Rise of the YieldCos:
Can Tax Efficient Corporate Entities Spur Renewable
Electricity Generation?

Mohit Hajarnis*  Frederic Liegl†  Mark Jazbik‡  Lauren Weinberg§

December 5, 2015

*Math and Economics, Class of 2016
†Philosophy and Economics, Class of 2016
‡Economics, Class of 2016
§Economics, Class of 2017
# Contents

1 Introduction ............................................. 3

2 Master Limited Partnerships ................................. 4
   2.1 Introduction ........................................... 4
   2.2 Historical Overview of MLPs ......................... 5
   2.3 Economic Structure of MLPs .......................... 5
   2.4 Structural Advantages ................................ 6
   2.5 Growth and Innovation Through Acquisitions .......... 8
   2.6 Expansion Limitations ............................... 11
   2.7 MLP Parity Act and Renewable Energy ................. 13

3 YieldCos .................................................. 14
   3.1 Case Study: 8Point3 Energy Partners .................. 17

4 Developing a Pricing Model for YieldCo Returns ....... 23
   4.1 Introduction ........................................... 23
   4.2 Dependent Variable Overview ......................... 25
   4.3 Explanatory Variable Overview ....................... 26
   4.4 Regression using All eVars .......................... 29
   4.5 Regression using Selected eVars ..................... 34

5 Discussion of eVar Significance .......................... 38
   5.1 High Yield Credit Prices ............................. 38
   5.2 YieldCo Sponsors’ Equity Prices ................. 40
   5.3 MLP prices ........................................... 42
   5.4 Crude Oil Prices ..................................... 44
   5.5 XLU Prices ............................................ 45
   5.6 YieldCos Tax Credit Risk ............................. 48

6 Conclusion ............................................... 49

Appendix A ............................................... 51

Appendix B ............................................... 53

Appendix C ............................................... 54
1 Introduction

Our motivation is to understand if YieldCo investment vehicles can sustainably spur renewable electricity generation. Despite garnering a market capitalization of billions USD in just a handful of years\(^1\), there is little available research on what drives market valuations of YieldCos, and whether an exchange-traded and tax-efficient structure is the right approach to financing the underlying clean energy assets. Hence we want to investigate whether the high hopes that the energy and investment banking industries have placed into YieldCos are warranted. We will begin by introducing Master Limited Partnerships (MLPs), the tax-efficient corporate entities that own fossil-fuel related assets and inspired the creation of YieldCos. Next, we will discuss the YieldCo structure and examine the case of 8Point3 Energy Partners, which was recently floated and has been subject to large price drops, significantly hindering its ability to fund asset dropdowns without highly dilutive equity issuance. 8Point3 raises the question of what drives YieldCo prices, and so we turn to our model: a regression-based approach to decomposing YieldCo index returns into different explanatory variables. If YieldCos were fairly priced, then their returns would be representative of the prospective cash flows of their underlying assets, which in turn depend highly on the supply and demand of renewable energies production in North America. What we find in the data, however, is that we can assign the highest predictive power to factors that in reality are largely unrelated to clean energy, including crude oil prices, high yield credit, MLP prices, and utilities equities. The only related factor is that of the stock performance of YieldCo sponsors, although some of them operate in both the fossil fuel and renewables space. Our thesis is therefore two-fold. First, YieldCos run into trouble when they experience market price drops, because equity issuance becomes probitively dilutive. Second, the majority of variation in YieldCo market prices can be explained by factors unrelated to the fundamental performance of renewable energies, leading to returns that are driven by risk/reward.

characteristics of comparable asset classes, rather than underlying cashflows. As a result, we conclude that the YieldCo structure does not represent a sustainable way to grow renewables production in North America.

2 Master Limited Partnerships

2.1 Introduction

Master Limited Partnerships (MLPs) are hybrid entities that issue publicly traded equity interests and operate largely in the non-renewable energy sector. MLPs are integral to Economic and Energy policy in the United States as these entities are a way the private sector finances the infrastructure needed to fully utilize domestic energy resources. At a macro level, the MLP structure works to keep costs of production down and help American producers stay competitive in an international market.

The MLP structure is a publicly traded partnership (PTP) which combines the benefits of a corporation—an independent legal entity owned by shareholders, and a partnership—where two or more individuals share ownership. The MLP has tax pass-through benefits of a partnership, whereby the MLP does not pay any federal income taxes on income. The MLP is also publicly traded so owners have the ability to buy and sell interests in the MLP, which provides for the liquidity enjoyed by a public corporation. As such, the MLP must be listed on one of the major U.S. securities exchanges (NYSE or the NASDAQ). The advantages of the MLP structure include capital gains, consistent distributions over time, lower cost of capital, and ownership incentive alignment that lead to market efficiencies and increase competitive firm entrants in the energy sector.

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2.2 Historical Overview of MLPs

Apache Corp., the first MLP, was established in 1981 to consolidate 33 oil and gas drilling program limited partnerships. MLPs quickly became popular as the tax requirements and market expectations encouraged new entrants, however the 1987 federal tax legislation restricted the MLP structure to businesses generating income that is considered qualifying income. For a company to be eligible to operate as an MLP the business is required to generate at least 90% of its income from qualified sources, such as real estate, natural resources and minerals sector. The specific activities that constitute qualified income is exploration, development, mining or production, processing, refining, transportation and marketing of minerals and natural resources (section 7704(d)(1)(E) activities (8)). With the Emergency Economic Stabilization Act in 2008, the definition of qualifying income was broadened to incorporate the transportation and storage of certain renewable and alternative fuels (ethanol, biodiesel, and a series of liquefied fuels), as well as industrial-source carbon dioxide.

2.3 Economic Structure of MLPs

The MLP structure is generally split between two groups; the Limited Partner (LP), who provides the capital to the MLP, and the General Partner (GP), who is responsible for managing the MLP's operations. The GP operates the holding company (or an operating limited partnership) that directly or indirectly owns the energy assets and other energy subsidiaries of the MLP. GPs are usually energy companies that sponsor the creation of the MLP, provide a management team and oversee operations. GPs typically own a stake in the MLP enterprise (2%) and have claim on Incentive Distribution Rights (IDRs), which entitle the GP to a higher percentage of cash distributions on a performance basis.

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Figure 1: Typical Structure of a Publicly Traded MLP

The two-tiered structure provides the GP with the ability to increase financial leverage with a spread risk. With the two-tiered structure, the holding company can operate subsidiaries and create ventures that are isolated from one another. What this means is that GPs are encouraged to develop assets, given that the assets and liabilities of one activity can be held separately from the assets and liabilities of another venture held by the same holding corporation.

2.4 Structural Advantages

MLPs are attractive to investors due to overall returns in the form of consistent cash distributions and high yield as a result of tax protections. The outperformance of MLPs in respect to overall market returns is attributable to the combination of these two factors; however, the underlying economics aligns management-investor incentives and promotes high-valuations in energy asset development.

One of the primary mechanisms that align management and LP unit-holder incentives is cash distributions. The GP is required by their partnership agreements to distribute all available operating cash to unit-holders. The definition of all available cash is all operating
cash flow after accounting for cash needed for business operations, cash to cover debt obligations, working capital borrowings and cash needed for distributions over the course of the calendar year.

The result of having the cash distribution requirement is that MLPs are traded based on a multiple of cash flow, and thus management is incentivized to increase that multiple. In A Cash-Flow Concept of Profit, Diran Bodenhorn presents the cash-flow concept of profit to bridge the gap between the profit maximization assumption and the market valuation of an enterprise that is based on stockholders willingness to pay. For the purpose of his discussion Bodenborn defines a net cash flow as the cash flow between the firm and its stockholders, which is akin to the cash distributions made by the GP to unit-holders of the MLP. Bodenborn argues that the stock value is based entirely upon the present value of future net cash flows, and specifically those that can be received by shareholders in distributions.\(^6\) Given that the MLP is traded on a multiple of cash flow, the more assurance an investor has that he or she will receive cash distributions and tax benefits, the greater the market valuation. This aligns the incentives between the GP and unit-holders; The GP's objective is to maximize the market valuation of the MLP (based on the public's willingness to pay for common units in an IPO) and, to do so, The GP must be able to distribute consistent and growing cash flows.

The MLP's ability to profit from the tax pass-through partnership structure attracts investors and improves overall returns. The tax pass-through status granted to MLPs means they are not subject to corporate income tax. Instead, owners of an MLP are responsible for paying taxes on their own individual portions of the MLP's income, gains, losses, and deductions. The problem of double taxation generally applied to corporations is eliminated in this structure. Double taxation in the typical corporate structure is where the corporation pays taxes on its income and the corporation's shareholders also pay taxes on the corporation's dividends. As the United States has the third highest corporate income tax in the

world, companies able to avoid direct taxation have a sizable competitive advantage over their peers. The security of the partnership structure as a tax pass-through entity will be analyzed with respect to Yieldcos further in this paper; however, the crucial distinction for this discussion is the corporate tax exemptions for MLPs are legally codified in the partnership structure. Therefore, these corporate tax exemptions can only be reneged on if congress markedly amends section 7704 in the tax code.

The fact that the MLP's profits and earnings are not directly taxed changes the market dynamics of the profit-maximizing firm. In the general profit maximization problem, an external tax imposed on the firm reduces output given a constant or likely increased cost. The tax imposed creates a deadweight loss because of fewer mutually beneficial exchanges between buyers and sellers. In the case of the MLP, the corporate tax would be an additional constraint on the firm's ability to allocate capital towards costly innovative ventures. Additionally, because the MLPs product is not direct to consumers, these increased costs will trickle down the pipeline and increase the price of production across the energy industry. Especially in the current O&G environment of low prices due to a supply glut in the market, increasing the costs of production would likely exacerbate the number of firms currently operating in distress or bankruptcy. The tax pass-through exemption changes the market dynamics for MLPs given these firms can more readily achieve operational efficiency.

2.5 Growth and Innovation Through Acquisitions

The number of investors that seek high yield returns in MLPs has grown exponentially over the past decade, which is made possible by the MLP’s tax-pass-through and cash distribution structure. The Energy MLP sector has outperformed the market with annualized returns of 17% (based on the Alerian MLP Index) - 8% above the S&P returns over the same period.[7] This data is important as these high returns attract investors to MLP energy projects with two important economic reverberations: acquisition driven innovation and new entrants.

In the past, MLPs have predominantly pursued an acquisition strategy to drive growth; MLPs have acquired more than $30 billion in assets over the last 5 years\textsuperscript{8}. Phillips & Zhdanov (2013) present model-based tests demonstrating that an active acquisition market positively affects the incentives of small firms to innovate. To apply this model to the MLP midstream space, 'small firms' is interpreted as the owners of midstream assets and 'large firms' is interpreted as MLPs. MLPs have similar advantages to larger firms due to a lower cost of capital and a sizable investor base that supports acquisitions. In the Phillips & Zhdanov's model, which emphasizes asset complementarities and product market synergies, acquiring innovation through acquisition is a substitute for in-house research and asset development\textsuperscript{9}. The prospect of becoming an acquisition target for 'small firms' (owners of midstream energy assets) in turn increases incentives for innovation as it amplifies the potential gain from successful research and development. Rather than stifling innovation, as interpreted by Seru (2014), MLPs may actually be promoting greater innovation through

their acquisition activity, and through an ability of the merged MLP to apply innovation across its subsidiary asset base.

Figure 3: MLP Acquisitions by Asset Type in 2013 and 2014, respectively

The Texas-based Martin Midstream Partners (Martin Midstream) is one such example of an MLP that has achieved greater technological innovation through asset acquisition. Martin Midstream owns and operates 31 marine shore-based storage and processing facilities located in the U.S. Gulf Coast region. In 2014, the company acquired 20% ownership interest in Cardinal Gas Storage Partners, LLC. (CGSP), and subsequently began implementing CGSP’s IPOR (IsoPressure Open Refrigeration) technology to re-design their own storage facilities. Prior to the acquisition Martin Midstream was using a process that involved refrigeration, using propane as a refrigerant, with the addition of a turboexpander. While the addition of the turboexpander (a turbine through which a high-pressure gas is expanded at a temperature of -150 degrees Celsius or less) served to increase the extractable amount of NGLs, this solution came with high capital and operating costs. Using the Iso Pressure Open Refrigeration Process (an IPOR open-loop ethane-based refrigeration method) Martin

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Midstream was able to use a refrigerant that is extracted from the gas feed itself that enables storage and processing operation at lower temperatures. From a thermal efficiency perspective the IPOR process has proven to require 15-40% less compression power than the traditional turboexpander\textsuperscript{12}. The greater efficiency and reduction in power consumption means that Martin Midstream will also have lower emissions and a smaller carbon footprint.

As a result of growing investor interest in the MLP structure, new entrants are creating a competitive marketplace in the MLP midstream energy sector. As with most successful businesses, the new entrants to the midstream market are structuring themselves as MLPs. In fact, 92 MLPs have held IPOs since 2009 (Bloomberg, 2015). The aggregate market capitalization of Energy MLPs has grown to $677 billion in 2015, from $518 billion and $470 billion in 2014 and 2013 respectively\textsuperscript{13}. These 92 IPOs that have come to market in the last 6 years are a substantial portion of the $531 billion increase aggregate market capitalization over that time period\textsuperscript{14}.

\section{2.6 Expansion Limitations}

The analysis of midstream MLPs in relation to the overall midstream market would be futile given that most of the companies in the midstream energy industry are structured as MLPs. Thus, MLPs are currently expanding outside of the traditional operating streams to gain a competitive advantage. In an oversaturated MLP market, investor interest in the high overall returns of MLPs is the primary driver behind GPs to looking for new markets to establish MLP enterprises. Renewable energy is a market that is attractive for GP expansion, but remains relatively untouched due to restrictions that the MLP's qualifiable income definition imposes. In Section 7704, the tax code currently restricts MLPs to projects with depletable resources. This restriction was originally designed to prevent companies of all kinds from


reformulating themselves as MLPs to avoid corporate taxes, but it has the effect of supporting fossil fuel projects while shutting out renewable energy developments. In stark contrast to the 6-year growth in the MLP market, tax equity financing for renewable projects has been limited to $3-6 billion per year.\(^{15}\) SunEdison, Solar City, Sol-Wind, and Brookfield Renewable Energy Partners are renewable energy companies that have either already formed or are reviewing the process of forming MLPs. The ability for these companies to use the MLP partnership structure, and therefore have legal tax pass-through status, could result in a significant upside for these companies’ valuations.

Sol-Wind Renewable Power LP., (Sol-Wind) is one of the first renewable energy enterprises that sought to form themselves with the MLP financial structure by using a blocker corporation\(^{16}\) between the MLP and the assets. Because Sol-Wind’s underlying assets are


\(^{16}\)The blocker corporation is a limited liability company organized in Delaware that makes an election to be taxed as a corporation. A blocker corporation is set up to absorb the 35% corporate tax that would otherwise be applied to the partnership ’s assets.
renewable energy projects that do not generate qualifying income, the venture would have owed some corporate tax. Sol-Wind, in the MLP form, was structured like an upside down yieldco; in the Sol-Wind structure, the public entity is a partnership that owns a corporation, rather than a corporation that owns a partnership. Sol-Wind elected for the MLP structure over the yieldco structure due to the security of the tax benefits as they are legally codified and the greater internal rate of return (IRR). Unfortunately, lack investor confidence in Sol-Wind’s ability to capitalize on the MLP tax benefit caused the venture to cave in. In Feb. 2015 the management team announced the postponement of its $100 million initial public offering, and had trouble raising capital to fund its renewable assets the private markets. Even though this venture was unsuccessful, the potential for new MLP entrants in the renewable energy and power generation segment is an energized topic on the political agenda.

2.7 MLP Parity Act and Renewable Energy

The Master Limited Partnership Parity Act (The MLP Parity Act, H.R. 2883) sets out to make changes to the tax code that will help renewable energy generation and transmission companies form MLPs. The MLP Parity Act expands the definition of qualified sources to include the following renewable energy sources:

- closed and open loop biomass, geothermal, solar, municipal solid waste, hydropower, marine and hydrokinetic, fuel cells, and combined heat and power,
- waste-heat-to-power, carbon capture and storage, and energy-efficient buildings, and
- biodiesel, renewable fuels and renewable chemicals.

Previous versions of this act (H.R. 6437, H.R. 1696) were introduced in 2012 and 2013, respectively. The most recent MLP Parity Act (H.R. 2883) was assigned to a congressional
committee in June 2015, who will consider it before sending it on to the Senate or the House. The enactment of the MLP Parity Act is uncertain at this time, but it has a broad base of political and industry support. The MLP Parity Act, if enacted, would not adversely affect any current MLP. All projects currently eligible for inclusion in an MLP would continue to qualify exactly as under existing law.

 Provided that the MLP Parity Act passes, Sol-Wind's solar and wind projects would be deemed to generate qualifying income, and Sol-Wind could qualify as an MLP without the use of the corporate blocker. Enactment of the MLP Parity Act would mean that MLPs owning renewable energy assets, such as Sol-Wind, could use the traditional MLP structure and thus avoid the extra corporate level tax.

3 YieldCos

In 2013 a new type of vehicle went public with a stable dividend growth story similar to a traditional, non-renewable MLP but without pass-through tax treatment qualifying assets. The entity was a YieldCo, a publicly-traded corporation that owns long-term contracted assets and distributes significantly all of the free cash flows generated by these assets to investors as dividends. While the first YieldCo owned and operated contracted renewable and conventional electricity generation assets and thermal infrastructure assets, since the $495mm IPO of NRG Yield, YieldCos have focused on owning and operating exclusively renewable energy generation projects and electrical generation assets.

YieldCos are designed to provide a low-risk, high-return investment for investors in the renewables space. Renewable energy companies are often perceived as risky businesses (solar panel producer stocks tend to have betas around 2.00) because the technology utilized in projects tend to be unproven. This uncertainty means that investors require high levels of returns to compensate for the high probability of failure and cash-intensive nature of renewable energy investments.

renewable research and development. To reduce the risky nature of investing in the renewable
space, YieldCos tend to include completed electricity generating assets with predictable cash
flows backed by long-term power purchase agreements. Not only are YieldCos less susceptible
to the spot market, they tend to be backed by a parent sponsor with a long-dated pipeline of
operating assets that provide a source of future asset dropdowns, a transfer of ownership from
the sponsor to the YieldCo, on accretive terms. The role of the parent sponsor's pipeline helps
provide visibility to YieldCo investors regarding future growth of the YieldCo's discretionary
dividend.

![YieldCo History Diagram]

**Figure 5:** YieldCo History

Sponsors find YieldCos attractive because they allow the market to place higher valua-
tions on contracted renewables because the risks involved with holding contracted assets
(Role of the YieldCo) is far lower than the risks involved with developing renewable assets
(Role of the Sponsor), and thus investors demand a lower return for YieldCos (lower Yield,
higher Price), than Sponsors.

The federal solar investment tax credit (ITC) and synthetic MLP structure makes solar
electricity generation assets the assets of choice for sponsor-backed YieldCos. Section 48
provides commercial solar systems with a 30 percent tax credit, so many sponsors choose
to build strong solar-related pipelines of projects for YieldCos to take advantage of this tax
credit. In addition to this tax credit, while YieldCos do not generate pass-through qualifying
income like traditional MLPs, sponsors are able to minimize taxes even further by offsetting strong positive cash flow with high depreciation and amortization expenses and, eventually, net operating losses. This accounting offsets allows for YieldCos to minimize double taxation like MLPs without suffering from the strict rules governing pass-through qualifying income. These tax benefits result in investors placing higher valuations on these solar assets. Higher valuations allow the sponsor to redeploy capital from strong YieldCo IPOs into the retained businesses of the sponsor; therefore, the sponsor provides renewable investment opportunities for risk-averse investors while generating value for its more traditional shareholders via an accretive YieldCo IPO.

YieldCos are attractive to both renewable-focused investors and more traditional institutional investors due to the perceived stability of distributable cash available to shareholders and growth pipeline visibility with sponsor-backed asset dropdowns. These factors led to a pretty strong compression in YieldCo yields.

From a logistics point of view, YieldCos are also quite attractive due to their traditional corporation entity structure. MLPs, the more traditional entity for yield-hungry institutional investors, requires investors to fill out Schedule K-1s for tax purposes which can be quite a hassle. YieldCos, on the other hand, only require the traditional Form 1099. For offshore investors, YieldCos are even more attractive than MLPs because YieldCo dividends are only subject to federal withholding tax, which can be substantially reduced, while MLPs

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Renewable Assets (MW-electric)</th>
<th>Total Assets (MW)</th>
<th>Total Capital Raised</th>
<th>Market Cap</th>
<th>Yield (Annual)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NRG Yield, Inc.</td>
<td>Conventional, solar, wind, thermal</td>
<td>1401</td>
<td>2984</td>
<td>$840 million</td>
<td>$3.9 billion</td>
</tr>
<tr>
<td>Pattern Energy Group, Inc.</td>
<td>Wind</td>
<td>1932</td>
<td>1932</td>
<td>$938 million</td>
<td>$1.9 billion</td>
</tr>
<tr>
<td>Abengoa Yield Plc.</td>
<td>Solar, wind, conventional, electric transmission</td>
<td>710</td>
<td>1010; 1018 mi</td>
<td>$829 million</td>
<td>$3.0 billion</td>
</tr>
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<td>TransAlta Renewables, Inc.</td>
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<td>1378</td>
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<td>C$346 million (US$323)</td>
<td>$1.3 billion</td>
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<td>NextEra Energy Partners, LP</td>
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<td>989</td>
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<td>$3.1 billion</td>
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<tr>
<td>TerraForm Power, Inc.</td>
<td>Solar</td>
<td>523</td>
<td>523</td>
<td>$500 million</td>
<td>$3.0 billion</td>
</tr>
</tbody>
</table>
distributions are taxed at federal income tax rates which are harder for offshore investors to reduce.

3.1 Case Study: 8Point3 Energy Partners

To illustrate the strengths (and weaknesses) of the YieldCo. structure, it is useful to study the recent public offering of 8Point3 (NYSE: CAFD), a pure-play solar YieldCo. 8Point3 is a growth-oriented partnership between First Solar and SunPower designed to own and operate solar assets; as of August 31, 2015, the company owned 432.0 MW of solar assets (including a 49% interest in 242.0 MW of joint-venture assets with First Solar) across 10 states in the United States, but largely concentrated in California.

8Point3's sponsors, First Solar and SunPower, are leaders in advanced solar technologies. First Solar is a market-leader in the development, production, and deployment of Cadmium Telluride (CdTe) modules, which can achieve between 16.3% and 18.2% (CdTe advanced) specific annual energy yield (the ratio between MWh/year and installed nameplate capacity in MWp). First Solar's CdTe modules have a temperature coefficient of 0.34%/1 C, compared to 0.45%/1 C for c-Si (Crystalline-Silicon) modules, which means that their thin-film modules will generate more power (MWh) than traditional modules in hot environments.\(^{20}\)

\(^{21}\) First Solar's technology also outperforms traditional c-Si modules in humid conditions. Increased water in the atmosphere (humidity) increases the diffraction of light, but First Solar claims a Spectral Response Advantage, which gives it a 6% annual advantage over traditional c-Si modules in humid environments. Altogether, First Solar estimates that these technological advantages create an 11.2% advantage over competitors'solar modules. Similarly, Sun Power's high-performance crystalline silicon modules can achieve between 20% (E20) and 21% (X21) specific annual energy yield, and are estimated to produce 70% more energy over their lifetimes. Unfortunately, Sun Power does not provide a more detailed

\(^{20}\)First Solar, Technology Advantage August 2015

\(^{21}\)N. Strevel, L. Trippel & M. Gloeckler, *Performance characterization and superior energy yield of First Solar PV power plants in high-temperature conditions* (PhotoVoltaics International) 2012
explanation of its technology, and we could not find any academic papers which confirmed these figures in a laboratory settings.

Although 8Point3’s sponsors' technologies are not more efficient than multi-junction cells - which use multiple semiconducting materials and allow the absorption of a broader range of wavelengths - they are the most efficient c-Si and CdTe cells, and more cost-effective than multi-junction cells, whose high cost make them ideal for use in aerospace applications.

![Figure 7: Specific Annual Yield of Various Solar Module Technologies over Time](image)

The YieldCo structure, as described, is particularly attractive to conservative investors because of its predictable cash flows and growth in distributions. 8Point3's management estimates 16% distribution growth YoY in 2016 as it begins to acquire Right of First Offer (ROFO) assets from its parent companies, an aggregate 1.0 GW of solar assets in the United States, Japan, and Chile. This is above the company's stated long-term 12% - 15% distributions growth.

The YieldCo model assumes that 8Point3 will sell additional equity, and take on some amount of debt, using the combined proceeds to purchase solar assets from its sponsors, First Solar and SunPower, through a drop-down transaction. The sale price is determined by an
independent consultant who assigns a multiple to the EBITDA (Earnings before Interest, Taxes, Depreciation and Amortization) generated by the project, to determine the total price. The benefit of this arrangement is that by separating the risky functions of developing technology and building solar assets (Sponsor) from the low-risk functions of owning and operating the asset (YieldCo), the latter will benefit from a lower cost of capital, and reduce the total financing cost of these energy assets.

The YieldCo model is founded on two tenuous assumptions: first, every drop-down transaction will be accretive for existing shareholders and Cash Available For Distribution (CAFD) per unit will increase. Second, as CAFD per unit increases, the price of each unit will increase perpetually at some given ratio (EV/EBITDA multiple). Since the price per unit increases perpetually, the YieldCo will always be able to sell new units to fund future transactions without diluting post-transaction CAFD per share. When these assumptions break, the YieldCo model fails. We show in the following paper that YieldCo prices are largely disconnected from the performance of solar assets, but rather move in line with external market forces that are unrelated to the underlying solar assets. If YieldCo prices are artificially pressured by market factors and YieldCos issue an excessive number of units at lower prices per unit, existing shareholders are diluted; under these conditions YieldCos choose to put off selling new units and acquiring new assets. Given the lack of CAFD per unit growth, investors sell their YieldCo shares - putting additional pressure on the unit price and creating a negative feedback loop.

In the YieldCo model, existing unit holders are at risk of dilution each time the YieldCo issues additional equity units. Since the total cash flow generated by the new asset, plus all cash flows generated by existing assets, is independent of the number of units sold, the more units sold, the less total cash flow is available for distribution to each unit. Second, if the price of each existing unit is too low the YieldCo may choose to sell fewer units, but take on more debt - which decreases cash flow available for equity holders since some part is paid to debt holders, and thereby decreases cash flow per unit. Third, if the asset itself generates less cash
flow than anticipated, the total cash flow available for distribution decreases, and existing
unit holders receive less cash than before, given the increased number of shares. These risks
are quantified using the CAFD per unit (Cash Available For Distribution) dilution formula:

\[
CAF D_1 = \frac{CAF D_0 + \frac{U_N \times P_0 + D}{EV_{multiple}} - D \times R}{U_0 + U_N}
\]

\( CAF D_0 \) = Cash Available For Distribution before dilution
\( CAF D_1 \) = Cash Available For Distribution after dilution
\( U_N \) = Number of new units issued
\( U_0 \) = Number of existing units
\( P_0 \) = Price of each new unit
\( D \) = Debt issued
\( R \) = Cost of Debt
\( U_N \times P_0 + D \) = Cost of asset
\( EV_{multiple} \) = Ratio of price of asset to annual cash flow (EBITDA)

This risk is easily illustrated using 8Point3 Energy Partners. The recent decline in price
per unit from \$20 in June 2015 to \$12.01 (as of Nov. 20, 2015), has made future equity
raises difficult. In its S-1/A filing, 8Point3 identified a number of projects it expects to
acquire from its parent sponsors between 2015 and 2016. One of these assets is Stateline,
a 300.0 MW solar farm in California, expected to reach completion in September 2016. At
300.0MW, we expect 8Point3 will pay First Solar roughly \$450mm at a 1.5x EV/MW ratio
\[22\] Using a midpoint 18% Specific Annual Yield and \$0.135/KWh price for California \[23\]
we estimate \$63.9mm in annual EBITDA; this represents a 7.0x EBITDA multiple - in line
with precedent transactions in the North American solar market \[24\].

If 8Point3 Energy Partners were to raise the entire \$450.0mm by issuing new units at
\$21 per unit - the price they were initially offered to the market, we estimate that CAFD

\[22\] Deloitte, A market approach for valuing solar PV farm assets: Global results, April 2015
\[23\] EIA, State Electricity Profiles
\[24\] Ernst & Young, Capital Outlook: Power and Utilities
per unit would increase from $2.16 per unit to $2.59 per unit. See figure 8.

<table>
<thead>
<tr>
<th>USD millions</th>
<th>Pre-Dilution</th>
<th>Post-Dilution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Units$^1$</td>
<td>20.0</td>
<td>21.4</td>
</tr>
<tr>
<td>CAFD$^2$</td>
<td>43.3</td>
<td>41.4</td>
</tr>
<tr>
<td>CAFD/Unit</td>
<td>2.16</td>
<td>0.0</td>
</tr>
<tr>
<td>Cost per Unit</td>
<td>21.00</td>
<td>4%</td>
</tr>
<tr>
<td><strong>EV / MW$^3$</strong></td>
<td>1.5x</td>
<td><strong>CAFD</strong></td>
</tr>
<tr>
<td><strong>MW</strong></td>
<td>300.0</td>
<td><strong>2.59</strong></td>
</tr>
<tr>
<td>$/KWh$</td>
<td>0.135</td>
<td><strong>EBITDA</strong></td>
</tr>
<tr>
<td><strong>Specific Annual Yield</strong></td>
<td>18%</td>
<td><strong>Price</strong></td>
</tr>
<tr>
<td><strong>EBITDA</strong></td>
<td>63.9</td>
<td><strong>450.0</strong></td>
</tr>
<tr>
<td><strong>Price</strong></td>
<td>450.0</td>
<td></td>
</tr>
</tbody>
</table>

1. 10-Q 2Q2015  
2. S-1/A Pg. 87  
3. Deloitte analysis and Clean Energy Pipeline 2015  
4. EIA  

**Figure 8:** Issuing New Equity at $21.00 Increases CAFD per Unit

However, at its current price, if 8Point3 Energy Partners were to raise the entire $450.0mm by issuing new units at $12.01 per unit, it would need to issue 37.5mm new units - nearly twice the number of existing units outstanding. Using our estimate of $63.9mm EBITDA generation from the Stateline asset, we estimate that CAFD per unit would decrease from $2.16 per unit to $1.86 per unit. See figure 9.

If 8Point3 Energy Partners were to raise $360.0mm of debt (80% Loan-to-Value (LTV) Ratio) at an 4% annual debt service ratio, and $90.0mm of equity (20%) by issuing new units at $12.01, it would need to issue only 7.5mm new units. Using the same estimates, CAFD per unit would increase dramatically from $2.16 per unit to $3.37 per unit. See figure 10.

However, if the Stateline asset were damaged, did not reach Commercial Operation Date (COD) by September 2016, needed additional maintenance, or otherwise could not produce the estimated 18% Specific Annual Yield, existing unit holders would suffer as the $360.0mm in annual debt would need to be serviced, but the asset would not generate sufficient cash flows to cover debt service payments. See figure 11.

These scenarios demonstrate the risks to the YieldCo model using 8Point3 Energy Part-
ners as an illustrative example: existing unit holders risk CAFD per unit dilution when management chooses to issue new shares to fund asset acquisitions. If the price per unit is sufficiently high, the issuance of new units can be accretive to both existing and new unit holders (figure 9). If the price of existing units is too low, as it is today, management may have to issue a larger number of shares to earn the same proceeds, and this may dilute existing shareholders (figure 10). Management may also choose to use debt, which can be

<table>
<thead>
<tr>
<th>USD millions</th>
<th>Pre-Dilution</th>
<th>Post-Dilution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Units (^1)</td>
<td>20.0</td>
<td>New Units</td>
</tr>
<tr>
<td>CAFD (^2)</td>
<td>43.3</td>
<td>Total Units</td>
</tr>
<tr>
<td>CAFD/Unit</td>
<td>2.16</td>
<td>Debt</td>
</tr>
<tr>
<td>Cost per Unit</td>
<td>12.01</td>
<td>Cost of Debt</td>
</tr>
<tr>
<td>EV / MW(^3)</td>
<td>1.5x</td>
<td>CAFD</td>
</tr>
<tr>
<td>MW</td>
<td>300.0</td>
<td>CAFD/Unit</td>
</tr>
<tr>
<td>$/KWh(^4)</td>
<td>0.135</td>
<td></td>
</tr>
<tr>
<td>Specific Annual Yield</td>
<td>18%</td>
<td></td>
</tr>
<tr>
<td>EBITDA</td>
<td>63.9</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>450.0</td>
<td></td>
</tr>
</tbody>
</table>

1. 10-Q 2Q2015
2. S-1/A Pg. 87
3. Deloitte analysis and Clean Energy Pipeline 2015
4. EIA

**Figure 9:** Issuing New Equity at $12.01 Decreases CAFD per Unit

**Figure 10:** Using 80% LTV Increases CAFD per Unit
accrative for existing shareholders (figure 11), but if the new asset fails to deliver cash flows in excess of annual debt service payments, shareholders will suffer (figure 11).

We will proceed to show the factors that drive YieldCo unit prices, and conclude that because prices are driven by market factors and - as we have shown - the success of the YieldCo. model is predicated on being able to issue shares at a sufficiently high price, the YieldCo. model is not an appropriate long-term solution for promoting solar asset investment.

4 Developing a Pricing Model for YieldCo Returns

4.1 Introduction

In this section we attempt to develop a regression-based pricing model for YieldCo security returns in global financial markets, with a strong focus on North American issuers. It is our aim to show that we can decompose YieldCo returns into explanatory variables (henceforth eVars) that are not in fact driven by performance and popularity of renewable energy sources, but rather that track the prices of liquid equity, commodity, and credit investment.
options. We thus conclude that the exchange-traded nature of YieldCo securities may lead to an ultimate failure of the structure; falling YieldCo prices can come about even in periods of growing renewables appeal and capacity, because demand for the instrument appears to be a function of relative risk/reward characteristics to alternative widely-traded financial products, rather than an accurate reflection of renewables projects' cash-flow prospects. On basis of these findings, we believe that it is the retail-investor driven pitfalls of being an exchange-traded product that detract from importance of renewables' growth prospects in YieldCo pricing. This leads to price decreases in YieldCos that can be independent of renewables performance (as in current market conditions), consequently making capital raising needed for asset-dropdowns prohibitively dilutive. We see this as a serious threat to the future success of the YieldCo structure. We will begin by discussing our data for YieldCo prices and introducing a comprehensive set of eVars that we initially hypothesise to explain price variation in our dependent variables. We then use Cochrane-Orcutt iterative processes in Stata to test for the beta regression coefficients of these factors in the YieldCo data set. After evaluating test statistics for statistical significance of our comprehensive set of eVars, we refine our model by customizing the sets of eVars on which we regress our dependent variable. Once the selection process is completed, we present eVar sets and relevant metrics of accuracy of our final YieldCo pricing model, in support of our thesis. Throughout this process we attempt to stay diligent regarding tests for and adjustments to meet the validity of three criteria crucial to our econometric methods: a lack of serial correlation in specification residuals (typically a problem in time-series data), homoskedasticity in specification residuals, as well as a lack of multicollinearity in explanatory variables. Please find a copy of the original code, the Stata-generated log-file and graphs, as well as URLs for the full cross-sections of price data in the paper's Appendix.
4.2 Dependent Variable Overview

Our proxy for YieldCo security prices is the Indxx Global YieldCo Index (IYLCOT). This is a float-adjusted market-capitalization weighted index designed to reflect price performance of globally listed securities that are categorized as YieldCos. It has 20 constituents, of which around 70% are listed in North America, with an average Price/Earnings ratio of 23.74x and a Dividend Yield of 5.86%\textsuperscript{25} Its 5 largest YieldCo constituents are Brookfield Renewable Energy Partners, NextEra Energy Partners, TerraForm Power, NRG Yield, and Abengoa Yield. We used daily historical prices from the index initiation on December 20th, 2013 onwards, pulling values directly from Indxx, the index provider. IYLCOT is the oldest existing YieldCo index and gives us 476 data points to calculate beta estimates off of.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{YieldCo Prices Over Time}
\caption{Historical YieldCo Prices (20 Dec 2013 - 11 Nov 2015)}
\end{figure}

\textsuperscript{25}Indxx Global YieldCo Index (IYLCOT)
4.3 Explanatory Variable Overview

We begin our analysis with nine variables (Set 1) that represent exposure to a diverse range of fossil fuel-, renewables-, equity- and credit-related factors: MLP prices (MLPPrice$^{26}$), Crude Oil prices (CrudePrice$^{27}$), US energy equities (XLEPrice$^{28}$), US utilities equities (XLUPrice$^{29}$), Global Photovoltaic Installation Additions (PVInstallAdd$^{30}$), Photovoltaic Production in the US (PVProdUS$^{31}$), US high dividend yield equities (HighDivPrice$^{32}$), US high yield credit prices (HighYieldPrice$^{33}$) and finally a portfolio of stock prices of YieldCo sponsors (SponsorsPrice$^{34}$). Please note that in the actual data loaded into stata, all values were normalized on Date 1 to a base value of 100. Subsequent growth/declines are then calculated based off this Date 1 base, running daily until our last set of data points on November 10th, 2015.

The sponsors’ portfolio is unique in the set of eVars because we constructed it as an equally weighted composite index of the stock prices of Sun Power (NASDAQ:SPWR), First Solar (NASDAQ:FSLR), Sun Edison (NYSE:SUNE), NextEra Energy (NYSE:NEE), Abengoa (NASDAQ:ABGB), NRG (NYSE:NRG), and Brookfield Asset Management (NYSE:BAM). The portfolio is not rebalanced throughout the tested time period. These companies were selected as most prominent sponsors of YieldCos across North America; they are highly representative of the collective stock performance of all sponsors of the constituents of the IYLCOT index. Given our previous discussion of the MLP structure and emergence of the YieldCo in light of it, it is also important to briefly discuss the data source of MLP prices. For MLP security prices we use the Alerian MLP Index (AMZ): a float-adjusted

\[^{26}\text{Alerian MLP Index (AMZ)}\]
\[^{27}\text{Cushing, Oklahoma WTI Spot Price, quoted in US Dollars per barrel}\]
\[^{28}\text{State Street Global Energy Select Fund (ETF)}\]
\[^{29}\text{State Street Global Utilities Select Fund (ETF)}\]
\[^{30}\text{Earth Policy Institute, Additional and Cumulative Installations World Solar Photovoltaics Installations, 1996-2013, with Projection to 2015}\]
\[^{31}\text{Earth Policy Institute, Annual Solar Photovoltaics Module Production by Country, 2007-2013, with Projection to 2017}\]
\[^{32}\text{Vanguard High Dividend Yield Index, VHDYK}\]
\[^{33}\text{Standard & Poors U.S. Issued High Yield Corporate Bond Index, SPUSCHY}\]
\[^{34}\text{Yahoo Finance: Equal weight price portfolio without rebalancing of various equity prices}\]
market-capitalization weighted index of mid- and large-cap MLPs. It has 50 constituents and captures over three-fourths (76%) of available global market capitalization. It carries a yield of 8.3% and was initiated in December of 1995. For the sake of consistency we used the same dates for our MLP analysis as for the YieldCo analysis, taking prices from December 20th, 2013 onwards. Both IYLCOT and AMZ are generally regarded as the most representative indexes of their respective industries.

As a final note on data collection, our two measures of solar energy performance were very hard to find; they come from the Earth Policy Institute and are a blend of historical and projected prices that appeared in the article Statistical Review of World Energy June 2014, in cooperation with BP and Bloomberg New Energy Finance, and in PV Cell Module Production Data, compiled from GTM Research. We had to apply quite crude methods to arrive at daily data, breaking down yearly growth or reductions in photovoltaics installations and capacity and smoothening changes out over market calendar days. We use these as indicators of solar energy supply and demand in North America.

On the whole, Set 1 of proposed explanatory variables that we are testing thus includes fossil fuel commodity prices, two measures of renewables performance, two sector-specific equity ETFs, high dividend equities, YieldCo sponsor equities, high yield credits, and finally MLP prices. In essence we are trying to test as many relationships to YieldCo prices as possible, in order to make sure that we do not fundamentally misspecify the components of our final model. Admittedly, even though we are calling this the comprehensive set of 'all eVars', they already went through an initial selection round: further eVars that we considered include Eurodollar futures prices (continuous LIBOR-linked contract) for interest rate exposure, EUR/USD rates for currency exposure, TAN ETF prices for global solar energy equities, and US REIT prices for real estate market exposure. However, all of these had statistically extremely insignificant impacts on YieldCo prices, such that we decided to exclude them even from the more broadly arranged Set 1 of eVars.

Nonetheless, the variables we proceeded with in Set 1 still represent a wide variety of asset
classes and types of underlying cash flow promises; hence they exhibit a range of correlations both with each other and with the dependent variable.

Figure 13: Correlation Matrix (20 Dec 2013 - 11 Nov 2015)

Figure 14: Correlation Matrix Visualization (20 Dec 2013 - 11 Nov 2015)

Upon examining figure 13 and 14 we see tight correlations between crude oil and XLE, the energy sector Exchange Traded Fund (ETF). Photovoltaic installations and photovoltaic...
module production in the US, along with utility equities, on the other hand, have negative correlations with crude, and module production has a 0.6 positive correlation with YieldCo prices. Notably, the sponsors' portfolio is highly correlated with MLPs and high yield credit at 0.7. Next, we take a look at the individual relationships between eVars and YieldCo prices. For graphical representations of these relationships, see Appendix A: eVar Relationships with YieldCo Prices (page 51).

Here, we see some very dispersed relationships – such as for XLU and for the two Photovoltaics variables – as well as some tighter relationships – such as for the sponsors' portfolio and for higher range values of high yield credit. The red lines indicate linear fits applied automatically by Stata to the data, taking on quite flat slopes as in the fossil fuels graphs, or steeper slopes as in the Sponsors and US PV Production graphs. It appears that we have succeeded in constructing a set of eVars that represents a wide range of relationships both with each other and with YieldCo prices, our main dependent variable. We can now start with our derivation of coefficient estimates. As previously announced, we begin with the entire set of eVars and will then narrow it down post-estimation to a smaller set of target variables.

4.4 Regression using All eVars

We will now start conducting regressions of the YieldCo index onto our set of eVars. Given that we are trying to replicate price movement of the index, we mainly aim to maximise R-squared and therefore the sum of squares in the index returns that can be explained by our eVars. Meanwhile we make adjustments for violations of our three aforementioned assumptions, paying attention to t-statistics and associated p-values in order to assess the statistical significance of individual eVars, and examine F-tests for the overall significance of the relationships we are examining. Once we have collected these metrics, we will adjust our set of eVars in section 4e.) to improve on predictive power of individual eVars in the model, leading to our final proposition of a pricing model for YieldCo securities.
Initially we regress YieldCoPrice on set 1: MLPPrice, CrudePrice, XLEPrice, XLUPrice, PVInstallAdd, PVProdUS, HighDivPrice, HighYieldPrice, SponsorsPrice through a standard Ordinary Least Squares (OLS) procedure. However, given that we are dealing with time-series data and not cross-sectional data, we need to test for serial correlation in the error terms of index predictions (which we isolate and define as yhatols1 in the code). While such serial correlation does not make beta estimators biased or inconsistent, it does make them inefficient; estimated residual variance is underestimated and the resulting R-squared value is inflated. As a consequence, variables appear to be statistically significant even though they are not, giving them the appearance of more predictive power than warranted.

Figure 15: Alternative Durbin Test for Set 1 Serial Correlation of Residuals

Figure 16: Graph of OLS Set 1 Residual Autocorrelation Across Time
As we can see by means of the Durbin alternative test, the chi-square value of 1997 and p-value of 0.000 tells us we should reject the null hypothesis that there is no serial correlation in the residuals. This is not surprising; in price data of financial products we often have trends that develop across daily values, leading to cyclical residual values. We can observe this cyclicality in Figure 16, a graph of regression residuals over the number of days (defined as N). It follows that the above R-squared of 0.97 is higher than in the true relationship, and that we need to remodel our regression in order to account for this serial correlation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>VIF</th>
<th>1/VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLPPrice</td>
<td>38.66</td>
<td>0.025869</td>
</tr>
<tr>
<td>CrudePrice</td>
<td>36.16</td>
<td>0.027653</td>
</tr>
<tr>
<td>XLEPrice</td>
<td>27.88</td>
<td>0.035871</td>
</tr>
<tr>
<td>PVInstallAdd</td>
<td>17.54</td>
<td>0.057006</td>
</tr>
<tr>
<td>PVProdUS</td>
<td>14.72</td>
<td>0.067932</td>
</tr>
<tr>
<td>HighDivPrice</td>
<td>9.44</td>
<td>0.105936</td>
</tr>
<tr>
<td>HighYieldP-e</td>
<td>9.06</td>
<td>0.110354</td>
</tr>
<tr>
<td>SponsorsPr-e</td>
<td>8.88</td>
<td>0.112554</td>
</tr>
<tr>
<td>XLUPrice</td>
<td>7.93</td>
<td>0.126036</td>
</tr>
</tbody>
</table>

| Mean VIF      | 18.92 |

**Figure 17**: Variance Inflation Factor for OLS Set 1

Before tackling this issue, however, we need to investigate two other important assumptions of OLS regressions: [1] lack of perfect multicollinearity of eVars and [2] homoskedasticity of residual distribution. We immediately see that no eVars fail [1], since Stata will warn us if this is the case and delete the guilty variable(s) from the regression. However, by inspecting the Variance Inflation Factor (vif) above, we see that MLPPrice and CrudePrice have high linear dependence with other eVars. This hurts identification in the process of determining what variation in YieldCoPrice is coming from MLPs and what variation is coming from crude oil, versus the remaining set of eVars. Hence we will need to revisit this topic when we design the final pricing model.

Regarding [2], we can run the Cook-Weisberg test for heteroskedasticity. This test is based on the null hypothesis that there is constant variance; at a chi-square of 1.59 and a p-
value of 0.2071, we cannot reject the null hypothesis of homoskedasticity and thus do not need to make immediate adjustments for residuals' variance in the model. We can visually confirm this by examining the plot of residuals against fitted values (rvf plot) in Figure 19 below; the points are distributed with relatively equal variance across fitted values, confirming the Cook-Weisberg result.

In order to circumvent the serial correlation problem and arrive at accurate beta coefficient estimates, we turn to using an estimation procedure called Cochrane-Orcutt iterations. Here we transform the regression model through quasi-differencing to generate successive versions of dependent and independent variables which, step for step, are being cleared of
serial correlation in residuals. To achieve this, we specify in Stata that we want to run as many iterations as needed until the Durbin-Watson tests indicates no more serial correlation.

![Figure 20: Cochrane-Orcutt Regression Fit Set 1 on YieldCo Prices](image)

We see in the results in Appendix B (page 53) that it took eight iterations for the Durbin-Watson statistic to go from 0.169613 (a level at which serial correlation is assumed as present) to 1.953427 (a level close to the ideal level of 2 where it is assumed not to be present) through quasi-differencing. We see that our overall R-squared has fallen to 0.6911 (70% of variation explained), but that the overall regression is still statistically significant, given the F-statistic of 115.59 and resulting p-value of 0.000. We can visually confirm this in the graph of YieldCoPrice onto predicted residuals, where our regression models data well but tends to underestimate predicted values for YieldCo prices around 100 and 110. Furthermore, the t-statistics of individual eVars are deflated but also accurate now, indicating that significant variables at a 90% confidence level (i.e. a statistic higher than 1.833) include MLPPrice, CrudePrice, XLUPrice, HighYieldPrice, and SponsorsPrice. These are the variables with which we will proceed in the final pricing model, and constitute Set 2 of eVars.

Before we move on to regressing YieldCo prices on the slimmer Set 2 of eVars, we will
briefly examine the variables that turned out to fail in predicting YieldCo prices. For instance, both solar energy related metrics (PVInstallAdd and PVProdUS) fail; global photovoltaics installation additions have a 95% confidence interval of $[-0.0804531, 0.235252]$ and US photovoltaics module production has a 95% confidence interval of $[-0.2460053, 0.809359]$. Since both intervals include zero, we reject them from the model, suggesting that YieldCos (especially the solar-driven IYLCOT index) are not in fact significantly affected by changes in demand and supply of solar energy. Energy equities, too, are discarded; we believe that this is caused mainly by high correlation to MLP and crude oil prices, such that variation in Yield-Cos that could be attributed to XLE is rather attributed to these other eVars, and that MLP and crude oil are essentially better versions of XLE in predicting YieldCo prices. Finally, we also discard high dividend US equities. The idea in including this eVar was that high, stable cash dividend yielding stocks would exhibit similar return characteristics as YieldCos, which are advertised on similar grounds. However, as we see in the $[-0.0335836, 0.2161451]$ confidence interval, we do not observe a significant relationship in the data, showing that high dividends do not give US equities similar historical returns to YieldCos. This is likely due to the fundamentally different cash-flow prospects between earnings associated with the constituents of the stock index (which stem from a variety of sectors) and prospects of the energy generation based YieldCos. As mentioned above, we will instead progress by regressing YieldCoPrice onto MLPPrice, CrudePrice, XLUPrice, HighYieldPrice, and SponsorsPrice; while this will reduce our R-squared, it will equip us with a regression specification that only contains relevant variables and their associated betas (which vary based on partialling out of other eVars included).

4.5 Regression using Selected eVars

We begin again by running a standard OLS regression in order to check for serial correlation, multicollinearity, and homoscedasticity. As before, Durbin's alternative test for autocorrelation gives us a chi-square value of 2515.425, such that we reject the null hypothesis and
conclude strong autocorrelation in residuals. This means that we will need to use Cochrane-Orcutt iterations again to derive accurate beta coefficients, standard errors, and hypothesis testing.

![Durbin's alternative test for autocorrelation](image)

**Figure 21:** Alternative Durbin Test for Set 2 Serial Correlation of Residuals

Next, the variance inflated factors show us whether multicollinearity in the eVars is a problem again; we see that because all values are within the target boundaries of [1,10] of vif values, we have greatly improved upon identification of the sources of variance in the dependent variable from the individual independent variables. We mainly achieved this by excluding XLE, which was highly correlated to crude oil and MLPs. CrudePrice carries the highest vif value at 9.0 and HighYieldPrice the lowest vif value at 3.71.

![Variance Inflation Factor for OLS Set 2](image)

**Figure 22:** Variance Inflation Factor for OLS Set 2

Finally, we check for homoscedasticity in residuals distribution. Using the Cook-Weisberg test with null hypothesis of constant variance we attain a chi-square value of 0.32, which is sufficiently small such that we cannot reject the null hypothesis at a p-value of 0.5729. We can find visual confirmation of this by the relatively equal dispersion of residuals over fitted values in the 'residuals-versus-fitted plot' below. Hence, just like when we regressed YieldCo prices on Set 1, we do not need to worry about heteroscedasticity in Set 2.
We can now proceed with the Cochrane-Orcutt regression.

In the second regression (results in Appendix C, page 53) it also took eight iterations to clear the model of autocorrelation in residuals. We see that all five variables are significant at the 95% level, with the lowest t-statistic calculated for CrudePrice at 2.13 and the highest t-statistic calculated for SponsorsPrice at 19.43. The overall regression carries a R-squared of 0.6835, such that we manage to explain nearly 70% of variation in YieldCo prices through our eVars. On a variable-by-variable basis, the coefficient estimates (standard errors) are 0.15 (0.03) for MLP prices, 0.05 (0.02) for crude prices, 0.18 (0.03) for utilities equities, 0.82 (0.16) for high yield prices, and 0.25 (0.01) for prices of the sponsors' portfolio. The F-test is also higher this time, taking a statistic value of 202.59 that once again indicates a very high
chance that the overall test is significant. In the plot of YieldCoPrice to predicted residuals, we observe a very tight fit of our regression estimates to the actual data since December 2013. However, we also see that our estimation is generally better at predicting lower rather than higher YieldCo index prices.

Figure 25: Cochrane-Orcutt Regression Fit Set 2 on YieldCo Prices

We can therefore summarize our final pricing model as follows, based on dependent and independent variable prices normalized to a base value of 100 on December 20th, 2013 and running through to November 10th, 2015, and estimated by 8 iterations of the C-O regression:

$$YieldCoPrice = -40.04 + 0.15 \times MLPPrice + 0.05 \times CrudePrice + 0.18 \times XLUPrice + 0.82 \times HighYieldPrice + 0.25 \times SponsorsPrice + \hat{u}$$

We see confirmation of our thesis that YieldCo prices are primarily driven by non-renewables factors; MLPs, crude oil, utilities equities, and high yield credit are all unrelated with the performance of solar, wind, geothermal, etc. energy in the US. Furthermore, of the eight companies that went into the sponsors' portfolio, two run diversified operations, with renewables comprising a minor portion of their energy production. While the t-statistic of
the sponsors' portfolio is very high, our argument still holds without it; if we regress YieldCo prices on Set 1 with the exception of switching crude oil with XLE (again due to multicollinearity considerations), we arrive at a R-squared of around 50%. Given that sponsors contribute around 20% of Regression 2 r-squared, and a significant portion of sponsors also operate outside of the realm of renewables, we have more than 50% of variation in YieldCo prices driven by factors that are purely fossil fuel plays. We can thus formulate our thesis in both ways, either with or without the sponsors' portfolio. In any of the two cases, we hope to have quantitatively shown that the majority of predictive power in YieldCo pricing stems from sources that are not related to renewable energies. This makes them unsustainable drivers of clean energy growth, since YieldCo prices can drop heavily with little attention paid to what actually is happening to supply and demand of renewable energy sources. We will now discuss these sources on an individual basis.

5 Discussion of eVar Significance

5.1 High Yield Credit Prices

High Yield Credit Prices were demonstrated to be an important component of the YieldCo pricing model, with a beta of 0.822, significant at the 99.99% level. There are two mechanisms by which High Yield Credit Prices affect YieldCo returns: YieldCos use public debt as a source of funding for asset drop-down transactions with their Sponsors when they are not able to issue equity at a price that is accretive to existing shareholders and an increase in High Yield Credit Prices and a decrease in yields makes debt capital cheaper as a source of funding. However, YieldCos may be able to access Investment Grade credit markets given their Sponsors' backing and high-quality asset portfolios. Second, when High Yield Credit Prices rise and yields fall, High Yield Credit investors may not be sufficiently compensated for the risk associated with High Yield instruments and move towards safer, but lower yield instruments such as YieldCos. Although we believe both mechanisms are important to
YieldCo pricing, we focus on the latter as the primary mechanism linking High Yield Credit Prices and YieldCo returns given some YieldCos' access to Investment Grade credit markets.

As High Yield Credit Prices rise, and High Yield Credit Spreads rise, investors may believe that they are not being sufficiently compensated for the additional risk they take by holding High Yield products [(Bankruptcy, credit risk, and high yield junk bonds, Altman 2002)]. To rebalance risk in their portfolios, investors elect to sell High Yield Credit products and purchase YieldCo equity, which yields only slightly less than High Yield Credit, but has lower volatility of returns given the stability of project cash flows once assets reach COD. YieldCos are also a good substitute for some kinds of High Yield Credit, namely energy. Energy, particularly US Shale Producers, represents 13.6% of the High Yield Credit market [(Source: Hotchkis & Wiley)]. Investors seeking exposure to energy and underlying drivers such as crude prices and energy demand, which move both YieldCos and High Yield Energy Credit, may switch between High Yield products and YieldCos because of the aforementioned risk benefits of YieldCos over High Yield Credit. As investors sell low yielding High Yield Credit products and purchase YieldCo Equity, the price of YieldCo Equity rises, explaining the co-movement of High Yield Credit prices and YieldCo Equity prices.
5.2 YieldCo Sponsors' Equity Prices

YieldCo Sponsors' Equity prices were demonstrated to be an important component of the YieldCo pricing model, with a beta of 0.253 significant at the 99.99% level. This statistical dependence is reflective of mechanisms connecting YieldCos and their sponsors: the nature of drop-down transactions between YieldCos and their Sponsors, and management overlaps between YieldCos and Sponsors.

One of the main attractions of any YieldCo is the high perpetual cash yield. However, to continue growing the annual cash distribution at 12% - 15% per year, the YieldCo needs to grow its portfolio of energy assets beyond the inflationary cost of electricity. For this reason, Sponsors agree to build a predetermined portfolio of electricity generating assets and drop these assets into the YieldCo's portfolio (i.e. sell them to the YieldCo) at a predetermined date, if the YieldCo and Sponsor can agree on a price. The YieldCo's ability to choose whether it purchases each asset before the Sponsor approaches any other bidders (i.e. optionality) is known commercially as the Right of First Offer (ROFO); as such, the portfolio of assets sold by the Sponsor to the YieldCo is called the ROFO portfolio. The YieldCo model is designed to isolate the riskier development of alternative energy assets (Sponsor) from the stable, low-risk ownership of these assets (YieldCo); However, YieldCos remain dependent on their Sponsors to deliver assets from the ROFO portfolio by a given date 2 - 5+ years in the future. If the Sponsor were to go bankrupt, or could not deliver the project by the given date, the YieldCo's stable long-term cash flows would suffer.

The risk contamination between YieldCos and their Sponsors is compounded because of the degree of exclusivity between the two parties. Since the Sponsor agrees to take on the risk of developing solar assets, the YieldCo and Sponsor will generally reach an exclusivity agreement that bars the YieldCo from acquiring assets from other parties for a given period of time, generally the life of the ROFO portfolio. This means that YieldCos are unable to grow their portfolio using outside acquisitions - in the event that the sponsor were unable to deliver assets in the ROFO portfolio - unless the Sponsor agrees to nullify its agreement.
Despite claims that the YieldCo model isolates the risks of developing and risks of owning alternative energy assets, the high statistical dependence of YieldCo prices on Sponsors' equity prices reflects the market's awareness that YieldCos share the same risks as their Sponsors, given the dependence of the former on the Sponsors' ability to deliver high-quality assets.

The dependence of the YieldCo on the Sponsor is amplified when considering the competing motivations of the Sponsor: first, to maximize the value of its stake in the YieldCo by offering the most competitive assets to the YieldCo at a reasonable price, and second, to receive the highest price for the asset that the Sponsor can sell to the YieldCo, or offer to the general market. Assuming consistent expectations of annual EBITDA generated by the asset, the bidder with the lowest cost of capital will offer the highest price:

\[
\text{Price} = \frac{\text{Annual EBITDA}}{\text{Annual Cost of Capital}}
\]

The Sponsor may reasonably choose to sell an asset to an outside bidder (i.e. not its dependent YieldCo) offering a sufficiently higher price. The YieldCo is left to choose between growing its portfolio, which is necessary to grow dividends perpetually, and pay a high premium, or forgoing one of its limited growth opportunities (given its exclusivity agreement with its Sponsor and finite quantity of assets in the ROFO portfolio): The YieldCo loses either way.

The risks are more pronounced when considering a Sponsor's more nefarious motivations. Since the Sponsor initially floats the YieldCo to the public, it often owns a majority of the outstanding shares, giving it the majority voting share - and control over the decisions to sell and buy an asset. The Sponsor can agree to sell the YieldCo an asset at an egregious premium, and then agree to pay the unreasonable premium because it owns a majority voting share in the YieldCo. This can help the Sponsor move sub-par assets off its books and into the portfolio of the YieldCo. Although this may seem unlikely to happen, Hedge Fund Appaloosa Management LP has alleged that SunEdison (SUNE) - a major YieldCo sponsor - is dropping low-quality residential solar assets into one of its YieldCos, Terraform
Power (TERP), and - because SunEdison has a majority stake in Terraform - stacking the Terraform board with SunEdison managers who will agree to the acquisitions (Source: Business Insider).

Clearly, the YieldCo is at risk of mismanagement by its Sponsors, and the claims of risk isolation between the businesses are at best tenuous. The market understands the connections between YieldCo performance and Sponsors' performance, which is reflected in the tight statistical relationship between the dVar and eVar.

5.3 MLP prices

MLP unit prices were demonstrated to be an important component of the YieldCo pricing model, with a beta of 0.151 significant above the 99.99% level. We believe this statistical dependence is reflective of the relationship between YieldCos and MLP which depends on two primary drivers: high yields and tax advantages. We also believe that liquid exposure to a specific pure-play investments also plays a role in the relationship between MLPs and YieldCos. These factors lead us to conclude that YieldCos are complementary to MLPs investors looking for liquid, pure-play investments with high yields and significant tax advantages rather than explicit exposure to renewable electricity generation. While market participants have postulated this relationship, we believe we are the first to substantiate this claim. In addition, we believe that we have shown the argument made by other market participants that YieldCos and MLPs are substitutes as not being supported by our research.

We believe the primary driver of the relationship between MLP unit prices and YieldCo prices are high cash distribution to equity holders relative to equity value invested (commonly referred to as high yield). Within equity capital markets, MLPs have been historically very attractive to investors due to overall returns in the form of high yield returns generated by assets producing toll-road revenues relative to other equities and fixed income securities.

Even with the introduction of publicly-traded real estate investment trusts (REITs), no major asset class could come close to the high yields MLPs offered to retail investors. As
shown by the graph below, traditional equity sources of stable high yields such as REITs (introduced in 1960), utilities (introduced in 1816), and general stock market indices tend to offer yields much lower than MLPs, defined as the AMZ index, and with much higher volatility⁴⁵.

With the introduction of YieldCos, MLPs will no longer the only publicly-available assets trading with high single-digit yields and significant tax advantages. Thus, we believe YieldCos provided a complement for yield-hungry investors as YieldCo issuances greatly increased between 2013 and 2015 while MLP issuances remained robust during the same time period. This relationship has been postulated before, but, to our knowledge, has never been substantiated by empirical data before.

A more interesting conclusion in our opinion is the implication the data provides us regarding the substitution effect of these two asset classes. Many market participants argued that the implied shadow costs of climate change will increase exponentially in the future, thus driving investors from greenhouse-gas dependent MLPs to cleaner YieldCos. This argument implied that as the future expected returns on MLPs were driven lower today, investors would invest in higher yielding YieldCos. Market participants were thus arguing MLPs and YieldCos are substitutes. Looking at our model we believe that YieldCos and MLPs cannot be substitutes as these asset classes do not exhibit positive cross price elasticity. The implications of no substitution effect is quite significant as it goes against the argument that YieldCos can be a market-derived driver of shifting capital from natural resource-related MLPs to renewable-focused YieldCos. Merely unleashing a new financially-engineered asset mimicking a traditional product does not seem significant enough to revolutionize an entire sector.

⁴⁵REIT.com, History of REITs Timeline
5.4 Crude Oil Prices

Crude Oil prices were demonstrated to be an important component of the YieldCo pricing model, with a beta of .055 significant at the 98.4% level. We selected crude oil as a highly liquid financial proxy for coal and natural gas prices, the two most significant fossil fuels used in electricity generation. We had to use a proxy rather than natural gas and coal prices directly because coal markets are much less liquid than natural gas and crude oil markets and coal prices are not as readily available as natural gas and crude oil prices.

First, we established that coal and natural gas prices tend to be indexed to one another, barring logistics constraints in the supply chain, such as exhibited in the beginning of 2015.

Using the relationship between natural gas and coal, we established that natural gas prices tend to be correlated to crude oil prices by looking at supply contracts executed by the likes of Gazprom, a Russian natural gas producer that supplies 30% of Europe's natural gas demand. Using the transitive property, we also establish that coal prices are linked to crude oil prices. This allows us to use crude oil prices as a proxy for the two most important fossil fuel inputs for North American electricity generation.

Our empirical process resulted in a positive relationship between YieldCos and Crude Oil
prices, which makes sense because as fossil fuel prices increase, the barriers for renewables to be cost-competitive with fossil-fuel generation effectively decreases. We surmise this as a negative relationship between YieldCos and Crude Oil prices implies investors see YieldCos as a hedge against spot fossil fuel prices rather than the long-dated, commodity price agnostic assets they are marketed as.

5.5 XLU Prices

XLU prices were demonstrated to be an important component of the YieldCo pricing model, with a beta of .180 significant at the 99.99% level. We believe this statistical dependence is reflective of a relationship between YieldCos and XLU that is very similar to the relationship between YieldoCos and MLPs. Instead of looking at yield-hungry investors, comparing XLU prices to YieldCos prices allows us to look at investors who are interested in gaining exposure to primarily North American electricity demand growth.

Historically North American electricity demand growth has moved in-line with GDP growth, but in the mid-2000s the U.S. economy, in particular, started to move towards being less energy intense.
The decoupling between GDP growth and electricity demand meant that utilities investors would have to look to specific niches in electricity generation to capture returns at or above GDP growth. Market participants hypothesized that the renewable space (alongside natural gas) was destined to grow more quickly than overall North American electricity
demand over the coming decades.

The YieldCo was hypothesized to be a convenient way to provide utilities investors with exposure to higher returns than the general utilities investment space while still maintaining the low-risk profile of the more traditional utility stocks.
While this hypothesis is neat, we believe, much like the argument that YieldCos are substitutes for MLPs, that this line of thinking is flawed based on our empirical work because traditional utility stocks held within XLU have a positive cross price elasticity. Therefore, rather than YieldCos acting as an invisible hand to move utility investors from fossil fuel-burning electricity generating companies, YieldCos seemed to have been adopted by utility investors as a higher-risk complement to low risk traditional generators.

5.6 YieldCos Tax Credit Risk

YieldCos are at a disadvantage to MLPs because their tax credits are not secured by legislation and need to be continuously renewed every few years. This leads to greater uncertainty in the YieldCos structure, as the 30 percent tax credit is one of the primary competitive advantages for these renewable energy companies. MLPs, on the other hand, have the tax pass-through qualification intrinsic in the corporate structure because they generate qualifiable income. Though it is hard to quantify the degree to which this uncertainty is reflected in the overall valuation of YieldCos, our analysis indicates that the market has priced-in the prospect that the YieldCo tax structure may be less suitable for long-term growth. The potential outcome of the upcoming election is a sizable concern for the YieldCos structure. While the aftereffect is difficult to predict, if a Republican takes the White House (in addition to the current Republican controlled Senate and House of Representatives), it is probable that the YieldCo tax credits will be sizably reduced or cut entirely. The downward shift in the YieldCo market this year, which our analysis attributes to external commodity and energy factors, are further exacerbated by investor skepticism regarding the future of these tax benefits. For the YieldCos structure to be a sustainable growth mechanism for the renewable energy market, there needs to be codified amendments like the inclusion of renewable activities as qualifiable income in the tax code. Without the security of tax credits and structural advantages, renewable energy companies will continue to face challenges with investor interest and sustaining a profitable operating cost of capital.
6 Conclusion

Since the beginning of the modern environmental movement, there have been calls for society to take steps to reduce its reliance on fossil fuels and increase its usage of renewable energy sources. Many of the barriers inhibiting rapid rollout of renewable energy source utilization appeared to be related to financial incentives both on the research side and implementation side. Without the much-needed capital, the critical research and development necessary to improve renewable energy efficiency and the critical rollout and realization of energy generation technologies was quite slow.

In 2013 financial markets created the YieldCo in the image of MLPs in a market-driven attempt to increase capital available to help rapidly increase renewable electricity generation. By mimicking the various structural advantages natural resource-related MLPs benefit from and by taking advantage of federal tax credits on a large scale, market participants hoped to align financial incentives in such a manner that capital would recycle out of fossil fuel generation into cleaner, sustainable renewable electricity generation.

Unfortunately, over the last two years, YieldCos have failed to live up to the initial optimism they created. We believe the main weakness of the YieldCo is that, as derived from our regression-based empirical approach, external factors that have little to do with the underlying fundamentals of renewable electricity generation explain the majority of variation in YieldCo returns. The result that large external shocks can drive down YieldCo equity values is significant because without the ability to issue more equity on accretive terms, YieldCos cannot fund additional renewable electricity generation innovation or additional operating projects. Thus, we believe the YieldCo structure has failed to solve renewable energy's long-term capital funding shortage.

We believe that we are among the first to attempt to understand what drives the YieldCo corporate structure and returns. Because of this, and due to the limited data we have on YieldCos given their recent inception, we encourage our peers to continue to evaluate YieldCos over complete macroeconomic cycles and as the long-term benefits of renewable
energy sources become more visible to the public.
Appendix A. eVar Relationships with YieldCo Prices

- **YieldCo Prices vs Crude Oil Prices**
- **YieldCo Prices vs High Dividend Equities**
- **YieldCo Prices vs High Yield Credit**
- **YieldCo Prices vs MLP Prices**
- **YieldCo Prices vs PV Installation Additions**
- **YieldCo Prices vs US PV Production**
Appendix B. Cochrane-Orcutt Regression Results Set 1

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<th>Source</th>
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<th>MS</th>
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<th>Prob &gt; F</th>
<th>R-squared</th>
<th>Adj R-squared</th>
<th>Root MSE</th>
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<td>47.8222961</td>
<td>475</td>
<td>115.59</td>
<td>0.0000</td>
<td>0.6911</td>
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<td>0.413735255</td>
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<td></td>
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<td></td>
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<td>1.3138978</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| YieldCoPrice | Coef. | Std. Err. | t | P>|t| | [95% Conf. Interval] |
|--------------|-------|-----------|---|------|---------------------|
| MLPPrice     | 0.1359774 | 0.0317704 | 4.28 | 0.000 | 0.0735459 | 0.2641408 |
| CrudePrice   | 0.0500672 | 0.0271091 | 1.85 | 0.065 | -0.032042 | 0.132176 |
| XLEPrice     | 0.012912 | 0.0497134 | 0.26 | 0.795 | -0.0847787 | 0.1006027 |
| XLUPrice     | 0.1484794 | 0.031335 | 4.74 | 0.000 | 0.0869037 | 0.210055 |
| PVInstallAdd | 0.0773994 | 0.003289 | 0.96 | 0.336 | -0.0084531 | 0.235252 |
| PVPodUS      | 0.2816768 | 0.2685298 | 1.05 | 0.295 | -0.2460053 | 0.809359 |
| HighDivPrice | 0.0912888 | 0.0635417 | 1.44 | 0.152 | -0.0335836 | 0.2161451 |
| HighYieldPrice | 0.7891855 | 0.1613255 | 4.89 | 0.000 | 0.4721152 | 1.106256 |
| SponsorsPrice | 0.2426152 | 0.0145379 | 16.69 | 0.000 | 0.2140471 | 0.2711833 |
| cons         | -0.8313542 | 0.3844286 | -2.16 | 0.031 | -158.6787 | -7.592175 |

Durbin-Watson statistic (original)  0.169613
Durbin-Watson statistic (transformed)  1.953427
Appendix C. Cochrane-Orcutt Regression Results Set 2

Iteration 0: rho = 0.0000
Iteration 1: rho = 0.9176
Iteration 2: rho = 0.9687
Iteration 3: rho = 0.9845
Iteration 4: rho = 0.9867
Iteration 5: rho = 0.9869
Iteration 6: rho = 0.9869
Iteration 7: rho = 0.9869
Iteration 8: rho = 0.9869

Cochrane-Orcutt AR(1) regression — iterated estimates

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<th>Source</th>
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<th>df</th>
<th>MS</th>
<th>Number of obs</th>
<th>F(5, 469)</th>
<th>Prob &gt; F</th>
<th>R-squared</th>
<th>Adj R-squared</th>
<th>Root MSE</th>
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</thead>
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<td>83.9337822</td>
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<td>0.0000</td>
<td>0.6835</td>
<td>0.6802</td>
<td>0.64366</td>
</tr>
<tr>
<td>Residual</td>
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<td>469</td>
<td>.414302319</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>613.976699</td>
<td>474</td>
<td>1.29530949</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| YieldCoPrice | Coef. | Std. Err. | t     | P>|t| | [95% Conf. Interval] |
|--------------|-------|-----------|-------|-----|-----------------------|
| MLPPrice     | .150604 | .0275393 | 5.47  | 0.000 | .0964884 to .2047196  |
| CrudePrice   | .0553711 | .0228149 | 2.43  | 0.016 | .010539 to .1002032   |
| XLUPrice     | .1800189 | .0269767 | 6.67  | 0.000 | .1270089 to .233029   |
| HighYieldPrice | .8221772 | .1590258 | 5.17  | 0.000 | .509686 to 1.134669   |
| SponsorsPrice | .2527766 | .0130129 | 19.43 | 0.000 | .2272058 to .2783475  |
| _cons        | -40.04164 | 16.11455 | -2.48 | 0.013 | -71.70728 to -8.375994 |
| rho          | .9869395  |          |       |      |                       |

Durbin-Watson statistic (original) 0.162044
Durbin-Watson statistic (transformed) 1.950721
Appendix D. STATA Input Code

cap log close
clear all
set graphics on
log using "Energy&EnergyPolicy_RegressionLog.log", replace
sysdir set PERSONAL "H:\Documents"
net set ado "H:\Documents"
qui net install st0085_2.pkg, from( http://www.stata-journal.com/software/sj14-2)
///----------------------------------------------------------------------------
///----------------------Energy & Energy Policy: YieldCos----------------------
///----------------------------------------------------------------------------
use "H:\EnergyData3.dta", clear
qui drop in 477/482
gen N = _n
qui tsset N
rename XLUPrice XLUPrice
qui destring Date, replace
qui destring YieldCoPrice, replace
qui destring MLPPrice, replace
qui destring CrudePrice, replace
qui destring EurodollarPrice, replace
qui destring TANPrice, replace
qui destring EURUSDPrice, replace
qui destring USREITPrice, replace
qui destring HighDivPrice, replace
qui destring HighYieldPrice, replace
qui destring XIVPrice, replace
label variable YieldCoPrice "YieldCo Basket Price"
label variable MLPPrice "MLP Basket Price"
label variable CrudePrice "Crude Oil Price"
label variable XLEPrice "US Energy Equities ETF Price"
label variable XLUPrice "US Utilities Equities ETF Price"
label variable SPINDPrice "S&P500 Price"
label variable PVInstallAdd "Photovoltaic Installations"
label variable PVProdUS "Photovoltaic Production in US"
label variable SponsorsPrice "YieldCo Sponsors Basket Price"
label variable EURUSDPrice "Eur/Usd Exchange Rate"
label variable USREITPrice "US Reit Index Price"
label variable HighDivPrice "US High Dividend Equities"
label variable HighYieldPrice "US High Yield Credit"

/// Correlation of explanatory and dependent variables.

 correlat YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd
              PVProdUS HighDivPrice HighYieldPrice SponsorsPrice

 graph matrix YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd
              PVProdUS HighDivPrice HighYieldPrice SponsorsPrice
 qui graph export "eVar Correlation Matrix.pdf", replace

 /// Graphs relevant to YieldCo pricing relationships.

 twoway (scatter YieldCoPrice MLPPrice) (lfit YieldCoPrice MLPPrice) ///
      , title("YieldCo Prices vs MLP Prices")
 qui graph export "YieldCo Prices vs MLP.pdf", replace

 twoway (scatter YieldCoPrice CrudePrice) (lfit YieldCoPrice CrudePrice) ///
      , title("YieldCo Prices vs Crude Oil Prices")
 qui graph export "YieldCo Prices vs Crude.pdf", replace

 twoway (scatter YieldCoPrice XLEPrice) (lfit YieldCoPrice XLEPrice) ///
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 qui graph export "YieldCo Prices vs XLE.pdf", replace

 twoway (scatter YieldCoPrice XLUPrice) (lfit YieldCoPrice XLUPrice) ///
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 qui graph export "YieldCo Prices vs XLU.pdf", replace

 twoway (scatter YieldCoPrice PVInstallAdd) (lfit YieldCoPrice PVInstallAdd) ///
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 qui graph export "YieldCo Prices vs PVInstall.pdf", replace

 twoway (scatter YieldCoPrice PVProdUS) (lfit YieldCoPrice PVProdUS) ///
      , title("YieldCo Prices vs US PV Production")
 qui graph export "YieldCo Prices vs PVProd.pdf", replace

 twoway (scatter YieldCoPrice HighDivPrice) (lfit YieldCoPrice HighDivPrice) ///
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 qui graph export "YieldCo Prices vs HighDivPrice.pdf", replace

 twoway (scatter YieldCoPrice HighYieldPrice) (lfit YieldCoPrice HighYieldPrice)
      ///
      , title("YieldCo Prices vs High Yield Credit")
qui graph export "YieldCo Prices vs HighYieldCredit.pdf", replace
twoway (scatter YieldCoPrice SponsorsPrice) (lfit YieldCoPrice SponsorsPrice) ///
, title("YieldCo Prices vs Sponsors Price Portfolio")
qui graph export "YieldCo Prices vs SponsorsPrice.pdf", replace

///We regress the YieldCo price basket on all explanatory variables.
///We also check for autocorrelation of residuals, multicollinearity and
///heteroscedasticity.

qui regress YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd
     PVProdUS HighDivPrice HighYieldPrice SponsorsPrice
qui predict yhatols1
estat durbinalt
twoway scatter yhatols1 N ///
, title("YieldCo Residual Autocorrelation Over Time")
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vif
estat hettest
rvfplot ///
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prais YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd PVProdUS
     HighDivPrice HighYieldPrice SponsorsPrice, corc rhotype(tsc)
eststo model1
qui predict yhatprais1
twoway (scatter YieldCoPrice yhatprais1) (lfit YieldCoPrice yhatprais1) ///
, title("YieldCo Regression Fit -- All eVars")
qui graph export "RegFitAllVars.pdf", replace

///We regress the YieldCo price basket on selected explanatory variables.
///We also check for autocorrelation of residuals, multicollinearity and
///heteroscedasticity.
///Here we propose our final YieldCo pricing model in consideration of above
///metrics.

qui regress YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice HighYieldPrice
     SponsorsPrice
qui predict yhatols2

57
estat durbinalt
disturb
estat heterest
rvfplot
, title("RVF Plot: Selected eVars")
qui graph export "RVFSeleVars.pdf", replace
prais YieldCoPrice MLPPrice CrudePrice XLUPrice HighYieldPrice SponsorsPrice,
corc rhotype(tsc)
eststo model2
qui predict yhatprais2
twoway (scatter YieldCoPrice yhatprais2) (lfit YieldCoPrice yhatprais2)
, title("YieldCo Regression Fit -- Selected eVars")
qui graph export "RegFitSelVars.pdf", replace

esttab, r2 ar2 se scalar(rmse)

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Appendix E. STATA Log

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.net set ado "H:\Documents"

.qui net install st0085_2.pkg, from(http://www.stata-journal.com/software/sj14-2)

///--------------------------------------------------------------
> ///----------------------Energy & Energy Policy: YieldCos----------------------
> ///--------------------------------------------------------------
> use "H:\EnergyData3.dta", clear

.qui drop in 477/482

.gen N = _n

.qui tsset N

.rename XLUPrice XLUPrice

.qui destring Date, replace

.qui destring YieldCoPrice, replace

.qui destring MLPPrice, replace

.qui destring CrudePrice, replace

.qui destring EurodollarPrice, replace
. qui destring TANPrice, replace

. qui destring EURUSDPrice, replace

. qui destring USREITPrice, replace

. qui destring HighDivPrice, replace

. qui destring HighYieldPrice, replace

. qui destring XIVPrice, replace

. label variable YieldCoPrice "YieldCo Basket Price"

. label variable MLPPrice "MLP Basket Price"

. label variable CrudePrice "Crude Oil Price"

. label variable XLEPrice "US Energy Equities ETF Price"

. label variable XLUPrice "US Utilities Equities ETF Price"

. label variable SPINDPrice "S&P500 Price"

. label variable PVInstallAdd "Photovoltaic Installations"

. label variable PVProdUS "Photovoltaic Production in US"

. label variable SponsorsPrice "YieldCo Sponsors Basket Price"

. label variable EURUSDPrice "Eur/Usd Exchange Rate"

. label variable USREITPrice "US Reit Index Price"

. label variable HighDivPrice "US High Dividend Equities"

. label variable HighYieldPrice "US High Yield Credit"
Correlation of explanatory and dependent variables.

correlate YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd PVProdUS HighDiv

Price HighYieldPrice SponsorsPrice
(obs=476)

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<table>
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<tr>
<td>SponsorsPrice</td>
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\lgraph matrix YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd PVProdUS High

DivPrice HighYieldPrice SponsorsPrice

\qui graph export "eVar Correlation Matrix.pdf", replace

///Graphs relevant to YieldCo pricing relationships.

///----------------------------------------------------------------------------
twoway (scatter YieldCoPrice MLPPrice) (lfit YieldCoPrice MLPPrice) ///
> , title("YieldCo Prices vs MLP Prices")

qui graph export "YieldCo Prices vs MLP.pdf", replace

twoway (scatter YieldCoPrice CrudePrice) (lfit YieldCoPrice CrudePrice) ///
> , title("YieldCo Prices vs Crude Oil Prices")

qui graph export "YieldCo Prices vs Crude.pdf", replace

twoway (scatter YieldCoPrice XLEPrice) (lfit YieldCoPrice XLEPrice) ///
> , title("YieldCo Prices vs XLE ETF")

qui graph export "YieldCo Prices vs XLE.pdf", replace

twoway (scatter YieldCoPrice XLUPrice) (lfit YieldCoPrice XLUPrice) ///
> , title("YieldCo Prices vs XLU ETF")

qui graph export "YieldCo Prices vs XLU.pdf", replace

twoway (scatter YieldCoPrice PVInstallAdd) (lfit YieldCoPrice PVInstallAdd) ///
> , title("YieldCo Prices vs PV Installation Additions")

qui graph export "YieldCo Prices vs PVInstall.pdf", replace

twoway (scatter YieldCoPrice PVProdUS) (lfit YieldCoPrice PVProdUS) ///
> , title("YieldCo Prices vs US PV Production")

qui graph export "YieldCo Prices vs PVProd.pdf", replace

twoway (scatter YieldCoPrice HighDivPrice) (lfit YieldCoPrice HighDivPrice) ///
> , title("YieldCo Prices vs High Dividend Equities")

qui graph export "YieldCo Prices vs HighDivPrice.pdf", replace

twoway (scatter YieldCoPrice HighYieldPrice) (lfit YieldCoPrice HighYieldPrice) ///
> , title("YieldCo Prices vs High Yield Credit")

62
. qui graph export "YieldCo Prices vs HighYieldCredit.pdf", replace

. twoway (scatter YieldCoPrice SponsorsPrice) (lfit YieldCoPrice SponsorsPrice) ///
> , title("YieldCo Prices vs Sponsors Price Portfolio")

. qui graph export "YieldCo Prices vs SponsorsPrice.pdf", replace

. ///------------------------------
> ///We regress the YieldCo price basket on all explanatory variables.
> ///We also check for autocorrelation of residuals, multicollinearity and heteroskedasticity.
> ty.
> ///------------------------------
> qui regress YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd
> PVProdUS HighD
> ivPrice HighYieldPrice SponsorsPrice

. qui predict yhatols1

. estat durbinalt

Durbin's alternative test for autocorrelation
---------------------------------------------------------------------------
| lags(p) | chi2   | df | Prob > chi2 |
|---------+--------+----+-------------|
| 1       | 2404.535 | 1  | 0.0000      |
---------------------------------------------------------------------------
H0: no serial correlation

. twoway scatter yhatols1 N ///
> , title("YieldCo Residual Autocorrelation Over Time")

. qui graph export "ResidualAutocorrelation.pdf", replace

. vif
<table>
<thead>
<tr>
<th>Variable</th>
<th>VIF</th>
<th>1/VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLPPrice</td>
<td>38.66</td>
<td>0.025869</td>
</tr>
<tr>
<td>CrudePrice</td>
<td>36.16</td>
<td>0.027653</td>
</tr>
<tr>
<td>XLEPrice</td>
<td>27.88</td>
<td>0.035871</td>
</tr>
<tr>
<td>PVInstallAdd</td>
<td>17.54</td>
<td>0.057006</td>
</tr>
<tr>
<td>PVProdUS</td>
<td>14.72</td>
<td>0.067932</td>
</tr>
<tr>
<td>HighDivPrice</td>
<td>9.44</td>
<td>0.105936</td>
</tr>
<tr>
<td>HighYieldP~e</td>
<td>9.06</td>
<td>0.110354</td>
</tr>
<tr>
<td>SponsorsPr~e</td>
<td>8.88</td>
<td>0.112554</td>
</tr>
<tr>
<td>XLUPrice</td>
<td>7.93</td>
<td>0.126036</td>
</tr>
</tbody>
</table>

Mean VIF | 18.92

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of YieldCoPrice

chi2(1) = 1.59
Prob > chi2 = 0.2071

. rvfplot ///
> , title("RVF Plot: All eVars")

. qui graph export "RVFAlleVars.pdf", replace

. prais YieldCoPrice MLPPrice CrudePrice XLEPrice XLUPrice PVInstallAdd PVProdUS
   HighDivPrice
> e HighYieldP~e SponsorsPr~e, corc rhotype(tsc)

Iteration 0: rho = 0.0000
Iteration 1: rho = 0.9143
Iteration 2: rho = 0.9671
Iteration 3: rho = 0.9780
Iteration 4: rho = 0.9794
Iteration 5: rho = 0.9796
Iteration 6: rho = 0.9796
Iteration 7: rho = 0.9797
Iteration 8: rho = 0.9797

Cochrane-Orcutt AR(1) regression -- iterated estimates

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs =</th>
<th>475</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>430.400665</td>
<td>9</td>
<td>47.822961</td>
<td>Prob &gt; F =</td>
<td>0.0000</td>
</tr>
<tr>
<td>Residual</td>
<td>192.386894</td>
<td>465</td>
<td>0.41375255</td>
<td>R-squared =</td>
<td>0.6911</td>
</tr>
<tr>
<td>Total</td>
<td>622.787559</td>
<td>474</td>
<td>1.3138978</td>
<td>Root MSE =</td>
<td>0.64322</td>
</tr>
</tbody>
</table>

| YieldCoPrice | Coef. | Std. Err. | t     | P>|t| | [95% Conf. Interval] |
|--------------|-------|-----------|-------|-----|-----------------------|
| MLPPrice | 0.1359774 | 0.0317704 | 4.28 | 0.000 | 0.0735459 | 0.1984088 |
| CrudePrice | 0.0500672 | 0.0271091 | 1.85 | 0.065 | -0.0032042 | 0.1033387 |
| XLEPrice | 0.012912 | 0.0497134 | 0.26 | 0.795 | -0.084787 | 0.1106027 |
| XLUPrice | 0.1484794 | 0.031335 | 4.74 | 0.000 | 0.0869037 | 0.210055 |
| PVInstallAdd | 0.0773994 | 0.0803289 | 0.96 | 0.336 | -0.0804531 | 0.235252 |
| PVProdUS | 0.2816768 | 0.2685298 | 1.05 | 0.295 | -0.2460053 | 0.809359 |
| HighDivPrice | 0.0912808 | 0.0635417 | 1.44 | 0.152 | -0.0335836 | 0.2161451 |
| HighYieldPrice | 0.7891855 | 0.1613525 | 4.89 | 0.000 | 0.4721152 | 1.106256 |
| SponsorsPrice | 0.2426152 | 0.0145379 | 16.69 | 0.000 | 0.210471 | 0.2711833 |
| _cons | -83.13542 | 38.44286 | -2.16 | 0.031 | -158.6787 | -7.592175 |
| rho | 0.9796521 |

Durbin-Watson statistic (original) 0.169613
Durbin-Watson statistic (transformed) 1.953427

. eststo model1

. qui predict yhatprais1

. twoway (scatter YieldCoPrice yhatprais1) (lfit YieldCoPrice yhatprais1) ///
> , title("YieldCo Regression Fit -- All eVars")
We regress the YieldCo price basket on selected explanatory variables. We also check for autocorrelation of residuals, multicollinearity and heteroscedasticity.

Here we propose our final YieldCo pricing model in consideration of above metrics.

qui regress YieldCoPrice MLPPrice CrudePrice XLUPrice HighYieldPrice SponsorsPrice

qui predict yhatols2

estat durbinalt

Durbin's alternative test for autocorrelation

<table>
<thead>
<tr>
<th>lags(p)</th>
<th>chi2</th>
<th>df</th>
<th>Prob &gt; chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2515.425</td>
<td>1</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

H0: no serial correlation

vif

<table>
<thead>
<tr>
<th>Variable</th>
<th>VIF</th>
<th>1/VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>CrudePrice</td>
<td>9.00</td>
<td>0.111158</td>
</tr>
<tr>
<td>MLPPrice</td>
<td>7.56</td>
<td>0.132249</td>
</tr>
<tr>
<td>SponsorsPrice</td>
<td>5.94</td>
<td>0.168478</td>
</tr>
<tr>
<td>XLUPrice</td>
<td>4.25</td>
<td>0.235395</td>
</tr>
<tr>
<td>HighYieldPrice</td>
<td>3.71</td>
<td>0.269342</td>
</tr>
</tbody>
</table>

Mean VIF | 6.09
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
  Ho: Constant variance
  Variables: fitted values of YieldCoPrice

    chi2(1)    =    0.32
    Prob > chi2 =   0.5729

. rvfplot ///
> , title("RVF Plot: Selected eVars")

. qui graph export "RVFSeleVars.pdf", replace

. prais YieldCoPrice MLPPrice CrudePrice XLUPrice HighYieldPrice SponsorsPrice,
corc rhotype
> (tsc)

Iteration 0:  rho = 0.0000
Iteration 1:  rho = 0.9176
Iteration 2:  rho = 0.9687
Iteration 3:  rho = 0.9845
Iteration 4:  rho = 0.9867
Iteration 5:  rho = 0.9869
Iteration 6:  rho = 0.9869
Iteration 7:  rho = 0.9869
Iteration 8:  rho = 0.9869

Cochrane-Orcutt AR(1) regression -- iterated estimates

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 475</th>
<th>F(5, 469) = 202.59</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>419.668911</td>
<td>5</td>
<td>83.9337822</td>
<td>Prob &gt; F = 0.0000</td>
<td></td>
</tr>
<tr>
<td>Residual</td>
<td>194.307788</td>
<td>469</td>
<td>.414302319</td>
<td>R-squared = 0.6835</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>613.976699</td>
<td>474</td>
<td>1.29530949</td>
<td>Root MSE = .64366</td>
<td></td>
</tr>
</tbody>
</table>

--------------------------------------------------------------------------
| YieldCoPrice | Coef.  | Std. Err. | t     | P>|t| | [95% Conf. Interval] |
|--------------|--------|-----------|-------|------|------------------------|
| MLPPrice     | 0.150604  | 0.0275393  | 5.47  | 0.000 | 0.0964884 - 0.2047196  |
| CrudePrice   | 0.0553711 | 0.0228149  | 2.43  | 0.016 | 0.010539 - 0.1002032   |
| XLUPrice     | 0.1800189 | 0.0269767  | 6.67  | 0.000 | 0.1270089 - 0.233029   |
| HighYieldPrice | 0.8221772 | 0.1590258  | 5.17  | 0.000 | 0.509686 - 1.134669    |
| SponsorsPrice | 0.2527766 | 0.0130129  | 19.43 | 0.000 | 0.2272058 - 0.2783475  |
| _cons        | -40.04164 | 16.11455   | -2.48 | 0.013 | -71.70728 - 8.375994   |

---

rho | 0.9869395

Durbin-Watson statistic (original) 0.162044
Durbin-Watson statistic (transformed) 1.950721

eststo model2

qui predict yhatprais2

twoway (scatter YieldCoPrice yhatprais2) (lfit YieldCoPrice yhatprais2) ///
> , title("YieldCo Regression Fit -- Selected eVars")

qui graph export "RegFitSelVars.pdf", replace

//-------------------------------
> esttab, r2 ar2 se scalar(rmse)

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>YieldCoPrice</td>
<td>YieldCoPrice</td>
</tr>
<tr>
<td>MLPPrice</td>
<td>0.136***</td>
</tr>
<tr>
<td></td>
<td>(0.0318)</td>
</tr>
<tr>
<td>CrudePrice</td>
<td>0.0501</td>
</tr>
<tr>
<td></td>
<td>(0.0271)</td>
</tr>
<tr>
<td>XLEPrice</td>
<td>0.0129</td>
</tr>
<tr>
<td></td>
<td>(0.0497)</td>
</tr>
<tr>
<td>Variable</td>
<td>Estimate 1</td>
</tr>
<tr>
<td>-------------------</td>
<td>------------</td>
</tr>
<tr>
<td>XLUPrice</td>
<td>0.148***</td>
</tr>
<tr>
<td></td>
<td>(0.0313)</td>
</tr>
<tr>
<td>PVInstallAdd</td>
<td>0.0774</td>
</tr>
<tr>
<td></td>
<td>(0.0803)</td>
</tr>
<tr>
<td>PVProdUS</td>
<td>0.282</td>
</tr>
<tr>
<td></td>
<td>(0.269)</td>
</tr>
<tr>
<td>HighDivPrice</td>
<td>0.0913</td>
</tr>
<tr>
<td></td>
<td>(0.0635)</td>
</tr>
<tr>
<td>HighYieldP\textsuperscript{e}</td>
<td>0.789***</td>
</tr>
<tr>
<td></td>
<td>(0.161)</td>
</tr>
<tr>
<td>SponsorsPr\textsuperscript{e}</td>
<td>0.243***</td>
</tr>
<tr>
<td></td>
<td>(0.0145)</td>
</tr>
<tr>
<td>_cons</td>
<td>-83.14*</td>
</tr>
<tr>
<td></td>
<td>(38.44)</td>
</tr>
</tbody>
</table>

---

<table>
<thead>
<tr>
<th>Summary Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
</tr>
<tr>
<td>R-sq</td>
</tr>
<tr>
<td>adj. R-sq</td>
</tr>
<tr>
<td>rmse</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001