	18	38	65	80	97	114	123	131	141	158	174	191	211	231	249	266	294	333
29	12	30	63	88	109	127	142	153	164	177	191	208	224	241	258	277	297	320	352
30	41	88	110	136	148	159	178	197	215	233	249	264	277	291	315	331	367	413	425
31	53	83	101	116	127	138	151	165	176	188	199	210	224	238	257	278	303	336	376
32	33	64	88	99	110	122	134	145	155	166	179	191	204	219	238	260	285	317	339
33	3	41	67	85	96	107	119	132	145	159	171	183	197	213	228	246	266	287	319

Table 13. RSX Forecasted Quantiles Interpolated from Prediction Markets

RSX – Monthly Percentage Change in Retail Sales Ex-Auto																			
No.	Quantiles																		
	.05	.10	.15	.20	.25	.30	.35	.40	.45	.50	.55	.60	.65	.70	.75	.80	.85	.90	.95
1	-0.68	-0.65	-0.53	-0.35	-0.24	-0.20	-0.15	-0.08	-0.01	0.06	0.12	0.17	0.21	0.26	0.32	0.39	0.46	0.55	0.69
2	-0.49	-0.34	-0.23	-0.15	-0.08	-0.02	0.04	0.08	0.13	0.18	0.23	0.27	0.30	0.33	0.35	0.40	0.45	0.51	0.62
3	-0.48	-0.33	-0.25	-0.11	-0.03	0.06	0.11	0.17	0.23	0.28	0.33	0.37	0.40	0.43	0.47	0.53	0.60	0.70	0.87
4	-0.32	-0.13	-0.01	0.10	0.19	0.27	0.34	0.41	0.48	0.54	0.60	0.66	0.72	0.78	0.84	0.93	1.03	1.17	1.28
5	-0.97	-0.91	-0.80	-0.70	-0.62	-0.52	-0.42	-0.33	-0.26	-0.19	-0.12	-0.05	0.02	0.07	0.12	0.19	0.29	0.41	0.60
6	-0.47	-0.35	-0.15	-0.03	0.07	0.15	0.22	0.29	0.36	0.42	0.49	0.57	0.64	0.74	0.82	0.91	0.99	1.05	1.15
7	-0.68	-0.66	-0.63	-0.58	-0.51	-0.43	-0.36	-0.29	-0.22	-0.16	-0.09	-0.03	0.04	0.10	0.17	0.24	0.32	0.42	0.62
8	-0.66	-0.51	-0.36	-0.30	-0.24	-0.15	-0.07	0.01	0.08	0.16	0.23	0.30	0.38	0.46	0.55	0.62	0.70	0.82	0.97
9	-0.56	-0.49	-0.36	-0.22	-0.13	-0.02	0.08	0.14	0.20	0.25	0.29	0.33	0.37	0.42	0.46	0.51	0.57	0.63	0.74
10	-0.02	0.11	0.22	0.31	0.37	0.41	0.45	0.50	0.54	0.59	0.63	0.69	0.75	0.81	0.88	0.96	1.08	1.23	1.30
11	0.18	0.32	0.44	0.49	0.54	0.62	0.69	0.75	0.82	0.89	0.95	0.98	1.00	1.03	1.07	1.12	1.20	1.28	1.35
12	-0.13	0.02	0.11	0.19	0.28	0.37	0.45	0.51	0.56	0.60	0.64	0.68	0.72	0.78	0.85	0.91	0.98	1.09	1.20
13	-0.53	-0.43	-0.35	-0.26	-0.18	-0.10	-0.03	0.02	0.07	0.12	0.17	0.20	0.24	0.28	0.32	0.37	0.45	0.55	0.70
14	-0.29	-0.13	-0.03	0.04	0.09	0.14	0.18	0.21	0.25	0.29	0.32	0.36	0.41	0.47	0.55	0.63	0.73	0.84	0.97
15	-0.15	-0.03	0.05	0.09	0.13	0.18	0.24	0.30	0.36	0.39	0.43	0.47	0.52	0.57	0.63	0.71	0.80	0.90	1.04
16	-0.08	0.06	0.14	0.20	0.26	0.35	0.43	0.49	0.55	0.61	0.67	0.74	0.81	0.87	0.90	0.94	1.01	1.10	1.24
17	-0.66	-0.54	-0.50	-0.45	-0.38	-0.30	-0.20	-0.11	-0.02	0.05	0.13	0.20	0.26	0.33	0.40	0.48	0.60	0.73	0.93
18	-0.42	-0.27	-0.17	-0.10	-0.03	0.03	0.09	0.15	0.20	0.26	0.33	0.40	0.46	0.51	0.57	0.63	0.71	0.80	0.94
19	-0.25	-0.08	0.05	0.16	0.27	0.34	0.41	0.48	0.54	0.61	0.67	0.72	0.78	0.84	0.91	0.98	1.07	1.18	1.34
20	-0.63	-0.42	-0.30	-0.20	-0.12	-0.05	0.01	0.07	0.13	0.19	0.25	0.31	0.38	0.45	0.53	0.63	0.75	0.91	0.99
21	-0.36	-0.23	-0.14	-0.07	-0.02	0.03	0.10	0.18	0.25	0.33	0.39	0.45	0.52	0.60	0.67	0.74	0.83	0.95	1.12
22	-0.36	-0.18	-0.04	0.06	0.15	0.22	0.29	0.35	0.41	0.47	0.53	0.59	0.65	0.71	0.78	0.86	0.95	1.08	1.26
23	-0.06	0.06	0.17	0.25	0.34	0.42	0.50	0.57	0.64	0.70	0.76	0.81	0.86	0.93	1.00	1.08	1.18	1.32	1.52
24	-0.15	-0.01	0.09	0.17	0.24	0.30	0.36	0.41	0.46	0.51	0.56	0.62	0.68	0.74	0.82	0.91	1.01	1.13	1.27
25	-0.02	0.14	0.24	0.32	0.39	0.46	0.51	0.57	0.62	0.68	0.73	0.79	0.85	0.90	0.97	1.05	1.13	1.22	1.35
26	-0.40	-0.27	-0.19	-0.13	-0.09	-0.05	0.00	0.06	0.13	0.18	0.24	0.30	0.36	0.43	0.50	0.58	0.66	0.75	0.89

Table 14. ISM Forecasted Quantiles Interpolated from Prediction Markets

ISM – Institute for Supply Management's Manufacturing Diffusion Index																			
No.	Quantiles																		
	.05	.10	.15	.20	.25	.30	.35	.40	.45	.50	.55	.60	.65	.70	.75	.80	.85	.90	.95
1	43.49	44.08	44.62	45.02	45.42	45.90	46.34	46.63	46.93	47.22	47.52	47.79	48.11	48.48	48.87	49.40	49.86	50.24	50.83
2	47.35	48.03	48.43	48.79	49.21	49.75	49.98	50.20	50.60	50.86	51.03	51.20	51.56	51.93	52.24	52.60	52.96	53.32	53.83
3	49.17	49.75	50.19	50.66	51.20	51.57	51.93	52.29	52.66	53.08	53.44	53.74	54.20	54.63	54.91	55.13	55.36	55.73	56.36
4	48.24	49.36	49.96	50.40	50.73	51.02	51.31	51.57	51.84	52.09	52.35	52.60	52.83	53.05	53.26	53.61	54.07	54.67	55.33
5	44.50	45.06	45.66	46.36	46.75	47.06	47.35	47.58	47.81	47.99	48.18	48.35	48.51	48.67	48.93	49.29	49.90	50.32	50.88
6	43.30	44.29	44.76	45.12	45.44	45.73	45.99	46.24	46.48	46.72	46.96	47.20	47.50	47.83	48.17	48.55	48.98	49.52	50.19
7	45.33	45.92	46.35	46.75	47.11	47.46	47.80	48.14	48.34	48.48	48.62	48.75	48.93	49.10	49.29	49.58	49.87	50.16	50.46
8	47.51	48.45	48.94	49.34	49.68	49.92	50.13	50.39	50.74	51.05	51.36	51.66	51.93	52.20	52.51	52.82	53.13	53.52	54.07
9	47.77	48.73	49.44	49.86	50.21	50.51	50.78	51.00	51.22	51.40	51.58	51.76	52.14	52.52	52.93	53.35	53.84	54.44	55.23
10	51.43	52.21	52.60	52.94	53.26	53.56	53.81	53.95	54.10	54.25	54.57	54.85	55.10	55.34	55.57	55.81	56.13	56.44	56.94
11	50.33	51.26	51.42	51.59	51.75	52.11	52.40	52.65	52.87	53.08	53.29	53.49	53.69	53.97	54.31	54.66	55.05	55.53	56.39
12	52.80	53.53	53.98	54.35	54.68	54.98	55.27	55.54	55.79	55.99	56.19	56.46	56.75	57.07	57.42	57.77	57.99	58.21	58.43
13	54.01	54.91	55.58	56.18	56.62	57.00	57.36	57.69	58.02	58.34	58.67	58.99	59.29	59.48	59.67	59.82	59.92	60.03	60.14
14	60.34	61.37	61.92	62.58	63.07	63.48	63.86	64.24	64.61	64.84	64.99	65.14	65.31	65.55	65.81	66.17	66.60	67.09	67.75
15	57.42	57.96	58.52	58.95	59.37	59.76	60.13	60.49	60.65	60.81	60.96	61.12	61.27	61.43	61.69	62.04	62.39	62.99	63.87
16	55.98	56.76	57.09	57.42	57.75	58.11	58.49	58.88	59.25	59.62	59.84	59.98	60.11	60.25	60.50	60.75	61.17	61.75	62.63
17	59.02	59.75	60.21	60.57	60.88	61.16	61.41	61.65	61.88	62.10	62.35	62.68	63.03	63.39	63.76	64.09	64.53	64.87	65.06
18	58.66	59.38	59.75	60.04	60.33	60.60	60.82	61.04	61.27	61.49	61.82	62.16	62.50	62.78	63.06	63.35	63.73	64.22	64.95
19	57.33	57.86	58.25	58.54	58.84	59.18	59.47	59.75	60.01	60.27	60.49	60.71	60.92	61.13	61.41	61.75	62.15	62.67	63.52
20	58.54	59.25	59.68	59.98	60.25	60.51	60.78	61.09	61.37	61.61	61.84	62.04	62.25	62.53	62.81	63.10	63.42	63.80	64.44
21	55.98	56.68	57.16	57.57	57.89	58.15	58.45	58.78	59.07	59.33	59.56	59.79	60.02	60.24	60.50	60.76	61.10	61.58	62.34
22	54.98	55.68	56.16	56.57	56.94	57.30	57.64	57.97	58.28	58.46	58.64	58.83	59.03	59.24	59.49	59.74	60.07	60.57	61.81
23	54.81	55.50	55.96	56.32	56.62	56.88	57.13	57.35	57.56	57.78	58.12	58.46	58.79	59.13	59.49	59.88	60.30	60.81	61.55
24	53.13	53.77	54.16	54.60	55.02	55.38	55.66	55.99	56.34	56.69	56.98	57.25	57.66	58.03	58.39	58.74	59.10	59.52	60.16
25	54.19	55.13	55.77	56.22	56.66	57.00	57.31	57.62	57.90	58.15	58.40	58.65	58.90	59.17	59.45	59.75	60.17	60.70	61.48
26	53.31	54.01	54.55	54.95	55.29	55.58	55.86	56.13	56.39	56.65	56.90	57.15	57.42	57.69	57.99	58.29	58.64	59.06	59.64
27	53.35	54.05	54.52	54.89	55.22	55.49	55.75	55.99	56.22	56.47	56.72	57.05	57.38	57.72	58.07	58.45	58.88	59.39	60.11
28	51.39	52.08	52.61	53.06	53.46	53.84	54.20	54.51	54.81	55.13	55.40	55.65	55.93	56.21	56.54	56.90	57.29	57.83	58.75
29	51.58	52.22	52.61	52.93	53.21	53.44	53.67	53.87	54.06	54.25	54.57	54.91	55.24	55.58	55.94	56.32	56.77	57.30	58.00
30	47.95	48.82	49.44	49.96	50.38	50.69	50.89	51.06	51.23	51.39	51.55	51.71	52.01	52.36	52.72	53.09	53.50	54.02	54.73

Table 15. ICL Forecasted Quantiles Interpolated from Prediction Markets

ICL – Weekly Initial Unemployment Claims (in thousands)																			
No.	Quantiles																		
	.05	.10	.15	.20	.25	.30	.35	.40	.45	.50	.55	.60	.65	.70	.75	.80	.85	.90	.95
1	328.3	334.1	337.7	340.1	342.5	344.7	346.8	349.0	351.0	353.2	355.4	357.6	360.2	362.7	364.2	365.8	367.3	370.9	377.0
2	321.1	326.3	329.4	331.9	333.6	335.1	336.6	338.4	340.8	343.0	344.7	346.4	348.1	349.9	351.6	353.9	356.8	360.7	366.3
3	324.0	328.3	330.4	332.5	334.0	335.4	336.9	338.4	339.9	341.3	342.9	344.8	346.7	348.4	350.0	351.6	353.9	357.0	361.7
4	321.4	324.7	327.2	328.7	330.0	331.3	332.6	333.6	334.7	335.8	336.8	338.1	339.6	341.1	342.7	344.9	347.1	350.0	353.8
5	319.6	323.6	326.3	328.6	330.7	332.6	333.2	333.9	334.5	335.2	335.8	336.5	337.1	338.3	340.2	342.2	344.7	347.2	351.3
6	313.7	317.8	320.3	322.8	324.9	327.0	328.5	329.8	331.1	332.3	334.3	336.4	338.3	340.0	341.7	344.2	347.5	349.4	351.4
7	317.8	322.3	324.4	326.5	328.8	331.4	333.9	336.1	338.3	340.6	342.7	344.3	345.8	347.4	350.3	353.1	355.6	358.1	360.3
8	322.9	327.6	330.7	333.1	334.7	336.3	337.8	339.2	340.6	342.0	343.5	345.2	346.8	348.3	349.5	350.8	352.0	354.8	359.3
9	301.3	302.5	306.7	309.5	311.9	313.7	315.3	316.9	318.4	320.0	321.6	323.3	325.4	327.5	329.7	331.8	334.1	336.5	340.7
10	304.6	309.4	312.8	315.0	317.2	319.0	320.8	322.6	323.9	325.2	326.5	328.1	330.4	332.6	333.8	334.9	336.0	337.2	341.3
11	314.6	319.2	322.5	324.2	325.8	327.5	329.0	330.5	332.0	333.6	335.3	337.0	338.4	339.6	340.9	342.2	344.3	346.8	351.3
12	313.8	317.9	321.4	323.9	326.0	327.9	329.3	330.7	332.2	333.5	334.8	336.2	337.5	339.2	340.8	342.5	345.6	348.9	352.3
13	314.6	319.2	322.5	323.9	325.3	326.7	328.3	330.4	332.5	334.1	335.7	337.3	339.5	341.9	344.6	347.5	350.1	352.7	358.8
14	319.6	324.4	327.8	329.6	331.5	333.1	334.4	335.6	336.9	338.1	339.2	340.4	341.6	342.8	344.6	346.3	348.4	351.6	356.4
15	313.5	320.0	323.8	326.9	328.7	330.1	331.6	333.2	334.9	336.7	338.4	340.2	341.9	343.9	345.9	348.0	350.8	354.1	358.8
16	321.8	327.4	331.1	334.2	336.9	339.3	341.6	343.6	345.5	347.4	349.1	350.8	352.5	354.2	355.8	357.5	359.8	362.0	366.3
17	326.0	334.3	339.2	342.8	345.6	348.2	350.6	353.3	357.1	359.8	362.5	365.9	368.3	370.0	371.6	373.7	376.4	379.5	383.1
18	321.8	327.0	329.8	332.3	333.9	335.4	336.9	338.9	341.2	343.5	345.7	347.9	349.6	351.4	353.4	355.7	358.3	362.7	368.9
19	316.1	321.2	324.6	327.5	329.6	331.7	333.5	335.3	337.1	338.6	340.0	341.4	342.8	344.5	346.1	347.9	350.6	353.8	359.0
20	314.6	318.7	321.4	323.2	324.2	325.3	326.4	327.5	329.2	330.9	332.6	334.3	335.9	337.6	339.3	341.1	343.2	346.5	352.5
21	314.7	320.5	323.9	326.5	328.7	330.6	332.4	334.0	335.6	337.1	338.5	339.9	341.3	342.7	344.4	346.2	348.3	351.8	357.5
22	325.5	328.6	330.4	332.1	334.4	336.8	338.4	339.6	340.9	342.1	343.4	344.8	346.2	347.7	349.3	351.0	352.9	356.0	360.7
23	316.8	321.7	324.9	327.7	329.9	332.0	333.7	335.2	336.7	338.2	339.7	341.3	342.8	344.7	346.5	348.8	351.6	355.6	362.3
24	317.8	322.7	325.7	328.2	329.9	331.6	333.1	334.4	335.7	337.0	338.8	340.8	342.8	344.3	345.9	347.5	350.2	353.6	362.5
25	323.2	327.8	330.5	333.1	335.9	338.2	339.7	341.3	342.8	344.3	345.8	347.3	349.3	351.4	353.9	356.7	359.3	361.8	365.9
26	333.9	338.2	340.9	343.3	345.0	346.8	348.5	350.2	351.9	353.5	355.2	356.8	358.7	360.7	362.8	365.0	367.1	370.7	376.1
27	316.7	323.2	326.8	329.2	331.3	333.2	335.0	336.8	338.6	340.5	342.4	343.8	345.1	346.5	348.1	350.6	353.2	356.3	360.9
28	326.1	330.4	333.6	336.0	338.2	340.1	342.0	343.9	345.8	347.7	349.5	351.2	352.9	354.2	355.5	356.8	358.8	361.7	367.0
29	312.2	317.1	320.4	323.2	325.3	327.3	329.1	330.9	332.7	334.3	336.0	337.7	339.7	341.6	343.8	346.3	349.2	352.6	358.3
30	318.3	322.8	325.5	328.0	329.9	331.8	333.5	335.0	336.6	338.1	339.6	341.1	342.7	344.4	346.2	348.1	350.6	353.4	357.7
31	314.9	319.6	322.9	325.2	327.5	329.4	331.3	333.1	334.9	336.6	338.3	340.0	341.6	343.3	345.2	347.0	349.7	352.7	357.4
32	307.6	312.3	315.3	317.9	319.9	321.9	323.7	325.3	326.9	328.5	330.0	331.6	333.3	335.2	337.1	339.5	341.9	345.7	350.7
33	310.8	315.6	318.9	321.5	323.7	325.6	327.5	329.2	330.9	332.6	334.2	335.9	337.6	339.5	341.3	343.5	346.1	349.4	354.1
34	305.6	310.4	313.7	316.3	318.6	320.5	322.5	324.2	325.8	327.5	329.2	330.9	332.6	334.4	336.3	338.4	340.9	344.1	349.0
35	311.7	316.9	319.8	322.5	324.3	326.1	327.9	329.4	331.0	332.5	334.5	336.5	338.4	340.3	342.1	344.4	346.8	350.2	355.0
36	315.1	319.9	323.2	325.5	327.9	330.3	332.7	334.7	336.7	338.8	340.8	342.9	345.0	347.1	349.7	352.3	355.8	359.9	364.0
37	314.5	318.7	321.4	323.6	325.4	327.2	328.7	330.2	331.6	333.0	334.4	335.9	337.3	338.9	340.6	342.3	344.8	347.3	351.5
38	309.6	313.4	315.1	316.8	319.0	321.5	323.7	325.6	327.5	329.0	330.6	332.1	333.7	335.3	336.9	338.9	341.2	344.1	347.8
39	310.9	315.8	319.1	321.9	324.0	326.0	327.9	329.6	331.2	332.9	334.6	336.3	338.0	339.8	341.6	343.8	346.3	349.6	354.2
40	319.7	325.3	328.9	331.7	333.9	335.8	337.9	340.1	342.4	345.0	347.6	350.0	352.4	354.8	357.2	359.8	362.4	364.1	365.8
41	321.1	326.0	329.3	332.0	334.1	336.1	338.0	339.8	341.5	343.2	344.8	346.4	348.2	350.2	352.3	354.8	357.4	361.4	366.5
42	310.4	314.8	317.9	319.9	321.9	323.5	325.0	326.4	327.9	329.2	330.6	332.0	333.4	334.8	336.3	337.9	340.2	342.5	346.2
43	311.0	315.0	317.9	319.8	321.7	323.3	324.8	326.2	327.6	329.1	330.5	331.9	333.4	334.9	336.5	338.3	340.6	343.2	346.8
44	306.1	309.8	312.7	315.0	317.4	319.2	321.0	322.7	324.3	325.9	327.5	329.3	331.0	333.0	335.5	338.1	340.5	343.1	346.3
45	290.1	294.4	297.5	300.5	303.2	305.3	307.3	309.0	310.7	312.3	314.0	315.6	317.2	319.0	320.9	322.9	325.5	328.4	333.3
46	287.8	292.4	295.0	297.5	299.2	301.0	302.7	304.2	305.7	307.1	308.6	310.1	311.6	313.3	315.1	317.0	319.6	322.5	326.7
47	286.4	291.6	294.6	297.1	299.1	301.1	302.9	304.6	306.3	308.0	309.6	311.3	313.1	315.0	317.0	319.1	321.2	323.8	327.2
48	292.6	295.4	297.9	299.5	301.2	302.7	304.0	305.2	306.4	307.6	308.9	310.2	311.5	312.9	314.4	316.0	317.5	320.3	323.7
49	292.0	296.6	299.6	302.3	304.2	306.1	307.9	309.4	310.9	312.4	314.0	315.6	317.2	318.9	320.7	322.5	325.0	327.5	332.0
50	293.8	298.8	301.9	304.1	306.1	307.9	309.4	310.8	312.3	313.6	315.0	316.4	317.8	319.6	321.4	323.5	326.0	329.5	336.3

51	297.9	302.7	305.5	308.1	310.0	311.8	313.5	315.0	316.6	318.1	319.8	321.4	322.9	324.4	325.9	327.4	329.9	332.6	337.2
52	306.7	311.3	314.3	316.9	319.0	320.9	322.7	324.3	326.0	327.6	329.2	330.8	332.4	334.3	336.2	338.3	340.8	343.8	348.3
53	308.1	313.1	315.9	318.4	320.3	322.2	323.8	325.4	327.0	328.6	330.2	331.7	333.5	335.5	337.5	339.7	341.9	345.0	349.5
54	312.8	316.0	318.4	320.1	321.8	323.2	324.5	325.7	326.9	328.1	329.3	330.5	331.7	333.1	334.6	336.2	337.9	340.4	343.5
55	293.4	297.7	300.1	302.5	304.3	306.0	307.9	310.0	312.2	314.0	315.9	317.7	319.5	321.3	323.3	325.5	327.7	331.2	335.9
56	300.1	304.7	308.1	310.8	313.2	315.2	317.2	319.1	321.0	322.9	324.8	326.6	329.0	331.9	333.9	335.7	337.5	340.3	343.8
57	302.0	307.6	310.9	313.6	315.7	317.9	320.0	322.0	324.0	325.8	327.7	329.5	331.4	333.2	335.2	337.2	339.7	342.3	346.7
58	307.6	312.2	315.2	317.9	319.8	321.7	323.4	325.1	326.7	328.3	329.9	331.6	333.3	335.1	336.9	339.3	341.9	345.2	349.6
59	301.6	306.0	309.1	311.6	313.7	315.6	317.4	319.0	320.6	322.1	323.7	325.3	326.8	328.6	330.6	332.6	335.3	338.3	342.4
60	302.0	307.0	310.2	312.9	314.7	316.5	318.1	319.6	321.0	322.4	323.8	325.2	326.6	328.2	330.0	331.9	334.3	337.0	341.9
61	304.1	310.0	313.5	316.0	318.3	320.3	322.2	323.9	325.5	327.2	328.9	330.6	332.3	334.3	336.3	338.7	341.6	344.9	348.9
62	309.2	313.8	316.8	318.9	320.7	322.5	323.9	325.3	326.7	328.1	329.5	330.9	332.2	333.8	335.5	337.1	339.5	342.2	346.7
63	307.9	312.7	315.4	318.0	320.1	322.2	324.0	325.7	327.5	329.1	330.8	332.5	334.3	336.1	337.9	340.0	342.0	345.1	349.3
64	299.4	305.0	308.8	311.8	313.8	315.5	317.2	318.7	320.1	321.5	322.9	324.3	325.7	327.1	329.2	331.4	334.1	337.3	342.2

Table 16. R^1 for Prediction Markets Interpolated Quantiles and Quantile Regressions

Quan-tiles	NFP			RSX			ISM			ICL			NORM		
	PM quant	EX qreg	PM qreg	PM quant	EX qreg	PM qreg	PM quant	EX qreg	PM qreg	PM quant	EX qreg	PM qreg	PM quant	EX qreg	PM qreg
.05	.1396	.2191	.2737	.2802	.3496	.5841	.6419	.7802	.8395	.0094	.0939	.1136	.2444	.1770	.2421
.10	.1735	.2583	.2571	.3407	.3287	.5170	.6846	.7905	.8236	.0301	.0751	.1106	.2484	.1865	.2157
.15	.1887	.2800	.2770	.2845	.2098	.3981	.7106	.7870	.8091	.0487	.0609	.1014	.2618	.2160	.2267
.20	.1661	.2904	.2919	.2353	.1720	.2845	.7405	.7902	.7993	.0532	.0823	.1105	.2587	.2354	.2441
.25	.1767	.3062	.3017	.2066	.1460	.2108	.7593	.7911	.7972	.0583	.1018	.1204	.2603	.2469	.2553
.30	.2099	.3169	.3169	.1734	.1241	.1596	.7603	.7897	.7960	.0609	.1161	.1277	.2585	.2509	.2556
.35	.2438	.3213	.3203	.1371	.1022	.1432	.7564	.7812	.7894	.0504	.1121	.1273	.2530	.2506	.2556
.40	.2626	.3217	.3120	.1222	.1055	.1419	.7608	.7731	.7865	.0368	.0959	.1177	.2505	.2477	.2569
.45	.2698	.3086	.3002	.1221	.0977	.1532	.7657	.7628	.7820	.0314	.0863	.1093	.2502	.2419	.2590
.50	.2796	.3004	.2936	.1317	.0951	.1607	.7732	.7556	.7831	.0394	.0738	.1002	.2598	.2358	.2671
.55	.2791	.2848	.2793	.1316	.0849	.1613	.7772	.7488	.7798	.0591	.0686	.0985	.2698	.2299	.2701
.60	.2667	.2654	.2747	.1513	.0807	.1576	.7794	.7421	.7772	.0681	.0639	.1046	.2714	.2163	.2663
.65	.2589	.2530	.2766	.1483	.0823	.1469	.7718	.7337	.7698	.0788	.0500	.1015	.2715	.2003	.2570
.70	.2584	.2505	.2796	.1601	.0934	.1574	.7582	.7252	.7621	.0739	.0481	.0886	.2676	.1830	.2401
.75	.2734	.2518	.2841	.1703	.1053	.1740	.7235	.7109	.7524	.0510	.0491	.0808	.2593	.1758	.2275
.80	.3194	.2735	.3048	.1807	.1045	.1731	.6741	.6903	.7305	.0128	.0250	.0509	.2448	.1513	.2091
.85	.3144	.2912	.3092	.1638	.0808	.1698	.6098	.6578	.6883	-.0116	.0174	.0309	.2188	.1226	.1749
.90	.2850	.2670	.2788	.1725	.0468	.1634	.5273	.6083	.6051	-.0625	.0343	.0627	.1665	.0842	.1346
.95	.2638	.2084	.2604	.2195	.0404	.2129	.3797	.4815	.5189	-.0827	.1082	.1603	.1342	.0685	.1361

Table 17. R[1] for Prediction Markets Interpolated Quantiles and Quantile Regression on Prediction Markets Interpolated Quantiles

Quan-tiles	NFP		RSX		ISM		ICL		NORM	
	PM quant	PMQ qreg	PM quant	PMQ qreg	PM quant	PMQ qreg	PM quant	PMQ qreg	PM quant	PMQ qreg
.05	.1396	0.2309	.2802	0.4519	.6419	0.8204	.0094	0.0865	.2444	0.2603
.10	.1735	0.2212	.3407	0.4656	.6846	0.8162	.0301	0.1091	.2484	0.2527
.15	.1887	0.2027	.2845	0.3919	.7106	0.8039	.0487	0.1048	.2618	0.2662
.20	.1661	0.2137	.2353	0.3250	.7405	0.7916	.0532	0.1142	.2587	0.2631
.25	.1767	0.2493	.2066	0.2525	.7593	0.7923	.0583	0.1206	.2603	0.2606
.30	.2099	0.2788	.1734	0.1804	.7603	0.7921	.0609	0.1266	.2585	0.2606
.35	.2438	0.3020	.1371	0.1455	.7564	0.7906	.0504	0.1247	.2530	0.2595
.40	.2626	0.3093	.1222	0.1552	.7608	0.7907	.0368	0.1157	.2505	0.2608
.45	.2698	0.3049	.1221	0.1687	.7657	0.7818	.0314	0.1098	.2502	0.2640
.50	.2796	0.3019	.1317	0.1800	.7732	0.7839	.0394	0.1018	.2598	0.2707
.55	.2791	0.2939	.1316	0.1909	.7772	0.7822	.0591	0.1022	.2698	0.2785
.60	.2667	0.2958	.1513	0.1989	.7794	0.7795	.0681	0.1116	.2714	0.2776
.65	.2589	0.3003	.1483	0.1843	.7718	0.7783	.0788	0.1105	.2715	0.2743
.70	.2584	0.2952	.1601	0.1847	.7582	0.7698	.0739	0.0950	.2676	0.2676
.75	.2734	0.2971	.1703	0.1886	.7235	0.7566	.0510	0.0861	.2593	0.2605
.80	.3194	0.3275	.1807	0.2005	.6741	0.7297	.0128	0.0678	.2448	0.2454
.85	.3144	0.3448	.1638	0.2015	.6098	0.6711	-.0116	0.0492	.2188	0.2190
.90	.2850	0.3485	.1725	0.2127	.5273	0.5663	-.0625	0.0781	.1665	0.1846
.95	.2638	0.3377	.2195	0.2440	.3797	0.4084	-.0827	0.1568	.1342	0.1712