# Noisy Macroeconomic Announcements, Monetary Policy, and Asset Prices*
## *PRELIMINARY and INCOMPLETE*
## *Do not quote.*

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## 1 Introduction

The relationship between macroeconomic shocks with asset prices and monetary policy is perhaps one of the most studied questions in macroeconomics. This questions started to be answered by looking at relatively low frequency data, dealing with the problem of simultaneity, and the measurement of expectations. Lately, with the advent of market surveys and the "almost" real time data we have improved tremendously our understanding of the relationship between macroeconomic shocks and asset prices. The survey of market participants has being used as a very good measure of market expectations, while the high frequency data has eliminated the issues of edogeneity almost entirely.[1] The recent literature using high frequency data has being able to find statistically significant coefficients, that most of the time coincide with what the theory predicts.[2] However, with only the exception of monetary policy shocks, the coefficients are extremely small − indeed, implausible small.

In this paper we argue that the main problem is that the measurment of the macro "news" is noisy, and therefore, the estimates used in the standard literature are plagged with error-in-variable biases. We propose a new methodology to improve the estimates, and applied to several macroeconomic variables, asset prices, and monetary policy. We find tremendous improvements in the estimated coefficients − some of them increase in more than 10 times! As an additional outcome, the methodolgy estimates the average noise that each macro announcement posses.

*We thank...*Comments are welcome* to bsack@frb.gov or rigobon@mit.edu. The opinions expressed are those of the authors and do not necessarily reflect the views of the Board of Governors of the Federal Reserve System or other members of its staff.

[1] See XXXXX

[2] Anderson finds XXXX, Faust finds XXX, summarize a little bit what people get at the macro level and in the exchange rate

The paper is organized as follows: Section 2 describes the problem and describes the methodology in detail. Section  applies the methodology to several macroeconomic announcements, asset prices, and monetary policy. We compare the estimates from the standard specification, from those obtained using our methodology. Section  concludes.

## 2 Estimating the Effect of Macroeconomic Announcements

The most recent papers measuring the impact of macroeconomic announcements on asset prices use the following two sources of data.

EXPLAIN MMS (to be completed)

EXPLAIN REAL DATA (to be completed)

The typical especification estimated in all these papers is the following:

$$\Delta s_t = \gamma z_t + \varepsilon_t \tag{1a}$$

$$z_t = M_t - E_{t-\tau}\left[M_t\right] \tag{1b}$$

where $E_{t-\tau}\left[M_t\right]$ is the survey collected by MMS where agents indicate their expectations at time $t-\tau$ of the macroeconomic announcement at time $t$. $M_t$ is the macroeconomic announcement, and therefore $z_t$ defined as the differencde is a measure of the news. Finally, $\Delta s_t$ is the change of the asset price aroung the macroeconomic announcement, and the coefficient of interest is $\gamma$.

This specification has been very useful to improve our understanding of how macroeconomic effects impact asset prices; and rightfuly so. First, in this specification there is a measurement of the market expectations. the older literature had to model expectations either as past realized values of the macroeocnomic variables, or as the outcome of forecasting models - which usually depended on dubious identification assumptions. Second, and perhaps the most important one, is the fact that at high frequencies the feedback of asset price changes on macroeconomic variables is almost entirely eliminated. The only exception might be monetary policy, but excluding that, all macro announcements are clearly measured before the asset price movement actually takes place.

One immediate payoff of using this specification has been that the coefficients are statistically significant and of the correct sign - which was almost never the case when papers were using quarterly or anual data. Although this is encouraging, the main problem of those papers is that the coefficients are implausible small.

For example, (to be completed)

### 2.1 The econometric problem

In model (1) implicitly it is assumed that the expectation are indeed a correct measure of what the market expects. This is a strong assumption. First, the survey is by construction a random variable that at best is unbiased but not without error. Second, agents might change their views from the time the survey was conducted until the time the actual announcement takes place.

Therefore, our view is that the macro-news measured in this literature is a noisy measure of the true announcement. Implying that the coefficients we have estimated suffer from error-in-variable biases.

To understand the source of the problem, as before, assume the asset price change between time $t-dt$ and $t$ is denoted by $\Delta s_t$. Assume that the announcement or macro release takes place at time $t$ and the news measured by the difference between the MMS survey and the release is $z_t$. However, assume that the release is an imperfect measure of the underlying "truthful" macro new. Formally,

$$\begin{aligned} z_t &= M_t - E_{t-\tau}\left[M_t\right] \\ z_t^* &= M_t - E_{t-dt}\left[M_t\right] \end{aligned}$$

The change in the asset price is govern by the "truthful" news

$$\Delta s_t = \gamma z_t^* + \varepsilon_t.$$

Notice that the two news are related as follows:

$$\begin{aligned} z_t &= z_t^* + \eta_t \\ \eta_t &= E_{t-dt}\left[M_t\right] - E_{t-\tau}\left[M_t\right]. \end{aligned}$$

where $\eta_t$ can be interpreted as an error-in-variables. Which indeed captures exactly our intuition that the error in the measurement of the news is coming entirely from the mismeasurement of the expectations. Obviously there can be another source of miss-measurement that can be summarized by the fact that $M_t$ is incorrectly measured, but that the market participants know the true realization. This noise can have two sources: one is that in fact macro announcements are quite complex and there are several dimensions that can move markets. In general we concentrate on those figures that are the ones that receive most of the attention. However, it is possible that the complexity of the announcement implies that not always the market is fully reacting to the particular number we are measuring. The second source is that the macro announcement has a bias and the market is able to resolve the signal extraction problem better than the econometrician. All these sources of noise have the exact same reduced form as the one we will deal in this paper, and therefore, the methodology we develop might help to solve those instances as well. Nevertheless, the interpretation of our results is different depending on what is the source of the error-in-variables. We prefer the explanation based on the miss-measurement of the expectations because we believe is the most relevant one - and therefore, all our interpretations will assume as if we were dealing exclusively with that source of noise.

We do not observe $z_t^*$ and therefore, we end up estimating

$$\Delta s_t = \gamma z_t + \nu_t, \tag{2a}$$

$$v_t = \varepsilon_t - \gamma \eta_t. \tag{2b}$$

Assume that the true news have variance of $\sigma_{z^*}$, that the error-in-variables has mean zero conditional on all shocks and macro realizations ($E\left[\eta_t | \varepsilon_t, z_t^*\right] = 0$) and variance $\sigma_\eta$. Finally, assume that the residual of the asset price not explained by the macro shock has mean zero conditional on the news, and the error-in-variables ($E\left[\varepsilon_t | \eta_t, z_t^*\right] = 0$) and has variance $\sigma_\varepsilon$. These assumptions imply that the OLS estimate on equation (2) is

$$\hat{\gamma}_{OLS} = \gamma - \gamma \frac{\sigma_\eta}{\sigma_{z^*} + \sigma_\eta}$$

Under our simplifying assumptions, the error-in-variables is classical and therefore the OLS estimates are downward biased. The usual solution would be to find an instrument, something that is correlated with the macro news, but that is correlated with the error of the expectations. In practice, those instruments do not exist, leaving the problem of estimation unresolved.

### 2.2 Identification Through Censoring

The problem of error-in-variables is indeed a problem of identification. The issue is that in the data we can only compute three statistics: the variance of the asset price, the variance of the macro news, and their covariance, but these sample moments are explained by four possible parameters: $\gamma$, $\sigma_\varepsilon$, $\sigma_\eta$, and $\sigma_{z^*}$. In particular

$$\begin{aligned} var\left(\Delta s_t\right) &= \gamma^2 \sigma_{z^*} + \sigma_\varepsilon \\ var\left(z_t\right) &= \sigma_{z^*} + \sigma_\eta \\ cov\left(\Delta s_t, z_t\right) &= \gamma \sigma_{z^*} \end{aligned}$$

There are three equations and four unknowns and that means that there is a continuum of solutions. The instrumental variable solves this problem of identification. Formally,

$$\begin{aligned} \Delta s_t &= \gamma z_t^* + \varepsilon_t \\ z_t &= z_t^* + \eta_t \\ z_t^* &= \beta w_t + \nu_t \end{aligned}$$

where the instrument is $w_t$, which it is assumed to be uncorrelated with all shocks. Notice that we observe three variables: $\Delta s_t$, $z_t$, and $w_t$. This implies that we can estimate 6 moments in the data, three variances and three co-variances. The unknowns are $\beta$, $\gamma$, $\sigma_\varepsilon$, $\sigma_\eta$, $\sigma_\nu$, and $\sigma_w$. Six equations and six unknowns. We still have to show that these are independent equations (satisfying the rank condition), but that only requires that $\beta$ is different from zero.

In the absence of a valid instrument, the question is how can we solve the problem of identification. The next section describes the methodology we use in the simplest case. This explains the intuition behind the *identification through censoring*. Later we extend the methodology in several directions.

#### 2.2.1 Case I: One macro announcement with homoskedastic asset price innovations

Assume the innovations to the asset price are homoskedastic, and assume there is only one shock. One feature of macro announcements is that they occur at pre-specified days - which means that by construction they are exactly equal to zero in the other days. This is important because when the variable is exactly equal to zero it means that its error-in-variables is zero as well.[3]

Formally, this means that

$$\Delta s_t = \begin{cases} \gamma z_t + \varepsilon_t & t \in D \\ \varepsilon_t & t+1 \in D \end{cases}$$

[3] This intuition comes from Rothemberg (19XX) who argues that the variance of the error-in-variables in survey data depends on the size of the announcement. If you ask any of us how many cigarettes we smoke we will answer zero - which has no error-in-variables whatsoever. A one cigar a day smoker clearly will have a much smaller error than someone that smokes pack and a half a day. Hence, censoring implies no error-in-variables as well. We are extending this simple observation to finance where several of the macro variables are censored.

where $D$ is the day (or time) when the announcement takes place.

Assume that we observe the volatility of the asset price an instant before the macro news is released, then, under the assumption of homoskedasticity this is a measure of $\sigma_{\varepsilon}$. Therefore, the system of equations is

$$\begin{aligned} var\left(\Delta s_{t-1}\right) &= \sigma_{\varepsilon} \\ var\left(\Delta s_{t}\right) &= \gamma^{2}\sigma_{z^{*}}+\sigma_{\varepsilon} \\ var\left(z_{t}\right) &= \sigma_{z^{*}}+\sigma_{\eta} \\ cov\left(\Delta s_{t}, z_{t}\right) &= \gamma\sigma_{z^{*}} \end{aligned}$$

which has four equations and four unknowns!

Notice that $\gamma$ can be recovered exactly as

$$\gamma=\frac{var\left(\Delta s_{t}\right)-var\left(\Delta s_{t-1}\right)}{cov\left(\Delta s_{t}, z_{t}\right)}. \tag{3}$$

This estimator is in the spirit of Rigobon and Sack (2004) where we also compute the change in the variance of the macro variable and the change in the covariance between the macro variable and monetary policy. Here, however, the change in the covariance is just the covariance, because the macro announcement takes the value of zero before the release.

Notice that this procedure is very different from the typical procedure. The idea of solving the problem of identification is to find additional equations, the IV achieves that by offering additional covariances of the observed variables and the instrument, here, we use the information prior to the release as a measure of one of the structural shocks. In the end, the procedure is essentially the same - find additional equations.

#### 2.2.2 Case II: One macro announcement with heteroskedastic asset price innovations

The previous procedure obviously relies on the homoskedasticity of the structural shocks in the asset price equation ($\varepsilon_t$). Obviously this is a strong assumption. Rarely, those shocks will have invariant second moments. However, it is possible to learn about their path by observing the behavior of the variance when the macro shocks are absent.

For example, assume that we observe some release at 9:30. The assumption in the previous case is that the variance of $\varepsilon_t$ between 8:00 and 8:30 is the same as the variance between 9:30 and 10:00. If we observe the days in which there are no macro announcements this hypothesis is easily rejdected for almost all asset prices. However, imagine that we can assume that the change in the variance of the structural shocks is the same regardless if there are macro shocks or not. In this case,

$$\begin{aligned} var\left(\Delta s_{t-1,8:00}\right) &= \sigma_{\varepsilon,t-1,8:00} \\ var\left(\Delta s_{t-1,9:30}\right) &= \sigma_{\varepsilon,t-1,9:30} \\ var\left(\Delta s_{t,8:00}\right) &= \sigma_{\varepsilon,t,8:00} \\ var\left(\Delta s_{t,9:30}\right) &= \sigma_{\varepsilon,t,9:30}+\gamma^{2}\sigma_{z^{*}} \\ var\left(z_{t}\right) &= \sigma_{z^{*}}+\sigma_{\eta} \\ cov\left(\Delta s_{t}, z_{t}\right) &= \gamma\sigma_{z^{*}} \end{aligned}$$

identification will be achieved if

$$\sigma_{\varepsilon,t-1,9:30} - \sigma_{\varepsilon,t-1,8:00} = \sigma_{\varepsilon,t,9:30} - \sigma_{\varepsilon,t,8:00}.$$

In other words, if we can assume that the change in the variance of the shocks driving asset prices that are not explained by the macro announcements evolve similarly, then we can still obtain an estimate of $\sigma_{\varepsilon,t,9:30}$ and solve the problem of identification.

Notice that this is NOT assuming that the variance of the asset price changes by the same amount in the days of the macro announcement and in the days of no announcements. What we are assuming is that this is true only for the variance of $\varepsilon_t$.

An important question that should arise at this time is what happens if the change in the variance of $\varepsilon_t$ is not exactly the same. For example, it is possible to argue that in anticipation to the macro release, activity at 8:00 could bre particularly low. If that is the case, then the estimate of $\sigma_{\varepsilon,t,9:30}$ is smaller than the true one. This is indeed a plausible case. Notice that the estimator is given by equation (3), where $var\,(\Delta s_{t-1})$ is substituted by $\sigma_{\varepsilon,t,9:30}$. If the estimate of $\sigma_{\varepsilon,t,9:30}$ is smaller than the true one, the estimator of $\gamma$ is biased upward. On the other hand, if the estimate of $\sigma_{\varepsilon,t,9:30}$ is larger than the true one (maybe there is more volatility in anticipation of the macro release) then the estimator would be upward biased.

To assess the importance of this effect, in the empirical application we compare the variances at 8:00 in those days with and without macro announcements. Also, we use different periods and check the robustness of our results by defining the period of reference as the 2:30-4:00 of the previous day.

Before studying the next case it is important to mention that the procedure possibly does not fully corrects the OLS coefficients when there is heteroskedasticity. However, it will provide an improvement, if the change in the variance can be approximated.

### 2.2.3 Case III: Multiple macro announcements

The previous cases study the very simple case in which there is one macro announcement. With very few exceptions, this never occurs. Almost every single announcement occurs at the same time than others. For simplicity, let us study first the case of two announcements and understand that the identification is lost. Also for simplicity let us assume that the structural shock $\varepsilon_t$ is homoskedastic.

Assume that the model is the following

$$\begin{aligned}
\Delta s_t &= \gamma_1 z_{1,t}^* + \gamma_2 z_{2,t}^* + \varepsilon_t \\
z_{1,t} &= z_{1,t}^* + \eta_{1,t} \\
z_{2,t} &= z_{2,t}^* + \eta_{2,t}
\end{aligned}$$

where the errors in the variables are likely to be correlated. How many equations do we have? The covariance matrix of the asset price and the two macro announcements that provides 6 equations, plus the variance of the asset price when there are no macro announcements which provides another moment, and provides directly information on the variance of $\varepsilon_t$. These are 7 equations. But the model has more unknowns! $\gamma_1$, $\gamma_2$, $\sigma_\varepsilon$, $\sigma_{z_1^*}$, $\sigma_{z_2^*}$, $\sigma_{\eta_1}$, $\sigma_{\eta 2}$, and the covariance between $\eta_1$ and $\eta_2$. These are 8 unknowns. In fact, if we have three macro variables the number of unknowns grows faster than the computed moments.

There are two solutions to this problem, and indeed, we use both simultaneously in the empirical application.

**Non-coincident Censoring Announcements:** Assume that there are days in which $z_{1,t}$ is released, other days in which $z_{2,t}$ is released, and days in which both are released. This means that some days, when there is only one macro announcement being released, the noise in the other macro announcement is zero, and therefore the covariance between the noises is also zero. Which means that the problem of identification will be solved.

By eliminating the variable in some of the days, we are transforming the problem of multiple macro variables into a problem of only one macro announcement in a subset of them. This should be a simple solution.

However, there are some announcements that always come together. Hence, this trick would not work.

**Several Asset Prices:** Assume, that the announcements occur at the exact same time, and that now we have several asset prices. For simplicity, assume that there are two assets and two macro shocks that occur together all the time — so, we cannot use the strategy we described before.

Assume that the asset prices and the noisy macro announcements are described as follows:

$$
\begin{aligned}
\Delta s_{1,t} &= \gamma_{1,1} z_{1,t}^* + \gamma_{1,2} z_{2,t}^* + \varepsilon_{1,t} \\
\Delta s_{2,t} &= \gamma_{2,1} z_{1,t}^* + \gamma_{2,2} z_{2,t}^* + \varepsilon_{2,t} \\
z_{1,t} &= z_{1,t}^* + \eta_{1,t} \\
z_{2,t} &= z_{2,t}^* + \eta_{2,t}
\end{aligned}
$$

where the structural shocks ($\varepsilon$) are possible correlated, and the noises of the macro announcements are, as before, also correlated.

Let us count the number of knowns and unknowns in case: In the days in which there are announcements we have four variables, which account for 10 moments. Also, when there are no news we estimate the covariance matrix of the two asset prices which provides 3 more equations. This is a total of 13 equations or moments that can be estimated in the data taking into account the censoring and uncensoring samples. The number of unknowns is: we have four parameters ($\gamma's$) — which are the parameters of interest — the covariance matrix of the structural shocks $\varepsilon's$ (3), the covariance matrix of the noises $\eta's$ (3) and the covariance matrix of the true news $z^{*\prime}s$ (3). Notice that we allow the macro fundamentals to be correlated. This accounts for exactly 13 unknowns — this satisfies the rank condition. In the end, the system is just identified if all the equations are independent.

What achieves identification? The reason behind the identification of the parameters is the fact that the noise in the macro announcement has to be the same independently of the asset price we are estimating. Hence, those natural restrictions allow us to estimate the whole system.

### 2.2.4 Asymptotic properties

(to be completed)

Consistency under the assumptions:

Asymptotic Normality:
Asymptotic Variance:

# 3 Estimating the impact of macroeconomic announcements

## 3.1 Data

DESCRIBE THE DATA!! summarize some of the properties of the data. like number of concurrent news, which ones are together, which ones are not. also, number of days without news. draw the variance in the days withouth news through out the day, and compute their variances

## 3.2 Results

We estimated the OLS coefficients for several macro announcements on interest rates and stock markets by OLS. The results are shown in Table 1. The table organized as follows. All the macro announcements at 8:30 are shown first, then the announcements at 9:15, and then the announcements at 10:00. The name of the macro announcements are shown in the first column. We study the effect of these macro news on 7 asset prices. The two year rate (Y2), the 10 years rate (Y10), four short term rates on eurodollars (1, 2, 3, and 4 months) and the S&P 500. We have included more assets, and eliminated some of these assets and the results are almost identical. For every entry we show the point estimate and its standard deviation. Separate regressions are indicated by the thin line. In other words, whenever two (or more) macro releases are considered together in the estimations, the results are presented together. Finally, because there is no trade on the S&P 500 at 8:30, but there is trade on future markets, we can only estimate the impact of the 8:30 releases on the interest rate.

[very preliminary, needs to be completed]

In Table 1 the first entry is the impact of non-farm payrolls and unemployment news. These news always occur at the same time and therefore are estimated together. The estimates are similar to those obtained in other studies. An increase in unemployment tends to deruce interest rates in the future. The short term rates can be interpreted as the expectation the market has on what is the path of monetary policy given the announcement. Because all the variables have been normalized by their standard deviation, the coefficients imply that a one standard deviation increase in unemployment reduces the expected short term rate by 0.39 standard deviations. Note that all estimates have the same signs (with the expected sign) and all are statistically significant.

ICLM (explain).

The third set of announcements analized are the GDP advancements. Notice that the effects in the short end of the interest rate are barely significant, and insignificant at one or 2 months. The impact is relatively large for the 2 year and 10 year rates. This is also a known result in the literature. The effect of GDP announcements are in general insignificant in the short run. One reason is that GDP shocks might have an ambiguous effect on interest rates. If the expansion of GDP is driven by a demand shock, then interest rates should increase in the short run, but if it is driven by a supply shock, interest rates might come down in the short run. We explore this further when estimating the model using our GMM procedure.

Fourth, we study a pure demand shock - retail sales. As can be seen the effects are all positive and statistically significant. Roughly, a one standard deviation shock in the short run increases the interest rate by approximately half of its standard deviation. The elasticities in the long run are relatively small for a pure demand shock, however.

(to be completed)

CPI - the effects are small and relatively insignificant.

PPI - is worse than CPI.

Housing starts is very small, and also insignificant.

DGORDS - also small.

9:15 news

industrial production has a negligible effect

10:00 news

consumer confidence is perhaps the most important one. the effect is small. also new homes is small. explain factory orders as well.

In Table 2 we present the estimates using our procedure.

Here we should highlight that the estimates are much larger in absolute value in almost all the entries - although not all of them. important items are those such as unemployment, cpi, ppi, for the 8:30. interestingly the effects in the short run sometimes are reduced, although in the long run they are all increased tremendously (more than twice in almost all estimates). Significance however is improved all around.

for the 9:15 and 10:00 estimates the effects are even bigger. industrial production is perhaps the one that has the largest improvement - both in the estimates and the significance. consumer confidence, factory orders, and new homes also show a remarkable improvement. actually the effects on the stock markets are much larger, and more reasonable - elasticities around 1). Talk about LDER because there is a tremendous deterioration in the estimation for this news. (STUDY MORE!!!)

## 4 Robustness

(to be completed)

1. change what we define as the tranquil period.

2. obtain futures data on the s&p

## 5 Conclusions

For the moment, we just conclude.

| | OLS Estimates | | | | | | |
|---|---|---|---|---|---|---|---|
| | Y2 | Y10 | ED1 | ED2 | ED3 | ED4 | S&P |
| | | | 8:30 | | | | |
| NFPAYS | 2.130 | 1.840 | 0.741 | 1.279 | 1.507 | 1.103 | |
| | 0.115 | 0.116 | 0.144 | 0.139 | 0.137 | 0.097 | |
| UNEMPS | -1.586 | -1.312 | -0.392 | -0.808 | -0.927 | -0.627 | |
| | 0.137 | 0.138 | 0.172 | 0.167 | 0.164 | 0.116 | |
| ICLMS | -0.551 | -0.459 | -0.115 | -0.228 | -0.260 | -0.204 | |
| | 0.068 | 0.065 | 0.082 | 0.082 | 0.082 | 0.058 | |
| GDPADVS | 2.589 | 1.497 | 0.491 | 0.853 | 0.965 | 0.724 | |
| | 0.368 | 0.353 | 0.447 | 0.446 | 0.446 | 0.316 | |
| RETLSS | 1.462 | 1.193 | 0.446 | 0.731 | 1.015 | 0.683 | |
| | 0.176 | 0.168 | 0.210 | 0.210 | 0.209 | 0.148 | |
| CPIXFES | 1.432 | 1.555 | 0.279 | 0.510 | 0.607 | 0.476 | |
| | 0.185 | 0.177 | 0.223 | 0.223 | 0.223 | 0.158 | |
| PPIXFES | 1.110 | 1.014 | 0.053 | 0.160 | 0.220 | 0.162 | |
| | 0.178 | 0.171 | 0.213 | 0.213 | 0.213 | 0.151 | |
| HSTARTS | 0.396 | 0.346 | -0.013 | 0.056 | 0.042 | 0.024 | |
| | 0.146 | 0.139 | 0.175 | 0.175 | 0.175 | 0.124 | |
| DGORDS | 0.930 | 0.721 | 0.105 | 0.237 | 0.308 | 0.246 | |
| | 0.135 | 0.130 | 0.163 | 0.163 | 0.163 | 0.115 | |
| | | | 9:15 | | | | |
| CAPAS | 0.998 | 0.784 | 0.668 | 1.385 | 1.200 | 0.968 | 0.204 |
| | 0.160 | 0.163 | 0.187 | 0.201 | 0.196 | 0.188 | 0.151 |
| INDPRDS | -0.018 | 0.032 | 0.155 | -0.248 | -0.034 | 0.101 | -0.179 |
| | 0.158 | 0.160 | 0.184 | 0.198 | 0.194 | 0.186 | 0.149 |
| | | | 10:00 | | | | |
| NAPMS | 1.871 | 1.782 | 1.515 | 2.029 | 2.154 | 2.065 | 0.122 |
| | 0.117 | 0.115 | 0.129 | 0.135 | 0.133 | 0.129 | 0.102 |
| PMIS | 0.848 | 0.822 | 0.911 | 1.031 | 1.221 | 1.170 | 0.632 |
| | 0.239 | 0.232 | 0.266 | 0.284 | 0.281 | 0.276 | 0.204 |
| LDERSS | 0.051 | 0.060 | 0.007 | 0.124 | 0.202 | 0.172 | -0.031 |
| | 0.147 | 0.142 | 0.162 | 0.174 | 0.172 | 0.169 | 0.125 |
| CCONFS | 1.326 | 1.050 | 1.353 | 1.539 | 1.523 | 1.297 | 0.282 |
| | 0.122 | 0.119 | 0.136 | 0.143 | 0.142 | 0.140 | 0.105 |
| NHOMESS | 0.939 | 0.735 | 1.060 | 1.063 | 1.045 | 0.964 | -0.151 |
| | 0.130 | 0.126 | 0.144 | 0.154 | 0.152 | 0.150 | 0.111 |
| FACORDS | 0.359 | 0.475 | 0.350 | 0.433 | 0.447 | 0.461 | -0.066 |
| | 0.115 | 0.111 | 0.128 | 0.136 | 0.135 | 0.133 | 0.098 |

Table 1: OLS Estimates

| | GMM Estimates | | | | | | |
|---|---|---|---|---|---|---|---|
| | Y2 | Y10 | ED1 | ED2 | ED3 | ED4 | S&P |
| | | | 8:30 | | | | |
| NFPAYS | 4.780 | 4.359 | 0.381 | 1.789 | 2.166 | 1.689 | |
| | 0.009 | 0.009 | 0.006 | 0.008 | 0.005 | 0.006 | |
| UNEMPS | -4.626 | -4.411 | -0.344 | -1.952 | -2.815 | -2.007 | |
| | 0.006 | 0.007 | 0.008 | 0.009 | 0.006 | 0.010 | |
| ICLMS | -1.109 | -1.277 | -0.020 | -0.052 | -0.075 | -0.121 | |
| | 0.003 | 0.003 | 0.001 | 0.001 | 0.001 | 0.001 | |
| GDPADVS | 3.609 | 2.073 | 0.103 | 0.281 | 0.587 | 0.609 | |
| | 0.802 | 0.747 | 0.114 | 0.092 | 0.149 | 0.215 | |
| RETLSS | 4.727 | 3.904 | 0.109 | 0.448 | 1.722 | 1.125 | |
| | 0.073 | 0.066 | 0.014 | 0.012 | 0.027 | 0.025 | |
| CPIXFES | 3.788 | 4.419 | 0.098 | 0.433 | 0.934 | 0.804 | |
| | 1.496 | 0.154 | 0.028 | 0.024 | 0.040 | 0.047 | |
| PPIXFES | 5.133 | 5.161 | 0.011 | 0.054 | 0.121 | 0.191 | |
| | 0.473 | 0.457 | 0.198 | 0.068 | 0.053 | 0.084 | |
| HSTARTS | 2.040 | 2.236 | -0.003 | 0.014 | 0.011 | 0.013 | |
| | 0.303 | 0.331 | 0.451 | 0.104 | 0.142 | 0.264 | |
| DGORDS | 2.393 | 2.297 | 0.022 | 0.073 | 0.156 | 0.263 | |
| | 0.057 | 0.050 | 0.021 | 0.010 | 0.009 | 0.014 | |
| | | | 9:15 | | | | |
| CAPAS | 0.995 | 0.246 | 0.205 | 1.181 | 0.137 | -0.082 | 1.401 |
| | 0.286 | 0.650 | 0.123 | 0.624 | 0.576 | 0.424 | 0.192 |
| INDPRDS | 1.749 | 2.789 | 3.038 | 2.369 | 4.313 | 4.124 | -1.929 |
| | 0.374 | 0.778 | 0.162 | 0.797 | 0.667 | 0.487 | 0.187 |
| | | | 10:00 | | | | |
| NAPMS | 3.680 | 3.696 | 3.030 | 3.751 | 3.910 | 3.604 | 1.279 |
| | 0.028 | 0.012 | 0.019 | 0.015 | 0.012 | 0.010 | 0.004 |
| PMIS | 2.273 | 2.173 | 2.519 | 2.550 | 2.995 | 2.705 | 1.496 |
| | 0.497 | 0.580 | 0.441 | 1.234 | 0.801 | 0.461 | 0.580 |
| LDERSS | 2.713 | 11.677 | 0.003 | 0.122 | 0.126 | 0.105 | -6.481 |
| | 12.017 | 50.649 | 28.590 | 1.675 | 1.097 | 1.228 | 36.558 |
| CCONFS | 3.368 | 2.717 | 4.457 | 3.867 | 3.915 | 3.360 | 0.761 |
| | 0.022 | 0.035 | 0.016 | 0.019 | 0.024 | 0.031 | 6.997 |
| NHOMESS | 2.513 | 2.219 | 3.008 | 2.982 | 2.953 | 2.747 | -1.215 |
| | 0.051 | 0.072 | 0.133 | 0.087 | 0.112 | 0.187 | 0.021 |
| FACORDS | 2.105 | 2.121 | 1.777 | 1.355 | 1.113 | 1.512 | -1.049 |
| | 0.031 | 0.206 | 0.042 | 0.023 | 0.017 | 0.026 | 0.018 |

Table 2: GMM Estimates

# 6 References

If you are not find your paper here, do not worry, at least we can say that you are in good company.