

# Supplementary Material for “*On Achievable Rates of Line Networks with Generalized Batched Network Coding*”

## APPENDIX A

### PROOFS ABOUT CONVERSE

*Proof of Lemma 3:* Denote by  $\mathbf{y}^* = (y^* \cdots y^*)$ . We have

$$W(\mathbf{y}|\mathbf{x}) = \begin{cases} \frac{Q^{\otimes N}(\mathbf{y}^*|\mathbf{x}) - p_0}{1 - p_0} & \mathbf{y} = \mathbf{y}^*, \\ \frac{Q^{\otimes N}(\mathbf{y}|\mathbf{x})}{1 - p_0} & \text{otherwise.} \end{cases} \quad (51)$$

Let  $P(\mathbf{y}) = \sum_{\mathbf{x}} Q^{\otimes N}(\mathbf{y}|\mathbf{x})p(\mathbf{x})$  and  $P'(\mathbf{y}) = \sum_{\mathbf{x}} W(\mathbf{y}|\mathbf{x})p(\mathbf{x})$ . We have

$$P'(\mathbf{y}) = \begin{cases} \frac{1}{1 - p_0}(P(\mathbf{y}) - p_0) & \mathbf{y} = \mathbf{y}^*, \\ \frac{1}{1 - p_0}P(\mathbf{y}) & \text{otherwise.} \end{cases} \quad (52)$$

Substituting (51) and (52) into  $I(p, W)$ , we get

$$I(p, W) = \sum_{\mathbf{x}} p(\mathbf{x}) \sum_{\mathbf{y}} W(\mathbf{y}|\mathbf{x}) \log \frac{W(\mathbf{y}|\mathbf{x})}{P'(\mathbf{y})} \quad (53)$$

$$= \frac{1}{1 - p_0} I(p, Q^{\otimes N}) + \frac{1}{1 - p_0} U(\mathbf{y}^*), \quad (54)$$

where

$$U(\mathbf{y}^*) \triangleq \sum_{\mathbf{x}} p(\mathbf{x}) \left( (Q^{\otimes N}(\mathbf{y}^*|\mathbf{x}) - p_0) \log \frac{Q^{\otimes N}(\mathbf{y}^*|\mathbf{x}) - p_0}{P(\mathbf{y}^*) - p_0} - Q^{\otimes N}(\mathbf{y}^*|\mathbf{x}) \log \frac{Q^{\otimes N}(\mathbf{y}^*|\mathbf{x})}{P(\mathbf{y}^*)} \right). \quad (55)$$

Using  $P(\mathbf{y}^*) = \sum_{\mathbf{x}} Q^{\otimes N}(\mathbf{y}^*|\mathbf{x})p(\mathbf{x}) \geq \sum_{\mathbf{x}} \epsilon^N p(\mathbf{x}) = \epsilon^N$ , we have

$$U(\mathbf{y}^*) = -p_0 \sum_{\mathbf{x}} p(\mathbf{x}) \log(Q^{\otimes N}(\mathbf{y}^*|\mathbf{x}) - p_0) + P(\mathbf{y}^*) \log \frac{P(\mathbf{y}^*)}{P(\mathbf{y}^*) - p_0} \quad (56)$$

$$+ p_0 \log(P(\mathbf{y}^*) - p_0) + \sum_{\mathbf{x}} p(\mathbf{x}) Q^{\otimes N}(\mathbf{y}^*|\mathbf{x}) \log \frac{Q^{\otimes N}(\mathbf{y}^*|\mathbf{x}) - p_0}{Q^{\otimes N}(\mathbf{y}^*|\mathbf{x})} \quad (57)$$

$$\leq -p_0 \log(\epsilon^N - p_0) + q^* \log \frac{\epsilon^N}{\epsilon^N - p_0} + p_0 \log(q^* - p_0) + q^* \log \frac{q^* - p_0}{q^*} \quad (58)$$

$$= (q^* + p_0) \log \frac{q^* - p_0}{\epsilon^N - p_0} + q^* \log \frac{\epsilon^N}{q^*} \quad (59)$$

The proof is completed by combining (54) and (59). ■

*Proof of Lemma 5:* We relax  $N$  to a real number and solve  $\frac{dF(N)}{dN} = 0$ , i.e.,

$$1 - \epsilon^N + LN\epsilon^N \ln \epsilon = 0, \quad (60)$$

or

$$\epsilon^{-N} - 1 + LN \ln \epsilon = 0. \quad (61)$$

Let  $t = -N \ln \epsilon$ , and denote by  $t^*(L)$  the solution of  $g(t) \triangleq e^t - 1 - Lt = 0, t > 0$ . Then the solution of (60) is  $N^* = t^*(L)/\ln(1/\epsilon)$ .

We know that  $g(t) < 0$  for  $0 < t < t^*(L)$ ; and  $g(t) > 0$  for  $t > t^*(L)$ . Since  $g(\ln L) = L - 1 - L \ln L < 0$  and  $g(2 \ln L) = L^2 - 1 - 2L \ln L > 0$  when  $L > 1$ , we have  $\ln L < t^*(L) < 2 \ln L$  when  $L > 1$ . Last, using  $\epsilon^{N^*} = e^{-t^*(L)}$ ,

$$0.25 \leq (1 - 1/L)^L \leq (1 - \epsilon^{N^*})^L \leq (1 - 1/L^2)^L < 1, \quad (62)$$

and hence  $F(N^*) = \frac{(1 - \epsilon^{N^*})^L}{N^*} = \frac{\ln \frac{1}{\epsilon} (1 - \epsilon^{N^*})^L}{t^*(L)} = \Theta(\frac{\ln \frac{1}{\epsilon}}{\ln L})$ . ■

*Proof of Lemma 6:* We group the elements of  $\mathcal{S}_i$  into  $\lceil |\mathcal{S}_i|/2 \rceil$  pairs, denoted collectively as  $\mathcal{S}_i^{(2)}$ , where each element of  $\mathcal{S}_i$  appears in exactly one pair. When  $|\mathcal{S}_i|$  is even, all pairs have distinct entries. When  $|\mathcal{S}_i|$  is odd, exactly one pair has the two entries same and the other pairs have distinct entries.

For each pair  $(x, x') \in \mathcal{S}_i^{(2)}$ , fix  $y_{x,x'}$  such that  $Q(y_{x,x'}|x) \geq \varepsilon_Q$  and  $Q(y_{x,x'}|x') \geq \varepsilon_Q$ . Define  $\mathcal{Z}$  as the collection of  $z = (z_x, x \in \mathcal{Q}_i)$  such that  $z_x = y_{x,x'}$  and  $z_{x'} = y_{x,x'}$  for all pairs  $(x, x') \in \mathcal{S}_i^{(2)}$ . Let  $\mathcal{S}_o = \{y_{x,x'} : (x, x') \in \mathcal{S}_i^{(2)}\}$ . Therefore,  $|\mathcal{S}_o| \leq \lceil |\mathcal{S}_i|/2 \rceil$ . Hence for any  $x \in \mathcal{S}_i$  and  $z \in \mathcal{Z}$ ,  $\alpha(x, z) = z_x \in \mathcal{S}_o$ . When  $\mathcal{A}$  is even,

$$P(Z \in \mathcal{Z}) = \prod_{(x,x') \in \mathcal{S}_i^{(2)}} P(Z[x] = y_{x,x'}) P(Z_{x'} = y_{x,x'}) \quad (63)$$

$$= \prod_{(x,x') \in \mathcal{S}_i^{(2)}} Q(y_{x,x'}|x) Q(y_{x,x'}|x') \geq \prod_{(x,x') \in \mathcal{S}_i^{(2)}} \varepsilon_Q^2 = \varepsilon_Q^{|\mathcal{S}_i|}. \quad (64)$$

When  $\mathcal{A}$  is odd,

$$P(Z \in \mathcal{Z}) = \prod_{(x,x') \in \mathcal{S}_i^{(2)}: x \neq x'} P(Z[x] = y_{x,x'}) P(Z_{x'} = y_{x,x'}) \prod_{(x,x) \in \mathcal{S}_i^{(2)}} P(Z[x] = y_{x,x}) \quad (65)$$

$$= \prod_{(x,x') \in \mathcal{S}_i^{(2)}: x \neq x'} Q(y_{x,x'}|x) Q(y_{x,x'}|x') \prod_{(x,x) \in \mathcal{S}_i^{(2)}} Q(y_{x,x}|x) \geq \varepsilon_Q^{|\mathcal{S}_i|}. \quad (66)$$

■

*Proof of Theorem 7:* Consider a line network of length  $L$  of general DMCs  $Q_\ell$  with  $\varepsilon_{Q_\ell} \geq \epsilon > 0$  and a GBNC as described in §II. Without loss of optimality, we assume a deterministic recoding scheme, i.e.,  $\phi_\ell$  are deterministic. Channel  $Q_\ell^{\otimes N}$  can be modelled by the function  $\alpha_\ell^N$  with the channel status variable  $Z_\ell = (Z_\ell[\mathbf{x}], \mathbf{x} \in \mathcal{Q}_\ell^N)$  so that

$$\mathbf{Y}_\ell = \alpha_\ell^N(\mathbf{U}_\ell, Z_\ell). \quad (67)$$

As  $\varepsilon_{Q_\ell^{\otimes N}} \geq \varepsilon_{Q_\ell}^N > 0$ , the condition of applying Lemma 6 on  $Q_\ell^{\otimes N}$  is satisfied.

Let  $\mathcal{S}_1^{(1)} = \mathcal{Q}_1^N$ . Applying Lemma 6 on  $Q_1^{\otimes N}$  w.r.t.  $\mathcal{S}_1^{(1)}$ , there exists subsets  $\mathcal{Z}^{(1)}$  and  $\mathcal{S}_o^{(1)} \subseteq \mathcal{Q}_o^N$  with  $|\mathcal{S}_o^{(1)}| \leq \lceil |\mathcal{S}_1^{(1)}|/2 \rceil$  such that  $\alpha_1^N(\mathbf{x}, z_1) \in \mathcal{S}_o^{(1)}$  for any  $\mathbf{x} \in \mathcal{S}_1^{(1)}$  and  $z_1 \in \mathcal{Z}^{(1)}$ , and  $P(Z_1 \in \mathcal{Z}^{(1)}) \geq \varepsilon^{N|\mathcal{Q}_1|^N}$ . Fix an integer  $K = \lceil N \log |\mathcal{Q}_1| \rceil$ . For  $i = 2, 3, \dots, K$ , define recursively  $\mathcal{S}_i^{(i)}$ ,  $\mathcal{S}_o^{(i)}$  and  $\mathcal{Z}^{(i)}$  as follows:  $\mathcal{S}_i^{(i)} = \left\{ \mathbf{x} \in \mathcal{Q}_i^N : \mathbf{x} = \phi_{i-1}(\mathbf{y}) \text{ for certain } \mathbf{y} \in \mathcal{S}_o^{(i-1)} \right\}$ , and  $\mathcal{S}_o^{(i)}$  and  $\mathcal{Z}^{(i)}$  are determined as in the proof of Lemma 6 w.r.t.  $Q_i^{\otimes N}$  and  $\mathcal{S}_i^{(i)}$  so that  $\alpha_i^{\otimes N}(\mathbf{x}, z) \in \mathcal{S}_o^{(i)}$  for any  $\mathbf{x} \in \mathcal{S}_i^{(i)}$  and  $z \in \mathcal{Z}^{(i)}$ , and  $P(Z_i \in \mathcal{Z}^{(i)}) \geq \varepsilon^{N|\mathcal{S}_i^{(i)}|}$ .

According to the construction,  $|\mathcal{S}_i^{(i)}| \leq |\mathcal{S}_o^{(i-1)}|$  and  $|\mathcal{S}_o^{(i)}| \leq \lceil |\mathcal{S}_i^{(i)}|/2 \rceil$ . Hence  $|\mathcal{S}_o^{(K)}| \leq \lceil |\mathcal{S}_1^{(1)}|/2^K \rceil = 1$ . Since the set  $\mathcal{S}_o^{(K)}$  is non-empty, we have  $|\mathcal{S}_o^{(K)}| = 1$ , i.e., there exists an output of  $Q_K^{\otimes N}$  that occurs with a positive probability for all inputs of  $Q_1^{\otimes N}$ . Define the channel  $G_1 = Q_1^{\otimes N} \phi_1 Q_2^{\otimes N} \cdots \phi_{K-1} Q_K^{\otimes N}$ . Under the condition  $Z_i \in \mathcal{Z}^{(i)}, i = 1, \dots, K$ , the output of  $G_1$  must be unique for all possible channel inputs, i.e.,  $G_1$  is canonical. Note that

$$P(Z_i \in \mathcal{Z}^{(i)}, i = 1, \dots, K) \geq \varepsilon^{N \sum_{i=1}^K |\mathcal{A}_i|} \geq \varepsilon^{N(2|\mathcal{Q}_1|^N + K)}. \quad (68)$$

Let  $L' = \lfloor L/K \rfloor$ . For  $i = 2, \dots, L'$ , define  $G_i = Q_{K(i-1)+1}^{\otimes N} \phi_{K(i-1)+1} Q_{K(i-1)+2}^{\otimes N} \cdots \phi_{Ki-1} Q_{Ki}^{\otimes N}$ . Similar as  $G_1$ , we know that  $G_i, i = 2, \dots, L'$  are all canonical. We see that  $G_i, i = 1, \dots, L'$  forms a length- $L'$  network. Let  $\tilde{W}_{L'} = \phi_0 G_1 \phi_K G_2 \phi_{2K} \cdots G_{L'}$ , which is the end-to-end transition matrix of a GBNC with inner block length 1 for the length- $L'$  network of canonical channels  $G_i$ . By the data processing inequality,  $I(p_{\mathbf{X}}, W_L) \leq I(p_{\mathbf{X}}, \tilde{W}_{L'})$ . Based on this relation, we are ready to prove the theorem, similar to that of Theorem 4. ■

## APPENDIX B

### PROOFS ABOUT ACHIEVABILITY

*Proof of Lemma 9:* Suppose that the node  $\ell - 1$  transmits  $u_\ell(x)$  for  $N$  times, where  $x \in \mathcal{A}$ . We know that the entries of  $\mathbf{y}_\ell$  are i.i.d. random variables with distribution  $Q_\ell(\cdot | u_\ell(x))$ . The

error probability for ML decoding at the node  $\ell$  satisfies

$$\epsilon_\ell(x) \leq P(\bigvee_{\bar{x} \neq x} \mathcal{L}_\ell(\bar{x}; \mathbf{y}_\ell) \geq \mathcal{L}_\ell(x; \mathbf{y}_\ell)) \quad (69)$$

$$\leq \sum_{\bar{x} \in \mathcal{A}: \bar{x} \neq x} P(\mathcal{L}_\ell(\bar{x}; \mathbf{y}_\ell) \geq \mathcal{L}_\ell(x; \mathbf{y}_\ell)), \quad (70)$$

where the second inequality follows from the union bound. For fixed  $\bar{x} \in \mathcal{A}$  so that  $\bar{x} \neq x$ , we bound the probability  $P(\mathcal{L}_\ell(\bar{x}; \mathbf{Y}_\ell) \geq \mathcal{L}_\ell(x; \mathbf{Y}_\ell))$  by considering two cases.

If there exists a non-empty subset  $\mathcal{Y}_0 \subseteq \mathcal{Q}_o$  so that for any  $y_0 \in \mathcal{Y}_0$ ,  $Q_\ell(y_0 | u_\ell(x)) > 0$  but  $Q_\ell(y_0 | u_\ell(\bar{x})) = 0$ , as long as  $\mathbf{y}_\ell[i] \in \mathcal{Y}_0$  for some  $i$ , we can assert that  $\mathcal{L}_\ell(\bar{x}; \mathbf{y}_\ell) < \mathcal{L}_\ell(x; \mathbf{y}_\ell)$ . Therefore,

$$P(\mathcal{L}_\ell(\bar{x}; \mathbf{y}_\ell) \geq \mathcal{L}_\ell(x; \mathbf{y}_\ell)) \leq P(\mathbf{Y}_\ell[i] \notin \mathcal{Y}_0, i = 1, \dots, N) \quad (71)$$

$$= \left[ \sum_{y \notin \mathcal{Y}_0} Q_\ell(y | u_\ell(x)) \right]^N = \exp \left( -N \log \frac{1}{\sum_{y \notin \mathcal{Y}_0} Q_\ell(y | u_\ell(x))} \right), \quad (72)$$

where  $\sum_{y \notin \mathcal{Y}_0} Q_\ell(y | u_\ell(x)) = 1 - \sum_{y \in \mathcal{Y}_0} Q_\ell(y | u_\ell(x)) < 1$ .

Otherwise, consider that the support of  $Q_\ell(\cdot | u_\ell(x))$  belongs to the support of  $Q_\ell(\cdot | u_\ell(\bar{x}))$ . For  $i = 1, \dots, N$ , define the random variable  $D_i = \log \frac{Q_\ell(\mathbf{Y}_\ell[i] | u_\ell(\bar{x}))}{Q_\ell(\mathbf{Y}_\ell[i] | u_\ell(x))}$ . We see that  $D_i$  are i.i.d., and satisfy

$$\log \varrho_\ell \leq D_i \leq -\log \varrho_\ell, \quad (73)$$

where  $\varrho_\ell = \min_{x \in \mathcal{Q}_i, y \in \mathcal{Q}_o: Q_\ell(y|x) > 0} Q_\ell(y|x)$ , and

$$\mathbb{E}[D_i] = E'_\ell \triangleq -\mathcal{D}_{\text{KL}}(Q_\ell(\cdot | u_\ell(x)) \| Q_\ell(\cdot | u_\ell(\bar{x}))), \quad (74)$$

where  $\mathcal{D}_{\text{KL}}$  denotes the Kullback-Leibler divergence. We see that  $E'_\ell > -\infty$ . Moreover, as  $u_\ell(x) \neq u_\ell(\bar{x}) \in \mathcal{Q}_i^\ell$ ,  $Q_\ell(\cdot | u_\ell(x)) \neq Q_\ell(\cdot | u_\ell(\bar{x}))$  and hence  $E'_\ell \neq 0$ . Applying Hoeffding's inequality, we obtain

$$P(\mathcal{L}_\ell(\bar{x}; \mathbf{y}_\ell) \geq \mathcal{L}_\ell(x; \mathbf{y}_\ell)) = P\left(\sum_{i=1}^N D_i \geq 0\right) \quad (75)$$

$$= P\left(\sum_{i=1}^N (D_i - E'_\ell) \geq -NE'_\ell\right) \quad (76)$$

$$\leq \exp\left(-\frac{NE_\ell'^2}{2\log^2 \varrho_\ell}\right). \quad (77)$$

The proof is completed by combining both cases. ■

*Proof of Lemma 11:* Suppose  $Q$  has size  $m \times n$ . As  $C(Q) > \epsilon > 0$ ,  $m \geq 2$ . Let  $\mathbf{a} = (a_1, \dots, a_n)$  be a row of  $Q$ , and construct a new  $m \times n$  stochastic matrix  $\tilde{Q}$  with all the rows  $\mathbf{a}$ . We have  $C(\tilde{Q}) = 0$  and hence  $|C(Q) - C(\tilde{Q})| > \epsilon$ . Since channel capacity as a function of stochastic matrices is uniformly continuous [10, Lemma I.1], there exists a constant  $\delta > 0$  depending on  $\epsilon$  such that  $\|\tilde{Q} - Q\|_\infty > \delta$ . As a consequence, there exists another row  $\mathbf{a}' = (a'_1, \dots, a'_n)$  of  $Q$  such that  $\|\mathbf{a} - \mathbf{a}'\|_\infty > \delta$ . Denote by  $j$  the index such that  $|a_j - a'_j| > \delta$ .

Using the example of uniform reduction with  $s = 2$ , we can choose  $R$  so that  $RQ$  is formed by  $\mathbf{a}$  and  $\mathbf{a}'$ . Then we can find  $W$  so that  $RQW = U_2(\rho_1)$ , where

$$\rho_1 = \sum_{k: a_k + a'_k > 0} \frac{a_k^2}{a_k + a'_k} = 1 - \sum_{k: a_k + a'_k > 0} \frac{a_k a'_k}{a_k + a'_k}. \quad (78)$$

Based on the relation that

$$\frac{1}{2} - \sum_{k: a_k + a'_k > 0} \frac{a_k a'_k}{a_k + a'_k} = \frac{1}{4} \sum_{k: a_k + a'_k > 0} \frac{(a_k - a'_k)^2}{a_k + a'_k} \geq \frac{1}{4} \frac{(a_j - a'_j)^2}{a_j + a'_j} \geq \frac{\delta^2}{8}, \quad (79)$$

we have the lower bound  $\rho_1 \geq B$  with  $B = \frac{1}{2} + \frac{\delta^2}{8} > 1/2$ . For any  $\varrho$  such that  $1/2 < \varrho \leq B$ , we have  $U_2(\varrho) = U_2(\rho_1)U_2(\frac{\rho_1 + \varrho - 1}{2\rho_1 - 1})$ , and hence  $RQWU_2(\frac{\rho_1 + \varrho - 1}{2\rho_1 - 1}) = U_2(\varrho)$ . ■

*Proof of Lemma 13:* As  $\text{rank}(Q) = r \geq s$ , we can find stochastic matrices  $R$  and  $W$  such that  $\min \text{inv}(RQW) = \kappa_s(Q)$ . Let  $B = (RQW)^{-1}$ , and  $K = BU_s(\varrho)$ . As  $RQWK = U_s(\varrho)$ , we only need to show that for  $1/s < \varrho \leq \rho_s(Q)$ ,  $K$  is a stochastic matrix. Let  $\mathbf{1}$  be the all-one vector of certain length. We see that  $K\mathbf{1} = BU_s(\varrho)\mathbf{1} = B\mathbf{1} = \mathbf{1}$ , where the last equality follows because  $RQW\mathbf{1} = \mathbf{1}$  and  $RQW$  is invertible.

It remains to show that all the entries of  $K$  are nonnegative. Let  $b_{ij}$  be the  $(i, j)$  entry of  $B$ . The  $(i, j)$  entry of  $K$  is  $k_{ij} = \frac{1}{s-1} [(1 - \varrho) + b_{ij}(s\varrho - 1)] \geq \frac{1}{s-1} [(1 - \varrho) + \kappa_s(Q)(s\varrho - 1)]$ . When  $\kappa_s(Q) \geq 0$ , we have  $k_{ij} \geq 0$  for any  $\varrho \in (1/s, 1]$ . When  $\kappa_s(Q) < 0$ , we have  $k_{ij} \geq 0$  for any  $\varrho \in (1/s, \frac{\kappa_s(Q) - 1}{s\kappa_s(Q) - 1}]$ . ■

*Proof of Theorem 14:* Recall the Markov chain relation in (45), where the transition matrix  $\mathbf{P}$  is an  $(M + 1) \times (M + 1)$  matrix with the  $(i, j)$  entry  $(0 \leq i, j \leq M)$ :

$$p_{i,j} = \begin{cases} 0 & i < j, \\ \sum_{k=j}^N f(k; N, \epsilon) \zeta_j^{i,k} & i \geq j, \end{cases} \quad (80)$$

where  $f(k; N, \epsilon) = \binom{N}{k} (1 - \epsilon)^k \epsilon^{N-k}$  is the probability mass function (PMF) of the binomial distribution with parameters  $N$  and  $1 - \epsilon$ , and  $\zeta_j^{i,k}$  is the probability that the  $i \times k$  matrix with

independent entries uniformly distributed over the field  $\mathbb{F}_q$  has rank  $j$ . We know that (ref. [27,

(2.4)]  $\zeta_j^{i,k} = \frac{\zeta_j^i \zeta_j^k}{\zeta_j^j q^{(i-j)(k-j)}}$ , where

$$\zeta_r^m = \begin{cases} 1 & r = 0, \\ (1 - q^{-m})(1 - q^{-m+1}) \cdots (1 - q^{-m+r-1}) & 1 \leq r \leq m. \end{cases} \quad (81)$$

As shown in [29], the matrix  $\mathbf{P}$  admits the eigendecomposition  $\mathbf{P} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^{-1}$ , where  $\mathbf{V} = (v_{i,j})_{0 \leq i,j \leq M}$  and  $\mathbf{\Lambda} = \text{diag}(\lambda_0, \lambda_1, \dots, \lambda_M)$ . Here  $\lambda_j = \sum_{k=j}^N f(k; N, \epsilon) \zeta_j^k$ ,  $v_{i,j} = \zeta_j^i$  for  $i \geq j$  and otherwise  $v_{i,j} = 0$ . It can be checked that  $\lambda_0 > \lambda_1 > \dots > \lambda_M$ . Denote the  $(i, j)$  entry  $0 \leq i, j \leq M$  of  $\mathbf{V}^{-1}$  by  $u_{i,j}$ . We know that  $u_{i,j} = 0$  for  $i < j$  and  $u_{i,i} = 1/\zeta_i^i$ . Based on the formulation above, we have

$$\mathbf{E}[\pi_L] = \pi_0 \mathbf{V} \mathbf{\Lambda}^L \mathbf{V}^{-1} \begin{bmatrix} 0 & 1 & \cdots & M \end{bmatrix}^\top = \sum_{i=1}^M \lambda_i^L v_{M,i} \sum_{j=1}^i j u_{i,j} \quad (82)$$

$$= \lambda_1^L v_{M,1} u_{1,1} \left( 1 + \sum_{i=2}^M \frac{\lambda_i^L v_{M,i}}{\lambda_1^L v_{M,1} u_{1,1}} \sum_{j=1}^i j u_{i,j} \right) \quad (83)$$

$$= \Theta(\lambda_1^L), \quad (84)$$

where (83) follows from the fact that  $v_{M,1} u_{1,1} > 0$ , and (84) is obtained by noting that

$$\sum_{i=2}^M \frac{\lambda_i^L v_{M,i}}{\lambda_1^L v_{M,1} u_{1,1}} \sum_{j=1}^i j u_{i,j} = o(1) \quad (85)$$

as  $\lambda_i \leq \lambda_1$  for  $i \geq 2$ . By (81), we further have

$$\lambda_1 = \sum_{k=1}^N f(k; N, \epsilon) (1 - q^{-k}) = \sum_{k=1}^N f(k; N, \epsilon) - \sum_{k=1}^N f(k; N, \epsilon) q^{-k} \quad (86)$$

$$= 1 - f(0; N, \epsilon) - \sum_{k=1}^N \binom{N}{k} (1 - \epsilon)^k \epsilon^{N-k} q^{-k} = 1 - (\epsilon + (1 - \epsilon)/q)^N. \quad (87)$$

The proof is completed. ■