A cell–ECM screening method to predict breast cancer metastasis

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A cell–ECM screening method to predict breast cancer metastasis†

L. E. Barney, E. C. Dandley, L. E. Jansen, N. G. Reich, A. M. Mercurio and S. R. Peyton*

Breast cancer preferentially spreads to the bone, brain, liver, and lung. The clinical patterns of this tissue-specific spread (tropism) cannot be explained by blood flow alone, yet our understanding of what mediates tropism to these physically and chemically diverse tissues is limited. While the microenvironment has been recognized as a critical factor in governing metastatic colonization, the role of the extracellular matrix (ECM) in mediating tropism has not been thoroughly explored. We created a simple biomaterial platform with systematic control over the ECM protein density and composition to determine if integrin binding governs how metastatic cells differentiate between secondary tissue sites. Instead of examining individual behaviors, we compiled large patterns of phenotypes associated with adhesion to and migration on these controlled ECMs. In combining this novel analysis with a simple biomaterial platform, we created an in vitro fingerprint that is predictive of in vivo metastasis. This rapid biomaterial screen also provided information on how 

\[ b_1, a_2, \text{and } \alpha_6 \] integrins might mediate metastasis in patients, providing insights beyond a purely genetic analysis. We propose that this approach of screening many cell–ECM interactions, across many different heterogeneous cell lines, is predictive of in vivo behavior, and is much simpler, faster, and more economical than complex 3D environments or mouse models. We also propose that when specifically applied toward the question of tissue tropism in breast cancer, it can be used to provide insight into certain integrin subunits as therapeutic targets.

Insight, innovation, integration

We developed a high-throughput method to rapidly screen cell adhesion, motility, and growth factor responses on biomaterial surfaces. This approach is analogous to systems biology, relying on cell phenotypes in lieu of genetics. We used this technique to reveal patterns of phenotypes associated with breast cancer metastasis to possible tissue sites (bone, brain, lung). By comparing the phenotypic patterns between cell lines that metastasize to only one tissue site with heterogeneous cell lines, we provide the first method to connect in vitro phenotype to in vivo fate. This method is successful without genetic analysis, yet it also predicts outcomes related to integrin gene expression, potentially identifying new targets for tissue-specific metastasis.

Introduction

Breast cancer is the most common cancer in women, and metastasis is responsible for 90% of all cancer deaths. The microenvironment is a critical regulator of metastasis, and in vivo studies have provided insight into many microenvironment-mediated mechanisms.\(^2\text{-}^6\) However, these studies lack features of human physiology, contain uncontrolled variables, and are often not comparable across different mouse models. Thus, it is difficult to parse the varying contributions of each factor, limiting the broad applicability of these results. In contrast, in vitro models can be either oversimplified,\(^7\) or highly complex, expensive, low-throughput, and limited to highly specialized laboratories.\(^8\) Because metastasis remains both largely incurable and poorly understood, there is a need for quick, cost-efficient in vitro model systems with enough complexity to recapitulate certain aspects of in vivo biology, while maintaining affordability and efficiency.

Two-dimensional in vitro disease models are appropriately low cost and simple, however, it is now generally appreciated...
that two-dimensional cell behaviors are usually not conserved in a three-dimensional context. One recent example of this is work by Meyer et al., which showed that only two-dimensional growth-factor induced membrane protrusion, but not any other measured 2D motility parameter, accurately predicts 3D motility. This suggests that individual two-dimensional measurements will also not be predictive of even more complex in vivo cell phenotypes. We suggest that a better approach may be to avoid measurements of single, likely non-predictive metrics, and instead, measure patterns of many phenotypes across several conditions and several cell sources.

Breast cancer metastasis is a clear candidate for this type of approach because of its striking, yet unexplained, clinical patterns of metastatic spread (tropism) to the bone, brain, liver, and lung, but not to tissues such as the skin, heart, uterus, or spleen. This tropism is hypothesized to depend upon an unknown relationship between metastatic cells (the seeds) and hospitable microenvironments (the soils). Because the tissues often colonized by breast cancer cells each have a distinct ECM, we posit that integrin binding to the ECM is one feature that plays a critical role in the early stages of tissue-specific colonization and fate of extravasated cancer cells. It is known that secondary site colonization requires activation of integrin-mediated signaling, and several individual integrins have been implicated in breast cancer metastasis in vivo. However, this research is limited to metastasis at a single tissue site, or to the effect of a single integrin, which is not representative of the variety of cell–matrix interactions simultaneously occurring in vivo during cell adhesion to a secondary tissue site–post-extravasation.

To this end, we created a novel biomaterial platform comprised of complex ECMS that can present any combination of full-length proteins with high fidelity, reproducibility, and is permanent during the cell culture period. We used this biomaterial to quantify how different metastatic breast cancer cell lines differentiate between secondary sites via integrin binding. We compiled sixty-six distinct cell phenotypes associated with cell adhesion and motility, both with and without epidermal growth factor (EGF) stimulation. By collating all the responses to each biomaterial ECM surface together, we created a phenotypic fingerprint of bone, brain, and lung metastasis, which is both capable of distinguishing between genetically related tropic cell subpopulations, as well as predictive of the in vivo metastasis of several other more heterogeneous cell lines, thereby predicting in vivo fate with a quick in vitro screen. Taken together, we propose this comprehensive analysis of cell–matrix interactions as a tool to predict in vivo fate, as well as understand the roles of integrins in tropism, thus providing insight toward integrins as druggable targets for metastatic disease.

## Results

Rapid biomaterial screening of cell–ECM interactions

The ECMS present in secondary tissues often recipient of breast cancer colonization are each strikingly complex and distinct, suggesting that cell–matrix interactions play a role in mediating metastasis. Our goal here was to create a simple in vitro biomaterial system to investigate the role of integrin binding in breast cancer tropism. These biomaterial surfaces are glass coverslips, modified via straightforward silane chemistry. They present covalently coupled ECM proteins, and they remain stable throughout the cell culture period (at least 72 hours). This method can be used to couple any combination of full-length proteins or peptides of interest, providing control over cell–matrix interactions in a highly robust (Fig. S1, ESIF), scalable, and facile process. It is particularly well suited to observe integrin-mediated phenotypes of adherent cell lines, and allows for functional investigation of real-time binding to the ECM.

We used this approach to create three biomaterial environments containing combinations of ECM proteins inspired by the biochemical cues found at the in vivo tissues to which breast cancer commonly spreads (Table 1). ECM at these tissues have significant patient-to-patient variability, and can be remodelled by both tumor and stromal cells over time. Our approach was to determine if integrin binding alone, at early time points (directly after extravasation), was sufficient to direct or predict tissue-specific spread. Therefore, we created three biomaterial surfaces containing combinations of ECM proteins that isolate distinct integrin heterodimers, independently of the in vivo heterogeneity, inspired by the ECM protein content of healthy tissues at these sites.

### Table 1 Composition of tissue-inspired biomaterial ECMS

<table>
<thead>
<tr>
<th>In vivo</th>
<th>ECM 1 (bone)</th>
<th>ECM 2 (brain)</th>
<th>ECM 3 (lung)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM density</td>
<td>High</td>
<td>Low</td>
<td>Moderate</td>
</tr>
<tr>
<td>Proteins</td>
<td>Collagen I, Fibronectin, Osteopontin</td>
<td>Laminin, fibronectin, collagen IV, tenascins, proteoglycans, Hyaluronic acid</td>
<td>Fibronectin, Collagens, laminins, elastin, tenascin C, proteoglycans</td>
</tr>
<tr>
<td>In vitro density</td>
<td>5 mg cm⁻²</td>
<td>1 mg cm⁻²</td>
<td>2 mg cm⁻²</td>
</tr>
<tr>
<td>Proteins</td>
<td>99% collagen I, 1% osteopontin</td>
<td>50% fibronectin, 25% vitronectin, 20% tenascin C, 5% laminin</td>
<td>33% laminin, 33% collagen IV, 15% collagen I, 15% fibronectin, 4% tenascin C</td>
</tr>
</tbody>
</table>
As a first attempt to capture the heterogeneity of breast cancer, we screened phenotypes associated with adhesion and motility across a large panel of human cell lines that span the clinical subtypes\(^{27}\) and metastatic specificity to the bone, brain, and lung sites\(^{2–4,28–33}\) (Fig. 1a). We first measured spreading and polarization of cells during initial adhesion to the ECMs, quantifying time-dependent cell area, spreading rate, and polarization of the population (Fig. 1c top and Fig. S2a–c, ESI†). Next, we observed long-term motility, and quantified cell migration speed, displacement, and chemotactic index (ratio of displacement to path length, quantifies migration straightness) (Fig. 1c bottom, Fig. S2d–f, ESI†). Altogether, 550 individual cell observations were made per cell line on average (Fig. 1c and Fig. S2, ESI†). In combination with an ELISA characterization of the protein coupling (Fig. S1, ESI†), these measurements validate the biomaterial platform as being able to elicit differential cell line responses via integrin binding alone (Fig. S2, ESI†).

Phenotypic screen predicts tissue tropism in vivo

We hypothesized that an in vitro analysis of integrin-mediated phenotypes would be capable of differentiating cell lines with different tropisms in vivo, reflecting the functional binding interactions required for successful metastatic outgrowth. We began by phenotyping three highly tropic subpopulations of the MDA-MB-231 parental cell line, which were selected from in vivo metastases by Massagué and colleagues.\(^{2–4}\) These genetically distinct MDA-MB-231 subpopulations each display strong tropism to either the bone (“bone tropic”),\(^{5}\) brain (“brain tropic”),\(^{6}\) or lung (“lung tropic”)\(^{3}\) in mice, and have been used to identify genetic determinants of tissue-specific metastasis. We found that these tissue-specific cell lines each responded to the ECMs in unique ways (Fig. S3, ESI†).

We immediately noticed that for each different measurement we took, the tropic cell lines were sensitive to the ECMs in some cases, while insensitive in others. As an example, when we quantified cell speed, the bone and brain tropic cell lines had very different cell speeds on each ECM surface, whereas the lung tropic cells had similar cell speeds on all three ECMs. To quantifiably demonstrate this, we applied a statistical tool called the coefficient of variation (CoV) to each set of measurements for a given cell line. This measurement quantifies dispersion of a data set, and is computed by dividing the standard deviation of a set of measurements by their mean. In its application here, higher CoV values identify adhesion or motility measurements where a cell line is highly sensitive to the different ECM surfaces (i.e., the relative standard deviation of the measurements across each ECM is at least 10%). Because these cell lines were created to exhibit strong in vivo metastasis to one site, we first wanted to validate that this in vivo selectivity was reflected in the in vitro cell–ECM screen. This CoV analysis showed that each of the tropic cell subpopulations was significantly more sensitive to the ECMs than the parental cell line in each of the adhesion and motility phenotypes we quantified (Fig. S4a, ESI†), validating this approach.

Given that tropic cell lines have heightened sensitivity to growth factors,\(^{34}\) we then quantified the change in each adhesion and motility metric in response to EGF stimulation, and found that the patterns of adhesion and motility across the ECMs under normal and EGF-stimulated conditions varied significantly between the tropic cell lines (Fig. S3, ESI†). The effect of EGF stimulation was especially striking in the tropic cell adhesion. EGF slowed spreading and polarization of the bone tropic cell line, while it increased the spreading rate of the brain and lung tropic cell lines in an ECM-dependent fashion (Fig. S3a–f, ESI†). Growth factor sequestration and growth
factor signalling both depend on the composition of the ECM, which, in addition to the differences in the tropic subpopulations, is likely one reason for the differences in EGF responses.

With this collection of measurements, we sought to identify all the phenotypes unique to cells metastasizing to the bone, brain, or lung by compiling them en masse into a heat map. All the adhesion and motility measurements were organized across three separate classes of observable responses to the ECMs (coefficient of variation, response to EGF, and pairwise ordering across ECMs, Fig. 2a–c).

As the first feature of these collective tropic phenotypes, measurements in which the cell line was either highly sensitive or insensitive to changes in the ECM were identified (Fig. 2a).
For example, the lung tropic line has a high spreading rate CoV, whereas the brain tropic cell line has a low chemotactic index CoV under EGF stimulation (Fig. 2a). We then quantified whether each phenotype measured increased, decreased, or remained unchanged in response to EGF stimulation on each of the three ECMs (Fig. 2b). As examples, the lung tropic cells increased their displacement with EGF stimulation, the bone tropic cell line spreading area was unchanged, and the brain tropic cell speed decreased upon EGF stimulation (Fig. 2b). Finally, a pairwise statistical test was used to compare each phenotype measured across each of the ECM surfaces, resulting in an “ECM ordering” (Fig. 2c). As an example, the lung tropic cell line has the statistically highest spreading rate on ECM 3, followed by ECM 1, and is lowest on ECM 2 (Fig. 2c). In contrast, the chemotactic index of the brain tropic cell line was statistically equivalent on all ECMs.

We computed each of these features for all phenotypes and compiled this into a heat map, creating a row for each tropic cell line (Fig. 2d, e and Fig. S4b, ESI†). The color of each box identifies the value of the phenotype for the respective cell line. For the CoV measurement, highly sensitive measurements (CoV < 0.1) are identified with a blue box, while insensitive measurements (CoV > 0.1) are identified with a grey box (Fig. 2d). In Fig. 2e, EGF changes are determined via fold change from the normal measurement. An increase (fold change ≥ 1.15) is red, a decrease (fold change < 0.85) is green, and no change (0.85 ≤ fold change ≤ 1.15) is grey (Fig. 2e). In Fig. S4b (ESI†), for each pairwise comparison, a blue box indicates that the first measurement is greater than the second, a grey box indicates that they are equal, and a red box indicates that the second measurement is greater than the first. Altogether, greater than 1000 individual cell observations per tropic cell line were quantified and compiled together to create sixty-six features of integrin-mediated phenotypes for each tropic cell subpopulation (Fig. 2d, e and Fig. S4b, ESI† rows).

Looking down each column in Fig. 2d, e and Fig. S4b (ESI†), we then identified behaviors that were specific to only one of the three tropic cell lines. These instances are identified by a dark shaded box of the appropriate color. Looking across each row, thirteen measured phenotypes are unique to bone tropism, a separate thirteen features are unique to lung tropism, and fifteen to brain tropism (Fig. 2d, e and Fig. S4b, ESI†). Although no singular adhesion or motility-associated phenotype was predictive of breast cancer tropism (not shown), this collective analysis of many cell responses to ECMs combined to create phenotypic fingerprints of bone, brain, and lung metastasis (Fig. 2d, e and Fig. S4b, ESI†).

We repeated all these measurements using more heterogeneous cell lines with known, literature-reported metastasis in vivo (Fig. 1a), and overlaid each cell line’s pattern of behaviors onto the three fingerprints of tissue-specific metastasis we created (Fig. 2f). The measurements from each cell line can be compared to the tissue-specific fingerprints generated from the tropic cell lines, resulting in a fractional similarity value that represents the amount of unique phenotypic features shared with the cell lines that specifically metastasize to either the bone, brain, or lung (Fig. S5a, ESI†).

As a control, a null distribution of 10 000 cell lines with random phenotypes was generated in silico to represent “random metastasis” (Fig. S5a–d, ESI†). We determined how similar the patterns were between each of the heterogeneous cell lines and the bone, brain, and lung tropic fingerprints (Fig. S5a, ESI†), and represented this as a percentile of the respective null distribution (Fig. 2g).

With this in vitro method, we predicted the in vivo metastasis of seven out of the eight heterogeneous cell lines tested. First, the SUM1315 M02 cell line, which metastasizes highly to bone, most highly matches the bone fingerprint and is clearly anti-brain and anti-lung tropic. Both the MDA-MB-468 and BT549 cell lines metastasize to the lung in vivo, and are clearly lung tropic by our fingerprint. The HER2+ cell line HCC 1954 is lung metastatic and phenotypically lung tropic. The HER2+ MDA-MB-361 cell line was derived from a brain metastasis, metastasizes to the brain in mice, and is comparatively brain tropic by our fingerprint. The parental MDA-MB-231 is spontaneously metastatic to many sites upon orthotopic implantation into the mammary fat pad and intracardiac injection, and metastasizes to the bone more than to the brain or lung through the latter technique. Our fingerprint identified this cell line as highly bone tropic (0.62 fractional similarity, 90th percentile of the randomly generated bone tropism null distribution), significantly greater than the similarity to the brain and lung fingerprints, reflecting this feature of in vivo behavior (Fig. 2g and Fig. S5a, ESI†). We focused on this particular aspect of MDA-MB-231 behavior, as this is the parental cell line from which the bone, brain, and lung tropic cell lines were derived by Massagué. As a non-tropic control, the MCF7 cells are only moderately metastatic, and not tissue-specific, and were not tropic to any one tissue based on our fingerprint. Finally, the HER2+ SkBr3 cells were identified as brain tropic in our approach, but they are not highly tumorigenic or metastatic to the brain or other sites in vivo. HER2-overexpressing tumors often spread to the brain in humans, which may explain the prediction we obtained. However, we would argue that this example shows that this approach, although highly predictive, is not 100% accurate, and is only a predictor of tissue selectivity, not metastatic capability.

When looking more closely, we discovered that the unique features making up each fingerprint are primarily comprised of differential responses to EGF stimulation. In fact, all of the features in the bone tropic fingerprint are related to EGF stimulation, 80% for the brain fingerprint, and 62% for the lung fingerprint. Concurrently, we found that the cell lines with higher EGFR mRNA expression displayed stronger matching to just one of the tropic fingerprints than the cell lines with lower EGFR expression (Fig. 2g and Fig. S5e, ESI†). Using published proteomic data, we discovered a strong correlation between basal EGFR expression in our cell lines and the CoV of the in vitro tropism (Fig. S5e, ESI†), confirming this qualitative trend. Although outside the scope of this study, we speculate that a more exhaustive screen of additional growth factor responses, or across different ECM protein combinations, could
lend even more specificity for this fingerprinting approach, potentially resolving the inconsistency we observed in the SkBr3 cell line.

In sum, we compiled sixty-six features of integrin-mediated phenotypes observed in bone, brain, and lung tropic cell lines into an in vitro fingerprint, which predicted the in vivo metastasis of other more heterogeneous cell lines. We stress that this result was impossible to achieve using any single adhesion or motility measurement, and instead required quantification of patterns of behavior. Because only some singular features of two-dimensional cell behavior can predict responses in a more realistic three-dimensional environment, this requirement was perhaps not surprising. The divergence between two and three-dimensional phenotypes necessitated this new method of analysis to accurately connect measurements made in a two-dimensional context to in vivo outcomes.

Targeting integrin binding on in vitro ECMs reveals the need for subtype-specific analysis

Integrins have been explored as cancer therapeutics in preclinical and clinical trials, but many of these drugs have only shown limited success.42 We hypothesized that this lack of clinical efficacy may be in part from differential responses across the heterogeneity of breast cancer subtypes. Because we are controlling for integrin-binding on our ECM protein-coupled surfaces, our predictive phenotyping platform provides a unique opportunity to investigate integrins as therapeutic targets for metastatic disease. We focused on triple negative and HER2+ cancer, which both have particularly poor prognosis. As proof of concept, we chose MDA-MB-231 as a representative triple negative cell line, and used the SkBr3s to examine HER2+ breast cancer. We focused on integrin subunits with various affinities to the proteins on each of our ECMs: b1, which is involved in binding to many proteins across all the in vitro ECMs; a2, which binds primarily to collagens but also to laminin (collagen is present on ECMs 1 and 3; laminin is present on ECMs 2 and 3); and a6, which specifically binds laminin (present on ECMs 2 and 3).43

We performed the same adhesion and motility experiments from Fig. 1c in the presence of function-affecting antibodies to these three integrins. Targeting the function of each integrin reduced both cell adhesion and migration of the MDA-MB-231 cell line on the three ECMs. When cell adhesion measurements were plotted against cell migration measurements for each antibody of interest (as well as without antibody and with EGF stimulation), the responses clustered together (Fig. 3a and b). This revealed that the MDA-MB-231 cells were overall more sensitive to the antibody treatments and EGF stimulation than they were to the three ECMs. Each antibody had a different potency, resulting in a strong correlation between two measurements of cell adhesion (spreading rate and maximum area) and motility (migration speed and displacement, Spearman correlations and p-values shown in Fig. 3a and b).

This same clustering of responses around each ECM was not observed in the HER2+ SkBr3 cell line. Most surprisingly, treatment with the b1 and a2 integrin antibodies actually caused an increase in ECM sensitivity in these cells. Specifically, the SkBr3 cells migrated faster and farther on the collagen-rich ECM 1 (Fig. 3c and d, arrows) in the presence of both of these function-affecting antibodies. Looking more closely at videos of the cell behaviors, we determined that the increase in motility was caused by complete detachment of individual SkBr3 cells, which would then re-adhere at different locations, essentially hopping along the surface of the biomaterial (Fig. 3e, f and Fig. S6a, Movie S1, ESIF). This behavior resulted in a small population of cells that had abnormally fast migration speeds and long displacements (Fig. 3e, f and Fig. S6a, ESIF). This phenotype was observed most often on ECM 1 in the presence of the b1 and a2 integrin antibodies, and rarely in the three other conditions (Fig. S6b, ESIF). This was never observed in the MDA-MB-231 cells.

This behavior did not resemble traditional adherent cell motility, and we suspected that these weakly-to-non adherent cells might be highly invasive in a 3D context, perhaps resembling an amoeboid-type motility.44 When these same b1 and a2 integrin antibodies were administered to SkBr3 cells that were seeded onto ECM 1 overlaid with a 3D collagen gel, we observed increased upward 3D invasion by three to four fold compared to the control (Fig. 3g and Fig. S6c, ESIF). The SkBr3 cell line has lower integrin protein expression of each of these integrin subunits in comparison to the MDA-MB-231 cell line,45,46 which is potentially responsible for the detachment and invasion phenotypes. However, there were no differences in b1 integrin mRNA expression (Fig. S7a, ESIF), suggesting that a proteomic, but not a genomic analysis could have predicted this result. We propose that the motility and invasion of some cancer cell lines can actually be increased when targeting integrins,47 potentially limiting the efficacy of this class of therapeutics in some patients. The striking differences in antibody responses of the triple negative MDA-MB-231 and HER2+ SkBr3 cell lines highlight the heterogeneity in response to integrin therapeutics observed across different breast cancer clinical subtypes, potentially explaining the limited efficacy of these drugs thus far.

Integrin binding and expression dictates tropism

The b1, a2, and a6 integrin subunits each have a reported role in cancer: high expression of both b1 (ref. 48) and a6 (ref. 49) integrins drives tumorigenicity and metastasis, while a2 integrin is a tumor suppressor.50 Although all three integrins appear important in overall patient prognosis, none have been directly connected with tissue-specific metastasis. Given the results in Fig. 2, where tropic cells shared similar integrin-mediated phenotypes, and Fig. 3, where the triple negative MDA-MB-231 and HER2+ SkBr3 cell lines had divergent responses to integrin targeting, we hypothesized that targeting b1, a2, and a6 integrins could shift the observed in vitro tropism of these cell lines.

We compiled the adhesion and motility measurements for the MDA-MB-231 and SkBr3 cell lines that were performed in the presence of integrin antibodies into our predictive fingerprint. This treatment with integrin antibodies, which lowers the binding ability with these integrin subunits, shifted the tropism predictions of both cell lines (Fig. 4a and b). In the MDA-MB-231 cells,
treatment with any of the integrin antibodies shifted the tropism from bone to brain (Fig. 4a). In other words, blocking binding via $\beta_1$, $\alpha_2$, or $\alpha_6$ integrins made the MDA-MB-231 cells less similar to the bone tropic fingerprint, and instead, they more resembled the brain tropic cell subpopulation (compare the tropism category containing the highest black bar with the tropism category containing the highest colored bars for each integrin). The SkBr3 cells shifted from brain to bone tropic upon $\beta_1$ integrin inhibition, they became equally brain and lung tropic when $\alpha_2$ integrin was blocked, and $\alpha_6$ integrin targeting had no effect (Fig. 4b). Just as we found in Fig. 3, the MDA-MB-231 cell line was far less sensitive to differences in ECM during integrin targeting than the SkBr3 cell line. Interestingly, the only response that was shared between the MDA-MB-231 and SkBr3 cell lines was the “null effect” of targeting $\alpha_2$ and $\alpha_6$ integrins on lung tropism. Overall, these results suggest that targeting any one of these integrins may effectively prevent bone metastasis in the triple negative cell line, while $\beta_1$ integrin may be an efficacious therapeutic target to prevent brain and lung (but not bone) metastasis in the HER2+ cell line.

For this approach to have significant impact, it must be compared with clinical patient outcomes. We analyzed gene expression data from 630 breast cancer patients with known metastatic outcomes (combined from GSE 2034, GSE 2603, GSE 5327, GSE 12276; includes 214 bone metastases, 35 brain metastases, 101 lung metastases). We first determined whether expression of these integrin genes was associated with tissue-specific metastasis in the clinic (Fig. 4c–e), and then compared...
Integrin binding and gene expression predict breast cancer metastasis. Integrin antibodies shift tropic fingerprinting of (a) MDA-MB-231 and (b) SkBr3 cell lines. Compare the tropism containing the highest black bar (normal) with the category containing the highest value for each colored bar (blue: $\beta_1$, red: $\alpha_2$, orange: $\alpha_6$ integrin). (c–e) Magnitude of integrin gene expression dictates (c) bone, (d) brain, and (e) lung metastasis clinically (analysis of GSE 2034, GSE 2603, GSE 5327, GSE 12276). (f) Left, effect of $\beta_1$, $\alpha_2$, and $\alpha_6$ integrin gene expression on clinical metastasis in all patients, only triple negative patients, and only HER2+ patients. Right, effect of $\beta_1$, $\alpha_2$, and $\alpha_6$ integrin antibodies on tropic fingerprint in the MDA-MB-231 (triple negative) and SkBr3 (HER2+) cell lines. Red: high expression or binding predicts for increased metastasis; blue: low expression or binding predicts for increased metastasis; white: no effect. (g) Heat map displaying integrin genes that significantly predict for tissue-specific metastasis in patients. Blue: low expression of the gene predicts for increased risk of metastasis; red: high expression of the gene predicts for increased risk of metastasis; white: no effect on metastasis. Asterisks indicate statistically significant relationships, but other clearly visible trends are included for completeness. Abbreviations: Bo: bone metastasis; Br: brain metastasis; Lu: lung metastasis.

Using published annotations, survival analysis is repeated in these smaller, specific patient populations, the subtype-specific trends in tropism match the behavior of corresponding the cell line we examined (Fig 4f). We want to stress that this latter result was only one of two shared outcomes we found between the triple negative and HER2+ cell lines, highlighting the need for individual analysis of subtypes, as demonstrated in Fig 3.

Interestingly, when this clinical analysis is expanded to examine all integrin subunits, many are associated with metastasis to the brain, bone, or lung, but these same genes are not conserved within the triple negative and HER2+ subtypes.
(Fig. 4g and Fig. S7b, ES1†). Strong examples are α1, α3, and β2 integrins, where altered expression of these genes is correlated with tropism to a specific tissue across breast cancer broadly, but they are not correlated with tropism within these two subtypes. Instead, different integrin subunit genes are correlated with tissue-specific metastasis within each of these subtypes. As two examples, low α8 integrin expression is correlated with bone metastasis in the HER2+ subtype, and high β1 integrin expression is correlated with lung metastasis in the triple negative subtype.

When we compared our in vitro phenotyping approach to this existing gene data set, we found that our in vitro tropism responses imperfectly correlated with these genetic indicators. High β2 expression is associated with poor prognosis, and in our work, targeting β1 integrin makes the MDA-MB-231 cell line much less bone tropic, matching this result (Fig 4a). However, the SdbR3 cell line significantly increased in bone tropism upon targeting β1 integrin, (Fig 4b), and our clinical analysis surprisingly showed that the magnitude of β1 integrin gene expression is not predictive of bone metastasis in patients (Fig 4c). However, the divergent responses of the two candidate cell lines, from different clinical subtypes, combine to match the clinical pattern. Although our β1 integrin targeting results were not predictive of these clinical outcomes, we emphasize that this highlights the divergence expected between a genetic-focused approach and a protein-based, functional approach, as we have taken here.

In sum, we have used a simple integrin-mediated phenotyping approach to predict breast cancer metastasis in a large panel of cell lines, and we implicate β1, α2 and α4 integrin binding in tissue-specific spread distinctly across several disease subtypes, a phenomenon that is prevalent across many integrin gene-tissue combinations in clinical patient populations (Fig. 4g and Fig. S7b, ES1†). Importantly, our integrin targeting results provide many insights not apparent in gene expression data, highlighting the need for functional, protein-centric screens of cell behaviors. We emphasize the utility of this phenotyping approach as quick, bench-top screening tool that can be used to predict in vivo outcomes. Here, we have illustrated this functionality by predicting metastatic outcomes and identifying biomarkers potentially overlooked when analyzing gene data sets from heterogeneous clinical patient populations.

Discussion

Extracellular matrix (ECM) properties, such as tissue stiffness, local growth factors, stromal cells, and ECM proteins, can each individually promote metastasis. However, we are only beginning to understand the role of each of these properties in tissue-specific metastatic colonization. To truly understand the microenvironmental factors that mediate metastasis, each factor must be systematically isolated from other cues, and investigated functionally in a controlled system that closely represents the in vivo microenvironment. While others have used adhesion phenotyping to differentiate metastatic and non-metastatic cells, and tropic subpopulations, these studies have either used end-point analyses or have included multiple convoluted microenvironmental factors. The biomaterial platform we designed overcomes these limitations by mimicking some of the biochemical complexity present in in vivo ECMs, while limiting microenvironmental cues to only those ECM proteins presented by the system, with growth factors supplemented as desired. This can then be used for observing differences in adhesion and motility resulting from differential binding to these multi-protein ECMs.

We propose this system as a potential bridge between the overwhelming complexity of in vivo observations and simple in vitro cell biology, without the need for expensive or lab-specific 3D models. The first challenge we noted was that genomics is the increasingly popular approach for identifying cancer biomarkers due to its ease and increasingly low cost, facilitating large-scale patient-specific analysis. However, gene expression does not necessarily correlate with protein expression or function. Therefore, we attempted to connect gene-centric patient data with a protein-centric cell screening approach. Breast cancer was a suitably complex target to study, as it is a notoriously heterogeneous disease. This heterogeneity may be why integrins were not consistently strong genetic biomarkers across large, diverse patient populations (Fig. 4). Our protein-centered approach mirrored this inconsistency between the SKBr3 and MDA-MB-231 cell lines (Fig. 3 and 4), and we quantified significant differences in cell adhesion and motility between the three MDA-MB-231 tropic subpopulations (Fig. S3, ES1†), which have minimal differences in integrin gene expression (Fig. S7a and c, ES1†).

The immediate conclusion is that differences in gene expression of integrin subunits alone is not sufficient to mediate metastasis to different tissues. This remains an open question, as gene expression of several integrins was strongly correlated with tropic metastasis in patients (Fig. 4g), but most of these integrins have not yet been functionally examined in vivo. For those that have, the in vivo reports we found did not match the clinical correlations in our analysis of the gene data sets. For example, α3β1 integrin binding is known to mediate lung metastasis in rats and mice. However, high α3 integrin gene expression showed only a non-significant correlation with lung metastasis, and only when we isolated the analysis to triple negative patients. Across all subtypes of patients, high α3 integrin gene expression actually more highly correlated with bone metastasis (Fig. 4g). As another example, α3β3 integrin has been linked to bone metastasis in rats, however, β2 integrin gene expression in these data sets does not predict for bone metastasis, and αv integrin gene expression is only more strongly associated with bone metastasis in the triple negative and HER2+ subtypes than across all patients (Fig. 4g). It is important to note that clinical tumor samples contain stroma, are often contaminated with immune cells, fibroblasts, and epithelial cells, and even the best dissection techniques only produce tumor contents near 70%, which could skew genetic analysis. We stress that based on this conflict between our data and the genetic analysis we performed, alongside obvious conflicts between these gene data sets and literature reports,
successful risk assessments of tropic metastasis require an integrated proteomic and genetic approach.

Our results suggest that tropism depends more upon how cells are able to use their integrins to bind to the ECM, rather than variations in gene expression, even in genetically similar cell lines. We propose that this type of functional screen, across many heterogeneous cell lines, and many phenotypes, is independent of these conflicts observed between genetic and proteomic analyses. This is demonstrated by the fact that the bone, brain, and lung tropic phenotypes we obtained were well-conserved across cell lines that share the same preferred metastatic site, but that have very different integrin gene and protein expression (Fig. 2g). As an example, the MDA-MB-231 and SUM1315 M02 cells are both bone metastatic in mice, and both matched our bone fingerprint, even though the MDA-MB-231 cell line has significantly higher surface expression of $\alpha_2$ and $\alpha_3$ integrins, and lower expression of $\alpha_b$/$\beta_3$, than the SUM1315 M02 cell line. Others have shown that metastasis depends upon activation, rather than simply expression, of integrins. It is known that splicing variation of a single integrin can initiate cancer stem cell plasticity and likely impact tropism. Taken together, this suggests that understanding the true role of integrins in mediating tropism requires a functional analysis of how metastatic cells interact with the tissue site, as we have taken here, rather than a limited view of only gene expression profiles.

One study took a similar approach to ours and examined cancer cell behavior on different biomaterial surfaces, but focused on stiffness as the driving force. They found that measurements of cell area were not predictive of metastasis, but there was a weak correlation between both migration and proliferation with metastatic site preference. Upon our own closer examination, their data shows that tropic subpopulation cell areas were more sensitive to the biomaterial environments than the non-tropic subpopulations, consistent with our results (Fig. S4a, ESI†). This suggests that applying our approach to other microenvironment cues, such as material stiffness, would provide further insight into the biophysical regulation of tropism and add another dimension to the fingerprint reported here.

Integrins are attractive therapeutic targets for metastasis because they mediate adhesion to the tissue microenvironment, can confer resistance to treatments, and drive disease progression and stemness. However, integrin-targeted therapeutics have experienced limited clinical success, and some potentially dangerous outcomes have been reported. Others have shown that inhibiting $\beta_1$ integrin can reduce primary tumor growth, but this subsequently promotes lung metastasis by switching the migration mode of triple negative 4T1 mouse breast cancer cells from collective to single cell migration, observed both via knockdown and antibody targeting. Similar to these results, we saw both efficacious and dangerous cell adhesion and motility phenotypes when we targeted integrin binding on our ECMs. $\beta_1$ and $\alpha_2$ integrin antibody treatment on ECM1 prevented spreading, but increased both 2D motility and 3D invasion of the SkBr3 cell line (Fig. 3c–g). In the highly metastatic MDA-MB-231 cell line, our $\beta_1$, $\alpha_2$, and $\alpha_6$ integrin antibodies each reduced adhesion and motility (Fig. 3a and b), but also dangerously increased the phenotypic similarity to brain tropism (Fig. 4a). These dangerous phenotypes may result from plasticity and adaptability of metastatic cells when integrins are targeted, which is potentially responsible, in part, for the lack of clinical success of integrin therapeutics.

These results highlight the known heterogeneity challenge in breast cancer, and there is a ground swell toward personalized therapeutics. As proof of concept toward using our platform for discovery of treatments for metastasis in this heterogeneous disease, we examined cell lines from two clinical subtypes with poor prognosis, and found that they displayed striking differences in response to integrin antibodies. In our fingerprinting results, these cell lines only shared two of nine possible responses to the integrin antibodies, suggesting subtype-specific roles for $\beta_1$, $\alpha_2$, and $\alpha_6$ integrins in bone, brain, and lung metastasis. The MDA-MB-231 tropism was equally affected by each of these integrin antibodies, while the SkBr3 cell line was much more sensitive to $\beta_1$ integrin targeting than to targeting $\alpha_2$ or $\alpha_6$ integrins. Supporting the subtype-specific responses we observed, there is in vivo evidence for distinct roles of the same integrin in tumorigenesis and metastasis in different types of breast cancer. In PyV-MT tumors, $\beta_1$ integrin is required for tumor initiation. However, in mice that also express active erbB2 (HER2), $\beta_1$ integrin is only necessary to mediate lung metastasis, while tumorigenesis is independent of $\beta_1$ integrin. In our work, $\beta_1$ integrin targeting had no effect on the MDA-MB-231 lung tropism, but significantly decreased lung tropism in the HER2+ SkBr3 cell line. However, of the eleven cases where integrin gene expression predicts for tropic metastasis in the clinic, only two were conserved for both the triple negative and HER2+ patient subpopulations (Fig. 4). This indicates that integrins are not conserved biomarkers across the entire heterogeneous patient population, necessitating subtype- or even tumor-specific screening to identify successful integrin therapeutics. We suggest that this type of functional screening would be capable of identifying efficacious tumor-specific therapeutics, providing additional insight in combination with current genetics-based approaches.

Conclusions

Here, we developed a simple, yet robust in vitro biomaterial platform that allowed us to quantify many different cell phenotypes associated with adhesion and motility in order to take a comprehensive view of how integrin–ECM interactions regulate bone, brain, and lung metastasis. Importantly, these results would not have been realized by simply looking at individual measurements, and required us to instead quantify patterns of measurements. This compiled pattern of measurements created a phenotypic fingerprint, which is dependent only on integrin binding to the ECM, and can predict integrin-mediated metastatic spread in cell lines. Our results suggest that targeting integrins across the heterogeneous breast cancer clinical subtypes is not appropriate (Fig. 3 and 4), potentially explaining the
lack of success of integrin-targeted therapeutics thus far. Importantly, our results are largely independent of integrin gene or protein expression, highlighting the need for this type of functional approach, particularly when comparing among different breast cancer subtypes. We emphasize the utility of this biomaterial platform to screen integrin-ECM interactions rapidly and reproducibly, and by collectively quantifying patterns of phenotypes en masse, the ability to predict in vivo fate with a simple in vitro approach.

Materials and methods

Cell culture

Human breast cancer cell lines MDA-MB-231, BT549, MCF7, and SkBr3 were generous gifts from Shannon Hughes at the Massachusetts Institute of Technology. Highly metastatic MDA-MB-231 variants, isolated from in vivo selection, were kindly provided by Joan Massagué.2–4 These cell lines preferentially metastasize to the bone (1833 BoM), brain (831 BrM2a) or lung (4175 LM2). All were routinely cultured in Dulbecco’s Modified Eagle’s Medium supplemented with 10% fetal bovine serum (FBS), 1% penicillin–streptomycin (P/S), 1% v–glutamate, and 1% non-essential amino acids. The MDA-MB-361, SUM1315 M02, MDA-MB-468, and HCC 1954 cell lines were provided by Mario Niepel at Harvard Medical School. SUM1315 M02 cells were cultured in Ham’s F-12 medium supplemented with 5 mg ml⁻¹ insulin, 10 ng ml⁻¹ EGF, 10 mM HEPES, 10% FBS, and 1% P/S. MDA-MB-361 cells were cultured in Leibovitz’s L-15 medium with 20% FBS and 1% P/S. MDA-MB-468 cells were cultured in Leibovitz’s L-15 medium with 10% FBS and 1% P/S. HCC 1954 cells were cultured in RPMI medium with 10% FBS and 1% P/S. With the exception of the MDA-MB-361 and MDA-MB-468 cells, which were cultured without supplemental CO₂, all cell lines were cultured at 37 °C and 5% CO₂. All cell culture supplies were purchased from Life Technologies (Carlsbad, CA).

Preparation of ECMs

Glass coverslips (15 mm and 18 mm diameter, Fisher Scientific, Agawam, MA, USA) were oxygen plasma treated (Harrick Plasma, Ithaca, NY, USA), and silanized through vapor phase deposition of (3-aminopropyl)triethoxysilane (Sigma-Aldrich, St. Louis, MO, USA) at 90 °C for a minimum of 18 hours.55 The coverslips were rinsed sequentially in toluene (Fisher Scientific), 95% ethanol (Pharmco-AAPER, Brookfield, CT, USA), and water, and dried at 90 °C for one hour. They were then functionalized with 10 g L⁻¹ N,N,N′,N′-disuccinimidyl carbonate (Sigma-Aldrich) and 5% v/v disopropylcarbodiimide (Sigma-Aldrich) in acetone (Fisher Scientific) for two hours.66 Coverslips were rinsed three times in acetone and air-dried. ECM protein cocktails were then covalently bound to the glass coverslips through reactive amines,67 using cocktails that were inspired by the ECM of secondary sites as follows: ECM 1 (bone): 5 mg cm⁻² of 99% collagen I and 1% osteopontin; ECM 2 (brain): 1 mg cm⁻² of 50% fibronectin, 25% vitronectin, 20% tenasin C, and 5% laminin; and ECM 3 (lung): 2 mg cm⁻² of 33% laminin, 33% collagen IV, 15% collagen I, 15% fibronectin, and 4% tenasin C (all weight%). Rat-tail collagen I and natural mouse laminin were purchased from Life Technologies; human tenasin C, human vitronectin, and human osteopontin from R&D Systems (Minneapolis, MN, USA); human collagen IV from Neumorphics (Edina, MN, USA); and human plasma fibronectin from EMD Millipore (Billerica, MA, USA). Coverslips were incubated with proteins at room temperature for three hours, then with 10 ng cm⁻² MAPEG₁₂₄ (Thermo Scientific, Rockford, IL, USA) for two hours to block non-specific protein adsorption on any remaining surface area.

An ELISA was used to quantify coupling of collagen III (Fig. S1, ESI†, 0, 1, 10 and 50 ng cm⁻²; Fibrogen, San Francisco, CA, USA). Surfaces were blocked with 10 mg ml⁻¹ BSA (Fisher Scientific) for 1 hour, reacted with 1 : 200 primary antibody (Santa Cruz Biotechnology, Dallas, TX, USA) for 1.5 hours, and then 1 : 200 HRP-conjugated secondary antibody (Abcam, Cambridge, MA, USA) for 1 hour at room temperature, rinsing four times with PBS in between each step. Coverslips were incubated with 0.1 M sodium acetate (pH 5.5) containing 1 mg ml⁻¹ 3,3′,5,5′-tetramethylbenzidine (Sigma-Aldrich) and 0.05 wt% hydrogen peroxide (Fisher Scientific) and the reaction proceeded for 30 minutes, then was stopped with 1 M H₂SO₄ (Sigma-Aldrich). The absorbance at 450 nm was read immediately (Biotech ELx800, Winooski, VT, USA).

Cell adhesion and polarization

Cells were seeded at 4000 cells per cm² in growth medium, medium supplemented with 40 ng ml⁻¹ epidermal growth factor (EGF, R&D Systems) immediately, or with antibody pre-treatment, which occurred for 30 minutes prior to seeding. Anti-β₁ integrin (clone PS52, R&D Systems) was used at 0.83 mg ml⁻¹, and anti-α₂ and anti-α₆ integrins were used at 3.3 mg ml⁻¹ (α₂: clone PSE6, α₆: clone NK1-GoH3, both from Millipore). Cell adhesion was captured through imaging cells beginning 10 minutes after seeding in an environment-controlled Zeiss Axio Observer Z1 microscope (Carl Zeiss, Oberkochen, Germany) using an AxioCam MRm camera and an EC Plan-Neofluar 20× 0.4 NA air objective. Images were taken using AxioVision (Carl Zeiss) at five-minute intervals for a minimum of 2 hours until cells had reached steady-state. ImageJ (National Institutes of Health, Bethesda, MD, USA) was used to trace cell areas using the built-in measurement function. Spreading rate was defined as the slope of the linear portion of the area versus time graph during initial adhesion. Individual cells were marked when they had polarized, and the fraction of cells that had polarized at 2 hours post-seeding was quantified for comparison across conditions. Cells that contacted other cells, underwent division or apoptosis, or were not fully in frame were excluded. N ≥ 2 independent biological replicates, N ≥ 40 cells per condition.

Cell migration

Cells were seeded at 4000 cells per cm² and given 18 hours to adhere in growth medium. Seeded cells were treated with a live-cell fluorescent dye (CMFDA, Life Technologies), and then
provided fresh medium or medium supplemented with EGF and/or integrin antibodies (as described above) 4 hours prior to microscopy. Brightfield and fluorescent images were taken at 15 minute intervals for 12 hours using an EC Plan-Neofluar 10x 0.3 NA air objective (Carl Zeiss). Cells were tracked using Imaris (Bitplane, St. Paul, MN, USA) to generate individual cell paths. Individual cell speeds were determined by calculating a speed at every 15 minute time interval, then averaging these over the entire 12 hours. Displacement was defined as the net change in position of the cell over the total time. Chemotactic index is the ratio of a cell’s net displacement to path length. Individual cell average speeds, net displacements, and chemotactic indices were then averaged to determine a mean population value. Cells that contacted other cells, underwent division or apoptosis, or were not fully in frame for the entire 12 hours were excluded. N>2 independent biological replicates, N>90 cells per condition.

Fingerprinting

We quantified adhesion and migration phenotypes for the three tropic subpopulations, both under normal and EGF-stimulated conditions. To create phenotypic fingerprints, first, we calculated the CoV (standard deviation divided by average, calculated for final mean values for one measurement across the three ECMs) for each tropic cell line to determine their ECM-sensitivity in each parameter (a CoV greater than 0.1 was considered ECM-sensitive; Fig. 2a and d). Second, we quantified the fold-change in these metrics in response to EGF stimulation on each ECM (fold-changes greater than 1.15 or less than 0.85 were defined as significant; Fig. 2b and e). Finally, we did all pairwise statistical comparisons across ECMs (via a one-way ANOVA, described below), and quantified ordering of values (i.e., for normal speed measurements, was ECM 1 greater than, equal to, or less than ECM 2; Fig. 2c and Fig. S4b, ESI†). We then compiled this data to create a fingerprint of the 66 phenotypes associated with a specific tissue preference (Fig. 4d and e and Fig. S4b, ESI†). Upon comparison of each phenotype across the three tropic subpopulations, only those phenotypes which were identified in just one tropic cell line were retained, and all phenotypes shared in two or three of the cell lines were ignored (Fig. 4b–e, and Fig. S4b, ESI† dark colors). To validate these fingerprints, we calculated these same criteria for other cell lines with known in vivo metastasis. We then overlaid these patterns onto each tropic fingerprint, and quantified the fractional similarity between each cell line and the unique phenotypes within these fingerprints (Fig. 2g and Fig. S5a, ESI†).

Null distributions of bone, brain, and lung tropisms were generated via a custom code written in MATLAB R2012a (The MathWorks, Inc., Natick, MA). 10 000 random cell line phenotypes were generated and were compared with the unique features of the bone, brain, and lung fingerprints to obtain tropism similarity values. The distributions were ordered, percentiles assigned, and then the heterogeneous cell lines were compared with each of these null distributions, matching their similarity with the percentile associated with this same similarity in the appropriate null distribution. Because our distributions were comprised of 10 000 cells with only 13 or 15 possible discrete values, each percentile for a cell line had a range, illustrated via the error bars in Fig. 2g. Cell lines in the top or bottom 5% of the ordered distributions were considered to be significantly higher or lower than the null distribution. Specifically, the lowest and highest 500 randomly generated cells had p<0.05.

Collagen gel invasion

Cells were seeded at 600 cells per cm² in normal growth medium and given 12 hours to adhere. Collagen gels (2 mg ml⁻¹) were made by mixing 5% v/v 1 M NaOH (Fisher Scientific), growth medium and type I collagen (Life Technologies) on ice. The medium was removed from the seeded coverslips, and gel solutions were overlaid onto the cells. Gelation proceeded for 30 minutes at 37 °C and 5% CO₂, then 250 ml growth medium was added to each well. EGF and integrin antibodies were included in the gel solution and the supernatant medium as described above. For accurate comparisons, an equal number of randomly selected positions were observed in all conditions. N=2 independent biological replicates, each with three technical replicates, and 25 positions were imaged per technical replicate.

Gene expression analysis

Gene expression data from primary breast tumors (GSE 2034, GSE 2603, GSE 5327, and GSE 12276) was retrieved from the NCBI Gene Expression Omnibus (GEO) database. Each was RMA normalized using the R platform (Vienna, Austria).68 Datasets were cross-mapped based upon common probes, and batch effects were corrected with an Empirical Bayes method using the ComBat algorithm in R.69 Genes represented by more than one probe were collapsed to the probe with the highest mean value. For metastasis-free survival analysis, patients with known metastasis and clinical subtype information were classified into groups of high and low gene expression based upon median expression. Published survival and clinical subtype information was used.55 Survival was analyzed in Prism v6.0b (GraphPad Software, La Jolla, CA, USA), and significance was evaluated using a log-rank (Mantel–Cox) test. To analyze integrin expression in the tropic cell lines, GSE 2603 and GSE 12237 were retrieved from the NCBI GEO database, RMA normalized, combined using the ComBat algorithm as previously described, and data corresponding to the cell subpopulations used here (1833, BrM2a, and 4175) were extracted. Individual integrin genes were extracted, values were collapsed to the probe with the highest expression, and a heat map was generated in R.

Reverse-transcriptase PCR

Cells were seeded at 40 000 cells per cm² and allowed to adhere to coverslips or tissue culture plastic for a minimum of 18 hours. Coverslips or wells were washed with PBS prior to detaching cells with 0.05% trypsin–EDTA (Life Technologies). Total RNA was extracted using the Genelute Mammalian Total RNA kit (Sigma).
followed by cDNA synthesis using the RevertAid reverse transcriptase protocol, with the exception of using RNasein 40 U mL⁻¹, (Promega, Madison, WI) as the RNase inhibitor. The amplification was carried out with Jumpstart Taq polymerase according to the manufacturer’s instructions using a BioRad MJ Mini Personal thermal cycler (Hercules, CA). Primer sequences (Integrated DNA Technology, Coralville, IA) were as follows:

GAPDH (NM_001256799.1) forward 5’-CACGACAGTTGGCAGTGTT-3’
reverse 5’-CATGGAGAGGCCCTAGGCTC-3’
Integrin b1; (NM_0022113) forward 5’-GTTGGGTCTAC
GGGAACTT-3’
reverse 5’-GTCTTACACACCGCCCTCA-3’
Integrin a2; (NM_002203.3) forward 5’-CTGGTGTAGCC
GCTCAGTCA-3’
reverse 5’-CCAGGCTGAACCAGACGTA-3’
Integrin a6; (NM_001079818.1) forward 5’-CGAGGACAAGG
GCCGTGTT-3’
reverse 5’-TGACCCCCATCCACTGATCTTGC
EGFR (NM_005228.3) forward 5’-CTTCCGGAGGACGGCATG-3’
reverse 5’-CAGGCTCTCAGTCCGTTT-3’

Each reaction was analyzed on a 1% agarose gel with ethidium bromide staining, then visualized under ultraviolet light using the IN Sygnee Bioimaging platform (Frederick, MD). GAPDH was used as a housekeeping gene. N ≥ 2 independent biological replicates.

Statistical analysis and correlations
Statistical analysis was performed using Prism v6.0b. Data are reported as mean ± standard error. Statistical significance was evaluated using a one-way analysis of variance, followed by a Tukey’s post-test for pairwise comparisons. Significance between proportions (i.e., fraction of cells polarized) was evaluated with a Fisher’s exact test with two-tailed p-values. To determine significance between slopes (i.e., spreading rate), an analysis of covariance was used, with a one-way analysis of variance for multiple comparisons, defining the sample size as the degrees of freedom plus one. Spearman correlations were calculated from mean values paired by condition, and significance was determined using two-tailed p-values. p ≤ 0.05 was considered statistically significant. p ≤ 0.05 is denoted with *, r ≤ 0.01 with **, r ≤ 0.001 with ***; p ≥ 0.05 is considered not significant (’ns').

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Notes and references

68 R Core Team, 2014.