Discussion of "The Unintended Consequences of Rebalancing" by Harvey, Mazzoleni, and Melone

Jonathan A. Parker
MIT and NBER

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Motivate the paper in broader context of my own work

Recent papers focus on "demand" shocks for stocks and look for price impact at stock or asset-class level (Koijen, Yogo, Gabaix, etc)

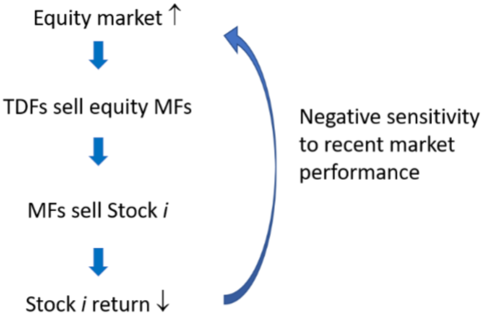
Example: Parker, Schoar, and Sun (2023) and Parker and Sun (2025) focused on the impact of re-balancing by Target Date Funds on individual stocks

- As costs of investing declined and DC pensions replaced DB, US households became investors & now manage portfolios
- Pension Protection Act of 2006 provided safe harbor for retirement plans use of TDFs as default investment vehicles
- By end of 2023: (Vanguard, 2024)
  - DC plans cover more than 100 million households and hold more than $10 trillion in assets
  - 96% of DC plans offer TDFs
  - 98% of plan default funds are TDFs
  - 83% of all participants used TDFs
  - 58% of all participants use **only** a TDF

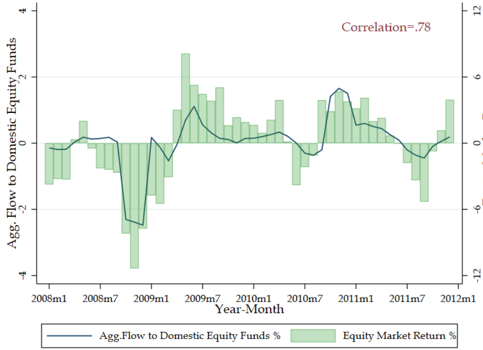
Target Date Funds as Asset Market Stabilizers

Target date funds maintain shares invested across asset classes at "age appropriate" amounts. To do so, they must be **macro-contrarian**.

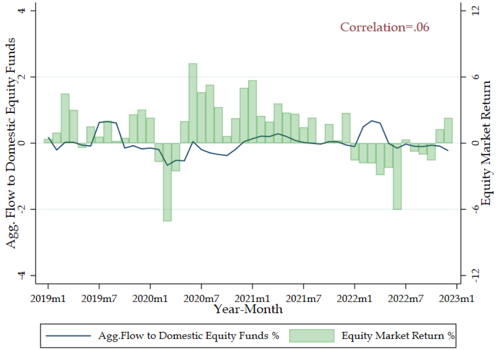
- TDFs maintain fixed shares of asset classes $\rightarrow$ Sell equity funds after equity gains, buy after equity losses
- Generate contrarian flows to underlying mutual funds
- **Market contrarian** trading potentially dampens asset-price fluctuations



Rise of TDFs Associated with Equity Fund Flow Becoming Contrarian



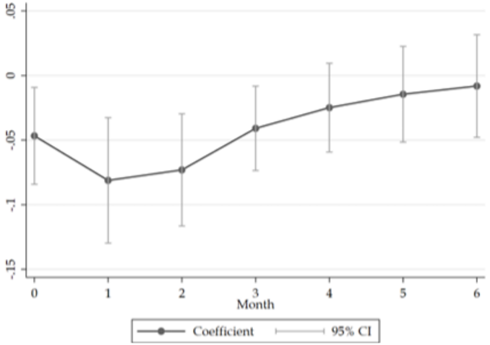
Fund Flows Trend Chasing 2008-2012



Fund Flows Trend Chasing 2019-2023

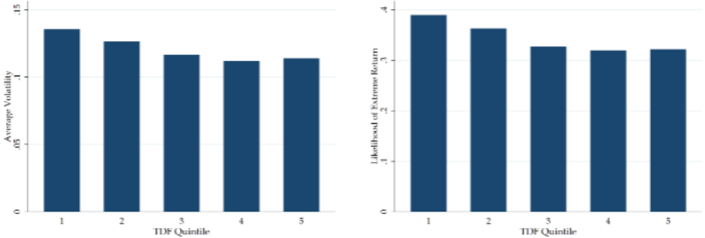
Our papers shows individual stock price impact of TDFs

This figure plots the effect of TDFs on cumulative 7-factor alphas from the month of the return shock (month m) to month $m+h$. The estimation follows equation (8), and the coefficients $\widehat{\lambda_h}$ are plotted as a function of h. Betas are calculated using the pre-PPA window 1996-2005. Confidence intervals are based on standard errors that are clustered two ways by stock and time.



Our papers shows individual stock price impact of TDFs

Correlation between Indirect TDF Ownership of Stock and Stock volatility in Pandemic



(a) Raw Return Volatility

(b) Likelihood of Extreme Returns

Note: This figure plots the average raw monthly return volatility and the likelihood of extreme returns of stocks during 2019-2022 by levels of TDF investment in 2018. Stocks are sorted into quintiles according to their average indirect TDF ownership during 2018. Raw return volatility is the standard deviation of

Also: Andonov, Eiling, and Xu, "Target Date Funds and International Capital Flows" 2025

- Foreign equity funds' outflow increasing in TDF ownership when $R^{U.S.} < R^{For}$
- Foreign stocks with higher TDF ownership have higher $cov(R_i, R^{U.S.})$, lower $cov(R_i, R^{For})$
- Currencies affected more by TDF rebalancing flows depreciate more when $R^{U.S.} < R^{For}$

But we have concerns and shortcomings . . .

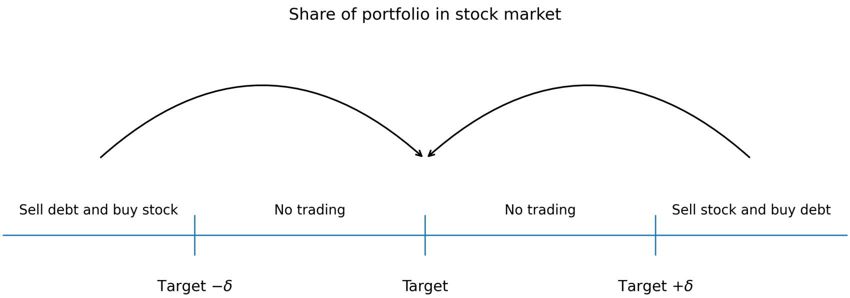
- Concern: What about pension funds and institutions that maintain target allocations? Omitted variables for us.
- Shortcoming: No robust measurable effect on aggregate returns. Monthly data, TDFs are only big recently and not **that** big, some TDFs rebalance quite slowly, some TDFs are active and have discretion (e.g. Fidelity), etc.

This paper walks away from measuring exact strategies (e.g. target equity shares) but gets more time-series and ends up showing a market-wide effect . . .

Summary of the paper

- Investors have **target** shares of their portfolios that they want invested in stocks
- Investors adjust their portfolios towards these shares **infrequently**, in either time-dependent or state-dependent manner
- Key assumption 1: These target shares are **fixed** so that the direction of rebalancing is naturally coordinated by past returns
- Key assumption 2:
  - For time-dependent: rebalancing occurs at the ends of calendar months
  - For state-dependent: regions of inaction and small and similar enough (and again, targets are fixed, not state-dependent or discretionary)
- Because rebalancing is coordinated in direction and time, it has **price impact**
- Because rebalancing depends on past returns, it creates **predictable** variation in returns

State-dependent rebalancing



Stock market has recently done poorly

Stock market has recently done well

Each investor will rebalance only once their portfolio share leaves its range of inaction

$\Rightarrow$ On average, a smooth and delayed rebalancing to excess returns

$\Rightarrow$ But a large and coordinated response to a very large daily return!

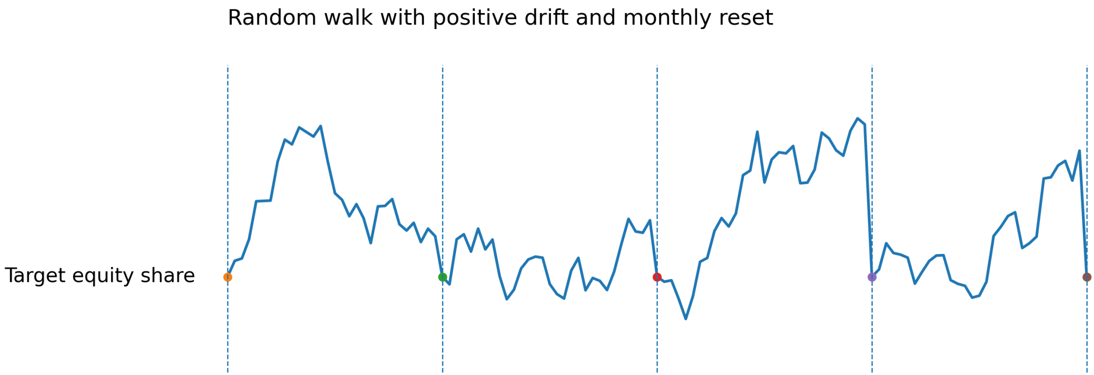
Data analysis

Construct a measure of likely rebalancing direction and magnitude

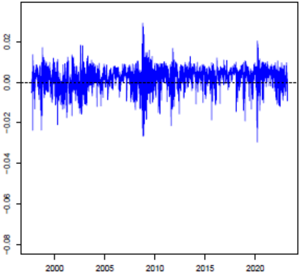
1. Assume desired 60-40 portfolio shares
2. Calculate deviation from target equity share based on daily excess returns
   - Time-dependent: reset to 60% on last few days of calendar month
   - State-dependent: reset to 60% when $|$ Equity share$_t$ — Target share $| \geq \delta$
     Calculate for many values of δ and average all deviations for $\delta \leq 2.5\%$
   - Comment: both ignore inflows and outflows (end of the month effect partly this?)
3. Predicted stock buying (selling) is proportional to **signal** of how much equity share below (above) 60% target:
   - Time-dependent: only during last week of the month
   - State-dependent: all the time

- Both the 2.5% threshold and the last week are 'model selection' by looking at predictive strength on returns. Take t-stats with grain of salt.

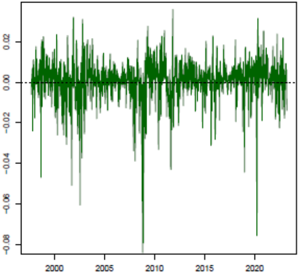
Time dependent deviations example



State dependent much smoother function of recent past returns



(a) Threshold Signal



(b) Calendar Signal

	Mean	SD	AR1	Skewness
Threshold Signal	0.49	0.08	0.61	-0.98
Calendar Signal	0.18	0.16	0.91	-1.43

Results: Deviations predict daily returns

	Ret_{t+1}				
	(1)	(2)	(3)	(4)	(5)
Threshold	−0.4144***	−0.4208***	−0.4254***	−0.4254***	−0.4226***
	(0.1148)	(0.1164)	(0.1098)	(0.1133)	(0.1139)
Calendar	0.0553	0.0689	0.0572	0.0542	0.0666
	(0.0709)	(0.0686)	(0.0696)	(0.0713)	(0.0686)
week4	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Calendar *week4	−0.3029***	−0.3036***	−0.3026***	−0.3032***	−0.3033***
	(0.0808)	(0.0808)	(0.0805)	(0.0806)	(0.0808)
Momemtum	0.0023***	0.0024***	0.0024***	0.0025***	0.0024***
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0007)
Ret	−0.0203	−0.0167	−0.0198	−0.0192	−0.0173
Observations	6,226	6,226	6,226	6,226	6,226
Adjusted R^2	0.0239	0.0252	0.0243	0.0242	0.0248

Main findings

1. The rebalancing signals predict returns as they should, with low R^2 as they should
2. Reasonable robust to controls, etc.
3. Weak statistical evidence that price impact decays over time
   - Time-dependent: not statistically significant after 7 trading days, back close to zero in two weeks
   - State-dependent: not statistically significant after two weeks, back near to zero after thee weeks
4. Some evidence that trading volume of the investors that have these inflexible targets moves with predicted rebalancing
5. Some evidence that hedge funds or sophisticates trade against rebalancing
6. Front running is profitable: Sharpe Ratio 0.90

Comment one: Is this big?

- The price impact implies that the trades move prices adversely so as to cost 5 basis points of AUM (if time-dependent rule) or 15 basis points of AUM (if state-dependent) annually
- Paper argues that random rebalancing within a month still has costs, but this cannot be right...
- In comparison, an idiosyncratic state dependent rule that re-balances only when 2.5% away from target with no price impact costs roughly 8 basis points of AUM in expectation (caveat: discussant quick calculation)
- These costs both seem small compared to the **relative to the cost of having such a simplistic target rule** instead of a some optimal state-dependent target!
- In a partial-equilibrium portfolio choice problem, shouldn't the share depend on volatility, on dividend price ratio, etc?

Comment two: Are these targets stable? Approximately 60-40?

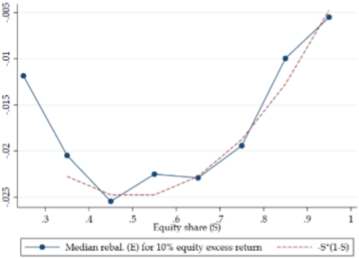
- A central assumption: there are a lot of 60-40 fixed rule traders in the market
- In response to stock market performance (or private asset or real estate or crypto performance), do these institutional investors adjust target shares?

- In TDF world, some funds have a lot of discretion to "take advantage of market opportunities" and fund classes sometimes change their glide paths a lot (Fidelity in 2016 was huge)

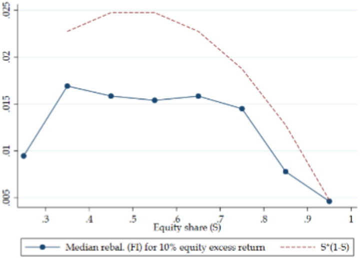
- Looking at the re-balancing by TDFs with different desired equity shares, it might be that the 60-40 approximates the average?

Rebalancing by TDFs

Data on TDFs from CRSP Mutual Funds database, Morningstar TDF reports, mutual fund holdings data (Form N-PORT), Stocks data from Compustat.



(a) Equity Rebalancing



(b) Bond Rebalancing

In response to returns, a TDF has to rebalance to return to desired equity share. Quarterly rebalancing in data (red), and in theory (blue); more rapidly for stocks than bonds.

Comment three: What is optimal?

- The paper focuses on price impact of predictable flows and suggests that different trading strategies could reduce costs
- But this cannot be close to optimal!
- Asset pricing theory: If the stock market booms, it comprises a larger share of the wealth portfolio, hold don't sell! No trade theorems!
- Even partial-equilibrium naive portfolio choice:
  - Half of movements in stock prices represent transitory movements and in response to these **reduce equity share**
  - Half of movements in stock prices are permanent, associated with permanently higher dividends, and in response to these **raise equity share**
- Main lesson for practitioners: Focus on making the rules state dependent!
- **If rules are optimal, then maybe all of these trades are pushing prices to where they should be based on aggregate risk sharing and past information not moving prices away from fundamentals!**

Conclusion

There are a lot of institutional investors that follow simplistic rules for investing across asset classes and these have predictable, transitory price impact on returns

- The paper's evidence is somewhat indirect (macro identification). And in asset pricing, it is always the case that at one person's liquidity premium is another's risk premium.
- But the balance of evidence here points to price impact and I find the paper credible: institutional simple rules lead to predictable flows that move market prices
- My take: Despite large Sharpe ratio, the actual dollar cost is small relative to the other errors being made
- While the costs of simple rules are much bigger in other ways than price impact when trading. But price impact may be the easiest to solve.