

Should Top Surgeons Practice at Top Hospitals? Sorting and Complementarities in Healthcare

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Introduction

- ▶ Worker sorting across firms is a longstanding research question
 - ▶ Critically related question: what is the “value-add” of firms?
 - ▶ Labor market: Abowd et. al 1999; Bonhomme, Lamadon, & Manresa 2022
 - ▶ Education: Abdulkadiroglu et. al 2020; Dale & Krueger 2002, 2011)
- ▶ In health care, large variation in quality (and costs) across providers and hospitals (Chandra et. al 2016; Currie et. al 2017; Einav, Finkelstein, Mahoney 2022; Doyle et. al 2012)
- ▶ Question: what is the optimal way to sort physicians into hospitals?
 - ▶ Do hospitals have a “value add” over the quality of the physicians it employs?
 - ▶ Is variation in hospital outcomes simply the result of physician sorting?

This Paper

- ▶ What is the value-add of surgeons and hospitals in their interaction in the production of quality?
 1. Are surgeons and hospitals complements or substitutes in the production function?
 2. Do surgeons positively or negatively sort?
 3. Synthesis: is this sorting optimal?
- ▶ Context: Coronary artery bypass surgery (CABG)
 - ▶ Quality outcome: 30-day survival
 - ▶ Data: Medicare claims
- ▶ Uses a TWFE strategy relying on physicians who practice in multiple hospitals (“multi-homers”)
 - ▶ Discrete choice hospital demand model to deal with patient selection
 - ▶ K-clustering by group to deal with measurement error

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 - ▶ Top-quality surgeons tend to have similar outcomes regardless of hospital
 - ▶ But top-quality hospitals add value to low-quality surgeons

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- 3. No!
 - ▶ Current allocation is worse than random
 - ▶ Counterfactual allocations achieve 25% reductions in mortality through negative sorting mechanism

Agenda

Setting and Data

Empirical Strategy

Results

Counterfactuals

Conclusion

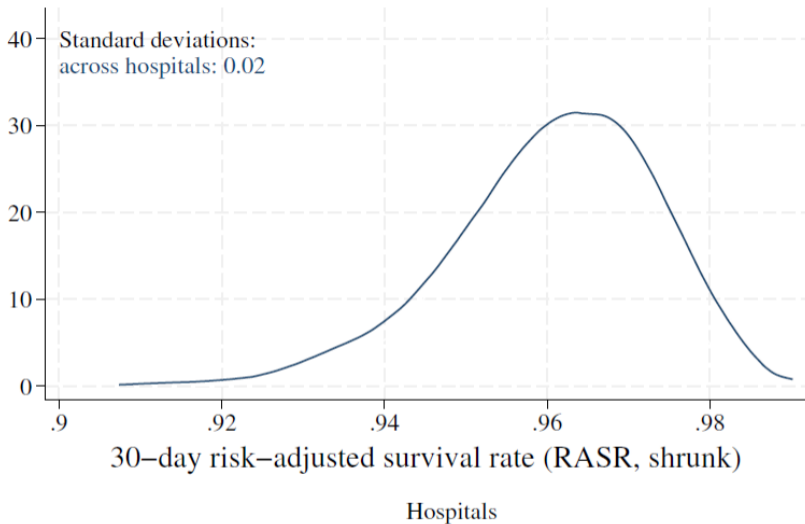
Discussion

Coronary Artery Bypass Surgery (CABG)

- ▶ Common procedure
 - ▶ About 200,000 patients per year
 - ▶ 40-50% are 65+
 - ▶ Average cost per stay: \$46,800
 - ▶ Total cost per year: \$7.3 billion
- ▶ Complex procedure
 - ▶ Performed by specialized surgeons
 - ▶ Takes 3-6 hours
- ▶ Large fraction of cardiac surgeons' activity
 - ▶ Most common surgery on average Medicare patients

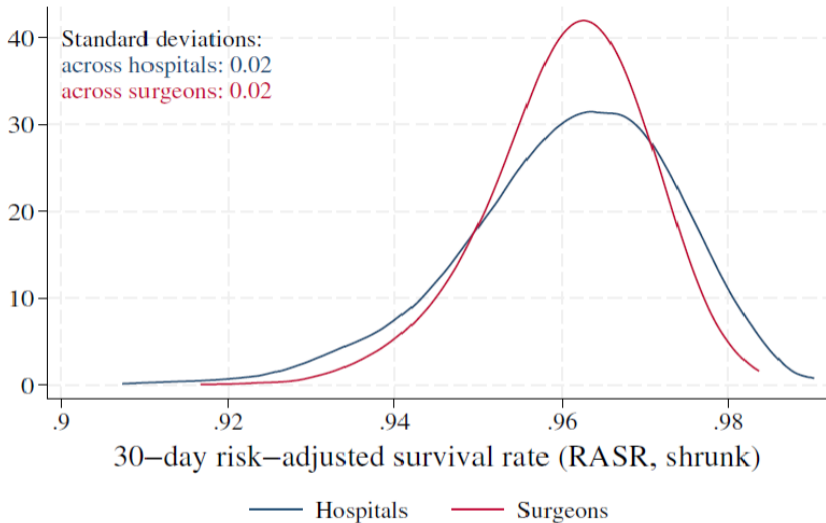
Data: Medicare Claims

- ▶ Claims data for Traditional Medicare 2011-2017
 - ▶ Identify CABG surgeries in 20% professional claims file
 - ▶ Match to hospital stay
- ▶ Outcome: 30-day risk-adjusted survival rate (RASR)
 - ▶ Easily observable
 - ▶ Started being reported in the 1990s as part of report-card programs
 - ▶ 30-day risk-adjusted mortality rates for hospitals publicly reported by CMS
 - ▶ Substantial variation across physicians and hospitals



Mean raw survival: 0.960(0.195).

Mean risk-adjusted survival rate (RASR): 0.961(0.197)



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Framework

Patient survival Y_{ijht}^* for patient i treated by surgeon j at hospital h in time t is:

$$Y_{ijht}^* = g(\alpha_j, \psi_h, X_{it}) + \epsilon_{ijht}$$

where:

- ▶ Y_{ijht}^* is an indicator for survival
- ▶ $g(\cdot)$ is the production function
- ▶ α_j and ψ_h are surgeon and hospital unobs. heterogeneity
- ▶ ϵ_{ijht} are unobservables, assumed independent s.t. $E[\epsilon_{ijht} | \alpha_j, \psi_h, X_{it}] = 0$

Complements or Substitutes

Since conditional expectation of errors are 0, you have conditional expectation of survival equal to the production function:

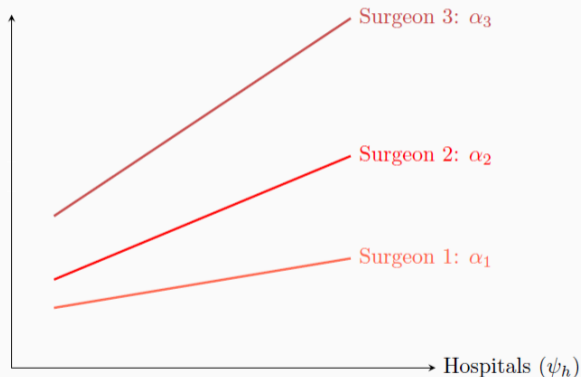
$$E[Y_{ijht}^* | \alpha_j, \psi_h, X_{it}] = g(\alpha_j, \psi_h, X_{it})$$

Take the second derivative of the production fct. wrt hospital and physician unobservables:

$$\frac{\partial^2 g(\cdot)}{\partial \alpha_j \psi_h} \leq 0$$

Complements

Predicted survival
 $g(\alpha_j, \psi_h, \bar{X})$



$$\alpha_1 < \alpha_2 < \alpha_3; b_1 < b_2 < b_3$$

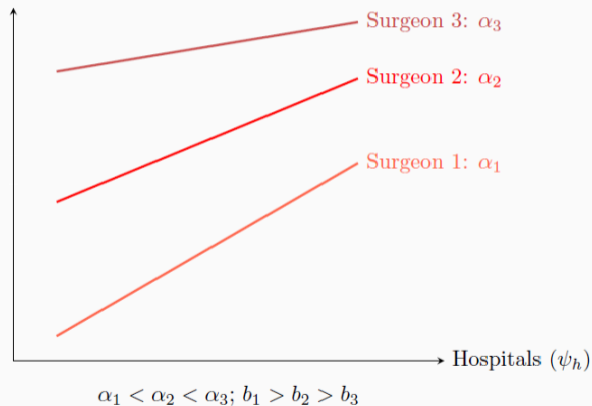
Larger slope for **high-type surgeons**

\Leftrightarrow marginal return of a higher hospital type is **larger for high-type surgeons**

$$\Leftrightarrow \frac{\partial^2 g(\alpha_j, \psi_h, \bar{X})}{\partial \alpha_j \partial \psi_h} > 0$$

Substitutes

Predicted survival
 $g(\alpha_j, \psi_h, \bar{X})$



Larger slope for **low-type surgeons**

\Leftrightarrow marginal return of a higher hospital type is **larger for low-type surgeons**

$$\Leftrightarrow \frac{\partial^2 g(\alpha_j, \psi_h, \bar{X})}{\partial \alpha_j \partial \psi_h} < 0$$

Empirical model

The observed 30-day survival is

$$Y_{ijht} = Y_{ijht}^* D_{ijht}$$

with $Y_{ijht}^* = g(\alpha_j, \psi_h, X_{it}) + \epsilon_{ijht}$

where D_{ijht} indicator if i treated by j at h in t .

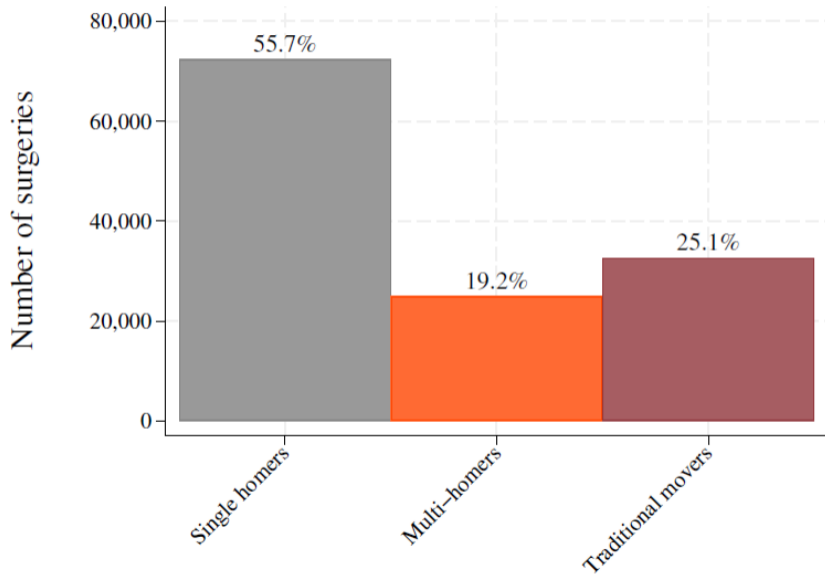
Estimation

- ▶ Key challenge: how to specify production function, $g(\cdot)$
 - ▶ Ideally just throw a boat-load of physician/hospital FE
- ▶ But:
 1. Extremely high dimensionality
 2. Outcome (mortality) extremely rare, so a ton of noise in α_j and ψ_h
- ▶ Solution: cluster/group providers using average RASR using k-means algorithm (Bonhomme, Lamadon, Manresa (2022))
 - ▶ Calculate each provider's RASR by projecting as a logit model onto patient characteristics
 - ▶ Group providers by similar RASRs together using a two-step GFE procedure (BLM 2015)
- ▶ By grouping into type, drastically reduces dimensionality issue and allows more within-group variation for identification...

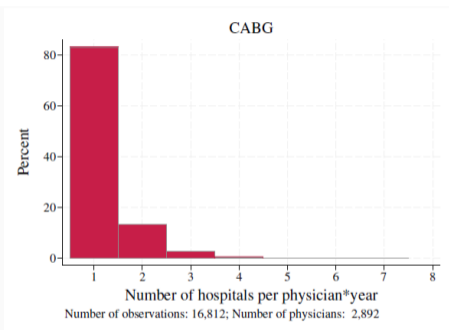
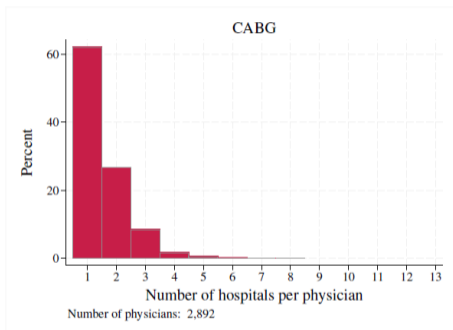
Identification

- ▶ How to separately identify physician from hospital quality (especially if positive or negative sorting)
- ▶ Classic TWFE: need substantial variation in physician practice locations
- ▶ Key data variation: physician “multi-homers” TM : admitting privileges in different hospitals in the same market (and traditional movers)

Substantial Share of Surgeries in Multiple Locations



Substantial Share of Physicians in Multiple Locations



Identification

- ▶ Key challenge: patient selection to hospitals, i.e. $\epsilon_{ijht} \not\perp D_{ijht} | \alpha_j, \psi_h$
- ▶ Solution: distance instrument using discrete-choice demand model for hospitals
 1. Estimate model of hospital choice as a function of distance and hospital FE
 2. Predict choice probabilities as a function of distance
 3. Stick residuals in main specification as control functions
 4. Controlling away for determinants of hospital choice not driven by distance
- ▶ (Surprisingly!) no relationship here. Use selection on observables as primary specification

Estimating equation

Main specification: network exogeneity conditional on observables

$$\epsilon_{ijht} \perp D_{ijht} \mid \alpha_{l(j)}, \psi_{k(h)}, \kappa_{l(j)k(h)}, X_{it}, \gamma_t$$

Estimating equation:

$$Pr[Y_{ijht} = 1 \mid X_{it}, \alpha_{l(j)}, \psi_{k(h)}, \kappa_{l(j)k(h)}] = \alpha_{l(j)} + \psi_{k(h)} + \kappa_{l(j)k(h)} + \sum_p \beta_p X_{it,p} + \gamma_t$$

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Note: **perfect separability** between hospital and surgeon value-added and patient observables

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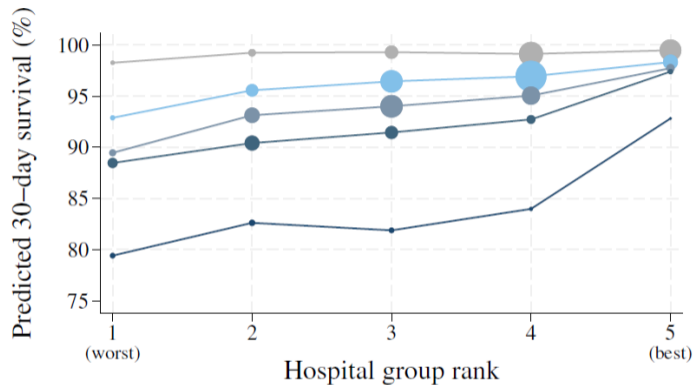
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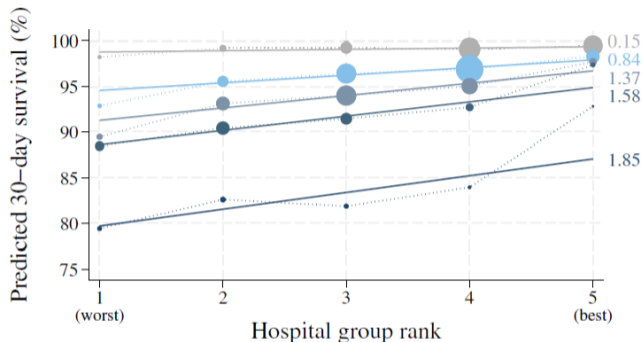
Surgeon and Hospital Value-Added Are Substitutes



Surgeon group ranks:

— 1 — 2 — 3 — 4 — 5

Surgeon and Hospital Value-Added Are Substitutes

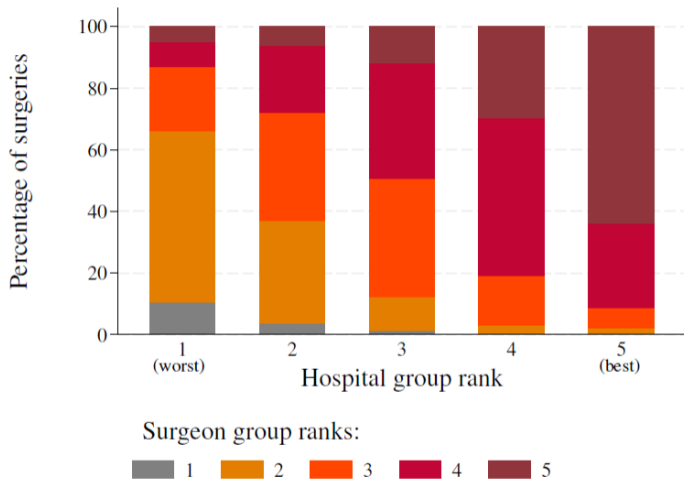


Surgeon group ranks:

— 1 — 2 — 3 — 4 — 5

	Predicted survival
Slope surgeon rank 1 (worst)	1.85 (0.07)
Slope surgeon rank 2	1.58 (0.01)
Slope surgeon rank 3	1.37 (0.01)
Slope surgeon rank 4	0.84 (0.00)
Slope surgeon rank 5 (best)	0.15 (0.00)
p-value: equality of slopes	< 0.01
p-value: slope rank 5 \geq 1	< 0.01
p-value: slope rank 4 \geq 2	< 0.01
Observations	130,075
R-squared	0.99
Physician type FEs:	X

Positive Sorting



Why Substitutes?

- ▶ Theory: **“Failure-to-Rescue”** (Silber et. al 1992, Ghaferi et. al 2009)
- ▶ Top hospitals have procedures in place that save patients when complications arise
- ▶ This is more effective for low-quality surgeons, where these complications are more likely to arise

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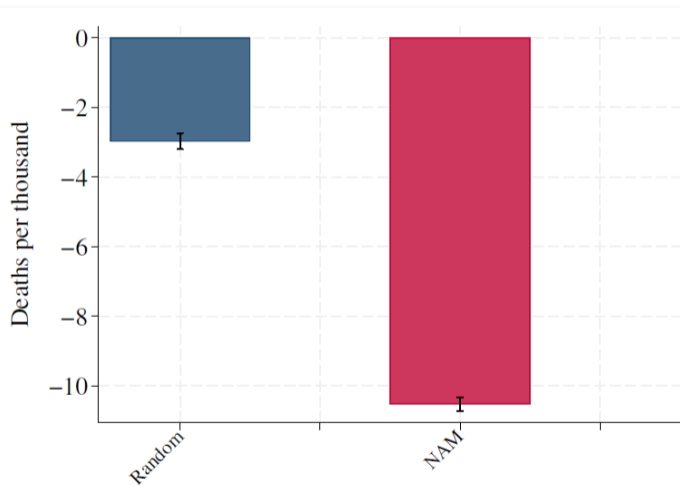
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Reallocations: Random and Negative Assortive



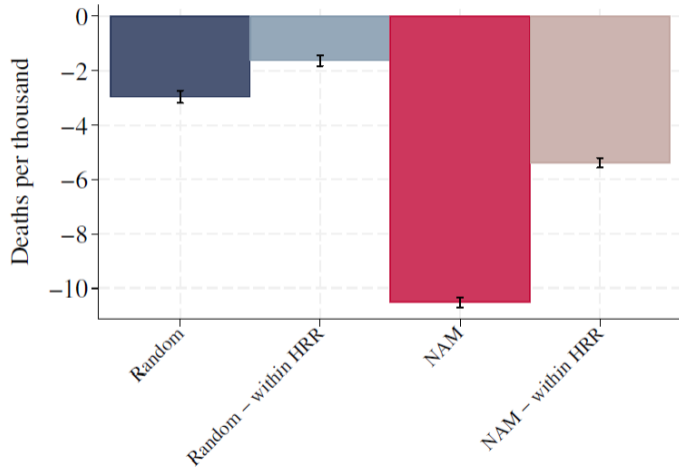
Random reallocation:
decreases mortality by 7%


NAM reallocation:
decreases mortality by
25%


Reductions in dispersion
are of similar magnitude

Within Medicare: 200 to
800 lives saved a year

Reallocations: Random and Negative Assortive



High-survival providers
co-locate in space... 

... but substantial PAM
within regions 

⇒ Reallocations within
regions: achieve 55% and
51% of gains from
national reallocations

Conclusion

Surgeon and hospital value-added in the production function of survival

1. Returns to high-survival hospitals: larger for low-survival surgeons
2. Operating surgeon: major driver of patient outcomes for CABG
3. Key role of hospital value-added for low-survival surgeons

What is the impact of surgeon sorting on aggregate patient survival?

1. Current sorting: positive assortative matching
2. Counterfactual allocations suggest the current sorting costs lives
 - ▶ Reduction in aggregate mortality: 7% in random allocation, 25% with negative assortative matching
3. Within-market reallocations: 50% of benefits from national reallocations

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Discussion

- ▶ Great paper!
- ▶ Interesting policy-question in health production, but using econometrics from literature from labor literature
- ▶ Extremely careful with k-means clustering and control function approach
- ▶ Interesting results!

Peer Effects

- ▶ “Failure to Rescue” is one story for what could be going on
 - ▶ But, by no means despositive
- ▶ Alternate story that fits the data: peer effects
 - ▶ Low-quality surgeons benefit not from high-quality hospitals per-se, but from high-quality surgeons that sort to high-quality hospitals
 - ▶ “Competitive spirit” or actual skill acquisition
 - ▶ Related to Chen (2011)
- ▶ Implication: overstate the gains Negative Assortive Matching
 - ▶ Imagine extreme scenario: all top-quality surgeons move to low-quality hospitals and all low-quality surgeons move to top-quality hospitals
 - ▶ Currently model implies huge gains (25% reduction in mortality)
 - ▶ But if peer effects are the driver, in some sense random reallocation might work better!

Quality is Dynamic

- ▶ Suppose you have 5 years of data and 2 hospitals: H (High Quality) and L (Low Quality)
- ▶ Consider Surgeon 1 with the following distribution of practice locations and mortality outcomes
 - ▶ HH, HH, HH, HL, LL
 - ▶ Low mortality across the board
 - ▶ $\implies \alpha_j$ is large, surgeon should move to L
 - ▶ \implies Surgeon should move to an L hospital
- ▶ Consider another Surgeon 2:
 - ▶ LL, LL, LL, HL, HH
 - ▶ High mortality until period 4, when switches to low mortality there and period 5
 - ▶ $\implies \alpha_j$ low, ψ_h high, surgeon should move to H
- ▶ Problem: they're the same surgeon! 2 is just earlier in the process
- ▶ To the extent Surgeon 1 acquired permanent skills at H, model would underestimate gains from having S1 at H

Probably Minor Econometrics Things

1. GFE

- ▶ BLM use the empirical CDF of $\log(\text{wages})$ within a firm as their classification rather than firm means (for reasons you allude to in the paper about monotonicity). Can you do this?
- ▶ They also restrict to job-stayers to satisfying a conditional independence assumptions (that conditional on worker type and observables, wage distributions are independent within firm). Do you do the same?

2. Monotonicity Assmpt

- ▶ Classification (step 1 of the GFE process) requires monotonicity assumption for surgeons
- ▶ But should the same apply for patient types?
- ▶ If a higher unobserved hospital type (higher quality hospital) is correlated with lower unobserved patient type (sicker patients), you could observe the same mortality rate for two different hospital types

3. Demand model

- ▶ Fairly surprising that seems to have no impact!
- ▶ Model is fairly parsimonious: just hospital FE and distance
- ▶ If unobserved health correlated with travel time (or rural vs. urban zip code etc), might help to specify a more flexible model with patient interactions

Conclusion

Great paper! Can't wait to see what's next!