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Proportional warm-glow theory and asset pricing

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ABSTRACT

Dreyer, Sharma and Smith (2023) conjecture that investors may feel good about themselves from making socially responsible investments; they may get a "warm glow" from going green. They estimate a model of "warm glow" investment where investors derive utility from the *total* amount invested in green assets. In this paper we quasi-replicate their paper to estimate an alternative form of warm-glow preferences where people get utility from the *share* of their wealth invested in green assets. We show that the green preference of investors has become significantly larger since the financial crisis of 2007.

1. Introduction

The increasing popularity of green investments over the last two decades has spawned a large empirical literature on their financial performance. This raises a fundamental theoretical question: What makes socially responsible investment different from investment in "conventional" assets?

Beal et al. (2005) argued that there might be "psychic" benefits from acting ethically. In an early paper Heinkel et al. (2001) analyzed the effects on the cost of capital when green investors refused to hold "unacceptable" shares. Fama and French (2007) asserted that people might get utility from investing in socially responsible assets, just as they do from consumption goods. In the last few years, a flurry of papers has expanded upon this insight by developing formal models where people get utility from the act of investing. Luo and Subrahmanyam (2019) and Pástor et al. (2021) focus upon how differences in investors' preferences about assets affect their prices; both are calibration exercises. Berk and Binsbergen (2021) study how divestiture initiatives by investors affect the cost of capital; Avramov et al. (2022) incorporate uncertainty about the reliability of ESG profiles. All these papers employ two-period models where cash flows are normally distributed, investors have constant absolute risk aversion (CARA) utility, and consumption and the holdings of green assets are perfect substitutes. Under these assumptions expected utility theory is consistent with mean-variance analysis, so it is possible to get closed-form solutions when investors have heterogeneous preferences. Pedersen et al. (2021) derive the efficient frontier when there are ESG preferences; they use a mean-variance setup amended to include an ESG preference function.

Dreyer et al. (2023) develop a model of "warm-glow" investment: Just as donors may derive a "warm-glow" from contributing to a public good (Andreoni, 1990), so too may investors feel good about themselves for investing in socially responsible assets. That paper incorporates warm-glow preferences into the canonical, representative-agent Consumption-based Capital Asset Pricing (CCAPM) model and estimate it using Generalized Method of Moments (GMM). This model is both more general and more restrictive than those mentioned about: it is more general because it is dynamic (with an infinite horizon), employs a very general specification of preferences, and only restricts the forcing processes to be discrete-time diffusions; it is less general because these assumptions make it impossible to derive analytical solutions when investors differ in their tastes about green assets. One virtue of the warm glow approach is that it yields Euler equations that can be brought to the data. To date, DSS has been the only effort to empirically estimate a structural model where people have tastes for the assets they purchase.

In this short paper we estimate an alternative version of warm-glow investment. This is intended as an exercise in *quasi-replication*, replicating the estimation under slightly different conditions to explore the robustness of the results. Since the main objective of this letter is to complement the warm-glow theory, we frequently refer to the original paper to avoid repetition. To explain how it differs from the earlier paper, we need to introduce some notation. If a person has warm-glow preferences, they derive utility from both consumption and holding a

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green asset, $U(C, \textit{investment in green})$. But what exactly does "investment in green" mean? One interpretation is that people care about their total investment in green assets: If their wealth is W and λ_g is the share of wealth invested in the green asset, then $U(C, \lambda_g W)$. We call this *total warm-glow*. Alternatively, however, they might derive utility from the *share* of wealth that they put in green, $U(C, \lambda_g)$. This we call *proportional warm-glow*. DSS estimated a form of total warm-glow investment; in this paper we estimate a form of relative warm-glow. We do this for three reasons:

- Models of total warm-glow $U(C, \lambda_g W)$ are first cousins to models of the spirit of capitalism (Zou, 1994; Bakshi and Chen, 1996; Smith, 2001), where wealth itself is an argument in the utility function, $U(C, W)$. It is difficult conceptually and empirically to disentangle total warm-glow from the spirit of capitalism. Here we restrict the warm-glow theory to a setting where the spirit of capitalism does not apply, so that the investor is not concerned about the level of their wealth per se.
- Empirical estimation of asset pricing with total warm-glow requires the use of data on the growth of wealth and stock market returns. However, these variables tend to be highly correlated.
- DSS document that the share of wealth invested in green assets has increased over the last two decades, dramatically so after the financial crisis.

To estimate the proportional warm-glow model, we postulate a representative agent with an infinite planning horizon and a constant discount rate β. He maximizes expected lifetime utility

$$\sum_{t=0}^{\infty} \beta^t \frac{\left(C_t^{1-b} \lambda_{g,t}^b\right)^{1-\gamma}}{1-\gamma}. \tag{1}$$

The parameter b measures the relative strength of preference for warm-glow; γ is relative risk aversion with respect to the aggregator in parentheses. The investor can hold a green, a non-green, or a riskless asset with returns in time $t+1$ $R_{g,t+1}$, $R_{n,t+1}$, and $R_{f,t+1}$, respectively. We show that the green coefficient is statistically and economically significant only after the financial crisis.

This quasi-replication study extends DSS in three ways:

- Econometrically, it permits a more "flexible" empirical estimation, where we do not fix any parameters.
- It validates the original article by showing that we generally find similar results although using a proportional warm-glow model instead of total warm glow. We show that the green coefficient is still statistically and economically significant only after the financial crisis. This also validates Pastor et al. (2021).
- It suggests that what really matters is the proportional size of green investments over an individual's wealth independently of the size of this wealth. This in theory could justify why poor people could decide to invest part of their small savings into green. If this is true, there could be an effect on asset pricing coming from the volume of small investors that "together may be able to make a difference."

2. Method

DSS show that the relative warm-glow preferences in Eq. (1) yield the following Euler equations, where Z_t is the information set at t:

$$\beta\left\{E\left(\frac{C_{t+1}}{C_t}\right)^{a(1-\gamma)-1}\left(\frac{\lambda_{g,t+1}}{\lambda_{g,t}}\right)^{b(1-\gamma)} R_{f,t+1}\middle| Z_t\right\} = 1+\frac{b}{a}\frac{C_t}{W_t-C_t}. \tag{2}$$

$$\beta\left\{E\left(\frac{C_{t+1}}{C_t}\right)^{a(1-\gamma)-1}\left(\frac{\lambda_{g,t+1}}{\lambda_{g,t}}\right)^{b(1-\gamma)} R_{n,t+1}\middle| Z_t\right\} = 1+\frac{b}{a}\frac{C_t}{W_t-C_t} \tag{3}$$

$$\beta\left\{E\left(\frac{C_{t+1}}{C_t}\right)^{a(1-\gamma)-1}\left(\frac{\lambda_{g,t+1}}{\lambda_{g,t}}\right)^{b(1-\gamma)} R_{g,t+1}\middle| Z_t\right\} = 1-\frac{1-\lambda_{g,t}}{\lambda_{g,t}}\frac{b}{a}\frac{C_t}{W_t-C_t}. \tag{4}$$

We will estimate Eqs. 2, 3, and 4 using GMM.

3. Data

For the same reasons reported by DSS we chose the data set the same way as the authors (from 1998 to 2015). We use quarterly data from the Fed on consumption and household wealth, both expressed in per capita terms and deflated using the CPI. For the risk-free asset, we follow (Dreyer et al., 2013, 2020) and use the rates on long term T-Bills. We take stock returns and market capitalization from the Center for Research in Security Prices (CRSP). All stocks listed at CRSP are considered.

We use the MSCI's ESG ratings to identify the environmental profile of the different stocks. To proxy the green portfolio, we first check each stock's strength and concern in the environmental rating. As in DSS, we follow Ghoul et al. (2011) and Chava (2014) to calculate a net strength measure of environmental scores. If the net strength is positive, a company is rated green; otherwise, non-green. We then market-weight our green and non-green portfolios according to each stock's market capitalization and adjust their final returns for inflation. The green share of wealth of investors $\lambda_{g,t}$ equals the total market capitalization of green stocks in per capita terms divided by total wealth per capita.[1]

There is a diversity of methodologies used by data providers to determine ESG ratings. Thus, one could consider the choice of ESG data provider a limitation of our empirical exercise. For example, Dreyer et al. (2023) show that the composition of sustainable and non-sustainable portfolios of stocks generated stochastically can be very different when using different providers such as Thomson Reuters and MSCI KLD. Part of this can be explained by differences in coverage; part by differences in the methodologies employed by the two rating agencies (Dorfleitner et al., 2015). Although we recognize this limitation, we decided to use the MSCI KLD ratings for two practical reasons: 1) the article we quasi-replicate (DSS) also does so; 2) it is one of the earliest and most complete ESG ratings available.

4. Estimations

Since the system of Eqs. (2), (3) and (4) is highly nonlinear we set the following boundaries for our parameter estimations. These boundaries will help us find the local minimum that is economic relevant, as discussed in DSS.

$$\beta = [0; \quad 100]$$

$$\gamma = [0; \quad 100]$$

$$b = [0; \quad 100]$$

Estimation with GMM requires us to define the instrumental vector:

$$Z_t = \left[k, \frac{c_t}{c_{t-1}}, \frac{c_{t-1}}{c_{t-2}}, R_{g,t}, R_{g,t-1}, R_{n,t}, R_{n,t-1}, \frac{\lambda_t}{\lambda_{t-1}}, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_t}{w_{t-1}}, \frac{w_{t-1}}{w_{t-2}}, R_{f,t}, R_{f,t-1} \right].$$

We started to select GMM instruments from the lags of the variables of the Euler equations. However, $R_{f,t}$ and $C_t/(W_t - C_t)$ were so highly autocorrelated that the GMM covariance matrix was not invertible. We therefore decided not to include their lags. Similarly, the cross-correlation between $R_{g,t}$ and $R_{n,t}$ is 0.94, so we decided not to use all lags of them together. Finally, we added what Ferson and Constantinides (1991) and Lund and Engstead (1996) call an "outsider" variable to the

[1] For descriptive statistics of our data, see the Appendix. A rich discussion on characteristics of the data is offered by DSS.

vector: the growth of wealth. Even though wealth growth does not appear directly in our Euler equations, we believe that it intuitively relates to the problem of asset-pricing.

To derive the instrumental vectors, we use a minimum of four variables and increase the number of instruments slowly, respecting the GMM identification condition.[2] We use a spectral covariance matrix for our estimations with a Parzen kernel (Smith, 2004). We also run stationarity tests of our variables following Dolado et al. (1990), and then follow with the GMM estimations for the period between 1998 and 2015 and using quarterly frequency. We break out our sample period in two, pre and post crisis. The DSS article we are replicating shows evidence of a dramatic increase in green wealth following the financial crisis. We choose this break to assure comparability with DSS, even though the choice of a different break might lead to similar results. All GMM estimations have a starting point where all parameters equal one. Tables 1–4.

4.1. Pre-Crisis period

We estimate Eqs. (2), (3) and (4) for the pre-crisis period using the following vectors of instruments:

None of the GMM estimations are rejected by the J-test of over-identifying restrictions. In all alternatives of instruments β is highly significant and has an unexceptionable average of 0.957. The estimates for $\gamma$are stable and statistically significant. The average of this estimate equals 1.6064; a reasonable range of values for relative risk aversion is often thought to be between 1 and 4 (for example, Gollier, 2001).

Estimates for the green taste parameter b are not statistically significant at the 10% level in alternatives 4.1.1, 4.1.2, 4.1.3 and 4.1.5. In the remaining ones, it is statistically significant with an average of 0.0045. Though statistically significant, this is so small as to be economically insignificant: investors seemed not to care about green prior to the crisis.

4.2. Post-Crisis period

For the post-crisis period we use the following vectors of instruments:

The alternative of instruments 4.2.3 is rejected by the J-test at the 10% significance level. Thus, we concentrate our analysis in all remaining ones, where β is again highly significant and has an average of 0.983. The estimates for γ are again stable and statistically significant; the average is 1.1402.

The estimates for the green taste parameter b are now statistically significant at the 10% level in all estimations and have an average of 0.054. This is much higher than for the pre-crisis period, suggesting that investors have developed a taste for green investing.

Table 1
GMM Vector of Instruments (Pre-Crisis).

4.1.1	$Z = \left[k, \frac{c_{t-1}}{c_{t-2}}, R_t^G, R_{t-1}^G, R_t^F\right]$
4.1.2	$Z = \left[k, \frac{c_{t-1}}{c_{t-2}}, R_t^G, R_{t-1}^G, R_t^F, \frac{w_{t-1}}{w_{t-2}}\right]$
4.1.3	$Z = \left[k, \frac{c_{t-1}}{c_{t-2}}, R_t^G, R_{t-1}^G, R_{t-1}^{NG}, R_t^F, \frac{w_{t-1}}{w_{t-2}}\right]$
4.1.4	$Z = \left[k, \frac{c_{t-1}}{c_{t-2}}, R_t^G, R_{t-1}^{NG}, R_t^F, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_{t-1}}{w_{t-2}}\right]$
4.1.5	$Z = \left[k, \frac{c_{t-1}}{c_{t-2}}, R_t^G, R_{t-1}^G, R_{t-1}^{NG}, R_t^F, R_{t-1}^F, \frac{w_{t-1}}{w_{t-2}}\right]$
4.1.6	$Z = \left[k, \frac{c_{t-1}}{c_{t-2}}, R_{t-1}^G, R_{t-1}^{NG}, R_t^F, \frac{\lambda_t}{\lambda_{t-1}}, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_{t-1}}{w_{t-2}}\right]$
4.1.7	$Z = \left[k, \frac{c_t}{c_{t-1}}, \frac{c_{t-1}}{c_{t-2}}, R_{t-1}^G, R_{t-1}^{NG}, R_t^F, \frac{\lambda_t}{\lambda_{t-1}}, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_{t-1}}{w_{t-2}}\right]$

Table 2
GMM Estimations (Pre-Crisis).

Instrument	β	γ	b	J-test
	Estimate	Estimate	Estimate	Qui sq.
4.1.1	0.9588 ***	1.7615 ***	0.0006	13.7726
	(0.0033)	(0.5941)	(0.0026)	
4.1.2	0.9612 ***	2.1797 ***	0.0008	11.9575
	(0.0034)	(0.5750)	(0.0023)	
4.1.3	0.9571 ***	1.6065 ***	0.0038	14.7243
	(0.0027)	(0.4677)	(0.0024)	
4.1.4	0.9564 ***	1.4790 ***	0.0048 *	15.2235
	(0.0029)	(0.4763)	(0.0025)	
4.1.5	0.9576 ***	1.5915 ***	0.0019	20.2421
	(0.0027)	(0.4223)	(0.0027)	
4.1.6	0.9558 ***	1.3956 ***	0.0039 *	9.4963
	(0.0017)	(0.3673)	(0.0023)	
4.1.7	0.9556 ***	1.2315 ***	0.0047 **	7.5892
	(0.0014)	(0.3182)	(0.0024)	

Note: *** , ** and * for significance at 1%, 5%, and 10% levels, respectively.

Table 3
GMM Vector of Instruments (Post-Crisis).

4.2.1	$Z = \left[k, R_t^G, R_{t-1}^G, R_{t-1}^F, \frac{\lambda_{t-1}}{\lambda_{t-2}}\right]$
4.2.2	$Z = \left[k, R_t^G, R_{t-1}^{NG}, R_t^F, \frac{\lambda_{t-1}}{\lambda_{t-2}}\right]$
4.2.3	$Z = \left[k, R_{t-1}^G, R_t^{NG}, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_{t-1}}{w_{t-2}}\right]$
4.2.4	$Z = \left[k, R_t^{NG}, R_{t-1}^{NG}, R_t^F, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_{t-1}}{w_{t-2}},\right]$
4.2.5	$Z = \left[k, R_t^G, R_{t-1}^{NG}, R_t^F, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_{t-1}}{w_{t-2}}\right]$
4.2.6	$Z = \left[k, R_{t-1}^G, R_t^{NG}, R_{t-1}^{NG}, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_t}{w_{t-1}}\right]$
4.2.7	$Z = \left[k, \frac{c_t}{c_{t-1}}, R_{t-1}^G, R_t^{NG}, R_{t-1}^{NG}, \frac{\lambda_{t-1}}{\lambda_{t-2}}, \frac{w_t}{w_{t-1}}\right]$

Table 4
GMM Estimations (Post-Crisis).

Instrument	β	γ	b	J-test
	Estimate	Estimate	Estimate	Qui sq.
4.2.1	0.9820 ***	1.1096 ***	0.0530 ***	12.2574
	(0.0024)	(0.0759)	(0.0119)	
4.2.2	0.9845 ***	1.1785 ***	0.0483 ***	10.9514
	(0.0022)	(0.1023)	(0.0103)	
4.2.3	0.9851 ***	1.0773 ***	0.0794 ***	19.8950 *
	(0.0017)	(0.0447)	(0.0089)	
4.2.4	0.9856 ***	1.1454 ***	0.0592 ***	17.1362
	(0.0014)	(0.0637)	(0.0072)	
4.2.5	0.9856 ***	1.1680 ***	0.0541 ***	14.4745
	(0.0016)	(0.0761)	(0.0071)	
4.2.6	0.9799 ***	1.1290 ***	0.0408 ***	15.0666
	(0.0020)	(0.1178)	(0.0076)	
4.2.7	0.9842 ***	1.1107 ***	0.0710 ***	13.8611
	(0.0022)	(0.1075)	(0.0076)	

Note: *** , ** and * for significance at 1%, 5%, and 10% levels, respectively.

5. Concluding discussion

We estimate a version of warm-glow asset-pricing where investors derive utility from the share of wealth they hold in green assets – "proportional warm-glow." Our estimates of the green coefficient b are close to 0.004 pre-crisis but increase dramatically to 0.054 post-crisis. This may be evidence that investors are becoming more aware of the importance of investing in green and now derive utility from engaging in it. Since the green preference we find is even stronger than in the article we replicate, we can claim that the model explains the negative alphas of

[2] For details, see DSS.

the green portfolios in the post-crisis period. Our promising results when using relative measures of green wealth for asset pricing buttresses the arguments of those who advocate for the adoption of relative rather than absolute measures of green or carbon emissions. Thus, as a further contribution to the literature, this article highlights the importance of the type of variable used when measuring green impact.

Both versions of the Warm-Glow theory suggest that green preferences affect decision making in such a way that the investor is not only concerned with consumption smoothing over time, but also with asset smoothing (green vs. conventional). Although we do not report it here, this implies mathematically an extra covariance in the explanation of stock returns. DSS further show that the demand for green stocks after the crisis period more than compensates for their increasing supply, which explains the negative green alpha they find. This contradicts to some extent the findings of Berk and van Binsbergen (2021), who defend no significant difference in returns of ESG stocks compared to the market as consequence of an insufficient demand.

We could further discuss risk aversion by looking at the decrease in gamma[3] over time. Risk aversion on average falls from 1.60 (se = 0.461) prior to the crisis to 1.14 (se = 0.084) after. A simple one tail test indicates at alpha = 5% that gamma is lower after the crisis (t = 1.995). Thus, one could associate this with a potential structural break in risk aversion given the increase in green preference.

Moreover, it could be interesting to study the performance of portfolios of green (SRI) stocks controlling for "good and bad economic times". For example, using MSCI KLD data until 2013, Bansal et al. (2022) show that SRI stocks outperform during good economic times, while the opposite happens in bad times. In a similar investigation, Dreyer et al. (2023) provide a theoretical explanation for the effect of market uncertainty on investor warm-glow preferences. In other words, future studies could imagine other possible economic contingency variables to warm-glow investing.

One might also think about country and industry conditions that could determine warm-glow behavior. For example, some industries might be recognized by investors as "greenwashers" (Tatomir et al., 2023). Thus, it would be surprising if warm glow would be detected in stocks of these industries. It might also be the case that individuals of different countries exhibit different behaviors towards SRI investments.

CRediT authorship contribution statement

Johannes Kabderian Dreyer: Economic Modelling, Methodology, Investigation, Software, Validation, Writing – review & editing, Writing – original draft preparation. **William Smith:** Conceptualization, Economic Modelling, Writing – original draft preparation, Writing – review & editing.

Declaration of Competing Interest

none.

Appendix. : Data Descriptive Statistics

Table A1
Mean and Standard Deviations.

Period	$\frac{C_{t+1}}{C_t}$	$\frac{C_t}{W_t - C_t}$	$\frac{w_{t+1}}{w_t}$	$R_{f,t+1}$ short	long	$R_{n,t+1}$	$R_{g,t+1}$
Pre-Crisis	2.33	15.06	4.08	3.31	5.17	13.57	8.98
	(0.82)	(0.94)	(11.62)	(1.79)	(0.48)	(41.93)	(32.13)
Post-Crisis	1.29	15.81	4.55	0.08	3.41	20.29	15.16
	(2.39)	(1.40)	(8.51)	(0.05)	(0.57)	(34.31)	(29.35)

Note: All data expressed in annual percentage terms

Table A2
Number of Green and non-Green Companies & Participation of Green Wealth over time.

Average Numbers per Year									
Year	1998	1999	2000	2001	2002	2003	2004	2005	2006
G	126	115	108	103	111	99	71	110	136
NG	2031	2120	2249	2380	2413	2458	2471	2413	2390
$\lambda_{g,t}$ (%)	6.05	6.45	7.32	4.75	4.06	3.81	4.47	4.80	6.24
Year	2007	2008	2009	2010	2011	2012	2013	2014	2015
G	143	189	186	519	503	276	444	495	495
NG	2291	2371	2422	2097	1993	2148	1667	1679	1589
$\lambda_{g,t}$	7.04	9.09	8.08	10.42	16.72	15.74	13.53	16.17	16.79

Note: "G" for green and "NG" for non-green companies; λ_g is the percentage of green wealth.

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[3] Since there are two "goods" in the utility function it is not immediately clear how to disentangle risk preferences from ordinal preferences over the goods. Since our utility function is homothetic, however, we can invoke (Kihlstrom and Mirman, 1981) to show that the γ is the correct measure of "effective" relative risk, while b measures the relative ordinal preference for the green asset. For further details see DSS.

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