Asymmetries in the Oil-Gasoline Price Relationship

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Introduction
Price Asymmetries in Energy Demand

- Energy demand models are often developed on the assumption that consumer behavior is defined by *symmetric responses* to rising or falling prices and income
- It is equally plausible, however, that consumers might react differently to price rises than they would to price falls, be it because of habit formation, the desire to improve life quality or any other reason
- Consequently, *asymmetric price decompositions* have found increasing use in the energy demand literature. See, for example, Dargay (1992), Gately (1993), Dargay and Gately (1995a, 1995b, 1997), Gately and Huntington (2002), Griffin and Schulman (2005), Ryan and Plourde (2002), Adeyemi and Hunt (2007)

Introduction

Price Asymmetries in Energy Demand

- An influential and often quoted paper by Gately and Huntington (2002, *EJ*) eloquently demonstrates why, and how, consumers of energy will respond differently to, not only price cuts and price rises, but also to price rises above the previous maximum and price recoveries below the previous maximum
- Gately and Huntington also demonstrate, on a sample of OECD countries, with annual per capita data over the period 1971-1997, that this might also apply to changes in economy activity. However, overall symmetry for the income responses is generally favoured over asymmetry
- Adeyemi and Hunt (2007, *EE*) obtain similar results on a panel of 15 OECD countries, with annual data over the broader period 1962-2003

Introduction

Asymmetric Price Transmission/Rockets and Feathers

- The relationship between the international price of oil and the local retail fuel prices *has been/is/will be* the subject of public debate in many countries

- The main reason for this concern is the "*belief that oil companies and retailers rush to increase prices in local markets as soon as international oil prices rise, but do not respond with the same eagerness when international oil prices fall*" [Clerides, 2010, *CEPR*]

- The economic literature refers to this phenomenon as the *Asymmetric Price Transmission* (APT) or the *Rockets and Feathers* (R&F) hypothesis

Introduction

Asymmetric Price Transmission, Rockets and Feathers, and Forecasting

- **Asymmetric Price Transmission (APT):**
  - Negative and positive **input** price changes have different impact on **output** prices (e.g. input price is more reactive to increases than to decreases in output price)
  - Empirical evidence suggests that APT is a feature of several markets
- **Rockets & Feathers (R&F) hypothesis**:
  - R&F is referred to as APT in fuel markets [Bacon, 1991, *EE*]
  - Fuel prices shoot up like **rockets** (both in terms of speed and magnitude) in response to positive shocks in crude oil prices, while floating down like **feathers** in response to negative oil price shocks
  - Empirical literature on R&F focuses mostly with *in-sample* analyses and results depend on a number of factors (type of data, econometric models, time and spatial aggregation) [Geweke, 2004, *FTC*]
- **Forecasting:** do asymmetries in the price of oil improve the *forecasting performance* of models for the spot and retail fuel prices?

Literature
Causes and consequences of APT/R&F

- **Causes**:
  - Main explanation: **Market Power** [Borestein et al., 1997, *QJE*]
  - Other explanations [Brown & Yücel, 2000, *EFPR*]: Search Costs, Menu Costs, Adjustment Costs, Inventories, Input Price Volatility, Structure of Intermediate Markets, etc.
  - No general consensus:
    - "*Empirical evidence linking market power and APT is mixed*" [Eckert, 2013, *JES*]
    - "*Price asymmetry is as characteristic of competitive as oligopoly market structures.*" [Peltzman, 2000, *JPE*]

- **Consequences**:
  - Welfare transfers and (if APT is an example of market failures) net welfare losses for consumers [Meyer & von Cramon-Taubadel, 2004, *JAgrEc*]
  - Policy uncertainty [Brown & Yücel, 2000, *EFPR*]: the type of intervention and its effectiveness depends on the cause of APT (unclear)
  - Gaps in economic theory: if APT is a general finding, "*it would point to a serious gap in a fundamental area of economic theory*" [Peltzman, 2000, *JPE*]

Literature
Empirical evidence of APT/R&F (in-sample analyses)

Selected contributions

- Faber (2015, *EJ*), gasoline market:
  - Two possible *aggregation* issues in studies to asymmetric price responses, namely aggregation *over time* and *over space*
  - The issue of *aggregation over time* has been confirmed by many empirical studies
  - This paper confirms the issue of *aggregation over space* by studying daily retail prices of individual gasoline stations
  - Results show that 38% of the stations respond asymmetrically to changes in the gasoline spot market price

Literature

Empirical evidence of APT/R&F (in-sample analyses)

- Bakucs et al. (2014, *JAgrEc*), agro-food market:
  - Relationship between APT and market structure
  - "*(…) asymmetries are present in sectors with higher number of fragmented farm producers and less likely to occur with more concentrated farm structures*"
  - "*(…) asymmetries are less likely in the presence of entry barriers to retail trade (…), more likely to occur in the presence of regulations limiting price competition between retailers*"
- Eckert (2013, *JES*), gasoline market:
  - "*… most studies, …, have found at least some statistical <u>evidence of asymmetry in the response of retail prices to upstream </u>(wholesale or crude oil) <u>prices</u>.*"
  - "*… <u>retail prices respond</u> differently, and <u>typically faster, to upstream price increases</u> than to decreases.*"

Literature

Empirical evidence of APT/R&F (in-sample analyses)

- Frey & Manera (2007, *JES*), various markets:
  - APT in <u>87%</u> of cases (total of 87 models in 70 surveyed papers)

- Grasso & Manera (2007, *EP*), gasoline market:
  - Use of three popular asymmetric models, namely A-ECM, TAR-ECM and TC-ECM
  - Monthly data over the period 1985-2003 for France, Germany, Italy, Spain and UK
  - In general, there is evidence of APT, although the type of market and the number of countries characterized by APT vary across models
  - A-ECM: LR APT in the distribution stage for many countries
  - TC-ECM: LR APT vary across markets and countries
  - TAR-ECM: SR APT at the distribution stage for all countries

Literature

Empirical evidence of APT/R&F (in-sample analyses)

- Meyer & von Cramon-Taubadel (2004, *JAgrEc*), various markets:
  - APT in <u>48%</u> of surveyed studies (total 205)
  - APT in <u>79%</u> of surveyed studies relying on A-ECM & TAR-ECM models (total 41)
- Galeotti, Lanza & Manera (2003, *EE*), gasoline market:
  - Comparison across countries using A-ECM
  - Bootstrapped F-statistic of the null hypothesis of asymmetry to overcome the low-power problem of conventional testing approaches
  - Results show widespread differences in both adjustment speeds and SR responses of gasoline prices when the price of oil rises or falls
- Peltzman (2000, *JPE*), various markets:
  - APT in <u>66%</u> of markets (total 242)

Literature

Empirical evidence of APT/R&F (out-of-sample analyses)

- Bachemeir & Griffin (2003, *REStat*) is the only contribution entertaining an out-of-sample analysis:
  - Point forecasts of U.S. spot gasoline prices with weekly data
  - R&F modeled with A-ECM
  - R&F are useless OOS: forecasts from symmetric ECM are as accurate as those from A-ECM

- Note: several empirical analyses deal with asymmetric transmission of oil shocks and their role in forecasting macroeconomic aggregates [e.g. Kilian & Vigfusson, 2013, *JBES*]

A Recent Contribution

Are Asymmetries Useful

in Forecasting the Oil-Gasoline Price Relation?

by

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Empirical questions and main results

- Point forecasts: are R&F useful when forecasting gasoline price **changes**? (**NO**)
- Direction-of-change/sign forecasts: are R&F useful when forecasting the **sign** of gasoline price movements? (**YES**)
- Probability forecasts: are R&F useful when forecasting the **probability** of gasoline price changes? (**YES**)
- Time-varying forecast accuracy: is the usefulness of R&F constant through **time** or time-varying? (**Time Varying**)
- Location of asymmetries: at which **stage** of the transmission mechanism (i.e. spot, retail, both) are R&F forecasts useful? (**Both, but only for sign and probability forecasts**)
- Sampling frequency: at which sampling **frequency** (daily, weekly or monthly) are R&F forecasts useful? (**Mixed findings**)

Motivations

Why an *out-of-sample* (OOS) analysis?

1. **Decision making** is an inherently forward looking activity:
   - Hedging, asset allocation, risk management, stockpiling (inventories and strategic reserves) depend on the OOS performance of models
   - (Profits are highly correlated with some forecast accuracy metrics [Leitch & Tanner, 1991, *AER*])
2. **Gap in the literature**: with the exception of Bachmeier & Griffin (2003, *REStat*), extant studies perform only in-sample (IS) analyses
3. **Forecasting performance as a diagnostic check**:
   - (IS tests have more power than OOS tests only when there is no model uncertainty and no instabilities [Goyal & Welch, 2008, *RFS*])
   - R&F models which are accurate IS do not necessarily produce accurate forecasts
   - OOS analyses complement IS tests

Data

- Upstream price: spot price of WTI crude oil (6/86-1/13)
- Downstream prices
  - Gasoline spot prices (daily, weekly, monthly):
    - New York Harbor Conventional Gasoline (6/86-1/13)
    - U.S. Gulf Coast Conventional Gasoline (6/86-1/13)
    - Los Angeles Reformulated RBOB Gasoline (4/03-1/13)
  - Gasoline and diesel retail prices (excl. taxes; weekly, monthly):
    - U.S. Regular All Formulations Gasoline (8/90-1/13)
    - U.S. No 2 Diesel (1/97-1/13)
- Note:

3 types of fore x 6 mod x [(3 spot x 3 freq) + [(2 retail x 2 freq)]

= 234 forecasts

Data

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3 types of fore x 6 mod x [(3 spot x 3 freq) + [(2 retail x 2 freq)]

= **234 forecasts**

Data

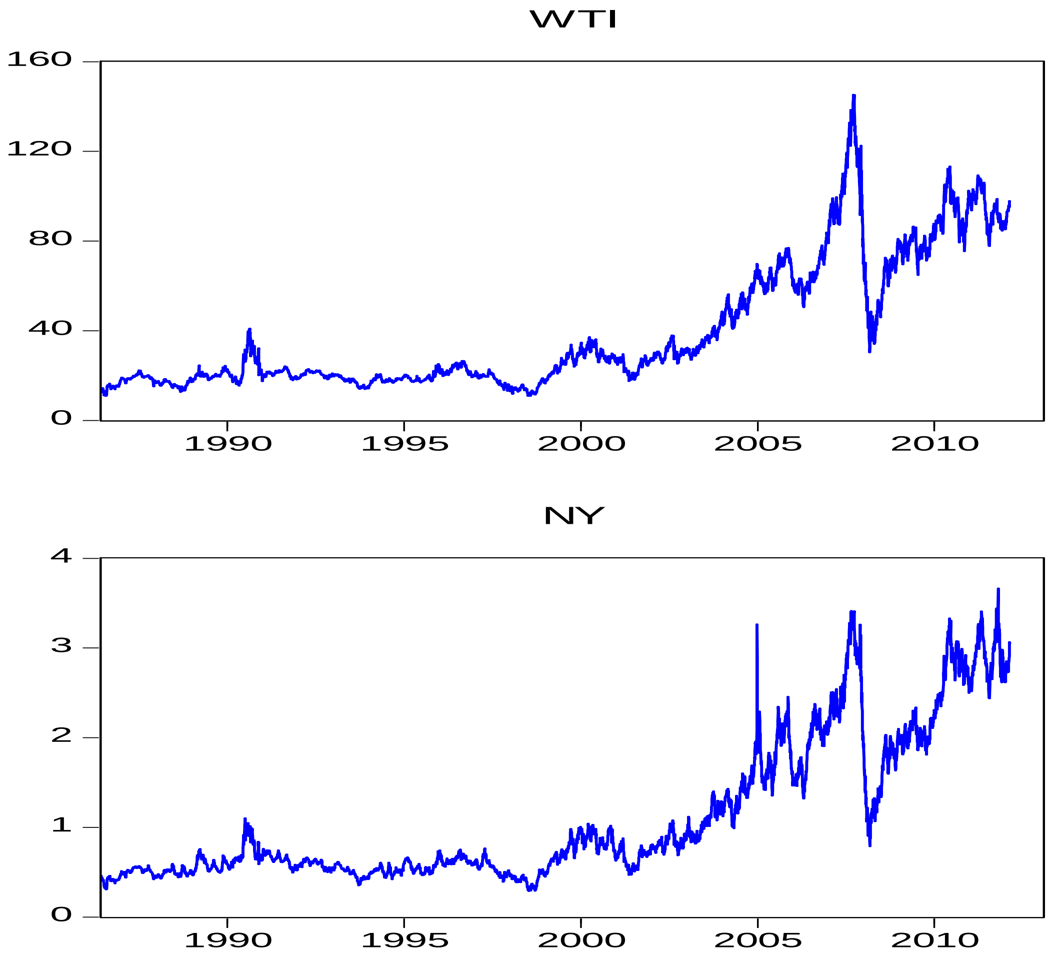
- Upstream price: spot price of WTI crude oil (6/86-1/13)
- Downstream fuel prices
  - Gasoline spot prices (daily, weekly, monthly):
    - **New York Harbor Conventional Gasoline (6/86-1/13)**
    - U.S. Gulf Coast Conventional Gasoline (6/86-1/13)
    - Los Angeles Reformulated RBOB Gasoline (4/03-1/13)
  - Gasoline and diesel retail prices (excl. taxes; weekly, monthly):
    - U.S. Regular All Formulations Gasoline (8/90-1/13)
    - U.S. No 2 Diesel (1/97-1/13)
- Note:

3 types of fore x 6 mod x [(3 spot x 3 freq) + [(2 retail x 2 freq)]

= 234 forecasts

Data

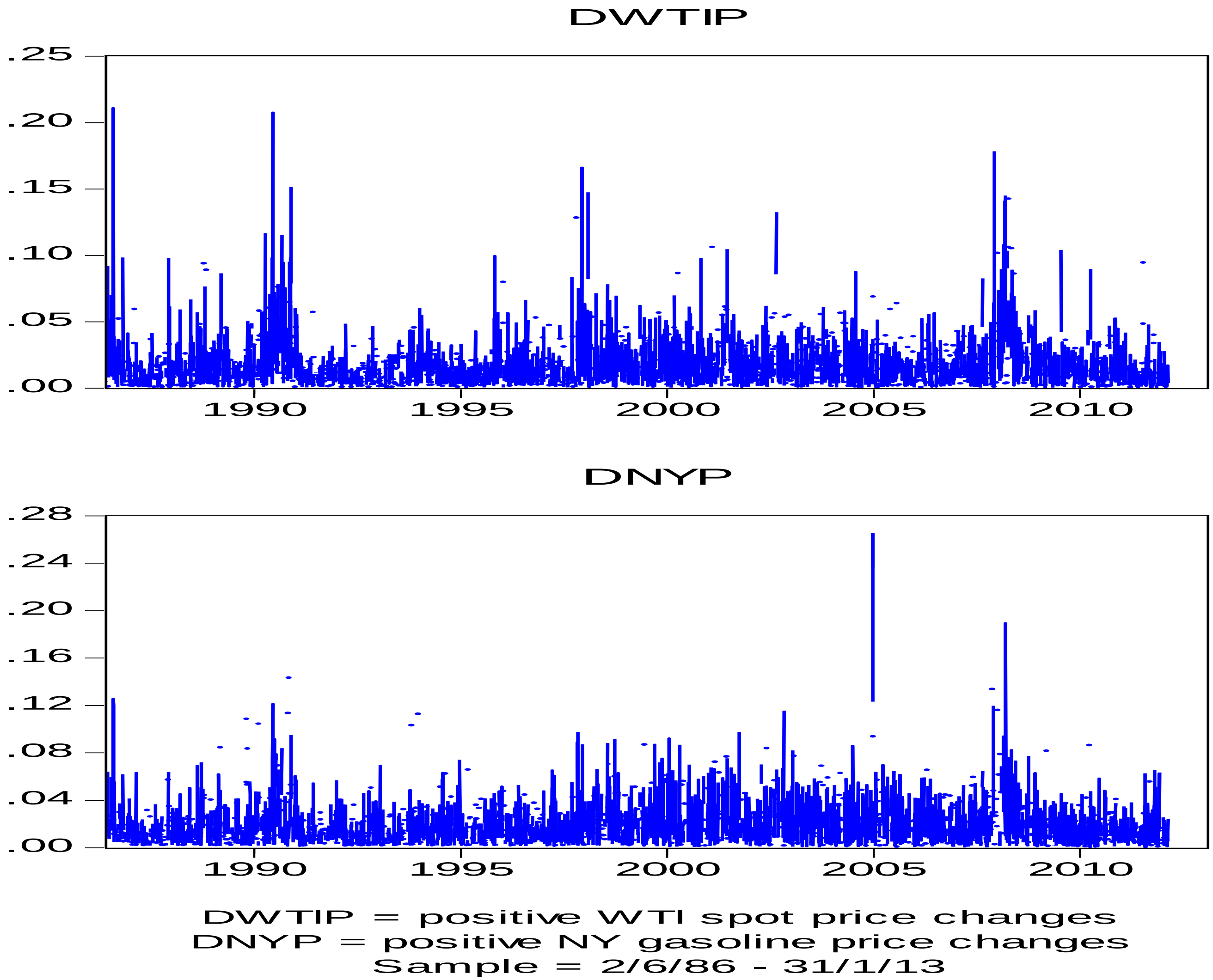
New York Harbor Conventional Gasoline and WTI Crude oil prices



WTI = West Texas Intermediate spot price FOB (USD/b)
NY = New York Harbor Conventional Gasoline Regular spot price FOB (USD/g)
Sample = 2/6/86 - 31/1/13

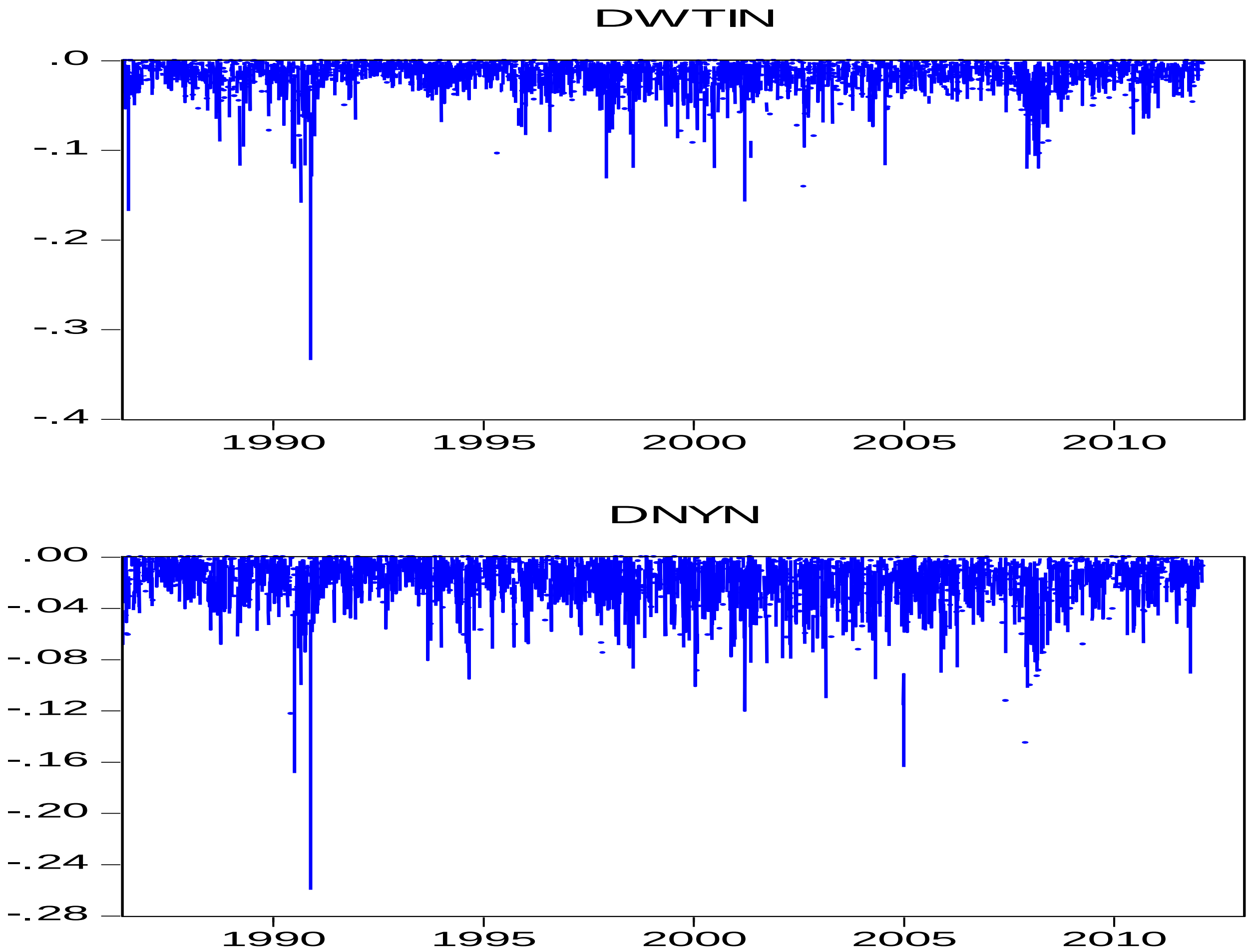
Data

New York Harbor Conventional Gasoline and WTI Crude oil prices



Data

New York Harbor Conventional Gasoline and WTI Crude oil prices



DWTIN = negative WTI spot price changes
DNYN = negative NY gasoline price changes
Sample = 2/6/86 - 31/1/13

Data

New York Harbor Conventional Gasoline and WTI Crude oil prices

	Full sample 2/6/86-31/1/13 (6959 obs)	Subsample 5/1/03-31/1/13 (2629 obs)	Very High WTI Volatility (48 obs)	Medium WTI Volatility (6547 obs)	Very Low WTI Volatility (122 obs)
Correlation between DWTIP and DNYP	0.50	0.62	0.20	0.45	0.99
Correlation between DWTIN and DNYN	0.55	0.12	0.72	0.49	-0.03

Data

New York Harbor Conventional Gasoline and WTI Crude oil prices

	Full sample 2/6/86-31/1/13 (6959 obs)	Subsample 5/1/03-31/1/13 (2629 obs)		Full sample 2/6/86-31/1/13 (6959 obs)	Subsample 5/1/03-31/1/13 (2629 obs)
Corr btw DWTIP and DNYP(+1)	0.13	0.01	Corr btw DWTIN and DNYN(+1)	0.21	0.17
Corr btw DWTIP and DNYP(+2)	0.01	-0.05	Corr btw DWTIN and DNYN(+2)	-0.03	-0.07
Corr btw DWTIP and DNYP(+3)	0.24	0.25	Corr btw DWTIN and DNYN(+3)	0.40	0.70
Corr btw DWTIP and DNYP(+4)	0.45	0.74	Corr btw DWTIN and DNYN(+4)	0.13	-0.07
Corr btw DWTIP and DNYP(+5)	0.43	0.54	Corr btw DWTIN and DNYN(+5)	0.19	0.68

Models & Methods
Models to forecast fuel prices

- Benchmark Model: symmetric price transmission from crude oil to fuel prices (no R&F)
  - (Symmetric) Error Correction Model (ECM)

- Asymmetric Models: APT from crude oil to fuel prices (R&F)
  - Asymmetric ECM (A-ECM): long & short-run asymmetries
  - SR-A-ECM: only short-run asymmetries
  - LR-A-ECM: only long-run asymmetries
  - Threshold AutoRegressive (TAR) ECM (TAR1): with 1-lag of oil price changes as threshold
  - TAR-ECM (TAR2): with average of most recent lags as threshold

- Notes:
  - ECM is nested in asymmetric specifications: restrictions on the parameters of the asymmetric models deliver the ECM
  - Model selection (i.e. no. of lags) is repeated each time a new forecast is issued
  - 45% of sample for (moving window) estimation, 55% for OOS evaluation

Models & Methods
Evaluation of forecasts

- Accuracy of point forecasts (of gasoline price changes):
  - Mean Squared Forecast Error (MSFE)

- Directional accuracy (ability to predict the sign of price changes):
  - Mean Forecast Trading Returns (MFTR): returns an investor obtains by using a model
  - Success Ratio (SR): % of forecasts with correct sign

- Accuracy of probability forecasts (ability to predict the probability of movements):
  - Quadratic Probability Score (QPS): same as MSFE, but for probability forecasts

- Forecast encompassing test (only for point and probability forecasts; Carriero & Giacomini, 2011, *JEct*) :
  - Aim: test whether param. restrictions are useful OOS (i.e. ECM nested in asy. models)
  - Global test: usefulness of R&F forecasts over the entire evaluation sample
  - Local test: time-varying usefulness of forecasts from asymmetric models

- Notes:
  - Accurate models deliver low MSFE and QPS and high MFTR and SR
  - (Prob. forecasts obtained by plugging (de-GARCHed) point forecasts in Normal CDF [Christoffersen & Diebold, 2006, *ManSc*; Granger & Pesaran, 2000, *JFore*])

Models & Methods

The forecast encompassing test

- (Restricted) Symmetric Forecast (f_{ECM}): ECM
- (Unrestricted) Asymmetric Forecast ($f_{R\&F}$): asymmetric ECMs & TARs
- Combined forecast (f_C): a weighted average of $f_{R\&F}$ and f_{ECM}

$$f_C = \lambda\, f_{ECM} + (1-\lambda)\, f_{R\&F}$$

- If $\lambda = 1$, then $f_C = f_{ECM}$: R&F are useless to forecast the price of gasoline
- If $\lambda = 0$, then $f_C = f_{R\&F}$: R&F are useful to forecast the price of gasoline
- If $0 < \lambda < 1$ R&F partially useful: forecast combination better than single $f_{R\&F}$ or f_{ECM}

- Global test: if H_0: $\lambda = 1$ is rejected and H_0: $\lambda = 0$ is not rejected, asymmetries increase forecast accuracy: R&F useful (on the entire evaluation sample)
- Local test. test whether the usefulness of R&F is constant through time or time-varying: λ_t is estimated over a moving window of observations

- Note: λ estimated (OLS or NLS) by regressing actual price changes on f_{ECM} and $f_{R\&F}$.

Results

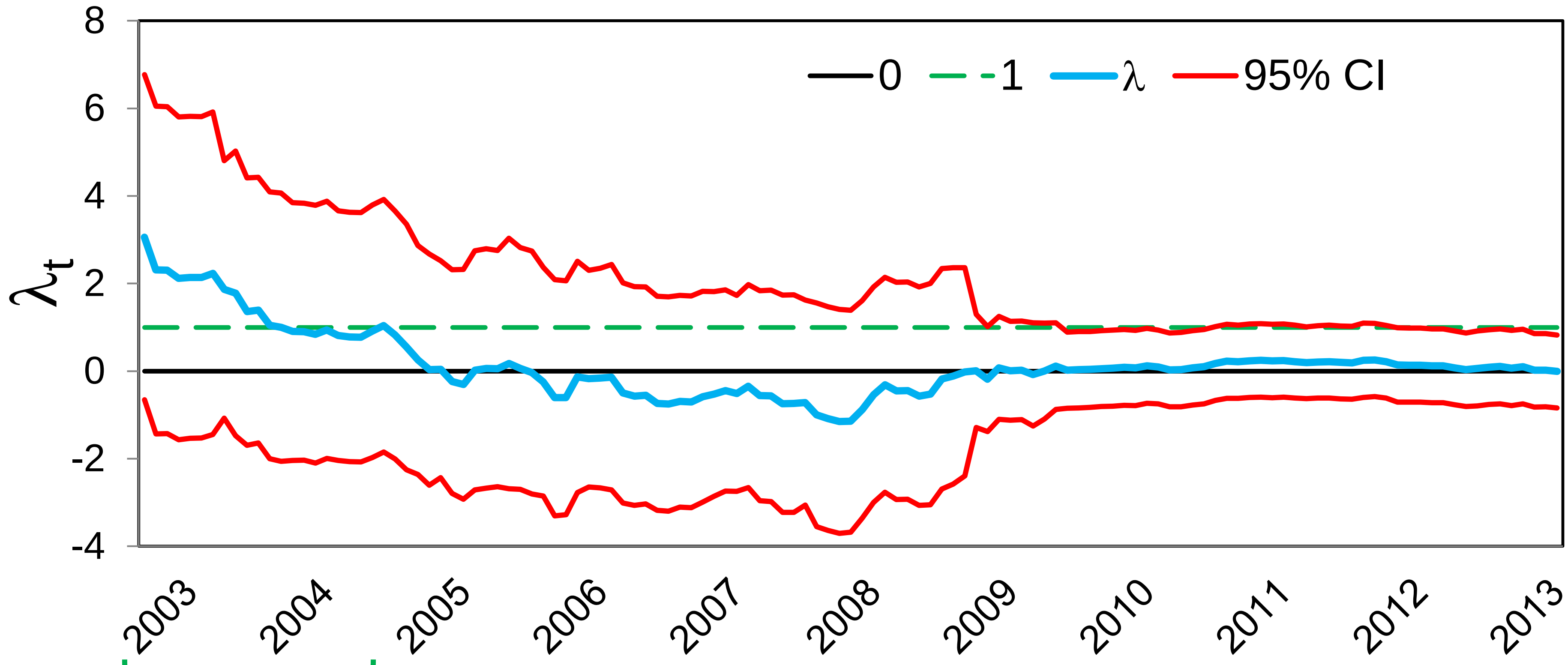
Point forecasts of the N.Y. gasoline price

Point forecasts: NY					
Panel (a): daily data					
Model	MSFE	Δ(MSFE)	λ	H_0: λ = 0	H_0: λ = 1
ECM	4.89	-	-	-	-
A-ECM	4.92	0.56	**1.48**	**2.249****	**0.724**
SR-A-ECM	4.92	0.44	**1.84**	**2.178****	**0.996**
LR-A-ECM	4.90	0.20	1.35	1.612	0.417
TAR1	4.98	1.75	**1.46**	**3.186*****	**0.997**
TAR2	5.00	2.24	**1.42**	**2.910*****	**0.862**
Panel (b): weekly data					
ECM	15.07	-	-	-	-
A-ECM	15.12	0.29	0.59	1.260	-0.885
SR-A-ECM	15.05	-0.18	0.44	0.813	-1.050
LR-A-ECM	15.16	0.57	**1.62**	**2.003****	**0.770**
TAR1	15.43	2.40	**1.00**	**2.905*****	**0.007**
TAR2	15.55	3.15	**0.99**	**3.190*****	**-0.032**
Panel (c): monthly data					
ECM	35.18	-	-	-	-
A-ECM	33.71	**-4.15**	**0.17**	**0.687**	**-3.443*****
SR-A-ECM	33.62	**-4.42**	**0.14**	**0.619**	**-3.839*****
LR-A-ECM	35.64	1.31	1.59	1.457	0.540
TAR1	38.38	9.10	**0.92**	**3.959*****	**-0.330**
TAR2	44.90	27.64	**0.89**	**9.376*****	**-1.195**

Results

Point forecasts of the N.Y. gasoline price: λ_t and A-ECM

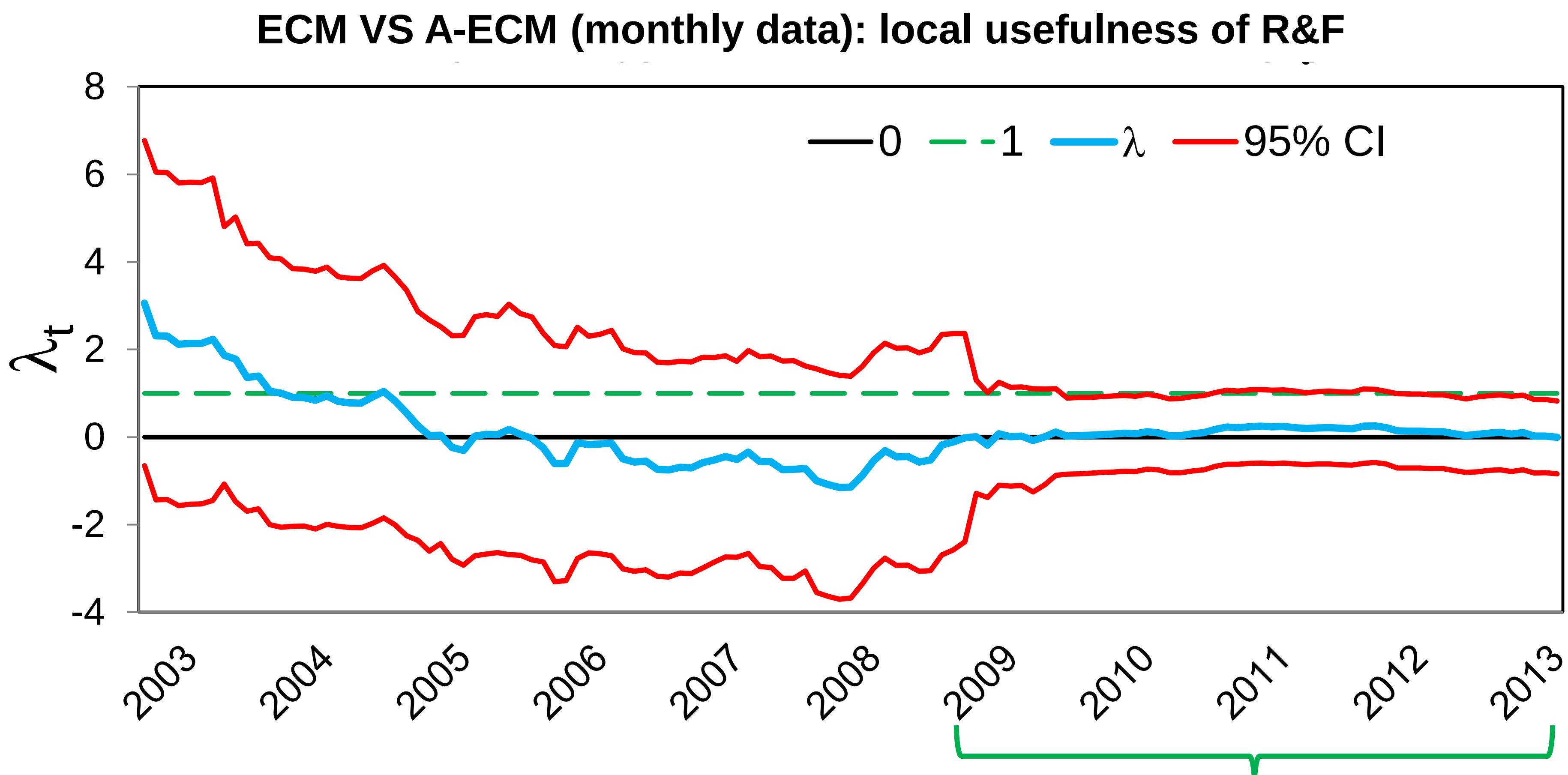
ECM VS A-ECM (monthly data): local usefulness of R&F



- Estimates of λ_t closer to 1 than to 0 until mid 2004
- both 0 and 1 in 95%CI (i.e. test is inconclusive)
- **R&F useless:** optimal forecast combination assigns weight = 1 to f_{ECM}

Results

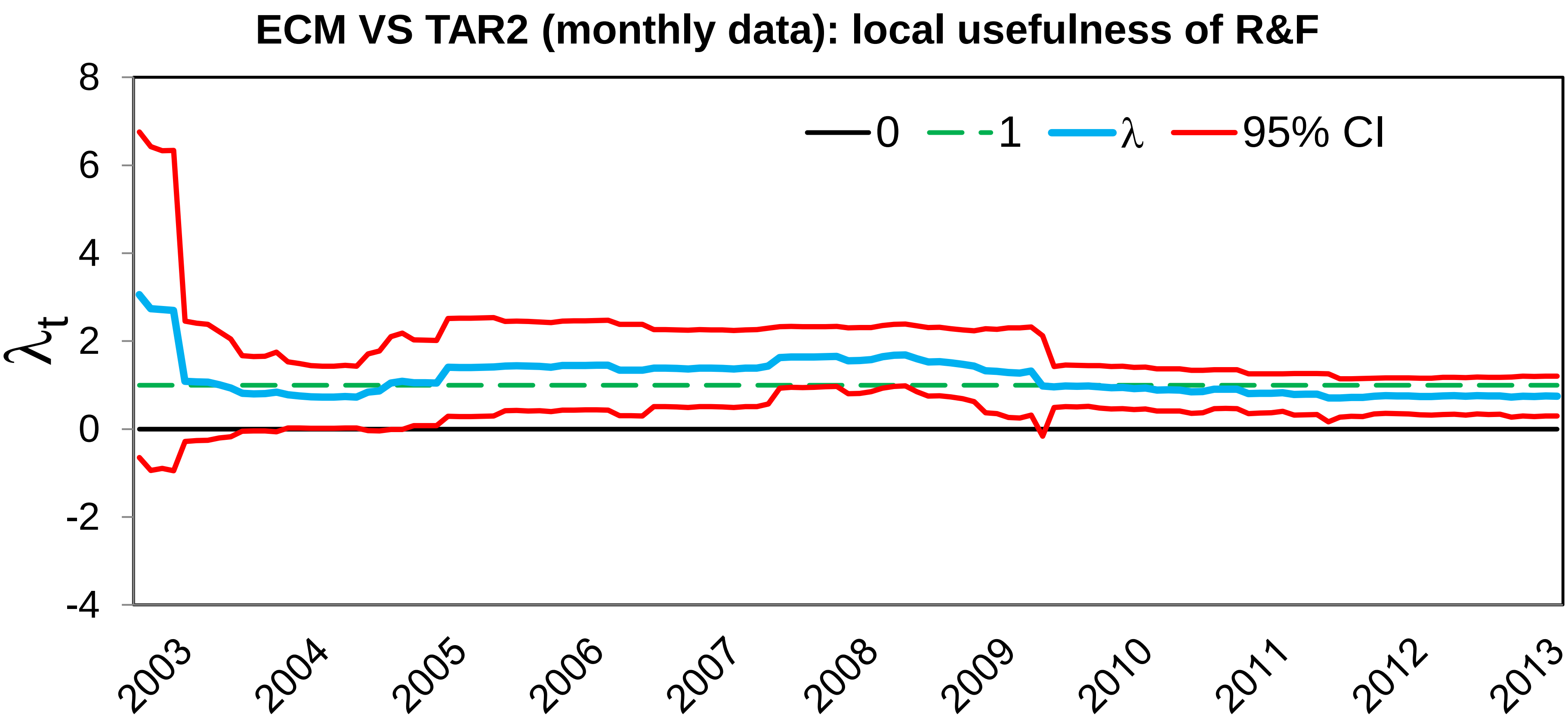
Point forecasts of the N.Y. gasoline price: λ_t and A-ECM



- Estimates of λ_t close 0 after the burst of the oil price bubble in 2008
- 0 in 95% CI, 1 outside 95% CI
- **R&F useful:** optimal forecast combination assigns weight = 1 to $f_{A\text{-}ECM}$

Results

Point forecasts of the N.Y. gasoline price: λ_t and TAR-ECM



- Estimates of λ_t close to 1
- 1 always in 95%CI, 0 outside
- **R&F useless:** optimal forecast combination assigns weights = 1 to f_{ECM}

Results

Sign forecasts of the N.Y. gasoline price

Model	MFTR	Δ(MFTR)	SR	Δ(SR)
Panel (a): daily data				
ECM	1.512	-	76.896	-
A-ECM	1.514	**0.148**	77.059	**0.211**
SR-A-ECM	1.517	**0.308**	77.004	**0.141**
LR-A-ECM	1.516	**0.231**	77.221	**0.423**
TAR1	1.488	-1.609	76.327	-0.740
TAR2	1.508	-0.250	76.490	-0.528
Panel (b): weekly data				
ECM	2.926	-	76.893	-
A-ECM	2.868	-1.989	76.240	-0.849
SR-A-ECM	2.910	-0.526	77.154	**0.340**
LR-A-ECM	2.886	-1.362	77.024	**0.170**
TAR1	2.901	-0.866	76.762	-0.170
TAR2	2.913	-0.437	76.762	-0.170
Panel (c): monthly data				
ECM	7.376	-	81.818	-
A-ECM	7.487	**1.511**	83.523	**2.083**
SR-A-ECM	7.483	**1.450**	83.523	**2.083**
LR-A-ECM	7.455	**1.071**	82.386	**0.694**
TAR1	7.519	**1.940**	82.386	**0.694**
TAR2	6.914	-6.263	80.114	-2.083

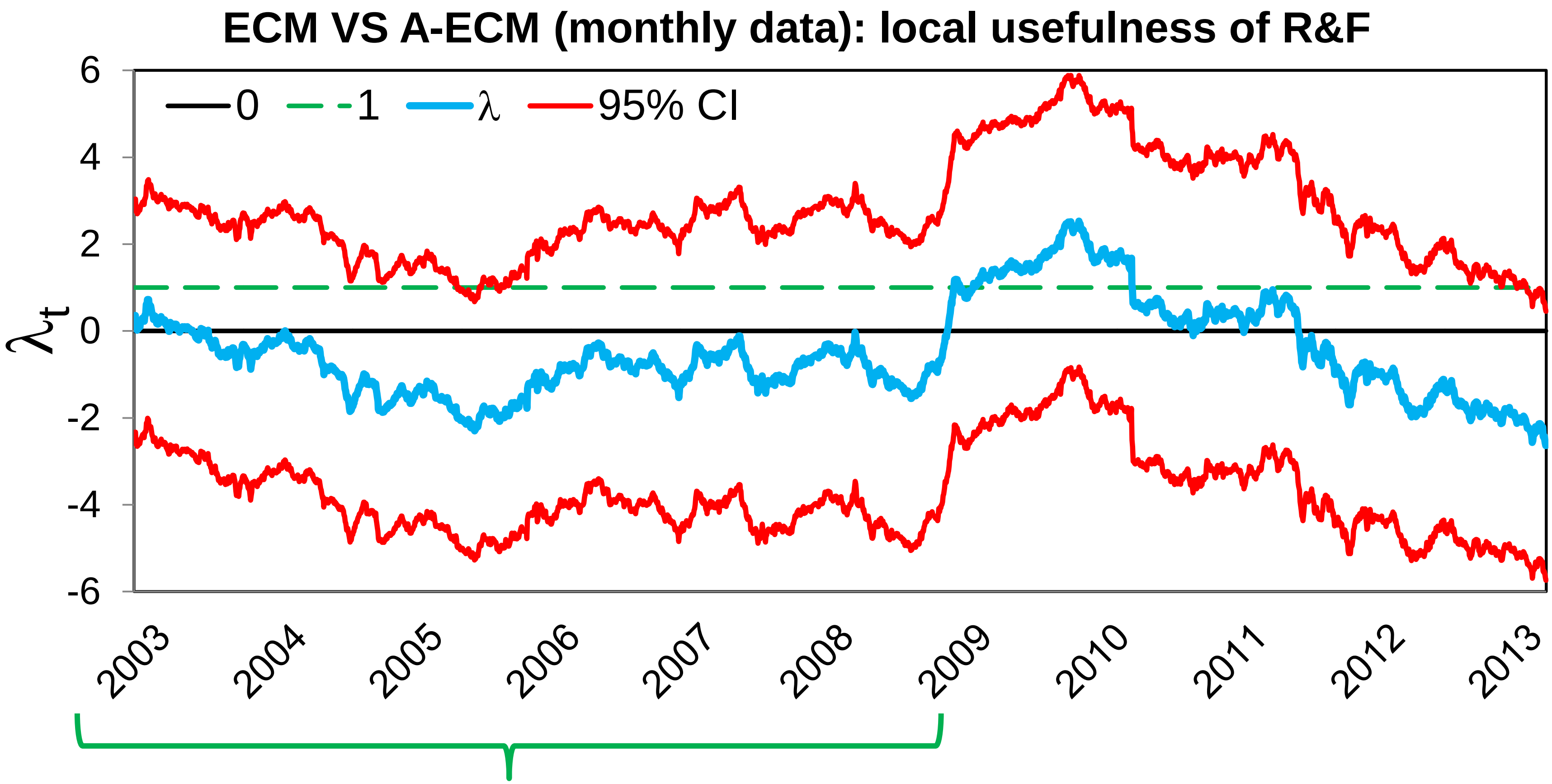
Results

Probability forecasts of the N.Y. gasoline price

Accuracy of probability forecasts: NY					
Panel (a): daily data					
Model	QPS	Δ(QPS)	λ	H_0: λ = 0	H_0: λ = 1
ECM	0.38141	-			
A-ECM	0.38097	**-0.115**	**-0.313**	**-0.587**	**-2.463****
SR-A-ECM	0.38116	**-0.065**	**-0.281**	**-0.394**	**-1.796***
LR-A-ECM	0.38124	**-0.045**	-0.088	-0.114	-1.409
TAR1	0.38151	0.028	**0.876**	**2.656*****	**-0.377**
TAR2	0.38303	0.424	**1.415**	**4.566*****	**1.339**
Panel (b): weekly data					
ECM	0.36703	-			
A-ECM	0.36609	**-0.256**	**-0.092**	**-0.159**	**-1.893***
SR-A-ECM	0.36578	**-0.341**	**-0.348**	**-0.564**	**-2.182****
LR-A-ECM	0.36754	0.140	1.728	1.415	0.596
TAR1	0.36869	**0.452**	**1.085**	**2.442****	**0.192**
TAR2	0.36559	-0.392	**0.221**	**0.622**	**-2.191****
Panel (c): monthly data					
ECM	0.29534	-	-		
A-ECM	0.28984	**-1.861**	**-1.026**	**-1.442**	**-2.847*****
SR-A-ECM	0.28939	**-2.014**	-1.217	-1.681*	-3.061***
LR-A-ECM	0.29652	0.400	2.370	1.173	0.678
TAR1	0.29697	0.553	0.806	1.382	-0.334
TAR2	0.32316	9.423	**1.421**	**3.302*****	**0.979**

Results

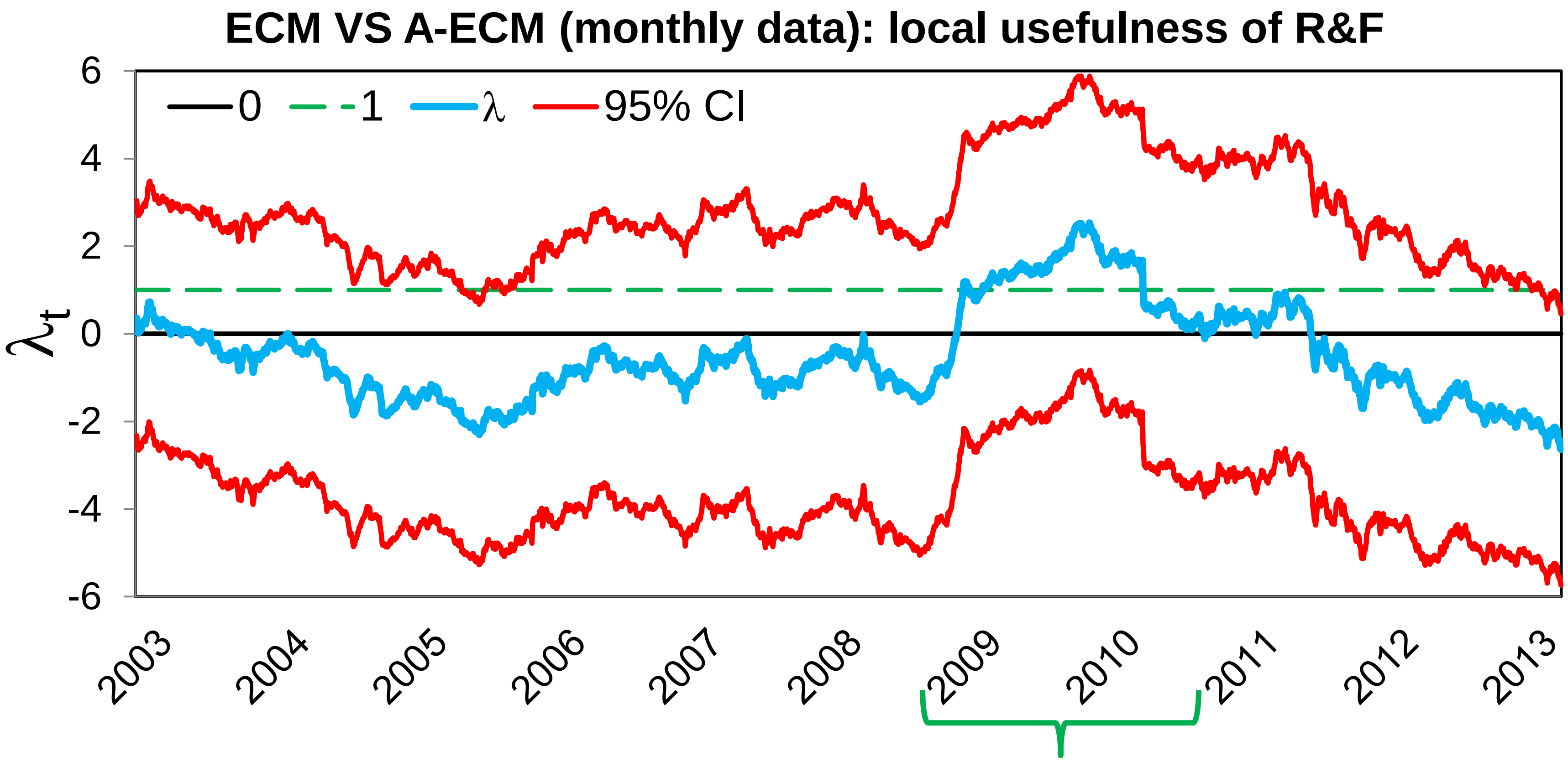
Probability forecasts of the N.Y. gasoline price: λ_t and A-ECM



- Estimates of λ_t closer to 0 than to 1 until mid 2009
- 0 in 95%CI and 1 outside 95%CI
- **R&F useful:** optimal combination of Prob. forecasts = A-ECM

Results

Probability forecasts of the N.Y. gasoline price: λ_t and A-ECM



- Estimates of λ_t closer to 1 than to 0
- **R&F useless:** optimal combination of Prob. for. = ECM

Results

Summary of results

Panel (a): Point Forecasts (MSFE reductions due to R&F)						
	Spot		Retail		Spot & Retail	
	#	%	#	%	#	%
Daily	2 / 18	11,1	- / -	-	- / -	-
Weekly	2 / 18	11,1	4 / 12	33,3	6 / 30	**20**
Monthly	6 / 18	33,3	1 / 12	8,3	7 / 30	**23,3**
Total	10 / 54	18,5	5 / 24	20,8	13 / 78	16,7
Panel (b): Directional Accuracy (SR increases due to R&F)						
	Spot		Retail		Spot & Retail	
	#	%	#	%	#	%
Daily	13 / 18	72,2	- / -	-	- / -	-
Weekly	9 / 18	50	9 / 12	75	18 / 30	**60**
Monthly	13 / 18	72,2	9 / 12	75	22 / 30	**73,3**
Total	35 / 54	64,8	18 / 24	75	40 / 78	51,3
Panel (c): Probability Forecasts (QPS reductions due to R&F)						
	Spot		Retail		Spot & Retail	
	#	%	#	%	#	%
Daily	9 / 18	**50**	- / -	-	- / -	-
Weekly	7 / 18	38,9	4 / 12	33,3	11 / 30	36,7
Monthly	10 / 18	**55,6**	6 / 12	**50**	16 / 30	53,3
Total	26 / 54	48,1	10 / 24	41,7	27 / 78	34,6

Conclusions

Should we care about R&F eventually?

- Point Forecasts: R&F generally useless
- Directional Accuracy: R&F generally useful
- Probability Forecasts:
  - R&F useful at daily and monthly frequencies for spot prices and at monthly frequency for retail prices
  - Median λ close to 0.5: combination of the symmetric ECM and asymmetric models might improve probability forecasts
- Time Dimension: for all frequencies and prices the relative usefulness of predicting with symmetric (no R&F) and asymmetric (R&F) models is time-varying

Further Developments

Fast-ups and Slow-downs

in European Gasoline Markets:

A Tale of Two Speeds

by

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Further Developments

- Empirical papers in the R&F literature apply (many variants of) A-ECM
- Asymmetric responses of gasoline prices to movements in oil prices are just one side of the coin
- The other side of the coin involves *duration dependence* and, more generally, the *definition and dating of fast-ups and slow-downs*

Further Developments

Duration dependence

- Are fast-ups and slow-downs more likely to end as they become older (i.e. positive duration dependence)?
- Is it possible to explain the length and the amplitude of fast-ups and slow-downs? Is R&F a *tale* of two speeds?
- Which covariate (e.g. oil, macro, speculation, survey expectations) can explain the hazard rate of fast-ups and slow-downs?

Further Developments

Defining and dating fast-ups and slow-downs

- Definition of phases and turning points (refer to the vast literature on forecasting and dating business cycle turning points)
- Dating algorithms
- Explanatory variables

Further Developments

Some dating algorithms

- Bry-Boschan dating algorithm

- Non-parametric algorithm that selects local extrema, given a set of thresholds (i.e. min duration and amplitude of cycles)

- Barrier algorithm (Lunde & Timmerman, 2005)

- This algorithm looks at “completion time structures”, i.e. the time distance (duration) between price movements of a given magnitude. How long does it take for the price of gasoline to go up or down by a given amount?

- Signed gasoline returns

- Use the indicator d = I(gasreturns>0) to identify fast-ups and slow-downs and calculate durations