Online Appendix to

"A New Predictor of U.S. Real Economic Activity: The S&P 500 Option Implied Risk Aversion"

Renato Faccini[a], Eirini Konstantinidi[b],

George Skiadopoulos[c] and Sylvia Sarantopoulou-Chiourea[d]

January 5, 2018

In this Online Appendix we provide additional results on whether U.S. implied relative risk aversion (IRRA) predicts U.S. real economic activity (REA) both in- and out-of-sample once we control for well-known REA predictors. We examine the predictive power of IRRA in the case where we extract IRRA (i) by an alternative method than the Kang et al. (2010), (ii) using alternative sample sizes in the rolling GMM estimation, and (iii) from options with maturities longer than one month. We also examine the predictive power of IRRA in the case where we consider alternative out-of-sample periods and an alternative benchmark model with respect to which we evaluate the forecasting performance of the U.S. IRRA predictor.

1. Alternative method to extract IRRA: Bliss and Panigirtzoglou (2004)

We explore whether U.S. IRRA predicts U.S. REA when we extract U.S. IRRA by an alternative method to that of Kang et al. (2010). We use the Kostakis et al. (2011) U.S. IRRA dataset extracted from the Bliss and Panigirtzoglou (2004) approach. They have extracted IRRA in line with Bliss and Panigirtzoglou (2004) by using a rolling window.

[a]School of Economics and Finance, Queen Mary, University of London, UK, r.faccini@qmul.ac.uk

[b]Alliance Manchester Business School, University of Manchester, UK, eirini.konstantinidi@mbs.ac.uk

[c]Corresponding author. School of Economics and Finance, Queen Mary, University of London, UK, and Department of Banking and Financial Management, University of Piraeus, Greece. Also Associate Research Fellow with Cass Business School and Warwick Business School, g.skiadopoulos@qmul.ac.uk, gskiado@unipi.gr

[d]Independent Authority for Public Revenue (IAPR), s.sylvanna@gmail.com

Following the three-step procedure of Bliss and Panigirtzoglou (2004), Kostakis et al. (2011) estimate IRRA from S&P 500 future options at any point in time. In the first step, monthly fixed-expiry risk-neutral probability density functions (PDFs) are extracted from the market option prices. In the second step, the extracted risk-neutral PDFs are converted to the corresponding subjective risk-adjusted PDFs for any given value of the risk aversion parameter. In the third step, the estimated IRRA is the risk aversion parameter value that maximizes the forecasting ability (i.e. the p-value of Berkowitz (2001) likelihood ratio statistic) of the risk-adjusted PDFs with respect to future realizations of the underlying index over a rolling window of N months. We are grateful to Kostakis et al. (2011) who have kindly shared their IRRA estimates with us. They have extracted U.S. IRRA from futures S&P 500 options over July 1998 - May 2010 by assuming a representative agent whose preferences are described by a power utility function and $N = 36$, 48, 60 and 72 months.

We use the Kostakis et al. (2011) IRRA data and we estimate equation (5) for various REA horizons ($h = 1$, 3, 6, 9 and 12 months) over July 1998 - May 2010. In addition to IRRA, we use as predictors the lagged REA and a set of control variables: term spread (TERM), default spread (DEF), TED spread (TED), Fama-French (1996) Small-Minus-Big factor (SMB), Fama-French (1996) High-Minus-Low factor (HML), Baltic Dry Index (BDI), forward variance (FV), hedging pressure commodity factor (HP), momentum commodity factor (MOM), basis commodity factor (BASIS), and commodities open interest (OI). Overall, the alternative measure of IRRA yields weaker results regarding predictability.

Table 1 shows indicatively the results for $N = 60$ months where we orthogonalize TED on IRRA ($\rho = 0.51$) to alleviate multicollinearity concerns. We can see that the evidence of predictability is weaker in the sense that the alternative IRRA estimate predicts REA only for a specific forecasting horizon ($h = 12$ months for IPI, $h = 9$ months for NFP, RRS, CFNAI and ADS) in all but one REA proxy; the only exception occurs for HS where IRRA is significant for more than one forecasting horizons ($h = 3$, 9 and 12 months).

Even though the period under scrutiny in this explorative exercise is significantly shorter from the one employed in the paper and hence results are not comparable, the weaker performance of the Bliss and Panigirtzoglou IRRA as a REA predictor may be attributed to the way the Bliss and Panigirtzoglou IRRA is extracted. The extraction of the Bliss and Panigirtzoglou (2004) IRRA requires a conversion of the implied to the subjective PDF by relying on a specific criterion. Hence, it relies on more transformation steps whereas the Kang et al (2010) IRRA does not require such transformations.

2. GMM and IRRA: Alternative rolling window sizes

We estimate the U.S. IRRA via GMM by using alternative sizes in the rolling window (namely, 45 and 60 months). Then, we repeat our in- and out-of-sample analysis using the estimated IRRA series, separately.

Tables 2 and 3 show the in-sample IRRA coefficient, Newey-West p-value and IVX-Wald p-value (Panel A), as well as the out-of-sample R^2 (Panel B) when we estimate IRRA using a rolling window size of 45 and 60 months, respectively. To alleviate multicollinearity concerns, we orthogonalize TED on IRRA in both cases ($\rho = 0.64$ and 0.76 for a rolling window size of 45 and 60 months, respectively). The results are qualitatively similar to those reported in the paper and they are in line with the theoretical prediction of our real business cycle model regarding the negative relation between relative risk aversion and future real economic activity. IRRA forecasts future REA and the IRRA coefficient is negative. This holds across REA proxies and forecasting horizons for IRRA estimated under both alternative rolling window sizes.

3. Extraction of IRRA from alternative option maturities

We repeat our empirical analysis by extracting IRRA from index options which have three months constant time-to-maturity. We do this additional analysis for U.S. and South Korea. These are the two countries for which we have documented in the main body of the paper that the IRRA extracted from the constant one-month maturity options predicts future REA both in- and out-of-sample. We do not consider longer option maturities (e.g., six months) because these have low liquidity; for instance, in South Korea we can estimate risk-neutral moments with six-months constant time-to-maturity only after 2014.

Table 4 shows the in-sample standardized IRRA coefficient (Panel A) and the out-of-sample R^2 (Panel B) for US and South Korea when IRRA is extracted from options with three months constant time-to-maturity. We consider the respective industrial production and unemployment as REA proxies to have a common set of REA proxies across countries. We find that U.S. IRRA does not predict U.S. REA neither in-sample nor out-of-sample when IRRA is estimated from options with three months to maturity. This is in line with the intuition that the prices of shorter maturity options may be more informative than the longer maturity ones because the former are more liquid. On the other hand, South Korea IRRA predicts South Korea REA in-sample across most forecasting horizons; an increase (decrease) in IRRA predicts a decrease (increase) in REA. This is in accordance with the in-sample results reported in the paper where we estimate IRRA using options with one-month to maturity. It is also consistent with our RBC model, which predicts a negative relation between risk aversion and future REA. Notably, South Korea IRRA has out-of-sample predictive power as well.

The ability of IRRA to predict REA when it is extracted from longer maturity in the case of South Korea comes as no surprise since the KOSPI 200 index options are the most actively traded contracts. For instance, when we extract IRRA using three-month constant maturity risk-neutral moments, we consider KOSPI 200 index option with 7 to 270 days to maturity that have a trading volume equal to 319 million in 2014 (versus 71 million for the respective S&P 500 index options in the U.S.). In conclusion, consistent with the results documented in the main body of the paper, our findings on IRRAs extracted from longer maturity options suggest that IRRA predicts future REA in the case where it is extracted from highly liquid options.

4. Evaluation of IRRA's predictive power: Alternative out-of-sample periods

We consider alternative out-of-sample periods by reducing the size of the sample used to initiate the out-of-sample experiment. This delivers January 2004 - August 2015, January 2005 - August 2015, January 2006 - August 2015, January 2007 - August 2015 as alternative out-of-sample periods. Tables 5 and 6 show the out-of-sample R^2 obtained from predictive regressions and the out-of-sample R^2 obtained from the Kelly and Pruitt (2015) three-pass regression filter (3PRF), respectively, for alternative out-of-sample periods.

The results are analogous to those reported in the main body of the paper. In particular, the out-of-sample R^2 obtained from the predictive regressions is positive in most cases, i.e. the full model performs better than the restricted model, suggesting that the inclusion of IRRA is statistically significant in an out-of-sample setting, too. The evidence is somewhat weaker for longer forecasting horizons. IRRA predicts RS and HS for all forecasting horizons and all out-of-sample periods. It also predicts NFP for short and intermediate horizons; we get a positive out-of-sample R^2 for $h = 1$ month for all out-of-sample periods, for $h = 3$ when the out-of-sample period starts after January 2006, and for $h = 6$ months when the out of sample period starts after January 2005. This also holds for CFNAI; we get a positive out-of-sample R^2 for $h = 1$ and 6 months for all out-of-sample periods. Finally, it predicts IPI only for short forecasting horizons ($h = 1$ month) when the out-of-sample period starts after January 2006. In the case of the 3PRF model, the out-of-sample R^2 is positive in all but one case. The only exception occurs for NFP at a one-month horizon when the out-of-sample period starts in January 2005 where the out-of-sample R^2 obtained from the 3PRF model is marginally negative (-0.001). Given the space limitations and the discussion above, we report results only for the out-of-sample period from October 2007 to August 2015 in the main body of the paper.

5. Evaluation of IRRA's out-of-sample predictive power: Alternative benchmark

We calculate the out-of-sample R^2 versus the moving average (MA) of past 30-month REA values for the U.S.[1] Table 7 shows the out-of-sample R^2 of our full model forecasts versus

[1]The sample mean of past returns has been used as a benchmark in the literature on whether the equity premium can be predicted. In fact, in that literature this is a natural choice for the benchmark model. This is because it is common practice to proxy expected returns by their average values over some past data in the asset pricing literature. In contrast, it is not a common practice to use the average of past values of real economic activity in the literature on whether REA can be predicted. The common practice in the REA literature is to use a well-established restricted model as a benchmark which contains some standard predictors such as different types of spread variables (e.g., Bakshi et al, 2011). Most importantly, the aim of our paper is to examine whether a new predictor of REA (i.e. IRRA) should be included in the list of already commonly used REA predictors. As a result, we report in the main body of the paper the out-of-sample R^2 where we compare the full model [equation (5)] versus the restricted model.

the MA for the U.S. In general, the results are in-line to those reported in the paper where the restricted model has been used. Our full model outperforms the naive MA model, which suggests that IRRA can serve as a predictor even under this alternative benchmark for U.S. The only exception occurs for retail sales (RS).

References

Bakshi, G., G. Panayotov, and G. Skoulakis (2011). Improving the predictability of real economic activity and asset returns with forward variances inferred from option portfolios, *Journal of Financial Economics* 100, 475-495.

Berkowitz, J., (2001). Testing density forecasts with applications to risk management, *Journal of Business and Economics Statistics* 19, 465-474.

Bliss, R. R., and N. Panigirtzoglou (2004). Option-implied risk aversion estimates, *Journal of Finance* 59, 407-446.

Kang, B. J., T. S. Kim, and S-J. Yoon (2010). Information content of volatility spreads, *Journal of Futures Markets* 30, 533-558.

Kelly, B., and S. Pruitt (2015). The three-pass filter regression filter: A new approach to forecasting using many predictors, *Journal of Econometrics* 186, 294-316.

Kostakis, A., N. Panigirtzoglou, and G. Skiadopoulos (2011). Market timing with option-implied distributions: A forward-looking approach, *Management Science* 57, 1231-1249.

Table 1: Alternative IRRA construction: Bliss and Panigirtzoglou (2004)

	$\mathbf{IPI_{t+h}}$	$\mathbf{NFP_{t+h}}$	$\mathbf{RRS_{t+h}}$	$\mathbf{HS_{t+h}}$	$\mathbf{CFNAI_{t+h}}$	$\mathbf{ADS_{t+h}}$
h = 1M	0.115	0.046	-0.020	0.007	0.024	0.016
	(0.260)	(0.437)	(0.808)	(0.932)	(0.747)	(0.726)
	[0.369]	[0.553]	[0.650]	[0.626]	[0.948]	[0.959]
h = 3M	0.052	0.014	-0.094	**-0.181*****	-0.074	-0.107
	(0.706)	(0.841)	(0.553)	(0.133)	(0.505)	(0.370)
	[0.653]	[0.822]	[0.364]	[0.057]	[0.258]	[0.291]
h = 6M	-0.092	-0.047	-0.292	-0.280	-0.298	-0.339
	(0.627)	(0.691)	(0.204)	(0.117)	(0.096)	(0.093)
	[0.782]	[0.760]	[0.207]	[0.140]	[0.202]	[0.253]
h = 9M	-0.236	**-0.143*****	-0.418*	**-0.349***	**-0.458****	**-0.455*****
	(0.308)	(0.368)	(0.049)	(0.063)	(0.027)	(0.031)
	[0.207]	[0.079]	[0.005]	[0.001]	[0.046]	[0.099]
h = 12M	**-0.347****	-0.344	-0.414	**-0.264****	-0.438	-0.419
	(0.141)	(0.035)	(0.031)	(0.067)	(0.023)	(0.027)
	[0.015]	[0.123]	[0.868]	[0.031]	[0.291]	[0.114]

Entries report results from the in-sample estimated multiple predictor regressions for various U.S. real economic activity (REA) proxies and for various REA horizons (h = 1, 3, 6, 9 and 12 months). The REA proxies considered are: industrial production (IPI), non-farm payrolls (NFP), retail sales (RS, proxied by real retail sales), housing starts (HS), the Chicago Fed National Activity Index (CFNAI) and the Aruoba-Diebold-Scotti business conditions index (ADS). The multiple predictor model includes the lagged REA and implied relative risk aversion (IRRA) as predictors and is augmented by a set of control variables: term spread (TERM), default spread (DEF), TED spread (TED), Fama-French (1996) Small-Minus-Big factor (SMB), Fama-French (1996) High-Minus-Low factor (HML), Baltic Dry Index (BDI), forward variance (FV), hedging pressure commodity factor (HP), momentum commodity factor (MOM), basis commodity factor (BASIS), and commodities open interest (OI). The U.S. IRRA is obtained from Kostakis et al. (2011) who follow the three-step procedure suggested by Bliss and Panigirtzoglou (2004). We report the standardized ordinary-least-squares (OLS) coefficient estimates, Newey-West p-values (within brackets) and IVX-Wald p-values (within squared brackets) of the IRRA predictor for any given REA horizon. One, two and three asterisks denote rejection of the null hypothesis of a zero coefficient based on the IVX-Wald test statistic at the 1%, 5% and 10% level, respectively. The sample spans July 1998 to May 2010.

Table 2: Rolling window size of 45 months

	$\mathbf{IPI_{t+h}}$	$\mathbf{NFP_{t+h}}$	$\mathbf{RRS_{t+h}}$	$\mathbf{HS_{t+h}}$	$\mathbf{CFNAI_{t+h}}$	$\mathbf{ADS_{t+h}}$
			Panel A: In-sample IRRA coefficient			
h = 1M	-0.089	**-0.119****	**-0.276***	**-0.248***	**-0.113****	**-0.070*****
	(0.354)	(0.011)	(0.000)	(0.000)	(0.065)	(0.068)
	[0.238]	[0.012]	[0.001]	[0.002]	[0.037]	[0.056]
h = 3M	**-0.159****	**-0.191***	**-0.567***	**-0.642***	**-0.246***	**-0.294***
	(0.166)	(0.005)	(0.000)	(0.000)	(0.008)	(0.004)
	[0.010]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
h = 6M	**-0.387***	**-0.321***	**-0.706***	**-0.944***	**-0.492***	**-0.544***
	(0.032)	(0.004)	(0.000)	(0.000)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
h = 9M	**-0.573***	**-0.449***	**-0.785***	**-1.146***	**-0.619***	**-0.698***
	(0.007)	(0.002)	(0.000)	(0.000)	(0.002)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
h = 12M	**-0.692***	**-0.553***	**-0.880***	**-1.211***	**-0.683***	**-0.721***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]
			Panel B: Out-of-sample $\mathbf{R^2}$ from predictive regressions			
h = 1M	0.053	0.143	0.212	0.040	0.098	0.117
h = 3M	0.071	0.127	0.211	0.030	0.085	-0.037
h = 6M	-0.144	0.115	0.321	0.500	0.010	-0.023
h = 9M	-0.308	0.010	0.358	0.780	0.016	-0.017
h = 12M	-0.353	-0.077	0.411	0.844	0.164	0.110

Panel A reports results from the in-sample estimated multiple predictor regressions for various U.S. real economic activity (REA) proxies and for various REA horizons (h = 1, 3, 6, 9 and 12 months) in the case where IRRA is estimated via GMM using a rolling window of size 45 months. The REA proxies considered are: industrial production (IPI), non-farm payrolls (NFP), retail sales (RS, proxied by real retail sales), housing starts (HS), the Chicago Fed National Activity Index (CFNAI) and the Aruoba-Diebold-Scotti business conditions index (ADS). The multiple predictor model includes the lagged REA and implied relative risk aversion (IRRA) as predictors and is augmented by a set of control variables: term spread (TERM), default spread (DEF), TED spread (TED), Fama-French (1996) Small-Minus-Big factor (SMB), Fama-French (1996) High-Minus-Low factor (HML), Baltic Dry Index (BDI), forward variance (FV), hedging pressure commodity factor (HP), momentum commodity factor (MOM), basis commodity factor (BASIS), and commodities open interest (OI). The IRRA is estimated according to Kang et al. (2010) using a rolling window of 45 months. We report the standardized ordinary-least-squares (OLS) coefficient estimates, Newey-West p-values (within brackets) and IVX-Wald p-values (within squared brackets) of the IRRA predictor for any given REA horizon. One, two and three asterisks denote rejection of the null hypothesis of a zero coefficient based on the IVX-Wald test statistic at the 1%, 5% and 10% level, respectively. The sample spans July 1998 to August 2015.

Panel B report the out-of-sample R^2 in the case where IRRA is estimated via GMM using a rolling window of size 45 months. For each REA proxy, we estimate equation (5) and the benchmark model recursively by employing an expanding window; the first estimation sample window contains observations spanning October 1999 to September 2007. At each point in time, we form h month-ahead REA forecasts (h = 1, 3, 6, 9 and 12 months). The benchmark model considers only lagged REA and the control variables as predictors.

Table 3: **Rolling window size of 60 months**

	$\mathbf{IPI_{t+h}}$	$\mathbf{NFP_{t+h}}$	$\mathbf{RRS_{t+h}}$	$\mathbf{HS_{t+h}}$	$\mathbf{CFNAI_{t+h}}$	$\mathbf{ADS_{t+h}}$
			Panel A: In-sample IRRA coefficient			
h = 1M	**-0.145*** **	**-0.147***	**-0.274***	**-0.218****	**-0.162****	**-0.096****
	(0.183)	(0.005)	(0.002)	(0.000)	(0.016)	(0.019)
	[0.081]	[0.002]	[0.004]	[0.014]	[0.019]	[0.027]
h = 3M	**-0.228***	**-0.240***	**-0.641***	**-0.594***	**-0.342***	**-0.402***
	(0.099)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
h = 6M	**-0.521***	**-0.414***	**-0.805***	**-0.847***	**-0.635***	**-0.705***
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
h = 9M	**-0.741***	**-0.586***	**-0.903***	**-1.026***	**-0.766***	**-0.862*** **
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.071]
h = 12M	**-0.872***	**-0.707***	**-0.968***	**-1.104***	**-0.796***	**-0.842***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
			Panel B: Out-of-sample R^2 from predictive regressions			
h = 1M	0.048	0.158	0.326	0.090	0.148	0.174
h = 3M	0.103	0.247	0.430	0.281	0.358	0.349
h = 6M	0.228	0.238	0.511	0.531	0.444	0.480
h = 9M	0.238	0.142	0.453	0.630	0.332	0.334
h = 12M	0.034	0.252	0.276	0.617	-0.352	-0.632

Panel A reports results from the in-sample estimated multiple predictor regressions for various U.S. real economic activity (REA) proxies and for various REA horizons (h = 1, 3, 6, 9 and 12 months) in the case where IRRA is estimated via GMM using a rolling window of size 60 months. The REA proxies considered are: industrial production (IPI), non-farm payrolls (NFP), retail sales (RS, proxied by real retail sales), housing starts (HS), the Chicago Fed National Activity Index (CFNAI) and the Aruoba-Diebold-Scotti business conditions index (ADS). The multiple predictor model includes the lagged REA and implied relative risk aversion (IRRA) as predictors and is augmented by a set of control variables: term spread (TERM), default spread (DEF), TED spread (TED), Fama-French (1996) Small-Minus-Big factor (SMB), Fama-French (1996) High-Minus-Low factor (HML), Baltic Dry Index (BDI), forward variance (FV), hedging pressure commodity factor (HP), momentum commodity factor (MOM), basis commodity factor (BASIS), and commodities open interest (OI). The IRRA is estimated according to Kang et al. (2010) using a rolling window of 60 months. We report the standardized ordinary-least-squares (OLS) coefficient estimates, Newey-West p-values (within brackets) and IVX-Wald p-values (within squared brackets) of the IRRA predictor for any given REA horizon. One, two and three asterisks denote rejection of the null hypothesis of a zero coefficient based on the IVX-Wald test statistic at the 1%, 5% and 10% level, respectively. The sample spans July 1998 to August 2015.

Panel B report the out-of-sample R^2 in the case where IRRA is estimated via GMM using a rolling window of size 45 months. For each REA proxy, we estimate equation (5) and the benchmark model recursively by employing an expanding window; the first estimation sample window contains observations spanning October 1999 to September 2007. At each point in time, we form h month-ahead REA forecasts (h = 1, 3, 6, 9 and 12 months). The benchmark model considers only lagged REA and the control variables as predictors.

Table 4: Alternative option maturities

	U.S.		South Korea	
	IPI	**NFP**	**IPI**	**U**
Panel A: In-sample IRRA coefficient				
h = 1M	-0.020	**-0.118***	-0.082	0.118
	(0.774)	(0.004)	(0.155)	(0.110)
	[0.717]	[0.007]	[0.529]	[0.371]
h = 3M	0.024	-0.062	**-0.210*****	**0.308***
	(0.699)	(0.207)	(0.024)	(0.016)
	[0.828]	[0.407]	[0.094]	[0.004]
h = 6M	0.059	-0.029	**-0.422***	**0.609***
	(0.458)	(0.615)	(0.029)	(0.000)
	[0.996]	[0.831]	[0.000]	[0.000]
h = 9M	-0.017	-0.057	**-0.543***	**0.810***
	(0.858)	(0.311)	(0.009)	(0.000)
	[0.995]	[0.799]	[0.000]	[0.000]
h = 12M	-0.141	-0.092	**-0.543***	**0.956***
	(0.166)	(0.090)	(0.000)	(0.000)
	[0.839]	[0.828]	[0.002]	[0.000]
Panel B: Out-of-sample $\mathbf{R^2}$				
h = 1M	-0.020	-0.018	-0.069	-0.035
h = 3M	-0.033	-0.056	-0.025	-0.077
h = 6M	-0.047	-0.038	0.573	0.358
h = 9M	-0.037	-0.066	0.525	0.526
h = 12M	-0.005	-0.120	0.088	0.365

Panel A reports results from the in-sample estimated multiple predictor regressions for various U.S. and South Korea real economic activity (REA) proxies and for various forecasting horizons (h = 1, 3, 6, 9 and 12 months) when estimate the respective IRRA using options with three-months time-to-maturity. The U.S. REA proxies considered are: industrial production (IPI) and non-farm payrolls (NFP). The South Korea REA proxies considered are: industrial production (IPI) and the unemployment rate (U). We report the standardized ordinary-least-squares (OLS) coefficient estimates, Newey-West p-values (within brackets) and IVX-Wald p-values (within squared brackets) of the IRRA predictor for any given forecasting horizon. One, two and three asterisks denote rejection of the null hypothesis of a zero coefficient based on the IVX-Wald test statistic at the 1%, 5% and 10% level, respectively. The U.S. sample spans September 1998 to August 2015 and the South Korea sample spans June 2006 to June 2015.

Panel B reports the out-of-sample R^2 in the case of U.S. and South Korea when estimate the respective IRRA using options with three-months time-to-maturity. For each REA proxy, we estimate equation (5) and the benchmark model recursively by employing an expanding window. The first estimation sample window contains observations spanning September 1997 to September 2007 in the case of U.S. and June 2006 to December 2008 in the case of South Korea. At each point in time, we form h month-ahead REA forecasts (h = 1, 3, 6, 9 and 12 months). The benchmark model considers only lagged REA and the control variables as predictors.

Table 5: **Out-of-sample R^2 from predictive regression for alternative out-of-sample periods**

	IPI	NFP	RS	HS	CFNAI	ADS
Panel A: Out-of-sample period January 2004 - August 2015						
h = 1M	-0.013	0.010	0.007	0.040	0.029	0.004
h = 3M	-0.013	-0.010	0.072	0.092	0.000	-0.059
h = 6M	-0.075	-0.009	0.136	0.358	0.007	-0.030
h = 9M	-0.188	-0.064	0.129	0.549	-0.060	-0.057
h = 12M	-0.296	-0.112	0.100	0.609	-0.118	-0.177
Panel B: Out-of-sample period January 2005 - August 2015						
h = 1M	-0.013	0.023	0.011	0.046	0.043	0.007
h = 3M	-0.019	-0.004	0.069	0.099	0.000	-0.064
h = 6M	-0.084	0.003	0.143	0.362	0.007	-0.029
h = 9M	-0.181	-0.050	0.138	0.554	-0.056	-0.050
h = 12M	-0.277	-0.105	0.138	0.617	-0.110	-0.168
Panel C: Out-of-sample period January 2006 - August 2015						
h = 1M	0.014	0.045	0.059	0.054	0.060	0.019
h = 3M	-0.005	0.021	0.106	0.099	-0.006	-0.055
h = 6M	-0.075	0.007	0.155	0.369	0.005	-0.025
h = 9M	-0.172	-0.053	0.161	0.560	-0.062	-0.045
h = 12M	-0.236	-0.107	0.160	0.629	-0.111	-0.133
Panel D: Out-of-sample period January 2007 - August 2015						
h = 1M	0.014	0.051	0.063	0.045	0.068	0.025
h = 3M	-0.003	0.031	0.114	0.107	-0.003	-0.051
h = 6M	-0.081	0.011	0.162	0.384	0.005	-0.024
h = 9M	-0.182	-0.046	0.172	0.580	-0.058	-0.043
h = 12M	-0.253	-0.106	0.184	0.659	-0.095	-0.113

Entries report the out-of-sample R^2 obtained from the full versus the restricted predictive regression model for various U.S. real economic activity (REA) proxies and for various forecasting horizons (h = 1, 3, 6, 9 and 12 months) over alternative out-of-sample periods. The U.S. REA proxies considered are: industrial production (IPI), non-farm payrolls (NFP), retail sales (RS, proxied by real retail sales), housing starts (HS), the Chicago Fed National Activity Index (CFNAI) and the Aruoba-Diebold-Scotti business conditions index (ADS).

Table 6: Out-of-sample R^2 Kelly and Pruitt (2015) three-pass regression filter for alternative out-of-sample periods

	IPI	NFP	RS	HS	CFNAI	ADS
Panel A: Out of sample January 2004 - August 2015						
h = 1M	0.003	0.002	0.005	0.004	0.009	0.013
h = 3M	0.005	0.011	0.003	0.029	0.009	0.010
h = 6M	0.013	0.017	0.025	0.066	0.019	0.019
h = 9M	0.018	0.022	0.027	0.099	0.033	0.032
h = 12M	0.022	0.027	0.038	0.098	0.035	0.011
Panel B: Out of sample January 2005 - August 2015						
h = 1M	0.003	-0.001	0.007	0.005	0.009	0.013
h = 3M	0.005	0.006	0.005	0.031	0.008	0.009
h = 6M	0.012	0.013	0.025	0.069	0.018	0.019
h = 9M	0.017	0.020	0.028	0.103	0.032	0.031
h = 12M	0.021	0.025	0.039	0.102	0.035	0.009
Panel C: Out of sample January 2006 - August 2015						
h = 1M	0.003	0.002	0.010	0.006	0.010	0.014
h = 3M	0.004	0.008	0.010	0.033	0.009	0.010
h = 6M	0.010	0.013	0.029	0.070	0.018	0.018
h = 9M	0.015	0.018	0.036	0.104	0.030	0.030
h = 12M	0.019	0.021	0.045	0.103	0.033	0.015
Panel D: Out of sample January 2007 - August 2015						
h = 1M	0.003	0.008	0.011	0.007	0.011	0.013
h = 3M	0.004	0.012	0.012	0.032	0.009	0.009
h = 6M	0.010	0.015	0.028	0.071	0.018	0.018
h = 9M	0.015	0.019	0.038	0.105	0.030	0.030
h = 12M	0.019	0.021	0.047	0.102	0.034	0.018

Entries report the out-of-sample R^2 obtained from the Kelly and Pruitt (2015) three-pass regression filter (3PRF) in equation (9) for various U.S. real economic activity (REA) proxies and for various forecasting horizons ($h = 1$, 3, 6, 9 and 12 months) over alternative out-of-sample periods. We apply the 3PRF to the set of variables consisting of IRRA and a large set of 135 macroeconomic variables compiled by McCracken and Ng (2015) versus the benchmark model which is the 3PRF applied to the 135 McCracken and Ng (2015) macroeconomic variables. The U.S. REA proxies considered are: industrial production (IPI), non-farm payrolls (NFP), retail sales (RS, proxied by real retail sales), housing starts (HS), the Chicago Fed National Activity Index (CFNAI) and the Aruoba-Diebold-Scotti business conditions index (ADS).

Table 7: **Out-of-sample R^2 of full model versus moving average**

	IPI	**NFP**	**RS**	**HS**	**CFNAI**	**ADS**
h = 1M	0.092	0.805	-0.116	0.117	0.689	0.850
h = 3M	0.375	0.798	-0.063	0.070	0.471	0.482
h = 6M	-0.203	0.528	-0.105	0.114	-0.291	-0.657
h = 9M	-0.861	0.125	-0.416	0.279	-1.176	-1.548
h = 12M	-0.880	-0.252	-0.283	0.427	-1.169	-1.748

Entries report the out-of-sample R^2 for U.S. obtained from the predictive model in equation (5) versus the benchmark, which is a naive moving average model. For each U.S. REA proxy, we estimate equation (5) for the respective full and the benchmark model recursively by employing an expanding window; the first estimation sample window spans July 1998 to September 2007. At each point in time, we form h =1, 3, 6, 9, 12 months-ahead U.S. REA forecasts. The positive (negative) sign of the out-of-sample R^2 indicates that our model which includes U.S. IRRA as a predictor outperforms (underperforms) the moving average model.