

Supplement to “A Simple and Computationally Trivial Estimator for Grouped Fixed Effects Models”

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Abstract

This supplement contains additional material to accompany the main text. First, I show that some results can be extended to allow for an increasing number of groups. Next, I discuss estimation in models with individual-specific and/or time effects. I report results from Monte Carlo simulations of a simple version of the model. Finally, I provide a short illustration to [Acemoglu, Johnson, Robinson, and Yared \(2008\)](#)’s panel data set of countries.

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S1 Increasing Number of Groups

Consider a simpler version of the model without covariates ($\beta^0 = 0$ is known). Proposition S1.1 shows that uniformly consistent classification of cross-sectional unit remains possible, even when there are “almost” as many groups as individuals asymptotically.

Proposition S1.1 *Suppose $\beta^0 = 1$, Assumption 1 holds, $G^0 = G_{NT}^0 \leq N/2$, and $\lambda_2 = o(1)$ such that $\lambda_2 \gtrsim T^{-\kappa}$ for some $0 < \kappa < 1/2$ as $T \rightarrow \infty$. Let $\hat{\beta}^1(\lambda_1) = 0$. Then, as N and T tend to infinity,*

$$\|\widehat{W} - W^0\|_{\max} = o_p(1) + o_p(N^2 T^{-\delta}) \text{ for all } \delta > 0.$$

Proof of Proposition S1.1 : Similar arguments as in the proof of Proposition 3.1 show that the probability of false-positive for the test $H_{0,ij} : \mathbf{1}\{g_i^0 = g_j^0\}$ based on the statistics $1 - \widehat{W}_{ij} = \mathbf{1}\{\widehat{d}_{\infty}^2(i, j) > \lambda_2\}$ is bounded asymptotically by $o_p(NT^{-\delta})$ uniformly across units. Similarly, outside of an event whose probability tends to zero (when there are at least two units in each group), the probability of false-negative can be shown to be bounded asymptotically as, for all $\delta > 0$,

$$G_{NT}^0(G_{NT}^0 - 1)o_p(T^{-\delta}) = o_p(N^2 T^{-\delta}).$$

□

S2 Extension of the Baseline Model

S2.1 Individual and Time-Specific Unobserved Heterogeneity

The original model (1.1) can be augmented with unit-specific and time-specific effects ν_i^0 and ξ_t^0 :

$$y_{it} = x'_{it}\theta^0 + \nu_i^0 + \xi_t^0 + \alpha_{g_i^0 t}^0 + v_{it}. \quad (\text{S2.1})$$

Without covariates, the two-step estimator could still be applied to within/across differenced versions of equation (S2.1). With covariates, one needs strong factors to apply [Moon and Weidner \(2019\)](#). Then, one can differentiate to eliminate ν_i^0 and

ξ_t^0 to estimate the groups. The last OLS linear regression step must be augmented with time and individual dummies. From a theoretical point of view, one needs to redefine separation assumptions as in [Bonhomme and Manresa \(2015\)](#)’s Supplemental Material but the overall methodology still applies. Allowing for group-specific slope is theoretically possible if one has access to a preliminary consistent estimator, as well as allowing for grouping in the longitudinal t dimension.

S2.2 Computational Gains in the Time-Invariant Model

If the clustered unobserved heterogeneity is time-invariant, one can relax Assumption 2(b) [Bonhomme and Manresa \(2015\)](#)’s Assumption 2(e). Also, it is recommended to use a simple within, first-difference, or instrumental differencing estimator as a first step in this case (see, e.g. [Arellano and Bonhomme, 2011](#); [Wooldridge, 2010](#)). The method becomes $O(N^2)$ without changing the asymptotic properties by considering the new distance

$$\hat{d}_{\infty, \text{time-inv}}^2(i, j) = \left(\frac{1}{T} \sum_{t=1}^T (\hat{v}_{it} - \hat{v}_{jt}) \right)^2. \quad (\text{S2.2})$$

I call the estimator based upon $\hat{d}_{\infty, \text{time-inv}}^2(i, j)$ the pairwise-distance (PWD) estimator.

S3 Monte Carlo Simulations

In this section, I investigate (i) the finite sample performance of the PWD estimator in the correctly specified model:

$$y_{it} = \alpha_{g_i^0}^0 + v_{it}, \quad (\text{S3.1})$$

and (ii) finite sample sensitivity to the choice of the thresholding parameter $c_T \equiv \lambda_2$. First, I assess consistency of the PWD estimator for $c_T = 2 \log(T)/\sqrt{T}$.¹ For each $(G^0, N) \in \{2, 5, 10, 50\} \times \{50, 100, 200, 500\}$ and T in a linearly equally spaced grid of 4 elements from $\lceil \sqrt{N} \rceil$ to N , I draw 1,000 Monte Carlo samples from model (S3.1), in which $(\alpha_1^0, \dots, \alpha_{G^0}^0)' = \text{linspace}(-G^0/2, G^0/2, G^0)$ and $(g_1^0, \dots, g_N^0) = (1, \dots, 1, \dots, G^0, \dots, G^0)$

¹I study sensitivity to this choice later.

are deterministic and each group has equal size N/G^0 . I consider three DGPs for the noise random variable v_{it} , summarized in Table 1. Tables 2-4 report Monte Carlo

Table 1: Data Generating Processes

DGP	Noise
1	$v_{it} \sim \mathcal{N}(0, 1)$ i.i.d. across i and t .
2	$v_{it} = 0.5v_{it-1} + \xi_{it}$ with $\xi_{it} \sim \mathcal{N}(0, 1)$ i.i.d. across i and t , independent of $v_{i0} \sim \mathcal{N}(0, 1)$.
3	$\sigma_i \sim \mathcal{U}[0.5, 1.5]$ and $v_{it} \mid \sigma_i \sim \mathcal{N}(0, \sigma_i)$ independent across i and i.i.d. across t for a given i .

averages of the estimated number of groups \hat{G}^{PWD} , the Hausdorff distance between estimated effects $(\hat{\alpha}_1^{\text{PWD}}, \dots, \hat{\alpha}_{\hat{G}^{\text{PWD}}}^{\text{PWD}})'$ and true effects $(\alpha_1^0, \dots, \alpha_{G^0}^0)'$, Rand Index (RI), and CPU time. RI is the proportion of correctly predicted pair (true or false) returned by the PWD estimator:

$$\text{RI} = \frac{TP + TN}{TP + TN + FP + FN},$$

where

$$\begin{aligned} TP &\equiv \text{True Positives} := \sum_{i < j} \mathbf{1} \{ \hat{g}_i^{\text{PWD}} = \hat{g}_j^{\text{PWD}} \} \mathbf{1} \{ g_i^0 = g_j^0 \}, \\ TN &\equiv \text{True Negatives} := \sum_{i < j} \mathbf{1} \{ \hat{g}_i^{\text{PWD}} \neq \hat{g}_j^{\text{PWD}} \} \mathbf{1} \{ g_i^0 \neq g_j^0 \}, \\ FP &\equiv \text{False Positives} := \sum_{i < j} \mathbf{1} \{ \hat{g}_i^{\text{PWD}} = \hat{g}_j^{\text{PWD}} \} \mathbf{1} \{ g_i^0 \neq g_j^0 \}, \\ FN &\equiv \text{False Negatives} := \sum_{i < j} \mathbf{1} \{ \hat{g}_i^{\text{PWD}} \neq \hat{g}_j^{\text{PWD}} \} \mathbf{1} \{ g_i^0 = g_j^0 \}. \end{aligned}$$

Results suggest good finite sample performance, although deteriorating with the degree of time-dependence of the idiosyncratic shocks. In the most favorable case of independent normal errors (Tables 2 and 4), it is remarkable how perfect or almost perfect classification is achieved for moderate sample sizes and even for a large number of groups (e.g., for $(N, T, G^0) = (50, 36, 2)$ or $(N, T, G^0) = (500, 500, G^0 = 50)$).

Second, I investigate the finite sample sensitivity of the results to the choice of the thresholding parameter c_T . I consider DGP 1 only, fix $N = 120$, and let $(G^0, T) \in \{2, 3, 4\} \times \{11, 66, 120\}$. Figures 2-6 plot Monte Carlo averages of \hat{G}^{PWD} , HD, RI, Precision (P) and Recall (R) rates as functions of $c \in \text{linspace}(0.1, 20, 40)$ with $c_T =$

$c \log(T)/\sqrt{T}$, where each colored line corresponds to $\sigma \in \{0.25, 0.5, 1\}$, where σ is the standard-deviation of the random noise v_{it} . The Recall rate (R) measures the ability of the PWD estimator to identify pairs that truly belong to the same group. The Precision rate (P) measures how precise the pairing prediction is: among all predicted pairs of units, what is the proportion of correct ones? Both formally write

$$R = \frac{TP}{TP + FN}, \quad P = \frac{TP}{TP + FP}.$$

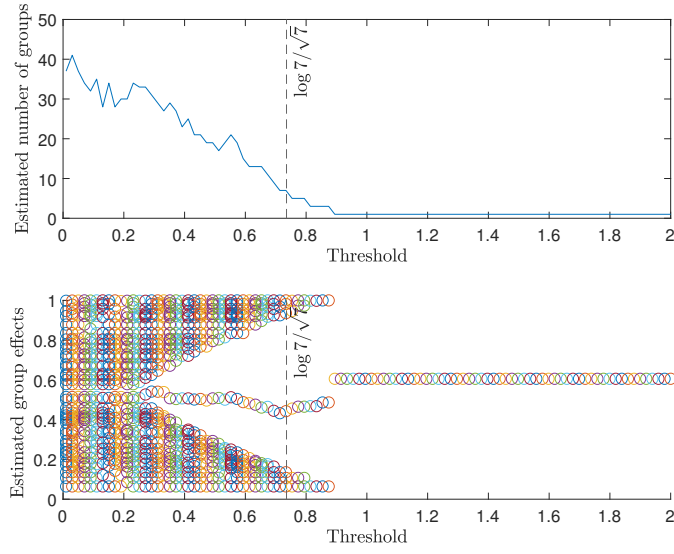
Figure 2 suggests that the larger the T , the larger the range of values for c for which $\hat{G}^{\text{PWD}} = G^0$. Figures 3-5, which inform about the grouping composition, confirm that the larger T the better in term of RI, Recall and Precision and that classification is fast (e.g., compare with $T = 66$). This is also exactly what the small Hausdorff distances suggest in Figure 6.

S4 Empirical Illustration

In this section, I give a short illustration of the PWD estimator which allows to visualize the grouping “regularization path”. I use the balanced subsample of [Acemoglu, Johnson, Robinson, and Yared \(2008\)](#) which contains the Freedom House Index of democracy for $N = 74$ countries (after dropping missing values) observed during $T = 7$ periods over the time span 1970-2000. I estimate model (S3.1) using the PWD estimator for different values of $c_T \in (0, 2)$. Figure 1 reports the estimated number of groups and group-specific effects as a function of c_T . The top-panel shows that the regularization path for $\hat{G}^{\text{PWD}}(c_T)$ is smooth and exhibits a general decreasing pattern from $\hat{G}^{\text{PWD}}(0.01) \approx 40$ to $\hat{G}^{\text{PWD}}(2) = 1$. The exact same pattern is observed when estimating model (1.1) under the constraint $\beta^0 = 0$. The bottom-panel suggests a convergence toward $\hat{G}^{\text{PWD}} = 3$ groups before a sudden phase-transition to $\hat{G}^{\text{PWD}} = 1$.

S5 Tables and Figures

Figure 1: PWD Regularization Path



Notes: *Acemoglu, Johnson, Robinson, and Yared (2008)*'s democracy data. The top-panel plots \hat{G}^{PWD} as a function c_T . The bottom-panel plots $\{\hat{\alpha}_g^{\text{PWD}} : g \in \{1, \dots, \hat{G}^{\text{PWD}}\}\}$ as a function of c_T .

Table 2: Consistency of the PWD estimator under i.i.d. errors

		$G^0 = 2$				$G^0 = 5$				$G^0 = 10$				$G^0 = 50$			
N	T	\hat{G}^{PWD}	HD	RI	CPU time	\hat{G}^{PWD}	HD	RI	CPU time	\hat{G}^{PWD}	HD	RI	CPU time	\hat{G}^{PWD}	HD	RI	CPU time
50	8	13.448	0.853	0.689	0.0231	31.569	0.6837	0.8347	0.0245	33.595	0.6025	0.9285	0.0268	41.097	1.0521	0.9918	0.0271
	22	3.12	0.2724	0.9679	0.0197	31.078	0.5124	0.8398	0.028	33.978	0.5033	0.9316	0.033	44.195	0.7252	0.9952	0.038
	36	2.057	0.0523	0.9987	0.0202	29.031	0.4071	0.8472	0.0351	34.036	0.4676	0.9318	0.0385	43.049	0.6741	0.9943	0.0384
	50	2.0	0.0318	1.0	0.0179	25.567	0.3422	0.8598	0.0392	34.006	0.4309	0.9332	0.0388	41.194	0.6594	0.9928	0.0363
100	10	20.265	0.8568	0.6847	0.0356	61.661	0.7014	0.8192	0.0514	66.048	0.6207	0.9167	0.0473	76.09	0.6061	0.9909	0.0468
	40	2.067	0.0431	0.9991	0.0365	54.776	0.4204	0.8283	0.1461	65.684	0.468	0.9184	0.159	77.127	0.521	0.9916	0.186
	70	2.0	0.0195	1.0	0.0366	36.093	0.3167	0.8603	0.1492	62.926	0.3492	0.9211	0.2321	75.669	0.5423	0.9907	0.2714
	100	2.0	0.0164	1.0	0.0464	19.101	0.2653	0.9213	0.1268	53.595	0.2724	0.9283	0.2673	75.805	0.5456	0.9911	0.3696
200	15	20.541	0.7577	0.7738	0.0388	121.746	0.6481	0.8105	0.2366	129.174	0.5911	0.9095	0.2539	142.493	0.518	0.9877	0.2808
	77	2.0	0.0129	1.0	0.0331	61.0	0.3285	0.8491	0.4463	119.47	0.3402	0.9122	0.8661	142.23	0.4934	0.9874	1.058
	139	2.0	0.0098	1.0	0.0387	13.602	0.2447	0.9704	0.2244	66.249	0.2485	0.934	0.8318	133.374	0.375	0.9892	1.719
	200	2.0	0.0082	1.0	0.0377	5.492	0.0657	0.9988	0.1662	26.174	0.2079	0.9774	0.4734	96.023	0.2161	0.9935	1.7135
500	23	17.832	0.6652	0.8941	0.2407	294.97	0.6124	0.8047	1.7975	319.05	0.5614	0.9041	1.9425	338.79	0.5145	0.9837	2.1004
	182	2.0	0.0054	1.0	0.2244	9.838	0.2209	0.993	0.5474	80.128	0.2383	0.9483	3.1459	236.88	0.2404	0.9868	9.3569
	341	2.0	0.0038	1.0	0.309	5.0	0.0085	1.0	0.5465	10.566	0.0589	0.9997	0.9849	60.138	0.1724	0.9992	4.3177
	500	2.0	0.0031	1.0	0.4193	5.0	0.0071	1.0	0.7088	10.0	0.012	1.0	1.2732	50.056	0.039	1.0	5.2066

Notes: Results are averaged over 1,000 Monte Carlo replications. $G^0 \equiv$ True number of groups; $\hat{G}^{\text{PWD}} \equiv$ Estimated number of groups; HD \equiv Hausdorff Distance between estimated and true group effects; RI \equiv Rand Index; CPU time \equiv MATLAB's `cputime`.

Table 3: Consistency of the PWD estimator under weakly dependent errors

		$G^0 = 2$				$G^0 = 5$				$G^0 = 10$				$G^0 = 50$			
N	T	\widehat{G}^{PWD}	HD	RI	CPU time	\widehat{G}^{PWD}	HD	RI	CPU time	\widehat{G}^{PWD}	HD	RI	CPU time	\widehat{G}^{PWD}	HD	RI	CPU time
50	8	28.595	1.4024	0.5414	0.0216	32.107	1.1536	0.8214	0.0275	33.375	0.9449	0.9176	0.028	35.682	1.3475	0.9855	0.0273
	22	17.803	0.9754	0.6238	0.0267	31.736	0.7796	0.832	0.03	33.706	0.6663	0.9254	0.0315	38.623	1.1209	0.9894	0.0325
	36	10.578	0.7982	0.7543	0.0246	31.378	0.6548	0.8374	0.039	33.919	0.5848	0.9293	0.0382	39.864	0.9718	0.9912	0.0386
	50	6.528	0.6328	0.8646	0.0245	30.584	0.5979	0.8417	0.0412	34.134	0.545	0.9309	0.0418	39.854	0.867	0.9915	0.0368
100	10	54.019	1.4465	0.5244	0.0466	63.822	1.2461	0.8121	0.0525	66.017	1.0834	0.9102	0.0495	69.514	0.9166	0.9864	0.0441
	30	17.864	0.8408	0.7239	0.051	61.334	0.6931	0.8205	0.1498	65.385	0.613	0.917	0.1548	74.838	0.6368	0.9904	0.178
	70	6.447	0.5802	0.9223	0.0457	55.833	0.5859	0.827	0.2099	65.453	0.5384	0.9187	0.2397	75.422	0.5907	0.9906	0.2736
	100	3.413	0.3072	0.9795	0.0419	48.448	0.5243	0.8368	0.2423	63.861	0.504	0.9204	0.3224	75.413	0.5825	0.9907	0.3614
200	15	91.877	1.3407	0.5195	0.1777	125.656	1.1787	0.8074	0.2408	130.224	1.0442	0.9063	0.2491	136.702	0.7222	0.9849	0.2714
	77	10.08	0.6585	0.9134	0.1068	106.55	0.6098	0.816	0.7937	127.67	0.5544	0.9102	0.9589	142.40	0.5066	0.9873	1.0767
	139	2.965	0.2254	0.9924	0.0463	71.937	0.4896	0.8375	0.9182	115.835	0.4826	0.9131	1.4926	142.416	0.4901	0.9878	1.8468
	200	2.166	0.0551	0.999	0.0502	41.683	0.4085	0.8811	0.778	92.895	0.4117	0.92	1.676	136.125	0.4528	0.9889	2.469
500	23	170.186	1.2131	0.5171	1.057	310.33	1.1007	0.8035	1.869	322.65	1.0035	0.9031	1.9837	337.404	0.7414	0.9827	2.0861
	182	3.232	0.2498	0.9958	0.2965	122.31	0.4737	0.8396	4.8164	247.13	0.4717	0.9081	9.8664	326.424	0.469	0.9841	13.09
	341	2.016	0.0115	1.0	0.3321	22.837	0.3443	0.9669	1.8112	96.738	0.3481	0.9392	6.9564	215.331	0.3505	0.9878	15.6834
	500	2.0	0.0063	1.0	0.4076	6.274	0.1528	0.9985	0.8521	30.89	0.2868	0.985	3.3249	108.39	0.2895	0.9949	11.2575

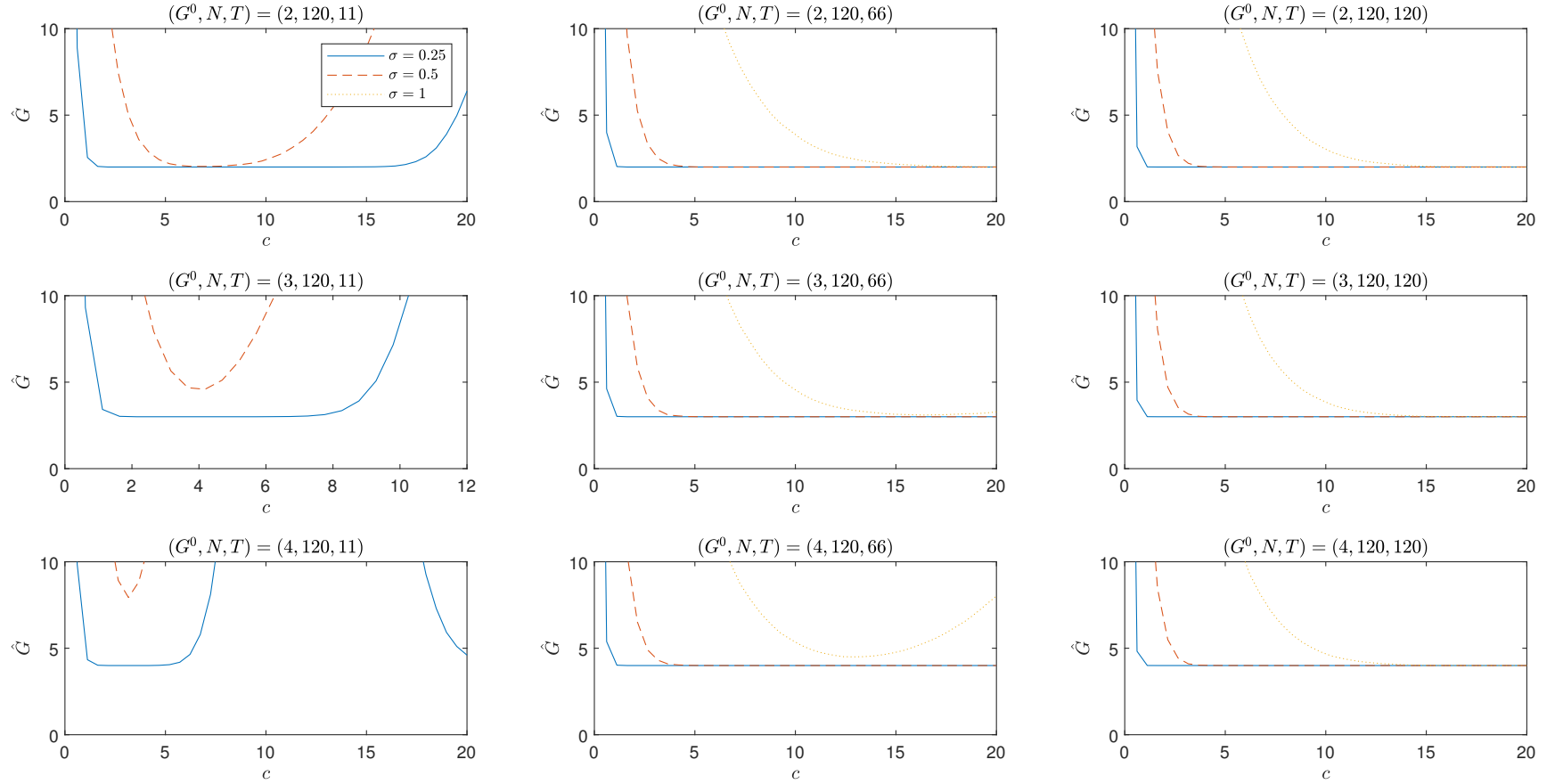
Notes: Results are averaged over 1,000 Monte Carlo replications. $G^0 \equiv$ True number of groups; $\hat{G}^{\text{PWD}} \equiv$ Estimated number of groups; HD \equiv Hausdorff Distance between estimated and true group effects; RI \equiv Rand Index; CPU time \equiv MATLAB's `cputime`.

Table 4: Consistency of the PWD estimator under heteroskedastic errors

		$G^0 = 2$				$G^0 = 5$				$G^0 = 10$				$G^0 = 50$				
N	T	\widehat{G}^{PWD}	HD	RI	CPU time	\widehat{G}^{PWD}	HD	RI	CPU time	\widehat{G}^{PWD}	HD	RI	CPU time	\widehat{G}^{PWD}	HD	RI	CPU time	
∞	50	8	15.869	0.9211	0.6471	0.0225	31.651	0.7309	0.8332	0.0255	33.744	0.6399	0.9268	0.026	40.022	1.0997	0.9906	0.0275
		22	4.841	0.4884	0.9134	0.0224	31.374	0.5593	0.8386	0.0311	34.255	0.5243	0.9313	0.0332	43.216	0.8085	0.9943	0.0365
		36	2.257	0.1016	0.9937	0.022	30.082	0.454	0.8442	0.033	34.272	0.4806	0.9316	0.0363	42.551	0.7016	0.9939	0.0443
		50	2.006	0.0381	0.9999	0.0185	26.943	0.3792	0.8545	0.0364	34.135	0.4532	0.9328	0.0355	41.12	0.679	0.9928	0.0415
	100	10	29.069	0.9689	0.605	0.0456	62.248	0.7981	0.8179	0.0568	65.794	0.7018	0.9153	0.0474	74.017	0.6838	0.9898	0.0549
		40	2.344	0.1132	0.9955	0.0457	56.172	0.4677	0.8265	0.1434	65.958	0.4917	0.9182	0.159	76.597	0.5338	0.9915	0.1772
		70	2.0	0.0213	1.0	0.0416	39.427	0.3467	0.8523	0.1642	63.817	0.3783	0.9205	0.2393	75.513	0.5473	0.9907	0.2803
		100	2.0	0.0177	1.0	0.0402	22.032	0.2861	0.9072	0.1375	55.448	0.2937	0.9267	0.2832	75.832	0.5458	0.9911	0.3649
	200	15	35.896	0.8967	0.6458	0.0561	122.235	0.7455	0.8101	0.226	129.324	0.6703	0.9089	0.2543	142.211	0.5459	0.987	0.2748
		77	2.0	0.0143	1.0	0.0307	68.329	0.3566	0.8408	0.4835	121.611	0.3689	0.9117	0.9058	142.751	0.4924	0.9874	1.0951
		139	2.0	0.0101	1.0	0.0396	16.56	0.2582	0.9591	0.2576	72.042	0.2621	0.9302	0.9223	134.743	0.3999	0.9891	1.8094
		200	2.0	0.0084	1.0	0.0454	5.76	0.087	0.9981	0.1657	28.772	0.2154	0.9736	0.5166	99.223	0.2239	0.9931	1.8396
	500	33	37.936	0.7906	0.7672	0.3116	298.003	0.6836	0.8046	1.8629	319.607	0.6228	0.904	1.9931	339.888	0.5361	0.9835	2.1764
		182	2.0	0.0056	1.0	0.2115	11.672	0.2355	0.9897	0.599	88.894	0.2462	0.9435	3.6233	245.004	0.2504	0.9865	10.57
		341	2.0	0.0041	1.0	0.3299	5.0	0.0088	1.0	0.5171	10.966	0.0819	0.9995	0.9751	63.247	0.18	0.9989	4.7129
		500	2.0	0.0033	1.0	0.4094	5.0	0.0073	1.0	0.7156	10.0	0.0124	1.0	1.271	50.098	0.0433	1.0	5.4568

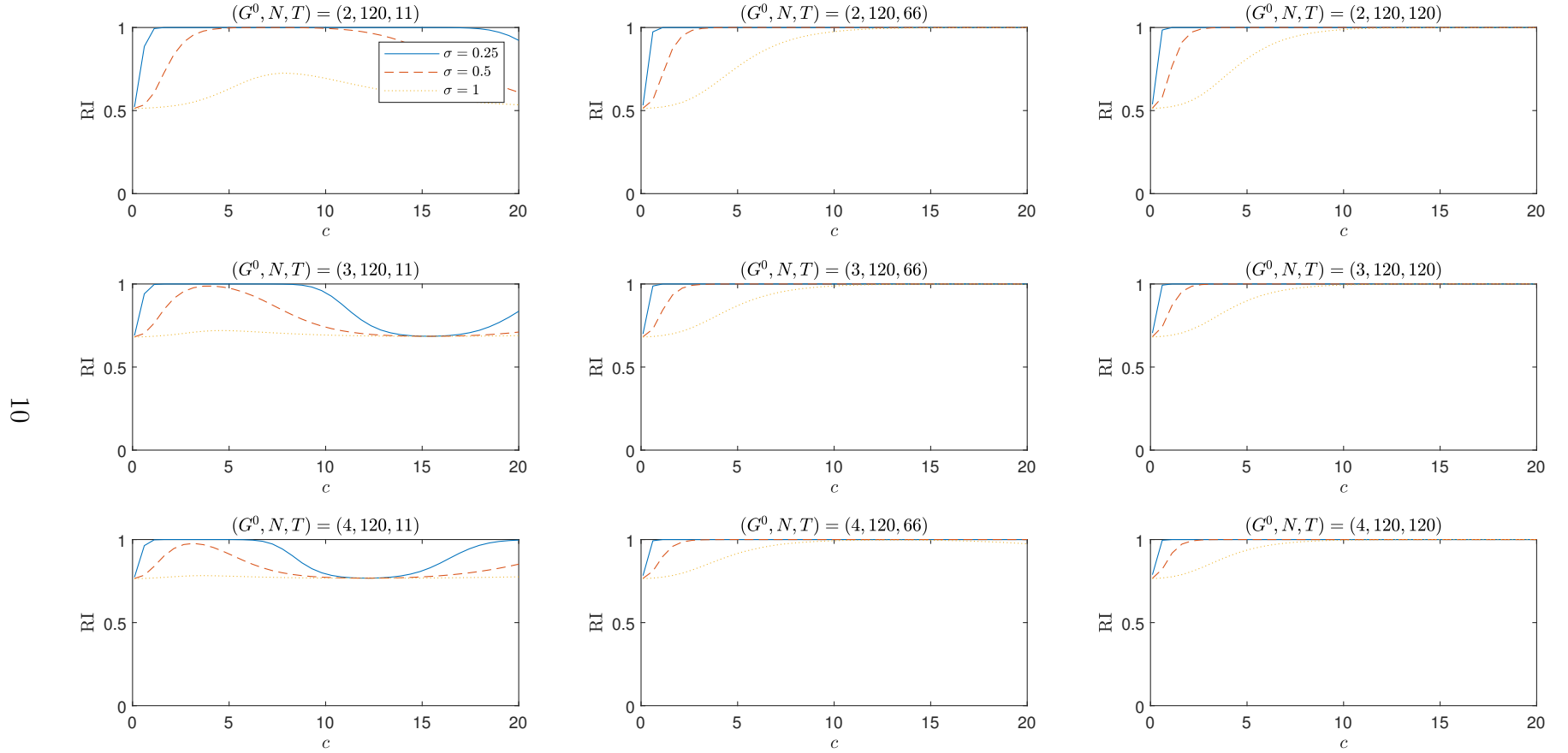
Notes: Results are averaged over 1,000 Monte Carlo replications. $G^0 \equiv$ True number of groups; $\hat{G}^{\text{PWD}} \equiv$ Estimated number of groups; HD \equiv Hausdorff Distance between estimated and true group effects; RI \equiv Rand Index; CPU time \equiv MATLAB's `cputime`.

Figure 2: Sensitivity of the estimated number of groups (\hat{G})



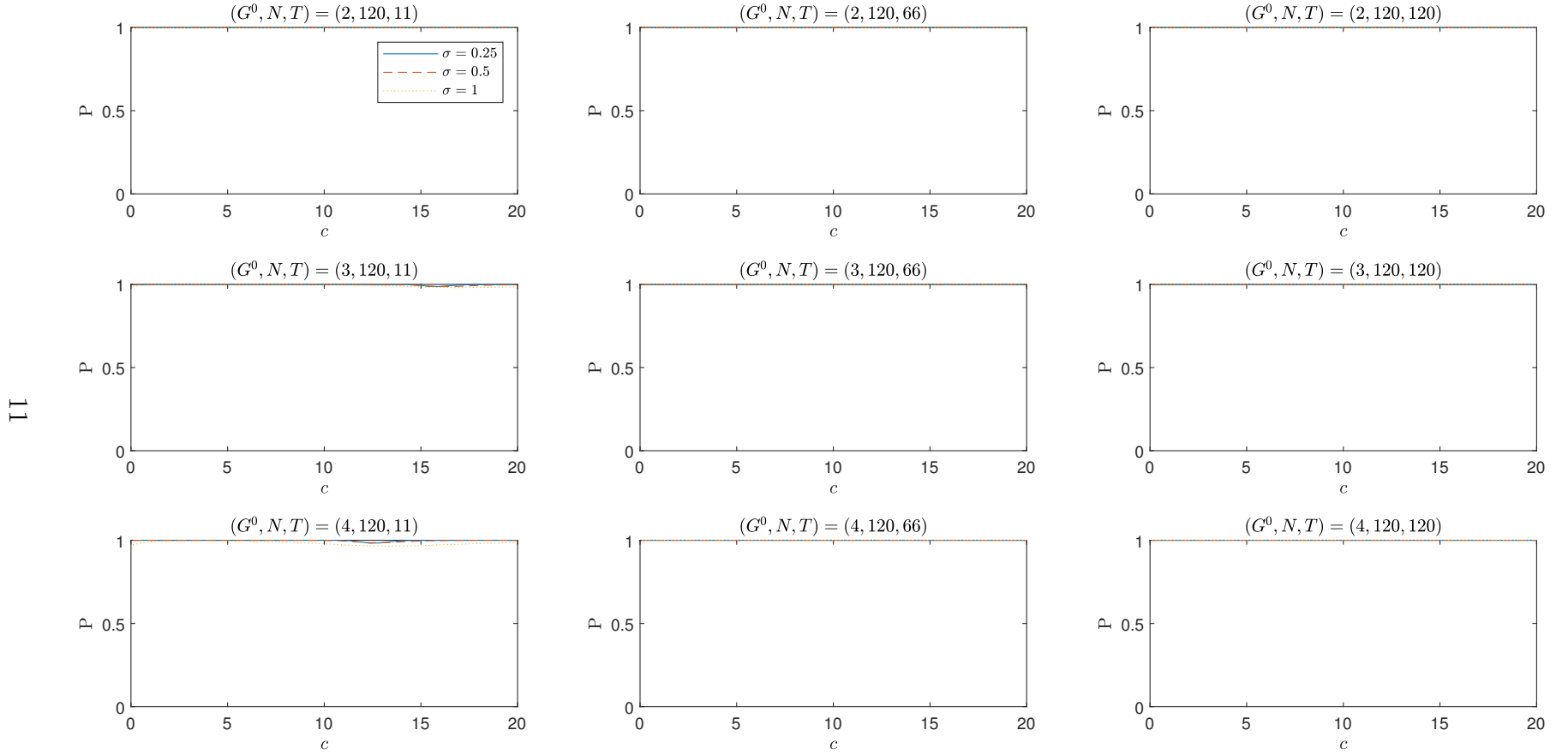
Notes: solid blue, dashed red, and dotted yellow lines report averages of \hat{G} with $c_T = cT^{-4/5}$ as a function of $c \in (0, 20)$ for noise standard deviation of .25, .5 and 1 respectively. In each plot, $N = 120$; from top to bottom $G^0 = 2, 3, 4$; from left to right $T = 11, 66, 120$. Results are averaged over 1,000 Monte Carlo replications.

Figure 3: Sensitivity of the Rand Index (RI)



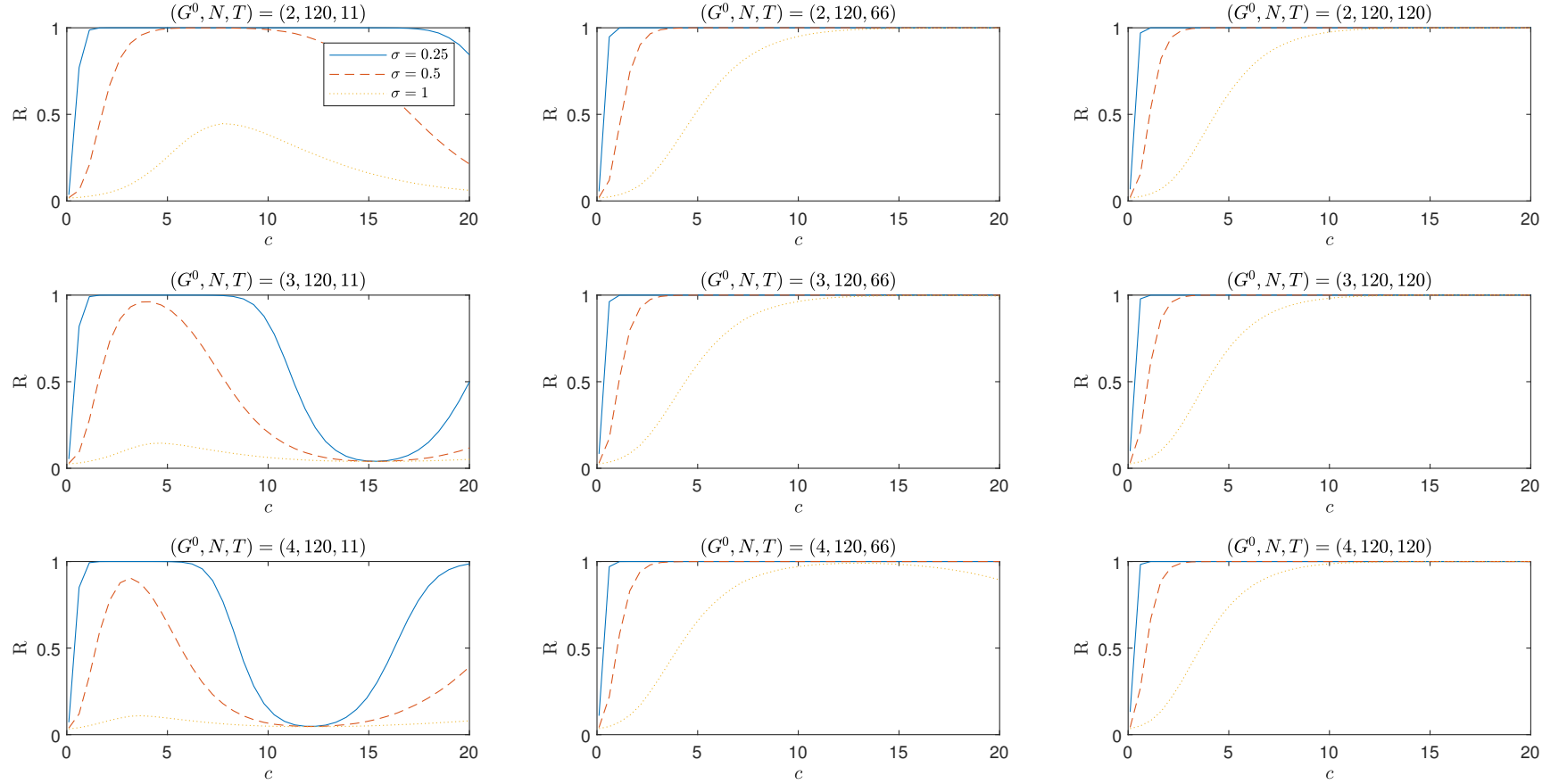
Notes: solid blue, dashed red, and dotted yellow lines report averages of RI with $c_T = cT^{-4/5}$ as a function of $c \in (0, 20)$ for noise standard deviation of .25, .5 and 1 respectively. In each plot, $N = 120$; from top to bottom $G^0 = 2, 3, 4$; from left to right $T = 11, 66, 120$. Results are averaged over 1,000 Monte Carlo replications.

Figure 4: Sensitivity of the Precision rate (P)



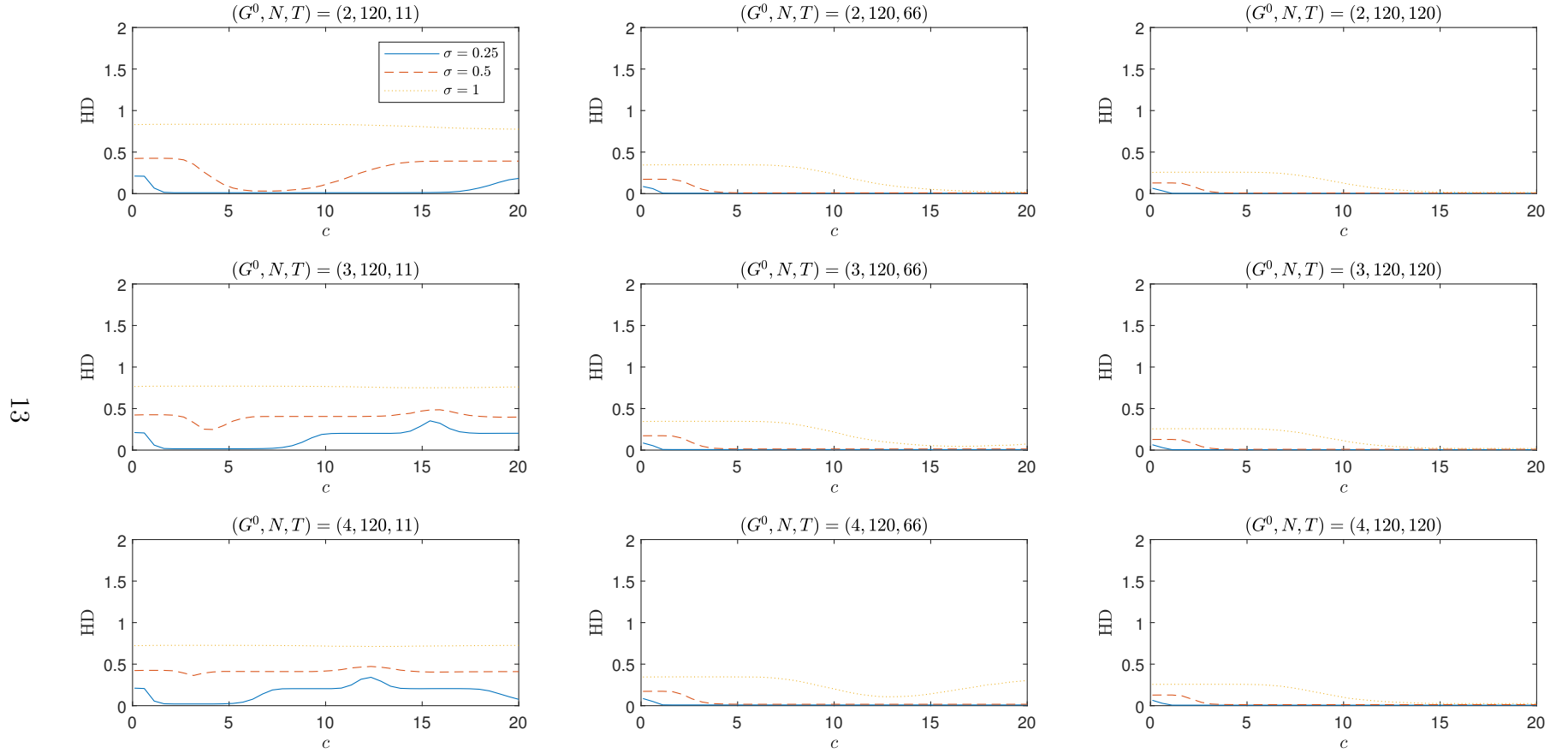
Notes: solid blue, dashed red, and dotted yellow lines report averages of P with $c_T = cT^{-4/5}$ as a function of $c \in (0, 20)$ for noise standard deviation of .25, .5 and 1 respectively. In each plot, $N = 120$; from top to bottom $G^0 = 2, 3, 4$; from left to right $T = 11, 66, 120$. Results are averaged over 1,000 Monte Carlo replications.

Figure 5: Sensitivity of the Recall rate (R)



Notes: solid blue, dashed red, and dotted yellow lines report averages of R with $c_T = cT^{-4/5}$ as a function of $c \in (0, 20)$ for noise standard deviation of .25, .5 and 1 respectively. In each plot, $N = 120$; from top to bottom $G^0 = 2, 3, 4$; from left to right $T = 11, 66, 120$. Results are averaged over 1,000 Monte Carlo replications.

Figure 6: Sensitivity of the Hausdorff Distance (HD)



Notes: solid blue, dashed red, and dotted yellow lines report averages of HD with $c_T = cT^{-4/5}$ as a function of $c \in (0, 20)$ for noise standard deviation of .25, .5 and 1 respectively. In each plot, $N = 120$; from top to bottom $G^0 = 2, 3, 4$; from left to right $T = 11, 66, 120$. Results are averaged over 1,000 Monte Carlo replications.

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