# Time Variation of Regression Coefficients related to Macroeconomic News affecting Currency Prices

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## Contents



abstract here when I'm done with the writing and have all results

# 1 Introduction

There exists a number of macroeconomic figures that are released on a predetermined schedule for certain countries. These include for example the Non-Farm Employment change that is released on the first friday of every month informing economists and investors alike of the status of employment in the United States.
Classic economic theory helps us understand that an increase of interest rates is warranted when economies are performing well and prices are generally increasing. Those who decide to increase national interest rates, the central banks, typically refer to measures of inflation in order to make their decisions. Because of this, investors and traders alike pay close attention to news releases (such as inflation, and also the Non-Farm-Payrolls in the case of the United States) and react according to the results. These news releases are not made public until specific times on specific days and since investors and traders react to the same news the moment it is released, the result is often a violent reaction of price in one direction or another. The

Table 1: Summary of the news figures considered in the study

| Country | News.Event | Pair.used | GMT.Time | Frequency | Observations | Dates |
|---|---|---|---|---|---|---|
| **Single News** | | | | | **NA** | |
| Canada | Consumer Price Index | USD/CAD | 13:30 | Monthly | 135 | Jan 2008 to Dec 2019 |
| Canada | Core Retail Sales | USD/CAD | 12:30 | Monthly | 144 | Oct 2008 to Dec 2019 |
| United States | Consumer Price Index | USD/CHF | 13:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| New Zealand | Consumer Price Index | NZD/USD | 21:45 | Quarterly | 43 | Jan 2009 to Oct 2019 |
| Australia | Consumer Price Index | AUD/USD | 00:30 | Quarterly | 48 | Jan 2008 to Oct 2019 |
| Australia | Retail Sales | AUD/USD | 00:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| United Kingdom | Consumer Price Index | GBP/USD | 09:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| United Kingdom | Retail Sales | GBP/USD | 09:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| **Grouped News** | | | | | **NA** | |
| United States | Average Hourly Earnings Change | USD/CHF | 13:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| United States | NonFarm Employment Change | USD/CHF | 13:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| United States | Unemployment Rate | USD/CHF | 13:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| Canada | Employment Change | USD/CAD | 13:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| Canada | Unemployment Rate | USD/CAD | 13:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| Australia | Employment Change | AUD/USD | 00:30 | Monthly | 135 | Oct 2008 to Dec 2019 |
| Australia | Unemployment Rate | AUD/USD | 00:30 | Monthly | 135 | Oct 2008 to Dec 2019 |

common discourse is that the direction and the magnitude of the change of price depends on the difference between the expectation of the market (combined expecation of worldwide investors) and the result of the news release.

In this paper, we decide to use currency pairs to measure the price shocks. As certain news pertaining to a particular country affects its respective currency more than other ones, it makes sense to observe the currency most relevant to the news announcement. As currency prices are typically measured in pairs, the second chosen currency will be another major currency that is known for its high liquidity (EUR, USD or CHF) and does not have any other news announcements at the same time[1]. As an example, we would use the USD/CAD currency pair to measure the effect of the Canadian Consumer Price Index (CPI).

The paper of (Andersen et al. 2003) reveals that over the time period between 1987 and 2002 there has been little time-variation in the reaction to news. Some more recently published literature of (Ben Omrane et al. 2019) involving an analysis on euro-dollar contracts has determined that unlike the the decade(s) encompassing the "Great Moderation" where there was lower relative volatility in the financial markets, the time period between 2004 and 2014 is characterized by evolving reactions to macroeconomic news.

This paper aims to detect whether or not there is instability in the reaction to news with the new data at hand with the help of several tests explored in previous literature. Furthermore, we explore methodologies to retrace a "parameter path" to meliorate our understanding of the evolution of the variable through time.

# 2 Data

The minute-by-minute OHLC Data of 7 currency pairs were collected from the Metatrader5 platform. This represents over 4 million data points for each pair. Only a small fraction of this data is actually used since we consider only the 5 time frame from when each piece of monthly or quarterly news is released until 5 minutSes afterwards.

# 3 Construction of the model

Being consistent with previous literature on the subject, the first step involves estimating the impact that each piece of news has on its respective currency assuming 1.) That the news effects are constant over time. 2.) The surprise element $S_t$ of the regression is evaluated as:

[1]When simultaneous news cannot be avoided, a sequence of stability tests will be applied to ensure time variation is identified on a specific news release

Table 2: Results of regressions tests - HAC standard errors

| News.Event | M5.Coefficient | std.error | HAC.std.error |
|---|---|---|---|
| **Single News** | | **NA** | **NA** |
| UK CPI | 12.681*** | 1.729 | 2.601 |
| CA CPI | -12.896*** | 2.254 | 2.673 |
| CA CRS | -13.773*** | 2.112 | 2.871 |
| US CPI | 3.968** | 1.207 | 1.230 |
| NZ CPI | 24.109*** | 2.910 | 4.727 |
| AU CPI | 22.293*** | 4.145 | 4.226 |
| AU RET | 9.647*** | 1.215 | 2.656 |
| UK RET | 16.574*** | 1.968 | 2.572 |
| **Grouped News** | | **NA** | **NA** |
| US AHE | 10.295*** | 2.577 | 2.665 |
| US NFP | 17.938*** | 2.572 | 4.143 |
| US URÂ° | 1.975 | 2.579 | 2.198 |
| CA EMC | -25.588*** | 3.940 | 4.211 |
| CA UR | 1.053 | 3.940 | 4.262 |
| AU EMC | 21.59571*** | 1.842 | 2.780 |
| AU UR | -11.93102*** | 1.842 | 1.828 |

$$S_t = \frac{A_t - E_t}{\sigma_d} \tag{1}$$

$A_t$ is the actual result of the news at time $t$, $E_t$ is the expected result aggregated from experts and $\sigma_d$ is the empirical standard deviation of this difference over the entire sample. We use the expectation numbers from the ForexFactory website[2] Thereafter, we use this surprise element in a first simple OLS model.

$$R_t = \beta_0 + \beta_1 S_t + \varepsilon_t \tag{2}$$

Moreover, because we are working with a dataset where subsequent observations are suspected to be related to one another, one could expect that the errors of the basic model above be autocorrelated. Specifically, adjacent $R_t$ would be more similar to one another than reactions that are separated in time to a greater extent. In this case, the inference on the $\beta_1$ would be flawed. Previous researchers have used what is called Heteroskedasticity and Autocorrelation-Consistent (HAC) estimators for the variance of the OLS estimator $\beta_1$. Using the Newey-West estimator for this variance from Newey and West (1987), we use modified standard errors of the $\beta_1$ in our results. If we are wrong in our assumption in some of the news instances, and there is no underlying autocorrelation of the $R_t$ observations, our estimation of $\beta_1$ is less efficient than the original estimator in those cases. Nonetheless, it remains consistent and ensures we avoid type 1 error of rejecting a true null hypothesis suggesting $\beta_1 = 0$.

Table 2 shows the result of the different $\beta_1$ coefficients for separate news reports. The construction of the truncation parameter in the Newey-West estimator is such that our monthly news reports consider 2 autocorrelation coefficients whereas the quarterly ones only contain 1. This is due to the difference in the number of observations in our data. A higher estimated autocorrelation between the errors of the regression will result in a stronger correction of the variance of $\beta_1$. In all of the news in Table 2, the higher standard error does not affect the significance of the term. While it is not formal evidence, we suspect that the news for which the HAC standard error is vastly different than its unedited counterpart contains many unknown

[2]The expectations of most online sources such as "Investing.com" or "DailyFX" are very similar. The aggregation methods are not disclosed to the public.

Table 3: Instability Test Results

| News.Event | qLL | CUSUM | CUSUM.sq |
|---|---|---|---|
| **Single News** | | | |
| UK CPI | -12.964*** | *** | ** |
| CA CPI | -18.387*** | n.s | *** |
| CA CRS | -14.445*** | *** | *** |
| US CPI | -21.582*** | *** | *** |
| NZ CPI | -7.267* | ** | ** |
| AU CPI | -9.022** | n.s | *** |
| AU RET | -17.623*** | *** | |
| UK RET | -4.503 | n.s | *** |
| **Grouped News** | | | |
| US Batch | | | |
| Test 1 All News | -28.14*** | *** | *** |
| Test 2 AHE&NFP | -24.015*** | | |
| Test 3 NFP&UR | -20.326*** | | |
| Test 4 AHE&UR | -7.078 | | |
| Test 5 NFP | -17.643*** | | |
| CA Batch | | | |
| Test 1 All News | -9.30 | ** | *** |
| AUD Batch | | | |
| Test 1 All News | -22.912*** | *** | ** |
| Test 2 EMC | -6.85 | | |
| Test 3 UR | -5.66 | | |

Table 4: Asymptotic Critical Values of the qLL Statistic

| k | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1% | -11.05 | -17.57 | -23.42 | -29.18 | -35.09 |
| 5% | -8.36 | -14.32 | -19.84 | -25.28 | -30.60 |
| 10% | -7.14 | -12.80 | -18.07 | -23.37 | -28.55 |

regressors that come from any of the findings that are summarized in Goldberg and Grisse (2013) (mentioned in the introduction).

$$R_t = \beta_0 + \beta_{1,t} S_t + \varepsilon_t \tag{3}$$

### 3.1 Two Directions Considered

## 4 Testing for instability of the news impact parameter

### 4.1 The quasi-Local-Level Test

There exists many ways to test whether $\beta_t$ is time dependent or not. We first choose the methodology of the authors of (Elliott and Müller 2006) and briefly replicate their method. The advantage of their test is that it identifies instability no matter whether it comes in the form of a single break, many breaks, or a continuous change (all of which are feasible in our context).
The quasi-Local-Level (qLL) test enables one to test for many different types of persistent processes of the $\beta_t$.

It is explained that many of these breaking processes can have a “temporary memory” (strictly speaking are strongly mixing) but will be well approximated by a Wiener process.[3]. This is extremely practical in our scenario as there are many possiblities for the possible variation of the $\beta_t$. The Null Hypothesis implies there is a stable parameter as in a familiar OLS regression. We obtain the likelihood under the Null assuming that the $R_t$ observations are independently and identically distributed (and therefore so are their first differences):

$$L_{H0}(\beta_0, \beta_1, \sigma^2) = log \prod_{t=1}^{T} p(\Delta R_t | S_t; \beta_0, \beta_1, \sigma^2) \tag{4}$$

$$= -\frac{T}{2} log(2\pi) - Tlog(\sigma) - \frac{1}{2\sigma^2} \sum_{t=1}^{T} (\Delta R_t - (\Delta\beta_0 + \Delta\beta_1 S_t))^2 \tag{5}$$

Only the last term of (5) is kept as the first constants will cancel out. $\Delta\beta_0 + \Delta\beta_1 S_t$ becomes 0 as the terms do not change with time.

$$L_{H0} = \frac{1}{2\sigma^2} \sum_{t=1}^{T} (\Delta R_t)^2 \tag{6}$$

This contrasts with the alternative where instability is implied. We assume $\beta_t - \beta_0$ is approximated by the Gaussian random walk and $\Delta R_t$ is therefore a Gaussian moving average of order 1 MA(1) with the specification: $\Delta R_t \sim \eta_t + \psi_\eta \eta_{t-1}$, $\eta_t \sim iidN(0, \sigma_\eta^2)$, constant $\psi_\eta < 1$. Using the same *i.i.d* assumption we obtain the likelihood of this alternative process:

$$L_{HA} = \frac{1}{2\sigma^2} \sum_{t=1}^{T} \eta^2 \tag{7}$$

The qLL statistic is obtained by subtracting $L_{HA}$ from $L_{H0}$: $\frac{\sigma^2}{\sigma^2} \sum_{t=1}^{T} \eta^2 - \sum_{t=1}^{T} (\Delta R_t)^2$. The test is therefore a variant of the Likelihood Ratio Test ($LR_T$), so while it does not follow a chi-square distribution exactly, it does follow a certain related distribution that has its percentiles defined by Elliott and Müller (2006) and reported in their table, reproduced here as Table 4. The general extension to the $LR_T$ can be made where we can reject the model related to the Null Hypothesis (the stable model) if the critical value is sufficiently negative. To obtain the $\eta$ term it is necessary to follow additional matrix algebra and use the result of regressions (Elliott and Müller 2006). The appropriate steps are available in Appendix Section 9.2.

## 4.2 CUSUM and CUSUM-squared tests

Separate tests to the one explained previously are considered. We explore the ones elaborated in Brown, Durbin, and Evans (1975) named the CUSUM and CUSUM-squared. These tests use the successive error terms of predictions of a standard Recursive-Least-Squares (RLS) model that assumes stability of the $\beta$ parameter (Young 2011). In this specific application, we use the result of the standard OLS as a baseline *prior* or initial value for the algorithm (ie. $\beta_0$) and we use an empirical $\hat{\sigma}_\varepsilon$ residual error that is based on the entire sample. By examining the prediction errors, one can observe whether or not they violate the $N(0, \sigma^2)$ assumptions. Namely that they are a 1.) zero mean sequence $E(\varepsilon_t) = 0$ and 2.) that they are serially uncorrelated $E(\varepsilon_t \varepsilon_j) = 0$ when $t \neq j$. The first step consists in running a standard RLS algorithm and obtaining one-step-ahead errors from it. These errors are obtained as follows:

$$u_t = R_t - \hat{R}_t | R_{t-1} \tag{8}$$

[3]Theorem 7.30 of (White 2001) can be applied since certain assumptions are made about the process

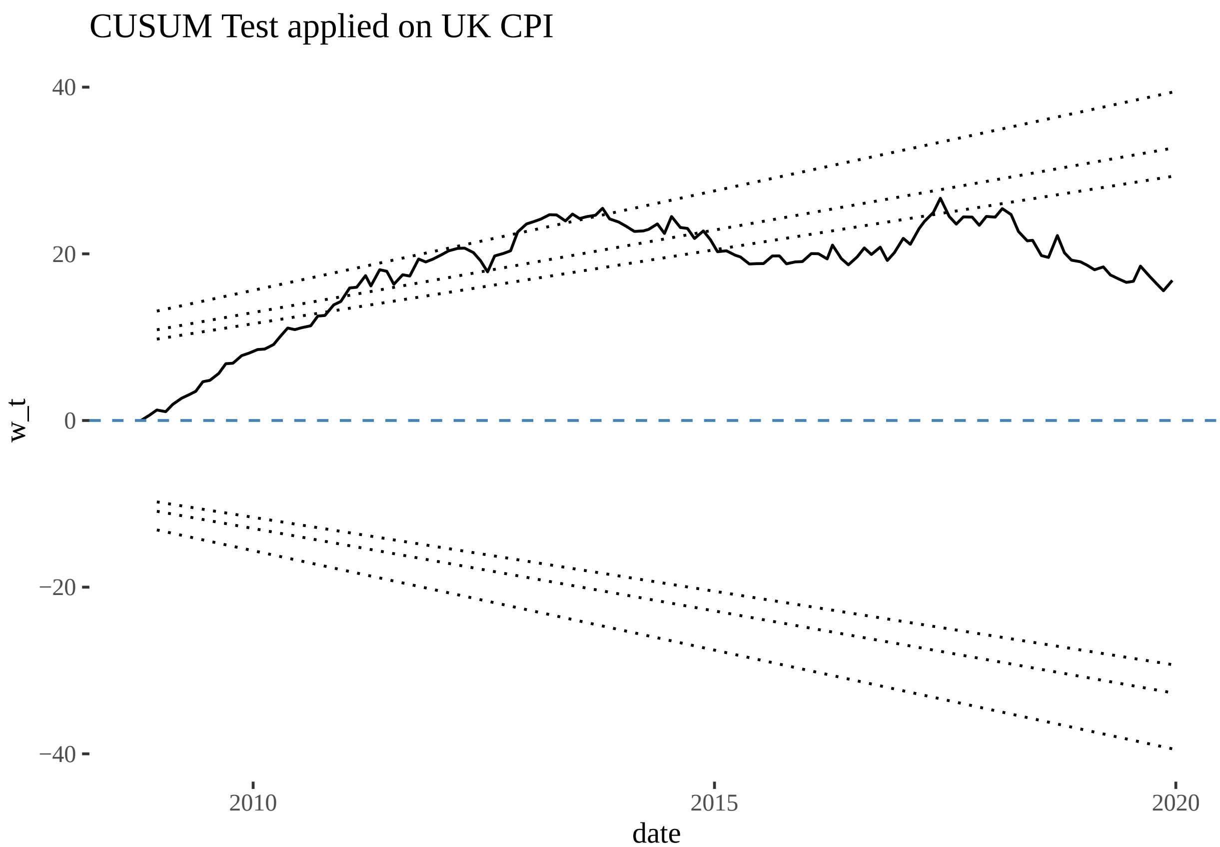
Effectively the realized price shock minus the predicted price shock at each observation. A transformation of these errors enables us to obtain a homoscedastic series.

$$u_{n,t} = \frac{u_t}{(1 + S_t^T P_t S_t)^{0.5}} \tag{9}$$

Where $P_t$ is the covariance (or variance if there is only one news element at a time) of the $\beta_t$. A new series of summed up and standardized for use in the CUSUM test.

$$W_t = \frac{1}{\hat{\sigma}_{cs}} \sum_{i=k+1}^{t} u_{n,i} \tag{10}$$

In theory, these successively compounded errors should not stray too far from the zero-line if the true $beta_t$ is constant. We also use the confidence bands suggested by Brown, Durbin, and Evans (1975). They are constructed by constructing pairs of lines starting at time $k$: $\pm a(T-k)^{0.5}$ and ending at time $T$: $\pm 3a(T-k)^{0.5}$

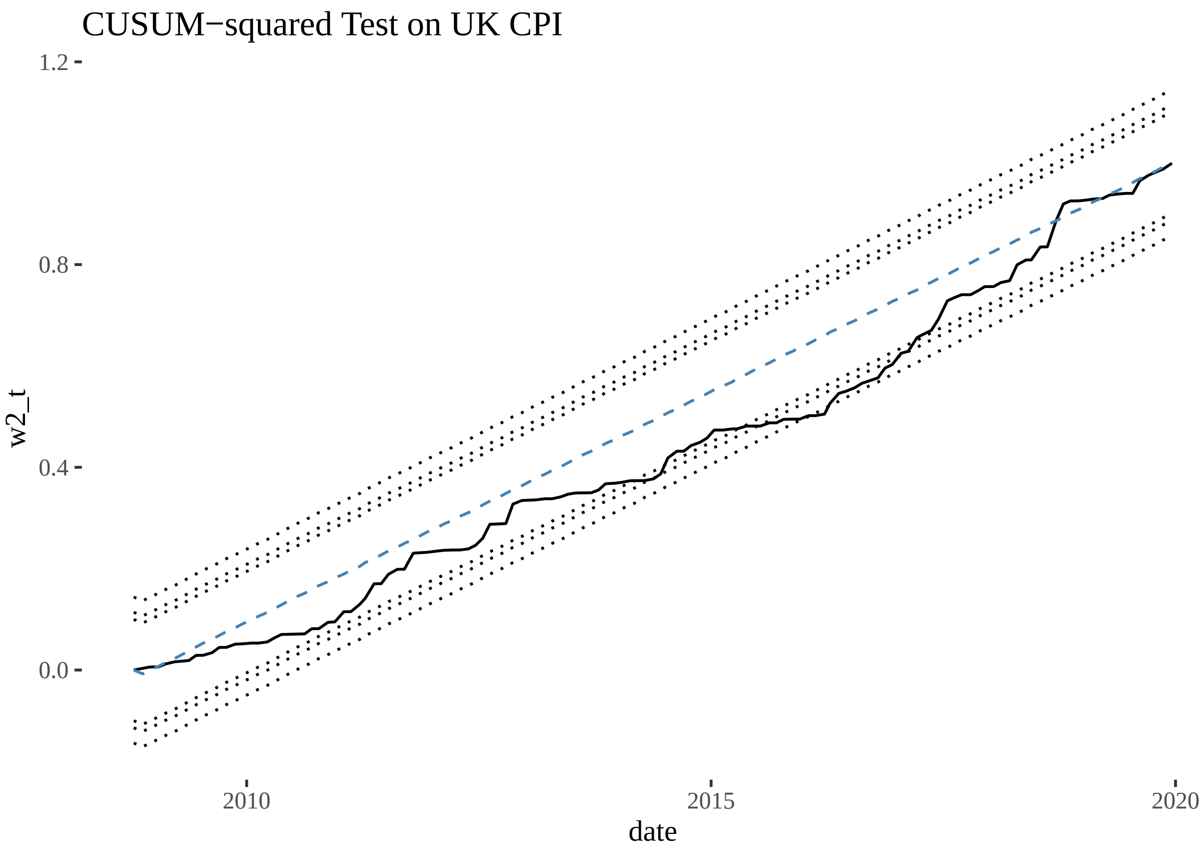



The second test, the CUSUM-squared can be run by once more by creating a new series, similar to the $W_t$ from earlier. Here we consider:

$$V_t = \frac{\sum_{i=k+1}^{t} u_{n,i}}{\sum_{i=k+1}^{T} u_{n,i}} \tag{11}$$

With a Null-Hypothesis of a constant parameter(s), these cumulative sum of squares should follow a beta distribution and its mean should be $(k-h)/(N-h)$. As significance levels, we use the bounds set as:

$\pm c_o + (k-h)/(N-h)$. The values of $c_0$ depend on the sample size. Our sample sizes are typically larger than the maximum value given in Brown, Durbin, and Evans (1975). For those cases where




# 5 Parameter Path Estimations

Having established that there is instability over time in the market reactions to at least some of the news, we take on the task of obtaining a time series that conveys the change over the timeframe considered. Specifically, we would like to obtain a visual representation of the change of the parameter such that a researcher or investor is able to easily gather information from.

## 5.1 Weighted Average Risk Minimization

Conveniently, there is a natural extension of the qLL test elaborated in Section 4.1. It provides a herusitic means means to approximate a parameter path (Müller and Petalas 2010).

First, we consider our stable model which is analogous to the linear regression model that is presented in the Equation (2). The resulting $\beta_{MLE/OLS}$ parameter obtained either through maximum likelihood estimation or minimization of ordinary least squares (depicted as the dot-dashed line in Figure 1) is representative of a scenario where it is assumed there is no time-related evolution of market reaction to news. As seen before, the likelihood in this case can be developed as Equation (4) or also written more generally as $\sum_{t=1}^{T} l_t(\theta)$ with $\theta$ containing the constant parameters.

We then turn to the case of varying $\beta_t$. Here, the general likelihood is the same but with time varying parameter(s) contained in $\theta_t = \theta + \delta_t$ in $t = 1, ..., T$. The $\delta_t$ can be imagined as the vertical distances in Figure 1) between the constant $\beta$ case and the *true* parameter path at time $t$ that is unknown and that we are attempting to approximate. The main argument for the method is that this general likelihood function can be approximated by a second-order Taylor expansion of the likelihood function around $\beta_{MLE}$ and as a result an approximate estimate of the $\delta_t$ term mentioned earlier is obtainable. Effectively, the approximation of the log-likelihood function of the parameter path is re-arranged until a log-likelihood function of a gaussian random variable is recognizable and results in a "pseudo model" as:

$$\beta_{MLE} = \beta_t + T^{-1/2}\hat{H}^{-1}v_0 \tag{12}$$

$$s_t(\beta) = \hat{H}\delta_t + v_t, t = 1, ..., T \tag{13}$$

$\hat{H}$ is the Hessian of the Taylor approximation divided by the sample size T, $s_t$ is the score function for the stable model. The exact derivations are elaborated in Müller and Petalas (2010).

The weights in step (e) of the Appendix Section 9.3 depend on the sample size and the qLL statistic that are obtained using the qLL test statistic from Section 4.1. It can be observed that the more negative the statistic becomes for the associated random walk function, the more importance is placed on that particular weight. The random walk that contributes the most weight for the UK CPI case is the 4th one in our example case.

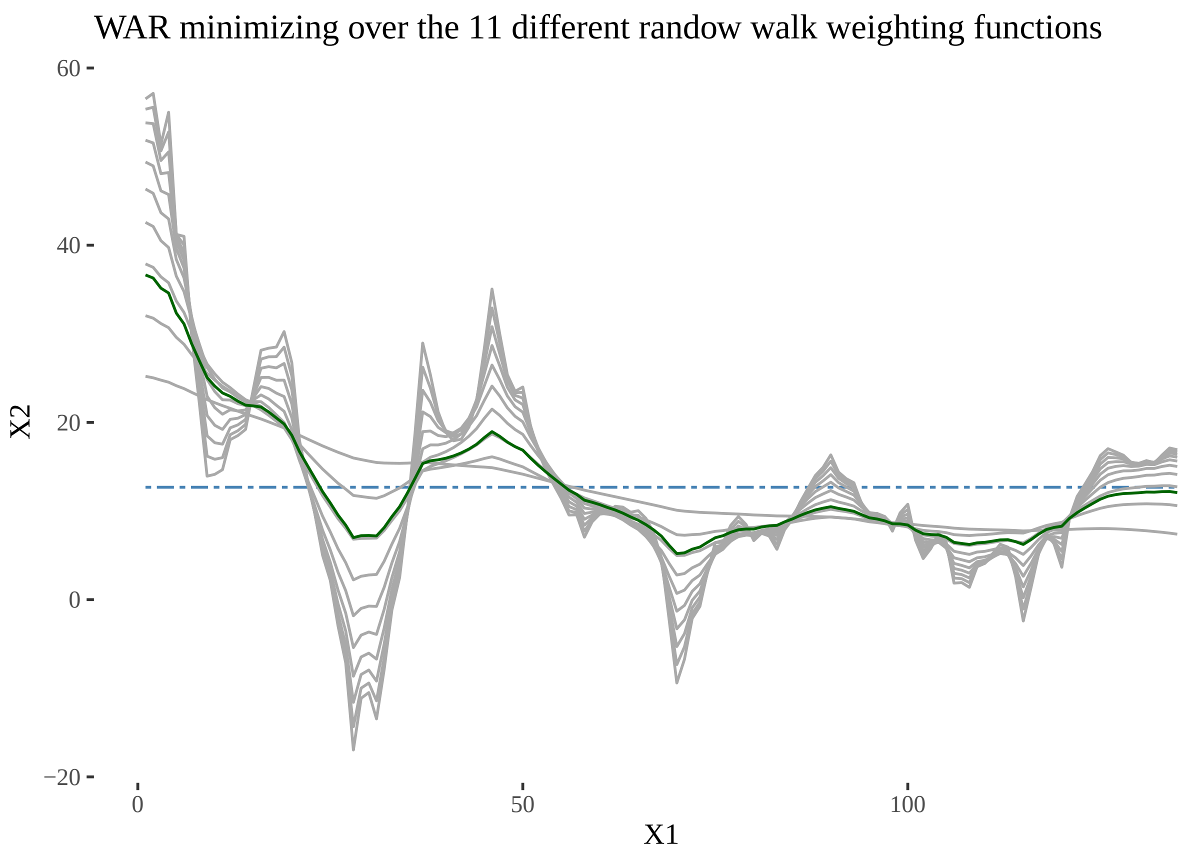



Figure 1: WAR minimizing over the 11 different randow walk weighting functions

# 6 Stochastic Recursive Linear Least Squares Algorithm

# 7 Discussion - A comparison of methods

# 8 Conclusion

# 9 Appendix

## 9.1 Steps to obtain qLL statistic

## 9.2 Steps to obtain WAR minimization path

1. For t = 1,…,T, let $a_t$ and $b_t$ be the first $p$ elements of $\hat{H}^{-1}s_t(\hat{\theta})$ and $\hat{H}\hat{V}^{-1}s_t(\hat{\theta})$ respectively.

2. For $c_i \in C = 0, 5, 10, ..., 50, i = 1, ..., 11$ compute

(a) $r_i = 1 - c_i/T$, $z_{i,1} = x_1$ and $z_{i,t} = r_i z_{i,t-1} + x_t - x_{t-1}, t = 2, ..., T$;

(b) the residuals $\{\tilde{z}_{i,t}\}_{t=1}^{T}$ of a linear regression of $\{z_{i,t}\}_{t=1}^{T}$ on $\{r_i^{t-1} I_p\}_{t=1}^{T}$

(c) $\bar{z}_{i,T} = \tilde{z}_{i,T}$, and $\bar{z}_{i,t} = r_i \bar{z}_{i,t+1} + \tilde{z}_{i,t} - \tilde{z}_{i,t+1}, t = 1, ..., T-1$;

(d) $\{\hat{\beta}_{i,t}\}_{t=1}^{T} = \{\hat{\theta} \ + a_t - r_i \bar{z}_{i,t}\}_{t=1}^{T}$;

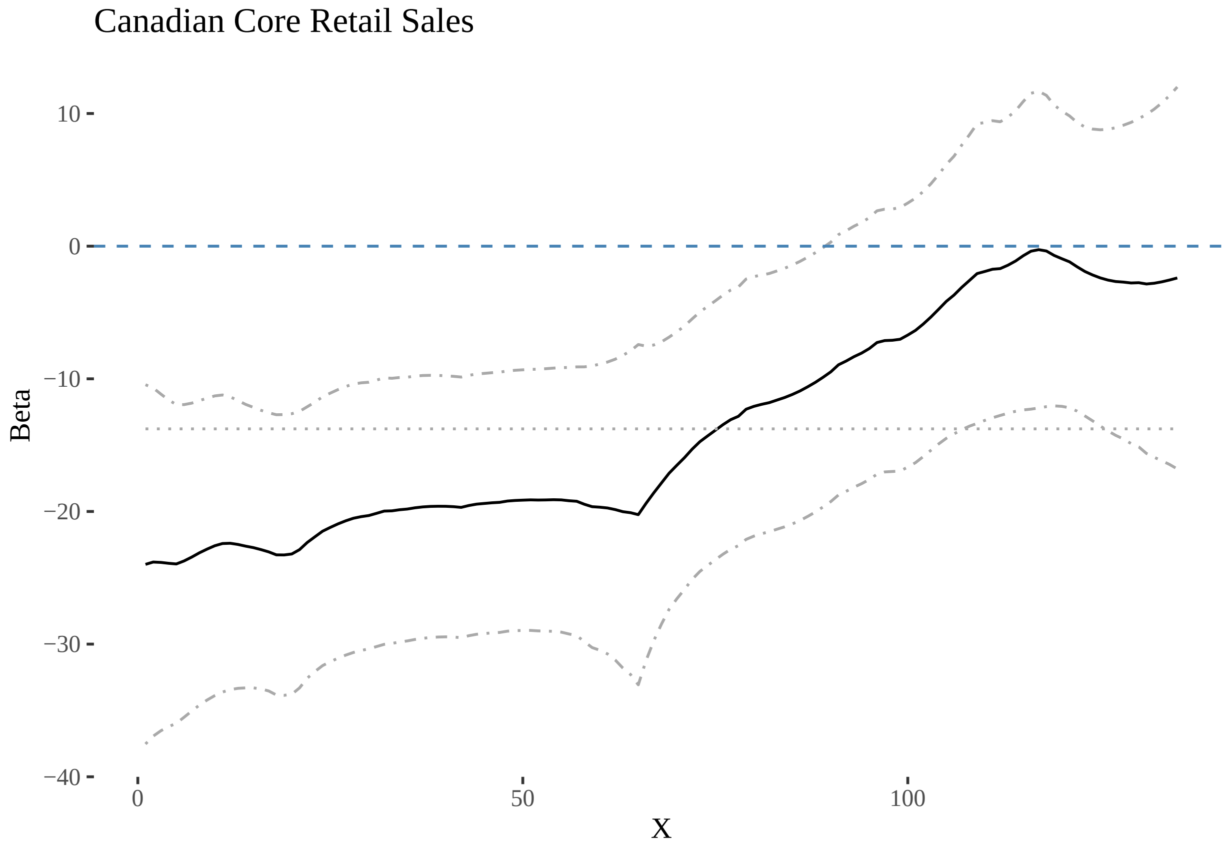
(e) $qLL(c_i) = \sum_{t=1}^{T}(r_i)\bar{z}_{i,t} - a_t)'\tilde{b}_t$ and $\tilde{w}_i = \sqrt{T(1-r_i^2)r_i^{T-1}/(1-r_i^{2T})}e^{-\frac{1}{2}qLL(c_i)}$ (set $\tilde{w}_0 = 1$)

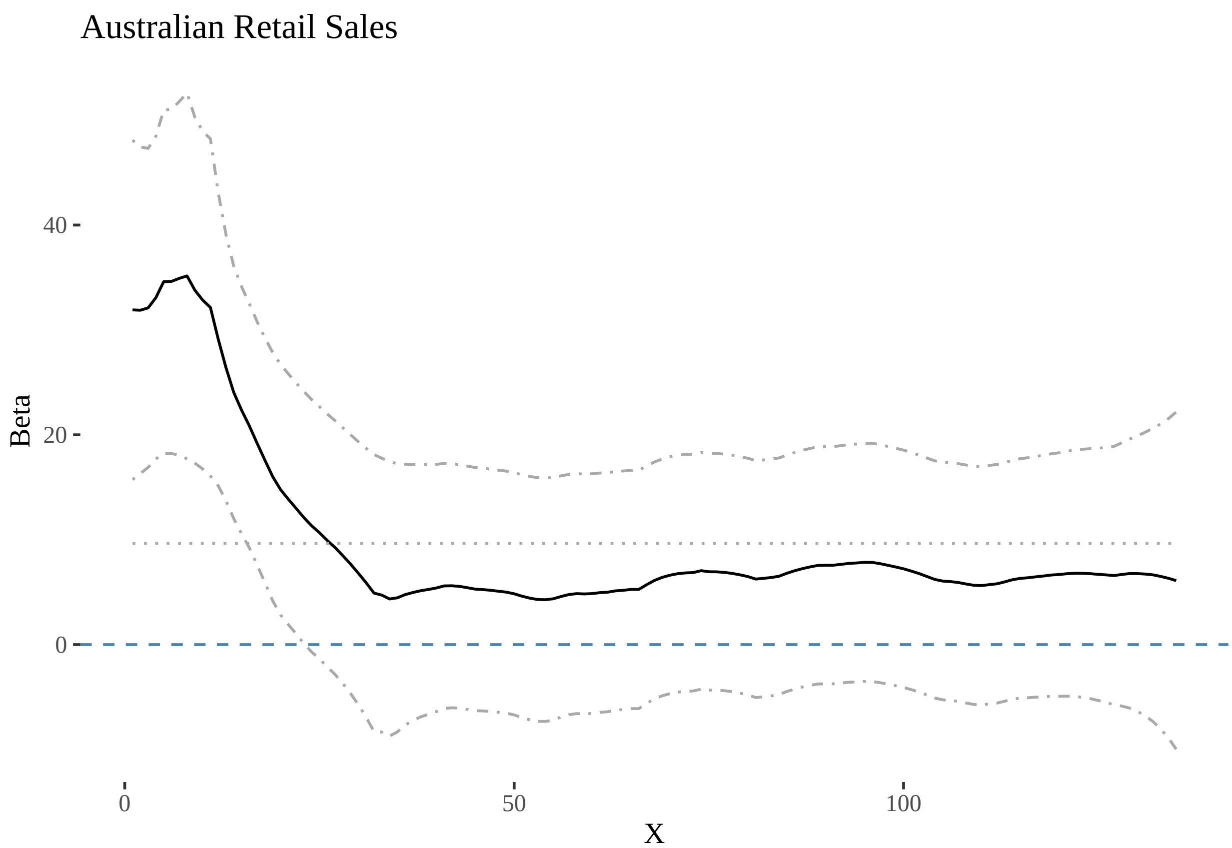
3. Compute $w_i = \tilde{w}_i / \sum_{j=1}^{11} \tilde{w}_j$.

4. The parameter path estimator is given by $\{\hat{\beta}_t\}_{t=1}^{T} = \{\sum_{i=1}^{11} w_i \hat{\beta}_{i,t}\}_{t=1}^{T}$.

5. The statistic qLL(10) tests the null hypothesis of stability of $\beta$ and rejects for small values. Critical values depend on $p$ and are tabulated in Table 1 of Elliott and Müller (2006).

### 9.3 Parameter Paths

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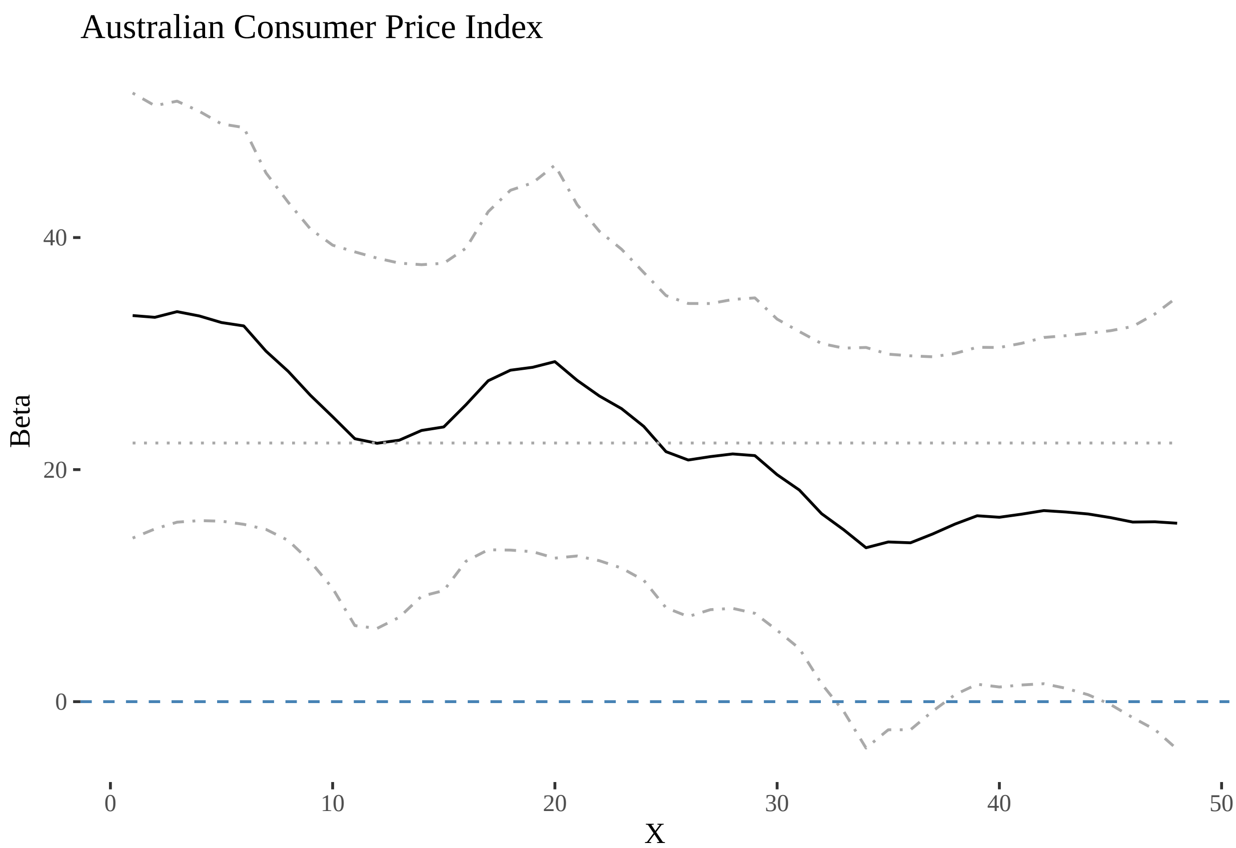
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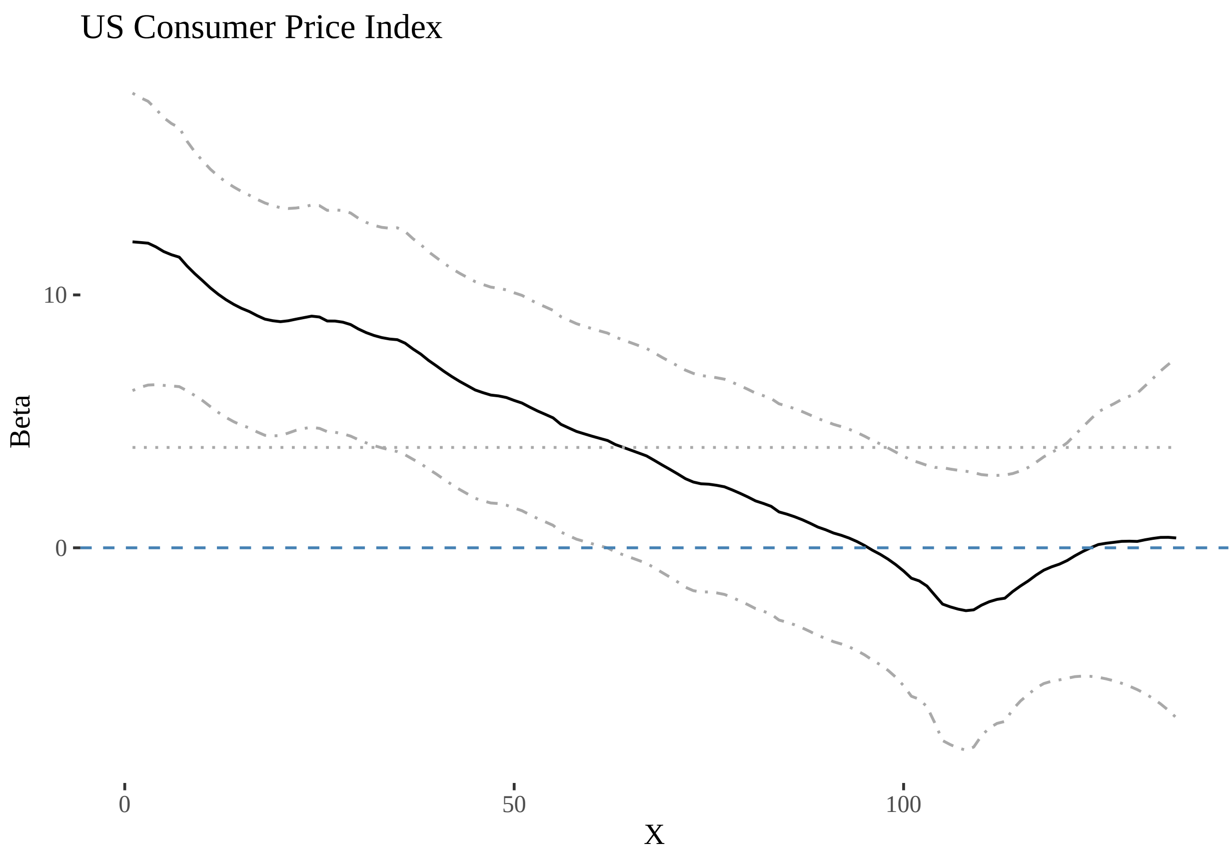
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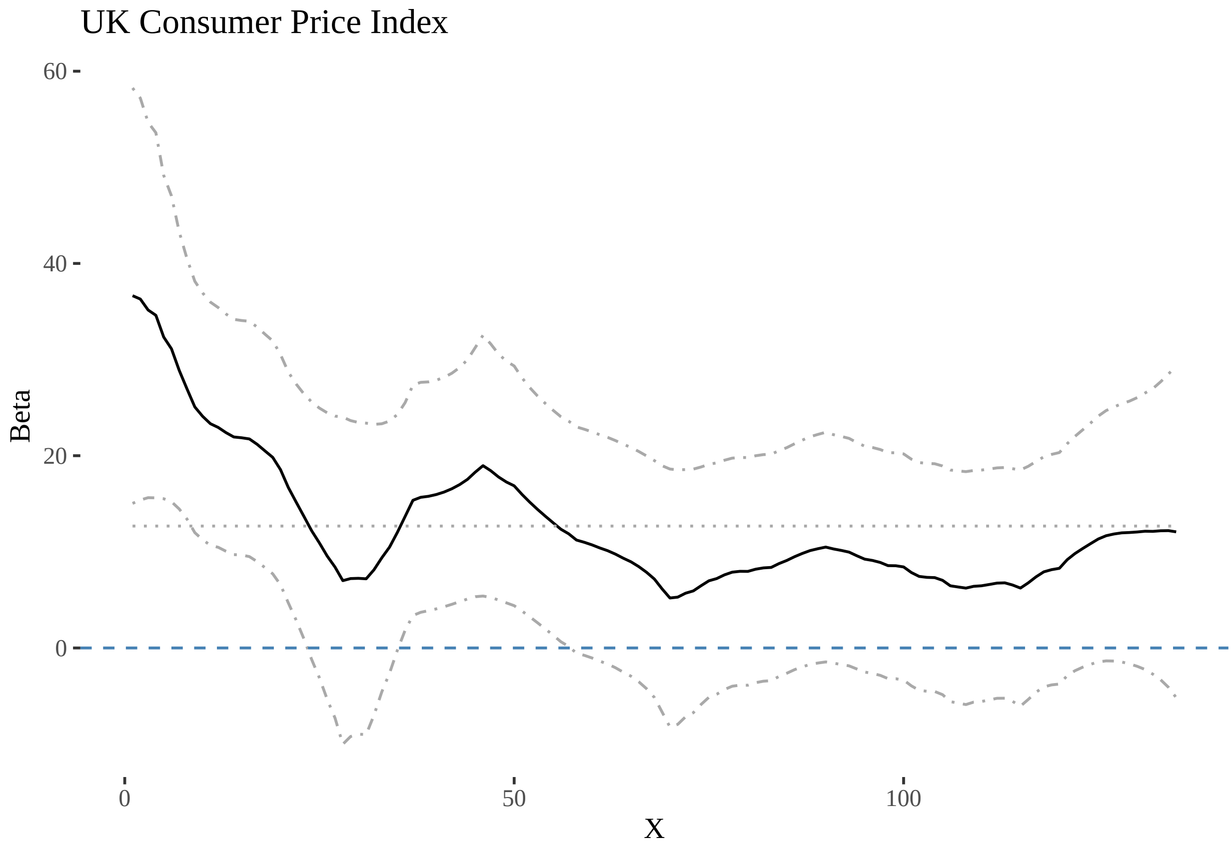
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