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Evidence for Menu Cost Models

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How Prices Change in a High-Inflation Economy: Evidence for Menu Cost Models*

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Abstract

This paper provides evidence on two features of menu-cost pricing in a high-inflation economy. Using Iranian consumer price quotes from 2006–2022 and generalizing the inflation decomposition method from Klenow and Kryvtsov (2008), we find that 78% of the variance of inflation is explained by the covariance between the frequency and the size of price changes, while the frequency and the size margins on their own are comparatively small. The results suggest that aggregate shocks and selection are central to price adjustment in high inflation and help distinguish among menu-cost models in high-inflation environments.

Keywords: inflation decomposition, Selection effect, inflation volatility, price rigidity, menu cost
JEL Classification: E31, E52

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1 Introduction

High and volatile inflation provides a natural laboratory for studying which pricing rules are relevant in practice. A large empirical literature has compared time-dependent and state-dependent pricing models and has documented a broad set of facts on pricing behavior. This literature shows that in low-inflation environments, both time-dependent and state-dependent models can account for some aspects of the evidence, but in high-inflation environments the explanatory power of state-dependent models becomes more pronounced.[1] Much less attention has been paid to distinguishing between different *state-dependent* specifications, in particular between menu-cost models that differ in the role of idiosyncratic shocks and in the mechanisms that generate selection, such as the shape of the hazard function. This distinction matters for both theory and policy: different menu-cost models deliver different implications for how inflation shocks are transmitted and for how costly it is to stabilize inflation.

In this paper we study pricing behavior in Iran over 2006–2022, a period characterized by high and volatile inflation. Using a large micro dataset of monthly consumer price quotes, we examine how the frequency and the size of price changes contribute to fluctuations in inflation. Our analysis builds on two complementary decomposition approaches. First, we replicate the inflation decomposition of Klenow and Kryvtsov (2008) as a benchmark and highlights where its approximation breaks down in a high-inflation environment. Second, we develop and implement an exact item-level decomposition of inflation variance that separates the contributions of the intensive margin (IM), the extensive margin (EM), the covariance between frequency and size, and a within-item interaction term. This framework allows us to quantify how each margin contributes to inflation variability and to assess which features of state-dependent pricing models are most consistent with the data.

The decomposition in Klenow and Kryvtsov (2008) is a natural starting point for thinking about how the frequency and the size of price changes contribute to inflation changes. In their low and relatively stable inflation sample for the United States (1988-2005), the resulting variance decomposition can be matched by both time-dependent and state-dependent pricing models, so it does not sharply discriminate between them. Moreover, the framework groups the covariance between frequency and size, as well as higher-order terms, with the EM, which is innocuous when these components are small but becomes problematic when they are not. In a high-inflation environment, these components

[1] For example, see Bils and Klenow (2004), Nakamura and Steinsson (2008), Klenow and Kryvtsov (2008), Gagnon (2009), Alvarez et al. (2019), and Karadi et al. (2024).

can become quantitatively important. Therefore, we generalize their decomposition to a setting in which the covariance between frequency and size is treated as a separate margin and the contribution of each component can be measured without relying on assumptions that are specific to low-inflation economies.

Using our generalized decomposition, we find that the covariance margin explains almost 80% of the variance of inflation, whereas the IM and EM together account for roughly 12% and the remaining components are small. This pattern indicates that, in a high-inflation environment, aggregate shocks increase both the frequency and the size of price changes. It also suggests the presence of selection: following aggregate shocks, the outlets that adjust are those with larger price gaps, and they change their prices by larger amounts.

These findings support two key features of menu-cost models in high-inflation environments. First, the dominant role of the covariance margin is consistent with menu-cost models in which aggregate shocks, rather than idiosyncratic shocks, are the main drivers of pricing decisions. Alvarez et al. (2019) show theoretically when aggregate shocks are very large, as under hyperinflation, the effect of idiosyncratic shocks on pricing behavior becomes negligible, even in frameworks that allow for both types of shocks. In this sense, in a high-inflation environment it can be a reasonable simplification to model menu costs without idiosyncratic shocks, which also reduces the computational burden. Second, following Karadi et al. (2024), the covariance between the frequency and the size of price changes can be interpreted as evidence of selection, so that in high-inflation conditions our results point to selection mechanisms playing an important role.[1]

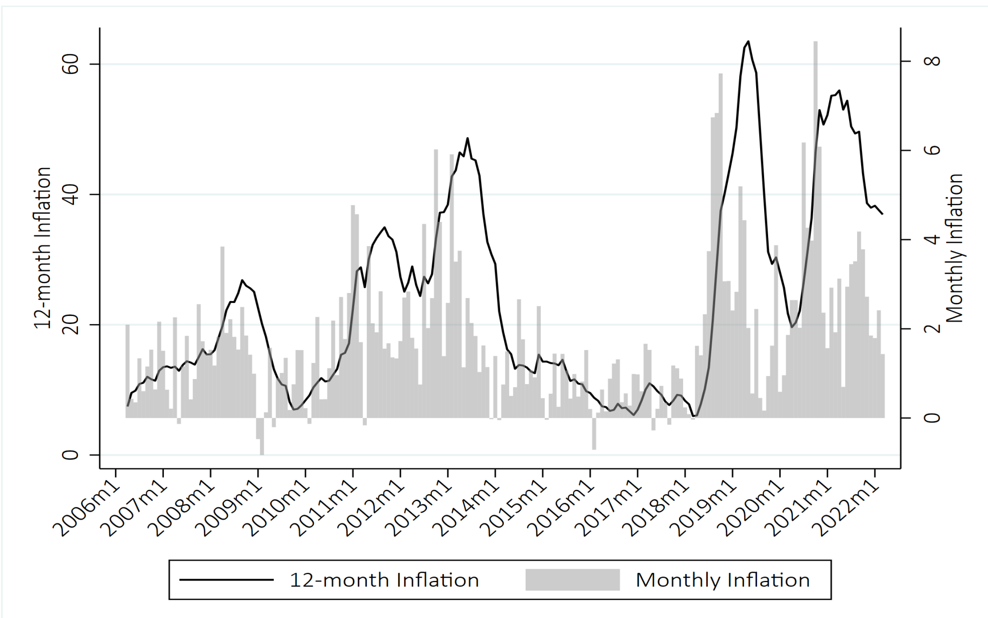
2 Data and Evidence

In this paper, we use consumer price quotes for Iran covering the period 2006–2022, collected by the Statistical Center of Iran (SCI) for urban areas. The dataset includes 453 items, accounting for approximately 66% of household expenditure (excluding rent). The SCI survey covers all 31 provinces and includes more than 310,000 retail outlets and 1.6 million product–outlet price trajectories over time. In total, our sample contains over 37 million individual price quotes. Further details on data collection, structure, and cleaning are provided in Aziminia et al. (2024).

[1]We do not estimate structurally the model in Caballero and Engel (2007) or Karadi et al. (2024). Our approach is based on a reduced-form variance decomposition of inflation over time. We use the distinction between gross and narrow EMs in Karadi et al. (2024) only as a conceptual guide to interpret the covariance between the frequency and the size of price changes, as discussed in the methodology and results sections.

Iran experienced substantial inflation volatility over the sample period, making it a natural case for studying pricing behavior in a high-inflation environment. Between 2006 and 2022, the mean monthly inflation rate was 1.77%, corresponding to an average 12-month inflation rate of about 23%. Although inflation was persistently high, it also fluctuated sharply: the standard deviation of monthly inflation was 1.57 percentage points, with individual months ranging from –0.82% to 8.44%. Figure 2 displays the evolution of both monthly and 12-month inflation over this period.

Figure 1: Monthly and 12-month inflation in Iran, 2006–2022



Notes: Inflation rates are based on the monthly and 12-month growth of the SCI urban CPI, excluding housing rent.

To characterize pricing behavior, we focus on two standard measures: the *frequency* and the *size* of price changes. At the outlet level, we define the frequency of price changes as the fraction of items whose price differs from the previous month, and the size of price changes as the average size of nonzero price changes.[1] We then aggregate these measures to the product-month level by averaging across outlets, and finally construct aggregate indices by taking CPI-expenditure-weighted averages across products.

Figure 2 summarizes the joint behavior of these two margins. Each point represents a month, with the horizontal and vertical axes showing the aggregate frequency and size of price changes, respectively, and the color indicating the level of monthly inflation. The

[1]Calculating price changes in percentage points, as in Wulfsberg (2016), or in log differences, as in Klenow and Kryvtsov (2008), does not materially change the pattern of results. We report results based on percentage-point changes.

Figure 2: Frequency and size of price changes across monthly inflation levels

Notes: Each point represents a month. The horizontal and vertical axes show the CPI-expenditure-weighted mean frequency and size of price changes across products. The color of each point indicates the level of monthly urban CPI inflation (excluding housing rent), with yellow corresponding to lower inflation and red to higher inflation.

Table 1: Pairwise correlations between frequency, size, and inflation

	Size of price changes	Frequency of price changes	Monthly inflation
Size of price changes	1.00		
Frequency of price changes	0.71*	1.00	
Monthly inflation	0.78*	0.76*	1.00

Notes: Frequency and size of price changes are calculated as CPI-expenditure-weighted means across products. Monthly inflation is calculated as the growth rate of the urban CPI (excluding housing rent). * denotes significance at the 1% level.

figure shows that months with higher inflation tend to combine both higher frequency and larger size of price changes. This pattern is confirmed in Table 1, which reports pairwise correlations between monthly inflation, the aggregate frequency of price changes, and the aggregate size of price changes. All three series are strongly positively correlated, suggesting that higher inflation is associated with joint movements in both margins rather than with changes in only one margin.

3 Methodology

The starting point for our analysis is the standard decomposition of inflation into two components: an extensive margin (EM), capturing variation in the frequency of price changes, and an intensive margin (IM), capturing variation in the size of those changes. Both margins are present in time-dependent and state-dependent pricing models, but they respond differently to shocks. In time-dependent models, where the timing of price adjustment is largely exogenous, shocks mainly affect the IM. In menu-cost, state-dependent models, shocks also change the probability of adjustment, so the EM and its interaction with the size margin play a more prominent role.

To explore the roles of the IM and EM in inflation movements, we follow Klenow and Kryvtsov (2008) and decompose the variance of inflation into contributions from the frequency and the size of price changes. Let π_t denote monthly inflation, fr_t the aggregate frequency of price changes, and Δp_t the aggregate size of price changes in month t. The starting point is the identity $\pi_t = fr_t \Delta p_t$, which expresses inflation as the product of the frequency and the size of price changes at the aggregate level. A first-order Taylor expansion of π_t around the mean values of fr_t and Δp_t, followed by taking the variance over time, yields

$$\mathrm{var}(\pi_t) = \underbrace{\mathrm{var}(\Delta p_t)\, \bar{fr}^2}_{\text{IM term}} + \underbrace{\mathrm{var}(fr_t)\, \bar{\Delta p}^2 + 2\, \bar{fr}\, \bar{\Delta p}\, \mathrm{cov}(fr_t, \Delta p_t) + O_t}_{\text{EM term}}, \tag{1}$$

where bars denote time averages and O_t collects higher-order terms from the Taylor expansion. In this decomposition, the first term, $\mathrm{var}(\Delta p_t)\, \bar{fr}^2$, captures the contribution of the IM, while the second term, $\mathrm{var}(fr_t)\, \bar{\Delta p}^2$, captures the contribution of the EM. Klenow and Kryvtsov (2008) show that, in their low-inflation data, the covariance term and the higher-order term O_t are quantitatively small and can be largely subsumed under the EM for interpretation.

In a high-inflation environment such as Iran, applying the variance decomposition in equation (1) can generate sizable contributions from the covariance term and from the higher-order term O_t. The approximation in Klenow and Kryvtsov (2008) that these components are negligible is therefore no longer valid. Moreover, while the covariance term has a clear interpretation, the higher-order term O_t is a remainder from the Taylor expansion with no simple economic meaning. To avoid relying on such a residual term, we follow the same logic but start from a more general inflation identity at the item level. Let

w_i denote the CPI expenditure weight of item i. We can write aggregate inflation as

$$\pi_t = \sum_i w_i \, fr_{it} \, \Delta p_{it},$$

where fr_{it} and Δp_{it} are the frequency and size of price changes for item i in month t. Taking the variance over time on both sides yields

$$\operatorname{var}(\pi_t) = \underbrace{\sum_i w_i^2 \operatorname{var}\big(fr_{it} \, \Delta p_{it}\big)}_{\text{within-item component}} + \underbrace{\sum_{j \neq z} w_j w_z \operatorname{cov}\big(fr_{jt} \, \Delta p_{jt}, \, fr_{zt} \, \Delta p_{zt}\big)}_{\text{cross-item covariance component}} . \quad (2)$$

This identity decomposes the variance of inflation exactly into a weighted sum of within-item variances and a cross-item covariance component, without leaving a Taylor-residual term. In what follows, we focus on the within-item component and further decompose $\operatorname{var}(fr_{it} \, \Delta p_{it})$ into contributions from the IM, the EM, and their covariance at the item level, while treating the cross-item component as a separate term that we report but do not further break down.

By expanding the within-item component in equation (2), we obtain a decomposition of the variance of inflation into four economically interpretable parts at the item level: an IM component, an EM component, some terms capturing the covariance between the frequency and the size of price changes, and a small within-item interaction term. Aggregating across items with CPI weights yields the schematic expression

$$\operatorname{var}(\pi_t) = \sum_i w_i^2 \big(\mathrm{IM}_i + \mathrm{EM}_i + \mathrm{Cov}_i + \mathrm{Int}_i\big) \; + \; \mathrm{CrossItem}, \quad (3)$$

where Cov_i denotes the item-level contribution of the covariance between frequency and size, and CrossItem corresponds to the cross-item covariance component in equation (2). The exact algebraic expression for this decomposition, including all terms, is provided in Appendix A[1].

To interpret the covariance between the frequency and the size of price changes in terms of pricing models, we follow the framework in Karadi et al. (2024). Building on the decomposition in Caballero and Engel (2007), they split the EM into two parts. The first, which they label the gross EM, captures the effect of a higher frequency of price changes when the additional price changes occur with the historical average size. The second, the narrow EM, captures the effect of a higher frequency of price changes when the additional

[1] All variances and covariances in equations (1) and (3) are computed over the full monthly sample from 2006 to 2022.

price changes are larger than the historical average size among adjusters and is interpreted as a selection margin. In their model, selection arises because aggregate shocks move outlets with large price gaps above the adjustment threshold, so that the outlets that start adjusting after a shock also have larger optimal price changes.[1]

This perspective suggests a natural interpretation of the covariance term in our decomposition. In a time-dependent model, where the adjustment hazard is largely independent of the price gap, we expect aggregate shocks to show up mainly in the IM, and the covariance between frequency and size should be limited. In a menu cost model with selection, large aggregate shocks both increase the share of outlets that adjust and raise the size of their price changes, generating a positive covariance between frequency and size. In this view, a large EM and a sizable covariance term are more consistent with state-dependent pricing, such as menu-cost models. Moreover, the shares of the EM and, in particular, the covariance term in equation (3) provide evidence on the strength of selection and on the shape of the menu-cost mechanism: a small covariance term is consistent with weak selection and price changes drawn from across the price-gap distribution, whereas a large covariance term indicates that adjusters are disproportionately drawn from the tails of the price-gap distribution, near the adjustment boundary.

4 Results

We begin by replicating the inflation decomposition for Iran using the methodology in Klenow and Kryvtsov (2008), equation (1). Klenow and Kryvtsov (2008) report that in the United States over 1988–2005, the IM explained 94% of the variance of inflation, while the remaining 6% was attributed to the EM, including the covariance and higher-order terms. Applied to our data, the IM accounts for only 22.5% of the variance of inflation. In the baseline interpretation of Klenow and Kryvtsov (2008), the covariance between the frequency and the size of price changes, together with the second-order terms from the Taylor expansion, are grouped with the EM. If we separate these components and compute each term individually, as reported in Table 2, the EM accounts for 17.5%, the covariance term for 28.5%, and the remaining 31.5% reflects the higher-order residual. Taken together, these results suggest that in an environment with high and volatile inflation, the

[1] The decomposition in Caballero and Engel (2007) is structural and defined in terms of price gaps and the response of pricing to shocks, whereas our approach follows Klenow and Kryvtsov (2008) and is based on a variance decomposition of inflation over time. The objects are not identical, but both frameworks distinguish between contributions coming from the EM and from selection within state-dependent pricing models. We do not estimate the structural models in Caballero and Engel (2007) or Karadi et al. (2024); instead, we use the distinction between gross and narrow EM in Karadi et al. (2024) to interpret the covariance between the frequency and the size of price changes in our decomposition.

approximation that the covariance and higher-order terms are negligible no longer holds, and a more general decomposition framework is needed to quantify the contribution of each margin.

Table 2: Inflation decomposition using the Klenow and Kryvtsov (2008) formula

	IM	EM	CM	Residual
US (1988-2005)	94	6		
Iran (2006-2022)	22.5	17.5	28.5	31.5

Notes: This table reports the variance decomposition of monthly inflation using the formula in Klenow and Kryvtsov (2008). For the US sample (1988–2005), the IM share and the combined contribution of the EM, the covariance term, and higher-order terms are taken from Klenow and Kryvtsov (2008). For Iran (2006–2022), *IM* denotes the share of the intensive margin, *EM* the extensive margin term, *CM* the covariance margin between the aggregate frequency and size of price changes, and *Residual* the contribution of higher-order terms from the Taylor expansion. All entries are expressed as percentages of the variance of inflation.

We next apply our decomposition in equation (3) to Iranian data. Table 3 reports the contributions of the IM, EM, the covariance term, the within-item interaction term, and the cross-item component to the variance of inflation. The covariance term is the dominant source of variation, accounting for almost 80% of the variance of inflation, while the IM and EM together explain about 12%. The interaction term contributes around 5%, and the cross-item component accounts for only about 4%. This pattern indicates that, in a high-inflation environment, most of the variability in inflation arises from periods in which the frequency and the size of price changes move together, rather than from movements in either margin in isolation.

Table 3: Inflation variance decomposition based on equation (3)

	IM	EM	Cov	Int	CrossItem
Iran, 2006–2022	7	5.5	78.5	5	4

Notes: This table reports the decomposition of the variance of monthly inflation for Iran over 2006–2022 implied by equation (3). *IM* and *EM* denote the aggregate contributions of the intensive and extensive margins, *Cov* is the contribution of the covariance between the frequency and the size of price changes, *Int* is the within-item interaction term, and *CrossItem* is the cross-item covariance component. All entries are expressed as percentages of the variance of inflation and are rounded to one decimal place.

How do these results guide us about pricing decision rules? The decompositions based on equation (3) and on the Klenow and Kryvtsov (2008) formula in Table 2 both indicate that, in a high-inflation environment, the predictions of menu cost models are closer to the data than those of time-dependent models. This is consistent with previous evidence in Alvarez et al. (2019), Gagnon (2009), and Wulfsberg (2016). The more novel question is what these findings imply for the *shape* of menu cost models and how they help distinguish between different versions of state-dependent pricing.

Our results help in understanding menu cost pricing in high inflation economies in two related ways. First, a large covariance between the frequency and the size of price changes is a prediction of models such as Sheshinski and Weiss (1977), where aggregate shocks are the main driver of pricing and idiosyncratic shocks are absent. In such models, an aggregate shock like inflation raises both the probability of adjustment and the desired size of price changes, generating a positive covariance between the two margins. Alvarez et al. (2019) show that when aggregate shocks are very large, as under hyperinflation, the role of idiosyncratic shocks is greatly reduced and pricing behavior is effectively driven by aggregate conditions, even in a framework such as Golosov and Lucas Jr (2007) that allows for both aggregate and idiosyncratic shocks.

Second, following Karadi et al. (2024), we interpret the covariance between the frequency and the size of price changes as a proxy for the presence of selection. In their framework, the distinction between gross and narrow EM isolates the contribution of selection within state-dependent pricing. In our setting, the dominant role of the covariance term in the decomposition suggests that, in a high-inflation environment, selection plays an important role: periods with higher inflation are precisely those in which more outlets adjust and the average size of their price changes is larger.

Taken together, these two points suggest that in a high-inflation environment, menu cost models without idiosyncratic shocks, such as Sheshinski and Weiss (1977), may provide a good approximation and can reduce the computational complexity of the analysis. At the same time, assumptions that effectively shut down selection are difficult to reconcile with the data, as they would downplay the joint movement in the frequency and the size of price changes that appears to be central in our decomposition.

5 Conclusion

This paper has examined how the frequency and the size of price changes contribute to inflation changes in a high-inflation economy. Using detailed micro price data from Iran over 2006–2022, we first replicated the standard decomposition of Klenow and Kryvtsov (2008) and showed that the approximation underlying their framework breaks down when inflation is high and volatile. We then implemented an exact item-level decomposition that separates the contributions of the intensive margin, the extensive margin, their covariance, a within-item interaction term, and a cross-item component. Our results show that the covariance between the frequency and the size of price changes dominates the variance of inflation, while the other components play comparatively limited roles.

These findings shed light on the types of state-dependent pricing models that are most relevant in high-inflation settings. The dominance of the covariance margin is consistent with menu-cost models in which aggregate shocks play the central role and the influence of idiosyncratic shocks is limited, as suggested by the theoretical results in Alvarez et al. (2019). The evidence also points to the importance of selection, in the sense that firms adjusting after aggregate shocks tend to have larger price gaps and adjust by larger amounts. Taken together, our results indicate that simplified menu-cost models that emphasize aggregate shocks and selection may provide a tractable and empirically grounded description of pricing behavior in high-inflation economies, with implications for understanding inflation dynamics and for evaluating stabilization policies.

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Appendix A Technical details

This appendix provides the full algebraic expansion underlying equation (3) and clarifies its relation to the standard decomposition in Klenow and Kryvtsov (2008). Starting from the item-level identity $\pi_t = \sum_i w_i fr_{it} \Delta p_{it}$, we apply the variance–covariance decomposition to obtain an exact expression for $\mathrm{var}(\pi_t)$ with no Taylor-residual term. The within-item component $\mathrm{var}(fr_{it}\Delta p_{it})$ is expanded into contributions from the IM, EM, the covariance between frequency and size, and a within-item interaction term. Aggregating these components using CPI expenditure weights yields the schematic decomposition in equation (3). The resulting aggregate IM, EM, and covariance terms coincide conceptually with those in the KK-style decomposition applied to aggregate indices, although the numerical values differ because the aggregation structure operates at the item level rather than directly on the aggregate frequency and size series. The full expression is given by:

$$\begin{aligned}
\mathrm{var}(\pi_t) = \sum_i w_i^2 \Big[& \mathrm{var}_i(\Delta p_{it})\, \bar{fr}_{it}^{\,2} + \mathrm{var}_i(fr_{it})\, \bar{\Delta p}_{it}^{\,2} + \mathrm{var}_i(fr_{it})\, \mathrm{var}_i(\Delta p_{it}) \\
& + \mathrm{cov}_i(fr_{it}^2, \Delta p_{it}^2) - \mathrm{cov}_i^2(fr_{it}, \Delta p_{it}) - 2\, \bar{fr}_{it}\, \bar{\Delta p}_{it}\, \mathrm{cov}_i(fr_{it}, \Delta p_{it}) \Big] \\
& + \sum_{j \neq z} w_j w_z\, \mathrm{cov}\big(fr_{jt}\Delta p_{jt},\, fr_{zt}\Delta p_{zt}\big). \qquad (4)
\end{aligned}$$

Table 4 reports the full decomposition of the variance of inflation implied by the detailed expression in equation (4). Panel A shows the contributions of the intensive margin (IM), the extensive margin (EM), the within-item interaction term (TM), the covariance margin (CM), and the cross-item covariance component (Residual). Panel B further splits the covariance margin into its algebraic subcomponents. These results are not required for the interpretation in the main text but document how the summary terms IM, EM, Cov, Int, and CrossItem in Table 3 map into the underlying variance and covariance expressions.

Table 4: Full inflation variance decomposition

Panel A: Main components				
IM	EM	TM	CM	Residual
7	5.5	5	78.5	4

Panel B: Covariance margin components		
First part	Second part	Third part
87	6	2

Notes: This table reports the full decomposition of the variance of inflation implied by equation (4). Panel A reports the contributions of the intensive margin (IM), the extensive margin (EM), the within-item interaction term (TM), the covariance margin (CM), and the cross-item covariance component (Residual), expressed as fractions of total variance. Panel B decomposes the covariance margin into its algebraic subcomponents.