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Volatility in electricity derivative markets: the Samuelson effect revisited[☆]

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Abstract

This article proposes an empirical study of the Samuelson effect in electricity markets. Our motivations are twofold. First, although the literature largely assesses the decreasing pattern in the volatilities along the price curve in commodity markets, it has not extensively tested the presence of such a dynamic feature in electricity prices. Second, the analysis of a non-storable commodity enriches the literature on the behavior of commodity prices. Indeed, it has been sometimes asserted that the Samuelson effect results from the presence of inventories. We examine the four most important electricity futures markets worldwide for the period from 2008 to 2014: the German, Nordic, Australian, and US markets. We also use the American crude oil market as a benchmark for a *storable* commodity negotiated on a *mature* futures market. Our analysis has two steps: i) in addition to the traditional tests, we propose and test a new empirical implication of the Samuelson effect: price shocks should spread *from* the physical market *to* the paper market, and not the reverse; ii) based on the concept of "indirect storability", we investigate the link between the Samuelson effect and the storability of the commodity. We find evidence of a Samuelson effect in all of the electricity markets and show that storage is not a necessary condition for such an effect to appear. These results should be taken into account for the understanding of the dynamic behavior of commodity prices, for the valuation of electricity assets, and for hedging operations.

Keywords: Samuelson effect, Commodity futures, Energy derivative markets, Electricity, Volatility spillovers, Indirect storability.
JEL Codes: C22, G13, G15, Q41

1. Introduction

The most important dynamic feature of commodity futures prices is probably the difference between the behavior of the prices of the first-nearby and deferred contracts. The movements of the former are large and erratic, while the latter are relatively stable. This difference results in a decreasing pattern in the volatilities along the price curve. The same is true for the correlations between the nearest futures price and subsequent prices, which decline with the maturity. This phenomenon is usually called the Samuelson effect or the maturity effect. The reasoning behind this phenomenon is that a shock that affects the short-term price has an effect on the succeeding prices that decreases as the maturity increases (Samuelson (1965)). Indeed, when a futures contract reaches its expiration date, it reacts more strongly to information shocks because of the ultimate convergence of the futures to the spot prices at maturity. The demand and supply shocks borne in the physical market are responsible for this price disturbance that mostly influences the short-term

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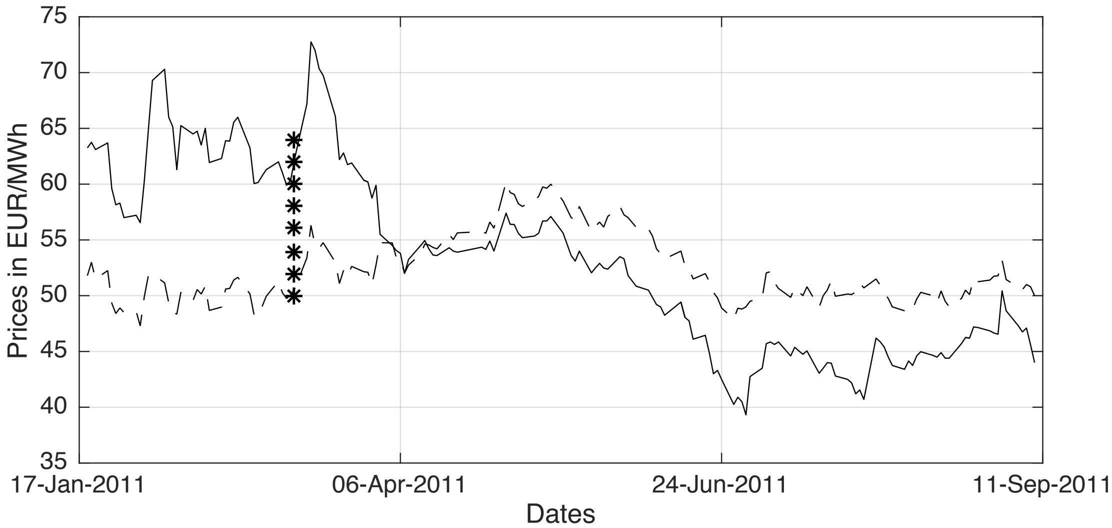
part of the curve. Figure 1 gives an example of such an effect. It represents the prices of electricity on a European futures market (the Nasdaq OMX commodities market, also called the NordPool) around the Fukushima nuclear disaster of March 2011. The jump recorded in the prices just after the plant failure is far more important for the short- rather than the long-term prices. This higher volatility clearly continues in the weeks following the disaster.



This figure displays the prices of electricity futures for two different maturities on the NordPool market around the Fukushima disaster of March 2011. The solid line corresponds to one-month futures prices; the dashed line to four-month futures prices. The vertical line of stars identifies the day of the accident.

Figure 1: Electricity futures prices on the NordPool market around the Fukushima catastrophe

In this article, we offer a large scale study of the Samuelson effect on different electricity markets worldwide. We enlarge the spectrum of the empirical studies on the maturity effect and we address the question of non-storability.

The literature devoted to empirical tests of the Samuelson effect on storable commodities and financial assets is quite large[1]. This literature has reached an overall consensus about the Samuelson effect, and finds a strong effect on energy products and agricultural commodities (grains, soft commodities, meats). The picture is more nuanced for metals, with weak or null evidence for precious metals. Further, there is no Samuelson effect on financial assets. As far as electricity is concerned, the only available studies, to the best of our knowledge, are the article by Walls (1999) (14 futures contracts traded on the Nymex between March and November 1996 for two US markets) and the working paper of Allen and Cruickshank (2002) (42 futures contracts for two Australian electricity markets, from 1997 to 1999).

Regarding the economic explanation of the Samuelson effect, the literature is mixed about its origins. Bessembinder et al. (1996) establish a relation between the Samuelson effect and the mean reversion in the dynamics of commodity prices. For them, these dynamics are the direct consequence of storability and reflect the behavior of the operators in the physical market. Other studies use this kind of analysis, such as Schwartz (1997). In the same line of reasoning, a temporary excess in inventories in the physical market

[1]see among others; Anderson (1985) for a study on nine markets for agricultural products and metals; Milonas (1986) who examines 11 markets for agricultural products, financial assets, and metals; Duong and Kalev (2008): 20 futures markets for agricultural products, financial assets, and metals (these authors are the only ones who examine high frequency data. However, such a study is out of reach in the case of electricity, due to a lack of data), from 1996 to 2003; Lautier and Raynaud (2011): 13 commodity and financial futures markets from 1998 to 2012; and Brooks (2012): 50 futures markets for commodities and financial assets, from 1993 to 2012.

might act as a cushion and decrease the volatility of short-term prices. Fama and French (1988), among others, find that violations of the Samuelson effect might occur at short-term horizons when inventories are high. They show that for industrial metals, when the inventory is high, the spot and futures prices have the same variability. But in the case of scarcity, there is a decreasing pattern in the volatilities. This finding is consistent with the storage theory (Working (1949), Brennan (1958)). In this framework, the marginal convenience yield is a nonmonotonic and decreasing function of the inventory level. Routledge et al. (2000) reiterate the proposition of Fama and French with an equilibrium model of the term structure of forward prices for storable commodities.

In contrast Anderson and Danthine (1983) propose a theoretical framework that allows for an analysis of the relation between the Samuelson effect and the resolution of uncertainty over time. In this setting, storage does not remain the most important explanatory factor for the behavior of volatility. What matters more is production uncertainty and the way this uncertainty diffuses into the market. According to the authors, "futures prices are volatile in times when much uncertainty is resolved and are stable when little uncertainty is resolved. Whether most uncertainty is resolved near the delivery date of a futures contract is an empirical matter".

This debate naturally raises questions about the dynamic behavior of the futures prices of a non-storable commodity like electricity. We thus examine this behavior in the four most important electricity futures markets worldwide for the period from 2008 to 2014: the German market, NordPool (representative of European Nordic countries), Australian market, and the PJM Western Hub in the United States. We also rely on the American crude oil market as a benchmark for a storable commodity and as an example of a mature futures contract. We adopt a two-step process.

The first step is to test the Samuelson effect on electricity markets, which requires a thoughtful analysis of its empirical implications. To the best of our knowledge, the research has only tested two implications of this dynamic behavior up to now. The first is the closest to the idea developed by Samuelson: if price shocks arising from the physical market influence the futures contracts particularly when these contracts are close to their expiration date, then the volatility must be a decreasing function of the remaining days before maturity (Anderson (1985), Milonas (1986), Walls (1999), Bessembinder et al. (1996)). The second implication is that if there is a decreasing relation between the volatility and the time-to-maturity, then the volatility of the one-month contract should be higher than that of a two-month contract, which in turn should be higher than that of a three-month contract, and so on. In other words, there should be an ordering in the time series of the volatilities across maturities that results in a decreasing pattern (Duong and Kalev (2008), Lautier and Raynaud (2011)). In this article, we propose and test a third empirical implication: the shocks emerging in the physical market should spillover *in the direction* of the futures market with a decreasing intensity when the contract's maturity rises. Thus, not only should the volatilities be ordered according to the maturity; there should also be volatility spillovers from the physical to the paper markets and not the reverse. Such reasoning is consistent with what is expected from a derivative market as regards to the risk management function it performs. In order to test this assumption, we rely on the method developed by Diebold and Yilmaz (2012) for the analysis of volatility spillovers between the markets for US stocks, bonds, foreign exchanges, and commodity markets.

The second step of our analysis aims to give insights into the debate about the role of inventories in the existence of the Samuelson effect. We rely on the third empirical implication of the Samuelson effect, and on the recent concept of "indirect storability": there could be some storability in electricity due to its inputs[2]. In this context, if there is an indirect storability effect in the market of electricity, then one possible explanation for the presence of a Samuelson effect is that price shocks borne in the markets for the inputs spread to the electricity market. Should that be the case, then electricity should not be considered as very different from any other storable commodity.

The large-scale investigation of the Samuelson effect on electricity markets performed in this article is

[2]As early as in 2001, Routledge et al. (2001) underline that the potential storability in the form of fuels motivates the exploration of the relation between electricity and fuel prices. This idea was latter reformulated under the idea of "indirect storability". Going further, Aïd et al. (2013) propose considering electricity as a portfolio of futures contracts on its inputs and show that this is the case in the French market. For a short review on this concept, see e.g., Huisman and Kilic (2012).

important for at least two reasons.

First, although most developed countries have considered electricity a public good over time, it is now regarded as a tradable commodity. Since they were launched 20 years ago, electricity derivative markets have had sustained increases in their transaction volumes. Even if these markets are still young, which raises empirical issues such as the lack of historical data or of long-dated contracts, there is now enough information to understand precisely how they function and to compare them with other markets for traditional commodities.

A second and more general reason is that industrial and financial agents as well as regulatory authorities need a deeper knowledge of the Samuelson effect. The traditional hedgers on commodity markets are producers, industrial processors, and trading companies. They use the futures markets to hedge their physical exposure, and they are rationally induced to minimize their hedging costs. The existence of the Samuelson effect could affect the choice of their hedging horizon and/or their hedging ratio. Moreover, volatility is one of the most important parameters in the pricing of options. Whenever the framework of a constant volatility (as in the Black and Scholes (1973) model) is relaxed (see, for e.g., the Heston (1993) model), the Samuelson effect must be taken into account. Further, the maturity effect concerns clearing houses and regulatory authorities when setting margin requirements and managing risk exposures.

The remainder of the article is organized as follows. In section 2 we describe the data. Section 3 has an explanation of how we test the three empirical implications of the Samuelson effect and displays our results. In section 4 we further examine the maturity effect by introducing the concept of "indirect storability" to the analysis. Section 5 is the conclusion.

2. Data and descriptive statistics

Our database comprises the daily settlement prices of monthly futures contracts[3] that we extract from Datastream. These data cover the four following electricity futures markets: the German, NordPool, Australian, and the American PJM. These markets are characterized, worldwide, by the most important trading volumes on electricity. In addition, we collect data for the Light Sweet Crude Oil contract (also known as the West Texas Intermediate, hereafter WTI). This market is used as a benchmark in this study for three reasons: i) in the period under examination, it is the largest commodity market in regard to transaction volumes; ii) it is storable; and iii) the mean reversion in the behavior of the futures prices is established in the literature (see among others, Gibson and Schwartz (1990), Schwartz (1997), Routledge et al. (2000)). Further, we collect price data for the analysis of the indirect storability of electricity performed in Section 4. These are nearby futures prices for the main inputs used in the production of electricity in the American PJM market (heating oil, natural gas, and coal) and in the German market (natural gas and coal). Table 1 summarizes the most important characteristics of our data set.

As specified in Table 1, our study covers more than five years. It starts at different dates in 2008 (August for crude oil, December for the German market, October for the PJM, July for the Australian market) and ends in August 2014. Due to a lack of data for some expiration dates, we reduce the time period for the NordPool contract, which starts in January 2011. This change leaves a total of 319 futures contracts used for the study of the Samuelson effect and 375 futures contracts for the study of the indirect storability.
Most of our empirical tests rely on the continuous time series of the futures prices with constant maturities. Thus while keeping the raw data, we use them to reconstitute the daily term structures of the futures prices. Because our data set contains futures contracts that mature periodically and because on the same observation date there are quotes for contracts with different maturities, we create the continuous time series by using a rollover technique. In our case, the rollover takes place at each expiration date; for example, the first time series contains futures prices for the nearest contract, and the second futures prices for the second closest-to-maturity contract.

[3]The Australian market, with quarterly expiration dates, is the exception.

	Futures contract	Exchange (Country)	Frequency of expiration	# of contracts	Start date	# of dates	# of fixed mat. time series
Crude Oil	WTI	NYMEX (United States)	monthly	79	08/21/08	1 518	7
Electricity	Phelix	EEX (Germany)	monthly	78	12/01/08	1 457	5
	PJM	NYMEX (United States)	monthly	79	10/01/08	1 490	6
	NEC	Nasdaq OMX Com (Norway)	monthly	47	01/19/11	906	4
	NSW	ASX (Australia)	quarterly	36	07/01/08	1 563	6
Inputs (PJM market)	Heating Oil	NYMEX (United States)	monthly	75	10/01/08	1 490	1
	Natural Gas	NYMEX (United States)	monthly	75	10/01/08	1 490	1
	Coal	NYMEX (United States)	monthly	75	10/01/08	1 490	1
Inputs (Phelix market)	TTF Natural Gas	ICE (United Kingdom)	monthly	75	12/01/08	1 457	1
	Rotterdam Coal	ICE (United Kingdom)	monthly	75	12/01/08	1 457	1

This table sums up the features of the data contained in our data set: for the analysis of the Samuelson effect, there are 319 futures contracts including 240 on electricity from different start dates in 2008 to 28 August, 2014; for the analysis of the indirect storability of electricity, there are 375 futures contracts for the inputs of the PJM and the Phelix markets. The names of the futures contracts are the following: WTI stands for West Texas Intermediate, Phelix for Physical Electricity Index, NEC for Nordic Electricity Contract, NSW for New South Wales, and TTF for Title Transfer Facility. The acronym PJM Western Hub is based on the corresponding regional transmission organization in the United States. As far as the exchanges are concerned, NYMEX stands for the New York Mercantile Exchange, EEX for the European Energy Exchange, Nasdaq OMX Com for the Nasdaq Options Market Exchange Commodities, ASX for the Australian Securities Exchange, and ICE for the Inter Continental Exchange. The "# of contracts" column gives the information about the raw data we start with. The "# of dates" column shows the number of daily observation dates. The "# of fixed mat. time series" stands for the maturity up to which we create fixed maturity time series.

Table 1: Futures price data

Further, the length of the term structure is different for each market: we have maturities up to six months for the PJM contract, five months for the German market, four months for the NordPool market, and up to six quarters for the Australian market. As far as crude oil is concerned, even if the traded maturities reach several years (nine) in the American market, we retain only the first seven months. Because inputs futures prices enter the analysis only in Section 4 which does not rely on their term structure, we construct only one continuous fixed maturity time series for each of these markets.

Figure 2 presents these continuous time series of futures prices for the WTI and the German electricity markets for two different maturities. Initially, there are no common trends nor similar behaviors in these prices. Crude oil is clearly less volatile than electricity, and the distance between the two maturities is lower for the first of these two markets. The same is true when we compare different electricity markets against each other (the figures for all other contracts are available in Appendix A.1).

Table 2 gives more insight into the electricity and crude oil markets: it displays the average number of contracts traded each day over the study period, both for all of the maturities and maturity by maturity[4]. Even if there are important differences between these contracts because of their underlying assets (crude oil *vs* electricity) and because of the contract specifications for the electricity markets (MW per contract, delivery hours...), the transaction volumes show that electricity futures markets, with daily average volumes ranging from 22.9 to 112.6 contracts, are much smaller than the crude oil market that is characterized by 75,701.8 contracts per day on average for all of its maturities. Further, as far as the electricity markets are concerned, the NordPool and the German markets have higher volumes. Finally, for all of the markets, the trading volume is concentrated at the first maturity and decreases regularly with the time to expiration. This feature is typical of derivative markets.

Maturity	**WTI**		**Phelix**		**PJM**		**NEC**			**NSW**	
All	75,701.8		95.5		47		112.6		**All**	22.9	
M1	264,302.1	49.9%	287.4	60.2%	84.7	30%	305.1	67.7%	**Q1**	12.9	9.4%
M2	133,455.7	25.2%	129.1	27.1%	42.7	15.1%	90.1	20%	**Q2**	29.4	21.5%
M3	54,494.8	10.3%	38.1	8%	37	13.1%	33.9	7.5%	**Q3**	25.1	18.3%
M4	30,888.6	5.8%	15.2	3.2%	40.2	14.3%	21.4	4.8%	**Q4**	25.8	18.8%
M5	20,301.3	3.8%	7.3	1.5%	38.6	13.7%			**Q5**	25.3	18.5%
M6	15,025.8	2.8%			39	13.8%			**Q6**	18.6	13.5%
M7	11,444.4	2.2%									

This table shows the transactions recorded between 2008 and 2014 on each electricity market (German, American, Australian and Nordic) and on the American crude oil market. The first line displays the average daily volume for all maturities, the others give details for each monthly or quarterly maturity. The percentages represent the share of each maturity in the total volume traded. In the electricity markets, the volumes are in MW and the nominal is one contract per MW, except for the PJM contract, where it is 1 for 2.5. In the crude oil market, the volume is in contracts; one contract represents 1,000 barrels.

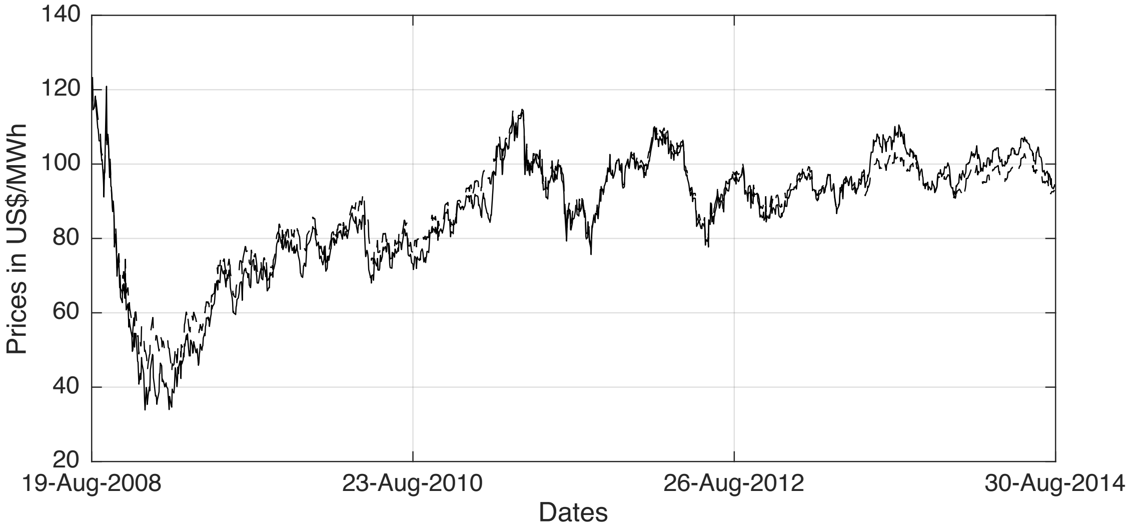
Table 2: Transaction volumes, crude oil and electricity markets, 2008-2014

Table 3 provides another comparison between the markets under consideration. For each market, it displays some descriptive statistics about the volatility of the nearby futures prices. Specifically, at t we measure the daily realized volatility σ_t^k of a futures contract with fixed maturity k. To do so we retain, as in Bessembinder et al. (1996), the absolute value of the daily futures price returns:

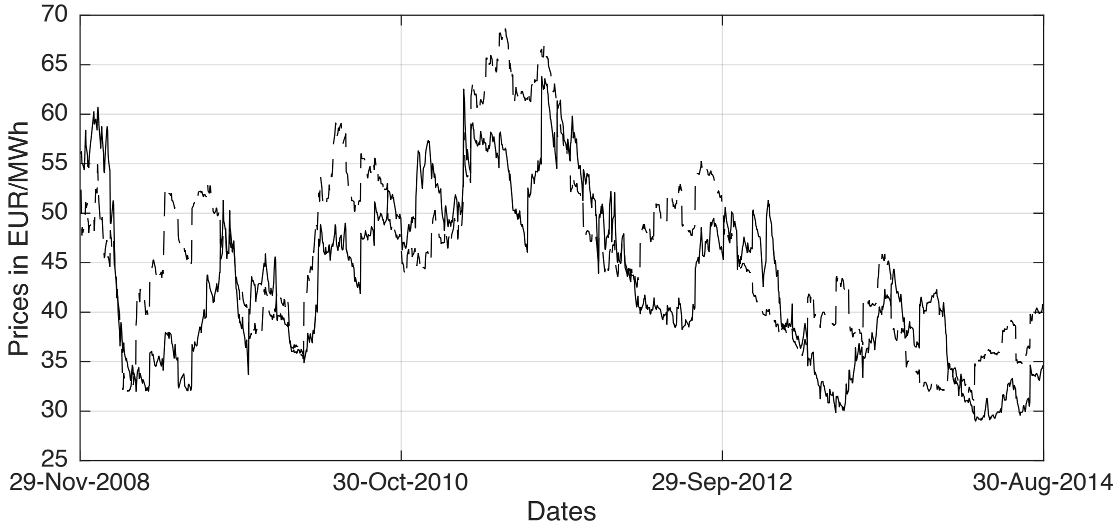
$$\sigma_t^k = |\ln\left(\frac{F_t^k}{F_{t-1}^k}\right)| * 100 \tag{1}$$

where F_t^k and F_{t-1}^k are the settlement prices of the futures contract with fixed maturity k at dates t and $t-1$.

[4]Note that The PJM contract size corresponds to 2,5 MW, whereas it amounts to 1 MW for all of the other electricity contracts.



(a) WTI contract



(b) Phelix contract

This figure shows the continuous time series of the prices for two different maturities in two different markets. The solid line is for the nearest maturity, and the dashed line is for the most distant maturity; that is, the one- and the six-month contracts in the crude oil market and the one- and the five-month contracts for the German electricity market.

Figure 2: Time series of prices of fixed maturity contracts, WTI and Phelix markets, 2008-2014

The use of the other measures of daily volatility, such as the High-Low volatility measure of Parkinson (1980) and Garman and Klass (1980), is not possible because of the lack of data on high and low prices in certain markets and/or periods. And we do not use the usual measure of volatility, which is the standard-error of the daily returns on a rolling window, because we want to have a daily measure and to avoid some overlapping issues.

	WTI	**Phelix**	**PJM**	**NEC**	**NSW**
# of observations	1 518	1 457	1 490	906	1 563
Mean	1.597	1.133	1.676	1.998	1.052
Median	1.055	0.793	1.178	1.451	0.272
Standard-deviation	1.774	1.139	2.415	1.902	2.438
Skewness	2.72	3.40	10.01	2.23	7.73
Kurtosis	13.21	30.08	164.62	10.96	96.71
ADF	-19.22*	-19.60*	-17.93*	-14.52*	-26.10*
LB	2 314*	234*	1 508*	367*	432*
Jarque-Bera	8 452*	47 315*	1 646 644*	3 139*	587 510*

This table sums up the descriptive statistics of the daily volatilities $\sigma_t^k = |\ln\left(\frac{F_t^k}{F_{t-1}^k}\right)| * 100$ recorded on the closest-to-maturity contracts for each electricity market (German, American, Australian, and Nordic) and for the American crude oil market from 2008 to 2014. The "ADF", "LB", and "Jarque-Bera" respectively stand for the test statistics of the Augmented Dickey-Fuller test for unit roots without a lag, the Ljung-Box test for autocorrelation with 15 lags, and the Jarque-Bera test for normality. The associated null hypothesis H_0 are the presence of a unit root for the ADF test, that the data are independently distributed for the LB test, and that the data follow a normal law for the JB test. The star (*) means that we reject the assumption H_0 at the 1% level of confidence.

Table 3: Descriptive statistics of the daily volatilities, crude oil and electricity markets, 2008-2014

Table 3 displays the mean, median, standard-deviation, and the skewness and kurtosis for the daily volatilities from 2008 to 2014. The charts of the daily volatilities are available in Appendix A.2. We also conduct some statistical tests for the autocorrelation (Ljung-Box test[5]) and the normality (Jarque-Bera test[6]) of the series, as well as for the presence of unit roots (ADF test[7]).

The table shows the following: first, the NordPool appears to be the most volatile market, according to both the mean and the median. The PJM market comes second. Then the crude oil market, followed by the two other electricity markets. The volatility of the crude oil market is rather surprising. Because it is the only storable commodity in the sample, it should be the less volatile. Second, there are some doubts about the normality of our time series of volatilities: all of the markets have a non-normal skewness with coefficients ranging from 2.23 to 10.01, which is well above zero. In the same way, with values between 10.96 and 164.62, all of the markets have a non-normal kurtosis. Third, the results are homogeneous as regards to the statistical tests: i) no series contains unit roots which allows us to study them without pretreatment; ii) the results of the Ljung-Box test show the presence of autocorrelations in the time series of volatilities; and iii) the Jarque-Bera test confirms that the series do not follow a normal distribution. These results justify the use of nonparametric tests[8] to study the maturity effect on the electricity derivative markets.

3. Does the Samuelson effect hold for electricity markets?

This section examines whether or not the Samuelson effect is a common feature in electricity markets, as is the case for other energy and agricultural commodities. We define and test three different empirical implications of the Samuelson effect on the electricity and the crude oil markets.

[5] H_0: The data are independently distributed.
[6] H_0: Normality.
[7] H_0: Presence of a unit root.
[8] Or, at least, methods that are compatible with non-normal data.

3.1. Is volatility a function of the Time-To-Maturity (TTM) of the contracts?

We test the first implication of the Samuelson effect by using a linear regression between the volatility of the futures prices and the time-to-maturity of the contracts. Theoretically, the volatility should increase when the maturity of the futures contract comes near.

There are several methods to perform such a regression. The first one relies on raw data: it consists of extracting the prices of a futures contract during its whole life and running the analysis on these prices (see Walls (1999)). In our case, with 319 futures contracts, this method means running and interpreting 319 regressions. We thus use the continuous times series of the futures prices presented in section 2, as done in Anderson (1985), Milonas (1986) and Bessembinder et al. (1996). In this case, each time series corresponds to a "fixed maturity". For example, the time-to-maturity of the first month contract ranges from 1 to 20 trading days and that of the second contract ranges from 21 to 40 days. If we take the example of crude oil, there are 61 months between August 2008 and August 2014. Consequently, there are 61 TTM of one day, 61 of two days... up to 61 TTM of 140 days because the longest maturity retained for this market is seven months.

With the continuous time series, the regression between the volatility and the time-to-maturity can be expressed as follows:

$$\sigma_i^k = \alpha + \beta TTM_i^k + \varepsilon_i, \, \forall k \tag{2}$$

where σ_i^k is the volatility of the futures prices, the superscript k stands for the maturity of the futures contracts (in month or in quarter), and the index i corresponds to the Time-To-Maturity in days. The α is a constant, the TTM_i^k is the number of days until the expiration of the contract k. The ε_i stands for noise. Because our volatility measure is by definition positive, the same must be true for α. Moreover, if the volatility increases when the contract reaches maturity, we expect β to be negative.

Table 4 has the values of the coefficients obtained for each market. The results are homogeneous; for all four electricity markets and for the WTI we obtain positive constants and negative betas. Moreover, all of these coefficients (both α and β) are statistically significant at the 1% level. This significance is consistent with the Samuelson effect. Nevertheless, our coefficients of determination are low. There are at least two reasons for this result. First, the time-to-maturity explains only a small part of the volatility. If our objective were to *explain* volatility, we should add other explanatory variables to the regression. The second reason is that our data violate some assumptions[9] of the linear regression. We thus consider these results as a first step in the validation, which must be confirmed with nonparametric tests.

	WTI	**Phelix**	**PJM**	**NEC**	**NSW**
α	1.5870	1.0781	1.6596	1.9624	0.8104
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β	-0.0022	-0.0037	-0.0063	-0.0097	-0.0010
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.0036	0.0152	0.0295	0.0266	0.0086
# of observations	10 626	7 285	8 940	3 624	9 378

This table provides the results obtained when testing the first implication of the Samuelson effect on the four electricity derivative markets (German, American, Australian, and Nordic) and on the American crude oil market. The table shows the coefficients of a linear regression between the daily volatilities σ_i^k of the futures prices with maturity k and the Time-To-Maturity TTM_i^k, that is, the number of days between i and the maturity k of the contract: $\sigma_i^k = \alpha + \beta TTM_i^k + \varepsilon_i, \, \forall k$. This regression uses all of the available maturities. The daily volatility is computed as follows: $\sigma_i^k = |\ln\left(\frac{F_i^k}{F_{i-1}^k}\right)| * 100$. The p-values of the coefficients (in brackets) and the coefficients of determination R^2 are also displayed.

Table 4: Relation between the daily volatilities and the Time-To-Maturity, crude oil and electricity markets, 2008-2014

[9] Principally homoscedasticity, no-autocorrelation, and normality.

3.2. Are the time series of volatilities ordered?

The second implication of the Samuelson effect is a consequence of the first one. If there is a decreasing relation between volatility and the time-to-maturity, then the volatility of the one-month contract should be higher than that of the two-month, and so on.

In order to examine this second implication, we use two different methods. The first one consists of computing the daily volatilities according to the maturity of the futures contracts and to compare them (see Lautier and Raynaud (2011)). The second, which is more formal, is a nonparametric test that checks whether or not the volatilities significantly decrease in order by maturity (see Duong and Kalev (2008)). Table 5 contains the results obtained with the first method. It reproduces the median volatilities for each maturity and for each market under consideration. The results support the Samuelson effect for three contracts: the entire term structure of the volatilities is downward sloping for the WTI, the PJM, and the NEC. However, for the Phelix contract, the last maturity, which is also the least liquid maturity (see Table 2), is higher than expected. Further, the volatility curve is S-shaped in the Australian market (NSW futures contract). But the maturities for this market range from 3 to 18 months.

Medians	WTI	Phelix	PJM	NEC	NSW
$\bar{\sigma}_1$	1.055	0.793	1.178	1.451	0.272
$\bar{\sigma}_2$	0.999	0.654	0.909	1.208	0.365
$\bar{\sigma}_3$	0.962	0.578	0.830	1.069	0.281
$\bar{\sigma}_4$	0.941	0.576	0.777	1.020	0.269
$\bar{\sigma}_5$	0.904	0.585	0.758		0.289
$\bar{\sigma}_6$	0.880		0.742		0.279
$\bar{\sigma}_7$	0.860				

This table shows the median $\bar{\sigma}_k$ of the daily volatilities $\sigma_t^k = |\ln\left(\frac{F_t^k}{F_{t-1}^k}\right)| * 100$ for each maturity k of each electricity market (German, American, Australian, and Nordic) and for the American crude oil market.

Table 5: Median volatilities, crude oil and electricity markets, 2008-2014

At first glance, if the results on the term structure of the volatilities are globally consistent with the Samuelson effect, this is more evident for the short- rather than for the long-term maturities.

To gain more insight into the phenomenon, following Duong and Kalev (2008), we complement this analysis with a nonparametric test. The latter is especially suited in our case because the time series are non-normal. More precisely, we use the Jonckheere-Terpstra (hereafter JT) test developed by Jonckheere (1954) and Terpstra (1952) that shows if the medians of the time series of volatilities significantly decrease in order of maturity. The following are the null and the alternative hypotheses (respectively H_0 and H_1) of the JT test:

$$\begin{cases} H_0 : \bar{\sigma}_k = \bar{\sigma}_{k-1} = ... = \bar{\sigma}_1 \\ H_1 : \bar{\sigma}_k \leq \bar{\sigma}_{k-1} \leq ... \leq \bar{\sigma}_1 \end{cases} \tag{3}$$

where $\bar{\sigma}_k$ is the median volatility of the kth maturity. We accept the existence of a maturity effect when the null hypothesis of the JT test is rejected.

To perform this test we have to compute two statistics, Z and J. In order to obtain J, we compare the observations of each time series of volatilities to those in the successive time series. In other words, we pair each volatility recorded in the first maturity time series with each one recorded in the second maturity, in the third, and so on. For each comparison, we attribute a value of one (zero) if the first component of the pair is bigger (smaller) than the second one. A value of 0.5 is recorded in the case of a tie. Finally, we sum up all of these values to get the test statistic J. The statistic Z is then computed as follows:

$$Z = \frac{J - [(N^2 - \sum_{i=1}^{k} n_i^2)/4]}{\sqrt{[N^2(2N+3) - \sum_{i=1}^{k} n_i^2(2n_i+3)]/72}} \tag{4}$$

where N is the total number of observations, and n_i is the number of observations in the time series of volatility with maturity i. For large sample sizes like ours, the JT test statistic, Z, is approximately normally distributed with a zero mean and a variance equal to one.

Table 6 reports the results of the JT test. It shows that we can reject the null hypothesis at a 1% level for all of the markets; the Samuelson effect holds for the WTI market and for all four of the electricity futures markets.

	WTI	**Phelix**	**PJM**	**NEC**	**NSW**
Z-statistics	6.04	9.51	14.40	8.41	2.38
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
# of observations by maturity	1518	1 457	1 490	906	1 563
# of maturities	7	5	6	4	6

This table reports the results (Z-statistics, associated p-values) obtained with the Jonckheere-Terpstra test for each electricity market (German, American, Australian, and Nordic) and for the American crude oil market. This nonparametric test examines the null hypothesis of equal volatilities against the alternative hypothesis of ordered volatilities. The rejection of H_0 means the acceptance of the Samuelson effect. The test statistic Z is computed as follows: $Z = \frac{J-[(N^2-\sum_{i=1}^{k} n_i^2)/4]}{\sqrt{[N^2(2N+3)-\sum_{i=1}^{k} n_i^2(2n_i+3)]/72}}$.

Table 6: Ordering of volatilities across maturities, crude oil and electricity markets, 2008-2014

Taking into account the non-normality of the time series gives results that are now fully consistent with the second empirical implication of the Samuelson effect. This is especially remarkable for the Australian market (NSW futures contract) and can probably be explained by the lack of liquidity in certain maturities (see Table 2) because it is the market with the lowest transaction volumes.

3.3. Do the price shocks spread from the physical to the paper market?

In what follows, we propose and test a third empirical implication to the Samuelson effect. Following Lautier et al. (2014), we assume that when a derivative market performs its hedging function correctly, the price shocks in the paper market should be the result of the price shocks emerging from the physical market, and not the reverse. Because we measure the price shocks with volatility, we should thus observe a volatility that transmits *from* the physical *to* the paper market with a decreasing intensity when the contracts' maturity rises. In other words, not only should the volatilities be ordered according to the maturity; there should also be a direction to the propagation.

A preliminary answer to this question could be tackled with a Granger analysis (Granger (1969)). However, with this method, we would only have information about the direction of the price shock. To make sure that the volatility transmitted from the physical to the paper markets diminishes with the maturities, we also need information about quantities. The method developed by Diebold and Yilmaz (2012), hereafter DY, gives such indications. Whereas those authors apply it to different assets, we use it for different maturities of the same futures contract. Moreover, we use the first nearby futures price as a proxy for the spot price.

3.3.1. Volatility spillover measures: the method

The DY method (2012) is an extension of the index they developed three years before (Diebold and Yilmaz (2009)). This method improves the previous index in two ways. First, the 2009 index provides aggregated information about the *total* spillover of volatilities; it tells how much volatility spreads across all of the markets and gives a measure of the markets' integration. By comparison, the method developed in 2012 provides disaggregated information about how much volatility spreads *from* one market *to* one or to all of the others; it gives information about the direction of the spillover. Second, the previous method is based on a vector autoregressive (VAR) framework for which the results can be order-dependent due to the Cholesky factor orthogonalization: to make sure that a shock impacts one variable at a time, there is an ordering of the variables impacted by the shock. This choice can influence the results. By comparison, the measures of 2012 are based on a generalized VAR framework in which the forecast-error variance decompositions are invariant to the variable ordering.

In what follows, we explain how we apply this method. We retain for each market only three maturities: the nearest, the longest, and one situated in the middle of the curve. For example, in the case of the PJM contract, we use the first month M1, six months M6, and three months M3. The first step of the method consists of setting the generalized VAR framework. The second leads to the total spillover index. The third indicates the directionality.

Generalized vector autoregressive framework. We first build a generalized VAR framework that states the dependencies between the three series of volatilities. We consider the following covariance stationary[10] N-variable VAR(p), where $N = 3$:

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t \tag{5}$$

where:

- x_t is a (3x1) vector gathering the values of daily volatilities at date t,
- p is the number of lags in days,
- phi_i is the (3x3) coefficient matrix at lag i,
- $\varepsilon \sim (0, V)$ is a (3x1) vector of independently and identically distributed disturbances.

Using the Wold's representation theorem (Wold (1938)), we can write the moving average representation of x_t as follows:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{6}$$

where the $N \times N$ coefficient matrices A_i obey the recursion:

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + ... + \phi_p A_{i-p} \tag{7}$$

with A_0 being an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. Once the moving average coefficients are determined, they can be used to understand the dynamics of the system with variance decompositions.

These decompositions allow the assessment of the fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall j \neq i$, for each i where H is the horizon of forecasting and x_i is the volatility that corresponds to maturity i. In order to make sure that forecast-error variance decompositions are invariant to the variable ordering (i.e., to avoid the use of the Cholesky factorization), DY rely on the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) - hereafter KPPS. The KPPS H-steap-ahead forecast error variance decompositions $\theta_{ij}(H)$, for $H = 1, 2, ...$, is:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h V e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h V A_h' e_i)} \tag{8}$$

where σ_{jj} is the standard deviation of the error term for the jth maturity, e_i is the (3x1) selection vector with one as the ith element and zeros otherwise, and V is the (3x3) variance matrix of the error vector ε. The terms with an apostrophe are transposes of the original matrixes.

Further, each entry of the variance decomposition matrix $\theta_{ij}(H)$ is normalized by the row sum that gives the spillover measures from maturity i to maturity j at horizon H, $\tilde{\theta}_{ij}(H)$:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{9}$$

Using the KPPS variance decomposition, the authors propose one index of total spillover, and two measures of directional spillovers and net pairwise spillovers.

[10] As stated in Table 3, our time series of volatilities are stationary.

Total spillover index. This quantity measures the contribution of spillovers of volatility shocks across maturities to the total forecast error variance. In other words, this index gives information about the degree of integration of the market under study. In percentage, it is constructed as follows:

$$S(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \cdot 100 = \frac{\sum_{i,j=1,j\neq i}^{N} \tilde{\theta}_{ij}(H)}{N} \cdot 100 \tag{10}$$

Directional spillovers. The total spillover index can be decomposed into directional spillovers, also expressed in percentage, that give information about the direction of the volatility spillovers across maturities. The volatility spillover received by maturity i from all others is:

$$S_{i.}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \cdot 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ij}(H)}{N} \cdot 100 \tag{11}$$

In a similar way, the volatility spillovers transmitted by the maturity i to all others is written as:

$$S_{.i}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}(H)} \cdot 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ji}(H)}{N} \cdot 100 \tag{12}$$

The net pairwise volatility spillover gives information about how much maturity i contributes to the volatility of maturity j:

$$S_{ij}(H) = \left(\frac{\tilde{\theta}_{ji}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}(H)} - \frac{\tilde{\theta}_{ij}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}(H)} \right) \cdot 100 = \left(\frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{N} \right) \cdot 100 \tag{13}$$

For the estimation, as in DY we use the following parameters: $p = 4$ lags for the VAR and $H = 10$ for the forecast error variance decompositions. We also perform estimations with other values for the parameters (the range chosen for p is from 2 to 6, and the one for H from 6 to 9) without any change in our results (this sensitivity analysis is available on request).

3.3.2. Static analysis of volatility spillovers between maturities

We first measure the total spillover index and then the directional and the net pairwise spillovers between the futures prices for different maturities in each market for the sample period. To simplify the interpretation of the results, we focus on three of the available maturities: the nearest contract (Q1 for the NSW, M1 for all others), the intermediate maturity (M3 or Q3), and the longest maturity. Except for the NSW contract, the results of the static analysis are quite homogeneous, as Table 7 shows.

The second column reproduces the total spillover index of each market. It shows that crude oil is the most integrated market: in this case, almost 65% of the volatility of the prices are due to co-movements. This ranking of the WTI contract is reasonable because crude oil is the only storable commodity in our study. Moreover, oil is characterized by very high transaction volumes. Maturities are thus linked by arbitrage strategies. With the total spillover indexes of 57.34%, 51.42%, and 46.75%, respectively, the different maturities of the NEC, the Phelix, and the PJM futures contracts remain quite heavily integrated. The lowest value is obtained for the NSW contract with a total spillover index of only 24.79%. This is probably due to the fact that the maturities under consideration are quarters and not months.

The third column is devoted to the decomposition of the total spillover index into directional spillovers. It is separated into four sub-columns. The first indicates the maturity, the second provides the directional spillovers from one maturity i to all of the others; the third, from all of the others to the maturity i; and the fourth gives the difference between the second and third sub-columns. First, for each futures contract, the volatility sent by the nearest maturity to all of the others is always higher than the volatility received. Because the nearest maturity is the closest to the physical market, this finding is in line with what is expected: the shocks arising in the physical market are higher than those coming from the paper market. Second,

	# of observations	Total spillover index (%)		Directional spillovers To all	From all	Net	Net pairwise spillovers	
			M1	23.05	20.085	2.965	**M1-M3**	0.989
WTI	1 518	64.76	**M3**	22.042	21.986	0.055	**M1-M6**	1.976
			M6	19.673	22.693	-3.020	**M3-M6**	1.044
			M1	21.462	13.439	8.023	**M1-M3**	3.889
Phelix	1 457	51.42	**M3**	15.784	19.178	-3.394	**M1-M5**	4.135
			M5	14.176	18.806	-4.630	**M3-M5**	0.495
			M1	18.734	7.130	11.605	**M1-M3**	6.43
PJM	1 490	46.75	**M3**	15.984	20.038	-4.054	**M1-M6**	5.174
			M6	12.036	19.587	-7.551	**M3-M6**	2.376
			M1	21.642	14.786	6.856	**M1-M3**	3.501
NEC	906	57.34	**M3**	18.418	21.456	-3.037	**M1-M4**	3.355
			M4	17.279	21.098	-3.819	**M3-M4**	0.464
			Q1	12.050	1.917	10.133	**Q1-Q3**	6.167
NSW	1 563	24.79	**Q3**	6.018	13.553	-7.535	**Q1-Q5**	3.966
			Q5	6.723	9.320	-2.598	**Q3-Q5**	-1.368

This table shows the total spillover indexes and the directional volatility spillover measures between maturities for each electricity market (German, American, Australian, and Nordic) and for the American crude oil market. The total spillover index measures the contributions of the spillovers of volatility shocks across maturities to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by the maturity i to all others (see equations 12) and the volatility spillover received by maturity i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a maturity contributes more than it receives. The net pairwise volatility spillover gives information about how much the maturity i contributes to the volatility of maturity j (see equation 13). In the column representing the directional spillovers, "Net" stands for "To all - From all". In the column headed "Net pairwise spillovers", "Mi-Mj is the measure "From Mi to Mj - To Mi from Mj".

Table 7: Static analysis: Volatility spillovers between maturities, crude oil and electricity markets, 2008-2014

the longer maturities are characterized by negative net spillovers. This reinforces the previous observation. Third, if we compare the volatility sent by the nearest maturity with those sent by more deferred contracts, a decreasing pattern emerges (except for the NSW). This is consistent with the third empirical implication of the Samuelson effect.

These findings are corroborated by the figures for the net pairwise spillovers shown in the last column. The latter is divided into two sub-columns. The first sub-column indicates the pair of maturities taken into account, that is, (M1 - M3), (M1 - M6) and (M3 - M6); the second gives the difference between the two directional spillovers. First, we always obtain a positive measure of the net pairwise spillover when the pair includes the first maturity. Second, the net spillover between the two extreme maturities (M1 - M6) is always higher than the one linking the intermediate and last maturities (M3 - M6).

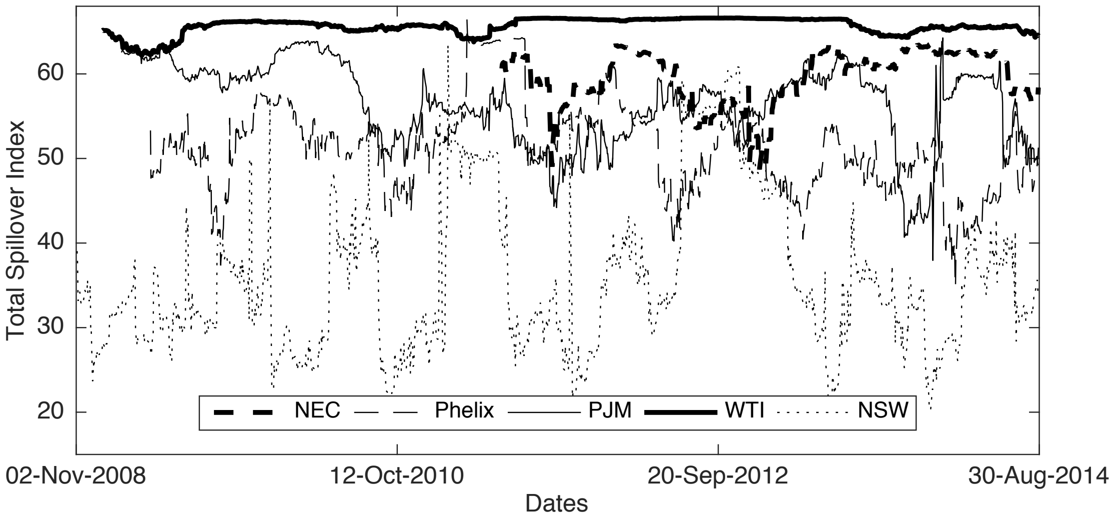
The dynamic analysis gives more insights about the evolution of the volatility spillover through time and reinforces the conclusions made in the static case.

3.3.3. Dynamic analysis of volatility spillovers between maturities

This analysis relies on a rolling window of 90 days (increasing or decreasing the length of the rolling window only smooths or un-smooths the results). The dynamic analysis globally reinforces the conclusions made in the static case.

Figure 3 depicts the evolution of the total spillover indexes during the period. It shows that the stability of integration changes dramatically with the futures contract. The most integrated market, crude oil, is also the most stable by far. As far as electricity contracts are concerned, the most stable is the PJM, the least is the NSW.

Table 8 contains the descriptive statistics on the time series of spillover measures in a dynamic framework for each market. It provides information on the total spillover indexes and on the net spillover measures. First, the frequency of the positive values for the net directional spillover when considering the volatility



This figure exhibits the total spillover index measures in a dynamic framework for each electricity market (German, American, Australian, and Nordic) and for the American crude oil market on the basis of a 90-day rolling window. The total spillover index measures the contribution of spillovers of volatility shocks across maturities to the total forecast error variance (see equation 10).

Figure 3: Dynamic analysis: total spillover index between maturities, crude oil and electricity markets, 2008-2014

sent by the first maturity (M1) is very high: over 88% for all of the markets (around 98% for the WTI and the NEC contracts). In contrast, the frequency of the positive values for the volatility sent by the last maturity (M_L) is very low, except for the NSW where the contracts send volatility to the other maturities in 25% of the cases. The standard deviation of the net spillover is also the lowest for the WTI and the NEC contracts. We observe the lowest extreme values (minimum and maximum) recorded for the net spillover from M1 to all of the other maturities for the WTI. A more precise examination, through Figure B.8 in Appendix B, shows that for this market, the number of high values is concentrated in very short periods. These findings are consistent with the high level of integration previously observed for the WTI market.

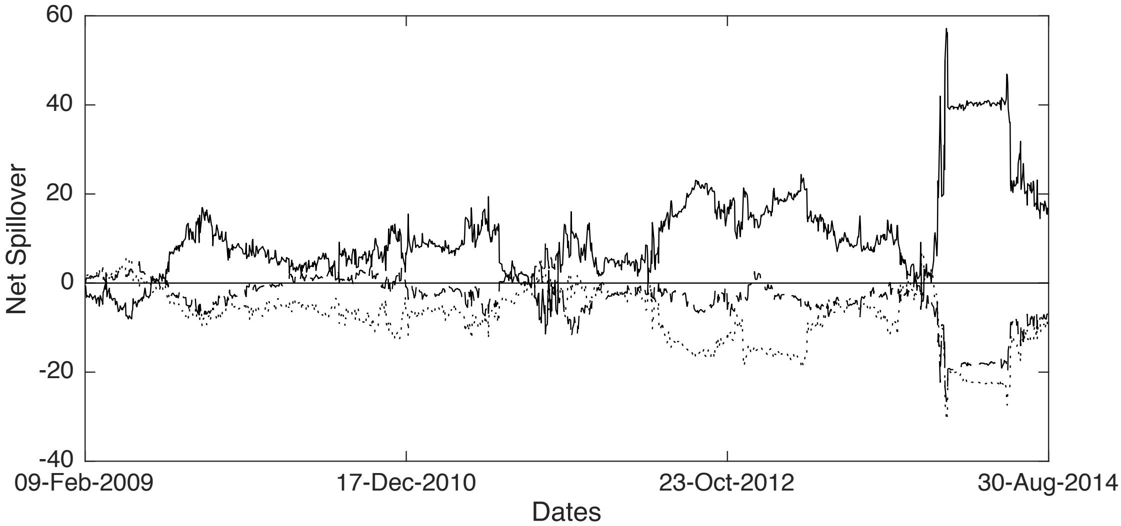
Figure 4 gives a good illustration of the results provided by Table 8. It reproduces the example of the PJM contract and is representative of what can be seen in electricity markets (the figures for all of the other markets are in Appendix B). The first part of the figure is devoted to net directional spillovers, the second to the net pairwise spillovers. The first part shows that the M1 contract has a positive volatility spillover and transmits shocks. The periods in which the nearest contract receives the volatility are exceptional. Another striking feature is that the value of the net directional spillovers emanating from the longest maturity (M_L) apparently mirror those obtained for the M1 (a more precise analysis, relying on Table 8 gives a different picture, especially for the Phelix and even more so for the NSW contracts). As far as the second part of the Figure 4 is concerned, it shows that the solid line that represents what is sent by the first pair of maturities (M1 and M3) is above the dashed line, which represents what is sent by the last pair of maturities (M3 and M_L).

For the electricity markets other than the Australian as well as for crude oil, there is a transmission of the price shocks from the physical to the paper markets with a decreasing intensity. This transmission confirms the previous results of this article that are based on the two first empirical implications of the Samuelson effect. Further, for very short periods of time, the direction of the transmission changes significantly, and the Samuelson effect is less important for the crude oil market. This difference between electricity and crude oil might be explained by the storability of the latter, which allows for a better transmission of the shocks.

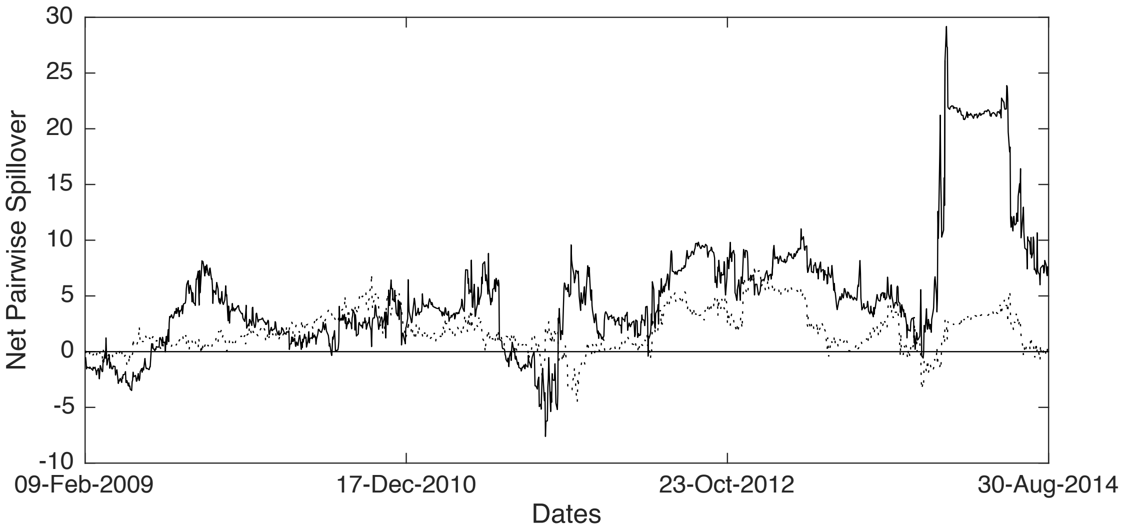
	# of		Total Spillover	Net Directional		Net Pairwise		
	observations		Index	For M1	For M_L	M1M3	M3M_L	M1M3-M3M_L
		Min	62.19	-2.77	-8.67			
		Max	66.62	11.27	0.38			
WTI	1 518	**StDev**	0.98	1.98	1.79			
		$\oplus$(%)		97.97	0.07	93.98	100	
		>(%)						15.20
		Min	34.69	-10.75	-19.31			
		Max	66.46	28.88	13.89			
Phelix	1 457	**StDev**	5.35	7.12	5.36			
		$\oplus$(%)		91.44	15.22	92.17	55.45	
		>(%)						82.44
		Min	37.95	-11.43	-30.52			
		Max	64.26	57.19	7.16			
PJM	1 490	**StDev**	4.82	10.78	6.44			
		$\oplus$(%)		89.71	9.79	87.50	87.86	
		>(%)						73.71
		Min	48.71	-1.46	-11.63			
		Max	63.63	29.55	1.66			
NEC	906	**StDev**	3.18	4.59	2.4			
		$\oplus$(%)		98.16	3.68	96.32	65.93	
		>(%)						87.13
		Min	17.96	-22.58	-30.79			
		Max	63.49	57.89	52.81			
NSW	1 563	**StDev**	9.09	11.99	7.73			
		$\oplus$(%)		88.12	25.19	86.29	42.77	
		>(%)						84.11

This table shows the summary statistics of the total spillover indexes and the directional volatility spillover measures between maturities, in a dynamic framework, for each electricity market (German, American, Australian, and Nordic) and for the American crude oil market on the basis of a 90-day rolling window. The total spillover index measures the contribution of the spillovers of volatility shocks across maturities to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by maturity i to all others (see equations 12) and the volatility spillover received by maturity i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a maturity contributes more than it receives. The net pairwise volatility spillover gives information about how much maturity i contributes to the volatility of maturity j (see equation 13). The M_L is the longest maturity available for each contract. The $\oplus$(%) represents the percentage of positive values recorded over the period. The >(%) is used for net pairwise measures only. The M1M3-M3M_L represents the percentage of measures of net pairwise volatility between the maturities M1 and M3, which are higher than those between M3 and M_L. The study of the net pairwise volatility spillovers confirms that the intensity of the volatility spillover decreases as the maturity increases: the frequency of the positive values of the net pairwise spillover measures are higher with the pair of maturities (M1 - M3) than with the pair (M3 - M_L). One exception is the WTI market.

Table 8: Dynamic analysis: volatility spillovers between maturities, crude oil and electricity markets, 2008-2014



(a) Net Spillovers between maturities, PJM market



(b) Net Pairwise Spillovers, between maturities, PJM market

This figure displays the directional volatility spillover measures between the maturities for the electricity contract PJM traded in the United States in a dynamic framework. A 90−day rolling window is used. The first chart represents the net directional spillovers. The solid line is for the nearest maturity, the dashed line for the intermediate maturity, and the dotted line for the most distant one. The second chart represents the net pairwise spillovers. The solid line depicts the spillover from the nearest to the intermediate maturities (M1 - M3); the dotted line is the spillover from the intermediate to the most distant maturities (M3 - M_L). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by the maturity i to all others (see equations 12) and the volatility spillover received by maturity i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a maturity contributes more than it receives. The net pairwise volatility spillover gives information about how much maturity i contributes to the volatility of maturity j (see equation 13)

Figure 4: Dynamic analysis: directional spillovers between maturities, PJM market, 2008-2014

4. Going deeper in the analysis of the maturity effect: the link with the indirect storability

Up to now we have shown, via three different empirical implications, that the Samuelson effect is an important feature of electricity markets. This confirms and extends the results of Walls (1999) and Allen and Cruickshank (2002) with a large database. Moreover, as is the case for a vast majority of studies in this literature (see Bessembinder et al. (1996), Brooks (2012), Lautier and Raynaud (2011), Daal et al. (2006) and Galloway and Kolb (1996)), we also find a Samuelson effect in the crude oil market[11].

Finding a strong decreasing pattern in the volatilities for electricity seems to go against the conclusions of Bessembinder et al. (1996), who emphasize the importance of storability. Nevertheless, at this point, one could imagine that the existence of the Samuelson effect in electricity markets is due to its potential storability in the form of its inputs, also called indirect storability. This concept, recently proposed for electricity markets (see Routledge et al. (2001), Aïd et al. (2009) or Aïd et al. (2013)), could indeed reconcile the existence of the Samuelson effect in electricity markets and the storability as a necessary condition for it. In order to explore this assumption we study the relation between the prices of electricity and those of its inputs, and we examine whether or not the price shocks borne in the input markets are transmitted to the electricity markets.

In what follows we investigate the effect of indirect storability in the American and German electricity markets. Compared with the others, these two markets are characterized by the fact that a significant part of their inputs are tradable commodities: the electricity traded under the PJM contract is mainly produced on the basis of coal, natural gas, and petroleum products. According to the PJM Regional Transmission Organization (RTO), in 2014 these inputs accounted for 76% (40%, 28%, and 8% respectively) of the installed capacity in the geographical area under consideration. As far as the Phelix contract is concerned, according to the Fraunhofer Institute, coal and natural gas accounted for 43.8% (27.8% and 16.11% respectively) of the net installed generation capacity in 2014.

We retain the same time period and prices for the electricity contracts (see Table 1). For the inputs of the PJM market, the heating oil, natural gas, and coal prices correspond to the futures contracts negotiated on the NYMEX. For the inputs of the Phelix market, we use the prices of the Rotterdam coal futures and those of the TTF natural gas futures. Both contracts are traded on the ICE. Tables C.11 and C.12 in Appendix C display the descriptive statistics of the time series of volatilities of the input prices. They show that the series do not contain unit roots, are autocorrelated, and do not follow a normal distribution.

To study the potential effect of indirect storability, we rely on the Diebold and Yilmaz (2012) method. For all of the markets, we retain the one-month continuous time series (M1). As before, we use $p = 4$ lags for the VAR and $H = 10$ for the forecast error variance decompositions[12]. We first perform a static, and then a dynamic, analysis on the two electricity markets. Because the results are similar for the two contracts, we only give those for the PJM market. The study of the Phelix market is in Appendix C.2.

Table 9 displays the results of the static analysis. First, the total spillover index is 26.25%, which means that the volatility in the PJM market is mainly explained by its own shocks rather than by links with its inputs. Further, this figure is much lower than those found for the different maturities of each contract, with the exception of the NSW market (see Table 7). Moreover the heating oil and the coal markets receive the most important amount of volatility from the three others. The heating oil and coal are characterized by net directional spillovers of −3.66 and −4.03 respectively. Moreover, with positive net pairwise spillovers the PJM market delivers volatility to the three input markets.

The dynamic analysis, performed on the basis of 90-day rolling windows and illustrated by Figure 5 and Table 10 gives further insights. In net terms, the PJM and the natural gas markets respectively send volatility 58.62% and 92.35% of the time, while the heating oil and the coal markets respectively receive it 83.92% and 97.43% of the time. At the end of our period, during the winter of 2014, there is a sudden

[11]This result in the crude oil market goes against the finding of Duong and Kalev (2008). This divergence could be due to the difference in the frequency of the data used (daily versus intraday). High frequency data indeed give insights into microstructure effects that can not be seen with daily data

[12]These choices do not affect our results; we have computed the volatility spillover measures with other parameters and find no significant changes. The results are available on request.

# of observations		Total spillover index (%)	Directional to all others	Directional from all others	Net	Net Pairwise against PJM
1 490	**PJM**	26.25	6.48	4.23	2.25	
	Heating oil		4.47	8.13	-3.66	0.81
	Natural gas		11.51	6.07	5.44	0.67
	Coal		3.79	7.82	-4.03	0.78

This table shows the total spillover index and the directional volatility spillover measures in a static framework between the PJM prices and three inputs: heating oil, natural gas, and coal. The total spillover index measures the contribution of the spillovers of volatility shocks across markets to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by the market i to all others (see equations 12) and the volatility spillover received by market i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a market contributes more than it receives. The net pairwise volatility spillover gives information about how much market i contributes to the volatility of market j (see equation 13).

Table 9: Static analysis: volatility spillovers between electricity and its inputs, PJM and inputs markets, 2008-2014

change in the behavior of the prices and the PJM market turns into a volatility emitter. This exceptional period coincides with a higher integration of our markets (high total spillover index) than usual and leads to an overestimation in the static case of the net volatility spillover coming from the PJM market. However, as is the case in the static framework, the dynamic pairwise analysis shows that most of the time, the PJM market sends volatility to the heating oil and the coal markets and receives volatility from the natural gas market.

# of		Total Spillover	Net Directional				Net Pairwise		
observations		**Index**	**PJM**	**HO**	**NG**	**Coal**	**PJM-HO**	**PJM-NG**	**PJM-C**
1 490	**Min**	26.84	-13.37	-20.94	-19.63	-20.75			
	Max	68.16	60.48	14.44	32.31	12.18			
	StDev	6.83	11.26	6.37	8.95	3.99			
	$\oplus$(%)		58.62	16.08	92.35	2.57	77.34	14.65	88.28

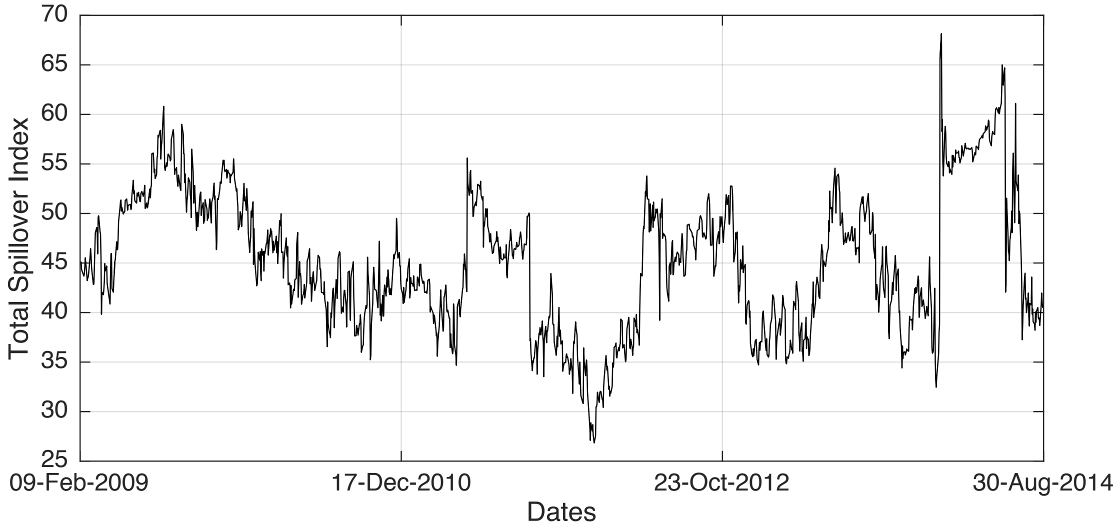
This table shows the summary statistics for the total spillover indexes and the directional volatility spillover measures between the PJM market and its inputs, in a dynamic framework, on the basis of a 90-day rolling window. In this table, HO stands for Heating Oil, NG for Natural Gas, and C for Coal. The $\oplus$(%) represents the percentage of positive values recorded over the period. The total spillover index measures the contribution of the spillovers of volatility shocks across markets to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by market i to all others (see equations 12) and the volatility spillover received by market i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a market contributes more than it receives. The net pairwise volatility spillover gives information about how much market i contributes to the volatility of market j (see equation 13).

Table 10: Dynamic analysis: volatility spillovers between electricity and its inputs, PJM and inputs markets, 2008-2014

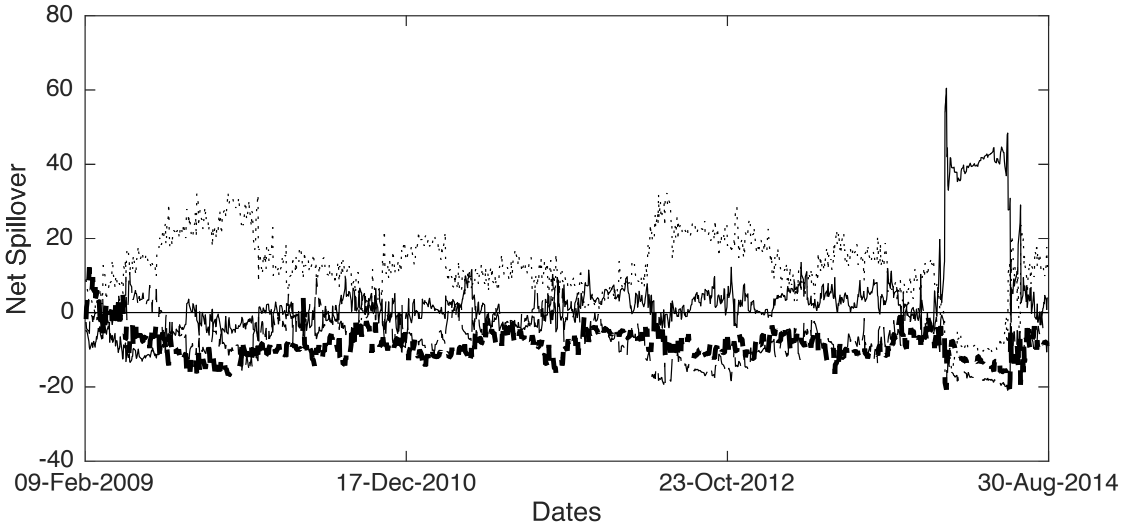
All of these findings are in contradiction with what we expected: under the influence of an indirect storability effect, the PJM prices should *receive* the volatility from the input markets. We reach the same conclusion for the German market (see Appendix C.2). So even if these two electricity markets interact with their input markets, only a small part of the behavior of the electricity prices can be explained by that of its inputs.

In the presence of a Samuelson effect without storage or indirect storage, where do we stand in the debate on the economic explanation of the Samuelson effect? One would be tempted, at first, to conclude that our findings are consistent with the theoretical framework of Anderson and Danthine (1983), where what matters is the resolution of production uncertainty over time, and inconsistent with that of Bessembinder et al. (1996) who focuses on inventories. However, the answer is more nuanced. Bessembinder et al. (1996) rely primarily on the negative covariance between net carrying costs and spot prices to explain the Samuelson effect. Then they assume that such a negative covariance is due to the presence of inventories and convenience yields [13].

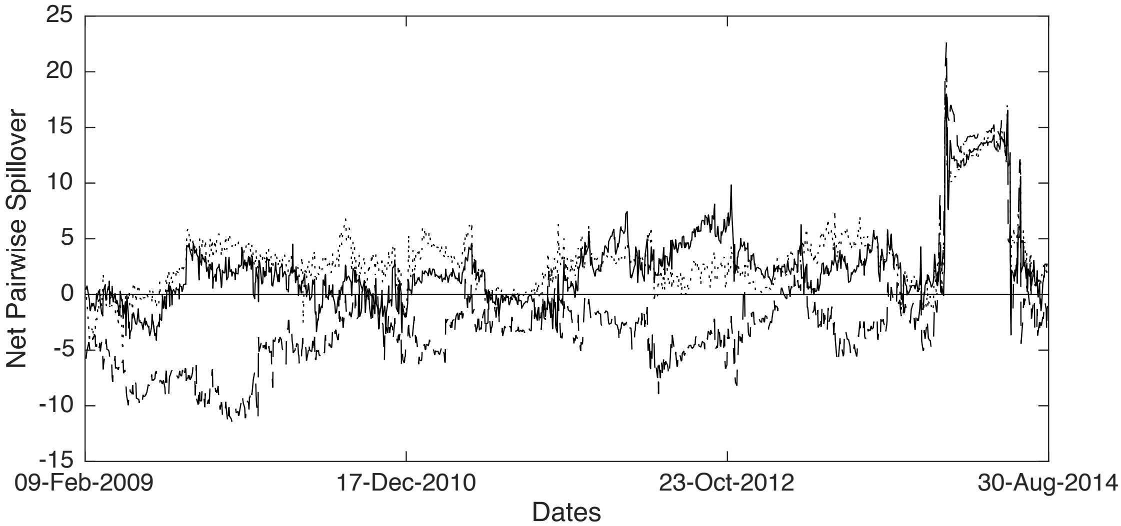
[13] Bessembinder et al. (1996): " (...) we argue that the most plausible reason for substantial time variation in inventory



(a) Indirect Storability in the American market: Total Spillover Index



(b) Indirect Storability in the American market: Net Directional Spillover



(c) Indirect Storability in the American market: Net Pairwise Spillover

This figure shows the total spillover index and directional volatility spillover measures between electricity prices and input prices in the PJM market and in a dynamic framework with a 90-day rolling window. The first chart represents the total spillover index. The second chart represents the net directional spillovers. The solid line is used for the PJM market, the dashed line for the heating oil market, the dotted line for the natural gas market, and the bold dashed line for the coal market. The third chart represents the net pairwise spillovers against the PJM market. The solid line is used for the heating oil market, the dashed line for the natural gas market and the dotted line for the coal market. The total spillover index measures the contribution of the spillovers of volatility shocks across markets to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by market i to all others (see equations 12) and the volatility spillover received by market i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a market contributes more than it receives. The net pairwise volatility spillover gives information about how much market i contributes to the volatility of market j (see equation 13).

Figure 5: Dynamic analysis: volatility spillovers between electricity and its inputs, PJM and inputs markets, 2008-2014

Further, in the case of electricity, we also find a negative covariance between the net carrying costs and the spot prices (results are available from the authors on request). Yet there is no stock, nor indirect storability, at play. Why? Because even in the absence of a buffering effect on prices due to inventories, there is still some flexibility in the electricity markets. This flexibility is associated with flexible production capacities, like thermal units.

Thus, as in Bessembinder et al. (1996), Daal et al. (2006), and Duong and Kalev (2008), our results on electricity do not definitively reject or validate one of the two theoretical frameworks used to explain the Samuelson effect; both frameworks are helpful. However, the analysis proposed by Bessembinder et al. (1996) should not be restricted to storable commodities.

5. Conclusion

This article provides insights for the literature on commodity derivative markets in several directions. First, it proposes a new empirical implication of the Samuelson effect and offers a method to test it. Second, it enhances the knowledge about the dynamics of the futures prices in the four most important electricity markets in the world, and we find evidence of a Samuelson effect for all of the markets under consideration. Even if electricity is non-storable, the comparison with crude oil does not give evidence of a specific behavior. Third, contrary to what was proposed by Bessembinder et al. (1996), this empirical study shows that storage is not a necessary condition for a Samuelson effect to appear. This is interesting, as most of the models of the term structure of commodity prices rely on the storage theory (see, e.g., Brennan (1958), Brennan and Schwartz (1985), and Cortazar and Schwartz (2003)). This result is reinforced by our finding that there is no evidence of an "indirect storability" effect in the markets under examination. The results do not show the presence of persistent directionality effects from the inputs to the electricity prices.

This evidence of an existing time-to-maturity effect for electricity markets calls for improvements in the valuation of electricity derivative assets. This need is all the more true because maturity and volatility are essential components of the asset's value. For example, this is the case, for term structure models of futures prices and for options. This improvement in the valuation should be followed by an enhancement of risk management procedures: it is necessary to take the Samuelson effect into account for hedging operations in electricity markets and for the design of markets protection tools by clearing houses and regulatory authorities.

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carrying costs derives from the variation of real service flows or 'convenience yields'. In particular, a positive covariation between convenience yields and spot prices leads to mean-reverting spot prices in equilibrium, and is sufficient to support the Samuelson hypothesis. Since financial assets do not provide service flows, we predict that the Samuelson hypothesis will not hold for financial futures".

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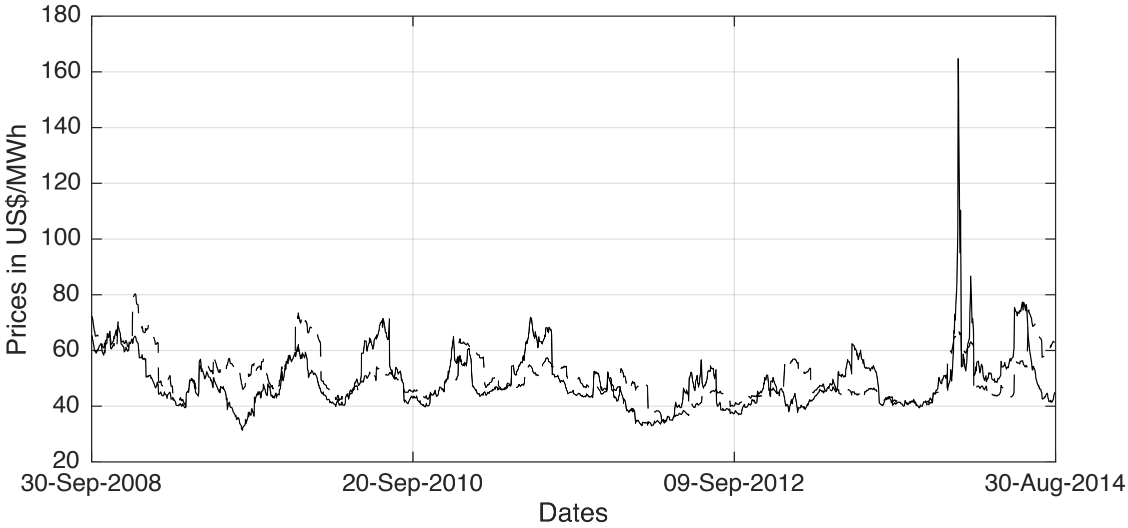
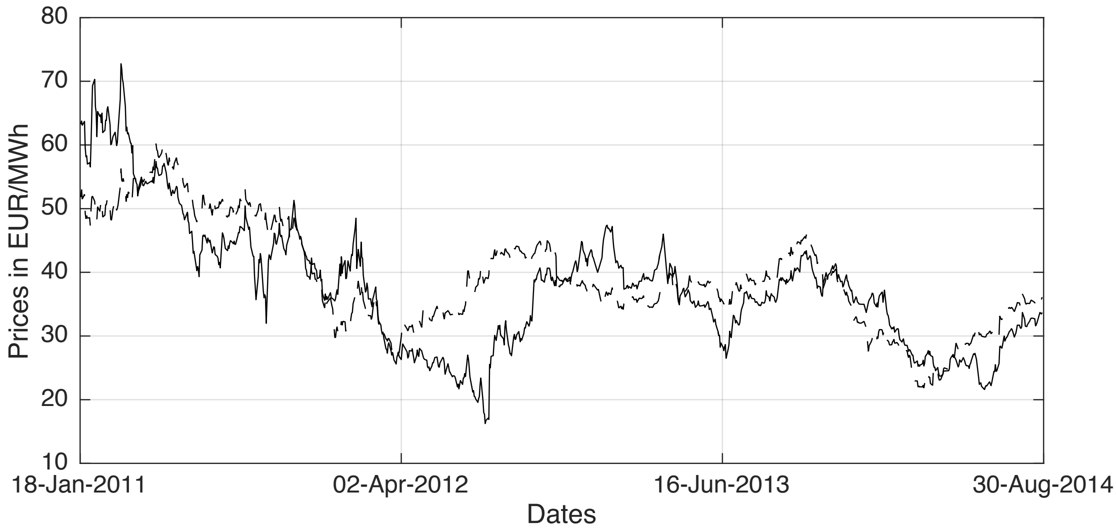
Appendix A. Prices and volatilities

Appendix A.1. Continuous time series of prices for different maturities

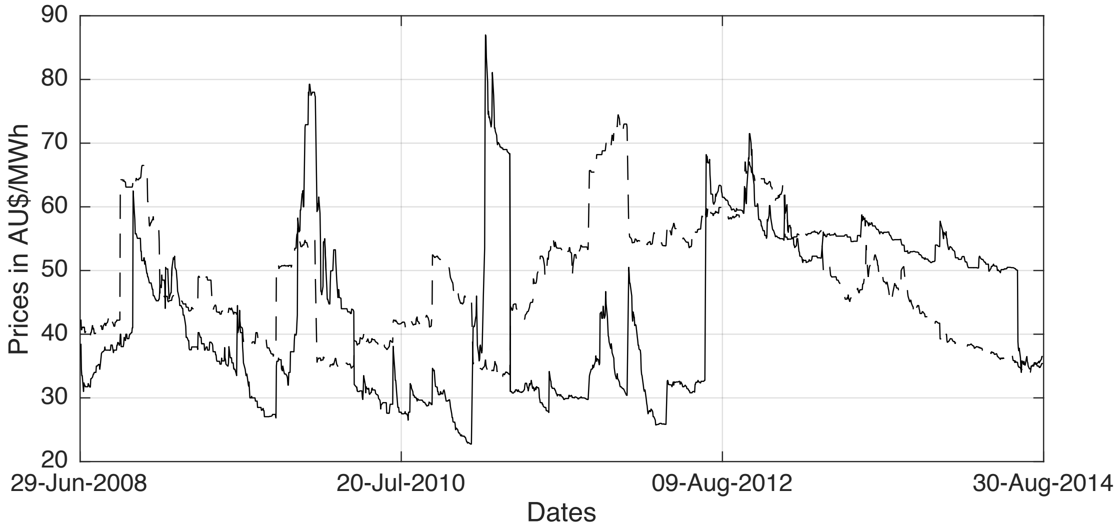
This figure displays the continuous time series of prices for two different constant maturities in three electricity futures markets: the PJM, the NEC, and the NSW. The solid line is for the nearest maturity, the dashed line for the most distant one.



(a) PJM contract



(b) NEC contract



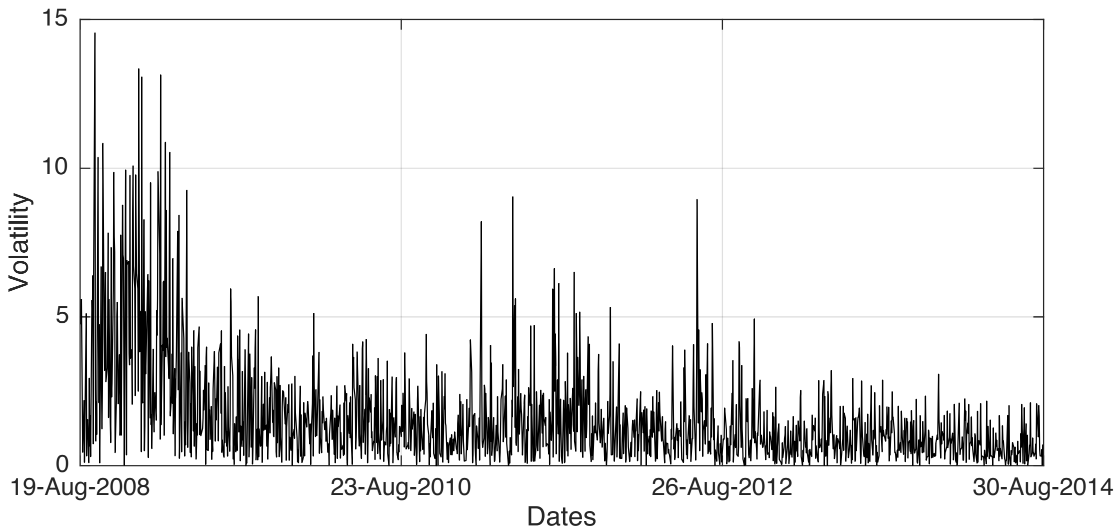
(c) NSW contract

This figure shows the continuous time series of the prices for two different maturities in three different markets. The solid line is for the nearest maturity, and the dashed line is for the most distant maturity; that is, the one- and the six-month contracts for the PJM, the one- and the four-month contracts for the NEC, and the one- and the six-quarter contracts for the NSW.

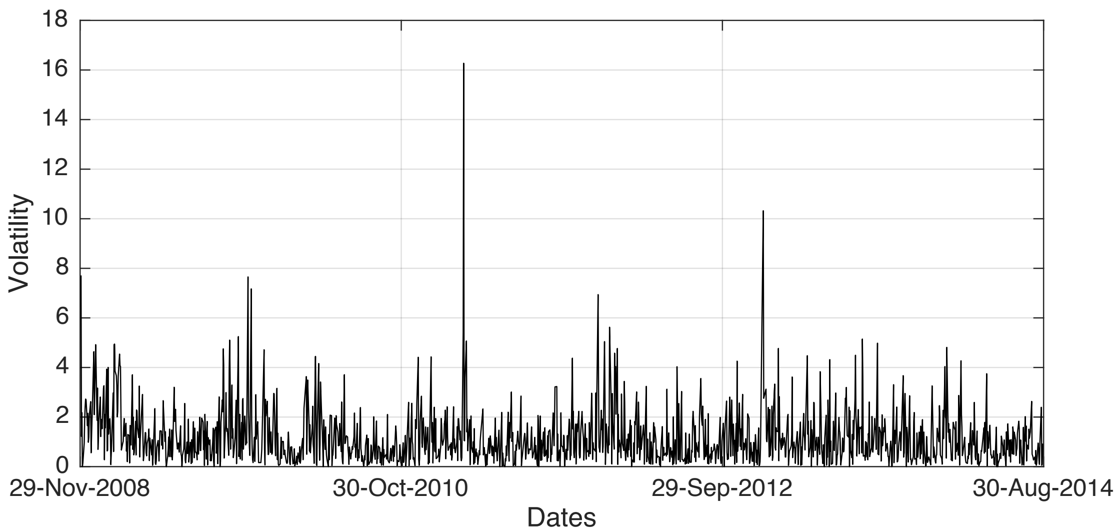
Figure A.6: Time series of prices of fixed maturity contracts, PJM, NEC and NSW markets, 2008-2014

Appendix A.2. Daily volatilities of the closest-to-maturity time series

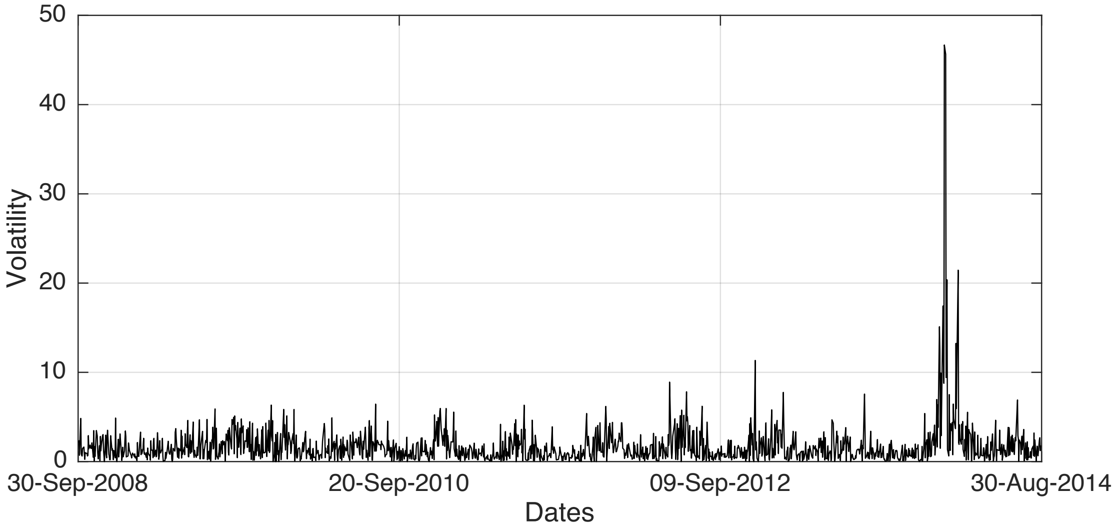
This appendix contains a chart for each market, displaying the volatility of the closest-to-maturity time series.



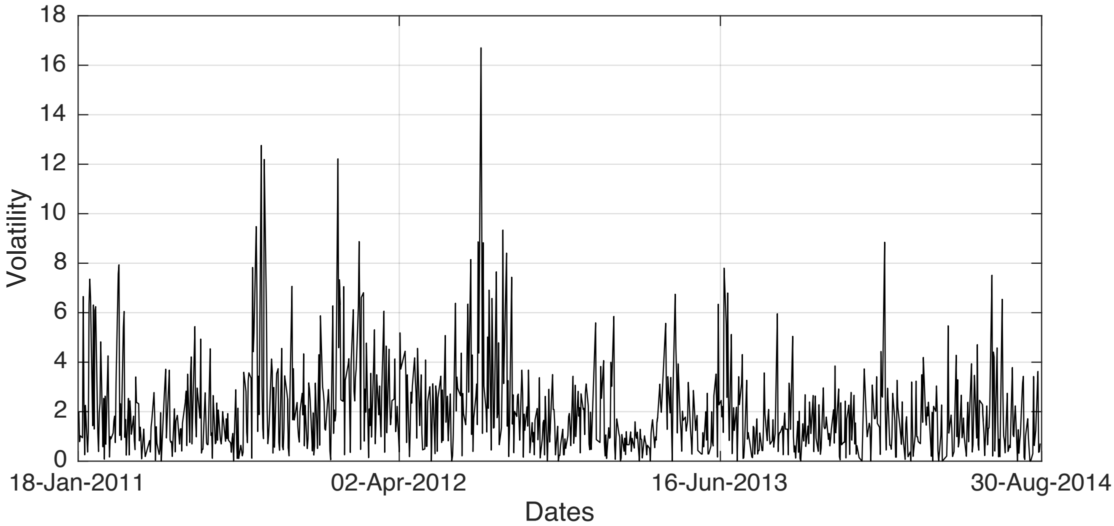
(a) WTI contract



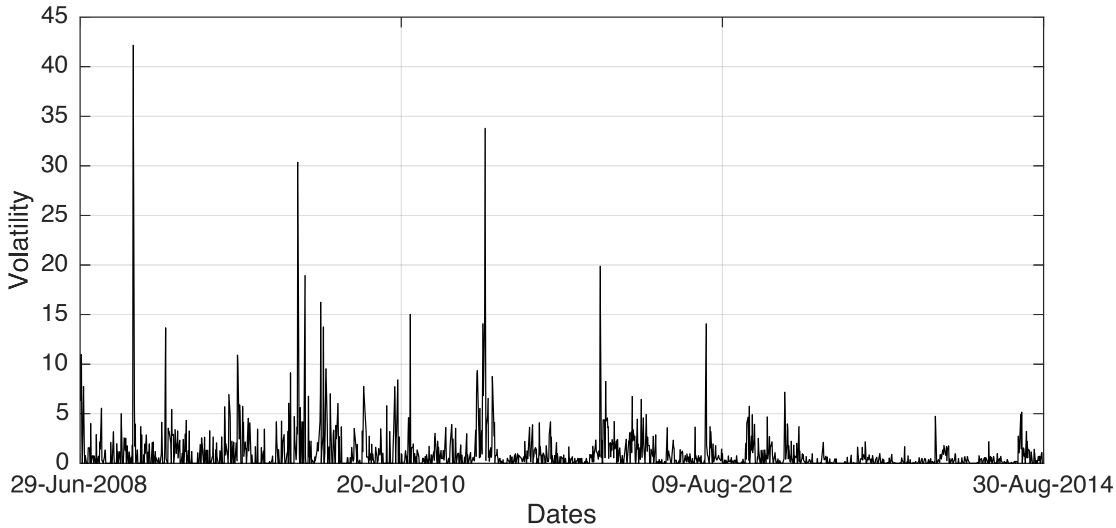
(b) Phelix contract



(c) PJM contract



(d) NEC contract



(e) NSW contract

This figure shows for each market, the time series of the daily volatilities $\sigma_t^k = |\ln\left(\frac{F_t^k}{F_{t-1}^k}\right)| * 100$ for the closest-to-maturity contract.

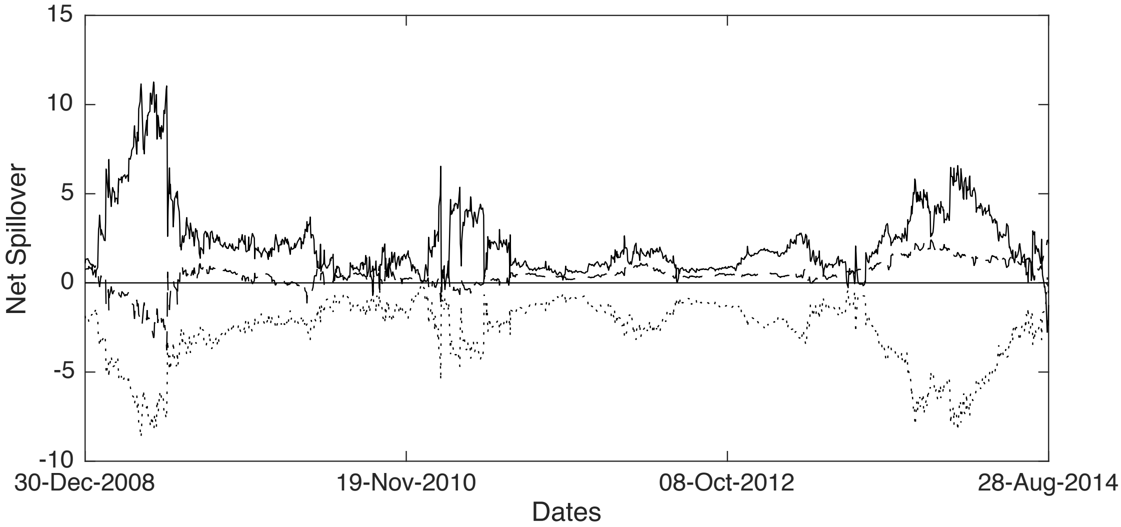
Figure A.7: Daily Volatilities of the closest-to-maturity contract, crude oil and electricity markets, 2008-2014

Appendix B. Dynamic analysis of spillovers from the physical to the paper markets

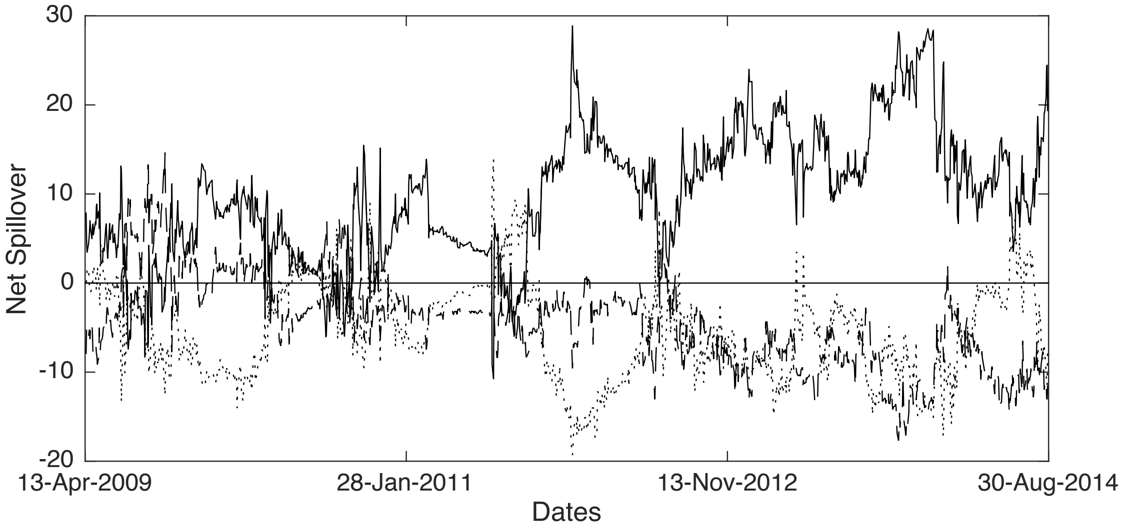
This appendix contains complementary charts for the spillover measures in a dynamic framework, that is, two charts by market not presented in the main sections of the article (WTI, Phelix, NEC, NSW).

Appendix B.1. Dynamic net spillovers from the physical to the paper markets

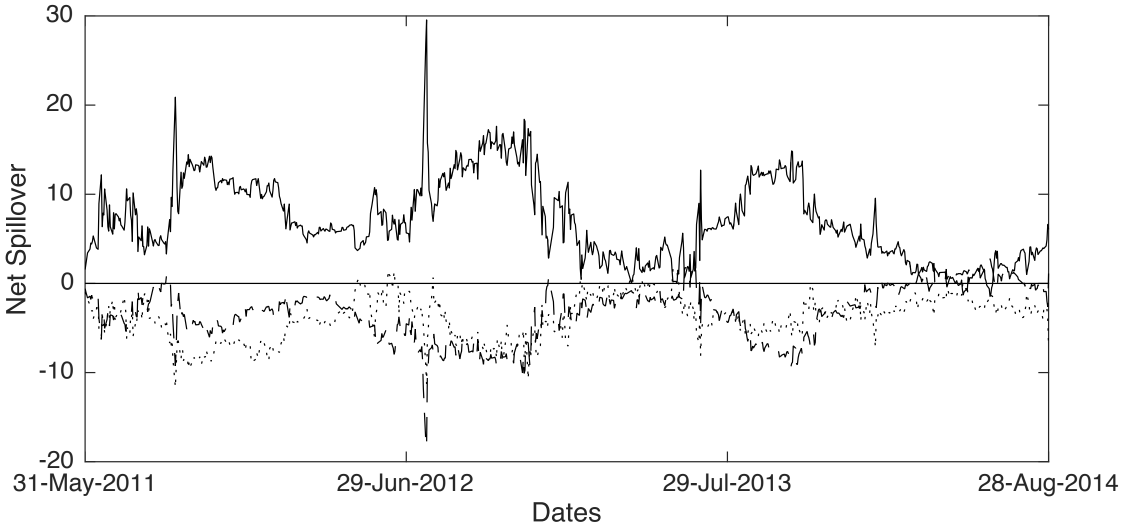
These charts display the dynamic net spillovers from the physical to the paper markets for each contract.



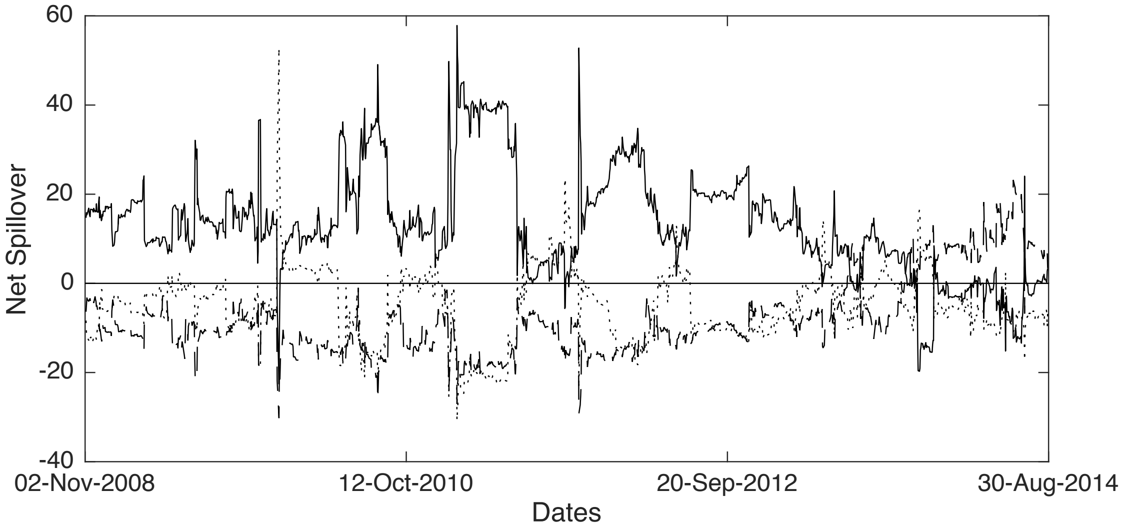
(a) WTI contract



(b) Phelix contract



(c) NEC



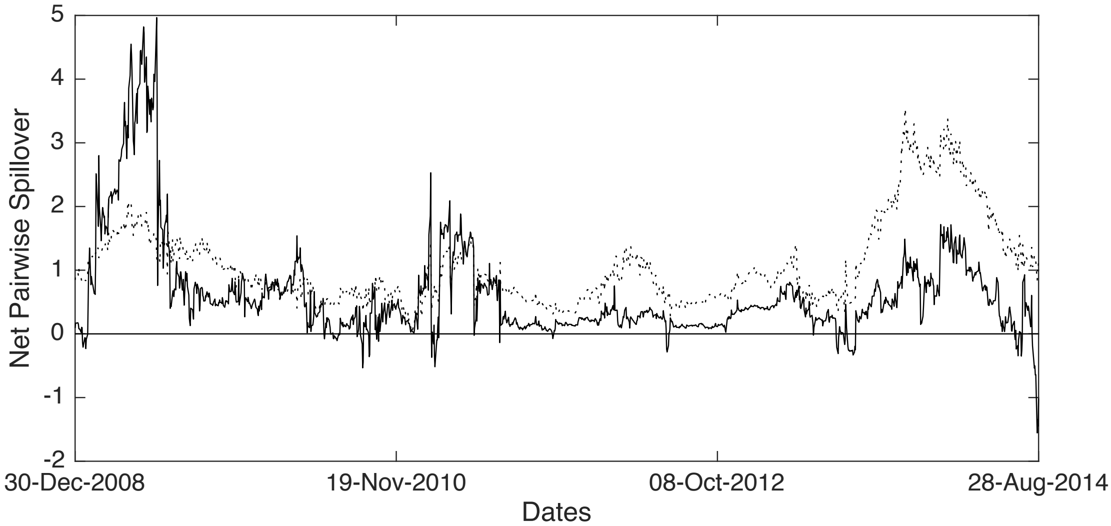
(d) NSW contract

This figure shows the net directional volatility spillover measures between maturities for each market in a dynamic framework using a rolling window of 90 days. The solid line is for the nearest maturity, the dashed line is for the intermediate maturity, and the dotted line is for the most distant maturity. The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by maturity i to all others (see equations 12) and the volatility spillover received by maturity i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a maturity contributes more than it receives.

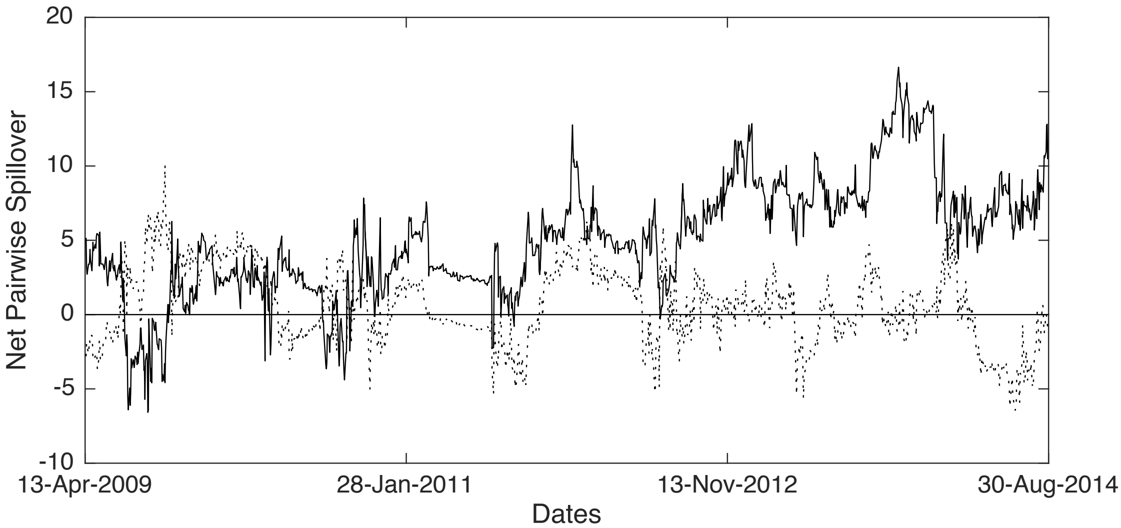
Figure B.8: Dynamic analysis: net spillovers between maturities, crude oil and electricity markets, 2008-2014

Appendix B.2. Dynamic net pairwise spillovers from the physical to the paper markets

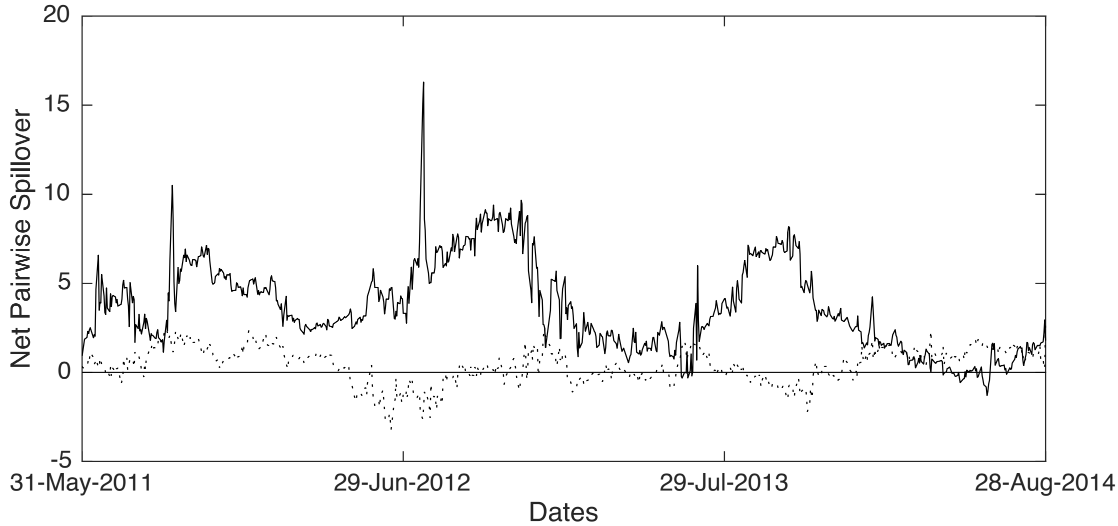
These charts display the dynamic net pairwise spillover from the physical to the paper market for each market.



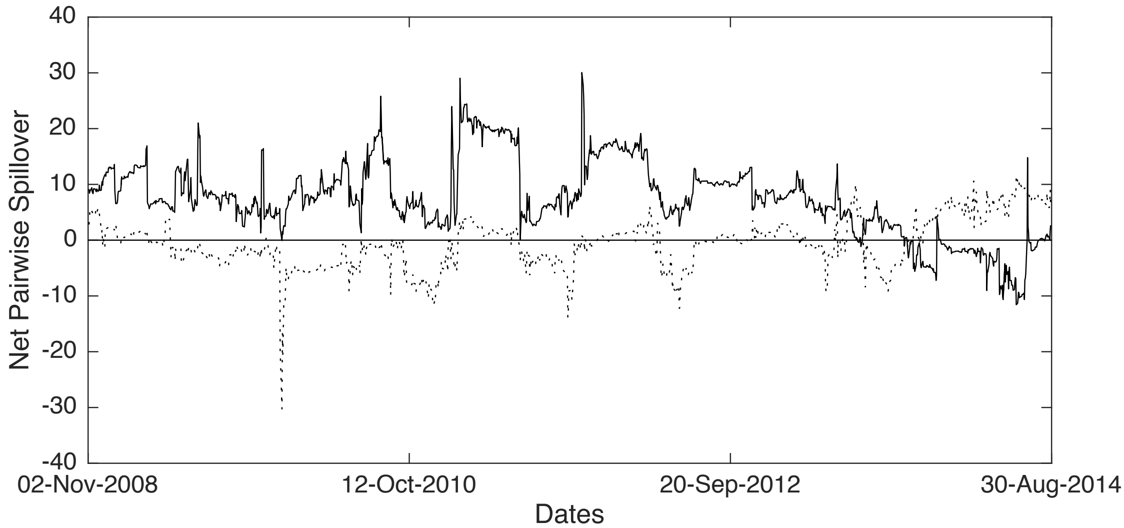
(a) WTI contract



(b) Phelix contract



(c) NEC contract



(d) NSW contract

This figure shows the net pairwise directional volatility spillover measures between two consecutive maturities for each market in a dynamic framework using a rolling window of 90 days. The solid line is for the spillover from the nearest to the intermediate maturity and the dotted line is for the intermediate to the most distant maturity. The net pairwise volatility spillover gives information about how much maturity i contributes to the volatility of maturity j (see equation 13)

Figure B.9: Dynamic analysis: net pairwise spillovers between maturities, crude oil and electricity markets, 2008-2014

Appendix C. Analysis of the indirect storability on the American and the German markets

Appendix C.1. Complements of the analysis on the PJM market

Table C.11 sums up the descriptive statistics of the daily volatilities recorded on the closest-to-maturity contracts for each market from 2008 to 2014.

	PJM	Heating Oil	Natural Gas	Coal
# of observations	1 490	1 490	1 490	1 490
Mean	1.676	1.344	2.309	0.96
Median	1.178	0.950	1.759	0.651
Standard-deviation	2.415	1.366	2.18	1.09
Skewness	10.01	2.361	2.76	3.04
Kurtosis	164.62	10.76	18.886	17.69
ADF	-17.93*	-19.05*	-20.06*	-18.82*
LB	1 508*	1 118*	471*	1 364*
Jarque-Bera	1 646 644*	5 123*	17 559*	15 688*

This table sums up the descriptive statistics of the daily volatilities $\sigma_t^k = |\ln\left(\frac{F_t^k}{F_{t-1}^k}\right)| * 100$ recorded on the closest-to-maturity contracts for the PJM market and its inputs (heating oil, natural gas, and coal) from 2008 to 2014. The "ADF", "LB", and "Jarque-Bera" respectively stand for the test statistics of the Augmented Dickey-Fuller test for unit roots without a lag, the Ljung-Box test for autocorrelation with 15 lags, and the Jarque-Bera test for normality. The associated null hypothesis H_0 is the presence of a unit root for the ADF test, that the data are independently distributed for the LB test, and that the data follow a normal law for the JB test. The star (*) means that we reject the assumption H_0 at the 1% level of confidence.

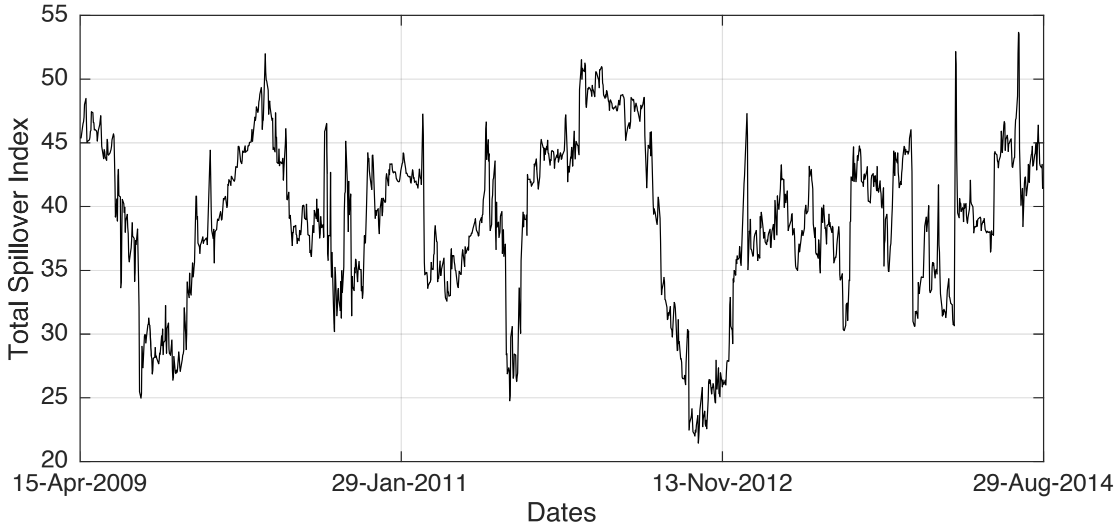
Table C.11: Descriptive statistics of the daily volatilities, PJM and inputs markets, 2008-2014

Appendix C.2. Analysis of the Phelix market

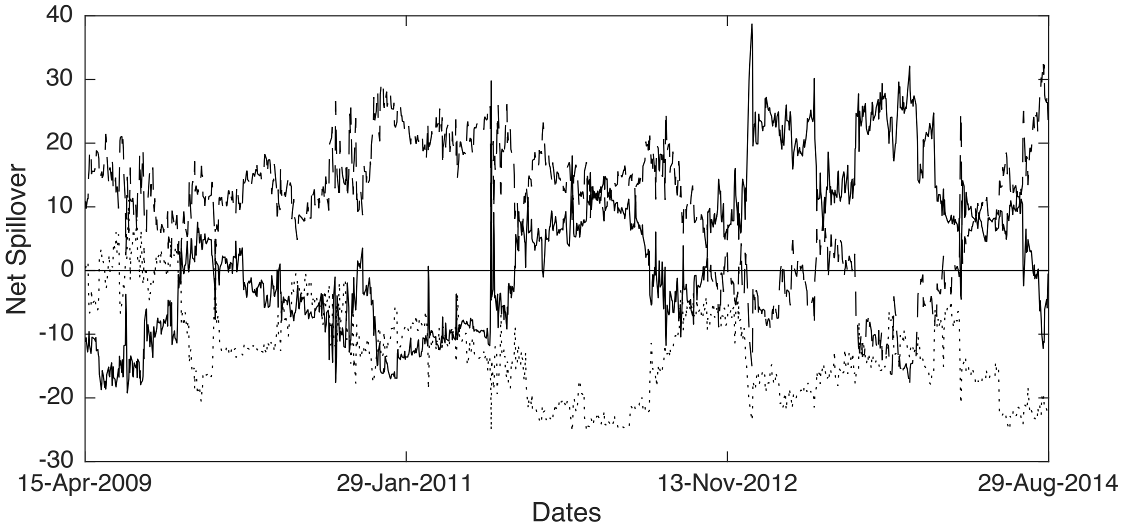
In this paragraph we reproduce for the Phelix market the same analysis as for the PJM market regarding the concept of indirect storability. In 2014, on the Phelix market, the coal and the natural gas accounted respectively for 27.8% and 16.11% of the net installed generation capacity according to the Fraunhofer Institute. The analysis uses prices for the one-month Phelix futures contract, the one-month Rotterdam coal futures, and the one-month TTF natural gas futures traded on the ICE. Table C.12 sums up the descriptive statistics of the daily volatilities recorded on the closest-to-maturity contracts from 2008 to 2014 for each market. The results obtained are the same as before, that is, our series do not contain unit roots, are autocorrelated, and do not follow a normal distribution.

Table C.13 displays the results of the static analysis on the entire sample. First, the total spillover index is 28.58%, near the one recorded in the analysis for the PJM. This value shows that the volatility on these markets is mainly explained by their own shocks and not by the links between markets. Moreover, the results show that the Phelix and the coal markets receive most of their volatility from natural gas. The Phelix and the coal markets are indeed characterized by a net directional spillover of -1.24 and -8.957 respectively. With a positive net pairwise spillover of 10.197, the natural gas market *delivers* volatility to the two other markets.

A more dynamic analysis performed on the basis of 90-day rolling windows and illustrated by Figure C.10 and Table C.14 gives more insights. In net terms, the Phelix and the natural gas markets send volatility respectively 54.61% and 80.75% of the time, while the coal market receives it 93.92% of the time.
However, as was the case in the static framework, the dynamic pairwise analysis shows that most of the time, the Phelix market sends volatility to the coal markets and receives volatility from the natural gas market.



(a) Indirect Storability in the German market: Total Spillover Index

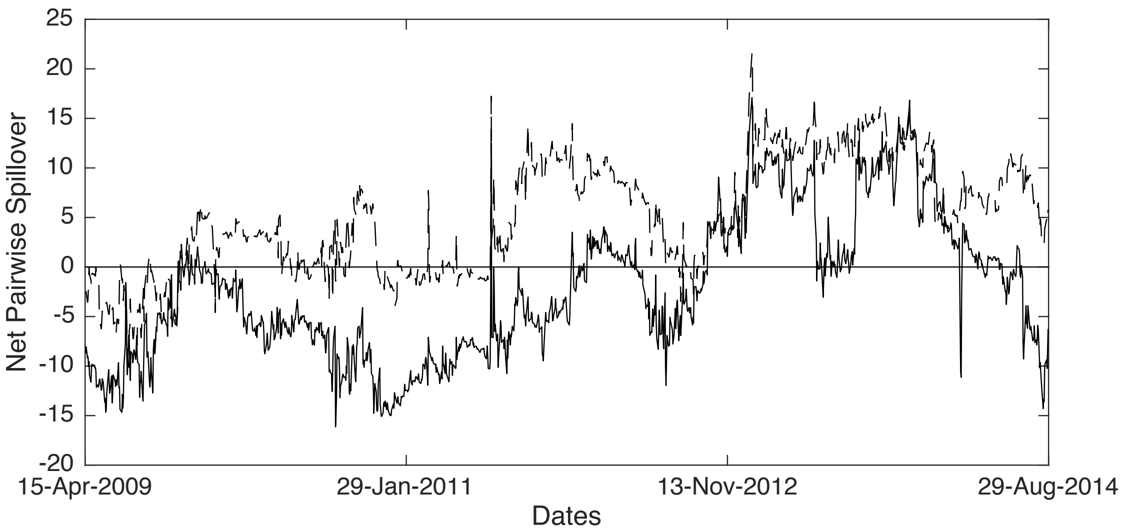


(b) Indirect Storability in the German market: Net Directional Spillover

	Phelix	Natural Gas	Coal
# of observations	1 457	1 457	1 457
Mean	1.133	1.598	0.613
Median	0.793	1.051	0.341
Standard-deviation	1.139	1.72	0.816
Skewness	3.40	2.176	3.116
Kurtosis	30.08	9.12	15.88
ADF	-19.60*	-18.11*	-19.64*
LB	234*	1 563*	1 033
Jarque-Bera	47 315*	3 423*	12 430*

This table sums up the descriptive statistics of the daily volatilities $\sigma_t^k = |\ln\left(\frac{F_t^k}{F_{t-1}^k}\right)| * 100$ recorded on the closest-to-maturity contracts for the Phelix market and its inputs (natural gas and coal) from 2008 to 2014. The "ADF", "LB" and "Jarque-Bera" respectively stand for the test statistics of the Augmented Dickey-Fuller test for unit roots without a lag, the Ljung-Box test for autocorrelation with 15 lags, and the Jarque-Bera test for normality. The associated null hypothesis H_0 is the presence of a unit root for the ADF test, that the data are independently distributed for the LB test, and that the data follow a normal law for the JB test. The star (*) means that we reject the assumption H_0 at the 1% level of confidence.

Table C.12: Descriptive statistics of the daily volatilities, Phelix and inputs markets, 2008-2014



(c) Indirect Storability in the German market: Net Pairwise Spillover

This figure displays the total spillover index and directional volatility spillover measures between electricity prices and input prices in the Phelix market and in a dynamic framework with a 90-day rolling window. The first chart represents the total spillover index. The second chart represents the net directional spillovers. The solid line is used for the Phelix market, the dashed line for the natural gas market, and the dotted line for the coal market. The third chart represents the net pairwise spillovers against the Phelix market. The solid line is used for the natural gas market and the dashed line for the coal market. The total spillover index measures the contribution of the spillovers of volatility shocks across markets to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by market i to all others (see equations 12) and the volatility spillover received by market i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a market contributes more than it receives. The net pairwise volatility spillover gives information about how much market i contributes to the volatility of market j (see equation 13).

Figure C.10: Dynamic analysis: volatility spillovers between electricity and its inputs, Phelix and inputs markets, 2008-2014

# of observations		Total spillover index (%)	Directional to all others	Directional from all others	Net	Net Pairwise against Phelix
	Phelix		7.76	8.999	-1.24	
1 457	**Natural gas**	28.58	16.45	6.254	10.197	-3.693
	Coal		4.367	13.324	-8.957	2.454

This table shows the total spillover index and the directional volatility spillover measures between electricity prices and natural gas and coal in a static framework. The total spillover index measures the contribution of the spillovers of volatility shocks across markets to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by market i to all others (see equations 12) and the volatility spillover received by market i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a market contributes more than it receives. The net pairwise volatility spillover gives information about how much market i contributes to the volatility of market j (see equation 13)

Table C.13: Static analysis: volatility spillovers between electricity and its inputs, Phelix and inputs markets, 2008-2014

# of observations		Total Spillover Index	Net Directional			Net Pairwise	
			Phelix	**NG**	**Coal**	**Phelix-NG**	**Phelix-C**
1 457	**Min**	21.44	-19.22	-18.47	-25.31		
	Max	53.66	38.7	32.93	11.09		
	StDev	6.32	12.08	10.21	7.15		
	⊕(%)		54.61	80.75	6.08	35.72	75.84

This table shows the summary statistics of the total spillover indexes and the directional volatility spillover measures between the Phelix market and its inputs, in a dynamic framework, on the basis of a 90-day rolling window. In this table, NG represents natural gas and C represents coal. The ⊕(%) represents the percentage of positive values recorded over the period. The total spillover index measures the contribution of the spillovers of volatility shocks across markets to the total forecast error variance (see equation 10). The directional spillovers "To all (from i)" and "From all (to i)" respectively give information about the volatility spillovers transmitted by market i to all others (see equations 12) and the volatility spillover received by market i from all others (see equations 11). The net directional spillover is the difference between the two and shows if a market contributes more than it receives. The net pairwise volatility spillover gives information about how much market i contributes to the volatility of market j (see equation 13).

Table C.14: Dynamic analysis: volatility spillovers between electricity and its inputs, Phelix and inputs markets, 2008-2014